# Decomposing long-run carbon abatement cost curves - robustness and uncertainty

**by**

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I, Fabian Kesicki, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Fabian Kesicki, 9 January 2012

## Publications based on this PhD thesis

*Peer-reviewed journals:*

- **Kesicki, Fabian and Paul Ekins** (2011): "Marginal abatement cost curves: a call for caution", Climate Policy, in press
- **Kesicki, Fabian and Neil Strachan** (2011): "Marginal abatement cost (MAC) curves: confronting theory and practice ", Environmental Science and Policy 14 (8), p. 1195-1204
- **Kesicki, Fabian and Gabrial Anandarajah** (2011): "The role of energy-service demand reduction in global climate change mitigation: combining energy modelling and decomposition analysis ", Energy Policy 39 (11), p. 7224-7233

*Conferences:*

- **Kesicki, Fabian** (2011): "Why are MAC curves robust to different fossil fuel prices? An application to the UK power sector", Stanford: Semi-annual ETSAP workshop, July 9th 2011
- **Kesicki, Fabian** (2011): "Intertemporal Issues and Marginal Abatement Costs in the UK Transport Sector", Rome: 18th Annual Conference of the EAERE, June 29th-July 2nd 2011
- **Anandarajah, Gabrial and Fabian Kesicki** (2010): "Global Climate Change Mitigation: What is the Role of Demand Reduction," Vilnius: 11$^{th}$ IAEE European Conference, August 25$^{th}$ -28$^{th}$ 2010
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**Abstract**

Policy makers in the United Kingdom (UK), as in many countries around the world, are confronted with a situation of legally binding commitments to reduce carbon emissions. In this context it remains an open question of how to find a cost-efficient approach to climate change mitigation. Marginal abatement cost (MAC) curves have already been applied to help understand the economics of many different environmental problems and can likewise assist with illustrating the economics of climate change mitigation. Current approaches to generate MAC curves rely mostly on the individual assessment of each abatement measure, which are then ranked in order of decreasing cost-efficiency. These existing ways of generating MAC curves fail to allow both the graphical representation of the technological detail and the incorporation of system-wide behavioural, technological, and intertemporal interactions. They also fail to provide a framework for uncertainty analysis. This dissertation addresses these shortcomings by proposing a new approach to deriving MAC curves through the combination of an integrated energy system model, UK MARKAL, and index decomposition analysis. The energy system model is used to capture system-wide interactions, while decomposition analysis permits the analysis of measures responsible for emissions reduction. Sensitivity analysis and stochastic modelling are also employed to represent how sensitive the measures are to variations of the underlying drivers and assumptions, as well as how they interact. With a focus on the UK and the year 2030, as an important intermediate emissions reduction target, system-wide MAC curves are presented accompanied by a detailed analysis of the power, transport, and the residential sectors. This analysis allows important insights to be made into the economics of emissions mitigation, as well as investigating the robustness of findings. The results of the dissertation project represent a suitable orientation base for decision making in long-term climate policy.

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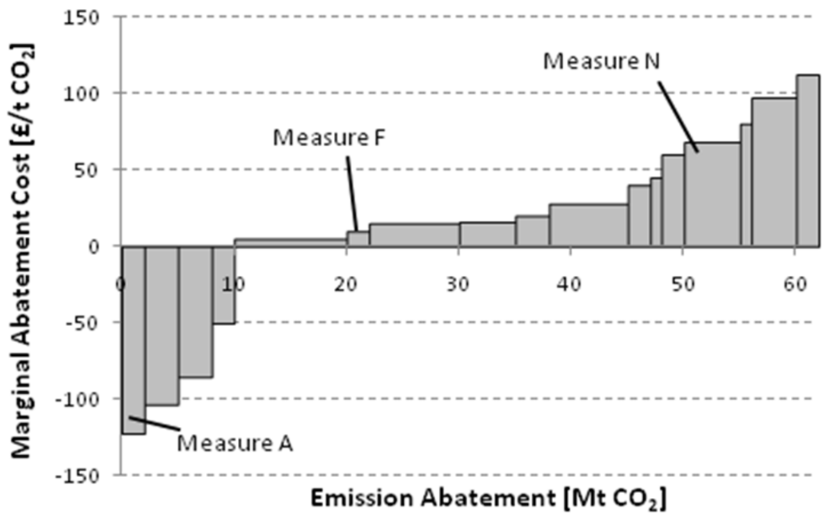
# 1 INTRODUCTION

## 1.1 Abatement cost curves and climate policy

Policy makers in many countries around the world are confronted with the task of how to reduce carbon emissions. The first concerted, multilateral effort to tackle rising greenhouse gas emissions (GHG) was undertaken at the third Conference of the Parties (COP 3) of the United Nations Framework Convention on Climate Change (UNFCCC) with the Kyoto Protocol (United Nations 1998). In this Protocol, mostly industrialised countries commit themselves to a reduction target of six GHGs for the years 2008 to 2012. Within the European Union, member states agreed to reduce GHG emissions by at least 20% by 2020 compared to 1990 (Commission of the European Communities 2008). Additionally, the United Kingdom (UK) has adopted a law with the goal to ensure that carbon emissions in 2050 are 80% below the level in 1990 (The Parliament of the United Kingdom of Great Britain and Northern Ireland 2008).

**Figure 1.1: Sample MAC curve**




Confronted with a situation of legally binding commitments, the question arises of how to reduce carbon emission in a cost-efficient way. For this purpose, marginal abatement cost (MAC) curves have frequently been used to illustrate the economics of climate change mitigation and have contributed to decision making in the context of climate policy (see Figure 1.1). The complexity of climate change mitigation and the diversity of involved stakeholders make a shorthand communication like MAC curves very useful. In addition, economic criteria have been singled out as dominant in the policy discussion (see e.g. DECC 2009b).

A MAC curve is the first derivative of the total cost curve, which is dependent on the abatement level. A MAC curve is defined as a graph that indicates the marginal cost of emission abatement for varying amounts of emission reduction (Ellerman and Decaux 1998, p. 3). It allows one to analyse the cost of the last abated unit of emissions, such as carbon dioxide ($CO_2$), for a defined abatement level while obtaining insights into the total abatement costs through the integral of the abatement cost curve.

$CO_2$ emissions are seen as an externality whose cost do not have to be borne by the emitters. To change this situation a range of climate policy instruments are at the disposal of policy makers, ranging from taxes and cap-and-trade schemes, to standards and deployment policies. MAC curves can be used as a first tool to assess the impact and usefulness of different climate policy instruments. Kesicki and Strachan (2011) discuss in more detail the use of MAC curves for the assessment of specific policy instruments and the implicit $CO_2$ price for policy instruments.

## 1.2 Use of MAC curves in the United Kingdom and beyond

MAC curves are used in many countries. In 2005, a report for the UK Department for the Environment, Food and Rural Affairs (Watkiss et al. 2005, p.10) did not find many governments using MAC curves for policy and decision making. Since then many countries have begun to assess their climate policies through MAC curves. Within the scope of the attempt to introduce a carbon tax in France for example, model-based estimations of MACs were used during the consultation process (Quinet 2009).

Official institutions of the European Union (EU) have relied heavily on MAC curve studies for the cost assessment of emissions reductions concerning different sectors and gases (see e.g. Blok et al. 2001). Similarly, the US Environmental Protection Agency (2006) and the US Climate Change Science Program (Clarke et al. 2007) have commissioned reports using MAC curves as an illustrative tool.

Moreover, MAC curves have influenced actions of supranational bodies, such as the World Bank and the International Maritime Organisation (Buhaug et al. 2009), and governments in many other countries around the world including Ireland (Kennedy 2010), Mexico (Johnson et al. 2009), and China (World Bank 2004). While most of the

MAC curve studies have focused on the energy sector, cost curves have also gained in importance in the agriculture and forest sector over the last years. From the early 2000s, studies have examined abatement costs for methane and nitrous oxide emissions from agriculture (Vermont and De Cara 2010). In the mid-2000s, MAC curves started to be used in the forest sector as reducing emissions from deforestation and forest degradation (REDD) increasingly became to be seen as a low-cost abatement alternative to the energy sector (Dresner et al. 2007). They have been used, for example, by national governments for their REDD readiness plan, e.g. Congo (Ministry of Environment Conservation of Nature and Tourism 2010, p. 49).

The UK provides a good and transparent example, in the sense that many policy support documents are published, of the extensive use of MAC curves in shaping Government's climate change policy. This is emphasised by government reports that use MAC curves, such as the UK Low Carbon Transition Plan (HM Government 2009) and the carbon valuation approach by the Department of Energy and Climate Change (DECC) (2009a).

On a domestic level, the Committee on Climate Change (CCC), an independent body set up to advise the UK Government on reducing GHG emissions, established MAC curves for several sectors. These include the waste sector (Hogg et al. 2008), the transport sector (AEA Energy & Environment et al. 2008), renewable heat (NERA Economic Consulting and AEA Energy & Environment 2009) and industry and buildings (Weiner 2009). In total, ten studies have been commissioned either by the CCC and other Government departments to establish MAC curves for various parts of the energy sector. In addition, some findings are based on earlier MAC curves, which have been calculated by McKinsey & Co. for the Confederation of British Industry (2007).

The sectoral abatement reports influence the recommendations of the CCC presented to the Parliament (Committee on Climate Change 2008; Committee on Climate Change 2009; Committee on Climate Change 2010). Furthermore, the UK government itself used MAC curves as a guide to the potential and future costs of technical measures for the Energy White Paper (HM Government. Department of Trade and Industry 2007, p. 286), the UK Low Carbon Transition Plan (HM Government 2009, p. 40ff) and the Government's report entitled "Warm Homes, Greener Homes: A Strategy for Household Energy Management" (HM Government 2010). However, there are difficulties in transforming insights from these curves into political action since a government does not always target individual technologies and has to deal with overlapping policies.

For carbon reduction in an international context, the decisions of DECC in international negotiations for a post-Kyoto protocol are to some extent based on the results of the Global Carbon Finance model (GLOCAF) (Carmel 2008; Gallo et al. 2009). This model uses a business-as-usual emission scenario as well as MAC curves for different regions and sectors as inputs. With these assumptions, the model can be used to estimate costs and international financial flows that arise from international emission reduction commitments.

Further to these practical applications, MAC curves have been used in theoretical policy considerations of emission abatement and the influence of innovation (McKitrick 1999; Klepper and Peterson 2006; Bauman et al. 2008). These theoretical discussions focus on the abatement possibilities of single enterprises, rather than the whole economy or the energy sector as is the case in policy-directed MAC curves. Klepper and Peterson (2006) describe how an economy-wide MAC curve is linked to a curve for a single production plant.

## 1.3 Main research objectives

The goal of this thesis is to generate technologically detailed, consistent MAC curves with the help of an energy system model considering behavioural, intertemporal, technological and economic interactions. Furthermore, the sensitivity of the MAC curve in respect to the key assumptions should be studied giving an indication of the robustness of the curve. This is of particular importance because of uncertainties concerning assumptions on technology costs, technology availability or energy prices, as well as interactions between technologies and intertemporal interactions, i.e. how earlier actions determine later abatement costs.

With the proposed approach, it will be also possible to open the black box nature of the energy model to a certain extent. The importance of drivers in the model can be represented in greater detail with a technologically detailed MAC curve. Moreover, this can give information on the basic assumptions and parameters of the model (see also 2.4).

Accordingly, the thesis turns towards the following questions:

- What contribution can measures (technologies, behavioural changes, efficiency gains, fuel switches) achieve for the reduction of $CO_2$ up to the year 2050?

- What influences the abatement costs and to what extent? (e.g. emission driver, energy prices, emission trade, level of substitution possibilities)

- How do the reduction measures interact, and what then is the robustness of otherwise economically attractive portfolios and abatement strategies?

The relevance of this thesis in the context of climate change mitigation consists in advancing current research in the way that it presents a MAC curve with a detailed description of technologies in the energy system. By the means of an energy system model, it will be possible to quantify effects of changes in the choice of substitution possibilities or fuel prices on the MAC curve. In this way not only technological detail, but also a degree of uncertainty in the form of sensitivity analysis and stochastic modelling is integrated into a model-based abatement curve. This again can give insights into the cost efficiency of strategies for the reduction of $CO_2$ emissions and represents a suitable orientation base for robust decision making in long-term climate policy. Consequently, policy decisions that are currently partially based on MAC curves, as e.g. in the UK, can be improved by considering system-wide interactions and a degree of robustness by highlighting the results' dependency on key drivers. To present the best information taking into account associated uncertainties is crucial, as it is the basis for long-lasting decisions in the context of climate policy. The reason is that the transition period to a low-carbon world is likely to take 40 to 60 years (Weyant 1993) because of long-lasting investments in the energy sector.

## 1.4 Focus of thesis

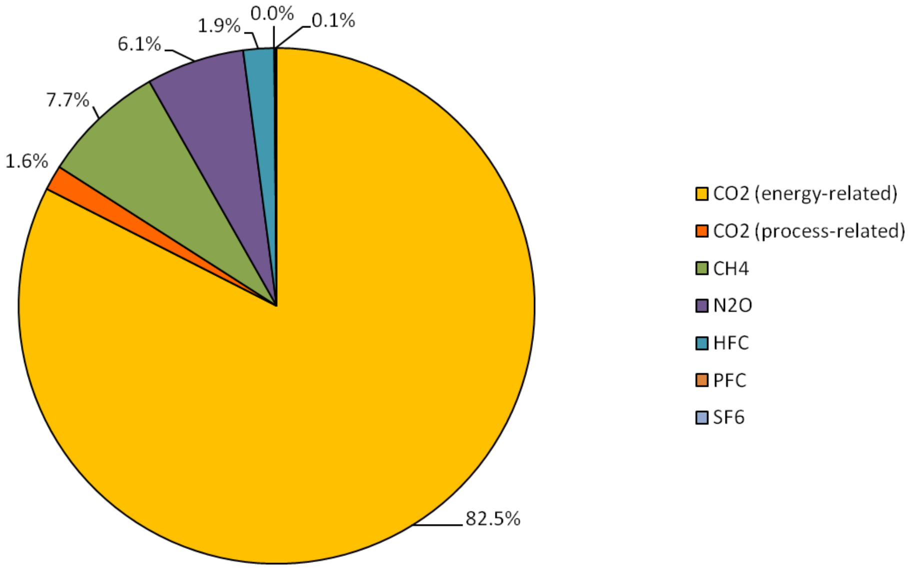
This section outlines the focus of the thesis and sets out the scope of the study. In the context of climate change, this thesis focuses on the mitigation of climate change. Therefore, it does not consider any costs or actions associated with adaptation to climate change nor any damage costs provoked by climate warming.

Furthermore, the focus is on the UK as one developed country committed to carbon emission reduction. Thus, the thesis does not consider the option to buy carbon permits from other countries in order to offset emissions.

As the MAC curve is a key concept in this thesis, it has to be made clear what terms are contrasted in such a graph. On one side, the thesis studies energy-related $CO_2$ emissions, and does not consider "land-use" $CO_2$, forest related emissions or other GHGs, like methane ($CH_4$), nitrous oxide ($N_2O$), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulphur hexafluoride ($SF_6$) emissions. Kesicki and Ekins (2011), for example, discuss the use of MAC curve in the forestry sector.

Figure 1.2 shows that the restriction to energy-related $CO_2$ emissions still captures the vast majority of all GHG emissions with 82.5%. This restriction can be put into perspective in the light of the political focus on $CO_2$ emissions and the fact that part of $CH_4$ and $N_2O$ emissions have the same source as $CO_2$emissions. Nevertheless, MAC curves have been equally applied for non-$CO_2$ GHGs. For examples see Reilly et al. (1999), Hayhoe et al. (1999), and US EPA (2006).

**Figure 1.2: Anthropogenic greenhouse gas emissions (weighted according to global warming potential) in the UK in 2009**




**Source: Based on DECC (2011)[1]**

On the other side, the costs considered in the MAC curves rely on calculation with an energy system model. Therefore, costs presented in this thesis are direct costs in the energy system for which other macro-economic variables are assumed to be given. That means no macro-economic costs or social costs, which include the value of externalities, are considered in the calculation. Externalities arising from $CO_2$ are to some extent

[1] Permission to reproduce this Figure has been granted by the National Archives

considered via pricing $CO_2$ emissions although the tax level does not necessarily reflect the value of externalities. For a more detailed discussion of costs see chapter 3.4 and Halsnaes et al. (2007, p. 134).

At the same time, the model does not capture any ancillary benefits generated by implementing restrictions on $CO_2$ emissions. In detail, that means that all the costs associated with $CO_2$ reduction are completely attributed to $CO_2$ even when they reduce the emissions of other GHGs or local air pollution. The reduction of air pollution and particulate emissions can improve health and therefore offset part of the costs of $CO_2$ abatement. In addition, the use of fossil fuels is responsible for the biggest share of $CO_2$ emissions. Reducing the consumption of fossil fuels and thereby the reliance on imports of crude oil, natural gas or coal can significantly improve energy security, as long as local energy forms such as wind or tidal energy are used. Accelerating energy efficiency in homes by improving insulation or double glazing can help to reduce fuel poverty. This can be a very effective way to reduce excess winter deaths, which amount to 30,000 per year in the UK (Whitty and Cooper 2000).

## 1.5 Overview

The rest of the thesis is structured as follows: Chapter 2 reviews the literature on different methodologies to generate MAC curves. This includes abatement cost curves generated with expert judgement and those based on different types of models. This chapter concludes with a review of index decomposition analysis before explaining the contribution of this thesis to the existing literature.

Chapters 3 to 5 explain the methods used in this thesis, including energy system modelling, decomposition analysis and uncertainty analysis. All three chapters describe possible other methods that can be used for the purpose of obtaining a MAC curve. The employed method is then discussed and further explanations about its use are given. Chapter 3 deals with different ways of energy modelling and energy system analysis. The focus of chapter 3 is on the partial-equilibrium model used in the context of this thesis. The goal of index decomposition, its history and methods are explained in chapter 4. In addition, this chapter explains the use of decomposition analysis in combination with an energy model to construct technologically detailed abatement curves. Chapter 5 concludes the methodological component of the thesis first by explaining the uncertainty inherent to abatement curves and second by demonstrating how sensitivity analysis and stochastic modelling can help to set out the uncertainty in reference to key assumptions.

Chapters 6 to 9 present the main results of the thesis. Chapter 6 presents abatement cost and abatement potential estimates in the form of MAC curves as a result of a sensitivity analysis for the electricity sector. Chapter 7 discusses the influencing factors on MAC curves for the transport sector, while chapter 8 is dedicated to the residential sector. Chapter 9 presents system-wide MAC curve and the influence of diverse factors on the cost curves. In addition, the stochastic variant of the energy system model is used to expand uncertainty analysis and derive further insights. Chapter 10 concludes the thesis.

## 1.6 References


AEA Energy & Environment, E4Tech, Metronomica, Ricardo, IEEP and CE Delft (2008). Building a UK Transport Supply-side Marginal Abatement Cost Curve. London, Committee of Climate Change.

Bauman, Y., M. Lee and K. Seeley (2008). "Does Technological Innovation Really Reduce Marginal Abatement Costs? Some Theory, Algebraic Evidence, and Policy Implications." Environmental and Resource Economics **40**(4): 507-527.

Blok, K., D. de Jager, C. Hendriks, N. Kouvaritakis and L. Mantzos (2001). Economic Evaluation of Sectoral Emission Reduction Objectives for Climate Change - Comparison of 'Top-down' and 'Bottom-up' Analysis of Emission Reduction Opportunities for $CO_2$ in European Union. Brussels, Ecofys Energy and Environment, National Technical University of Athens.

Buhaug, O., J. J. Corbett, V. Eyring, O. Endrese, J. Faber, S. Hanayama, D. Lee, D. Lee, H. Lindstad, A. Markowska, A. Mjelde, D. Nelissen, J. Nilsen, C. Palsson, W. Wanquing, J. J. Winebrake and K. Yoshida (2009). Second IMO GHG study 2009. London, International Maritime Organisation.

Carmel, A. (2008). Paying for mitigation - The GLOCAF model. United Nations Framework Convention on Climate Change COP 13. Bali, Indonesia.

Clarke, L., J. Edmonds, H. D. Jacoby, H. Pitcher, J. M. Reilly and R. Richels (2007). Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations. Sub-report 2.1A of Synthesis and Assessmnet Product 2.1 by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. Washington, DC., Department of Energy / Office of Biological & Environmental Research.

Commission of the European Communities (2008). 20 20 by 2020 - Europe's climate change opportunity. Brussels.

Committee on Climate Change (2008). Building a low-carbon economy - the UK's contribution to tackling climate change. London.

Committee on Climate Change (2009). Meeting Carbon Budgets - the need for a step change. London.

Committee on Climate Change (2010). Meeting Carbon Budgets - ensuring a low-carbon recovery. 2nd Progress Report to Parliament. London.

Confederation of British Industry (2007). Climate change: Everyone's business. London.

DECC (2009a). Carbon Valuation in UK Policy Appraisal: A Revised Approach. London, Department of Energy and Climate Change.

DECC (2009b). Climate Change Act 2008 Impact Assessment. London, Department of Energy and Climate Change.

DECC (2011). 2009 final UK greenhouse gas emissions: data tables. London, Department of Energy and Climate Change.

Dresner, S., P. Ekins, K. McGeevor and J. Tomei (2007). Forests and Climate Change: Global Understandings and Possible Responses. Forestry & Climate Change. P. H. Freer-Smith, M. S. J. Broadmeadow and J. M. Lynch. Wallingford, CAB International**:** 38-48.

Ellerman, A. D. and A. Decaux (1998). Analysis of Post-Kyoto $CO_2$ Emissions Trading Using Marginal Abatement Curves. Cambridge, MA, Massachusetts Institute of Technology.

Gallo, F., A. Carmel, S. Prichard, J. Rayson, N. Martin, R. Dixon and A. MacDowall (2009). Global Carbon Finance - A quantitative modelling framework to explore

scenarios of the Global Deal on Climate Change. London, Office of Climate Change.
Halsnaes, K., P. Shukla, D. Ahuja, G. Akumu, R. Beale, J. Edmonds, C. Gollier, A. Grübler, M. H. Duong, A. Markandya, M. McFarland, E. Nikitina, T. Sugiyama, A. Villavicencio and J. Zou (2007). Framing Issues. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. B. Metz, O. R. Davidson, P. R. Bosch, R. Dave and L. A. Meyer. Cambridge, UK and New York, NY, USA, Cambridge University Press.
Hayhoe, K., A. Jain, H. Pitcher, C. MacCracken, M. Gibbs, D. Wuebbles, R. Harvey and D. Kruger (1999). "Costs of Multigreenhouse Gas Reduction Targets for the USA." Science **286**(5441): 905-906.
HM Government (2009). Analytical Annex - The UK Low Carbon Transition Plan. London.
HM Government (2010). Warm Homes, Greener Homes: A Strategy for Household Energy Management. London.
HM Government. Department of Trade and Industry (2007). Meeting the energy challenge : a white paper on energy. London, Stationery Office.
Hogg, D., A. Baddeley, A. Ballinger and T. Elliot (2008). Development of Marginal Abatement Cost Curves for the Waste Sector. Committee on Climate Change. Bristol, eunomia research & consulting.
Johnson, T. M., C. Alatorre, Z. Romo and F. Liu (2009). Low-Carbon Development for Mexico. Washington D.C., World Bank.
Kennedy, M. (2010). Ireland's Future: A Low Carbon Economy? The Impact of Green Stimulus Investment. IAEE European Conference. Vilnius, Lithuania.
Kesicki, F. and P. Ekins (2011). "Marginal Abatement Cost Curves: A call for caution." Climate Policy(forthcoming).
Kesicki, F. and N. Strachan (2011). "Marginal abatement cost (MAC) curves: confronting theory and practice." Environmental Science & Policy **14**(8): 1195-1204.
Klepper, G. and S. Peterson (2006). "Marginal abatement cost curves in general equilibrium: The influence of world energy prices." Resource and Energy Economics **28**(1): 1-23.
McKitrick, R. (1999). "A Derivation of the Marginal Abatement Cost Curve." Journal of Environmental Economics and Management **37**(3): 306-314.
Ministry of Environment Conservation of Nature and Tourism (2010). Readiness Plan for REDD 2010-2012. Kinshasa, Democratic Republic of Congo.
NERA Economic Consulting and AEA Energy & Environment (2009). The UK Supply Curve for Renewable Heat - Study for the Department of Energy and Climate Change. London.
Quinet, A. (2009). La valeur tutélaire du carbone. Paris, Centre d'analyse stratégique - Premier Ministre. **N°16**.
Reilly, J., R. Prinn, J. Harnisch, J. Fitzmaurice, H. Jacoby, D. Kicklighter, J. Melillo, P. Stone, A. Sokolov and C. Wang (1999). "Multi-gas assessment of the Kyoto Protocol." Nature **401**(6753): 549-555.
The Parliament of the United Kingdom of Great Britain and Northern Ireland (2008). Climate Change Act 2008. London.
United Nations (1998). Kyoto Protocol to the United Nations Framework Convention on Climate Change. United Nations. New York.
United States Environmental Protection Agency (2006). Global Mitigation of Non-$CO_2$ Greenhouse Gases. Washington, DC.

US EPA (2006). Global Mitigation of Non-$CO_2$ Greenhouse Gases. Washington, DC, United States Environmental Protection Agency.

Vermont, B. and S. De Cara (2010). "How costly is mitigation of non-CO2 greenhouse gas emissions from agriculture?: A meta-analysis." Ecological Economics **69**(7): 1373-1386.

Watkiss, P., D. Anthoff, T. E. Downing, C. Hepburn, C. Hope, A. Hunt and R. S. J. Tol (2005). The Social Costs of Carbon (SCC) Review - Methodological Approaches for Using SCC Estimates in Policy Assessment. London, AEA Technology Environment.

Weiner, M. (2009). Energy Use in Buildings and Industry: Technical Appendix. London, Committee on Climate Change.

Weyant, J. P. (1993). "Costs of Reducing Global Carbon Emissions." Journal of Economic Perspectives **7**(4): 27-46.

Whitty, J. L. and Y. Cooper (2000). Fuel Poverty and Health. Department of Health.

World Bank (2004). Clean Development Mechanism in China. Washington, D.C.

# 2 LITERATURE REVIEW

This chapter gives an overview of the existing approaches explained in the literature concerning the elaboration of a key concept of this thesis – the marginal abatement cost (MAC) curve – and its wider role in the context of climate change mitigation. This section provides a summary of the literature in this field, while determining the most important works in the relevant areas and their impact on the research field.

The chapter starts by giving a broad overview of the most important literature on the financial costs associated with climate change mitigation. Subsequently, it turns to the concept of MAC curves and their role in the wider context of assessing a cost-effective pathway towards a decarbonisation of the energy system. The different methods to derive MAC curves are discussed in detail together with their respective strengths and weaknesses. In a further section, reasons for using decomposition analysis are given and the literature regarding this method is reviewed. Finally, the chapter is concluded with a section that explains research gaps in existing literature and details how the thesis' contribution fits into existing research on the economics of climate change mitigation.

## 2.1 International background to climate change mitigation

In general, decision makers have three possibilities to confront anthropogenic global warming: adaptation, mitigation and suffering (Holdren 2006, p. 12). Adaptation to climate change aims to reduce the adverse impacts of climate change, while mitigation aims to reduce greenhouse gas emissions. All three options are not mutually exclusive, e.g. a larger amount of mitigation can limit adaptation efforts or suffering from adverse impacts. For the reasons explained in chapter 1, this thesis focuses on mitigation. Issues concerning climate change adaptation were, for example, discussed by Parry et al. (2007) and Willows and Connell (2003). Literature on the trade-offs between mitigation of and adaptation to climate change can be found in Tol (2005) and van der Zwaan and Rabl (2008). In the Stern report (2007, p. 26), MAC curves were compared to the social cost of carbon in order to determine the optimal degree of abatement. Nevertheless, both cost estimates are subject to temporal dynamics and uncertainty.

Soon after $CO_2$ emissions aroused the interest of the research community, the quantification of the costs that are needed to abate greenhouse emissions provoked a great research effort, which started in the 1970s (see e.g. Nordhaus 1977).

The United Nations Framework Convention on Climate Change (UNFCCC), which is an international body to coordinate the intergovernmental efforts to tackle the challenge posed by climate change, highlighted in article 3 (United Nations 1992, p. 4)

*“[...] policies and measures to deal with climate change should be cost-effective so as to ensure global benefits at the lowest possible cost.”*

This highlights the fact that cost-effectiveness was considered a very important aspect from the beginning of international treaties on climate change mitigation.

On an international level, the Intergovernmental Panel on Climate Change (IPCC), a UN institution aiming to present a clear scientific view on the current state of knowledge in climate change and its potential environmental and socio-economic impacts, focused the research attempts in this area starting in 1988. The IPCC is composed of three working groups, where one of the core objectives of working group 3 (mitigation of climate change) is to analyse the costs and benefits of the different approaches to mitigation, considering equally the available instruments and policy measures. This was manifested in the four assessment reports that were published in 1990, 1995, 2001, and 2007 and represent the most comprehensive scientific report in this area. The fact that mitigation costs play a pivotal role in the IPCC’s reports can be seen in the Fourth Assessment Report that indicates estimates for a mitigation potential and a cost range for each sector in the energy system (Barker et al. 2007, p. 632).

## 2.2 MAC curve

Many studies have attempted to quantify the costs of reducing greenhouse gas emissions with respect to their potential and cost and to put them in the context of global mitigation strategies. Different modelling approaches were applied to this problem, and most of them reverted to the concept of MAC curves.

Such concepts are not only restricted to the reduction of greenhouse gases. Carbon MAC curves are inspired by earlier cost curves that were developed after the two oil price shocks in the 1970s for the saving of crude oil consumption [$/bbl]. Then in the early 1980s, technology cost curves where developed for the saving of electricity consumption [$/kWh]. In this context, the curves were called conservation supply curves (CSC) and date back to the work of Meier (1982). CSCs quickly became a widely-used, analytic tool for the assessment of efficiency improvements mainly in industry and buildings (Difiglio and Duleep 1990; Farugui et al. 1990; Ledbetter and Ross 1990; Rosenfeld et al. 1993; Blumstein and Stoft 1995). This was in parts supported by the requirement for utilities in the USA to implement cost-effective conservation measures before permitting the construction of a new power plant (Meier 1982, p. 7). Furthermore, MAC curves were widely used for the assessment of abatement potential and costs of air pollutants [$/kt] (Rentz et al. 1994), waste reduction [$/kg] (Beaumont and Tinch 2004) and lately for additional water availability [$/m$^3$] (Addams et al. 2009).

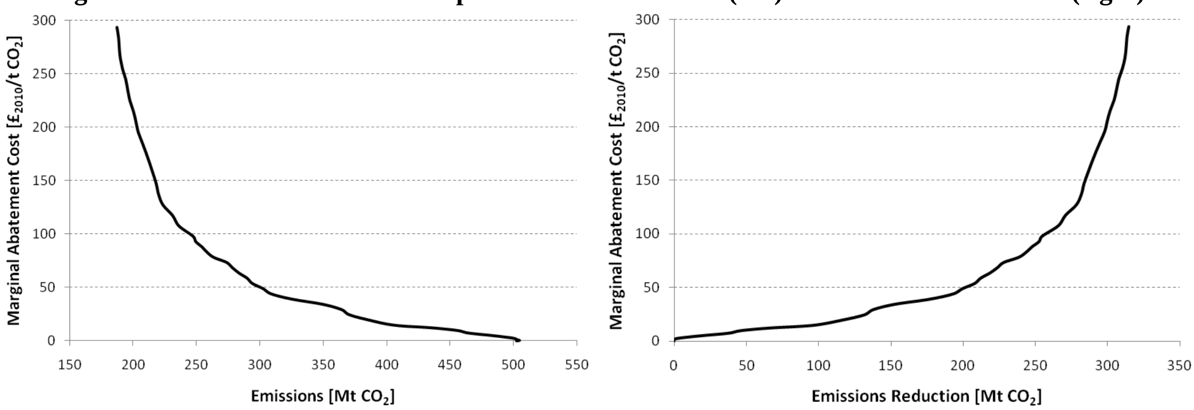
A MAC curve not only allows for the analysis of the cost of the last abated unit of $CO_2$ emissions for a defined abatement level, but also demonstrates insights into the total abatement costs via the integral of the curve. It provides an informative snapshot of emission mitigation options for decision-makers. The advantage of contrasting marginal cost to abatement level is that it shows in a very simple way the $CO_2$ tax (=marginal abatement cost) associated with a certain reduction level or the carbon price resulting from an emissions cap in a cap-and-trade system. This is based on the logic that all abatement measures up to the $CO_2$ tax will be implemented. Thus, MAC curves can be a first guide for policy makers concerning market-based climate policy instruments. For the other category of climate policy instruments, command-and-control measures, MAC curves can indicate subsidy levels for feed-in-tariffs or the abatement potential of building standards. Technology-specific MAC curves can also reveal what measures or sectors should be considered first for emissions reduction from a cost-effectiveness perspective. Summarising, MAC curves do not only reveal important information on the economics of climate change mitigation, but also provide helpful insights for the assessment of climate policy tools. Compared to more complex scenario analysis based on energy models, MAC curves have the advantage that essential information is presented in an easy-to-understand format. For these reasons, MAC curves are judged a good way to assess and communicate the cost-effectiveness of emissions reduction.

However, there are some weaknesses associated with MAC curves. Abatement costs are usually shown only for a specific year, although the MAC curve depends on actions in earlier time periods and also how much $CO_2$ emission are assumed to be abated in the following years. Thus, the MAC curve is subject to intertemporal dynamics. Moreover, MAC curves usually include direct costs, i.e. the cost reduction due to ancillary benefits, such as health improvement, and transaction/implementation costs are not considered in the abatement cost. Most MAC curves in the existing literature do not present the assumptions that were used for calculating abatement costs and potentials and do not represent the influence of uncertainty in their assumptions. This can reduce the usefulness of MAC curves. Comparative studies can help to make the influence of model assumptions on MAC curves more transparent.

Related to the graphical representation of a MAC curve, one can distinguish between those that specify abatement measures and those that merely show an abatement curve without showing the measures that are responsible for the abatement. This is important for decision-makers as technology-detailed MAC curves present a lot more information than a simple abatement curve. Referring to the underlying method used to construct a MAC curve, one can distinguish two categories of abatement curves: expert-based approaches and model-based approaches.

MAC curves can be either displayed with the emission level on the abscissa (see Figure 2.1, left) or the emissions reduction (see Figure 2.1, right). Both representations are MAC curves, but to avoid any confusion the former concept is described as an emission curve in this thesis. This representation not only allows insights into the emission reduction from a baseline, but also puts the absolute emissions into perspective.

**Figure 2.1: Different MAC curve representation: emissions (left) and emissions reduction (right)**

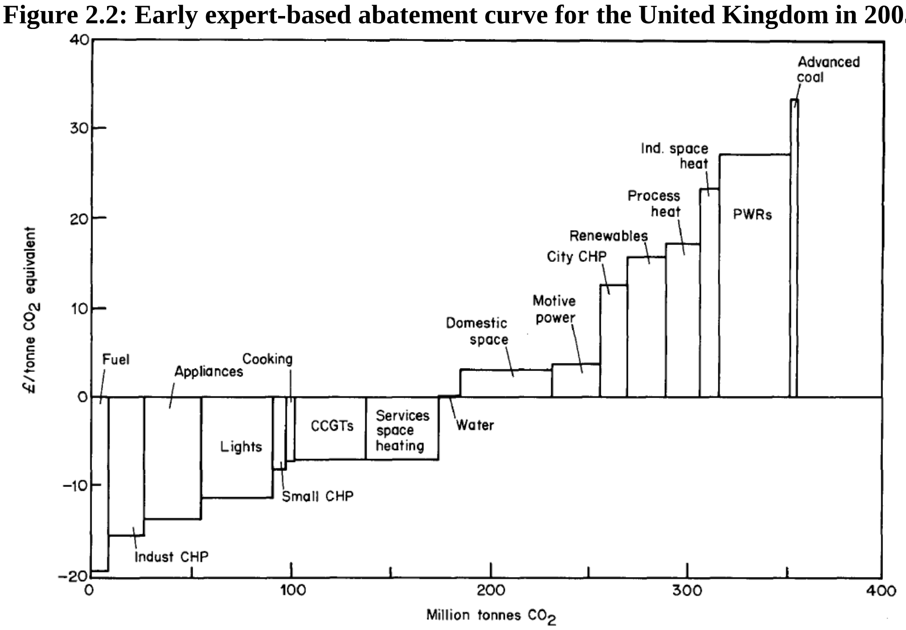



### 2.2.1 Expert-based approaches

Expert-based approaches, sometimes also called technology cost curves, are generated by assessing the emission reduction potential and the corresponding costs of individual measures or technologies. Subsequently, the technologies are ranked from the cheapest to most expensive to represent the costs of achieving incremental levels of emissions reduction. Expert information input in those studies can vary significantly from brainstorm meetings to detailed sectoral analysis combined with calculations in spreadsheets.

The earliest examples of carbon-focused expert-based curves, which used similar methods to the ones used by earlier cost curves for energy savings, date back to the early 1990s (Jackson 1991; Mills et al. 1991; Sitnicki et al. 1991). In Figure 2.2, one can see an early example of an abatement curve for the United Kingdom. In the graph, the width of each bar represents the abatement potential and the height represents the respective marginal abatement cost. In contrast to later studies, nuclear power is one of the most expensive abatement options. In contrast to many expert-based MAC curve at the time, Jackson (1991) tried to integrate a certain aspect of uncertainty into his work by varying the degree of leakage from natural gas pipelines. Further on, he pointed out the significance of the base case against which mitigation measures are judged. Building on this work similar studies on the costs associated with the reduction of energy-related $CO_2$ emissions were created, summarised in Grubb et al. (1993).

**Figure 2.2: Early expert-based abatement curve for the United Kingdom in 2005**




**Source: Jackson (1991)[1]**

In 1992, Rubin et al. (1992) presented a marginal cost curve for the abatement of $CO_2$ for the United States. In this context, the article focused in particular on end-use technologies in the building sector, but noted as well the significant differences in

[1] Permission to reproduce this Figure has been granted by Elsevier

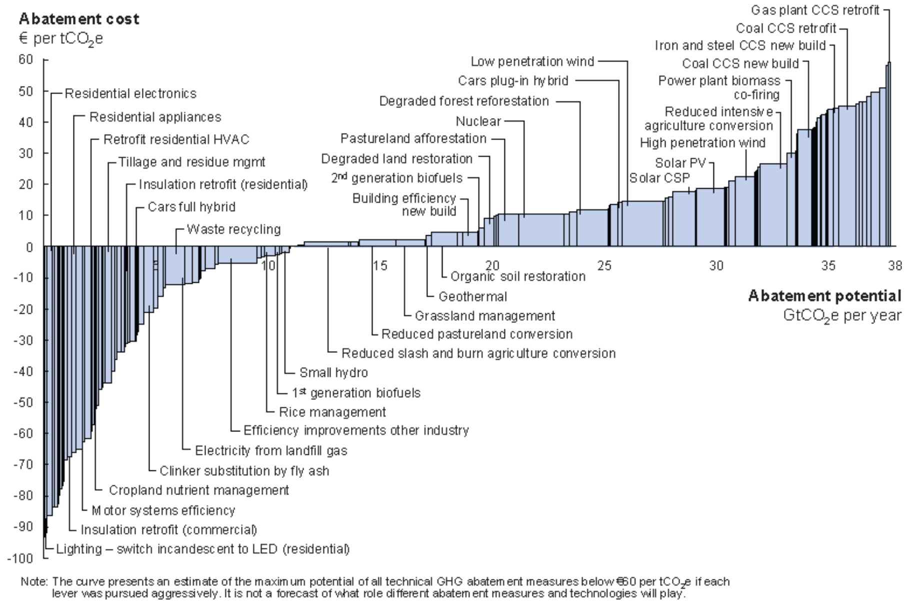
abatement potentials between the USA and the rest of the world. Furthermore, the authors mention problems when constructing MAC curves. Indirect costs and agency issues are discussed as reasons for much higher implicit discount rates of investments in mitigation measures.

Over the course of the last two decades many other abatement cost curves have been constructed for national economic sectors, whole countries or even on a global level. During this process the curves were refined by including more and more abatement measures and trying to incorporate more than technology inherent costs and barriers, such as a heterogeneous population or gradual technology diffusion. Blok et al. (1993) established, for example, a very detailed abatement cost curve for the Netherlands. In a next step, they considered the payout time of some of the mitigation measures under the assumptions of an investment grant or a carbon tax.

After a period at the start of the 21st century, where interest in expert-based MAC curves seemed to be limited, such curves again received much attention in recent years due to the work of McKinsey & Company (Enkvist et al. 2007; Vattenfall 2007; Nauclér and Enkvist 2009). While McKinsey & Company started with abatement cost curves on a country level (see for example Vahlenkamp et al. 2007), in 2009 they published one of the few global expert-based MAC curves (see Figure 2.3). This study shows not only a depth of detail concerning the different situations in various parts of the world, but also concerning the abatement possibilities in various sectors of the energy system and beyond. McKinsey & Company assessed every single measure drawing on expertise of many experts and associations. The global study stands out for its technological detail incorporated into the abatement cost curve, as well as for its attempt to bring in a certain degree of uncertainty into such cost curves. Various degrees of implementation of the abatement potential are discussed, as well as sensitivity to energy prices, technological learning rates and interest rates levels (Nauclér and Enkvist 2009, pp. 50ff).

This very significant work engaged many stakeholders into a debate about climate change mitigation that did not participate before. The simple layout of MAC curves illustrating the costs associated with $CO_2$ emissions reduction is well suited to communicate this issue to a broader audience and was well marketed by McKinsey & Company. Nevertheless, the McKinsey abatement curves were not only used as a communication device but were also presented as a decision-making aid for policy makers in the field of climate change mitigation. Regulatory measures were related to different parts of the abatement cost curve to provide insights for energy efficiency standards, deployment policies, and long-term incentives for the power sector (Nauclér and Enkvist 2009, p. 19). Next to the general disadvantages of the expert-based approach, the drawbacks of this work include the non-disclosure of the majority of all input assumptions, which makes it impossible to reproduce the results. Furthermore, all calculations are implemented from a societal perspective with an interest rate set at four percent. This can answer questions about what is best for a society as a whole, but it does not tell the reader what will happen in reality as investors and individuals face substantially higher interest rates.

**Figure 2.3: McKinsey global expert-based abatement curve in 2030**



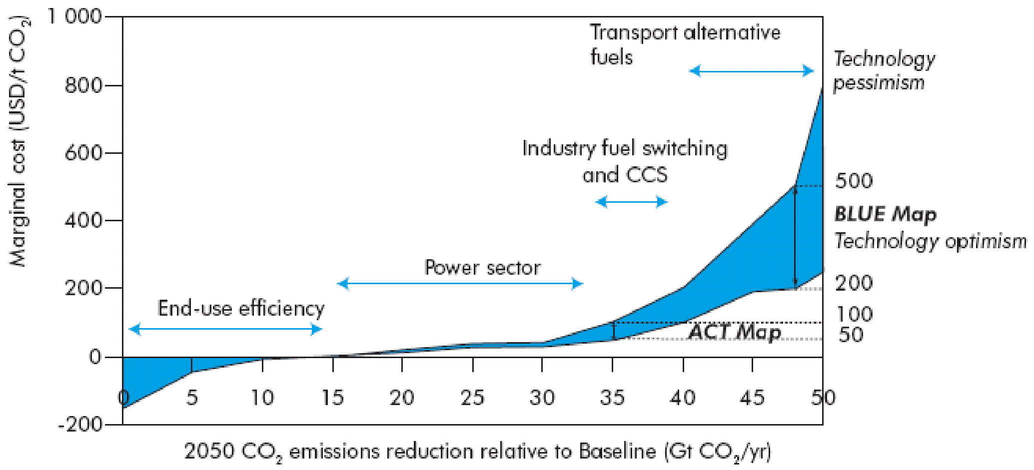

**Source: Nauclér and Enkvist (2009)[2]**

MAC curves gain also more and more importance in developing countries as emissions reduction is viewed as a potential path to address poverty and energy access. Casillas and Kammem (2010) published a MAC curve for a small community in Nicaragua based on monitoring. The authors point out that development in the context of climate change mitigation was hampered by the lack of easy-to-understand metrics that can be addressed by MAC curves. A report by the EBRD (2011) displays MAC curves for Russia and Turkey and noted particularly that the curves were influenced by political conditions in those countries, such as distortionary taxes and subsidies, an elevated investor risk and high transaction costs.

[2] Permission to reproduce this Figure has been granted by McKinsey & Company.

The International Energy Agency (IEA) adopted the approach to represent abatement potentials and costs in its Energy Technology Perspectives report based on expert information from the IEA Implementing Agreements (International Energy Agency 2008a). In this study, the authors use a cost band to represent optimistic and pessimistic assumptions on specific technology developments. Even if the cost curve is not technologically detailed, it gives some understanding of the cost of broad technological categories that have to be used to achieve predefined reduction scenarios.

**Figure 2.4: IEA global marginal abatement curve in 2050**




**Source: International Energy Agency (2008a)[3]**

The CCC established expert-based MAC curves for several sectors (Committee on Climate Change 2008). Results of this work were used as one decision-making aid to specify actions for the UK government on carbon reduction.

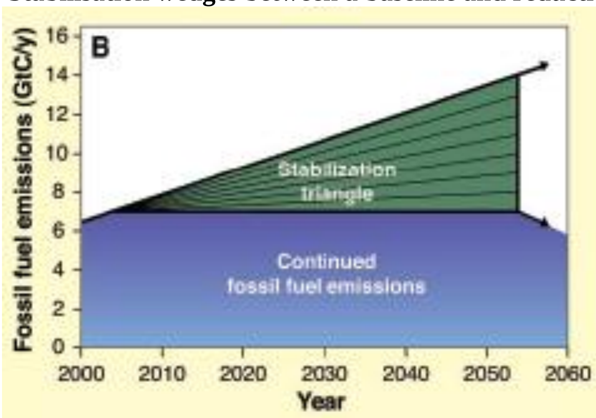
### 2.2.1.1 Mitigation wedges

A similar approach to MAC curves is the decomposition of emission pathways over time, also called mitigation wedges. In this expert-base case, an emission pathway is mapped for a reference case and usually one (sometimes more) reduction scenario. In a next step, the difference between both scenarios is decomposed into reduction amounts that are assigned to supply technologies and demand measures. In contrast to the usual MAC curves, this approach does not report the actual marginal cost of the mitigation measures, but includes a temporal component. In addition, these curves do not consider the market abatement potential, but limit the technical potential by considering some implementation constraints.

[3] Permission to reproduce this Figure has been granted by the International Energy Agency (Energy Technology Perspectives© OECD/International Energy Agency 2008, Figure 2.14, page 81)

The first such approach were the "stabilisation wedges" by Pacala and Socolow (2004) (see Figure 2.5). The stabilisation triangle, which represents the area between the baseline emission pathway and the reduction scenario emission pathway, is divided into seven equal wedges representing each a reduction measure. Each wedge represents a linearly increasing annual emission saving that reaches 1 Gt of Carbon in 2050. Examples for a wedge are efficient vehicles, $CO_2$ capture at baseload plants or wind power instead of coal power. Although possible interactions between the wedges are mentioned in the article, it is not clear to what extent they are considered.

**Figure 2.5: Stabilisation wedges between a baseline and reduction scenario**




**Source: Pacala and Socolow (2004)[4]**

A similar approach is the "PRISM" analysis of the Electric Power Research Institute (James et al. 2007; James 2008). The creators use the same graphical representation as Pacala and Socolow, but constrain their analysis to the electric sector in the United States up to 2030. In contrast to the stabilisation wedges, the "PRISM" approach is technologically more detailed, drawing on their own expertise in the power sector.

In the same way, the International Energy Agency compared in the World Energy Outlook 2008 (International Energy Agency 2008b, p. 446), a reference scenario with two different scenarios and decomposed the emission reduction into different measures. The authors distinguish between different supply options in the electricity sector, biofuels and end-use efficiency, but do not state how the emission saving is decomposed.

### 2.2.1.2 Advantages and disadvantages of expert-based MAC curves

MAC curves of the type presented in this section show some advantages, but also some drawbacks compared to other approaches. It should be noted that some of the

[4] Permission to reproduce this Figure has been granted by the AAAS.

disadvantages linked to expert-based abatement curves were already discussed in the context of conservation supply curves (CSC). Meier (1982) mentioned the problem to capture market failure (i.e. that the curves only show the technical potential) and demand response, while Stoft (1995) discussed measure interaction, consistent baseline assumptions and rebound effect as problems in the construction of CSCs. Willemé (2003) tried to overcome the problem of measure interaction by developing a statistical approach.

On the one hand, the biggest advantage of expert-based abatement cost curves is that they are easily understood. In most of the presented abatement cost curves, the marginal costs and the abatement potential can be unambiguously assigned to one mitigation option. Furthermore, the technological detail can be very extensive, depending on the refinement of the study. This is a major advantage, especially compared to model-based studies, which often lack the technological detail in the representation of MAC curves.

As expert-based MAC curves consider each measure individually, they can integrate technology-specific tax and subsidy distortion in their assessment. In most cases, a technical abatement potential is considered, which provides little information if important institutional and implementation barriers are neglected. For a further discussion on different definitions of abatement potentials see section 3.4. In most cases, MAC curves of this type focus on technical abatement measures without considering demand adaptations. An exception is Blom et al. (2007), who include demand-related factors although without taking into account interactions with supply.

On the other hand, these types of curves achieve some of the mentioned aspects by simplifying reality in a drastic way when assuming an “average world” (Fleiter et al. 2009). It is, for example, implausible to assign a technology only one cost level, as is done in most cases. The cost-effectiveness of many renewable energy sources, like photovoltaic or wind, however depends on the siting of the power generation capacities and its environmental conditions. In addition, an enormous effort in data collection is necessary to cover all technologies, their implementation potential, interactions and dependencies. That is why in certain cases only a selection of technologies are considered as mitigation options, e.g. according to the probability of realisation.

Most country studies do not consider international interactions. However, regional abatement cost curves can be heavily influenced by international trade according to

Klepper and Peterson (2003). This includes technology transfer and also indirect effects, e.g. via energy prices. For sectoral studies, a problem can arise when mitigation costs are implemented from perspectives of different decision makers, such as individuals or companies. This would mean that an accumulation of abatement costs across sectors is not possible.

Besides the use of average costs and the negligence of international interactions, expert-based cost curves can have possible inconsistencies in their baseline assumptions. This concerns, for example, the assumptions on the reference case. The calculation for the abatement potential and marginal cost is done by a comparison to a reference development. In this context, it is important to adapt the reference scenario to the extent that cheaper abatement options have already been implemented in order to avoid double counting.

A further inconsistent aspect can be the non-consideration of intertemporal interactions of emission abatement. The form of the emission pathway, i.e. the abated emission amount prior and after the considered point in time has a significant impact on the abatement curve.

A last disadvantage concerns the representation of uncertainty considering many factors, like technology costs, energy prices, discounting or demand development. Although there have been some attempts to consider a degree of uncertainty in expert-based abatement cost curves, in most cases this is missing. In particular, concerning curves for years far in the future, e.g. 2030 or 2050, there exist major uncertainties concerning several factors with an influence on the abatement curve. Moreover, this includes interdependencies between uncertainties and how they interact. Those uncertainties should be represented in an appropriate way as has been done for energy prices by McKinsey & Company in their latest study (Nauclér and Enkvist 2009, p. 54). The advantages and disadvantages of expert-based curves are summarised in Table 2.1.

**Table 2.1: Strengths and weaknesses of MACCs based on expert judgement**

| STRENGTHS | WEAKNESSES |
|---|---|
| ▪ Extensive technological detail<br>▪ Possibility of taking into account technology specific market distortions<br>▪ Easy understanding of technology-specific abatement curves | ▪ No consequent incorporation of behavioural factors<br>▪ No integration of different types of interaction and dependencies between mitigation measures<br>▪ Possibility of inconsistent baseline emissions<br>▪ No representation of intertemporal interactions<br>▪ Very limited representation of uncertainty<br>▪ In some cases, limited to one economic sector without the possibility to accumulate abatement curves across sectors<br>▪ No representation of macroeconomic feedbacks<br>▪ Simplified technological cost structure<br>▪ No consideration of international interactions |

### 2.2.2 Model-based approaches

Another widespread approach is to derive the cost and potential for emission mitigation from model runs. A number of models have been used in this way using a range of techniques (Barker et al. 2007). There have been various criteria established to differentiate modelling approaches: e.g. the purpose of the model, model structure, analytical approach, underlying methodology, geographical or sectoral coverage. The most common way is to distinguish models into economy-orientated top-down models and engineering-orientated bottom-up models (Hourcade et al. 2006; Böhringer and Rutherford 2008).

The two categories of models differ in certain ways. Bottom-up energy models represent only the energy sector. In contrast, top-down models endogenously cover economic responses. For more detail on the two modelling categories, refer to chapter 3.2.

#### 2.2.2.1 Top-down models

Top-down models can be distinguished into computable general equilibrium (CGE) models, growth models, and macroeconometric models (Löschel 2002). CGE-models are most often used for the calculation of MAC curves, while only a few macroeconometric models have been used in the past to derive such curves. For more detail on the different top-down model categories see section 3.2.2.

At the start of the 1990s, the Energy Modeling Forum (EMF) conducted a study, EMF-12, to compare the abatement cost for the United States primarily using top-down economic equilibrium models under standardised assumptions (Gaskins and Weyant 1993; Weyant 1993). In this context, different scenarios were calculated and MAC curves presented for 10 models, which were developed at different institutes.

The carbon tax, which is equal to the marginal abatement cost, required to reduce emissions to 80% of the 1990 level, varied enormously between $\$_{1990}$ 50 and $\$_{1990}$ 330. The difference in the estimates can be mainly explained with different baseline developments, which are strongly dependent on the assumed decrease in energy use per unit of economic output. Other factors explaining the differences are the price elasticity of energy demand and how fast the capital stock adapts to higher energy prices. In addition to that, a sensitivity analysis concerning the cost of non-carbon energy supply technologies, GDP growth and natural gas resources was performed within EMF-12. The result of the technology cost scenario is that the costs for emission mitigation can be substantially reduced in the latter part of the 21$^{st}$ century, but not as much in the earlier periods since fossil fuel technologies are still being used. A reduction of the assumed GDP growth can lead to significantly lower costs as the reference base line is reduced, while higher natural gas resources provide a comparably cheap abatement option in the supply sector in the near term.

Dean and Hoeller (1992) performed a similar study to the EMF-12 with 6 models with the difference being that the used models cover the whole world . Their results confirm the big difference in abatement costs between models from the EMF study. The reasons for the differences are the different assumptions concerning, e.g., the energy efficiency improvement and the substitution elasticity, but also large differences in the detail of the representation of mitigation options. Some general equilibrium models represent the energy sector only with a carbon and a carbon-free technology option. A big advantage of global studies is that they are able to take into account spillover that are created in one country by mitigation actions in another country. In the same way leakage effects can be considered, i.e. the relocation of carbon-intensive production or other distortions caused by unilateral implementation of carbon constraints.

More recently, the EMF conducted a project on the cost of the Kyoto Protocol (EMF-16) and a project on multi-gas mitigation, referred to as EMF-21, where the results of 19 mostly top-down models were compared. This study does not only cover $CO_2$ emissions, but also the emissions of other greenhouse gases, notably methane and nitrous oxide. Within the scope of this study, the costs associated with climate change policies were calculated and compared between the models in order to assess the range of results and what are the reasons for differences. The overall results were that the inclusion of non-carbon greenhouse gases can substantially decrease the marginal abatement cost. In 2025, the average reduction in marginal cost across the 19 models due to the inclusion of other greenhouse gases was 48 percent, which was slightly lower in 2100 with 39 percent. The large difference in the estimation of marginal abatement costs between the models is comparable to the EMF-12 project. For instance, the PACE model estimates a marginal cost of $\$_{2000}$10.3/t C in 2050, whereas GTEM estimates $\$_{2000}$1,806.9/t C for the same year when stabilising radiative forcing at 4.5 W/m$^2$ (Weyant et al. 2006). Some of the differences can be explained with the degree of carbon trading permitted in the models.

Next to those comparison projects, there exist a great number of national studies (see Hourcade et al. 1995). Major problems are found in studies that try to estimate mitigation costs in developing or emerging countries, because the usual model assumptions (i.e. perfect information, optimising behaviour and competitive economic dynamics) generally hold to a lesser extent than in developed countries. This is the case because some economies are no free market economies, where regulations, inefficiencies and subsidised energy prices hinder perfect competition. Moreover, income discrepancies in developing countries are larger than in developed countries, which makes the use of a representative agent particularly difficult. Consequently, models assuming a market equilibrium fail to represent energy use in an appropriate way. Abatement costs for developing countries have been only discussed together with other regions in the context of global studies (e.g. Dean and Hoeller 1992). They indicated relatively high cost estimates, reflecting the difficulties of such models to represent the economic restructuring in developing countries.

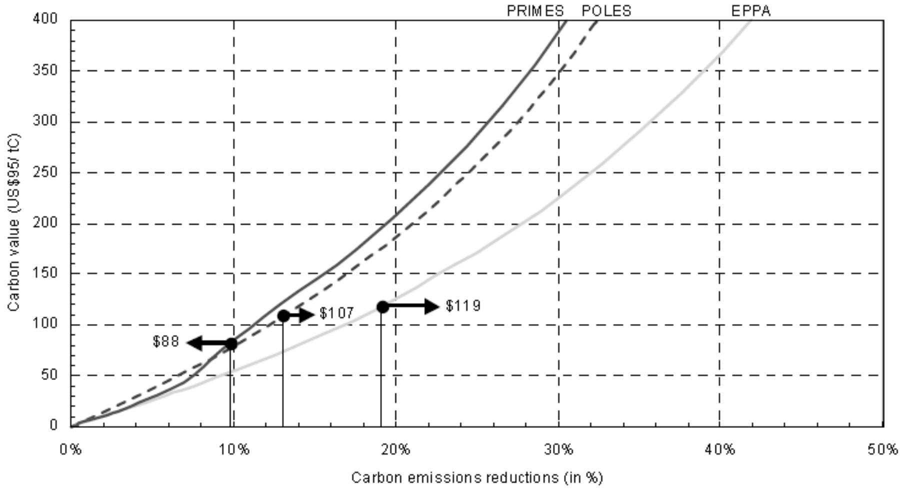
Compared to MAC curves from top-down models in the early 1990s, the calculation of MAC curves with the Emissions Prediction and Policy Analysis (EPPA) model (Paltsev et al. 2005) was a development step forward in the derivation of MAC curves from top-down models as it was much more detailed. The EPPA model belongs to the class of Computable General Equilibrium (CGE) models that model the flows of products, services and money in the whole economy.

Ellerman and Decaux (1998) were the first to use a top-down model, the EPPA model, to study the effect of international abatement with the help of MAC curves. One of their results was that the MAC curve of one country does not depend on the abatement level of other countries. Their findings concerning emission trading indicate that there can be huge potential gains for all regions resulting from international permit trading. However, the result of MAC curves being robust to fuel price changes is in strong contrast to the findings of Klepper and Peterson (2003). Theoretically, Klepper and Peterson (2003) show that a change in abatement level of one region can lead to a change in energy demand. If this region is large enough, this demand change can affect the price for internationally traded primary energy carriers, such as oil and gas, and influence the demand for energy in another region. This again will have an influence on the marginal abatement costs.

Moreover, Klepper and Peterson use the top-down Dynamic Applied Regional Trade (DART) model, which indicates that regional MAC curves can shift significantly depending on the level of emission mitigation in other regions. This is mainly due to the change in world energy prices. In a later study, Morris et al. (2008) address the differences between the Klepper and Peterson (2003) study and the Ellerman and Decaux (1998) study. They explain the difference with the fact that Klepper and Peterson did not adapt the baseline in the case of international trading, whereas Ellerman and Decaux did so. Consequently, one only sees a major difference between both curves in the case that the baseline remains fixed and is not adjusted for trade effects. Furthermore, Morris et al. (2008) address additional issues, such as path dependency, measures of welfare and other greenhouse gases apart from $CO_2$. The authors conclude that the stronger and longer the climate policy in the past, the lower the MAC curve in a given year. Concerning other GHG gases, it is noted that the MAC curve is altered in the way that it has a low shallow slope in the initial part of the curve caused by relatively cheap abatement options for non-$CO_2$ gases.

Viguier et al. (2003) studied the cost of the Kyoto Protocol in the European Union with the EPPA model. For this purpose, the authors calculated MAC curves for different European countries and compared them to curves from two bottom-up models (see Figure 2.6).

**Figure 2.6: MAC curve for Germany in 2010**




**Source: Viguier et al. (2003)[5]**

While the EPPA model explicitly takes into account economy-wide feedbacks and effects of climate change policies, those aspects are not considered in partial-equilibrium bottom-up models. An interesting result is that MAC curves from EPPA are in general lower than in the two bottom-up models. This is caused by different reference emissions and divergence in abatement measures. In addition, trade and income effects tend to decrease abatement costs.

*Advantages and disadvantages of top-down model-based MAC curves*

The most important advantage of top-down models for the calculation of MAC curves is that they are able to explicitly take into account macroeconomic feedbacks and effects of climate change policies on income and trade. In contrast to bottom-up models or expert-based MAC curves, the system boundaries are extended beyond the energy sector in top-down models (Hourcade et al. 2006). Moreover, international trade between regions, as well as the influence of global mitigation efforts on a single region can be taken into account in global models. A drawback concerning the representation

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of international trade, is that an absolute flexibility for carbon abatement is assumed. This, however, does not represent trade barriers in a realistic way, which causes the marginal costs to be lower limits of the actual marginal abatement costs.

In addition, top-down models permit the consistent, though possibly not always accurate, account of interactions between mitigation measures. There is also no problem in accumulating sectoral abatement curves, in contrast to some expert-based approaches. This is due to the fact that the models maximise welfare from a societal perspective. Top-down models are not nearly as susceptible to inconsistencies as expert-based approaches because overall welfare is optimised. Intertemporal interactions and consistent baseline emission pathways can be represented within the scope of a model (Zhang and Folmer 1998, p. 104). Models, in general, are far more capable in representing uncertainty. This has been demonstrated in comparison studies via structured sensitivity analyses, where the focus has been mainly on inter-model comparison.

Regarding the disadvantages of a MAC curve based on top-down models, one has to mention the lacking technological detail. Most MAC curves do not permit any insights into what technologies or measures are responsible for emission abatement. Top-down models lack transparency because an explicit illustration of technologies used for emission reduction is difficult due to a high degree of aggregation in the model structure. Although there were some improvements, top-down models generally lack a sufficient technological detail, which can result in unrealistic physical implications. They do not reflect the different substitution possibilities in the energy system, their different costs and technical characteristics in the same way as bottom-up models.

Another disadvantage is that models often assume the behaviour of a rational agent. It is difficult to integrate more realistic behaviour, such as existing market distortions, which are independent of cost. Furthermore, top-down models rely on nested production functions and substitution elasticities between input factors. Those substitution elasticities are, however, based on discrete historic data, and it is unlikely that the substitution elasticities will be constant in the future. Table 2.2 summarises the strengths and weaknesses of MAC curves derived with top-down models.

**Table 2.2: Strengths and weaknesses of MACCs generated by top-down models**

| STRENGTHS | WEAKNESSES |
|---|---|
| ▪ Consideration of macroeconomic feedbacks<br>▪ Incorporation of behavioural changes in the presence of price signals<br>▪ Marginal abatement cost are macro-economic cost that can be put in context to welfare measures<br>▪ Representation of international trade in global models<br>▪ Integration of interactions between mitigation measures<br>▪ Consistent baseline emission pathway<br>▪ Taking into account intertemporal interactions<br>▪ Possibility to represent uncertainty | ▪ No representation of trade barriers<br>▪ Lack of technological detail and transparency<br>▪ Possibility of unrealistic physical implications for energy use<br>▪ Assumption of a rational agent, without taking into account market distortions<br>▪ Reliance on substitution elasticity, estimated on historic data, for the calculation of future abatement cost |

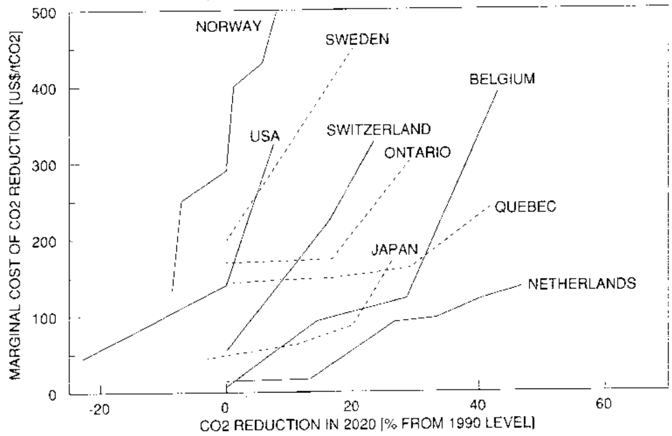
#### 2.2.2.2 Bottom-up models

Compared to top-down models, bottom-up models are not as frequently used for the calculation of MAC curves. In contrast to top-down models, bottom-up models do not cover the whole economy, but pursue a partial equilibrium approach of the energy system or simulate the energy system (see also 3.2.3). Specific technologies and their emissions, inputs, outputs, variable costs and further technological and economic costs are integrated in such models (Hourcade et al. 2006). This section also includes hybrid models, i.e. those models that combine bottom-up models with top-down characteristics. The reason for this is that hybrid models, which are used for the calculation of MAC curves, have been bottom-up model with a reduced form representation of a top-down model.

Similar to the comparison studies with top-down models, there have been projects to compare the abatement cost estimates from bottom-up models since the early 1990s. The third assessment report of the IPCC gives an overview of the early bottom-up approaches to marginal abatement costs (Hourcade et al. 1995, p. 317ff). One example is a study by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) (Kram 1993). In this research project the efforts of nine research groups were compared, where all teams applied the bottom-up model

MARKet ALlocation (MARKAL) for different regions (for more details on MARKAL see chapter 3.3) in order to derive MAC curves (see Figure 2.7).

**Figure 2.7: Bottom-up marginal abatement cost of $CO_2$ in 2020 by country**




**Source: Kram (1993)[6]**

One conclusion of the comparison study is that an emission abatement based on equal abatement in each country is significantly more expensive than global emissions reduction with an emissions trading system. Most of the lower abatement potential, in the majority of models, is represented by nuclear energy, whereas renewable energy is only used in categories of over \$100 per ton $CO_2$. Another finding is the big variety of marginal abatement costs for the various countries ranging from \$50 (Netherlands) to \$450/t $CO_2$ (Sweden) for a 20% reduction in 2020 compared to the 1990 level (Kram 1993). The stated reason is the different level of baseline emissions, which is to some extent due to the available energy resources and the heterogeneity of technology data used in the respective national studies (e.g. the availability of carbon capture and storage). The large difference in abatement costs between countries and models is similar to differences found when using different top-down models.

A similar study by the United Nations Environment Programme (UNEP) (Risø National Laboratory 1994) summarised the results of bottom-up models for France, Denmark, the Netherlands and a range of developing countries. While the studies for the Netherlands and Brazil used the MARKAL model, others relied on simulation tools and other bottom-up models. Two MAC curves were calculated with a hybrid model, where macro-economic assumptions were integrated into the model. MAC curves, which are presented for the year 2010 in the UNEP study (Risø National Laboratory 1994), exhibit some similarities between countries. In the developing countries included in the study

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there is a large potential for negative cost mitigation options up to almost 20% of emission reduction particularly in industry and households. Negative costs are related to the fact that these models represent direct costs including investment and running costs, but do not take into account institutional constraints, which limit the uptake of mitigation technologies. Furthermore, the shape of the mitigation curves is similar to the extent that they show negative abatement costs, while the middle part of the curve indicates a big potential of relatively low cost abatement options (up to $30), mostly in electricity supply. The similarity of the results can be explained by a similar optimisation approach and comparable energy demand assessment.

The results for the industrialised countries are more varied. Some models do not give any negative abatement potential, because they already include all negative abatement cost options in the reference scenario. Thus, the model choice is important for the shape of the MAC curve as no-regret options are integrated into the baseline development of an optimisation model in contrast to a simulation models. No-regret mitigation options describe those measures that are cost-effective to be realised even in the absence of any $CO_2$ policy. Furthermore, a comparison of long-term abatement curves and short-term abatement curves shows a lower and flatter long-term abatement curve. This reflects more effective future abatement technologies, which are cheaper than the replacement of existing equipment.

The latest comparison of MAC curves derived with bottom-up models is documented in the fourth IPCC assessment reports, which intends to assess scientific, technical and socio-economic information concerning climate change (Fisher et al. 2007). The overview of the results confirms the conclusions from earlier comparison projects with bottom-up, as well as top-down models, namely that mitigation costs tend to rise with a higher baseline scenario and with stricter reduction targets (Fisher et al. 2007). Furthermore, abatement costs are found to be significantly higher in 2100, than in 2050 and 2030 for the same radiative forcing target. In 2100 carbon prices tend to vary over a wider range, which can be explained with different baseline emissions and technology developments.

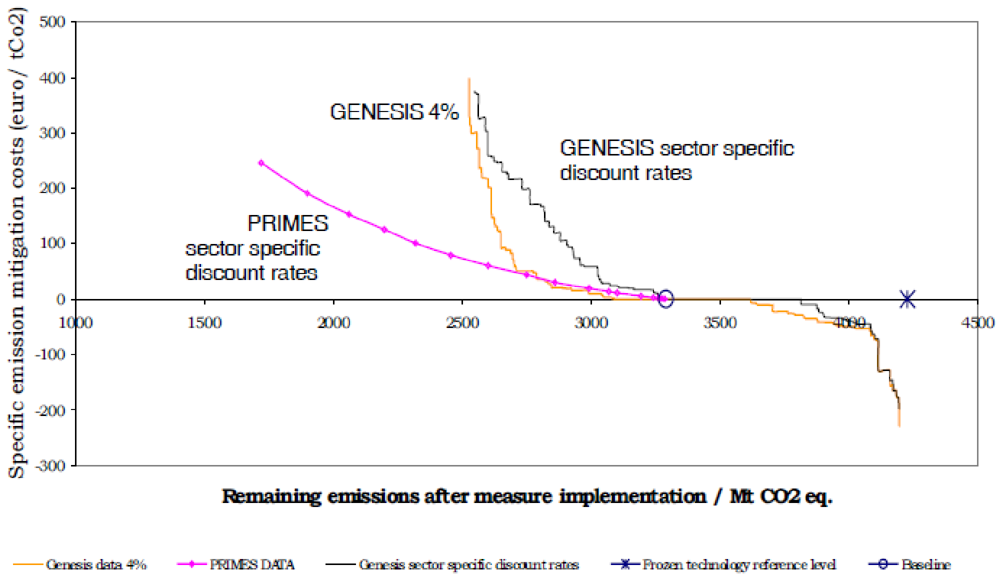
In addition to top-down models, bottom-up models are equally used for studying the benefits of an international trade in carbon permits via MAC curves. Criqui et al. (1999) conducted a study similar to the one with the EPPA model (Ellerman and Decaux 1998), with their Prospective Outlook on Long-term Energy Systems (POLES) model, which has mostly characteristics of a bottom-up model. It is a simulation model that calculates energy demand, supply and prices up to 2030 (see 3.2.3). The costs considered in POLES are restricted to the energy sector, in contrast to EPPA that takes into account the economy-wide impact of reduction policies.

Criqui et al. (1999) confirm the high cost reduction potential of international trade calculated with the EPPA model. Moreover, the authors find the MAC curves from POLES to be higher for all regions except Japan and the United States, despite the fact that EPPA shows higher $CO_2$ emissions in the reference scenario due to higher assumptions on economic growth. In this context, the authors give three causes for differences in abatement costs: the initial level of energy prices, the energy supply structure and the potential for developing carbon free energy sources.

A study for the European Commission (Blok et al. 2001) examined the emission reduction opportunities for $CO_2$ in the European Union in 2010 using MAC curves. This study compared the results of a bottom-up model, PRIMES (Capros et al. 2001), with an expert-based approach, the GENESIS database (Hendriks et al. 2001). MAC curves were derived for the whole energy system for the year 2010. Figure 2.8 shows the MAC curves for the bottom-up model and the expert-based approach. Whereas the expert-based approach (GENESIS) displays negative abatement costs, the corresponding measures are incorporated in the base case in the model runs, so that they do not figure in the curve of the PRIMES model. The model-based approach based on PRIMES shows a bigger abatement potential at higher carbon values compared to the individual assessment of abatement measures with the GENESIS database due to interaction in the system, structural changes, and demand adaptation.

There are equally some fundamental differences between both approaches: the expert-based approach uses a social discount rate of 4% p.a., while PRIMES uses substantially higher market discount rates; PRIMES explicitly models interactions in the energy system and GENESIS accounts for them on an ad-hoc basis; GENESIS uses project costs, while the cost definition in PRIMES is wider; GENESIS assumes a frozen technology reference development, while efficiency improvements are allowed in PRIMES; finally technology data differ between both approaches, e.g. the GENESIS database does not consider nuclear power as a mitigation option. In summary, the bottom-up model PRIMES is able to represent interactions and technology development in a superior way to the expert-based approach based on GENESIS.

**Figure 2.8: Comparison of PRIMES and GENESIS MAC curve for the EU in 2010**




**Source: Blok et al. (2001)**[7]

Not only pure bottom-up models, but also hybrid models are used to calculate abatement curves. Akimoto and Tomoda employed the model “Dynamic New Earth 21” (DNE 21) for an analysis of the cost connected to a stabilisation of the atmospheric $CO_2$ concentration and of the contribution of single technologies and measures (Akimoto et al. 2004; Akimoto and Tomoda 2006). The DNE 21 model is a model that links a macro economic model to an energy system model and a climate change model. The authors analyse different stabilisation scenarios ranging from 650 ppm (parts per million) to 450 ppm $CO_2$ in the atmosphere in 2100 and using different assumptions for underlying drivers, such as population and economic growth.

The findings indicate that global marginal abatement costs are more sensitive to the baseline assumptions, population, GDP and final energy demand, than the atmospheric concentration level of $CO_2$. In addition, a sensitivity analysis of the cost of $CO_2$ sequestration techniques show that the marginal abatement costs are relatively robust against those changes (Akimoto and Tomoda 2006). In their 2004 study, Akimoto et al. (Akimoto et al.) present a decomposition of emission pathways, similar to some bottom-up approaches. While this approach does not permit many insights into the marginal abatement costs, it decomposes emission reduction along different technologies over time. In the 550 ppm scenario, global $CO_2$ emissions reduction comes mainly from energy saving, biomass use and fossil fuel switching fossil fuels. For the decomposition,

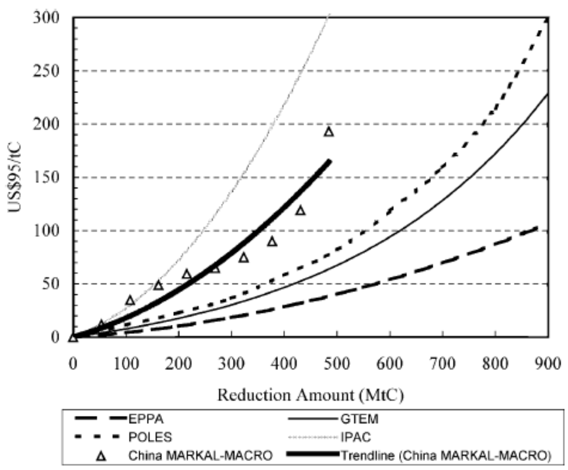
[7] Permission to reproduce this Figure has been granted by the European Commission.

the authors use a specific mixed Laspeyres/Paasche technique (see section 4.3), but give no reason for using it and do not explain the further technology breakdown.

Another example of a hybrid model employed for MAC curve calculation is the MARKAL-MACRO model. Chen (2005) used this model, which links the bottom-up model MARKAL with MACRO, a neoclassical macroeconomic growth model, to map interactions between the energy sector and the rest of the economy. In this study, Chen (2005) conducts a sensitivity analysis concerning the use of nuclear energy in China during the first half of the 21st century. She finds that the results are very dependent on the degree of expansion of nuclear energy and that the MAC curve between the reference and the restricted nuclear energy scenario enlarges significantly with the reduction amount. However, the model does not consider carbon capture and storage (CCS), so that nuclear power plants are the only non-$CO_2$ base-load option.

Chen also compares her findings with other results from top-down and bottom-up models (Figure 2.9). While it is questionable to present the results of MARKAL as a regression line due to the technology-explicit character of the model, the author concludes that MAC curves are lower in general equilibrium models than in partial equilibrium models. This can result from revenue recycling generated by a carbon tax. Other reasons given by Chen (2005) include the different scope of abatement opportunities, assumptions on basic drivers, and the handling of no-regret options.

**Figure 2.9: Comparison of MAC curve for China in 2010**



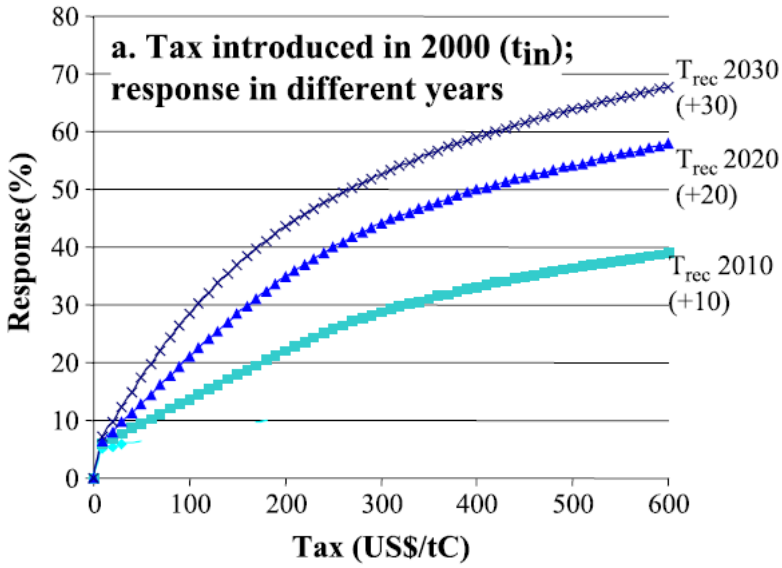

**Source: Chen (2005)[8]**

van Vuuren et al. (2004) used the Targets IMage Energy Regional (TIMER) model in order to quantify the impact of endogenous technological learning and temporal aspects

[8] Permission to reproduce this Figure has been granted by Elsevier.

on MAC curves. It focuses on several dynamic relationships within the energy system, such as inertia, endogenous learning-by-doing, fossil fuel depletion and trade among the different regions. The authors do not present a MAC curve, but they look at the ”system response” in periods after the introduction of a carbon tax (see Figure 2.10). The response characterises the emission reduction in percent a certain time period after the tax is introduced compared to baseline emissions. Abscissa and ordinate are interchanged in comparison to earlier figures of abatement curves.

**Figure 2.10: $CO_2$ reduction compared to baseline development against a carbon tax**




**Source: van Vuuren et al. (2004)[9]**

The results reveal that the same amount of emission reduction can be achieved at lower marginal costs in later periods. Here, induced technological learning, system immanent inertia and baseline learning, i.e. more rapid cost decrease of carbon-free options compared to fossil-based technologies, play a pivotal role. Nevertheless, the authors highlight how important baseline assumptions are, as they can heavily influence the marginal abatement costs.

Van Vuuren et al. (2004) present in the same way as Akimoto et al. (2004) the origin of emission reduction between a reference and stabilisation scenario of 550 ppm in 2100. They find the biggest contribution to come from energy efficiency in the first two decades of the 21st century and a fuel-switch away from coal. From 2030, biofuels and non-thermal electricity production options become important. However, the results depend on the order of attribution of emission reduction levels to measures as the contribution is apparently determined by different scenario runs.

[9] Permission to reproduce this Figure has been granted by Elsevier.

The MESSAGE model is one of the bottom-up models widely used in the assessment of mitigation costs in the scope of EMF studies and the IPCC (Rao et al. 2006; Rao and Riahi 2006). The model results indicate that carbon capture and storage technologies play an important role in the scenario where no technological change is implemented. Riahi et al. (2007) present mitigation wedges and discuss the robustness of mitigation technologies for various scenarios and their implementation over the 21st century. The authors identify the baseline development as an important driver of overall abatement and energy conservation, nuclear, biomass and $CH_4$ emissions reduction as key mitigation measures.

*Advantages and disadvantages of bottom-up model-based MAC curves*

In the same manner as top-down models, MAC curves calculated with bottom-up models permit to take into account system-wide interactions between mitigation measures and intertemporal interactions. Like top-down models, bottom-up models can more easily avoid inconsistencies, as e.g. the double counting of emission reduction, which are sometimes present in expert-based MAC curves. Nevertheless, the calculation of technology-rich bottom-up models are constrained to the energy system and can therefore not consider macro-economic feedbacks. In addition, the calculation of abatement curves in models is relatively simple, because the analyst merely needs to implement emissions restrictions or a $CO_2$ price.

Furthermore, bottom-up models have the big advantage of technological detail. This detail permits, in theory, the tracking of emission reductions to the measures and technologies that are responsible for this change, e.g. efficiency gains or technology switches. Decomposition analysis can help in this context to show how mitigation goals are achieved (see 2.5). Next to the influence of changing technologies on useful energy, the impact of behavioural aspects can be included in bottom-up models in the form of energy conservation and a price-elastic demand function. In the same way, uncertainty concerning technology costs, efficiencies, start date or limits of scope and its influence on cost curves can be addressed with bottom-up models via sensitivity analysis, stochastic or probabilistic modelling. In addition, it is possible to construct sectoral abatement cost curves or aggregate them to an abatement curve for the whole energy system in contrast to some expert-based curves.

Furthermore, as most bottom-up models are linear models and do not rely on substitution elasticity in contrast to most top-down models, the modeller has to limit the phenomenon of penny-switching. Penny-switching is a term to describe that very small changes in costs can initiate big shifts in technology portfolio. The phenomenon can be limited by adding more steps into the investment and variable cost function or limiting the uptake of new technologies. This approach was not implemented for fuel costs due to their exogenous character for the UK and modelling constraints (see also chapter 6.5).

A further disadvantage is the insufficient representation of technology specific imperfections in bottom-up models compared to cost curves that can in principle incorporate this. The result can be that bottom-up optimisation models show a high uptake of energy efficiency measures. Nevertheless, there are possibilities to incorporate higher hurdle rates and upper limits for the use of mitigation technologies to represent problems connected to high upfront investment costs and other non-cost aspects in bottom-up models. Upper bounds based on regulation or lacking information in a reference scenario, which are then gradually removed with rising $CO_2$ prices, can in theory clarify the abatement potential at negative costs. The problem with hurdle rates, however, is that non-financial costs would be quantified in monetary terms so that the marginal abatement cost shows at what tax level a measure would be realised, but the total costs of abatement would be diluted and overestimated. Kesicki and Ekins (2011) discuss the issue of negative costs in MAC curves.

Another problem linked to the use of bottom-up models is the procedure to calculate marginal abatement costs. Usually, a carbon price is implemented in the model, which corresponds to the marginal cost, or a limit is imposed on carbon emissions, which generates a shadow value, i.e. the marginal cost. However, other user constraints in the model on the capacity of a technology, and implemented taxes or subsidies can lead to a distortion of the marginal abatement costs. Table 2.3 summarises strengths and weaknesses of MAC curves generated by bottom-up models.

**Table 2.3: Strengths and weaknesses of MACCs generated by bottom-up models**

| STRENGTHS | WEAKNESSES |
|---|---|
| ▪ Great technological detail<br>▪ Incorporation of some behavioural changes via a price elastic demand function<br>▪ Integration of interactions between mitigation measures<br>▪ Consistent baseline emission pathway<br>▪ Taking into account intertemporal interactions<br>▪ Possibility to represent uncertainty | ▪ Limited to the energy sector, i.e. no representation of macroeconomic feedbacks<br>▪ Marginal abatement costs are direct cost in the energy sector<br>▪ Possibility of penny-switching<br>▪ Possibility of other constraints diluting marginal abatement costs<br>▪ No technological detail in graphical representation |

#### 2.2.2.3 Decomposing MAC curves

A couple of studies in the last years have tried to overcome the lacking technological detail in the graphical representation of most model-based marginal abatement cost curves. Therefore, approaches were spelled out to attribute emissions reduction levels to mitigation measures.

Hummel (2006), for example, developed an algorithm to decompose the sources of mitigation for different stabilisation scenarios in his PhD thesis. He used the results of three bottom-up models, MESSAGE-MACRO, MiniCAM and IMAGE. With his novel algorithm it is possible to decompose the emission pathway and attribute emission reductions to demand reduction, fuel switching, end-use efficiency or carbon sequestration.

However, this algorithm is flawed in a number of respects. First of all, while the decomposition is relatively detailed for the power sector, there is nothing said about mitigation measures in the industry or transport sector. Furthermore, the author assumes arbitrarily that in mitigation scenarios natural gas always replaces coal in electricity generation and hydrogen always petroleum. Any changes in the ratio of primary energy to final energy are considered as demand changes rather than efficiency changes. The biggest drawbacks of this approach is certainly that the attributed reduction amount depends on the order of analysis of mitigation sources, i.e. the reduction potential of a measure is different if it is considered in the first or last place. In addition, this approach tries to explain changes in $CO_2$ emission only with first-order changes. This will, however, always leave a residual term. Since the residual term is not explicitly disclosed in Hummel's approach, it is hidden in one of the first order changes, in this case in the change of carbon intensity, which contains higher order effects.

The European Environment Agency (EEA) pursued a similar approach to decompose historic $CO_2$ emissions from public electricity production, manufacturing industries and households (Jol and Karakaya 2006; Wiesenthal and Fernández 2006). For the public heat and electricity generation, $SO_2$ (sulphur dioxide) and $NO_x$ (nitrogen oxides) emission are also decomposed. Decomposed factors include efficiency improvement, fossil fuel switching, share of nuclear and share of renewable. The same problem as in the Hummel study can be found here, i.e. that the attribution of emissions reduction to measures is not exact. In this case, the explaining factors are interlinked, so that e.g. the results can indicate a $CO_2$ reduction due to fossil fuel switch when there is no change in fossil fuels but rather efficiency improvements. Summing up, Hummel (2006) and the EEA (Wiesenthal and Fernández 2006) tried to bring technological detail into emissions reduction, but their approaches are technically not precise.

Gracceva and Ciorba (2008) used the bottom-up model MARKAL to establish a technologically detailed abatement cost curve. The important advantage of this approach is that a MAC curve is constructed within the framework of a model, where emission amounts can be directly attributed to a mitigation group. The resulting cost curves are, though, not MAC curves, but rather specific policy scenario average abatement cost curves. The reason is that separate runs with the MARKAL model are used to determine the cost and the amount of emission reduction for each predefined policy scenario. Information on the contribution of specific technologies is not revealed in all cases because not each technology corresponds to a scenario. Crucially, the specific policy scenarios cannot guarantee that emission reduction is due to the specified changes, because interactions are not accounted for. Additionally, the emission reduction amount for one defined technology group depends on the logical order of the scenarios, and the scenarios will not exactly add up because of interactions.

In 2009, Renders (2009) proposed a representation of no-regret measures in marginal abatement costs based on the MARKAL model. The methodology based on the concept of marginal investment costs can reveal the negative marginal abatement costs for efficiency measures in the household sector. Nevertheless, this approach gives only insights into abatement costs, but not on the scope of emission reduction attributable to one measure.

## 2.3 Common aspects of all types of MAC curves

While model-derived and expert-based MAC curves have different strengths and weakness, which affect their suitability to derive MAC curves, all MAC curves share some common characteristics independent of the underlying methodology. Strengths of MAC curves include: first, they represent the marginal abatement cost associated with a given reduction level. Second, the total abatement costs can be derived by integrating the MAC curve up to the emission reduction level. Third, the average abatement costs can be calculated when the total abatement costs are divided by the amount of reduced emissions. Forth, MAC curves can be helpful for the assessment of climate policy tools. Expert-based MAC curves can indicate the reduction potential, e.g., associated with introducing a building standard, and model-derived MAC curves give an indication of the resulting carbon price in a cap-and-trade scheme or the reduction level when a carbon tax is introduced.

Weaknesses of the MAC curve concept include that it does not consider ancillary benefits of carbon emissions reduction, such as reduced air pollution or increased energy security. Furthermore, transaction and implementation costs of mitigation measures are not considered when establishing mitigation costs and costs related with policy implementation are beyond the scope of a MAC curve. Since a MAC curve is a snapshot of one point in time, it is not possible to depict the influence of intertemporal dynamics on abatement costs and potentials. Other weakness, which can be overcome in the future, include the lack of transparency concerning the input assumptions and the limited representation of uncertainty in MAC curves. Common characteristics for model and expert-based abatement cost curves are summarised in Table 2.4.

So far, an important weakness of model-based MAC curves has been the lacking technological detail in the representation of the results. While a technology rich representation is not possible to realise in top-down models, since they lack the necessary technological detail, it is in principle possible for bottom-up models. In combination with a bottom-up model, decomposition analysis can help to disentangle the contribution of different technologies, efficiency gains and behavioural aspects to the reduction of $CO_2$ emissions.

**Table 2.4: Common strengths and weaknesses of MAC curves of all three types**

| STRENGTHS | WEAKNESSES |
|---|---|
| ▪ Present the marginal abatement cost for any given total reduction amount<br>▪ Give the total cost necessary to abate a defined amount of carbon emissions<br>▪ Possible to calculate average abatement costs<br>▪ Give helpful information for the assessment of climate policy instruments | ▪ No consideration of ancillary benefits, transaction and implementation costs<br>▪ In general limited to one point in time, no consideration of intertemporal dynamics (path dependency)<br>▪ Lacking transparency of assumptions<br>▪ Limited representation of uncertainty |

## 2.4 Influencing factors of MAC curves

Several studies have looked into the influence of various factors on the shape of MAC curves. In a theoretical framework, a few researchers have studied the influence of technological learning and innovation on MAC curves. Amir et al. (2008) challenge the previously established belief that innovation always leads to a uniform downward shift of the MAC curve. He argues that this is only the case for end-of-pipe technologies, while efficiency gains or lower capital costs can lead to an upward shift. Bauman et al. (2008) argue in a similar way that production process innovations can lead to higher marginal abatement costs. Baker and Shittu (2007) review the literature on technological innovation and MAC curves. They find that the majority of studies indicate that innovation shifts a MAC curve downwards rather than upwards. Nevertheless, based on several examples, the authors stress the point that an upward shift of MAC curves at high abatement levels is perfectly possible.

Other categories of papers that have looked at quantifying the impact of influencing factors on MAC curves are model comparisons and meta analyses. The latter type employs econometric techniques in the form of regression analyses based on several MAC curve studies. While this statistical approach is not without problems, e.g. low statistical significance, selection bias, assumptions of linear relationship, multicollinearity and heteroskedasticity, it delivers some insights into what are the most important influencing factors of MAC curves.

Concerning the model type, Repetto and Austin (1997) find that the use of CGE models as opposed to macro models lower the cost related to emission reduction for the same carbon reduction target. The results from Barker et al. (2006) indicate that hybrid models tend to increase abatement costs compared to top-down models, which could result from a better representation of market constraints. In the presence of a comparably low coefficient of determination, Kuik et al. (2009) could not measure any significant influence on abatement costs due to the model type, i.e. top-down, bottom-up or hybrid. This result is confirmed by a model comparison undertaken by van Vuuren (2009). Amann et al. (2009) performed a model comparison of eight models of different type and come to the conclusion that top-down models show higher abatement potentials in particular at higher carbon tax levels compared with bottom-up models owing to the characteristic that they include trade-balances and that most bottom-up models in the study do not include behavioural change. Currently, however, the majority of bottom-up models incorporate price-elastic demand functions.

In the past, top-down models were accused of overestimating marginal abatement costs. These models rely in general on substitution elasticities between input factors, which are estimated using historic data and therefore project a limited transformation potential of the economy into the future. Consequently, they can generate comparably high costs for the mitigation of $CO_2$ emissions (Hourcade et al. 2006). Bottom-up models, on the other hand, were accused of underestimating marginal abatement costs. They rely on technology specifications and, in the case of simulation models, show an abatement potential at negative costs. Reasons for comparably low abatement costs are the failure to include micro- and macroeconomic feedback effects, such as e.g. price induced demand changes (Hourcade et al. 2006). Existing meta-analyses and model comparisons, however, do not give a consistent picture (Repetto and Austin 1997; Barker et al. 2006), while the latest studies do not find any influence of the model type on the MAC curve (Kuik et al. 2009; van Vuuren et al. 2009).

According to Repetto and Austin (1997) and Barker et al. (2006), the rather crude concept of backstop technologies, found in top-down models, generally reduces marginal abatement costs, while Fischer and Morgenstern's (2006) results indicate the opposite. Fischer and Morgenstern (2006) explain this rather surprising finding with the fact that modellers might include a backstop technology because other model assumptions lead to high marginal abatement costs.

Global emissions trading was identified by Repetto and Austin (1997), Fischer and Morgenstern (2006), Criqui et al. (1999) and Klepper and Peterson (2003) to lower abatement costs, while Ellerman and Decaux (Ellerman and Decaux 1998) indicate the opposite. Equally, abatement possibilities across greenhouse gases can lower abatement costs according to Stern (2007, p. 243ff), Kuik et al. (2009) and Morris et al. (2008). Incorporating efficient revenue recycling can additionally lower marginal abatement costs according to Repetto and Austin (1997). The influence of a higher detail of energy sources is not unambiguous: it does either have no influence (Repetto and Austin 1997), reduces abatement costs (Kuik et al. 2009) or can even lead to higher marginal abatement costs due to the better representation of rigidities (Fischer and Morgenstern 2006). Barker et al. (2006) come in their meta-analysis to the conclusion that the modelling of a higher disaggregation of sectors reduces marginal costs.

Barker et al. (2006), Edenhofer et al. (2006) and Clapp et al. (2009) pointed out that Induced Technological Change (ITC) can significantly drive down MACs. ITC represents endogenous, policy-influenced technological change where early policy action induces research and development into low-carbon technologies, which in turn lowers technology costs in later periods. Edenhofer et al. (2006) found via a model comparison that the transformation to a carbon-free energy system can become stable as renewable energy technologies turn out to be cost-effective resulting from induced technical progress. Amann et al. (2009) similarly find technological progress to have a large influence on MAC curves. Morris et al. (2008, p. 14) state in this context that MACs will be lower, the stronger and longer the policy has been in the past.

Another intensely debated influencing factor is fuel prices. McKinsey (Creyts et al. 2007, p.25) state, for example, that oil and gas prices have a substantial impact on the abatement curve for the United States, while this impact is found to be a lot more moderate on a global level (Nauclér and Enkvist 2009, p. 53). Moreover, the latest assessment report of the IPCC explains that estimated ranges of mitigation costs and potentials reflect key sensitivities to baseline fossil fuel prices (Barker et al. 2007, p. 621). Siddiqui (2010), using a general equilibrium approach, found a MAC curve for the Canadian economy to be sensitive to changes in the price for crude oil. The findings are dependent on the oil intensity of an economy and if the country is a fossil fuel exporter or importer.

Klepper and Peterson (2003) studied the influence of energy prices on MAC curves with a computable general equilibrium (CGE) model. Their results indicate that energy prices play a decisive role and that MAC curves depend strongly on energy prices (Klepper and Peterson 2003, p.25). This statement is, however, qualified in a later paper, where the authors state that relative price effects do not affect MAC curves in a significant way (Klepper and Peterson 2006, p. 18).

Three studies that looked at the influence of the availability of mitigation measures on marginal abatement costs are Clarke et al. (2007), Clapp et al. (2009) and Azar et al. (2010). MAC curves were found to be diverging owing to different assumptions on the availability of key mitigation options, such as biofuels, renewable electricity generation or the availability of CCS. Clapp et al. (2009) points out that the non-availability of nuclear and carbon capture and storage (CCS) technologies significantly increases abatement costs. While Azar et al. (2010) use a slightly different concept to MAC curves by presenting additional total costs associated with a lower atmospheric concentration of $CO_2$, they find that including CCS especially in combination with biomass reduces mitigation costs.

Lastly, concerning the choice of the discount rate, AEA et al. (2008) found that a shift from a social perspective to a private perspective significantly changes the MAC curve for the UK transport sector. Nauclér and Enkvist (2009) also study the influence of a different discount rate on MAC curves, but only disclose results on the average abatement costs, which indicate a substantial increase in costs for rising discount rates.

To summarise, the discussion on the robustness of MAC curves has mainly focused on fossil fuel prices, (induced) technological learning, model type, emission trading and inclusion of non-$CO_2$ greenhouse gases. The existing studies do not present uniform results, but generally report that fossil fuel prices have a moderate to significant influence on MAC curves, while induced technological change significantly lowers MACs. Emissions trading and including further greenhouse gases next to $CO_2$ is in most cases responsible for a reduction of abatement cost. The non-availability of key mitigation options, such as CCS, nuclear and renewables, is found to significantly increase abatement costs.

## 2.5 Decomposition analysis

Decomposition analysis (used as a synonym for index decomposition analysis) is chosen as a technique to attribute emission changes to mitigation measures. Using this method, the emissions reduction amount of a mitigation measure does not depend on the order of attribution nor are the effects interlinked. Such issues occur with other methods, which are very similar to decomposition analysis (see section 2.2.2.3). The goal of decomposition analysis is to explicitly set forth the contribution of driving factors behind the change of an aggregate variable

Decomposition analysis is a well established research methodology to decompose an aggregated indicator, usually either energy use or $CO_2$ emission, into its driving forces (Ang and Zhang 2000). After the two oil price shocks in the 1970s, this technique was used to determine the factors behind historical industrial energy use and how to reduce future energy consumption in the industry sector (Thomas and MacKerron 1982; Hankinson and Rhys 1983; Jenne and Cattell 1983). In the 1990s the focus of decomposition shifted from energy use towards $CO_2$ emissions (Torvanger 1991) based on the Kaya identity (Kaya 1989). The Kaya identity was the first identity to relate $CO_2$ emissions to the human impact via the factors population, GDP per capita, energy intensity of the economy and carbon intensity of energy. Over the course of the 1990s and the early 21$^{st}$ century there have been numerous studies for different regions and energy sectors that have tried to find the underlying causes of $CO_2$ emission development with the help of various decomposition techniques (see e.g. Diakoulaki et al. 2006; Shrestha et al. 2009). The International Energy Agency (2004) used decomposition analysis to perform a comprehensive study on energy use in IEA countries, in households, transport, service sector and manufacturing.

To illustrate the application of decomposition analysis, a simple example is given based on the Kaya identity. In this equation of several ratios, all numerators and denominators cancel out, except for the aggregated variable:

$$\boldsymbol{CO_2 = P * \frac{GDP}{P} * \frac{PEC}{GDP} * \frac{CO_2}{PEC}} \qquad (2.1)$$

where *P* stands for population, *GDP* for gross domestic product, *PEC* for primary energy consumption and $CO_2$ for $CO_2$ emissions.

Decomposing the change of $CO_2$ emissions according to the predefined drivers results in the following equation:

$$\Delta\, \boldsymbol{CO_2} = \left(\frac{\Delta \boldsymbol{P}}{\boldsymbol{P}} + \Delta \frac{\boldsymbol{GDP}}{\boldsymbol{P}} * \frac{\boldsymbol{P}}{\boldsymbol{GDP}} + \Delta \frac{\boldsymbol{PEC}}{\boldsymbol{GDP}} * \frac{\boldsymbol{GDP}}{\boldsymbol{PEC}} + \Delta \frac{\boldsymbol{CO_2}}{\boldsymbol{PEC}} * \frac{\boldsymbol{PEC}}{\boldsymbol{CO_2}}\right) * \boldsymbol{CO_2} + \boldsymbol{Res.} \tag{2.2}$$

In this equation the first term on the right hand side represents the implication of a change in population on the $CO_2$ emissions, the so called activity effect where population is the activity. The second summand represents the influence of affluence (measured in GDP per capita) on the aggregate variable, while the third summand represents the emission change due to energy intensity and the last ratio represents the impact of a change in $CO_2$ intensity on emission development. The latter three summands in the brackets are all intensity effects.

As the decomposition in equation (2.2) is a series expansion truncated at first order, a residual of higher order remains. The residual can be comparably large for large changes in the decomposed variable. To avoid this problem, several methods have been developed in the last years to distribute the residual among the factors, which are described in more detail in 4.3. It is important to keep the residual small because otherwise an important share of the change in the aggregate remains unexplained.

In recent years, studies have not only looked back into the past to decompose $CO_2$ emissions, but also into the future to decompose future mitigation scenarios. Kawase et al. (2006) compared the historical development of drivers of $CO_2$ emissions in European countries and Canada to projected developments up to 2050. Their results indicate that energy intensity (i.e. ratio of final energy consumption and economic activity) and carbon intensity (i.e. the ratio of $CO_2$ emissions and primary energy) must be improved more than 2-3 times as fast as the historical trend to meet reduction targets.

Another study that analyses forward-looking scenarios is a study by Hanaoka et al. (2009) that looks at the contribution of energy efficiency for future $CO_2$ emission reduction. Their results indicate that improvements in the energy intensity ratio, defined as total primary energy supply per economic activity, will play the most important role contributing to reduced $CO_2$ emissions. Agnolucci et al. (2009) used decomposition analysis to determine future $CO_2$ emissions. In this study decomposition was used to define the growth rate of the explaining variables and then to aggregate them to gain insight into the development of $CO_2$ emissions.

The IPCC (Rogner et al. 2007, p. 107ff) used decomposition analysis to separate the contribution of population growth, affluence, carbon and energy intensity of the reference IEA scenario. The findings confirm prior results that baseline energy efficiency improvements alone are not sufficient to stabilise global $CO_2$ emission over the next 20 years.

The cited examples show that decomposition analysis has moved from a narrow focus on industrial energy use towards a broader perspective, which includes the decomposition of $CO_2$ emissions. Furthermore, in recent years research studies have not only analysed historic data, but have looked at emission scenarios with a horizon up to 2050 (Kawase et al. 2006; Agnolucci et al. 2009). Issues that should be kept in mind when using decomposition analysis, is that results depend on the drivers included in the analysis. Moreover, most decomposition analyses presume that the drivers are independent of each other, which is not necessarily the case. However, one can notice that decomposition has always been applied through time to gain insight into the development of emissions in recent or future decades. This has not been extended to a decomposition along rising $CO_2$ taxes or stricter atmospheric $CO_2$ concentrations to obtain a technologically detailed MAC curve.

## 2.6 Critique and conclusions

The discussion of the present literature revealed that there are different approaches to presenting the cost associated with the mitigation of climate change. MAC curves, a major concept in this area, have been constructed with different methods, which have their respective advantages and disadvantages (see Table 2.1, Table 2.2 and Table 2.3). Expert-based abatement curves have the important advantage of technological and market detail, while they lack a representation of interactions and energy system-wide dependencies. Model-based approaches are capable of integrating interactions, but often lack the technological detail, so that there are insights into marginal costs without permitting any insights on mitigation sources. Recently, there have been some approaches in literature towards the decomposition of mitigation sources in model-based approaches, which either do not reveal the methodology or have an inadequate methodology (see section 2.2.2).

To conclude, so far no MAC curve has been constructed that presents the technological detail based on consistent assumptions, while being able to take into account technological, intertemporal, economic and behavioural interactions, to incorporate the technological complexity and to provide a framework for a structured consideration of uncertainty.

To fill in those gaps in research, combining energy system modelling with decomposition analysis is useful approach. An energy system model permits one to use consistent assumptions for the whole energy system, take into account technological, intersectoral and behavioural interactions. Moreover, a sensitivity analysis or stochastic modelling based on such a model provides a structured approach to study uncertainty. Decomposition analysis uses the technologically detailed results of the energy system model as an input in order to bring in the technological detail into the MAC curve. It is the time that decomposition analysis is used to decompose a MAC curve instead of historical emissions over time.

In a first step, model runs with an energy system model serve to construct a MAC curve by recording the emission reduction associated with imposed carbon prices. In a second step, decomposition analysis quantifies the changes in the energy system and traces back emission reduction to technologies and measures. By applying decomposition analysis to this new field, it is possible to explicitly attribute a reduction amount to the respective mitigation measure. The advantages of this approach are that it incorporates all the advantages of a model-based approach, while bringing in the technological detail into MAC curves usually attained with expert judgments.

Compared to expert-based MAC curves, the combination of decomposition analysis and an energy system model permits an adequate representation of technological complexity, for example with different cost steps for renewable energy, as wind or solar power. Furthermore, a model-based approach makes it much easier to avoid inconsistencies, and considers intertemporal and intersectoral interactions.

In comparison to usual top-down model-based MAC curves, the approach based on an energy system model and decomposition analysis allows the attribution of emission reduction amounts to measures, such as efficiency improvements of one technology, demand reduction or fuel switching to a carbon-free electricity source. In addition, the technological detail of a bottom-up model avoids possible technologically unrealistic results of top-down models. Compared to the current approaches to generate MAC curves with bottom-up models (see 2.2.2.3), the use of decomposition analysis does not depend on the logical order of mitigation measures in scenario runs. Decomposition analysis is theoretically sound and permits to assign unambiguously emission reduction amounts to mitigation measures. Moreover, this analysis can open the black box of a model, to a certain extent, by giving insights on the underlying assumptions, which are mostly lacking in current model-based MAC curves. In contrast to existing model-based studies that present mitigation wedges, the approach used in this thesis gives insights on marginal abatement costs and is transparent as well as mathematically sound.

Another component of the proposed approach is uncertainty analysis. MAC curves are only a snapshot of a specific point in time depending on many assumptions and uncertainty in relation to MAC curves has been poorly represented in the past. A sensitivity analysis and stochastic modelling of the most important input assumptions, such as technology costs, energy prices, discount rates or behavioural aspects can give insights into interaction of uncertainty for any given year. In addition, the variation of the carbon tax trajectory within a bottom-up model can reveal important insights with respect to time dynamic aspects.

In conclusion, the combination of a traditional model-based abatement curve with decomposition analysis and uncertainty analysis enables the derivation of a robust and technologically detailed MAC curve. This has clear advantages over conventional model-based MAC curves, which lack the technological detail in the graphical representation, and over expert-based MAC curves, which are, amongst others, not able to consider the full extent of technological, intersectoral and behavioural interactions.

## 2.7 References


Addams, L., G. Boccaletti, M. Kerlin and M. Stuchtey (2009). Charting Our Water Future - Economic frameworks to inform decision-making. New York, McKinsey & Company.

AEA, E4Tech, Metronomica, Ricardo, IEEP and CE Delft (2008). Building a UK Transport Supply-side Marginal Abatement Cost Curve. London, Committee of Climate Change.

Agnolucci, P., P. Ekins, G. Iacopini, K. Anderson, A. Bows, S. Mander and S. Shackley (2009). "Different scenarios for achieving radical reduction in carbon emissions: A decomposition analysis." Ecological Economics **68**(6): 1652-1666.

Akimoto, K. and T. Tomoda (2006). Costs and Technology Role for Different Levels of $CO_2$ Concentration Stabilization. Avoiding dangerous climate change. H. J. Schnellnhuber, W. P. Cramer, N. Nakicenovic, T. Wigley and G. Yohe. Cambridge ; New York, Cambridge University Press**:** 355-360.

Akimoto, K., T. Tomoda, Y. Fujii and K. Yamaji (2004). "Assessment of global warming mitigation options with integrated assessment model DNE21." Energy Economics **26**(4): 635-653.

Amann, M., P. Rafaj and N. Höhne (2009). GHG mitigation potentials in Annex I countries - Comparison of model estimates for 2020. Laxenburg, Austria, International Insitute for Applied Systems Analysis.

Amir, R., M. Germain and V. Van Steenberghe (2008). "On the Impact of Innovation on the Marginal Abatement Cost Curve." Journal of Public Economic Theory **10**(6): 985-1010.

Ang, B. W. and F. Q. Zhang (2000). "A survey of index decomposition analysis in energy and environmental studies." Energy **25**(12): 1149-1176.

Azar, C., K. Lindgren, M. Obersteiner, K. Riahi, D. van Vuuren, K. den Elzen, K. Möllersten and E. Larson (2010). "The feasibility of low $CO_2$ concentration targets and the role of bio-energy with carbon capture and storage (BECCS)." Climatic Change **100**(1): 195-202.

Baker, E. and E. Shittu (2007). Technical Change and the Marginal Cost of Abatement. Amherst, MA, University of Massachusetts.

Barker, T., I. Bashmakov, A. Alharthi, M. Amann, L. Cifuentes, J. Drexhage, M. Duan, O. Edenhofer, B. Flannery, M. Grubb, M. Hoogwijk, F. I. Ibitoye, C. J. Jepma, W. A. Pizer and K. Yamaji (2007). Mitigation from a cross-sectoral perspective. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. B. Metz, O. R. Davidson, P. R. Bosch, R. Dave and L. A. Meyer. Cambridge, United Kingdom and New York, NY, USA, Cambridge University Press.

Barker, T., M. S. Qureshi and J. Köhler (2006). The Costs of Greenhouse Gas Mitigation with Induced Technological Change: A Meta-Analysis of Estimates in the Literature. Tyndall Centre for Climate Change Research. Cambridge, Cambridge Centre for Climate Change Mitigation Research, Department of Land Economy, University of Cambridge. **89**.

Bauman, Y., M. Lee and K. Seeley (2008). "Does Technological Innovation Really Reduce Marginal Abatement Costs? Some Theory, Algebraic Evidence, and Policy Implications." Environmental and Resource Economics **40**(4): 507-527.

Beaumont, N. J. and R. Tinch (2004). "Abatement cost curves: a viable management tool for enabling the achievement of win-win waste reduction strategies?" Journal of Environmental Management **71**(3): 207-215.

Blok, K., D. de Jager, C. Hendriks, N. Kouvaritakis and L. Mantzos (2001). Economic Evaluation of Sectoral Emission Reduction Objectives for Climate Change - Comparison of 'Top-down' and 'Bottom-up' Analysis of Emission Reduction Opportunities for $CO_2$ in European Union. Brussels, Ecofys Energy and Environment, National Technical University of Athens.

Blok, K., E. Worrell, R. Cuelenaere and W. Turkenburg (1993). "The cost effectiveness of $CO_2$ emission reduction achieved by energy conservation." Energy Policy **21**(6): 656-667.

Blom, M., B. Kampman and D. Nelissen (2007). Price effects of incorporation of transportation into EU ETS. Delft, CE Delft.

Blumstein, C. and S. E. Stoft (1995). "Technical efficiency, production functions and conservation supply curves." Energy Policy **23**(9): 765-768.

Böhringer, C. and T. F. Rutherford (2008). "Combining bottom-up and top-down." Energy Economics **30**(2): 574-596.

Capros, P., N. Kouvaritakis and L. Mantzos (2001). Economic Evaluation of Sectoral Emission Reduction Objectives for Climate Change - Top-down Analysis of Greenhouse Gas Emission Reduction Possibilities in the EU. Athens, National Technical University of Athens.

Casillas, C. E. and D. M. Kammen (2010). "The Energy-Poverty-Climate Nexus." Science **330**(6008): 1181-1182.

Chen, W. (2005). "The costs of mitigating carbon emissions in China: findings from China MARKAL-MACRO modeling." Energy Policy **33**(7): 885-896.

Clapp, C., K. Karousakis, B. Buchner and J. Chateau (2009). National and Sectoral GHG Mitigation Potential: A Comparison Across Models. Paris, Organisation for Economic Co-operation and Development.

Clarke, L., J. Edmonds, H. D. Jacoby, H. Pitcher, J. M. Reilly and R. Richels (2007). Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations. Sub-report 2.1A of Synthesis and Assessmnet Product 2.1 by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. Washington, DC., Department of Energy / Office of Biological & Environmental Research.

Committee on Climate Change (2008). Building a low-carbon economy - the UK's contribution to tackling climate change. London.

Creyts, J., A. Derkach, S. Nyquist, K. Ostrowski and J. Stephenson (2007). Reducing U.S. Greenhouse Gas Emissions: How Much at What Cost? New York, NY, USA, McKinsey & Company.

Criqui, P., S. Mima and L. Viguier (1999). "Marginal abatement costs of CO2 emission reductions, geographical flexibility and concrete ceilings: an assessment using the POLES model." Energy Policy **27**(10): 585-601.

Dean, A. and P. Hoeller (1992). Costs of Reducing $CO_2$ Emissions: Evidence from Six Global Models. OECD Economic Studies. Paris, OECD.

Diakoulaki, D., G. Mavrotas, D. Orkopoulos and L. Papayannakis (2006). "A bottom-up decomposition analysis of energy-related $CO_2$ emissions in Greece." Energy **31**(14): 2638-2651.

Difiglio, C. and K. G. Duleep (1990). "Cost Effectiveness of Future Fuel Economy Improvements." Energy Journal **11**(1): 65-85.

EBRD and Grantham Institute (2011). The Low Carbon Transition. London, European Bank for Reconstruction and Development.

Edenhofer, O., K. Lessmann, C. Kemfert, M. Grubb and J. Köhler (2006). "Induced Technological Change: Exploring its Implications for the Economics of Atmospheric Stabilization: Synthesis Report from the Innovation Modeling Comparison Project." Energy Journal **27**(Special Issue: Endogenous Technological Change and the Economics of Atmospheric Stabilization): 57-107.

Ellerman, A. D. and A. Decaux (1998). Analysis of Post-Kyoto $CO_2$ Emissions Trading Using Marginal Abatement Curves. Cambridge, MA, Massachusetts Institute of Technology.

Enkvist, P. A., T. Naucler and J. Rosander (2007). "A cost curve for greenhouse gas reduction." The McKinsey Quarterly(1): 35-45.

Farugui, A., M. Mauldin, S. Schick, K. Seiden, G. Wikler and C. W. Gellings (1990). Efficient electricity use: Estimates of maximum energy savings. Palo Alto, Electric Power Research Institute.

Fischer, C. and R. D. Morgenstern (2006). "Carbon Abatement Costs: Why the Wide Range of Estimates?" Energy Journal **27**(2): 73-86.

Fisher, B., N. Nakicenovic, K. Alfsen, J. C. Morlot, F. d. l. Chesnaye, J.-C. Hourcade, K. Jiang, M. Kainuma, E. L. Rovere, A. Matysek, A. Rana, K. Riahi, R. Richels, S. Rose, D. V. Vuuren and R. Warren (2007). Issues related to mitigation in thel long-term context. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Inter-governmental Panel on Climate Change. B. Metz, O. R. Davidson, P. R. Bosch, R. Dave and L. A. Meyer. Cambridge, Cambridge University Press**:** 169-250.

Fleiter, T., W. Eichhammer, M. Hagemann, M. Wietschel and S. Hirzel (2009). Costs and potentials of energy savings in European industry - a critical assessment of the concept of conservation supply curves. ECEEE 2009 Summer Study, La Colle sur Loup, France.

Gaskins, D. W. and J. Weyant (1993). EMF 12: Model Comparisons of the Costs of Reducing $CO_2$ Emissions. Stanford, Energy Modeling Forum, Stanford University.

Gracceva, F. and U. Ciorba (2008). Abatement Cost Curves by (Group of) Technologies for Italy. ETSAP Semi-annual Workshop. IEA. Paris.

Grubb, M., J. Edmonds, P. ten Brick and M. Morrison (1993). "The Costs of Limiting Fossil-fuel $CO_2$ Emissions: A Survey and Analysis." Annual Review of Energy and the Environment **18**: 397-478.

Hanaoka, T., M. Kainuma and Y. Matsuoka (2009). "The role of energy intensity improvement in the AR4 GHG stabilization scenarios." Energy Efficiency **2**(2): 95-108.

Hankinson, G. A. and J. M. W. Rhys (1983). "Electricity consumption, electricity intensity and industrial structure." Energy Economics **5**(3): 146-152.

Hendriks, C., D. De Jager, K. Blok, J. de Beer, J. Harnisch, S. Joosen, D. Phylipsen, M. Kerssemeeckers, C. Byers, M. Patel, J. Bates, C. Brand, P. Davison, A. Haworth and N. Hill (2001). Economic Evaluation of Sectoral Emission Reduction Objectives for Climate Change - Bottom-up Analysis of emission Reduction Potentials and Costs for Greenhouse Gases in the EU. Utrecht, The Netherlands, ECOFYS Energy and Environment, AEA Technology Environment.

Holdren, J. P. (2006). "The Energy Innovation Imperative: Addressing Oil Dependence, Climate Change, and Other 21st Century Energy Challenges." Innovations: Technology, Governance, Globalization **1**(2): 3-23.

Hourcade, J.-C., K. Halsnaes, M. Jaccard, W. D. Montgomery, R. Richels, J. Robinson, P. Shukla and P. Sturm (1995). A Review of Mitigation Cost Studies. Climate

Change 1995: Contribution of Working Group III to the Second Assessment of the Intergovernmental Panel on Climate Change. J. J. Houghton, L. G. Meiro Filho, B. A. Callanderet al. Cambridge, United Kingdom, Cambridge University Press.

Hourcade, J.-C., M. Jaccard, C. Bataille and F. Ghersi (2006). "Hybrid Modeling: New Answers to Old Challenges - Introduction to the Special Issue of The Energy Journal." Energy Journal **27**: 1-11.

Hummel, H. (2006). Interpreting Global Energy and Emission Scenarios: Methods for Understanding and Communicating Policy Insights. Interdisciplinary Program on Environment and Resources. Stanford, Stanford University. **Doctor of Philosophy:** 482.

International Energy Agency (2004). Oil Crises & Climate Changes. OECD. Paris.

International Energy Agency (2008a). Energy Technology Perspectives 2008. OECD. Paris.

International Energy Agency (2008b). World Energy Outlook 2008. OECD. Paris.

Jackson, T. (1991). "Least-cost greenhouse planning supply curves for global warming abatement." Energy Policy **19**(1): 35-46.

James, R. (2008). The Full Portfolio. Electric Perspectives. E. P. R. Institute. Palo Alto, CA, Electric Power Research Institute**:** 36-51.

James, R., R. Richels, G. Blanford and S. Gehl (2007). The Power to Reduce $CO_2$ Emissions - The Full Portfolio. Palo Alto, CA, Electric Power Research Institute,.

Jenne, C. A. and R. K. Cattell (1983). "Structural change and energy efficiency in industry." Energy Economics **5**(2): 114-123.

Jol, A. and E. Karakaya (2006). Greenhouse gas emission trends and projections in Europe 2006. EEA Report. Office for Official Publications of the European Communities. Copenhagen, European Environment Agency. **9/2006**.

Kawase, R., Y. Matsuoka and J. Fujino (2006). "Decomposition analysis of CO2 emission in long-term climate stabilization scenarios." Energy Policy **34**(15): 2113-2122.

Kaya, Y. (1989). Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. IPCC Energy and Industry Subgroup - Response Strategies Working Group. (mimeo). Paris.

Kesicki, F. and P. Ekins (2011). "Marginal Abatement Cost Curves: A call for caution." Climate Policy(forthcoming).

Klepper, G. and S. Peterson (2003). On the Robustness of Marginal Abatement Cost Curves: The Influence of World Energy Prices. Kiel Working Papers. Kiel, Kiel Institute for World Economics. **1138**.

Klepper, G. and S. Peterson (2006). "Marginal abatement cost curves in general equilibrium: The influence of world energy prices." Resource and Energy Economics **28**(1): 1-23.

Kram, T. (1993). National Energy Options for Reducing $CO_2$ Emissions, Volume I: The International Connection. Energy Technology Systems Analysis Programme. Petten, Netherlands Energy Research Foundation ECN.

Kuik, O., L. Brander and R. S. J. Tol (2009). "Marginal abatement costs of greenhouse gas emissions: A meta-analysis." Energy Policy **37**(4): 1395-1403.

Ledbetter, M. and M. Ross (1990). A Supply Curve Of Conserved Energy For Automobiles. 25th Intersociety Energy Conversion Engineering Conference.

Löschel, A. (2002). "Technological change in economic models of environmental policy: a survey." Ecological Economics **43**(2-3): 105-126.

Meier, A. K. (1982). Supply Curves of Conserved Energy. Lawrence Berkeley Laboratory. Berkeley, University of California. **PhD:** 110.

Mills, E., D. Wilson and T. B. Johansson (1991). "Getting started: no-regrets strategies for reducing greenhouse gas emissions." Energy Policy **19**(6): 526-542.

Morris, J., S. Paltsev and J. M. Reilly (2008). Marginal Abatement Costs and Marginal Welfare Costs for Greenhouse Gas Emissions Recutions: Results from the EPPA Model. Cambridge, MA, MIT Joint Program on the Science and Policy of Global Change.

Nauclér, T. and P. A. Enkvist (2009). Pathways to a Low-Carbon Economy - Version 2 of the Global Greenhouse Gas Abatement Cost Curve, McKinsey & Company.

Nordhaus, W. D. (1977). Strategies for the Control of Carbon Dioxide. Cowles Foundation Discussion Paper. Cowles Foundation for Research in Economics. New Haven.

Pacala, S. and R. Socolow (2004). "Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies." Science **305**(5686): 968-972.

Paltsev, S., J. M. Reilly, H. D. Jacoby, R. S. Eckaus, J. McFarland, M. Sarofim, M. Asadoorian and M. Babiker (2005). The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4. Cambridge, MA, MIT Joint Program on the Science and Policy of Global Change.

Parry, M., O. Canziani, J. Palutikof, P. van der Linden and C. Hanson, Eds. (2007). Climate Change 2007: Impacts, Adaptation and Vulnerability - Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. New York, Cambridge University Press.

Rao, S., I. Keppo and K. Riahi (2006). "Importance of Technological Change and Spillovers in Long-Term Climate Policy." Energy Journal **27**(Endogenous Technological Change): 123-139.

Rao, S. and K. Riahi (2006). "The Role of Non-$CO_2$ Greenhouse Gases in Climate Change Mitigation: Long-term Scenarios for the 21st Century." Energy Journal **27**(Multi-Greenhouse Gas Mitigation): 177-200.

Renders, N. (2009). ECM Households: How to deal with no-regret measures? ETSAP Spring Workshop 2009. Venice, Italy.

Rentz, O., H. D. Haasis, A. Jattke, P. Ru, M. Wietschel and M. Amann (1994). "Influence of energy-supply structure on emission-reduction costs." Energy **19**(6): 641-651.

Repetto, R. C. and D. Austin (1997). The costs of climate protection : a guide for the perplexed. Washington, DC, World Resources Institute.

Riahi, K., A. Grübler and N. Nakicenovic (2007). "Scenarios of long-term socio-economic and environmental development under climate stabilization." Technological Forecasting and Social Change **74**(7): 887-935.

Risø National Laboratory (1994). UNEP Greenhouse Gas Abatement Costing Studies. United Nations Environment Programme. Roskilde.

Rogner, H.-H., D. Zhou, R. Bradley, P. Crabbé, O. Edenhofer, B. Hare, L. Kuijpers and M. Yamaguchi (2007). Introduction. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. B. Metz, O. R. Davidson, P. R. Bosch, R. Dave and L. A. Meyer. Cambridge, United Kingdom, Cambridge University Press.

Rosenfeld, A., C. Atkinson, J. Koomey, A. Meier, R. J. Mowris and L. Price (1993). "Conserved Energy Supply Curves for U.S. Buildings." Contemporary Economic Policy **11**(1): 45-68.

Rubin, E. S., R. N. Cooper, R. A. Frosch, T. H. Lee, G. Marland, A. H. Rosenfeld and D. D. Stine (1992). "Realistic Mitigation Options for Global Warming." Science **257**: 148-149 and 261-266.

Shrestha, R. M., G. Anandarajah and M. H. Liyanage (2009). "Factors affecting $CO_2$ emission from the power sector of selected countries in Asia and the Pacific." Energy Policy **37**(6): 2375-2384.

Siddiqui, M. S. (2010). Impacts of External Change on a Regional Marginal Abatement Cost Curve: A Canadian Perspective. Fourth World Congress of Environmental and Resource Economists. Montreal, Canada.

Sitnicki, S., K. Budzinski, J. Juda, J. Michna and A. Szpilewicz (1991). "Opportunities for carbon emissions control in Poland." Energy Policy **19**(10): 995-1002.

Stern, N. H. (2007). The economics of climate change : the Stern review. Cambridge, UK, Cambridge University Press.

Stoft, S. (1995). "The economics of conserved-energy `supply' curves." Energy Journal **16**(4): 109-140.

Thomas, S. and G. MacKerron (1982). "Industrial electricity consumption in the UK - Past determinants and possible futures." Energy Policy **10**(4): 275-294.

Tol, R. S. J. (2005). "Adaptation and mitigation: trade-offs in substance and methods." Environmental Science & Policy **8**(6): 572-578.

Torvanger, A. (1991). "Manufacturing sector carbon dioxide emissions in nine OECD countries, 1973-87 : A Divisia index decomposition to changes in fuel mix, emission coefficients, industry structure, energy intensities and international structure." Energy Economics **13**(3): 168-186.

United Nations (1992). United Nations Framework Convention on Climate Change. United Nations. New York.

Vahlenkamp, T., P. Beckmann, L. Birnbaum, P. Carlsson-Sziezak, D. Cornelius, K. Greven, A. Hartmann, J.-H. Hübner, F. Kühn, C. Malorny, C. Müller-Falcke, T. Parr, M. Peters, J. Riese, S. Weyers and R. Winkelmann (2007). Kosten und Potenziale der Vermeidung von Treibhausgasemissionen in Deutschland. Mc Kinsey & Company. Düsseldorf.

van der Zwaan, B. and A. Rabl (2008). A Cost-Benefit Analysis of climate change: Uncertainties and the Value of Information. International Energy Workshop (IEW). I. E. Agency. Paris, France**:** 1-23.

van Vuuren, D. P., B. de Vries, B. Eickhout and T. Kram (2004). "Responses to technology and taxes in a simulated world." Energy Economics **26**(4): 579-601.

van Vuuren, D. P., M. Hoogwijk, T. Barker, K. Riahi, S. Boeters, J. Chateau, S. Scrieciu, J. van Vliet, T. Masui, K. Blok, E. Blomen and T. Kram (2009). "Comparison of top-down and bottom-up estimates of sectoral and regional greenhouse gas emission reduction potentials." Energy Policy **37**(12): 5125-5139.

Vattenfall (2007). Vattenfall's Climate Map 2030. C. Fager and J. Bratt. Stockholm.

Viguier, L. L., M. H. Babiker and J. M. Reilly (2003). "The costs of the Kyoto Protocol in the European Union." Energy Policy **31**(5): 459-481.

Weyant, J. P. (1993). "Costs of Reducing Global Carbon Emissions." Journal of Economic Perspectives **7**(4): 27-46.

Weyant, J. P., F. C. de la Chesnaye and G. J. Blanford (2006). "Overview of EMF-21: Multigas Mitigation and Climate Policy." Energy Journal **27**(Multi-Greenhouse Gas Mitigation): 1-32.

Wiesenthal, T. and R. Fernández (2006). Energy and environment in the European Union. EEA Report. Office for Official Publications of the European Communities. Copenhagen, European Environment Agency,. **08/2006**.

Willemé, P. (2003). "A statistical approach to conservation supply curves." Energy Economics **25**(5): 553-564.

Willows, R. and R. Connell (2003). Climate adaptation: Risk, uncertainty and decision-making. Oxford, UK Climate Impacts Programme.

Zhang, Z. and H. Folmer (1998). "Economic modelling approaches to cost estimates for the control of carbon dioxide emissions." Energy Economics **20**(1): 101-120.

# 3 ENERGY SYSTEM MODELLING

This section explains the underlying modelling framework MARKAL (MARket ALlocation) used in this thesis to generate MAC curves. It starts with the background and goals of energy system analysis. Energy models, which help to simplify interactions in the energy system, are presented in the next section. Subsequently, the model structure of MARKAL (version 3.21), its implementation and the mathematical description is presented, followed by a subsection on the generation of MAC curves with MARKAL. The chapter concludes with a discussion of the cost and abatement potential concepts used in the context of climate change mitigation.

## 3.1 Energy system analysis

Energy system analysis is intended to help support decisions in energy policy and energy research with regard to technologies and infrastructures for the energy supply and behavioural aspects on the demand side in a scientific and systematic manner. In this context, the energy system can be investigated at very different scales, ranging from a global, continental, national or regional system towards an industrial site or a house. For this thesis the energy system is defined as that which includes the energy sector of the economy from energy supply, including energy transformation towards energy demand sectors. This system can in general be divided into the upstream sector for energy supply, electricity/heat/hydrogen/refining sectors as the transformation part and industry, transport, residential sector, service sector and agriculture as demand sectors.

In contrast to the assessment of single technologies, system analysis is concerned with the investigation of structural elements of a system, i.e. the descriptive representation of the functioning of a system. It takes a holistic, abstract and object independent view, i.e. it is not focused on a single, specific element of the system but is rather interested in the interactions within the whole system. A necessity for system orientated planning methods exists because of increasing technical knowledge and specialisation of knowledge areas, the increasing number of people involved, the impact of planning consequences and the need for integration of areas of knowledge. Developments in energy management and key technologies, limited fossil resources and climate change, demographic change, political, social and economic framing conditions, the ambition for sustainability – all these are only some of the factors that have to be taken into account in the analysis of the energy system. Integrated analysis is particularly important in the energy system because of the following characteristics.

Crucial parts of the energy system, such as infrastructure, possesses a long-term nature and bound change in the whole system. Changes in the power sector need several decades to materialise, even very fast adjustments, like for example the expansion of nuclear power plants in France, take more than a decade. However, developments in other sectors, such as vehicle or boiler replacement occur in smaller time intervals. Exceptions are demand-related measures, e.g. daily or seasonal changing transport or residential heating patterns. Single decisions, such as the construction of a refinery or the planning of an oil pipeline, have an impact on the whole energy system and have to be seen in the wider context, i.e. how they interact with other decisions. Complexity and multi-dimensionality appears not only in the technological structures of single plants but also in the interactions of different units, such as in the electricity system, and the interplay of different stakeholders participating in the energy sector (Voß 2009). Those stakeholders include people from the energy sector, politics, environment, resources and other parts of the economy. Like many other parts of the economy, the energy sector is subject to uncertain influencing factors (see chapter 5). The future development of key variables, such as fossil fuel prices, technology costs and availabilities are uncertain. A final point is that the energy sector is marked by conflicting goals. Accepted goals of many stakeholders include the pursuit of sustainability, energy security and making the energy infrastructure available to as many citizens as possible. While the use of domestic coal, for example, would satisfy the goal of energy security it stands in contrast to a sustainable, low-carbon society. In addition, the energy sector is characterised by market failures and market barriers, which hamper the realisation of such goals.

Closely connected to the term ‘system’ is the term ‘model’, which is an abstract representation of the real system describing the behaviour and interactions of system elements in a qualitative or quantitative manner (Möst and Fichtner 2009). Models are used to gain insights about the behaviour of the real system for example as a decision support aid and for the determination of consequences from decisions. Models are expected to identify the necessary part of reality and elaborate the crucial aspects, but nevertheless reduce the degree of complexity in order to remain manageable. The model building and the degree of aggregation is usually driven by the question the model is supposed to answer. Furthermore, models should be free of contradictions, verifiable, modifiable, comprehensible and user friendly. It is important to stress that the developed models are in general a quantitative support mechanism or an exercise to gain information and help in this way to arrive at well-informed decisions. A precise forecast of the future is not possible because of uncertain assumptions affecting the energy system, which become even less predictable with a model horizon of several decades. A model rather presents a consistent tool to investigate how a system develops under certain conditions. Huntington et al. (1982, p. 450) summarised this as using models to develop insights rather than forecast numbers.

## 3.2 Energy models

The oil embargo in 1973 and the unfamiliar circumstances at that time created the motivation for the development of energy modelling. Early models concentrated mostly on specific sectors, such as the electricity sector or oil sector (Huntington et al. 1982). A second-generation of energy models comprised energy system models that look at the whole energy system from energy supply via energy transformation to energy demand. A further development represented energy-economy models that not only focus on the energy sector but also include economy-wide interactions. Integrated assessment models represent again a more comprehensive category that include interactions across different sectors, such as forestry, agriculture and energy, as well as with the environment, i.e. the impact of rising emissions on the environment and in some cases feedback on the economy through a damage function. Those models try to address the issues of equity across space and time, possible damage costs and uncertainty (see e.g. Rotmans and van Asselt 2001; Stanton et al. 2008).

A modelling approach mainly used in other disciplines is agent-based modelling. These models consider the behaviour and interaction of individual agents and therefore provide insights into the behaviour of organisations and their implications for technology adoption (DeCanio et al. 2001; Worrell et al. 2004, p. 365). This approach tries to challenge the common objective in energy models of cost minimisation or profit maximisation by incorporating a more realistic organisational network structure to examine its overall influence. It can contribute to change implicit assumptions that are generally used when trying to find a solution for environmental problems. Bower et al. (2000) have applied an agent-based model to the UK electricity market.

Energy models can be distinguished according to their planning period. While short-term energy models are used for the portfolio management of single companies and consider a period of days to a year, medium to long-term models also include investment decisions. With the last category of models it is possible to explore questions in energy and environment policy. As this thesis focuses on long-term developments of carbon reduction portfolios the following categorisation focuses on long-term models.

### 3.2.1 Categorisation

Energy models can be distinguished by many characteristics. Many hybrid types of approaches make a clear distinction impossible and permit only a general categorisation. This is related to the fact that some models were initially built for a specific purpose and were then applied to integrate other aspects. Many models, for example, were developed with a fossil fuel-based energy system in mind that cannot represent intermittent systems based on renewable energy sources. Table 3.1 gives an overview of the possible classifications of energy models. Many researchers have reviewed existing energy models and classified them in various ways (Löschel 2002; Springer 2003; Jebaraj and Iniyan 2006).

The most common separation of such models is into bottom-up and top-down (see e.g. Hourcade et al. 1995). A top-down approach breaks down a system to gain insight into its compositional sub-systems, while a bottom-up approach puts together elements of a system to give rise to grander systems, thus making the original systems sub-systems of the emergent system. In the energy field, bottom-up models are used to describe the current and prospective competition of energy technologies in detail, both on the supply-side (the substitution possibilities between primary forms of energy) and on the demand-side (the potential for end-use energy efficiency and fuel substitution). Typical examples of bottom-up models are energy system models. Top-down models on the other side address the consequences of policies in terms of public finances, economic competitiveness and employment (Hourcade et al. 2006). Typical examples of top-down models are computable general equilibrium (CGE) models. Conventional bottom-up models are known for their technological detail and lack of microeconomic realism, whereas conventional top-down models include economy-wide interactions based on market behaviour, but lack the technological explicitness.

Both model types address the same problem from different perspectives. On the one hand, top-down models are based on historical trends and can therefore only give useful results in the case that historical relationships among key underlying variables remain constant. Bottom-up models, on the other hand, include predominantly only the energy sector and are therefore only suited for analytical purposes when there are no important feedbacks between the energy sector and the other sectors of the economy (van Beeck 1999).

The distinction between top-down and bottom-up models is almost two decades old (Grubb et al. 1993; Wilson and Swisher 1993). Since then it became more difficult to maintain this clear distinction between bottom-up and top-down models because bottom-up models have integrated microeconomic aspects like a price-elastic demand and top-down models have integrated more technological detail into the nested production functions (Hourcade et al. 2006, p. 5f). Moreover, hybrid models have been developed that combine in different ways the top-down and bottom-up approach in one model. Böhringer et al. (2008) distinguish in this context three different types of hybrid models: combination of independently developed bottom-up and top-down models, a bottom-up or top-down model used together with a reduced form representation of the other and a completely integrated model based on solution algorithms for mixed complementarity problems.

Another possibility to divide energy models is according to their treatment of uncertainty, i.e. if they are deterministic or for example stochastic. Many energy models were constructed as deterministic models thus relying on specific input assumptions. In this case uncertainty can only be considered via the variation of input assumptions, i.e. sensitivity analysis. In contrast, stochastic models incorporate uncertainty about technology development, energy prices or other parameters by assigning probabilities to different developments of these input assumptions. This enables the modeller to derive hedging strategies for different scenarios.

According to the time frame one can distinguish energy models into static, dynamic and recursive dynamic. Since many energy models cover several decades, static models, which optimise only one period, are relatively rare. Dynamic models describe states and changes in the system by means of differences and differentials over the course of time. Dynamic models possess perfect foresight, which means that they optimise the system over the whole planning period. Dynamic recursive models, also called myopic models, do not consider the whole planning period but optimise for a subset of periods, where decisions of earlier periods are inputs to the following period (Keppo and Strubegger 2010).

The mathematical implementation of energy optimisation models can broadly be divided into linear and non-linear with separate integer formulation or mixed integer variants when only a subset of the variables are required to be integers. Linear models need less computational capacities and calculate a global optimum but restrict the modelling to linear relationships, which sometimes approximate non-linear relationships. Non-linear models are in general more time intensive to optimise than a comparable linear model. They allow the consideration of non-linear relationships but may only find one of several local optima rather than a global optimum. One can assume an optimum to be global in the non-linear context only in the case of convex model equations and a convex objective function.

A further well-known differentiation between models is into simulation and optimisation. Optimisation models give an answer to the question of how to achieve a given goal described in an objective function subject to constraints. An example is cost minimisation, where many possible solutions exist and the model chooses the optimal, i.e. the most cost-effective one. One could say that optimisation models simulate some physical aspects of the energy system depending on the degree of endogenisation, i.e. the input parameters, and optimise the rest. Simulation models answer the question: what happens for a set of given conditions? This does not necessarily lead to a full equilibrium or an optimum. It means that these models investigate in an explorative manner the consequences for given options. Mathematically this corresponds to a set of equations with an equal number of variables. In contrast to an optimisation model, where the model chooses the optimum among possible solutions, a simulation model has no degrees of freedom. Optimisation models can also be described as prescriptive models as they give insights on what to do to make the best of a set of conditions, while simulation models can be characterised as descriptive since they clarify what would happen in a specified situation. The advantage of simulation models is that they can better model real, imperfect markets in contrast to optimisation models. Nevertheless, given decision making rules determine the model outcome and interactions between different rules are unclear (Möst and Fichtner 2009, p. 22). In this context, sensitivity analysis can help to a certain extent to shed some light on these interactions (see section 5.2.1).

The degree of endogenisation, i.e. the degree to which parameters are incorporated into the model, can be another metric for the categorisation of models. Energy models must have at least one external parameter and can have all parameters determined externally, while the majority of models lie in between. Exogenous assumptions include in most cases parameters, such as population growth, economic growth, price elasticity of energy demand and can further include energy demand, supply and existing taxes (van Beeck 1999). The degree of endogenisation tends to be higher in optimisation models compared to simulation models. In recent years several exogenous assumptions have been endogenised in bottom-up models, like price elastic demand curves, use of endogenous technological learning or stochastic programming in order to endogenise uncertainty related to input assumptions (Remme 2006, p. 81). In addition, top-down models endogenise economy wide interactions, while bottom-up models rely on external assumptions in this respect.

Lastly, one can distinguish energy models according to the geographical scope. This includes models on a local, regional, national, continental and global level. In addition, energy models differ according to the sectors they include. Models can be restricted to a single sector, such as electricity generation, the energy system or the whole economy.

**Table 3.1: Taxonomy for the differentiation of energy models**

| |
|---|
| *The analytical approach*: Bottom-up and top-down |
| *Treatment of uncertainty*: deterministic and stochastic |
| *Treatment of foresight*: static, dynamic and recursive dynamic |
| *Mathematical implementation*: linear and non-linear programming |
| *Underlying methodology*: optimisation and simulation |
| *Degree of endogenisation:* fuel prices, economic growth, taxes, energy demand |
| *Geographical scope*: local, regional, national, continental and global |

### 3.2.2 Top-down models

This section should give a brief overview of typical types of top-down models. Models in this category can be divided into growth models, CGE models and macroeconometric models.

**Growth models** are based on modern growth theory maximising aggregated social welfare, which is discounted over the future. Optimal growth models facilitate the understanding of growth dynamics, i.e. transition paths, over long term horizons under the assumption of what decentralised markets can achieve in the presence of appropriate policy instruments. Global growth is partly explained in terms of research and "learning by doing" affecting the stock of knowledge, which in turn enters the production functions of the model. Important assumptions include representative agents and full employment. In this context growth models can be distinguished as first best models, which implicitly assume perfect markets and optimal policy tools, whilst second best models include market imperfections and sub-optimal policy tools (Edenhofer et al. 2006, p. 62ff).

Examples of growth models are:

- DEMETER (**DE**-carbonisation **M**odel with **E**ndogenous **T**echnologies for **E**mission **R**eductions) (Gerlagh and van der Zwaan 2004; Gerlagh 2006)
- DICE (**D**ynamic **I**ntegrated **C**limate-**E**conomy) (Nordhaus 1993)
- FEEM-RICE (**R**egional **I**ntegrated Model of **C**limate and the **E**conomy) (Bosetti et al. 2006)

The most widely used type of top-down models are **CGE models**, which are, as their name implies, based on equilibrium theory and thus do not capture short term adjustments but concentrate on the long term. This model type also relies on the assumption of representative agents, but can incorporate the stock of knowledge and can include unemployed labour in contrast to growth models. CGEs optimise over a series of static equilibria, generating insights on how the economy shifts from one equilibrium to another and calculate numerically demand, supply and the resulting price. In these models every sector is mapped with a nested production function, where production factors are substitutable according to a defined elasticity, so that policy responses can be modelled.

Top-down models have been criticised for their dependence on the elasticity of substitution between energy and labour/capital and the autonomous energy efficiency index (AEEI). The elasticity of substitution represent price induced changes in the demand for energy and the AEEI represent the non-price induced energy intensity reduction. Both parameters are used to describe complex behaviour, but are neither observable nor measurable. Knowing that the rate of non-price induced efficiency improvement has changed historically, it is disputable to assume that it cannot change, or be changed, in the future as is assumed in top-down models (Wilson and Swisher 1993). In effect, this modelling approach assumes that market behaviour remains in line with historical observations, so that institutional innovations as well as technological adjustments beyond current practice aimed at improving energy efficiency are excluded. Provocatively, Wilson et al. (1993, p. 254) stated that top-down models tell us that if it had been expensive to reduce $CO_2$ emissions in the past, and the economy stays the same as it was at that time, it will also be expensive in the future.

That is the reason why top down models have been said to suggest that efforts to reduce carbon emissions are relatively costly, i.e. the economy's potential for technological transformation is limited as portrayed by historically-based elasticities (Hourcade et al. 2006, p.4). In recent years, this problem has been recognised and top-down modellers have tried to model induced technological change (ITC) in the presence of ambitious policies (Edenhofer et al. 2006).

In addition, top-down models can consider the rebound effect. This effect describes a phenomenon where efficiency improvements do not lead to the expected reduction in final energy consumption because part of it is compensated by an increase of energy service consumption due to a cheaper energy service (Sorrell 2007). Top-down models take account of the effect in the way that a price decrease results in the recycling of economic savings that leads to increased consumption. However, they do not consider that it can result in the substitution of energy consumption by the consumption of other economic inputs, such as labour.

Lastly, some CGE-models possess the abstract construct of a backstop technology, which can provide infinite energy at a comparably high price and thus set a maximum limit for a $CO_2$ price in the case of a carbon constraint. The reason for the modelling of a backstop technology can be found in the poor technological detail of top-down models.

Examples of CGE models are:

- AIM (**A**sia-Pacific **I**ntegrated **M**odel) (Fujino et al. 2006)
- EPPA (**E**missions **P**rediction and **P**olicy **A**nalysis) (Ellerman and Decaux 1998; Paltsev et al. 2005)

- GCAM (former MiniCAM) (**G**lobal **C**hange **A**ssessment **M**odel) (Clarke et al. 2008; Luckow et al. 2010)
- GEM-E3 (**G**eneral **E**quilibrium **M**odel for **E**nergy-**E**conomy-**E**nvironment) (van Regemorter 2005)
- MERGE (**M**odel for **E**valuating **R**egional and **G**lobal **E**ffects of GHG reduction policies) (Manne et al. 1995; Manne and Richels 2006)
- WIAGEM (**W**orld **I**ntegrated **A**ssessment **G**eneral **E**quilibrium **M**odel) (Kemfert 2002)
- WorldScan (Lejour et al. 2006)

A third category of top-down models is **macroeconometric models**. This model type is also called 'neo-Keynesian' as it assumes output to be demand determined in contrast to CGE models, which are supply driven. This approach simulates monetary flows between sectors, based on input-output tables. Therefore, a system of equations is created that map the economy. The equations are estimated with the help of statistical techniques, such as regression analysis based on time-series data. Thus, econometric methods are used to extrapolate past market behaviour into the future.

In contrast to CGE models, these models focus on the short to medium term with the focus on the dynamics of adjustment. They can explore the representation of growth pathways. This model type can explore pathways under disequilibrium at a high level of sectoral disaggregation linking investment to historical demand and investment trends. In this way, it enables the analysis of interactions in the economy and of consequences of policy changes, like the introduction of a $CO_2$ tax. Nevertheless, as it is based on historic estimations, this model is not able to integrate intertemporal preferences and structural breaks.

An example of macroeconometric models is:

- E3MG (**E**nergy-**E**nvironment-**E**conomy **M**odel of the **G**lobe) (Barker et al. 2006)

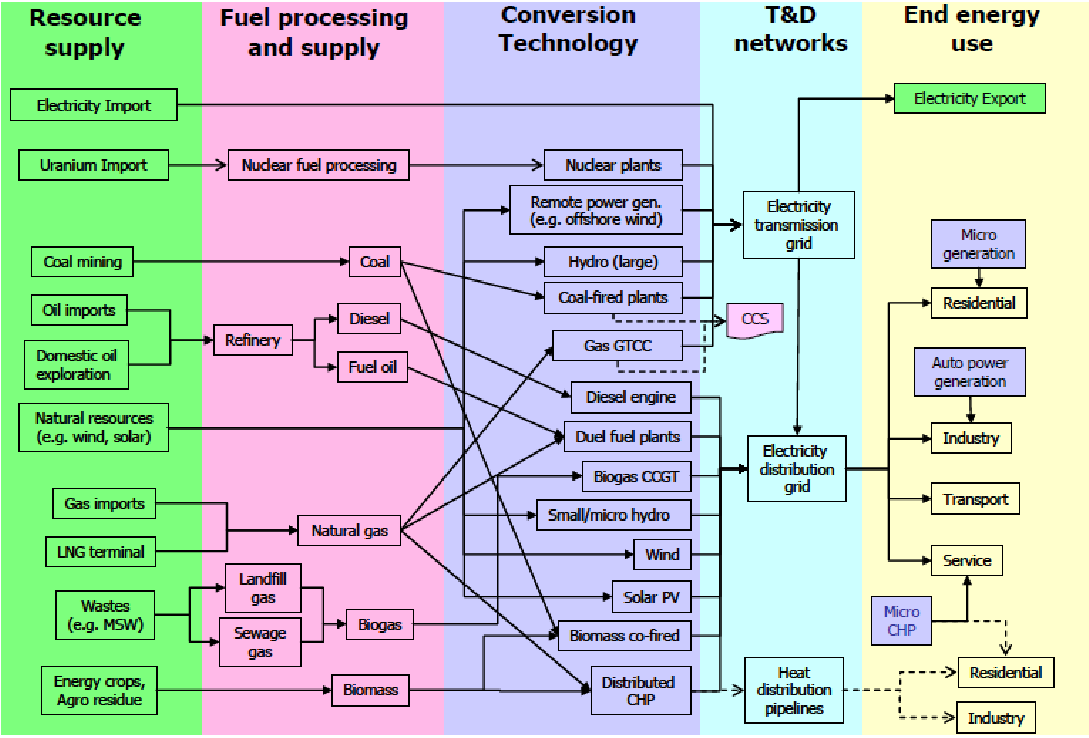
### 3.2.3 Bottom-up models

In contrast to top-down models, bottom-up models are predominantly partial equilibrium models that are limited to a part of the economy, the energy sector. Energy system models (the most common form of bottom-up models) usually derive a cost-minimum sequence of energy technologies for an exogenously given energy demand using linear programming. The focus is on the technological representation of the energy sector from primary energy through to the level of useful energy or energy service including energy transformation, transport and distribution of final energy. The main advantages of this approach are the detailed depiction of the energy sector and the possibility to base technological change on an engineering assessment of different technologies (Edenhofer et al. 2006). A key aspect of the approach to MAC curves presented in this thesis is the incorporation of technological detail into the representation of the curve. Since bottom-up models possess the technological detail, this type of model is used in the thesis. However, they do not take into account interactions with the wider economy and tend to neglect micro-economic aspects, such as market barriers or rebounds in demand.

The real energy system is represented via the flow of energy carriers and other commodities. Commodities are linked through technical facilities, such as power plants or refineries, which are described with technical and economic parameters. In general, technologies of the real system are aggregated, while the level of aggregation depends on the spatial and sectoral detail. Many energy system models use a network presentation as a mean of representing the real system that is based on a concept, which was developed in the early 1970s at the Brookhaven National Laboratory. This concept, the Reference Energy System (RES), is a physical representation of the energy flows from resources to end use.

The RES includes two types of objects: commodities and processes. The term commodities characterises all quantifiable factors, e.g. energy carriers, gases, services and industrial goods. Processes transform one or more commodities into other commodities. A link represents the flow of a commodity from or into a process, i.e. the produced or consumed good. The process “coal-fired power plant”, for example, consumes the commodity “coal” and produces the commodity “electricity” and “carbon dioxide”. A simplified RES from the UK MARKAL model is given in Figure 3.1. Since the RES is a bipartite graph, commodities and process alternate, so that a process cannot be linked directly to another process and a commodity not to another commodity. The reference contains, in addition to processes and commodities, attributes, which can be divided into process attributes, e.g. life time of a power plant, commodity attribute, e.g. the price of coal, process-commodity attributes, e.g. the variable costs of a power plant, process-commodity-commodity attributes, e.g. the efficiency of a power plant and lastly global attributes, such as the discount rate (Voß 2009).

**Figure 3.1: A simplified reference energy system from the UK MARKAL model**




**Source: Kannan et al. (2007)**[1]

The RES is designed to permit the assessment of individual technologies, explaining the associated impact on the cost of energy and environmental emissions, of technology groups and of policy options, including taxes and standards (Beller et al. 1979). Examples for the use of a RES include the assessment of combined cycle gas turbines instead of oil-fired power stations or the assessment of a large-scale electrification.

Some early versions of energy system models formed a special type of partial equilibrium models, which minimised the system cost assuming fixed energy service demands. This means, that energy service demand remained price independent and a change in useful energy could only be provoked by technological options including conservation. Energy service demands are either directly given or are assumed to be influenced by other given macroeconomic indicators. More recent versions of energy system models, however, can include a price elastic demand. If the model does not represent different efficiency options on the demand side (depending on the system boundaries), a price elastic characterisation can include more than pure price responsiveness. In a price-elastic version, the objective function changes from cost

[1] Permission to reproduce this Figure has been granted by UKERC.

minimisation to welfare (the sum of producer and consumer surplus) maximisation (Loulou and Lavigne 1996).

Energy system models cover different geographical levels, ranging from regional models to global models, as well as different time scales ranging from several years to many decades. In order to reduce the size of the model, the spatial resolution of energy system models is generally poor, incorporating only general distribution losses, instead of a geographical precise representation of energy facilities. The same holds true for the temporal resolution, where not every single year, season or time of day is optimised. Rather, several years are aggregated into a period, which is characterised by a representative year. In order to map daily or seasonal consumption patterns, energy system models revert to time slices, which should approximate for example the daily load curve for electricity.

The next few paragraphs briefly present the most widely used bottom-up models and their characteristics:

**MESSAGE**

The energy system model MESSAGE (**M**odel for **E**nergy **S**upply **S**trategy **A**lternatives and their **G**eneral **E**nvironmental Impact) was developed at the International Institute for Applied Systems Analysis (IIASA) in Laxenburg, Austria (Schrattenholzer 1981). The model represents all sectors of the energy system from energy supply including extraction and conversion via the distribution of energy to energy end-use sectors. The time horizon ranges from 1990 to 2100. Next to the six Kyoto greenhouse gases, such as $CO_2$ and $CH_4$, the model includes as well local pollutants like $SO_X$ and $NO_X$ and a simplified carbon cycle model for the estimation of atmospheric $CO_2$ concentrations (Rao and Riahi 2006). In the standard global version, the model optimises the energy system of 11 world regions by minimising total system costs. In addition, the most recent model version includes whole year storage and storage losses of electricity and the non-energy use of energy carriers. Other model variants include several versions of stochastic optimisation (Krey and Riahi 2009) and mixed integer programming.

The MESSAGE model can be linked to the MACRO model in order to include macro-economic impact of policies on energy demand. In the MACRO model the capital stock, labour and energy inputs determine the total output of an economy according to a nested constant elasticity of substitution (CES) production function. Both models are linked iteratively to obtain a fully consistent evolution of energy demand quantities, prices and macroeconomic indicators (Messner and Schrattenholzer 2000).

**TIMER / IMAGE**

IMAGE (**I**ntegrated **M**odel to **A**ssess the **G**lobal **E**nvironment) was developed in the late 1980s at the National Institute for Public Health and the Environment (RIVM) in Bilthoven, Netherlands, in order to describe global trends in the driving forces and the consequences of climatic change and impacts on key sectors (Kram and Stehfest 2006). The integrated assessment model, IMAGE, consists of different sub-models, such as an agricultural, land use and land cover and carbon cycle model. The energy system is represented within the TIMER (**T**he **IM**age **E**nergy **R**egional) model, which is an energy simulation model, describing the demand and supply of 12 different energy carriers for 17 world regions (van Vuuren et al. 2006). In contrast to MESSAGE, TIMER does not optimise the energy system, but simulates long-term trends in energy demand and efficiency and the possible transition towards renewable energy sources. It includes autonomous and price-induced changes in energy-intensity, fossil fuel exploration, including dynamics of depletion and learning and biomass-derived substitutes for fossil fuels and their impact on land-use (de Vries et al. 2001).

The model particularly focuses on several dynamic relationships within the energy system, such as inertia, learning-by-doing, depletion and trade among regions. The energy demand sub-model calculates the final energy demand for five end-use sectors as a function of changes in population, economic activity and energy efficiency.

**PRIMES**

PRIMES (**P**rice **I**nduced **M**odel of the **E**nergy **S**ystem), is a multi-regional energy system model, that maps similar to EFOM the energy supply and demand for the member countries of the European Union. It was developed within the JOULE II programme of the European Commission in the early 1990s amongst others at the National Technical University of Athens, Greece. It includes in its latest version all 27 EU member countries plus seven other European countries. The current version of the model is formulated as a non-linear mixed complementarity (MCP) problem. It simulates a market equilibrium solution for energy supply and demand in the EU member state (Capros 2005).

It is characterised by its modular structure, with separate modules for each demand and supply sector and separate decision making. This structure of PRIMES should reflect a distribution of decision making among agents that decide individually about their supply and demand. Thus, it tries to address issues that have been criticised in other models, such as the lack of explicit representation of markets and the lack of realism in formulating demand and the individual behaviour of agents. Market equilibrium prices drive energy balancing of demand and supply for each energy commodity. The supply sectors in PRIMES are optimised based on relative costs (i.e. cost minimisation), while the overall model is iteratively solved based on Gauss-Seidel iteration. Although the model is behavioural and price driven, it simulates as well the technology choice in energy demand and energy production, including technology dynamics and vintages. In addition, the modules include learning by doing curves and parameters that represent subjective perception of technology costs as seen by consumers (Capros 1995).

It can be used for medium- to long-term policy analysis up to 2030 referring to environmental issues, security of supply, pricing policies, taxation or standards, conversion decentralisation and many others. In PRIMES it is further possible to consider a wide range of policy instruments for the environment (Capros 2005).

**POLES**

The POLES (**P**rospective **O**utlook on **L**ong-term **E**nergy **S**ystems) model is a global, recursive simulation model for the analysis of energy systems and their environmental impacts up to 2050 for 46 different regions. It is disaggregated into 15 energy demand sectors and consists of 12 renewable and 12 power generation technologies. It was developed during the 1990s under different EU research programmes at the Laboratoire d'Economie de la Production et de l'Intégration Internationale (LEPII) (2006) of the University Pierre Mendès France in Grenoble, France. It combines features of a top-down approach, e.g. the importance of prices for adjustment of most variables, with bottom-up characteristics, for example the detail in the treatment of technologies.

POLES allows one to project the energy demand and supply for different regions, the simulation of technology development of electricity supply, as well as the simulation of $CO_2$ emissions and in particular the analysis of $CO_2$ abatement policies. Endogenous technological developments subject to an influence of public and private investment in R&D and cumulative experience with learning by doing, as well as induced technological change is incorporated into POLES. Furthermore, it simulates the discoveries and reserves of oil and gas and treats international energy prices and markets endogenously as a function of capacity utilisation and the world reserve to production (R/P) ratio.

Model applications include studies for the European Union, but also research projects for the calculation of MAC curves (Criqui et al. 1999; European Commission 2006).

## 3.3 Energy system model UK MARKAL

### 3.3.1 The choice for MARKAL

UK MARKAL was chosen for this thesis since the MAC curves are required to be technologically explicit and incorporate technological, behavioural and intersectoral interactions. While, top-down models lack the necessary technology detail, this issue can be addressed with a bottom-up, technology-oriented model, such as UK MARKAL. The macro-economic performance is not the focus of this study so that using a partial-equilibrium model is not a major disadvantage.

The advantages of UK MARKAL include its systems character, which allows one not only to consider interactions between mitigation measures but also between different sectors of the energy system, such as the power and transport sector. In contrast to some other bottom-up models, the demand-elastic version of UK MAKRAL takes into account price-induced demand changes and hence captures some behavioural aspects.

In addition, MARKAL is a model generator, which has been applied for more than 30 years and has been used since then in many international policy studies. This will help to disseminate the results of the thesis to decision makers that are already familiar with the features of this type of model.

### 3.3.2 Model development

The MARKAL (MARket ALlocation) model has been developed at the Brookhaven National Laboratory in Upton, USA, and the Kernforschungsanlage in Jülich, Germany within the scope of the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) in the late 1970s (Fishbone and Abilock 1981). MARKAL is a flexible, multi-time period, linear programming energy system model. In its standard version, MARKAL minimises the total system costs ensuring that all specified end-use demands for energy services are satisfied for every time period. The model specifies energy supply, transformation and conversion, demand for energy services and constraints or policy assumptions for the energy system. MARKAL can be used for different policy applications, such as least cost strategies to limit greenhouse gas emissions, identifying the potential role of new energy technologies, and assessing the impact of demand side influences. A detailed documentation of the MARKAL model can be found in Loulou et al. (2004).

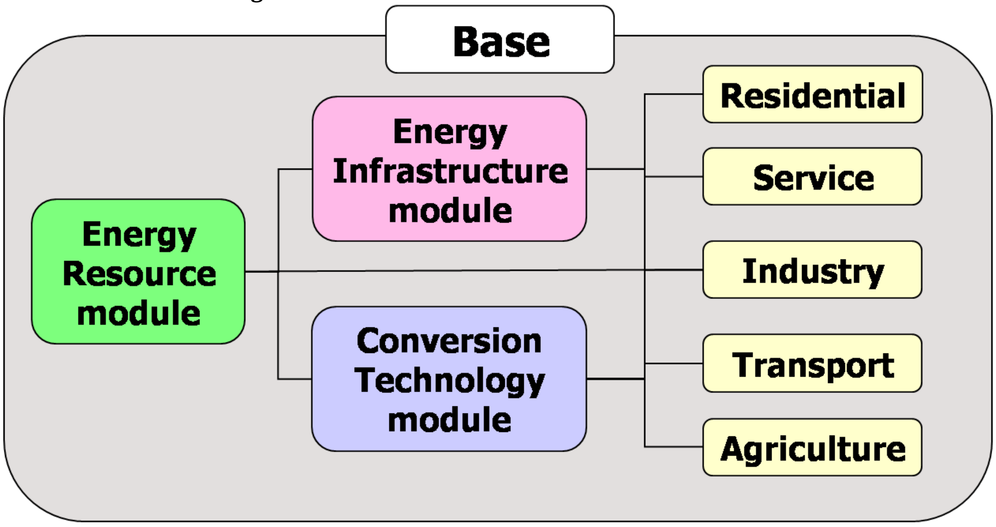
Since MARKAL was established as a model generator that enables the application of this general model schema to different energy systems it is comparably widely used in the field of energy system analysis (Goldstein and Tosato 2008). Over time a set of different MARKAL variants have been developed (Seebregts et al. 2001).

The current UK MARKAL model builds on an earlier model version from the year 2003 developed by AEA Technology and was extended by the Policy Studies Institute (PSI) and AEA Technology (Strachan et al. 2006). A documentation of the model can be found in Strachan et al. (2005; 2006) and Anandarajah et al. (2008). Since then it was used to inform policy makers for example in relation to the UK Energy White Paper's long term policy targets (HM Government. Department of Trade and Industry 2007). Furthermore, it was used in various academic studies (Strachan and Kannan 2008; Kannan and Strachan 2009; Strachan et al. 2009).

### 3.3.3 Model structure

The UK MARKAL model is a technology-rich model, including resource supplies, imports, energy conversion technologies, end use demands and the technologies used to satisfy these demands. As a perfect foresight model, all market participants are assumed to have perfect inter-temporal knowledge of future policy and economic developments. In its current version the model consists of one region for the entire United Kingdom. It is characterised by a modular approach to describe the overall Reference Energy System. These modules include on the supply side an energy resource module, which describes the extraction processes for fossil fuels, as well as the supply of renewable energy sources. The conversion module specifies the electricity, heat and hydrogen sector and the transmission of these secondary energy carriers. On the demand side, the model is divided into five different energy demand sectors: agriculture, industry, residential, service and transport (see Figure 3.2).

**Figure 3.2: Structure of the UK MARKAL model**




**Source: Kannan et al. (2007)**[2]

The model is based on range of different inputs. A wide-ranging application of policy and physical constraints, implementation of all taxes and subsidies, and inclusion of base-year capital stocks and energy flows enable the calibration to the UK energy system. Resource supply curves represent a key input parameter for the model. From these baseline costs, multipliers are used to generate both higher cost supply steps as well as imported refined fuel costs. A second key input are dynamically evolving technology costs. Future costs are based on expert assessment of technology vintages, or for less mature electricity and hydrogen technologies via exogenous learning curves derived from an assessment of learning rates combined with global forecasts of technology uptake. A third key input are assumptions on average infrastructures costs and distribution losses, physical and policy constraints. A final key input for the UK MARKAL model are exogenous demand levels for energy services – derived from standard UK forecasts for residential buildings, transport, service sector and industry. Generally these sources entail a low energy growth projection, with saturation effects in key sectors. This is reflective of recent historical trends on sustained modest economic growth and the continuing dematerialisation of the UK economy.

**Parameters**

MARKAL uses a variety of parameters, which can be divided into system parameters, useful energy demands, energy carriers, technology characterisation and environmental variables. System-wide parameters apply to the entire model. Two important such parameters are the discount rate and the temporal disaggregation, which affects the

[2] Permission to reproduce this Figure has been granted by UKERC.

treatment of intermittency. Useful energy demands or energy service demands describe the requirement for specific end-use energy services to be delivered to individuals and companies. This demand for an energy service does not refer to the consumption of a particular type of final energy, but rather to the provision of services such as lighting, cooling, travelling or machine drive. Useful energy demand development is one of the key assumptions, which has to be detailed for different sectors and for intraday patterns. In the elastic demand version, the own-price demand elasticity is a further parameter that indicates how much the demand changes with a change in the price for this energy service demand.

Energy carriers are various forms of energy produced and consumed in the energy system. They include fossil fuels, electricity, heat, synthetic fuels and renewable energy. The energy carriers provide the interconnections between the technologies (or processes) in the model. All energy carriers are tracked annually with the exception of electricity, which is divided into three seasons and day/night and heat, which is specified for different seasons. Data related to energy carriers involves overall transmission efficiency, a reserve margin and resource availability for primary energy carriers.

Technology parameters play an important role in the technology-rich energy system model. They include information on technology costs (investment cost, fixed and variable operating and maintenance costs), input and output commodities, technical efficiencies, the start year of a new technology, availability factors and current existing installed capacity. Furthermore, user limits can be specified in the form of absolute or growth constraints for the installed capacity or for future investment. Hurdle rates, or technology specific discount rates can be applied to represent non-economic, behavioural aspects of investment choices. Resource technologies, which represent all flows of energy carriers into and out of the system, are in general characterised using stepwise supply cost curves. Other technologies include process technologies that change the form of energy carriers, such as oil refineries and hydrogen production plants, and conversion technologies that model electricity and heat production. Lastly, demand technologies map those devices that are used to directly satisfy end-use service demands.

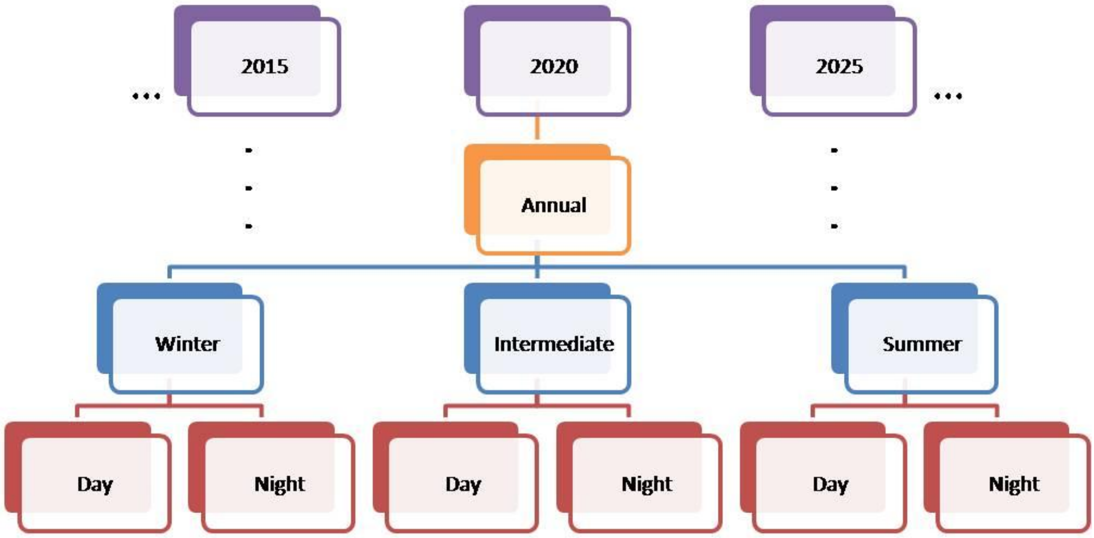
In addition to energy technologies, MARKAL has the capacity to track the production or consumption of environmentally-relevant gases. Emissions are specified per unit for relevant technology activity and emission constraints can be implemented. Finally, subsidies and taxes, as well as the representation of policy instruments are key parameters that help to map the political aspects in more detail.

**Temporal resolution**

The model horizon covers the time period from 2000-2050. This time period can be divided into an optional number of periods of an arbitrary but equal length. Those time periods are represented by a milestone year. Although the shortest length for a period is one year, this is generally not used as it would lead to a big model with a long computation time. The UK MARKAL model solves in 5-year time steps for an optimal evolution of energy pathways. Because of the dynamic structure of the MARKAL model there exist intertemporal relations between the model periods. An example is a power plants that is built in one period and, given a corresponding life time, can be used in the following periods. In contrast to TIMES (**T**he **I**ntegrated **M**ARKAL **E**FOM **S**ystem), which was built upon the MARKAL model generator, technical parameters cannot be modelled dependent on the construction period (vintage). Nevertheless, separate technologies can be implemented if technical parameters change over time.

Energy consumption can vary significantly during a year in most cases due to fluctuations in the demand sectors. Typical examples are the demand for heat, which is highest in the winter, or the demand for electricity, which is subject to fluctuations over the course of the day. On the supply side, fluctuations are caused by an unsteady electricity production from wind, photovoltaic and hydro power stations. In order to represent these temporal changes within a year, the model period can be divided in representative time slices. Concerning the annual temporal disaggregation, MARKAL can have an unlimited number of time slices. The UK MARKAL model is divided into three seasons (summer, winter and intermediate) and two times of day (day and night), i.e. six time slices in total (see Figure 3.3). In principle, it is possible to choose another segmentation, for example the representation of a year in twelve equal time slices, if intraday issues are of no concern.

**Figure 3.3: Temporal disaggregation in the UK MARKAL model**




Processes and commodities in MARKAL can, but do not have to, be described with the highest temporal resolution. It makes sense to specify the demand for residential heating differently for different seasons or for electricity in the form of load curves, because currently electricity supply has to match electricity demand as storage is not widely available. In the transport sector, a detailed temporal resolution is not required since fuel storage in vehicle is sufficient. However, this could change once electricity is used on a large scale in the transport sector.

**Different versions of MARKAL**

In its standard version, MARKAL is a linear program that minimises the total system costs while energy demand levels are given exogenously. Over time many different versions have been developed in order to improve the standard version and incorporate different aspects that address existing shortcomings (Seebregts et al. 2001). In the MARKAL Elastic Demand version (MARKAL-ED), which is used in this thesis, the exogenously given demand levels in the reference run are endogenously adjusted in response to price changes via own price elasticities. Thus, the optimisation is no longer a cost minimisation, but a welfare (consumer plus producer surplus) maximisation.

The standard MARKAL model is limited to the energy sector. In order to take into account economy-wide feedbacks, the model variant MARKAL-MACRO was developed. In this version, MARKAL is coupled to a simple macro-economic neoclassical growth model that maximises the discounted log of utility (derived as the log of consumption). Furthermore, a non-linear, convex programming variant developed to represent price sensitive useful energy demands and non-zero cross-price elasticities for different demand technologies is implemented in MARKAL-MICRO. Since this variant is non-linear, the demand curve does not have to be represented as step-wise linear approximation as it is the case in MARKAL-ED. In addition, cross-price elasticities allow inter-demand substitution, which is of interest in the transport sector, e.g. between car and rail transport.

A further alternative is the stochastic version of MARKAL. This version applies stochastic programming to the standard version of MARKAL in order to incorporate a degree of uncertainty. It enables the user to specify different states of the world with corresponding probabilities, which are provided by the analyst. Another extension is the MARKAL-ETL version, which represents endogenous technological learning based on learning-by-doing curves. This means that cost decreases of a technology are modelled as a function of cumulative installed capacity.

**Shortcomings**

Next to its strengths as a technology-rich model that encompasses the entire energy system and allows the analysis of different policy goals, MARKAL possesses, like all energy models, some weaknesses. These include the data intensiveness, including the characterisation of technologies. For an independent observer this might make the model look like a black-box. Nevertheless, clear indication of data sources and sensitivity analysis can help to prevent such problems. Small changes in data assumptions can cause big shifts in the model solution, but can be limited by stepped supply cost curves and market share constraints. Moreover, MARKAL has a limited ability to model behavioural aspects and the heterogeneity of energy consumption (see section 3.2.1). This concerns mainly hidden costs, such as the cost of searching for information and other market barriers and failures. But also a large variety in consumption patterns and the lack of specific details, such as downsizing of vehicles or speed limits in the transport sector, can significantly affect the outcomes of the model. Those factors can be addressed via growth constraints, demand elasticities and technology-specific hurdle rates in MARKAL.

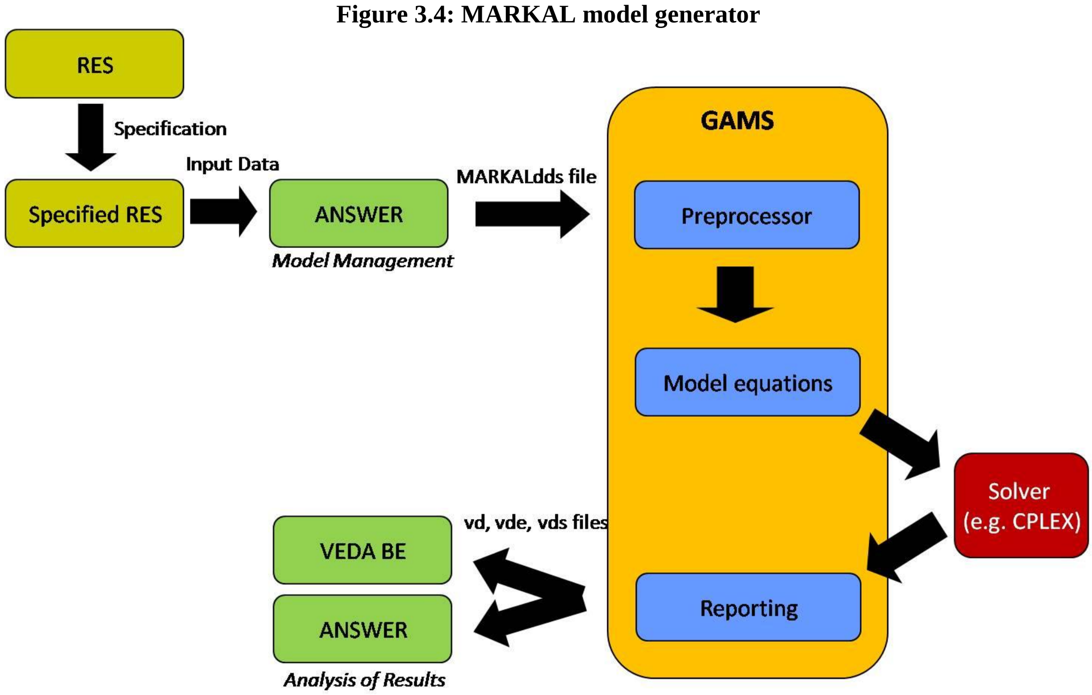
The MARKAL model is a perfect foresight optimisation model using a social discount rate, thus representing the perspective of a social planner under optimal conditions. Therefore, it tells decision makers how a given objective, e.g. environmental constraints, can be met with least costs. However, investors and individual neither operate under optimal conditions nor do they possess perfect foresight because in reality market barriers and failures exist and investors face various risks over the short- and long-term. Therefore, results from MARKAL should be seen as a lower bound to overall costs and results should not be expected to represent what will happen in reality in the future.

Another aspect concerns the limited scope of MARKAL as it is restricted to the energy sector. In this way, the model is not able to take into account macroeconomic feedback effects and the economic impact of energy policy. This means that the model considers only direct costs in the energy sector, which cannot be put into perspective with economic indicators, such as GDP. The linkage of MARKAL to a simple neoclassical growth module was implemented in a model variant in order to address this issue. Other shortcomings concern the poor spatial disaggregation and the poor representation of international trade relations. Lastly, MARKAL does not consider ancillary benefits of carbon reduction policies, such as improvements for human health, which can lead to an overestimation of carbon reduction costs.

### 3.3.4 Implementation

The structure of the model generator MARKAL is represented in Figure 3.4. The necessary input data includes qualitative information of the model, i.e. the topologic structure based on a RES, the model horizon, the time periods and time slices. Furthermore, this qualitative structure then has to be specified with quantitative information in the form of parameters, i.e. the technical and economic description of processes, demand levels, import/export prices. All this information can be entered into a windows-based graphical user interface, ANSWER (Noble 2007). This software supports the analysts during the construction of the model, the data input and scenario definition. ANSWER transforms the user's input data into DDS files, which can subsequently be read by the MARKAL model generator. MARKAL is programmed in the modelling environment GAMS (**G**eneral **A**lgebraic **M**odeling **S**ystem) (McCarl et al. 2009).

**Figure 3.4: MARKAL model generator**




Within MARKAL the data is processed in the pre-processor, where internal sets and parameters (energy carriers, technologies, demands, emissions) are calculated, lacking time series value are interpolated or extrapolated and default values put in place for lacking input data. In addition, parameters are aggregated or passed on to different levels of time slices and coefficients in the objective function are calculated. In a next step, model equations are either directly established to be passed on to a solver or the equation matrix is first reduced in a reduction algorithm to simplify and accelerate the optimisation. The solver optimises the energy system, for example via the simplex algorithm for a linear program, and gives the optimised matrix back to MARKAL, which is processed and exported in VD, VDE and VDS files. For a result analysis, those files can be read again by ANSWER or by another interface developed by KanORS Consulting (Kanudia 2010), VEDA (**VE**rsatile **D**ata **A**nalyst). Different extensions or variants of the standard version of MARKAL, which require special equations and parameters, can be activated in ANSWER before the input parameters are optimised in GAMS.

### 3.3.5 Mathematical description

This section gives an overview of the most important equations, on which the MARKAL model is based. Starting with the objective function and then explaining in more detail the most important constraints.

The abstracted energy system can be described via a system of equations. A linear optimisation problem consists either of a minimisation or maximisation problem. In the standard MARKAL version, the total cost of the energy system is minimised subject to different constraints. These constraints include the satisfaction of energy service demands, balance for commodities, peaking reserve constraint and emission constraints. Thus, in the most general form, an optimisation problem looks as follows:

Objective function:

$$Min \sum_i c_i x_i \tag{3.1}$$

subject to:

$$\sum_i a_{ji} x_i \geq b_j, \;\; j = 1,2,\dots,m \tag{3.2}$$

$$x_j \geq 0, \qquad i = 1,2,\dots,n \tag{3.3}$$

where $x_i$ is the decision variable of the primal problem, $c_i$ is the cost coefficient of variable $x_i$ , $a_{ji}$ is the coefficient of variable $x_i$ in equation $j$ and $b_j$ is the right hand side of equation $j$.

**Objective function in the standard version**

The objective function in the standard version is the minimisation of the total discounted energy system costs or the net present value of the total cost. It can be written as:

$$Min \sum_{t=1}^{t=p} (1+d)^{y*(1-t)} * ANNCOST(t) * (1 + (1+d)^{-1} + (1+d)^{-2} + \cdots + (1+d)^{1-y}) \tag{3.4}$$

where *ANNCOST(t)* is the annual cost for period $t$, $d$ is the general discount rate, $p$ is the number of periods in the planning horizon and $y$ is the number of years in each period $t$.

The first term in the equation is responsible for discounting the total cost of one period to its present value, the second term represents the annual costs and the third term in the bracket discounts the costs of each year in a period to the start of that period. Typical values for the parameters in the UK MARKAL model are for example *p*=10 periods (model horizon from 2000 to 2050), *y*= 5 years in one period and *d*=5%.

The term *ANNCOST(t)* can be further specified:

$$
\begin{aligned}
ANNCOST(t) = \sum_{k} \Bigg[ & \frac{INVCOST(t,k)}{\sum_{j_k=life}(1+h_k)^{-j}} * INV(t,k) \\
& + FIXOM(t,k) * CAP(t,k) \\
& + VAROM(t,k) * \sum_{s=time\ slice} ACT(t,k,s) \\
& + \sum_{c=commodity} \left( DELIVCOST(t,k,c) * INPUT(t,k,c) * \sum_{s} ACT(t,k,s) \right) \Bigg] \\
& + \sum_{c,s} \Big[ MININGCOST(t,c,l) * MINING(t,c,l) \\
& + TRADECOST(t,c) * TRADE\left(t,c,s,\frac{i}{e}\right) \\
& + IMPORTPRICE(t,c,l) * IMPORT(t,c,l) \\
& - EXPORTPRICE(t,c,l) * EXPORT(t,c,l) \Big] \\
& + \sum_{c} [TAX(t,p) * ENV(t,p)]
\end{aligned}
\tag{3.5}
$$

where in the first sum (corresponding to technology related costs)

- the first term represents the annualised investment costs, with *INVCOST(t,k)* being the specific investment costs of technology *k* in period *t*, *INV(t,k)* the new capacity addition for technology *k* in period t, $j_k$ the life time of technology *k* and $h_k$ the discount rate used for this technology, called hurdle rate.
- the second term represents the fixed operating and maintenance costs, where *FIXOM(t,k)* are the specific fixed operating and maintenance costs of technology *k* in period *t* and *CAP(t,k)* is the installed capacity of technology *k* in period *t*.
- the third term stands for the variable operating and maintenance costs, where *VAROM(t,k)* stands for the specific variable operating and maintenance costs of technology *k* in period *t* and *ACT(t,k,s)* is the activity level of technology *k*, period *t* and time slice *s*. This latter variable is summed over all time slices.
- the fourth term corresponds to the commodity costs, where *DELIVCOST(t,k,c)* stands for the delivery costs per unit of commodity *c* in period *t* and for technology *k* and *INPUT(t,k,c)* is the amount of commodity *c* required to operate one unit of technology *k* in period *t*, the inverse of the commodity specific efficiency.

in the second sum (corresponding to commodity related costs)

- the first term represents the mining costs, where *MININGCOST(t,c,l)* stands for the specific cost of mining commodity *c* at price level *l* and period *t* and *MINING(t,c,l)* represents the quantity of commodity *c* extracted at price level *l* and period *t*.
- the second term corresponds to trade or transaction costs, where *TRADECOST(t,c)* stands for specific transport cost for commodity *c* in period *t* and *TRADE(t,c,s,i/e)* is the quantity of commodity *c* sold (*e*) or purchased (*i*) from other regions in period *t* and time-slice *s* (only applicable to electricity).
- the third term stands for the import costs due to imports from regions within the model, where *IMPORTPRICE(t,c,l)* represents the exogenous specific import price of commodity c for price level *l* in period *t* and *IMPORT(t,c,l)* is the quantity of commodity *c* at price level *l* that is imported in period *t* (this is not applicable in a one-region model).
- the fourth term stands for the export profits due to exports to regions within the model, where *EXPORTPRICE(t,c,l)* represents the exogenous specific export price of commodity *c* for price level *l* in period *t* and *EXPORT(t,c,l)* is the quantity of commodity *c* at price level *l* that is exported in period *t* (this is not applicable in a one-region model).

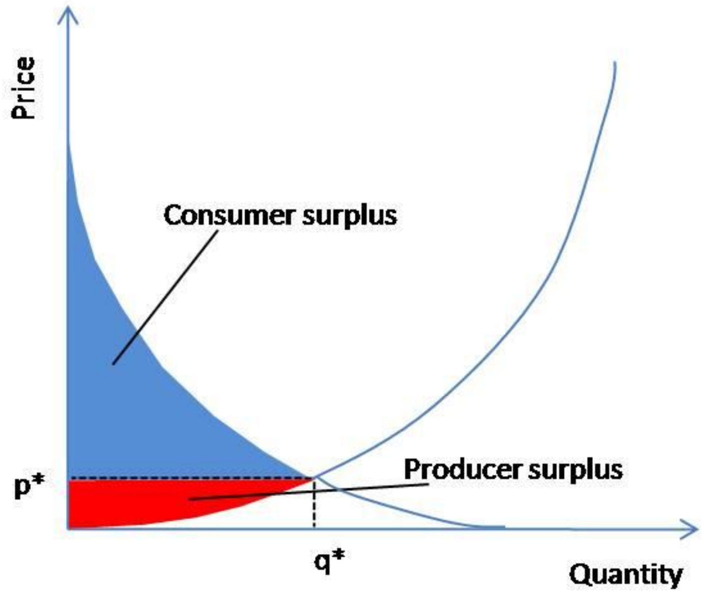
in the third sum (corresponding to costs related to emission taxes)

- the term stands for the costs associated with an emission tax, where *TAX(t,p)* is the specific tax on the emission of pollutant *p* in period *t* and *ENV(t,p)* represents the emission amount of pollutant *p* in period *t*.

**Objective function in the elastic demand version**

Since the thesis at hand uses the elastic demand version of MARKAL, its objective function is described in this section. In the elastic demand version of MARKAL, the objective function changes from total cost minimisation (standard version of MARKAL) to maximisation of welfare surplus by incorporating a linearly approximated price elastic demand function (see Figure 3.5).

**Figure 3.5: Consumer and producer surplus**




The MARKAL model variant assumes elastic demand in the way that:

$$q(p) = K * p^{E} \tag{3.6}$$

where *q(p)* is the demand (depended on the price *p*), *K* is a constant and *E* is the own price elasticity of demand. *K* can be known, if one point $(q_0,p_0)$ of the curve is known. Then the inverse price function becomes:

$$p(q) = p^{0}\left(\frac{q}{q^{0}}\right)^{\frac{1}{E}} \tag{3.7}$$

To maximise the total surplus, consumer and producer surplus have to be maximised at the same time. Regarding Figure 3.5, this corresponds to the maximisation of the area under the demand function up to the equilibrium price minus the area under the supply curve (blue plus red area).

Integrating the demand function from *0* to $q*$ yields the area under the demand curve up to $q*$:

$$\int_{0}^{q^{*}} p(q)dq \tag{3.8}$$

Inserting the inverse price function:

$$\int_{0}^{q^{*}} p^{0}\left(\frac{q}{q^{0}}\right)^{\frac{1}{E}} dq = p^{0}\left(\frac{1}{q^{0}}\right)^{\frac{1}{E}} * \int_{0}^{q^{*}} q^{\frac{1}{E}}\, dq \tag{3.9}$$

Integrating results in:

$$p^0 (\frac{1}{q^0})^{\frac{1}{E}} * \frac{1}{\frac{1}{E}+1} * q^{*\frac{1}{E}+1} \tag{3.10}$$

To obtain the welfare surplus, the area under the production function, which is nothing else than the discounted present value of the stream of annual costs for the entire model horizon, has to be deducted from equation (3.10). This corresponds to the objective function of the cost minimisation approach in the standard version of MARKAL (3.4). Here, this is abbreviated as $c*X$, where $c$ represents specific costs and $X$ is the vector of all decision variables.

Summing over all demands $d$ and over all time periods $t$, the new objective function becomes:

$$Max \sum_d \sum_t (p_{d,t}^0 (\frac{1}{q_{d,t}^0})^{\frac{1}{E_d}} * \frac{1}{\frac{1}{E_d}+1} * q_{d,t}{}^{*\frac{1}{E_d}+1}) - c * X \tag{3.11}$$

**Objective function in the stochastic version**

The stochastic version of MARKAL is one option to incorporate a degree of uncertainty into the optimisation of the energy system (see also 5.2.4 and 9.2.1). The stochastic MARKAL version is based on the two-stage stochastic programming paradigm, in which all uncertainties are resolved at a single future stage (Loulou et al. 2004, p.76). Stochastic MARKAL uses the concept of an event tree, where each scenario is represented by a path from beginning to end of horizon and each path has a discrete, user-specified probability of occurrence. In each period, there are as many replications of the MARKAL variables as there are different outcomes (states of the world) in that period. In addition, each set of variables corresponding to a possible scenario must satisfy all constraints, also multi-period constraints, such as cumulative emission limits. Then the objective function is equal to the weighted sum of the scenarios' objective functions, each weighted by the scenario's probability of occurrence.

Using again $c*X$ as a simplified version of the standard objective function (3.4), the stochastic objective function looks like:

$$Min \sum_{w \in W(t)} \sum_t c_{t,w} X_{t,w} * p_{t,w} \tag{3.12}$$

where $t$ is the time period, $w$ represents the state of the world and $W(t)$ is the set of states of the world for time period $t$. For all $t$ prior to resolution time $t^*$, $W(t)$ has a single element (stage one), for all $t$ subsequent to $t^*$, $W(t)$ has multiple elements (stage two). $c_{t,w}$ represents the specific costs and $X_{t,w}$ the vector of all decision variables. Finally $p_{t,w}$ is the probability of scenario $w$ in period $t$. $p_{t,w}$ is equal to 1 for all $t$ prior to $t^*$ and thereafter $\sum_{w \in W(t)} p_{t,w} = 1$. Note that it is possible to combine the stochastic version with the elastic demand version, where a simplified parameter is used for the elastic demand function.

**Main constraints**

One of the important equations is the satisfaction of demand, which says that energy service demands must be met.

$$\sum_{k\ supplying\ service\ d} ACT(t,k) \geq D(t,d) \tag{3.13}$$

The equation says that for each time period $t$ and demand $d$, the total activity of end-use technologies $k$ servicing demand $d$, $ACT(t,k)$, must be at least equal to the specified demand, $D(t,d)$.

The capacity transfer assures that the available capacity in one period corresponds to earlier investments. Mathematically this can be expressed as:

$$CAP(t,k) = \sum_{\substack{t'=preceding\ periods\ to\ t \\ with\ t-t'<LIFE(k) \\ and\ t'<t}} INV(t',k) + RESID(t,k) \tag{3.14}$$

where $CAP(t,k)$ is the installed capacity of technology $k$ in period $t$, the sum over $INV(t',k)$ includes all investments made by the model at past and current periods and whose physical life has not yet ended and $RESID(t,k)$ is the capacity of technology $k$ resulting from investments that were made prior to the initial model period.

The equation for the use of capacity makes sure that the activity of a technology does not exceed its available capacity:

$$ACT(t,k,s) \leq AF(t,k,s) * CAPUNIT * CAP(t,k) \tag{3.15}$$

where $ACT(t,k,s)$ is the activity of technology $k$ in time period $t$ and time slice $s$, $AF(t,k,s)$ stands for availability factor of technology $k$ in period $t$ and time slice $s$, *CAPUNIT* is the factor that converts capacity units into production units, e.g. 31.536 for the conversion of GW capacity into PJ/year production and $CAP(t,k)$ corresponds to the capacity of technology $k$ in period $t$.

The equation for the energy balance makes sure that consumption of a commodity does not exceed its supply or that the sum of the produced, mined and imported (either from another region or from outside the model scope) amount of a commodity is bigger than or equal to the sum of the exported (to another model region or an external region) and consumed amount of a commodity:

$$\begin{aligned}&\sum_k OUTPUT(t,k,c) * ACT(t,k,s)\\&\quad + \sum_l MINING(t,c,l)\\&\quad + \sum_l FR(s) * IMPORT(t,c,l) + XCVT(c,i) * TRADE(t,c,s,i)\\&\quad \geq XCVT(c,i/o) * TRADE(r,t,c,s,e)\\&\quad + \sum_l FR(s) * EXPORT(t,c,l) + \sum_k INPUT(t,k,c) * ACT(t,k,c,s)\end{aligned} \tag{3.16}$$

where *OUTPUT(t,k,c)* is the amount of commodity *c* produced per unit of technology *k* in period *t*, *MINING(t,c,l)* represents the quantity of commodity *c* extracted at price level *l* and period *t*, *FR(s)* is the fraction of the year covered by time-slice *s*, *IMPORT(t,c,l)* is the quantity of commodity *c* at price level *l* that is imported in period *t* (this is not applicable in a one-region model), *XCVT(c,i/o)* is a commodity conversion factor in the case that external trade relations are defined in another unit for commodity *c*, *EXPORT(t,c,l)* is the quantity of commodity *c* at price level *l* that is exported in period *t* (this is not applicable in a one-region model) and *INPUT(t,k,c)* is the amount of commodity *c* required to operate one unit of technology *k* in period *t*.

The electricity and heat peak reserve constraint guarantees that the installed capacity for electricity or heat exceeds the required capacity in the season with the largest electricity or heat demanded by a reserve factor:

$$\begin{aligned}&\sum_k CAPUNIT * PEAK(t,k,c) * FR(s) * CAP(t,k) + XCVT(c,i)\\&\quad * TRADE(t,c,s,i) + FR(s) * IMPORT(r,t,c)\\&\quad \geq\ [1 + ERESERVE(t,c)]\\&\quad * \sum_k INPUT(t,k,c) * FR(s) * ACT(t,k,s) + XCVT(c,o)\\&\quad * TRADE(t,c,s,e) + FR(s) * EXPORT(t,c,)\end{aligned} \tag{3.17}$$

where *PEAK(t,k,c)* specifies the fraction of technology *k*'s capacity for a period t and commodity *c* that is allowed to contribute to the peak load and *ERESERVE(t,c)* is the reserve coefficient for a commodity *c* and period *t*, which allows for unexpected down time of equipment, for demand at peak and for uncertain renewable availability.

An emission constraint can be introduced by an analyst in order to ensure that the total emission of pollutant *p* will not be greater than a user-defined upper bound:

$$\sum_k \left[ EMINV(t,p,k) * INV(t,k) + EMCAP(t,k,p) * CAP(t,k) \right. \\ \left. + EMACT(t,k,p) * \sum_s ACT(t,k,s) \right] \leq ENV\_LIMIT(t,p) \tag{3.18}$$

where *EMINV(t,p,k)* is the emission coefficient of pollutant p linked to the construction of technology *k* in period *t*, *EMCAP(t,k,p)* is the emission coefficient of pollutant *p* linked to the capacity of technology *k* in period *t*, *EMACT(t,k,p)* is the emission coefficient of pollutant *p* linked to the activity of technology *k* in period *t* and *ENV_LIMIT(t,p)* is the upper limit set by the user on the total emission of pollutant *p* in period *t*.

It is also possible for the analyst to implement various taxes and subsidies in the same way as described for an emission tax. Other typical constraints to represent the political reality are limitations on new technologies in the form that the new capacity addition *INV(t,k)* has to be less than a predefined number.

A further policy implemented in many industrialised countries is a minimum share of specific technologies, such as a minimum share of biodiesel or renewable electricity. This can be implemented in the following way for a biodiesel share:

$$\sum_k [(1 - SHARE) * FLO(t,k,s,c_1) + (-SHARE) * FLO(t,k,s,c_2)] > 0 \tag{3.19}$$

where *SHARE* is the specified minimum share of commodity $c_1$ in the sum $c_1 + c_2$. *FLO(t,k,s,c)* is the flow of commodity *c* into technology *k* in time period *t* and time slice *s*. In the case of a biodiesel constraint *k* includes all technologies that consume biodiesel $c_1$ and diesel $c_2$.

### 3.3.6 Generating MAC curves with MARKAL

In this thesis, MAC curves are derived based on the information of the UK MARKAL model. Therefore, scenarios with different strict constraints are generated in order to represent the resulting emission reduction for an increasing $CO_2$ tax or vice versa.

The analyst has three possibilities to derive a MAC curve in MARKAL: the implementation of a $CO_2$ tax, an annual emission limit and a cumulative emission limit over the entire model horizon. Implementing different $CO_2$ taxes for a specific year will result in different $CO_2$ reduction amounts, which can then be consolidated into a MAC curve. The same holds true for the implementation of an annual emission limit. The stricter the limit for a year is, the higher the marginal abatement costs will be. The third option, the cumulative emission limit, lets the model decide the emission pathway over the model horizon. As for the other two options, stricter bounds result generally in higher MACs for a year.

While the analyst has to specify the development of the $CO_2$ tax or the emission limits over time in the first two cases, the cumulative emission bound does not need this specification. In order to determine the impact of such intertemporal interactions, different emission pathways or $CO_2$ tax trajectories will be applied. The $CO_2$ tax can for example be flat, increase linearly or increase exponentially with the discount rate.

## 3.4 Concepts of abatement cost and abatement potential in energy modelling

**Abatement cost**

Costs play a pivotal role in MAC curves. As many different abatement cost definitions are used for the generation of MAC curves, this section gives an overview of different cost concepts and how they relate to energy modelling. The different cost concepts apply in the same way to marginal costs, average costs and total costs. For more detailed information, the third assessment report of the IPCC contains a whole chapter on costing methodologies (Markandya et al. 2001). Broadly, one can distinguish five different cost levels, from the narrowest to the widest, they are: project cost, technology cost, sectoral cost, macroeconomic cost and welfare cost.

Abatement cost at the lowest level, so called project cost, describes the cost of an individual abatement option, which is assumed not to have significant indirect economic impacts on markets and prices beyond its activity itself (Halsnaes et al. 2007, p.135). It considers for example technical change in production plants, efficiency improvements, fuel switches or the implementation of infrastructure. Cost measurement includes investment cost, operation and maintenance cost and fuel cost (Risø National Laboratory 1994, p. 11ff).

The next level, technology cost (or direct cost) considers cost related to mitigation technologies, usually with several applications in different projects (Halsnaes et al. 2007, p. 135). Thus cost components are the same as in the project cost and the analytical approach is also similar to project-level analysis.

Sectoral cost, also called partial equilibrium cost, since they can be derived from partial equilibrium models, represent the next level of the cost hierarchy. This cost definition is used in this thesis. In most cases, the cost is calculated for the energy sector, but can equally be calculated for forestry or agriculture sector. This level includes cost of implementing a comprehensive abatement strategy at the sector level, made up of several abatement options and assumes macroeconomic variables as given. As for project cost, investment cost, operation and maintenance cost, as well as fuel cost are included in this measurement. In addition to project level cost, sectoral cost also include indirect cost, such as the cost of foregone demand from consumers and non-financial costs. Demand-related cost, nevertheless, considers only adjustments in a sector, for example to changing electricity prices, but assumes that other prices are held constant. Non-financial cost includes the cost to wait for a craftsman at home when insulating the home, the cost of searching for information or the additional cost related to finance high upfront payments for certain investments.

Macroeconomic cost, the next more comprehensive cost level, is also called general equilibrium cost as it can be calculated by CGE models. It considers economy-wide costs across all sectors, where indirect impacts on economic decision in other markets are taken into account. For example if a company, which produces gas-fired boilers, is affected by a carbon price, then not only this particular company will be concerned, but also suppliers and labour income. This cost type can be measured as an impact on the gross domestic product (GDP) (Hourcade and Robinson 1996, p. 864).

Not all dimensions of human welfare are reflected in the value of goods and services. Therefore, the most comprehensive cost definition, welfare costs, reflects welfare implications such as consumption possibilities, environmental benefits and equity. More specifically, this can include the quantification of less leisure time for households in order to comply with environmental regulation or the increase of unemployment due to temporary adjustments (Söderholm 2007). Furthermore, welfare costs can include negative effects related to the introduction of renewable energy, such as the increase in local air pollution in the case of biomass power plants. It is important to note that there exist different welfare cost definitions, which do not include health and equity issues.

Other cost concepts include private, social and external costs. Private costs describe the costs faced by individual decision-makers based on market prices and include cost elements, like labour cost, fuel cost and equipment cost. Social costs are private cost plus external costs. External costs arise when markets do not provide a link between the entity that produces the externality and the entity that is affected by this externality. In the case of $CO_2$ emission it means that entities, which emit $CO_2$, do not have to bear the consequences of emitting $CO_2$. In other words there exist no property rights for a certain level of carbon concentration in the atmosphere (Halsnaes et al. 2007, p. 135). As well as external costs, there are also external benefits, for example the reduction of air pollution in the case of many $CO_2$ abatement options. An overview of possible external effects of carbon reduction is given in Markandya et al. (2001, p. 463).

**Abatement potential**

Often, the cost type used is unclear, and the abatement potential can also mean different things in different circumstances. The abatement potential can be differentiated into four broad categories: physical potential, technical potential, economic potential and market potential.

The physical potential is the theoretical upper limit to mitigation in a thermodynamic sense relying on the development of new technologies. This is the broadest definition, which is often uncertain and of little use in the context of MAC curves.

The technical abatement potential states by what amount a given increment of technological capacity within a particular system can reduce $CO_2$ emissions, when it is only limited by technical factors, such as appropriate sites for wind turbines or the number of gas boilers to be replaced. This definition is, in general, used in expert-based MAC curves as technologies are individually assessed. It is sometimes improved by considering technology-specific constraints imposed by the political or market context.

The market potential indicates the abatement amount that might be expected to occur under market conditions, including technological, behavioural and intersectoral interactions, policies and measures in place at the time, all market barriers in place and including hidden costs (Halsnaes et al. 2007, p. 140). The market potential can in theory be further distinguished according to the extent of interactions that are considered from sectoral to macro-economic. Energy models come close to this definition as they include different types of interactions, map a great amount of current policies and try to integrate market barriers and hidden costs.

Economic potential is defined as the abatement potential when non-market social costs and benefits are included with market costs and when using social discount rates instead of private ones (Halsnaes et al. 2007, p. 140). It includes explicitly the consideration of externalities, for example ancillary benefits such as the reduction of air pollution. A second difference compared with the market potential is that the economic potential applies a comparably low discount rate based on social costs. This definition is of limited use for MAC curves because the majority of existing abatement curves does not include any co-benefits of $CO_2$ emission reduction.

## 3.5 References


Anandarajah, G., N. Strachan, P. Ekins, R. Kannan and N. Hughes (2008). Pathways to a Low Carbon Economy: Energy systems and modelling. London, UKERC.

Barker, T., H. Pan, J. Köhler, R. Warren and S. Winne (2006). "Decarbonizing the Global Economy with Induced Technological Change: Scenarios to 2100 using E3MG." Energy Journal: 241-258.

Beller, M., A. Doernberg, A. Hermelee and K. C. Hoffman (1979). "Impacts of new energy technologies as measured against reference energy systems." Energy **4**(5): 891-909.

Böhringer, C. and T. F. Rutherford (2008). "Combining bottom-up and top-down." Energy Economics **30**(2): 574-596.

Bosetti, V., C. Carraro and M. Galeotti (2006). "The Dynamics of Carbon and Energy Intensity in a Model of Endogenous Technical Change." Energy Journal **27**(Endogenous Technological Change and the Economics of Atmospheric Stabilization): 191-205.

Bower, J. and D. W. Bunn (2000). "Model-Based Comparisons of Pool and Bilateral Markets for Electricity." Energy Journal **21**(3): 1-29.

Capros, P. (1995). Integrated Economy/Energy/Environment Models. International Symposium on Electricity, Health and the Environment. Vienna, IAEA.

Capros, P. (2005). The PRIMES Energys System Model - Summary Description. Athens, National Technical University of Athens.

Clarke, L., M. Wise, J. Edmonds, M. Placet, P. Kyle, K. Calvin, S. Kim and S. Smith (2008). $CO_2$ Emissions Mitigation and Technological Advance: An Updated Analysis of Advanced Technology Scenarios. U.S. Department of Energy. Richland, WA, Pacific Northwest National Laboratory.

Criqui, P., S. Mima and L. Viguier (1999). "Marginal abatement costs of CO2 emission reductions, geographical flexibility and concrete ceilings: an assessment using the POLES model." Energy Policy **27**(10): 585-601.

de Vries, B., D. Van Vuuren, M. den Elzen and M. A. Janssen (2001). The Targets IMage Energy Regional (TIMER) model. Bilthoven, National Institute of Public Health and the Environment.

DeCanio, S., C. Dibble and K. Amir-Atefi (2001). "Organizational Structure and the Behavior of Firms: Implications for Integrated Assessment." Climatic Change **48**(2): 487-514.

Edenhofer, O., K. Lessmann, C. Kemfert, M. Grubb and J. Köhler (2006). "Induced Technological Change: Exploring its Implications for the Economics of Atmospheric Stabilization: Synthesis Report from the Innovation Modeling Comparison Project." Energy Journal **27**(Special Issue: Endogenous Technological Change and the Economics of Atmospheric Stabilization): 57-107.

Ellerman, A. D. and A. Decaux (1998). Analysis of Post-Kyoto $CO_2$ Emissions Trading Using Marginal Abatement Curves. Cambridge, MA, Massachusetts Institute of Technology.

European Commission (2006). World Energy Technology Outlook 2050 - WETO $H_2$. Brussels.

Fishbone, L. G. and H. Abilock (1981). "Markal, a linear-programming model for energy systems analysis: Technical description of the bnl version." International Journal of Energy Research **5**(4): 353-375.

Fujino, J., R. Nair, M. Kainuma, T. Masui and Y. Matsuoka (2006). "Multi-gas Mitigation Analysis on Stabilization Scenarios Using Aim Global Model." Energy Journal **27**(Multi-Greenhouse Gas Mitigation and Climate Policy Special Issue): 343-353.

Gerlagh, R. (2006). "ITC in a Global Growth-Climate Model with CCS: The Value of Induced Technical Change for Climate Stabilization." Energy Journal **27**(Endogenous Technological Change and the Economics of Atmospheric Stabilization): 223-240.

Gerlagh, R. and B. van der Zwaan (2004). "A Sensitivity Analysis of Timing and Costs of Greenhouse Gas Emission Reductions." Climatic Change **65**(1): 39-71.

Goldstein, G. and G. Tosato, Eds. (2008). Global Energy Systems and Common Anlyses - Final Report of Annex X (2005-2008). Paris, International Energy Agency

Implementing Agreement for a Programme of Energy Technology System Analysis.

Grubb, M., J. Edmonds, P. ten Brick and M. Morrison (1993). "The Costs of Limiting Fossil-fuel $CO_2$ Emissions: A Survey and Analysis." Annual Review of Energy and the Environment **18**: 397-478.

Halsnaes, K., P. Shukla, D. Ahuja, G. Akumu, R. Beale, J. Edmonds, C. Gollier, A. Grübler, M. H. Duong, A. Markandya, M. McFarland, E. Nikitina, T. Sugiyama, A. Villavicencio and J. Zou (2007). Framing Issues. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. B. Metz, O. R. Davidson, P. R. Bosch, R. Dave and L. A. Meyer. Cambridge, UK and New York, NY, USA, Cambridge University Press.

HM Government. Department of Trade and Industry (2007). Meeting the energy challenge : a white paper on energy. London, Stationery Office.

Hourcade, J.-C., K. Halsnaes, M. Jaccard, W. D. Montgomery, R. Richels, J. Robinson, P. Shukla and P. Sturm (1995). A Review of Mitigation Cost Studies. Climate Change 1995: Contribution of Working Group III to the Second Assessment of the Intergovernmental Panel on Climate Change. J. J. Houghton, L. G. Meiro Filho, B. A. Callanderet al. Cambridge, United Kingdom, Cambridge University Press.

Hourcade, J.-C., M. Jaccard, C. Bataille and F. Ghersi (2006). "Hybrid Modeling: New Answers to Old Challenges - Introduction to the Special Issue of The Energy Journal." Energy Journal **27**: 1-11.

Hourcade, J.-C. and J. Robinson (1996). "Mitigating factors : Assessing the costs of reducing GHG emissions." Energy Policy **24**(10-11): 863-873.

Huntington, H. G., J. P. Weyant and J. L. Sweeney (1982). "Modeling for insights, not numbers: the experiences of the energy modeling forum." Omega The International Journal of Management Science **10**(5): 449-462.

Jebaraj, S. and S. Iniyan (2006). "A review of energy models." Renewable and Sustainable Energy Reviews **10**(4): 281-311.

Kannan, R. and N. Strachan (2009). "Modelling the UK residential energy sector under long-term decarbonisation scenarios: Comparison between energy systems and sectoral modelling approaches." Applied Energy **86**(4): 416-428.

Kannan, R., N. Strachan, N. Balta-Ozkan and S. Pye (2007). UK MARKAL model documentation. London, UKERC.

Kanudia, A. (2010). "VEDA Support." Retrieved April 14th 2010, from http://www.kanors.com/vedasupport/.

Kemfert, C. (2002). "An Integrated Assessment Model of Economy-Energy-Climate - The Model Wiagem." Integrated Assessment **3**(4): 281-298.

Keppo, I. and M. Strubegger (2010). "Short term decisions for long term problems – The effect of foresight on model based energy systems analysis." Energy **35**(5): 2033-2042.

Kram, T. and E. Stehfest (2006). The IMAGE model: History, current status and prospectsq. Integrated modelling of global environmental change. A. F. Bouwman, T. Kram and K. Klein Goldewijk. Bilthoven, MNP**:** 7-24.

Krey, V. and K. Riahi (2009). Risk Hedging Strategies under Energy System and Climate Policy Uncertainties. Laxenburg, IIASA.

Laboratoire d'Economie de la Production et de l'Intégration Internationale (2006). The POLES model. Grenoble, Université Pierre Mendès France.

Lejour, A., P. Veenendaal, G. Verweij and N. van Leeuwen (2006). WorldScan: a Model for International Economic Policy Analysis. Den Haag, CPB Netherlands Bureau for Economic Policy Analysis,.

Löschel, A. (2002). "Technological change in economic models of environmental policy: a survey." Ecological Economics **43**(2-3): 105-126.

Loulou, R., G. Goldstein and K. Noble (2004). Documentation for the MARKAL Family of Models, Energy Technology Systems Analysis Programme.

Loulou, R. and D. Lavigne (1996). MARKAL model with Elastic Demands: Application to Greenhouse Gas Emission Control. Operations Research and Environmental Management. C. Carraro and A. Haurie. The Netherlands, Kluwers Academic Publishers.

Luckow, P., M. Wise, J. J. Dooley and S. H. Kim (2010). Biomass Energy for Transport and Electricity: Large scale utilization under low $CO_2$ concentration scenarios. U.S. Department of Energy. Richland, WA, Pacific Northwest National Laboratory.

Manne, A., R. Mendelsohn and R. Richels (1995). "MERGE : A model for evaluating regional and global effects of GHG reduction policies." Energy Policy **23**(1): 17-34.

Manne, A. S. and R. G. Richels (2006). "The Role of Non-$CO_2$ Greenhouse Gases and Carbon Sinks in Meeting Climate Objectives." Energy Journal **27**: 393-404.

Markandya, A., K. Halsnaes, A. Lanza, Y. Matsuoka, M. Shakespeare, J. Pan, J. Shogren, R. Seroa de Motta and T. Zhang (2001). Costing Methodologies. Contribution of Working Group III to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). B. Metz, O. Davidson, R. Swart and J. Pan. Cambridge, UK, Cambridge University Press.

McCarl, B. A., A. Meeraus, P. van der Eijk, S. Dirkse and P. Steacy (2009). McCarl GAMS User Guide Version 23.0, Texas A&M University.

Messner, S. and L. Schrattenholzer (2000). "MESSAGE-MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively." Energy **25**(3): 267-282.

Möst, D. and W. Fichtner (2009). Einführung zur Energiesystemanalyse. Energiesystemanalyse - Tagungsband des Workshops „Energiesystemanalyse“ vom 27. November 2008 am KIT Zentrum Energie, Karlsruhe. D. Möst, W. Fichtner and A. Grunwald. Karlsruhe, universitätsverlag karlsruhe**:** 11-32.

Noble, K. (2007). ANSWERv6-MARKAL User Manual. The Ridgeway, Noble-Soft Systems Pty Ltd.

Nordhaus, W. D. (1993). "Rolling the 'DICE': an optimal transition path for controlling greenhouse gases." Resource and Energy Economics **15**(1): 27-50.

Paltsev, S., J. M. Reilly, H. D. Jacoby, R. S. Eckaus, J. McFarland, M. Sarofim, M. Asadoorian and M. Babiker (2005). The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4. Cambridge, MA, MIT Joint Program on the Science and Policy of Global Change.

Rao, S. and K. Riahi (2006). "The Role of Non-$CO_2$ Greenhouse Gases in Climate Change Mitigation: Long-term Scenarios for the 21st Century." Energy Journal **27**(Multi-Greenhouse Gas Mitigation): 177-200.

Remme, U. (2006). Zukünftige Rolle erneuerbarer Energien in Deutschland: Sensitivitätsanalysen mit einem linearen Optimierungsmodell. Fakultät Maschinenbau Stuttgart, Universität Stuttgart. **Dr.-Ing.**

Risø National Laboratory (1994). UNEP Greenhouse Gas Abatement Costing Studies. United Nations Environment Programme. Roskilde.

Rotmans, J. and M. B. A. van Asselt (2001). "Uncertainty Management in Integrated Assessment Modeling: Towards a Pluralistic Approach." Environmental Monitoring and Assessment **69**(2): 101-130.

Schrattenholzer, L. (1981). The Energy Supply Model MESSAGE. Laxenburg, International Institute for Applied System Analysis.

Seebregts, A. J., G. Goldstein and K. Smekens (2001). Energy/environmental modeling with the MARKAL family of models. International Conference on Operations Research. Duisburg, Springer Verlag.

Söderholm, P. (2007). Modelling the Economic Costs of Climate Policy. Luleå, Luleå University of Technology: Department of Business Administration and Social Sciences: Economics Unit.

Sorrell, S. (2007). The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency. London, UK Energy Research Centre.

Springer, U. (2003). "The market for tradable GHG permits under the Kyoto Protocol: a survey of model studies." Energy Economics **25**(5): 527-551.

Stanton, E. A., F. Ackerman and S. Kartha (2008). Inside the Integrated Assessment Models: Four Issues in Climate Economics. Somerville, MA, Stockholm Environment Institute.

Strachan, N., N. Balta-Ozkan, D. Joffe, K. McGeevor and N. Hughes (2009). "Soft-linking energy systems and GIS models to investigate spatial hydrogen infrastructure development in a low-carbon UK energy system." International Journal of Hydrogen Energy **34**(2): 642-657.

Strachan, N. and R. Kannan (2008). "Hybrid modelling of long-term carbon reduction scenarios for the UK." Energy Economics **30**(6): 2947-2963.

Strachan, N., R. Kannan, N. Ozkan, S. Pye and P. Taylor (2006). Development of the UK MARKAL Energy Systems Model 2nd Interim Report. Department of Trade and Industry and the Department of Environment Food and Rural Affairs. London.

Strachan, N., N. Ozkan, S. Dresner, D. Joffe, P. Taylor, J. Greenleaf and S. Pye (2005). 1st Interim Report on the Updated UK MARKAL Energy Systems Model. London, UKERC.

van Beeck, N. (1999). Classification of Energy Models. Tilburg, Tilburg University & Eindhoven University of Technology.

van Regemorter, D. (2005). Computable General Equilibrium Model for studying Economy-Energy-Environment Interactions for Europe and the World. Leuven, K. U. Leuven.

van Vuuren, D., B. Van Ruijven, M. Hoogwijk, M. Isaac and H. J. M. de Vries (2006). TIMER 2: Model description and application. Integrated modelling of global environmental change. A. F. Bouwman, T. Kram and K. Klein Goldewijk. Bilthoven, MNP**:** 7-24.

Voß, A. (2009). Systemtechnische Planungsmethoden in Wirtschaft und Technik - Skript zur Vorlesung. Stuttgart, Institut für Energiewirtschaft und Rationelle Energieanwendung, Universität Stuttgart.

Wilson, D. and J. Swisher (1993). "Exploring the gap : Top-down versus bottom-up analyses of the cost of mitigating global warming." Energy Policy **21**(3): 249-263.

Worrell, E., S. Ramesohl and G. Boyd (2004). "Advances in energy forecasting models based on engineering economics." Annual Review of Environment and Resources **29**: 345-381.

# 4 INDEX DECOMPOSITION ANALYSIS

The goal of this chapter is to present the second methodological tool, index decomposition analysis, used in this thesis for the generation of MAC curves. Index decomposition analysis (IDA) helps in this context to analyse the results of the energy system model and to disentangle the technological measures and behavioural aspects responsible for the reduction of carbon emissions.

The chapter begins by giving an introduction to decomposition analysis, which is used within this thesis as a synonym to index decomposition analysis. In the next step, the origins of decomposition analysis are traced back to the problem of index numbers. Subsequently, the mathematical foundation of the main decomposition methods are explained and the theoretical foundation on the index number problem demonstrated. These different methods are compared according to their properties and evaluated according to their usefulness. The chapter is concluded by a discussion of issues concerning the application of IDA for the derivation of a carbon abatement cost curve.

## 4.1 Introduction to decomposition analysis

Decomposition analysis is a statistical approach, which can be defined as:

> *“... techniques of decomposing an aggregate indicator to give quantitative measures of the relative contributions of a set of pre-defined factors leading to the change in the aggregate indicator (adapted from Ang and Liu 2001, p. 537).”*

Thus, the goal of decomposition analysis is to explicitly describe the contribution of driving factors behind the change of an aggregate variable. In the context of this thesis, decomposition analysis uses the results of the energy system model as an input. Based on this data, decomposition analysis allows one to attribute $CO_2$ emission changes to different measures. The insights on the driving forces can provide important information for decision makers. In the past, this technique has been widely applied to energy consumption or carbon emissions. This said, decomposition analysis can be used very broadly and is not restricted to an application in the energy/environment area. Methods used in decomposition analysis can be traced back to the calculation of price indices.

There are two specifications of decomposition analysis that can be distinguished: Index Decomposition Analysis (IDA) (the focus of this chapter) and Structural Decomposition Analysis (SDA), which was developed independently. The main difference between these two decomposition methodologies rests on the model being used. Whereas the first one decomposes an aggregate index using usually sector-level or country level data, the latter one uses the common economic concept of input-output tables as a basis for decomposition (Hoekstra and van den Bergh 2003). With SDA it is possible to include indirect demand effects used in the input-output model (see e.g. Dietzenbacher and Los 1998). In this way, SDA can achieve a greater detail of results, coming, however, with the necessity for more detailed data. Due to reduced data requirements, one can find more time and country studies using IDA.

## 4.2 Origin and development of IDA

Looking at the origins of index decomposition analysis, one has to distinguish between the methodological background and the conceptual origin. The methodologies used in decomposition analysis date back to index number problems, as discussed in section 4.3. The ideological inspiration of decomposition analysis in the energy/environment field goes back to the debate on deteriorating environmental conditions in the United States at the beginning of the 1970s. During that time the so-called IPAT (Impact, Population, Affluence, Technology) analysis started. The goal of this analysis is to determine the key drivers behind environmental impact, such as air pollution. The IPAT identity states very generally that impact is the result of the product of three different factors: population (P), affluence (A) and technology (T).

$$I = P * A * T \tag{4.1}$$

This undefined identity was suggested by Ehrlich and Holdren (1971) as a reaction to researchers doubting any causality between U.S. population growth and environmental impact. Originally, the purpose of this equation was to find the single variable that is most damaging to the environment. Soon a debate started of which variable was to blame. Whereas Commoner and others pointed to new production technologies as the source of more pollution, his opponents at that time, Ehrlich and Holdren, saw population growth as the predominant reason for damage to a broadly defined environment (Ridker 1972). Consequently, population control was considered as an option by Ehrlich and Holdren to control environmental pollution. Other researchers held the position that negative consequences of population growth and rising affluence would be balanced by technological improvements.

Commoner, the first to make the equation operational, chose production per capita as a measure of affluence and emission per production as a proxy for technology. In many studied examples, he found technology to be behind much of the environmental degradation. A question raised early on concerned the independence of the factors explaining the aggregate of environmental impact, such as interdependencies between affluence and technological improvement. This debate heavily influenced U.S. policy makers in the early 1970s and led to an unprecedented level of environmental legislative activity, leading to policies such as the Clean Air Act. Later on, the IPAT identity was extended to study causal linkages and to be applied to regression analysis (see e.g. Dietz and Rosa 1994; Rosa and Dietz 1998) or to include other factors such as intensity of use, e.g. energy intensity (Waggoner and Ausubel 2002).

The oil price shocks in the 1970s made the broader public aware of the reliance on energy and were a starting point for researchers to look more closely at energy consumption. The academic world was interested in quantifying the drivers behind changes of industrial energy demand and to single out the influence of structural changes in the industry sector. This was the starting point for index decomposition analysis in the context of energy. Although this research stream developed relatively independently from the IPAT analysis, the structure looked broadly similar despite its clear focus on energy. The first studies in the early 1980s therefore investigated how output growth, energy/electricity intensity, structural change and technological change influenced industrial energy/electricity demand (Thomas and MacKerron 1982; Hankinson and Rhys 1983; Jenne and Cattell 1983). New to this approach was an attempt to explain how structural changes in industrial output influenced energy demand. A typical decomposition equation looked like Equation (4.2), where the first term on the right hand side indicates the influence of output, the second the influence of industrial structure and the last the influence of sectoral energy intensity on overall industrial energy consumption.

$$Energy\ consumption_{ind.} = \sum_{i=sector} Output\ \frac{Output_i}{Output}\ \frac{Energy\ Consumption_i}{Output_i} \qquad (4.2)$$

While in 1987, a survey by Huntington and Myers (1987) found only eight decomposition studies undertaken up to this date in this area, the application of these techniques was becoming more and more popular in the 1990s so that Ang (1995a) listed 51 studies in the context of industrial energy decomposition. In the 1980s and early 1990s the focus of decomposition analysis was on industrial energy consumption or energy intensity, defined as a unit of energy consumption per unit of output. Differences had appeared, however, regarding the choice of studied fuel, the level of sector disaggregation and in particular the countries studied, ranging from industrialised countries like Japan, UK and Germany to developing countries like Mexico, China and South Korea.

From the 1990s, the focus of decomposition analysis was no longer mainly restricted to industrial energy use, but expanded to other sectors and to the analysis of gas emissions, predominantly $CO_2$ but also $SO_2$ and $NO_x$. Consequently, the last survey on decomposition studies performed by Ang and Zhang (2000) found that 33, out of a total of 124 studies, dealt with the decomposition of gas emissions. The first identity to be specified in the context of the analysis of carbon emission was the Kaya identity (Kaya 1989):

$$CO_2 = Population \frac{GDP}{Population} \frac{Primary\ Energy}{GDP} \frac{CO_2}{Primary\ Energy} \tag{4.3}$$

This identity looks very similar to the original IPAT identity simply with the technology factor detailed into both the energy intensity of the economy and the carbon intensity of energy. Torvanger (1991) was the first to quantify the impact of different drivers, such as industry structure, fuel share and energy intensity, on the development of $CO_2$ emissions within the scope of a cross-country analysis. Traditionally, decomposition techniques have been applied to decompose changes in an aggregate indicator over time. However, there exist some exceptions of the sort of Proops et al. (1992) and Zhang et al. (2001) that decompose the difference in an aggregate indicator between countries. This means that the factors on the right hand side capture differences between countries and not between points in time. Moreover, some studies applied the concept of decomposition analysis beyond energy onto manufacturing and transport issues (Ang and Zhang 2000, p. 1163).

Decomposition techniques have not only been applied to study historical data, but also to analyse future perspectives of the development of environmental indicators. Olsen (1994) for example, based on the traditional IPAT identity, studied three scenarios of future developments. In the same way, the Intergovernmental Panel on Climate Change

(IPCC) used decomposition analysis, based on the Kaya identity, to project future trends in $CO_2$ emissions. In this study, the importance of technological improvement in the light of population growth and economic growth is acknowledged:

> *"Admittedly, there are many possible combinations of the four Kaya identity components, but with the scope and legitimacy of population control subject to ongoing debate, the remaining two technology-oriented factors, energy and carbon intensities, have to bear the main burden (Rogner et al. 2007, p.108)."*

This confirms a more accepted view nowadays that technological systems offer the best possibility to balance environmental impacts of affluence and population increases.

After the last survey of studies on decomposition analysis, this research field has extended beyond the industry sector and now includes studies on electricity generation, the residential sector, the service sector and transport (see e.g. International Energy Agency 2004). Moreover, several studies have been published that project future developments of $CO_2$ emissions based on assumptions on key drivers (Kawase et al. 2006; Agnolucci et al. 2009). In addition, decomposition analysis has been used for energy efficiency monitoring and to study material flows (Ang 2004).

Summing up, decomposition analysis is based on the IPAT debate, which started in the 1970s. The quantification of energy intensity changes and structural changes in the industry sector were first studied after the first two oil price shocks. In the 1990s the focus of decomposition studies changed from energy towards environmental indicators, such as $CO_2$ emissions. Nowadays, decomposition analysis is a well-established research area, studying different energy sectors and different energy and environmental indicators. However, except for a couple of studies on cross-country comparisons, analyses have been restricted to decomposing the change of aggregate indicators over time. Further studies have been undertaken that decompose the share of measures towards emissions reduction over time, but do not represent marginal abatement costs. To the knowledge of the author, no studies have been undertaken to decompose changing $CO_2$ emissions over increasing $CO_2$ prices, i.e. to decompose a MAC curve, instead of doing so over time. In summary, the thesis at hand presents a transparent and methodologically detailed approach of bringing together energy system modelling and decomposition analysis to derive MAC curves.

## 4.3 Methods of IDA

This section explains the methods used in index decomposition analysis. After a brief overview, it first traces back the origins to the index number problems and then presents the different decomposition methods. This section concludes with an application example to the electricity sector.

### 4.3.1 Introduction

This section introduces in mathematical terms the intention of decomposition analysis and distinguishes between multiplicative and additive decomposition analysis. Furthermore, the approaches of different decomposition techniques to explain the change of an aggregate variable are graphically explained.

Assume an aggregate variable (for example $CO_2$ emissions or energy consumption) can be subdivided by an attribute *r* (e.g. a fuel type in the context of energy or an industry sector)

$$V = V_1 + V_2 \ldots + V_n = \sum_r V_r \tag{4.4}$$

and that $V$ changes in the range *t=[0,T]* from $V^0$ to $V^T$ (superscripts in this chapter denote either the base situation or the comparison situation). Equation (4.4) can be extended, assuming that $V_r$ is made up of different vectors $x_1, x_2, \ldots, x_n \in \mathbb{R}^N_{++}$ $(n = 1, \ldots, N)$

$$V = \sum_r x_{1,r} x_{2,r} \ldots x_{n,r} = \sum_r \prod_{i=1}^{n} x_{i,r} \tag{4.5}$$

The interest in decomposition is not directed at the level of an aggregate variable, but rather on its change. One usually differentiates between two possible forms of decomposition. The first is the multiplicative decomposition

$$R_{tot} = \frac{V_n^T}{V_n^0} = R_1 R_2 \ldots R_n \tag{4.6}$$

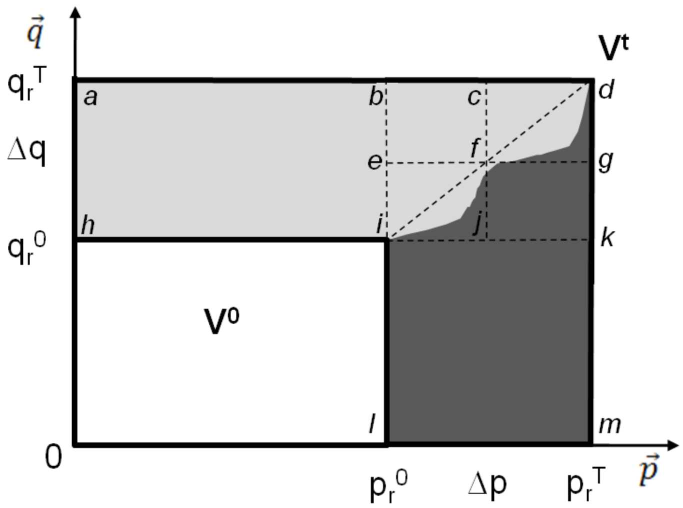
This decomposition form decomposes the relative change of a variable into the relative change of each factor. On the other hand, there exists the additive decomposition

$$\Delta V = V_n^T - V_n^0 = \Delta V_1 + \Delta V_2 + \cdots \Delta V_n = \sum_{i=1}^{n} \Delta V_i \tag{4.7}$$

,where $\Delta V$ represents the total change of the aggregate variable and $\Delta V_i$ the change of the aggregate *V* due to a change in factor *i*. This decomposition form regards absolute changes, i.e. the absolute change of the aggregate indicator is decomposed in an absolute change of each explaining driver. Since the goal of decomposition analysis in this thesis is on the decomposition of absolute changes in $CO_2$ emissions, the following discussion focuses exclusively on additive decomposition. For further detail on the relation between additive and multiplicative decomposition see Choi et al. (2003) and Balk (2003).

Assuming that the aggregate *V* depends only on two drivers, a change in this aggregate is depicted in Figure 4.1. This figure maps the change in a two-dimensional aggregate, in this case a value index consisting of a quantity vector and a price vector. The value index changes in this example from $i$ $(p_r^0, q_r^0)$ to $d$ $(p_r^T, q_r^T)$, which are the only data points known to the analyst. The light grey shaded area illustrates the change of variable $\vec{q}$ and the dark grey shaded area represents the change of variable $\vec{p}$. Thus, decomposition analysis can also be described as an approximation to a continuous integral describing a particular path. As the path is not known, it is not possible with decomposition analysis to correctly attribute the changes in the aggregate variable to the underlying driver.

**Figure 4.1: Graphical illustration of the index number problem**




The total change of the aggregate variable consists of three squares: *abih*, *bdki* and *ikml*. While it is plausible to attribute the area *abih* to a change in variable $\vec{q}$ and the area *ikml* to a change in variable $\vec{p}$, the situation for the area *bdki* is more complicated as the exact path is usually not known. Different solutions are proposed according to specific techniques. A possible approach is to attribute the problematic area to none of the underlying variables (Laspeyres index) or to both (Paasche index). This will result in an under- or overestimation of the aggregate indicator and in a residual. A residual is the portion of the change in an aggregate variable that is not attributed to an underlying driver and is therefore left unexplained. If this residual is large in comparison to the overall change of the aggregate, it can render the decomposition meaningless. Another procedure is to attribute one half of the whole area *egki* to variable $\vec{p}$ and the other half *bdge* to variable $\vec{q}$, the approach of the Edgeworth-Marshall index. This will yield a complete decomposition, i.e. without any residual, only in the 2-variable case. In other cases, the calculation will leave a residual, though smaller than the residual of the Laspeyres and Paasche index. If a decomposition does not leave a residual, the decomposition is called perfect or complete.

Another decomposition technique, the refined Laspeyres, always results in a complete decomposition because it splits the problematic area into two triangles and attributes the area *bdi* to variable $\vec{q}$ and area *idk* to variable $\vec{p}$. It is important to note that the refined Laspeyres is indeed complete or perfect, but does not necessarily attribute the overall change correctly. In the above example the refined Laspeyres would assign areas *abih* and *bdi* to a change in the aggregate variable due to quantity changes. Yet, this would not be correct, as the light grey shaded area extends into the triangle *idk*. Therefore, one has to be cautious with complete decomposition results. On the one hand, they possess the advantage of no residual, but on the other hand this is achieved by more or less arbitrarily allocating the residual to the variables.

### 4.3.2 Index number problem

The first decomposition was applied to the index number problem of price indices, which are used to determine inflation. Price indices try to answer the question of how much of the change of a given basket of goods can be explained with price changes and how much with changing commodity weights. Since the interest is on the relative change of prices, multiplicative decomposition is used throughout inflation calculation. Thus attribute *r* in Equation (4.5) are goods and the vectors are the price vector *P* and the quantity vector *Q*, which form the value index *V*

$$V = PQ = p_1q_1 + p_2q_2 + \cdots + p_nq_n = \sum_r p_rq_r \tag{4.8}$$

Comparing the wealth of Louis XII in the 16th century and Louis XV of France in the 18th century, Dutot (1738, p. 120) was the first to propose a price index:

$$\frac{P^T}{P^0}_{Dutot} = \frac{p_1^T + p_2^T + \cdots + p_n^T}{p_1^0 + p_2^0 + \cdots + p_n^T} = \frac{\sum_r p_r^T}{\sum_r p_r^0} \tag{4.9}$$

This price index is a ratio of the sum of all prices at the point in time $T$ and the point in time $0$. The unsuitability of this price index to calculate inflation becomes clear, if one imagines that the price index will change merely with a change in the unity of measurement of one good.

The earliest price index that was the first to be used in index decomposition analysis of the energy sector is the Laspeyres index (Laspeyres 1871) given by:

$$\frac{P^T}{P^0}_{Laspeyres} = \frac{p_1^T q_1^0 + p_2^T q_2^0 + \cdots + p_n^T q_n^0}{p_1^0 q_1^0 + p_2^0 q_2^0 + \cdots + p_n^0 q_n^0} = \frac{\sum_r p_r^T q_r^0}{\sum_r p_r^0 \, q_r^0} \tag{4.10}$$

At the time when Laspeyres proposed his price index, consumption and price statistics were so badly developed that his approach was only of little use. Nevertheless, price indices of this type are still used around the world as an indicator for inflation. Both, the Harmonised Index of Consumer Prices (HICP) of the European Union, as well as the United States Consumer Price Index (CPI) use the Laspeyres index. The characteristic of the Laspeyres index is that the goods' quantities are fixed in the base situation. The opposite, where the quantities are fixed in the observed situation, is called after Herrmann Paasche (1874), who applied this index to prices on the Hamburg exchange:

$$\frac{P^T}{P^0}_{Paasche} = \frac{p_1^T q_1^T + p_2^T q_2^T + \cdots + p_n^T q_n^T}{p_1^0 q_1^T + p_2^0 q_2^T + \cdots + p_n^0 q_n^T} = \frac{\sum_r p_r^T q_r^T}{\sum_r p_r^0 \, q_r^T} \tag{4.11}$$

A combination of the Laspeyres and Paasche approach, i.e. taking the arithmetic average of the quantities in the base situation and the observed situation, represents the Edgeworth-Marshall index

$$\frac{P^T}{P^0}_{E.-M.} = \frac{p_1^T \frac{(q_1^0 + q_1^T)}{2} + p_2^T \frac{(q_2^0 + q_2^T)}{2} + \cdots + p_n^T \frac{(q_n^0 + q_n^T)}{2}}{p_1^0 \frac{(q_1^0 + q_1^T)}{2} + p_2^0 \frac{(q_2^0 + q_2^T)}{2} + \cdots + p_n^0 \frac{(q_n^0 + q_n^T)}{2}} = \frac{\sum_r p_r^T \frac{(q_r^0 + q_r^T)}{2}}{\sum_r p_r^0 \frac{(q_r^0 + q_r^T)}{2}} \tag{4.12}$$

This index was independently suggested by Marshall (1887) and Edgeworth (1925).

Another milestone in the development of index numbers was the work by Fisher (1922), who developed the 'ideal' index, a geometric mean of the Paasche and Laspeyres index. As this index is only used in multiplicative decomposition, it is not discussed here in more detail. The last type of index to be proposed in the context of index numbers and heavily used in decomposition analysis is the Divisia index (Divisia 1925; Divisia 1928). Divisia based his reasoning on the equation of exchange. In this way, he defines the change of the value index *V* in Equation (4.8) as a total differential

$$\frac{dV(t)}{dt} = \frac{dP(t)}{dt}Q(t) + \frac{dQ(t)}{dt}P(t) = \sum_r \frac{dp_r(t)}{dt}q_r(t) + \sum_r \frac{dq_r(t)}{dt}p_r(t) \tag{4.13}$$

where the first summand is the price index and the second one the quantity index. Extracting the price index and dividing by *P(t)* yields

$$\frac{dP(t)}{dt} * \frac{1}{P(t)} = \sum_r \frac{dp_r(t)}{dt} \frac{q_r(t)}{\sum_r p_r(t) * q_r(t)} \tag{4.14}$$

Transforming the right hand side results in

$$\frac{dP(t)}{dt} * \frac{1}{P(t)} = \sum_r \frac{dp_r(t)}{dt} \frac{1}{p_r(t)} \frac{q_r(t) * p_r(t)}{\sum_r p_r(t) * q_r(t)} \tag{4.15}$$

Incorporating $\frac{dlnf}{dt} = \frac{df}{dt} * \frac{1}{f}$ (with *f* being an arbitrary function) gives

$$\frac{dln(P(t))}{dt} = \sum_r \frac{d\ln(p_r(t))}{dt} \frac{q_r(t) * p_r(t)}{\sum_r p_r(t) * q_r(t)} \tag{4.16}$$

Integrating

$$\ln(\frac{P^T}{P^0}) = \int_0^T \sum_r \frac{q_r(t) * p_r(t)}{\sum_r p_r(t) * q_r(t)} \frac{d\ln(p_r(t))}{dt} dt \tag{4.17}$$

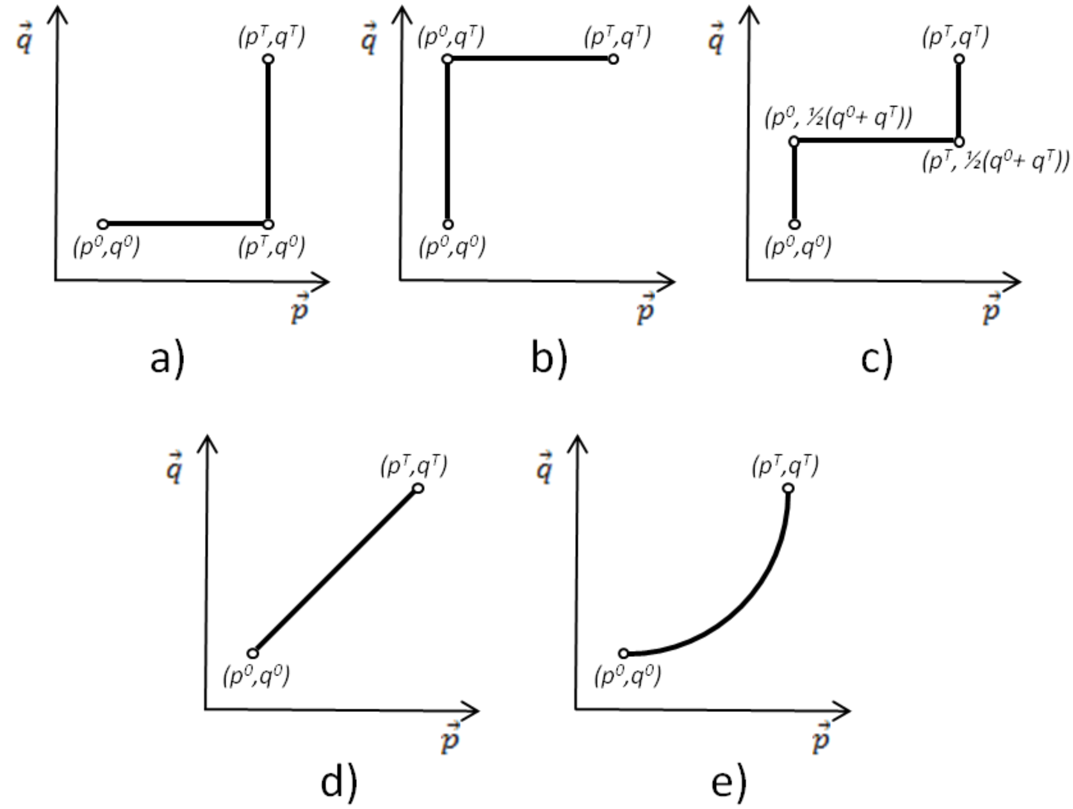
As a ratio the price index looks the following:

$$\frac{P^T}{P^0}_{Divisia} = \exp[\int_0^T \left(\sum_r \frac{q_r(t) * p_r(t)}{\sum_r p_r(t) * q_r(t)}\right) * \ln\left(\frac{p_r^T}{p_r^0}\right)]dt \tag{4.18}$$

Divisia was aware of the fact that his index was nothing more than a curvilinear integral (Divisia 1925, p. 1004) so that the calculation of the price index depends not only on the values in the base and observed situation, but on all values in between. As the Divisia index is an integral, it needs to be approximated in order to be used as a price index.

Vogt (1978) concluded that if it is assumed that the relationship, which is being decomposed, is continuous, each index represents a time path between two discrete points. This is illustrated in Figure 4.2, which presents different paths for price indices with the commodity vector on the ordinate and the price vector on the abscissa.

**Figure 4.2: Representation of the Index Problem in the 2n-dimensional Quantity-Price Space**




**Source: adapted from Vogt (1978)**[1]

The path in a) represents the Laspeyres index, b) corresponds to the Paasche index, c) corresponds to the Edgeworth-Marshall index and e) to the exponential Divisia index. The path in d) was called the "natural" index or the Divisia index on a straight line in the context of index number and became better known under the term Refined Laspeyres in the index decomposition context (see 4.3.3).

Montgomery (1937, p.51f) was the first to propose an approximation of the Divisia index using the logarithmic mean (without using the term logarithmic mean), defined as $L \equiv \frac{(a-b)}{\ln\left(\frac{a}{b}\right)}$ , resulting in the following Divisia index

$$\frac{P^T}{P^0}_{Montgomery} = \sum_r (p_r^T q_r^T - p_r^0 q_r^0)\, \frac{\ln(\frac{p_r^T}{p_r^0})}{ln(\frac{p_r^T q_r^T}{p_r^0 q_r^0})} = \sum_r L(p_r^T q_r^T, p_r^0 q_r^0) ln(\frac{p_r^T}{p_r^0}) \qquad (4.19)$$

[1] Permission to reproduce this Figure has been granted by Springer.

This approach has several desirable properties that will be discussed in section 4.4.

Other averages include the arithmetic mean (Hulten 1973; Törnqvist et al. 1985), geometric means (Theil 1973; Sato 1974) and rediscoveries of the logarithmic mean (Sato 1976; Vartia 1976; Törnqvist et al. 1985). In the context of decomposition analysis one speaks of the logarithmic mean I and II according to Vartia's (1976) definitions. All of the presented indices are possible approaches to the index number problem.

Series expansion is another way of explaining the nature of the residual term in decomposition analysis. Referring back to Equation (4.13), the total differential can be approximated in the following way, representing a first-order Taylor expansion

$$\frac{dV(t)}{dt} = \frac{dP(t)}{dt}Q(t) + \frac{dQ(t)}{dt}P(t) \approx \Delta PQ + \Delta QP \ = (P^T - P^0)Q + (Q^T - Q^0)P \quad (4.20)$$

The assumption is that the changes are very small so that the differential can be approximated. Nevertheless, infinitesimal calculus is only an approximation of differential calculus and therefore leaves a residual if only first order changes are considered as it is the case in decomposition analysis. The approximation on the right hand side is a series expansion that is truncated after the first order terms. Higher order terms or interaction terms form the residual in the case where it is not redistributed to the variables. Proops et al. (1992, Appendix A4) give an explanation on the use of differences instead of differentials.

### 4.3.3 Decomposition methods

After having discussed the origin of index decomposition in conjunction with the index number problem, the following discussion gives an overview of the additive decomposition methods used in the energy/environment context and their derivation. Early decomposition studies in the energy/environment context predominantly did not mention the method used, but it can be assumed that they used Laspeyres decomposition method, which was the most common at that time. In the late 1980s, Reitler et al. (1987) and Boyd et al. (1988) were the first to discuss methodological questions in the context of energy decomposition.

#### Laspeyres

The Laspeyres index decomposition, where all variables except for the explaining one are held constant in the base period, is rooted in the Laspeyres price index. Since it is one of the simplest decomposition forms, it was used from the very beginning of decomposition analysis (Hankinson and Rhys 1983).

Starting from Equation (4.5), the absolute change in the aggregate indicator due to variable $x_i$ in the Laspeyres form is mathematically described in the following way

$$\Delta V_{i,Laspeyres} = \sum_r x_{1,r}^0 x_{2,r}^0 \dots \left(x_{i,r}^T - x_{i,r}^0\right) \dots x_{n-1,r}^0 x_{n,r}^0 \tag{4.21}$$

#### Paasche

In contrast to the Laspeyres decomposition, the Paasche decomposition (named according to the Paasche price index) holds all variables except for the explaining variable constant at the observed period, resulting in the following formula

$$\Delta V_{i,Paasche} = \sum_r x_{1,r}^T x_{2,r}^T \dots \left(x_{i,r}^T - x_{i,r}^0\right) \dots x_{n-1,r}^T x_{n,r}^T \tag{4.22}$$

This decomposition method has been relatively rarely applied, one example is Thomas et al. (1982).

#### Edgeworth-Marshall

The Edgeworth-Marshall decomposition combines, like its corresponding price index, the Laspeyres and Paasche index by taking the arithmetic average of the values in the base and observed period.

$$\Delta V_{i,M.-E.} = \sum_r \frac{1}{2} \left( \prod_{\substack{j=1 \\ j \neq i}}^n x_{j,r}^T + \prod_{\substack{j=1 \\ j \neq i}}^n x_{j,r}^0 \right) (x_{i,r}^T - x_{i,r}^0) \tag{4.23}$$

This decomposition form was already applied in the 1980s by Reitler et al. (1987).

#### Refined Laspeyres

The Refined Laspeyres decomposition has been known under different names, which is due to the fact that it can be formulated in different ways. Sun (1998) was the first to suggest this method in the context of decomposition analysis. He started from the common Laspeyres index and had a closer look at the disregarded terms of higher order or so-called interactions terms. He coined the phrase “jointly created, equally distributed” to distribute the change arising from the interaction terms to the involved variables. An example in the three variable case looks like

$$\Delta V_{1,refined\ Laspeyres} = \sum_r \left(x_{1,r}^T - x_{1,r}^0\right)x_{2,r}^0 x_{3,r}^0 + \frac{1}{2}\left(x_{1,r}^T - x_{1,r}^0\right)\left(x_{2,r}^T - x_{2,r}^0\right)x_{3,r}^0 + \frac{1}{2}\left(x_{1,r}^T - x_{1,r}^0\right)\left(x_{3,r}^T - x_{3,r}^0\right)x_{2,r}^0 + \frac{1}{3}\left(x_{1,r}^T - x_{1,r}^0\right)\left(x_{2,r}^T - x_{2,r}^0\right)\left(x_{3,r}^T - x_{3,r}^0\right) \tag{4.24}$$

where the interaction terms are proportionally attributed to variable 1.

Another formulation dates back to a game theoretic approach of Shapley (1953). He gave a formula to evaluate the real power of a voter with transferable utility in a coalition voting game.

Dietzenbacher et al. (1998) used the same approach within structural decomposition analysis. They started from a combination of the Laspeyres and Paasche index, i.e. holding some of the variables in the base period and some in the observed period. Following this technique, there exist *n!* possible permutations and accordingly exactly the same number of decomposition methodologies. Taking the average of all possible permutations yields a complete decomposition.

Albrecht et al. (2002) suggested this method the first time within index decomposition analysis, referring to Shapley (1953). As some combinations appear more than once in the permutation, these are weighted according to the Shapley value (Shapley 1953, p. 311) $\frac{(s-1)!(n-s)!}{n!}$, where *n* is the total number of variables and *s* the number of variables held at the observed period *T* plus the studied variable. In the three variable case this results in

$$\Delta V_{1,Shapley} = \sum_r \frac{1}{3}\left(x_{1,r}^T - x_{1,r}^0\right)x_{2,r}^0 x_{3,r}^0 + \frac{1}{6}\left(x_{1,r}^T - x_{1,r}^0\right)x_{2,r} x_{3,r}^0 + \frac{1}{6}\left(x_{1,r}^T - x_{1,r}^0\right)x_{2,r}^0 x_{3,r}^T + \frac{1}{3}\left(x_{1,r}^T - x_{1,r}^0\right)x_{2,r}^T x_{3,r}^T \tag{4.25}$$

It can be shown that this formulation is equivalent to the refined Laspeyres formulation (Equation (4.24)). For a more detailed discussion on the equality of the Shapley and Refined Laspeyres decomposition, see Ang et al. (2003) and Lenzen (2006).

In the n-factor case, the refined Laspeyres decomposition takes the following form

$$\begin{aligned}
&\Delta V_{i,Refined\ Laspeyres} \\
&\quad = \sum_r \left[ \frac{V_n^0}{x_{i,r}^0}\left(x_{i,r}^T - x_{i,r}^0\right) + \frac{1}{2}\frac{V_n^0}{x_{i,r}^0 x_{j,r}^0}\left(x_{i,r}^T - x_{i,r}^0\right)\left(x_{j,r}^T - x_{j,r}^0\right) \right. \\
&\quad + \frac{1}{3}\frac{V_n^0}{x_{i,r}^0 x_{j,r}^0 x_{k,r}^0}\left(x_{i,r}^T - x_{i,r}^0\right)\left(x_{j,r}^T - x_{j,r}^0\right)\left(x_{k,r}^T - x_{k,r}^0\right) + \cdots \\
&\quad \left. + \frac{1}{n}\left(x_{1,r}^T - x_{1,r}^0\right)\left(x_{2,r}^T - x_{2,r}^0\right) \ldots \left(x_{n,r}^T - x_{n,r}^0\right) \right] \quad with\ i \neq j \neq k
\end{aligned} \tag{4.26}$$

The above formula demonstrates that the equation becomes more complicated as the number of factors increases. This can be a significant disadvantage in the context of $CO_2$ emission analyses with several explanatory variables.

The multiplicative equivalent to the refined Laspeyres is the generalised Fisher index (Ang et al. 2004).

**Mean Rate of Change Index**

In response to possible distortions in the Refined Laspeyres decomposition method, Chung and Rhee (2001) proposed the Mean Rate of Change Index (MRCI), which uses a more complicated form compared to the previous decomposition methods. The Refined Laspeyres, which is equal to the Edgeworth-Marshall decomposition in the two-factor case, was criticised for its uniform allocation of the residual term without taking into account the relationship between the original effects (Casler 2001, p. 146). In the presence of a comparably large residual, this can lead to a considerable change even with only a small scale effect. Therefore, de Bruyn (2000, p. 171) called for a method that is based on the condition that the relative increase due to the allocation of the residual remains the same for all effects. He introduced the concept of relative growth rates for the two-factor case to achieve this goal. Chung and Rhee (2001) extended this concept to a situation with multiple factors.

The decomposition makes use of the weight term $M_{i,r}(*)$, which involves the rates of change of all the relevant variables $A_{i,r}(*)$

$$\Delta V_{i,MRCI} = \sum_r M_r(*) \frac{1}{\frac{x_{i,r}^T + x_{i,r}^0}{2}} \left(x_{i,r}^T - x_{i,r}^0\right) \qquad with\ x_{i,r}^T + x_{i,r}^0 \neq 0 \tag{4.27}$$

where

$$M_r(*) = \frac{V_r^T - V_r^0}{A_r(*)} \tag{4.28}$$

and

$$A_r(*) = \sum_i \frac{x_{i,r}^T - x_{i,r}^0}{\frac{x_{i,r}^T + x_{i,r}^0}{2}} \qquad with\ x_{i,r}^T + x_{i,r}^0 \neq 0 \tag{4.29}$$

In words, the equation for the change due to one variable is described by the total change of the aggregate indicator $(V_r^T - V_r^0)$ times the relative change (the authors call it mean rate of change) of the analysed variable $\frac{(x_{i,r}^T - x_{i,r}^0)}{\frac{x_{i,r}^T + x_{i,r}^0}{2}}$ divided by the sum of the relative change of all variables $[A_{i,r}(*)]$. In this way, the weighting method makes sure that the decomposition does not leave a residual and is therefore perfect. However, in particular the sum of the relative change of all variables $[A_{i,r}(*)]$ is prone to distortions in the case of summands having mixed positive and negative signs. It can result in a situation where the sign in the decomposition term is opposite to the one in the relative change of the variable. In the extreme, this can lead to the sum becoming zero and therefore rendering the MRCI undefined. A general expression for the MRCI, which is not only restricted to mid-point weights, is given by Lenzen (2006, p. 193).

**Arithmetic Mean Divisia Index**

All of the following Divisia decomposition methods have their origin in the Divisia price index (Divisia 1925). The big difference between the previous decomposition forms and the Divisia index is that the Divisia decomposition methods are usually based on a logarithmic change in contrast to a change on a percentage basis. The general Divisia decomposition can be derived by differentiating Equation (4.5), which yields the total differential

$$\frac{dV(t)}{dt} = \sum_{i,r} \prod_{j \neq i} \frac{dx_{i,r}(t)}{dt}\ x_{j,r}(t) \tag{4.30}$$

Integrating one factor $i$, Equation (4.30) on both sides gives

$$V_i^T - V_i^0 = \Delta V_i = \int_0^T \sum_r \prod_{j \neq i} \frac{dx_{i,r}(t)}{dt}\ x_{j,r}(t)\, dt \tag{4.31}$$

Equation (4.31) can be rewritten in the following way

$$\Delta V_i = \int_o^T \sum_r \prod_j x_{j,r}(t) \frac{dx_{i,r}(t)}{dt} \frac{1}{x_{i,r}(t)} dt = \int_0^T \sum_r V_r(t) \frac{dx_{i,r}(t)}{dt} \frac{1}{x_{i,r}(t)} dt \qquad (4.32)$$

Incorporating $\frac{dlnf}{dt} = \frac{df}{dt} * \frac{1}{f}$

$$\Delta V_i = \int_0^T \sum_r V_r(t) \frac{dln(x_{i,r}(t))}{dt} dt \qquad (4.33)$$

An approximation to this path-dependent integral, proposed by Hulton (1973), is the arithmetic mean, which results in

$$\Delta V_i = \sum_r \left(\frac{V_r^T + V_r^0}{2}\right) \ln\left(\frac{x_{i,r}^T}{x_{i,r}^0}\right) \qquad (4.34)$$

Boyd et al. (1988) suggested the Arithmetic Mean Divisia Index the first time within the scope of decomposition analysis. It multiplies the logarithmic change in variable *i* with the mid-point weight of the aggregate indicator.

The multiplicative equivalent to the additive version of the Arithmetic Mean Divisia Index was first introduced in Boyd et al. (1987).

**Adaptive Weighting Divisia Index**

A further and more flexible way of specifying the weighting is presented in the Adaptive Weighting Divisia Index (AWDI) (Liu et al. 1992a), which is based on the generalised first mean value theorem. According to this theorem (see e.g. Spiegel 1963, p. 82), if *f(x)* and *g(x)* are continuous in *[a,b]*, and *g(x)* does not change sign in the interval, then there is a point $\xi$ in *(a,b)* such that

$$\int_a^b f(x)g(x)dx = f(\xi)\int_a^b g(x)dx \qquad (4.35)$$

According to this theorem, Equation (4.33) can be solved for *i=1,2,n*

$$\Delta V_1 = \sum_r [V_r^0 + \alpha_r(V_r^T - V_r^0)] \ \ln\left(\frac{x_{1,r}^T}{x_{1,r}^0}\right) \qquad (4.36)$$

$$\Delta V_2 = \sum_r [V_r^0 + \beta_r(V_r^T - V_r^0)] \ \ln\left(\frac{x_{2,r}^T}{x_{2,r}^0}\right) \qquad (4.37)$$

$$\Delta V_n = \sum_r [V_r^0 + \omega_r(V_r^T - V_r^0)] \ \ln\left(\frac{x_{n,r}^T}{x_{n,r}^0}\right) \qquad (4.38)$$

Liu et al. (1992a) refer to the above equation as the Parametric Divisia Method 1. This method is based on logarithmic changes. It is called parametric, because the choice of

$\alpha,\beta,\omega$ determines the weighting, where 0 would be a Laspeyres weighting, 0.5 a Edgeworth-Marshall weighting and 1 a Paasche weighting.

If one applies the mean value theorem to Equation (4.31), the result is as follows for $i=1,2,n$

$$\Delta V_1 = \sum_r \left[ \prod_{i \neq 1} x_{i,r}^0 + \alpha_r \left( \prod_{i \neq 1} x_{i,r}^T - \prod_{i \neq 1} x_{i,r}^0 \right) \right] \left( x_{1,r}^T - x_{1,r}^0 \right) \tag{4.39}$$

$$\Delta V_2 = \sum_r \left[ \prod_{i \neq 1} x_{i,r}^0 + \beta_r \left( \prod_{i \neq 1} x_{i,r}^T - \prod_{i \neq 1} x_{i,r}^0 \right) \right] \left( x_{2,r}^T - x_{2,r}^0 \right) \tag{4.40}$$

$$\Delta V_n = \sum_r \left[ \prod_{i \neq 1} x_{i,r}^0 + \omega_r \left( \prod_{i \neq 1} x_{i,r}^T - \prod_{i \neq 1} x_{i,r}^0 \right) \right] \left( x_{n,r}^T - x_{n,r}^0 \right) \tag{4.41}$$

The underlying condition in equations (4.36-4.41) is $0 \leq \alpha,\beta,\ldots,\omega \leq 1$. Analogue to the first three equations, the three equations above are called Parametric Divisia Method 2 (Liu et al. 1992a). The difference to method 1 is that it regards absolute changes and not logarithmic changes.

As Equations (4.36-4.38) and (4.39-4.41) are two different analytical expressions, but are mathematically equivalent, one can specify the parameters $\alpha,\beta,\ldots,\omega$. For the parameter $\alpha$ we have by identifying the $\alpha_r$-term in Equation (4.36) and the term in Equation (4.39)

$$\begin{aligned} &[V_r^0 + \alpha_r (V_r^T - V_r^0)] \; \ln \left( \frac{x_{1,r}^T}{x_{1,r}^0} \right) \\ &\quad = \left[ \prod_{i \neq 1} x_{i,r}^0 + \alpha_r \left( \prod_{i \neq 1} x_{i,r}^T - \prod_{i \neq 1} x_{i,r}^0 \right) \right] \left( x_{1,r}^T - x_{1,r}^0 \right) \end{aligned} \tag{4.42}$$

Transformation yields:

$$\alpha_r = \frac{\prod_{i \neq 1} x_{i,r}^0 \left( x_{1,r}^T - x_{1,r}^0 \right) - V_r^0 \ln \left( \frac{x_{1,r}^T}{x_{1,r}^0} \right)}{(V_r^T - V_r^0) \ln \left( \frac{x_{1,r}^T}{x_{1,r}^0} \right) - \left( \prod_{i \neq 1} x_{i,r}^T - \prod_{i \neq 1} x_{i,r}^0 \right) \left( x_{1,r}^T - x_{1,r}^0 \right)} \tag{4.43}$$

The parameter values, such as in this example $\alpha_r$, can then be entered in Equation (4.36) or (4.39) to solve the equation. The parameters give an indication of how to weight the basis and avoid any arbitrary guess work. Instead of choosing a value, as is done in the Arithmetic Mean Divisia Index or the Laspeyres index, the parameters can be analytically estimated based on the two deterministic approximations. In this way, the AMDI provides a basis for choosing the parameter values. Consequently, this method is superior to other decomposition methods on theoretical grounds.

**Logarithmic Mean Divisia Index I**

Instead of using the arithmetic mean for an approximation of the Divisia integral, Ang et al. (1998) proposed to use the logarithmic mean. This mean was independently described by Sato (1976, p.224) and Törnqvist et al. (1985, p.44). According to Törnqvist et al. (1985), this logarithmic mean was already presented by himself in a report for the Bank of Finland in 1935. The first to publish an approximation of the Divisia index based on the logarithmic mean (without using the term logarithmic mean) was Montgomery (1937, p.51f).

The logarithmic mean is defined as follows

$$L(x,y) = \frac{x-y}{\ln\left(\frac{x}{y}\right)} \tag{4.44}$$

where both $x$ and $y$ are positive numbers and $x \neq y$. Two further special cases are defined: $L(x,x)=x$ and $L(0,0)=0$. For nonnegative numbers the logarithmic mean lies between the arithmetic and the geometric mean (Vartia 1976, p. 122).

If one uses the logarithmic mean from (4.44), then equation (4.33) becomes

$$\Delta V_i = \sum_r \left[\frac{V_r^T - V_r^0}{\ln\left(\frac{V_r^T}{V_r^0}\right)}\right] \ln\left(\frac{x_{i,r}^T}{x_{i,r}^0}\right) \tag{4.45}$$

which gives a perfect decomposition.

Like the Arithmetic Mean Divisia Index, the Logarithmic Mean Divisia Index I (LMDI I) uses the logarithmic change of the variable. The weighting consists of the logarithmic mean instead of the arithmetic mean, which gives higher values than the logarithmic mean.

The equivalent multiplicative decomposition of the LMDI I is given in Ang et al. (2001).

### Logarithmic Mean Divisia Index II

Another Logarithmic Mean Divisia Index, suggested by Ang et al. (2003) is the Logarithmic Mean Divisia Index II (LMDI II), which is different to the LMDI I concerning its weighting.

Within the context of price index numbers Vartia (1976) proposed two different logarithmic mean index formulas for a multiplicative index. The Vartia Index I is used in the LMDI I and Vartia Index II in the LMDI II. Assuming $w_r = \frac{V_r}{V} = \frac{V_r}{\sum_r V_r}$, the weights in the Vartia Index I are

$$w_{r,Vartia\ I} = \frac{L(V_r^T, V_r^0)}{L(\sum_s V_s^T, \sum_s V_s^0)} \tag{4.46}$$

while in the Vartia Index II they are defined as

$$w_{r,Vartia\ II} = \frac{L(w_r^T, w_r^0)}{\sum_s L(w_s^T, w_s^0)} \tag{4.47}$$

Using Vartia Index II equation (4.33) is transformed into

$$\Delta V_i = \sum_r \left[\frac{L(w_r^T, w_r^0)}{\sum_s L(w_s^T, w_s^0)}\right] \mathrm{L}(\mathrm{V}^\mathrm{T}, \mathrm{V}^0) \ln\left(\frac{x_{i,r}^T}{x_{i,r}^0}\right) \tag{4.48}$$

In Equation (4.48), $\ln\left(\frac{x_{i,r}^T}{x_{i,r}^0}\right)$ describes the logarithmic change of the variable, $\mathrm{L}(\mathrm{V}^\mathrm{T}, \mathrm{V}^0)$ the logarithmic mean of the aggregate indicator and $\left[\frac{L(w_r^T, w_r^0)}{\sum_s L(w_s^T, w_s^0)}\right]$ a normalised weight function. The normalised weight function is used, because $L(w_r^T, w_r^0)$ on its own does not add up to unity (Sato 1976, p. 224). The Vartia II weighting is more complicated and is in contrast to the Vartia I weighting not consistent in aggregation (Ang et al. 2003).

The equivalent multiplicative decomposition of the LMDI II is given in Ang et al. (1997).

### 4.3.4 Illustrative example

This section presents an example, which helps to visualise decomposition analysis and show the outcome of different decomposition methods. In this example, the change in $CO_2$ emissions in the electricity generation between a scenario 0 without $CO_2$ price and 1 with $CO_2$ price is decomposed into the main categories of emissions reduction. Four effects are differentiated in the decomposition (4.49): activity effect (measures the influence of a change of the level of electricity generation), structure effect (measures the influence of structural changes in electricity generation, i.e. fuel switching), fuel intensity (measures the influence of changes in the fuel consumed per unit of electricity generated, i.e. efficiency changes) and $CO_2$ intensity (measures the influence of changes in the $CO_2$ emissions per unit of fuel consumed). The choice of these four factors is discussed in more detail in section 4.5.4.

$$\Delta CO_{2,Electricity\ Generation} = \Delta CO_{2,Activity} + \Delta CO_{2,Structure} + \Delta CO_{2,Fuel\ Int.} + \Delta CO_{2,Carbon\ Int.} + residual \tag{4.49}$$

Having a look at the data (Table 4.1), one sees that electricity generation rises by about 11%, while structural shifts occur towards nuclear and other renewables. With the introduction of carbon capture and storage (CCS) technology for coal the fuel intensity deteriorates (as CCS involves an efficiency loss), while the $CO_2$ intensity decreases for coal.

**Table 4.1: Fictitious data for electricity production in scenario 0 and 1**

| | **scenario 0** | | | | **scenario 1** | | | |
|---|---|---|---|---|---|---|---|---|
| Electricity Sector | Electricity [PJ] = $a$ | Structure = $s$ | Fuel Input [PJ] = $f$ | $CO_2$ [Mt] = $e$ | Electricity [PJ] = $a$ | Structure = $s$ | Fuel Input [PJ] = $f$ | $CO_2$ [Mt] = $e$ |
| Total | 1311 | | 2613 | 195 | 1459 | | 3208 | 138 |
| Coal | 1048 | 80% | 2183 | 192 | 821 | 56% | 1817 | 134 |
| Natural Gas | 30 | 2% | 56 | 3 | 48 | 3% | 86 | 5 |
| Nuclear | 31 | 2% | 97 | 0 | 297 | 20% | 940 | 0 |
| Hydro | 19 | 1% | 19 | 0 | 19 | 1% | 19 | 0 |
| Biomass | 37 | 3% | 112 | 0 | 38 | 3% | 110 | 0 |
| Oth. Renewables | 147 | 11% | 147 | 0 | 236 | 16% | 236 | 0 |

By way of example, the calculation steps for the LMDI I are subsequently presented in detail. Based on equation (4.45, the aggregate variable to be decomposed is $CO_2$ emissions and accordingly the emissions change due to changes in demand (activity effect) looks as follows:

$$\Delta CO_{2,Acticity} = \sum_{r=technology} \left[ \frac{CO_{2,r}^{1} - CO_{2,r}^{0}}{\ln\left(\frac{CO_{2,r}^{1}}{CO_{2,r}^{0}}\right)} \right] \ln\left(\frac{a_{total}^{1}}{a_{total}^{0}}\right) \tag{4.50}$$

Since only coal and gas power plants emit $CO_2$, it is sufficient to regard these two technologies to calculate $CO_2$ emissions changes:

$$\begin{aligned}\Delta CO_{2,Acticity} &\\ = &\left[\frac{134\text{ Mt CO}_2 - 192\text{ Mt CO}_2}{ln\left(\frac{134\text{ Mt CO}_2}{192\text{ Mt CO}_2}\right)}\right] ln\left(\frac{1459\text{ PJ}}{1311\text{ PJ}}\right)\\ &+ \left[\frac{5\text{ Mt CO}_2 - 3\text{ Mt CO}_2}{ln\left(\frac{5\text{ Mt CO}_2}{3\text{ Mt CO}_2}\right)}\right] ln\left(\frac{1459\text{ PJ}}{1311\text{ PJ}}\right) = 17.6\text{ Mt CO}_2\end{aligned} \tag{4.51}$$

The first summand represents the contribution from coal power plants and the second summand from gas power plants.

Similarly, the equation for structure-related changes is given by:

$$\Delta CO_{2,Structure} = \sum_{r=technology}\left[\frac{CO_{2,r}^1 - CO_{2,r}^0}{\ln\left(\frac{CO_{2,r}^1}{CO_{2,r}^0}\right)}\right]\ln\left(\frac{s_r^1}{s_r^0}\right) \tag{4.52}$$

Based on the data given in the example, the structure effect is calculated as follows:

$$\begin{aligned}\Delta CO_{2,Structure} &\\ = &\left[\frac{134\text{ Mt CO}_2 - 192\text{ Mt CO}_2}{ln\left(\frac{134\text{ Mt CO}_2}{192\text{ Mt CO}_2}\right)}\right] ln\left(\frac{0.56}{0.8}\right)\\ &+ \left[\frac{5\text{ Mt CO}_2 - 3\text{ Mt CO}_2}{ln\left(\frac{5\text{ Mt CO}_2}{3\text{ Mt CO}_2}\right)}\right] ln\left(\frac{0.03}{0.02}\right) = -55.2\text{ Mt CO}_2\end{aligned} \tag{4.53}$$

This emissions reduction amount can subsequently be attributed to low-carbon technologies according to their increased electricity production. In this case the majority of $CO_2$ emissions is saved due to an increase in electricity production from nuclear and other renewables (see third column in Table 4.1).

Third, emissions changes related to fuel efficiency are based on the following equation:

$$\Delta CO_{2,Fuel\ Intensity} = \sum_{r=technology}\left[\frac{CO_{2,r}^1 - CO_{2,r}^0}{\ln\left(\frac{CO_{2,r}^1}{CO_{2,r}^0}\right)}\right]\ln\left(\frac{\frac{f_r^1}{a_r^1}}{\frac{f_r^0}{a_r^0}}\right) \tag{4.54}$$

Inserting data into equation (4.62), yields:

$$\Delta CO_{2,Fuel\ Intensity} = \left[\frac{134\text{ Mt CO}_2 - 192\text{ Mt CO}_2}{ln\left(\frac{134\text{ Mt CO}_2}{192\text{ Mt CO}_2}\right)}\right] ln\left(\frac{\frac{1817\text{ PJ}}{821\text{ PJ}}}{\frac{2183\text{ PJ}}{1048\text{ PJ}}}\right) + \left[\frac{5\text{ Mt CO}_2 - 3\text{ Mt CO}_2}{ln\left(\frac{5\text{ Mt CO}_2}{3\text{ Mt CO}_2}\right)}\right] ln\left(\frac{\frac{86\text{ PJ}}{48\text{ PJ}}}{\frac{56\text{ PJ}}{30\text{ PJ}}}\right) = 9.6\text{ Mt CO}_2 \tag{4.55}$$

Last, $CO_2$ intensity-related emissions changes are calculated in the following way:

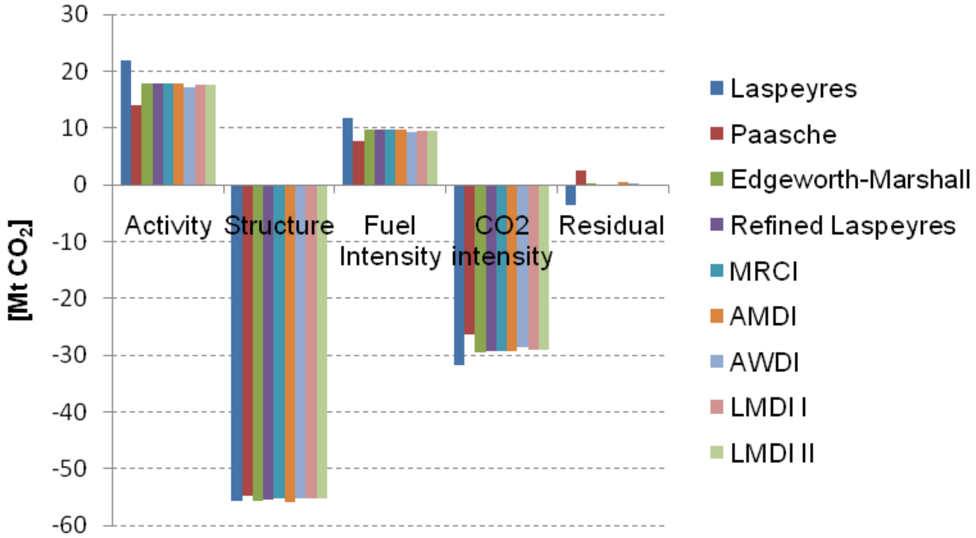
$$\Delta CO_{2,Carbon\ Intensity} = \sum_{r=technology}\left[\frac{CO^1_{2,r} - CO^0_{2,r}}{\ln\left(\frac{CO^1_{2,r}}{CO^0_{2,r}}\right)}\right]\ln\left(\frac{\frac{e^1_r}{f^1_r}}{\frac{e^0_r}{f^0_r}}\right) \tag{4.56}$$

Using the given data, results in:

$$\Delta CO_{2,Carbon\ Intensity} = \left[\frac{134\text{ Mt CO}_2 - 192\text{ Mt CO}_2}{ln\left(\frac{134\text{ Mt CO}_2}{192\text{ Mt CO}_2}\right)}\right] ln\left(\frac{\frac{134\text{ Mt CO}_2}{1817\text{ PJ}}}{\frac{192\text{ Mt CO}_2}{2183\text{ PJ}}}\right) + \left[\frac{5\text{ Mt CO}_2 - 3\text{ Mt CO}_2}{ln\left(\frac{5\text{ Mt CO}_2}{3\text{ Mt CO}_2}\right)}\right] ln\left(\frac{\frac{5\text{ Mt CO}_2}{86\text{ PJ}}}{\frac{3\text{ Mt CO}_2}{56\text{ PJ}}}\right) = -29\text{ Mt CO}_2 \tag{4.57}$$

Figure 4.3 indicates that the increase of electricity generation and the increasing fuel intensity have a positive effect on $CO_2$ emissions. By contrast, structural changes towards carbon-free energy sources and a decreasing $CO_2$ intensity have a comparably larger negative effect on $CO_2$ emissions.

**Figure 4.3: Decomposition results with different methods**



As all nine previously discussed decomposition methods are displayed, interesting insights are generated into the results depending on the applied method. First of all, the residual does not exceed 1% of the total change except for the Laspeyres and Paasche decomposition with 4% and 6% respectively. For all effects, the Laspeyres decomposition describes the largest value and the Paasche index the lowest one. This is not surprising because in the Laspeyres index all variables are fixed in scenario 0 (with comparably low electricity generation, low fuel intensity and high $CO_2$ intensity) and in the Paasche index they are fixed in scenario 1 (with comparably high electricity generation, high fuel intensity and low $CO_2$ intensity). For the rest of the decomposition methods, the similarity of the results is striking, having a maximum difference for one effect of less than 5% in this example. Although the results depend on the given data variability, choosing one method over the other does not have a distortionary effect on the decomposition results, except for the Laspeyres and Paasche decomposition. This does, however, require the compared $CO_2$ prices not to be far apart.

## 4.4 Comparison of methods

Fisher (1922) coined in his work the geometric mean of the Laspeyres and the Paasche index as the ideal index, also known as the Fisher index. Nonetheless, there is no ideal index, not even Fisher's ideal index. Acknowledging this fact, he wrote himself that "index numbers are not and never can be absolutely precise (Fisher 1922, p. 224)". This conclusion is typical for the axiomatic approach to index numbers. It analyses properties of indices, so that the judgement of an index depends on the axioms considered most important.

### 4.4.1 Theoretical soundness

To assess the theoretical soundness, one can use the same approach as with index numbers, i.e. to compare different methods along several axioms, tests and theorems. While axioms describe desired properties, which are used to define index numbers, theorems can be deduced from axioms. Tests cannot be deduced from axioms, but nevertheless require desirable properties (Vogt and Barta 1997, p.42).

Three relative well-known tests are the time-reversal test, the factor reversal test and the circular test. The time reversal test states that interchanging the base and comparison situation should result in the same decomposition result in absolute terms.

$$\Delta V_{0,T} = -\Delta V_{T,0} \tag{4.58}$$

Decomposition results are required to be consistent whether the decomposition is carried out prospectively or retrospectively. This test cannot be fulfilled by indices that rely on fixed weights, such as the Laspeyres and Paasche index.

The factor reversal test is another reversal test. This test requires all the decomposed components when summed up to give the observed change of the aggregate indicator.

$$\Delta V = \sum_{i} \Delta V_i \tag{4.59}$$

Decomposition methods that satisfy this property do not leave a residual term, i.e. they are called perfect or exact. As discussed earlier, this only means that the residual term is distributed to the explaining variables and does not tell the analysts anything about the soundness of the distribution. Advantages and disadvantages of a residual are explained in section 4.4.3.

The circular test determines whether the decomposition effect taken from situation *0* to *T* is the same as the sum of the decomposition effect from situation *0* to *S* and *S* to *T*, assuming that *S* is between *0* and *T*.

$$\Delta V_{0,T} = \Delta V_{0,S} + \Delta V_{S,T} \tag{4.60}$$

Passing this test means that the decomposition result does not depend on how the indicator develops between the periods *0* to T. Already Fisher (1922) pointed out that this test can only be fulfilled if an index possesses fixed weights. This is not the case for any practical index number so that all the decomposition methods fail this test.

Next to these three well-known tests, there exists a number of other tests. The linearity homogeneity test requires the decomposition result to vary by the same factor as the change in the underlying variable changes.

$$\Delta V_i(\dots, \lambda \Delta x_i, \dots) = \lambda * \Delta V_i(\dots, \Delta x_i^0, \dots) \tag{4.61}$$

As most of the decomposition methods do not only rely on the change of the observed variable, but also depend on other variables in order to eliminate the residual term, the majority of decomposition methods fails this test.

The monotonicity axiom states that $\Delta V_i$ is strictly increasing with respect to $x_i^T$ and strictly decreasing with respect to $x_i^0$.

$$\Delta V_i(\dots, x_i^0, x_i^T, \dots) > \Delta V_i(\dots, x_i^0, \hat{x}_i^T, \dots) \quad if\ x_i^T > \hat{x}_i^T \tag{4.62}$$

$$\Delta V_i(\dots, x_i^0, x_i^T, \dots) < \Delta V_i(\dots, \hat{x}_i^0, x_i^T, \dots) \quad if\ x_i^0 > \hat{x}_i^0 \tag{4.63}$$

While this axiom is fulfilled by the indices based on percentage changes it is not met by the Divisia indices as they involve the interaction with other variables in addition to the observed one.

The identity theorem expresses that the value of the decomposition is zero if the observed variable remains constant, irrespective of any change in the other variables.

$$\Delta V_i(\dots, x_i^0, x_i^T, \dots) = 0 \quad with\ x_i^0 = x_i^T \tag{4.64}$$

This test is met by all decomposition forms.

The plausibility test says that the sign of the decomposition effect always has the same sign as the change in the observed variable

$$\Delta V_i(\dots, \Delta x_i, \dots) > 0 \quad if\ \Delta x_i > 0 \tag{4.65}$$

$$\Delta V_i(\dots, \Delta x_i, \dots) < 0 \quad if\ \Delta x_i < 0 \tag{4.66}$$

Even if this condition seems simple to meet, distortions due to distributing higher order terms means that the refined Laspeyres and the MRCI decomposition fail this test. Betts (1989, p.152) showed that interaction terms in the refined Laspeyres decomposition can be higher compared with the ceteris paribus term and thereby change the sign of the expression. Lenzen (2006, p.194) showed the same distortive effects for the mean rate of change index.

Finally the zero-value robustness test, checks if a decomposition method is rendered zero, infinite or indeterminate by one variable becoming zero. None of the methods using logarithms pass this test nor does the mean rate of change index when the variable is zero in both periods. Table 4.2 provides an overview of the decomposition methods' properties.

Among all the tests, the plausibility test and time-reversal test are judged to be the most important. An index should show a plausible results, i.e. when a variable decreases, the associated effect should be negative and vice versa. Furthermore, the index should have the same result in the case that base and comparison period are interchanged. The factor reversal test is only fulfilled with perfect decompositions, which does not say anything about the theoretical soundness. The problem concerning the use of zero values in decomposition techniques using a logarithm can be overcome in practice.

**Table 4.2: Properties of decomposition methods**

| | Monotonicity | Linear Homogeneity | Identity | Circular Test | Time Reversal Test | Factor Reversal | Plausibility | Zero-value robustness |
|---|---|---|---|---|---|---|---|---|
| **Laspeyres** | Yes | Yes | Yes | No | No | No | Yes | Yes |
| **Paasche** | Yes | No | Yes | No | No | No | Yes | Yes |
| **Marshall-Edgeworth** | Yes | No | Yes | No | Yes | No* | Yes | Yes |
| **Refined Lapseyres** | Yes | No | Yes | No | Yes | Yes | No | Yes |
| **Mean Rate of Change Index (MRCI)** | Yes | No | Yes | No | Yes | Yes | No | No |
| **Arithmetic Mean Divisia Index (AMDI)** | No | No | Yes | No | Yes | No | Yes | No |
| **Adaptive Weighting Divisia Index (AWDI)** | No | No | Yes | No | Yes | No | Yes | No |
| **Logarithmic Mean Divisia Index I (LMDI I)** | No | No | Yes | No | Yes | Yes | Yes | No |
| **Logarithmic Mean Divisia Index II (LMDI II)** | No | No | Yes | No | Yes | Yes | Yes | No |

* only exception is the 2-variable case

### 4.4.2 Complexity of calculation

Next to the theoretical soundness of an index, the ease of application can be an important criterion for an analyst deciding whether to use or not to use a specific method. When a decomposition method is very hard to apply, because it involves many calculation steps, it may deter analysts from using the method. This section briefly reviews the complexity of each decomposition method. The formulae in section 4.3.3 already gave a first impression of the complexity involved with each decomposition.

The Laspeyres and Paasche index with their fixed weights are very easy to calculate and the Edgeworth-Marshall index as the arithmetic mean of both indices is only slightly more complicated. On the other side, the refined Laspeyres index, built upon the Laspeyres index, is relatively complicated compared to the standard Laspeyres. The big inconvenience of the refined Laspeyres index is that the formula becomes larger with the number of variables included in the aggregate indicator, as the number of higher order terms increases. This can lead to a considerable effort in applying the refined Laspeyres index. The same holds true for the mean rate of change index. This decomposition method involves the calculation of a weight term, which relies on the arithmetic mean of all variables. This means that the complexity of calculation increases linearly with the number of variables.

The Divisia indices, the LMDI I using a logarithmic mean, and the AMDI, using the arithmetic mean, are relatively simple to apply. The LMDI II uses a normalised weight function, which is more complicated to use in comparison to the mean function of the LMDI I. However, the most calculation intensive decomposition method is the Adaptive Weighting Divisia Index. It uses two different equations to calculate the adaptive parameter, which then has to be inserted into one of the equations. Additionally, the number of parameters to be calculated increases with the variables and the number of attributes.

### 4.4.3 Clarity of decomposition / importance of residual

In decomposition analysis literature there has been a long debate about the residual term (see e.g. Muller 2007, p. 14ff). On the one hand, it is argued that each decomposition method represents an approximation to an integral path that is not known. Therefore, it is only obvious that each decomposition should show a residual term and not assign it arbitrarily to the variable effects. On the other hand, a residual term, which is not allocated to one specific variable, raises questions in explaining the results and can pose significant problems if the residual becomes big in comparison to changes due to variable changes. This leads to a trade-off between the arbitrariness in allocating residuals and a non-exact decomposition method with a residual term.

The Laspeyres index, as well as the Paasche index, have the advantage of clear interpretation of the decomposition components. The same holds true for the Edgeworth-Marshall decomposition as the arithmetic mean of both. The interaction terms hidden in the Divisia indices are explicitly accounted for in the Laspeyres index approach. The downside is the resulting residual that creates problems in result interpretation. Since the residual can be considerable when there are large changes in the underlying data, Ang and Liu (2007a, p. 1431) classified the Laspeyres index not to be a good choice.

The disadvantage with all Divisia indices is that it arbitrarily assigns interaction terms to the factors (Howarth et al. 1991, p. 137). Looking again at Equation (4.34), this problem becomes obvious. The expression $\left(\frac{V_r^T+V_r^0}{2}\right)$ can be rewritten into $\left(\frac{V_r^0+\Delta V_r+V_r^0}{2}\right)$, thus $V_r^T$ is the sum of $V_r^0$ and $\Delta V_r$. Since $\Delta V_r$ not only depends on variable *i*, but also on the change in other variables, the decomposition result for variable *i* can change even if solely the other variables ($\neq i$) change. The same holds true for the logarithmic mean, for which there exists no reason from the integral and derivative approximations to use this weight.

Consequently, the calculation of the Divisia indices are more difficult to understand because of their complex procedure to distribute the higher order terms. This applies especially to the Adaptive Weighting Divisia Index, which requires a relatively complicated calculation and does not give a perfect decomposition. Within the Divisia indices, the Logarithmic Mean Divisia Index I and the Arithmetic Mean Divisia Index are the easiest of the perfect decomposition methods to understand.

The remaining indices, the Refined Laspeyres and the MRCI, are more complicated to assess. While the Refined Laspeyres index tries to logically distribute only those interaction terms (higher order terms) to a variable, in which the considered variable is involved, one cannot determine a logic in the MRCI concerning the elimination of the residual.

### 4.4.4 Rating

In the past, several researcher have attempted to rate decomposition methods and pick their preferred method. These ratings clearly depend on the preferences of the researcher, the problem to be solved, and on the criteria alongside the methods are compared.

Ang et al. (1994, p.88ff) comes to the conclusion (at a time where the LMDI and Refined Laspeyres methods had not yet been used in energy decomposition) that the Edgeworth-Marshall and the AMDI were the best decomposition methods. This selection is based on the robustness of the methods, i.e. giving stable results and not being subject to extreme results, and on the theoretical “superiority” of the AMDI compared to other methods. Ang et al. (1994) also generally prefer a small residual and ease of use in terms of computational complexity. The authors qualify this last aspect because computing no longer presents any significant limits, not taking into account the analyst’s efforts.

Six years later, Ang et al. (2000, p.1165ff) come to another conclusion, namely that the LMDI I and the Refined Laspeyres are the most robust methods. In this study, the authors base their decision on some index tests, the importance of the residual and the complexity of the formula. Given its ease of calculation the LMDI I (proposed by Ang) is preferred over the Refined Laspeyres. In a paper on the preferred decomposition method for policymaking in energy, Ang (2004) proposes again the LMDI I as the preferred decomposition method and recommended it for general use. This decision is based on the results of the factor reversal, time reversal, proportionality and consistency-in-aggregation tests, ease of use and ease of result interpretation. The consistency-in-aggregation test verifies that a single stage index can also be computed in two stages, i.e. by first computing the indices for subaggregates and from these the index for the aggregate indicator.

Ang (2004) reports that the LMDI I performed best in these tests, because the factor reversal test was judged to be the most important, a residual term is disapproved (complicating result interpretation) and the link between multiplicative and additive decomposition is easily established. Yet, from an unbiased point of view, there is no reason to prefer the factor reversal test over the others. From a mathematical point of view, rejecting a residual means accepting an arbitrariness in distributing the residual. Finally, the link between multiplicative and additive decomposition might be a beneficial feature, but is not essential when one concentrates only on additive decomposition, as in this thesis. Ang et al. (2009) give another reason in favour of the LMDI I, namely that this method distributes the residual term of each sub-category proportionately according the effects.

Diekmann et al. (1999, p. 100ff) base their decision on decomposition methods on the following criteria: size of the residual, theoretical soundness, complexity of calculation, comprehensibility of results and purpose of study. According to the authors, the purpose of the study can have an influence on the choice of the decomposition method depending on whether many sectors are considered and whether it is prospective or retrospective (to choose the index weights appropriately). Admitting that a silver bullet does not exist, Diekmann and his colleagues reach the conclusion that the complexity of calculation and the difficult comprehensibility of the AWDI outweigh the advantage of its theoretical soundness. Given its clarity and easier calculation, the authors recommend the Refined Laspeyres index to be generally used in decomposition analysis.

Muller (2007) questions the LMDI I method as the default best method because of reservations towards a zero residual and the consistency-in-aggregation. Nevertheless, he recommends the LMDI I as the currently most reliable method based on its performance in comparison to other methods for a wide range of functional forms.

Before coming to any conclusion, the statement of Diekmann et al. (1999) has to be reemphasised: there is clearly no superior decomposition method. If there were, the index number problem would no longer be one. Starting with the decomposition methods' theoretical soundness, Table 4.2 does not reveal one decomposition method as clearly the best. The preference of one decomposition method over another depends on the preference of certain tests or axioms. Based on the simplicity and comprehensibility of calculation, one should use either the Laspeyres, Paasche and Edgeworth-Marshall or one of the simple Divisia indices, the LMDI I or the AMDI. The Refined Laspeyres and the Adaptive Weighting Divisia Index are relatively complex to calculate. If a small residual is desired, one should use one of the perfect decomposition methods, such as the LMDI, the Refined Laspeyres or the MRCI.

Based on the previous discussion and on the requirements in this thesis, the LMDI I decomposition seems to be preferable over the other decomposition methods, because of its ease of use, its relatively easy comprehensibility and its zero residual. Even though this last property comes at the expense of an arbitrariness in assigning the residual term to a variable's effect.

## 4.5 Application of IDA in the context of carbon abatement curves

In the previous sections, the focus was on the origin of decomposition analysis and theoretical aspects. This section gives insights into some practical aspects of applying decomposition analysis to the results of an energy system model.

### 4.5.1 Zero and negative values

One major problem discussed in the literature is the occurrence of zero or negative values in the analysed data. Negative values occur very rarely in energy system models, except in the context of biomass CCS and associated negative emission values. They occur much more frequently in structural decomposition analysis involving input-output tables. In contrast to negative numbers, zeroes occur frequently as an output of energy system analysis, for example concerning the emissions from renewable sources or non-existing demand for specific end-use technologies. Therefore, the pick-up of one electricity generation technology from zero will pose problems when the Divisia indices are used. The reason is that Divisia indices are based on logarithms, which are undefined for zero.

The first researchers to note the problem of zero values in the energy decomposition context were Liu et al. (1992b, p. 692) in a study looking at fuel shares. As a solution they suggest to use a very small value of e.g. $\delta=10^{-5}$ instead of zero. Ang et al. (1997, p. 366) suggest aggregating data in order to avoid zero values or alternatively not making full use of the available data. As a consequence, the analysts can only use a part of the data. Ang et al. (1997, p. 68) also use the small value approach and vary the value $\delta$ between $10^{-8}$ and $10^{-20}$. They show that the LMDI I is not sensitive to the level of $\delta$, whereas the results of the Arithmetic Mean Divisia Index are highly dependent on the assumed level. Ang et al. (1998, p. 491f) also recommend using the small value approach and state that the decomposition results converge with a $\delta$ approaching zero. This is analytically demonstrated and the analytical limits of 8 different cases involving zeros are represented in a table. Wood et al. (2006, p. 1327) study the small value approach in more detail and come to the conclusion that it is an insufficient approximation for certain situations. They describe a situation where even a small value of $\delta=10^{-323}$ can lead to an error of almost 1%, particularly when data sets contain a sufficiently large number of zeroes and small values. The authors recommend using the analytical limits in the case of a zero in the underlying data set. A positive side-effect is the possible reduction of computation time, especially if the data sets contains a large number of zeroes. It was as a response to the non-robustness of existing methods to zero and negative values, that Chung et al. (2001) developed the MRCI. However, this index is also not robust to zero values if a variable is zero in the base as well as the observed situation (see Equation (4.27)).

In order to overcome the problem of zero value robustness, it is recommended to follow the analytical limit strategy in order to avoid any ambiguities in approaching the limits by small values.

Another important aspect concerning the results of energy system models, which has to be accounted for, is that there can be multiple changes from/to zero to/from a positive value when going from a carbon scenario with a lower $CO_2$ price to a higher price scenario. If, for example, diesel cars are no longer chosen by the model in a higher $CO_2$ price scenario, then its structural contribution, its fuel intensity, as well as its carbon intensity will drop to zero in parallel. The first to note this problem were Ang et al. (2007b, p. 243), who proposed that each of the *m* variables involved in a zero-change should account for *1/m* of the sub-category change. The authors give an example including a fuel-mix variable and the $CO_2$ emission factor, where this procedure makes sense. Yet, when a technology is first chosen in an energy system model along a rising carbon price, i.e. its activity increases from zero to a positive number, the structural contribution not only changes from zero to a positive number, but also the fuel intensity and possibly the carbon intensity. In this case, it is no longer reasonable to assume that each of the effects contributes the same share to the total change. Therefore, the analyst has to make sure to avoid multiple counting in this example by restricting the change in the aggregate indicator only to the activity effect. In general, special attention has to be paid to situations that involve more than one variable involved in a zero-change to obtain reasonable decomposition results.

Although negative values occur only in the context of negative emissions from biomass CCS or coal CCS power plants with biomass co-firing, they pose a problem when the analysis relies on the LMDI I. Chung and Rhee (2001, p. 15) were the first to point out difficulties when using a Divisia index for a dataset containing zeros. Wu et al. (2006, p. 3569) proposed a solution for a specific situation involving stock changes. Ang and Liu suggested (2007c, p. 740) a more general solution by distinguishing three different cases involving changes from a negative number to a negative number, to zero and to a positive number. If changes occur between negative values their respective additive inverse can be used to obtain a correct value. If a change involves zero values the strategy described above in combination with a replacement of the negative value by its additive inverse can be used. The most difficult case, however, are changes from/to a negative value to/from a positive value. Ang and Liu (2007c) analysed this situation by splitting the change from a positive number to a negative number into two intervals with zero taking as the point of separation. The authors conclude that only the variables that include a negative value account for the change in the aggregate factor. This strategy is adopted for this thesis.

### 4.5.2 Structural disaggregation

Another aspect of practical concern is the detail of structural disaggregation. This means how far aggregated variables are disaggregated according to an attribute $r$, e.g. into different sectors. A typical example is industry, which can be divided into energy intensive and non-energy intensive or in more detail into industrial sectors like iron & steel and pulp & paper, etc. But this can also include vehicle types in the transport sector, different demand types in the service and residential sector or generation technologies in the electricity generation. In the context of energy system models, electricity generation for example can be disaggregated along renewable/non-renewable generation, fuel group, specific fuel or employed technology. Existing studies on energy decomposition show that the level of disaggregation can have a significant influence on the decomposition results, in particular structural and intensity effects (Ang 1995b).

A possible consequence of an insufficient disaggregation level is that structural changes will be measured as changes in energy intensity. Different levels of aggregation can help to understand the robustness of the findings with regard to the disaggregation level. Boyd et al. (1987) for example studied sectoral shifts at three different levels. They found that a structural disaggregation of two-digit SIC (Standard Industrial Classification) code was enough to capture sectoral changes in the second half of the 1970s. Ang (1993, p. 1036f) approached the problem using different sectoral disaggregation levels and illustrating the change in structural contribution from one level to another. Therefore, he connected the different levels of disaggregation in a so-called decomposition tree in order to trace the source of variations between two levels of disaggregation. The results show that the sum of positive structural contributions minus the sum of negative structural contributions increases with the level of disaggregation, while one cannot make a statement on the overall structure effect since it is the remainder of both.

Furthermore, the total structure effect, composed of each individual structure effect *r* (according to the attribute *r*), can be misleading. It can be close to zero as a result of large positive structural contributions and large negative contributions, which cancel each other out. This can lead to the assumption that no structural change exists. Ang (1993, p. 1035f) developed an index to measure the level of cancellation, consisting of the positive structural contributions minus the negative contributions minus the absolute structural effect. If this index is large a significant part of structural change in the aggregate variable is not captured in the estimate of total structural change and thus provides additional information.

The approach used in this thesis is to look at the finest disaggregation level in order not to confuse structural effect and intensity effect. In addition, structural contributions of each attribute are reported individually to separate positive and negative contributions and to provide additional insights into the source of structural change.

### 4.5.3 Fixed base versus rolling decomposition

A decomposition analysis is usually carried out between different years. This can be done by either using only the first year and the last year of a time period (fixed base) or using yearly decomposition with increasing base years and cumulating the results for each year in order to obtain the result for the whole period (rolling). In the context of price indices, the latter method is also called chained principle since the price index of one year is chained to the preceding one. Ang et al. (1994, p. 89ff) examine the respective results for a fixed base and a rolling decomposition.

This concept can easily be transferred to carbon prices. A fixed base decomposition is carried out for the change between two significantly different carbon prices, whereas a rolling decomposition uses the additional information available by calculating the change between two adjacent carbon prices and then cumulating the results.

A rolling decomposition is nothing else than incorporating additional information on the integral path compared to the fixed base case. Therefore, a rolling decomposition is less dependent on the decomposition method and results for non-exact decomposition methods in a smaller residual. The reason is that the integral path, which is implied by all decomposition methods, is now applied between two adjacent data points. Minor data variations can also be better reflected using rolling decomposition. Diekmann et al. (1999, p. 101) come to the conclusion that a rolling decomposition is theoretically preferable in order to avoid a loss of information.

Decomposition with a fixed base is more practical, however, as it requires only one calculation. Rolling decomposition in contrast depends on the availability of data in intermediate data points. Since data availability poses no problem in the context of MAC curves based on an energy system model, rolling decomposition is used throughout this thesis because of its theoretical advantage.

### 4.5.4 Decomposition factors

The choice of which factors to include in a decomposition is of particular importance not only concerning the analysis of energy system models' results. Usually, the analyst has to consider two different aspects in reference to the choice of decomposition factors: factors included in the decomposition and mutual dependence of factors.

Referring to the IPAT equation mentioned previously in this chapter, this equation encompassed only two variables in an early version: population and a remainder. Results of a decomposition analysis built upon this equation will therefore always indicate that the driving force behind changes in environmental impact is population, because it is the only specified factor in the formula. Decomposition analysis can only distribute changes in an aggregate indicator to factors included in the equation. It should be noted that once a factor is included in decomposition, its contribution will remain the same independent of what other factors are included in the decomposition formula (Sun and Malaska 1998, p. 110f). The question therefore arises what factors are not included in the decomposition. A possible consequence of not including actual driving factors in the decomposition is that the effects are attributed to other factors that are specified in the formula. This highlights the importance of carefully choosing the factors to include in a decomposition.

Another aspect is the interdependence of factors in decomposition analysis. Again looking back on the IPAT identity, the identity was criticised because of its relationship between the variables, e.g. population and affluence. It was argued that both variables do not vary independently for the reason that the affluence level influences population growth. The consequence is that a contribution of a specific factor to the change of the aggregate variable is diluted if it interacts significantly. Nonetheless, it is difficult to completely exclude any interactions between decomposition factors.

Before starting to carry out decomposition analysis, the analyst has to carefully choose the explaining factors in the decomposition formula and check their interdependency. Decompositions including different factors can help to gain additional insights and to clarify the importance of specific factors.

Within this thesis, the resulting $CO_2$ emissions in the different sectors of the energy system are decomposed into four effects: activity effect, structure effect, fuel intensity effect, and carbon intensity effect:

$$\Delta CO_2 = \Delta CO_{2,Activity} + \Delta CO_{2,Structure} + \Delta CO_{2,Fuel\,Int.} + \Delta CO_{2,Carbon\,Int.} \qquad (4.67)$$

The activity affect describes changes in $CO_2$ emissions due to changes in the demand for energy services or for electricity in the case of the power sector. The structure effects represent emission changes caused by a technological switch, e.g. from petrol cars to electric cars. The fuel intensity effect explains emission changes caused by efficiency improvements and the carbon intensity effect those changes related to a changing carbon content of fuels, for example blending biodiesel with conventional diesel or mixing biogas with natural gas. These four effects were chosen as they represent the four categories to reduce emissions: demand reduction (activity effect), technology switches (structure effect), efficiency improvements (fuel intensity effect), and, in the supply sectors, carbon intensity reduction of secondary energy carriers (carbon intensity effect). Furthermore, existing studies decomposing historical $CO_2$ emissions have a similar structure (Hammond and Norman 2011).

With this decomposition it is believed to capture all the underlying drivers of $CO_2$ emission changes, while the development of the underlying factors is mainly independent. While the activity variable and the structure of energy supply can vary independently, interactions can occur between the two effects. When coal-fired power plants increase their electricity output, for example, while the output from other generation types remains constant, not only the activity effect will change, but also the structure effect.

## 4.6 References


Agnolucci, P., P. Ekins, G. Iacopini, K. Anderson, A. Bows, S. Mander and S. Shackley (2009). "Different scenarios for achieving radical reduction in carbon emissions: A decomposition analysis." Ecological Economics **68**(6): 1652-1666.

Albrecht, J., D. Francois and K. Schoors (2002). "A Shapley decomposition of carbon emissions without residuals." Energy Policy **30**: 727-736.

Ang, B. W. (1993). "Sector disaggregation, structural effect and industrial energy use: An approach to analyze the interrelationships." Energy **18**(10): 1033-1044.

Ang, B. W. (1995a). "Decomposition methodology in industrial energy demand analysis." Energy **20**(11): 1081-1095.

Ang, B. W. (1995b). "Multilevel decomposition of industrial energy consumption." Energy Economics **17**(1): 39-51.

Ang, B. W. (2004). "Decomposition analysis for policymaking in energy: which is the preferred method?" Energy Policy **32**(9): 1131-1139.

Ang, B. W. and K.-H. Choi (1997). "Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method." Energy Journal **18**(3): 59-73.

Ang, B. W., H. C. Huang and A. R. Mu (2009). "Properties and linkages of some index decomposition analysis methods." Energy Policy **37**(11): 4624-4632.

Ang, B. W. and S. Y. Lee (1994). "Decomposition of industrial energy consumption : Some methodological and application issues." Energy Economics **16**(2): 83-92.

Ang, B. W. and F. L. Liu (2001). "A new energy decomposition method: perfect in decomposition and consistent in aggregation." Energy **26**(6): 537-548.

Ang, B. W., F. L. Liu and E. P. Chew (2003). "Perfect decomposition techniques in energy and environmental analysis." Energy Policy **31**(14): 1561-1566.

Ang, B. W., F. L. Liu and H.-S. Chung (2004). "A generalized Fisher index approach to energy decomposition analysis." Energy Economics **26**(5): 757-763.

Ang, B. W. and N. Liu (2007a). "Energy decomposition analysis: IEA model versus other models." Energy Policy **35**(3): 1426-1432.

Ang, B. W. and N. Liu (2007b). "Handling zero values in the logarithmic mean Divisia index decomposition approach." Energy Policy **35**(1): 238-246.

Ang, B. W. and N. Liu (2007c). "Negative-value problems of the logarithmic mean Divisia index decomposition approach." Energy Policy **35**(1): 739-742.

Ang, B. W. and G. Pandiyan (1997). "Decomposition of energy-induced CO2 emissions in manufacturing." Energy Economics **19**(3): 363-374.

Ang, B. W. and F. Q. Zhang (2000). "A survey of index decomposition analysis in energy and environmental studies." Energy **25**(12): 1149-1176.

Ang, B. W., F. Q. Zhang and K.-H. Choi (1998). "Factorizing changes in energy and environmental indicators through decomposition." Energy **23**(6): 489-495.

Balk, B. M. (2003). "Ideal indices and indicators for two or more factors." Journal of Economic & Social Measurement **28**(4): 203-217.

Betts, J. R. (1989). "Two exact, non-arbitrary and general methods of decomposing temporal change." Economics Letters **30**(2): 151-156.

Boyd, G. A., D. A. Hanson and T. Sterner (1988). "Decomposition of changes in energy intensity : A comparison of the Divisia index and other methods." Energy Economics **10**(4): 309-312.
Boyd, G. A., J. F. McDonald, M. Ross and D. A. Hanson (1987). "Seperating the Changing Composition of U.S. Manufacturing Production from Energy Efficiency Improvements: A Divisia Index Approach." Energy Journal **8**(2): 77-96.
Casler, S. D. (2001). Interaction Terms and Structural Decomposition: An Application to the Defense Cost of Oil. Input-Output Analysis: Frontiers and Extensions. M. L. Lahr and E. Dietzenbacher. Basingstoke, United Kingdom, Palgrave**:** 143-160.
Choi, K.-H. and B. W. Ang (2003). "Decomposition of aggregate energy intensity changes in two measures: ratio and difference." Energy Economics **25**(6): 615-624.
Chung, H.-S. and H.-C. Rhee (2001). "A residual-free decomposition of the sources of carbon dioxide emissions: a case of the Korean industries." Energy **26**(1): 15-30.
de Bruyn, S. M. (2000). Decomposition analysis: a tool to investigate the relationship between emissions and income. Economic Growth and the Environment. S. M. de Bruyn. Dordrecht, Netherlands, Kluwer Academic Publishers**:** 163-184.
Diekmann, J., W. Eichhammer, A. Neubert, H. Rieke, B. Schlomann and H.-J. Ziesing (1999). Energie-Effizienz-Indikatoren : statistische Grundlagen, theoretische Fundierung, und Orientierungsbasis für die politische Praxis (Energy efficiency indicators : statistical basis, theoretical foundations, and guide for political practice). Heidelberg, Physica-Verlag.
Dietz, T. and E. A. Rosa (1994). "Rethinking the Environmental Impacts of Population, Affluence and Technology." Human Ecology Review **1**(Summer/Autumn): 277-300.
Dietzenbacher, E. and B. Los (1998). "Structural Decomposition Techniques: Sense and Sensitivity." Economic Systems Research **10**(4): 307 - 324.
Divisia, F. (1925). "L'indice monétaire et la théorie de la monnaie." Revue d'économie politique **39**(5): 980-1008.
Divisia, F. (1928). Economique rationnelle. Paris, Librairie Octave Doin.
Dutot, C. (1738). Réflexions politiques sur les finances et le commerce. Paris, Librairie E. Droz.
Edgeworth, F. Y. (1925). Papers relating to Political Economy. London, MacMillan and Co.
Ehrlich, P. R. and J. P. Holdren (1971). "Impact of Population Growth." Science **171**(3977): 1212-1217.
Fisher, I. (1922). The Making of Index Numbers - A Study of Their Varieties, Tests, and Reliability. Boston and New York, Houghton Mifflin Company.
Hammond, G. P. and J. B. Norman (2011). "Decomposition analysis of energy-related carbon emissions from UK manufacturing." Energy **In Press**.
Hankinson, G. A. and J. M. W. Rhys (1983). "Electricity consumption, electricity intensity and industrial structure." Energy Economics **5**(3): 146-152.
Hoekstra, R. and J. C. J. M. van den Bergh (2003). "Comparing structural decomposition analysis and index." Energy Economics **25**(1): 39-64.

Howarth, R. B., L. Schipper, P. A. Duerr and S. Strøm (1991). "Manufacturing energy use in eight OECD countries: Decomposing the impacts of changes in output, industry structure and energy intensity." Energy Economics **13**(2): 135-142.

Hulten, C. R. (1973). "Divisia Index Numbers." Econometrica **41**(6): 1017-1025.

Huntington, H. G. and J. G. Myers (1987). Sectoral shift and industrial energy demand: what have we learned. The changing structure of American industry and energy use patterns. A. Farunqui, J. Broehl and C. W. Gellings. Columbus, OH, Battelle Press**:** 353-388.

International Energy Agency (2004). Oil Crises & Climate Changes. OECD. Paris.

Jenne, C. A. and R. K. Cattell (1983). "Structural change and energy efficiency in industry." Energy Economics **5**(2): 114-123.

Kawase, R., Y. Matsuoka and J. Fujino (2006). "Decomposition analysis of CO2 emission in long-term climate stabilization scenarios." Energy Policy **34**(15): 2113-2122.

Kaya, Y. (1989). Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. IPCC Energy and Industry Subgroup - Response Strategies Working Group. (mimeo). Paris.

Laspeyres, E. (1871). "Die Berechnung einer mittleren Waarenpreissteigerung." Jahrbücher für Nationalökonomie und Statistik **16**: 296-314.

Lenzen, M. (2006). "Decomposition analysis and the mean-rate-of-change index." Applied Energy **83**(3): 185-198.

Liu, X. Q., B. W. Ang and H. L. Ong (1992a). "The Application of the Divisia Index to the Decomposition of Changes in Industrial Energy Consumption." Energy Journal **13**(4): 161-177.

Liu, X. Q., B. W. Ang and H. L. Ong (1992b). "Interfuel substitution and decomposition of changes in industrial energy consumption." Energy **17**(7): 689-696.

Marshall, A. (1887). "Remedies for Fluctuations of General Prices." The Contemporary Review **51**(January-June): 355-375.

Montgomery, J. K. (1937). The Mathematical Problem of the Price Index. London, P.S. King & Son, Ltd.

Muller, A. (2007). Putting decomposition of energy use and pollution on a firm footing - clarifications on the residual, zero and negative values and strategies to assess the performance of decomposition methods. Working Papers in Economics. Göteborg University - Department of Economics. Gothenburg, Center for Corporate Responsibility and Sustainability CCRS. **215**.

Olson, R. L. (1994). "Alternative images of a sustainable future." Futures **26**(2): 156-169.

Paasche, H. (1874). "Über die Preisentwicklung der letzten Jahre nach den Hamburger Börsennotierungen." Jahrbücher für Nationalökonomie und Statistik **22**(Miscellen): 168-178.

Proops, J., M. Faber and G. Wagenhals (1992). Reducing $CO_2$ Emissions - A Comparative Input-Output-Study for Germany and the UK. Berlin, Springer-Verlag.

Reitler, W., M. Rudolph and H. Schaefer (1987). "Analysis of the factors influencing energy consumption in industry : A revised method." Energy Economics **9**(3): 145-148.

Ridker, R. G., Ed. (1972). Population, Resources, and the Enivronment. Washington D.C., United States Commission on Population Growth and the American Future,.

Rogner, H.-H., D. Zhou, R. Bradley, P. Crabbé, O. Edenhofer, B. Hare, L. Kuijpers and M. Yamaguchi (2007). Introduction. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. B. Metz, O. R. Davidson, P. R. Bosch, R. Dave and L. A. Meyer. Cambridge, United Kingdom, Cambridge University Press.

Rosa, E. A. and T. Dietz (1998). "Climate Change and Society: Speculation, Construction and Scientific Investigation." International Sociology **13**(4): 421-455.

Sato, K. (1974). "Ideal Index Numbers that Almost Satisfy the Factor Reversal Test." The Review of Economics and Statistics **56**(4): 549-552.

Sato, K. (1976). "The Ideal Log-Change Index Number." The Review of Economics and Statistics **58**(2): 223-228.

Shapley, L. S. (1953). A Value for n-Person Games. Contriubtions to the Theory of Games. H. W. Kuhn and A. W. Tucker. Princeton, NJ, Princeton University Press. **5th:** 307-317.

Spiegel, M. R. (1963). Schaum's Outline of Theory and Problems of Advanced Calculus. New York, McGraw-Hill.

Sun, J. W. (1998). "Changes in energy consumption and energy intensity: A complete decomposition model." Energy Economics **20**(1): 85-100.

Sun, J. W. and P. Malaska (1998). "$CO_2$ Emission Intensities in Developed Countries 1980-1994." Energy **23**(2): 105-112.

Theil, H. (1973). "A New Index Number Formula." The Review of Economics and Statistics **55**(4): 498-502.

Thomas, S. and G. MacKerron (1982). "Industrial electricity consumption in the UK - Past determinants and possible futures." Energy Policy **10**(4): 275-294.

Törnqvist, L., P. Vartia and Y. O. Vartia (1985). "How Should Relative Changes Be Measured?" The American Statistician **39**(1): 43-46.

Torvanger, A. (1991). "Manufacturing sector carbon dioxide emissions in nine OECD countries, 1973-87 : A Divisia index decomposition to changes in fuel mix, emission coefficients, industry structure, energy intensities and international structure." Energy Economics **13**(3): 168-186.

Vartia, Y. (1976). "Ideal Log-Change Index Numbers." Scandinavian Journal of Statistics **3**(3): 121-126.

Vogt, A. (1978). Divisia Indices on Different Paths. Theory and Applications of Economic Indices, Karlsruhe, Physica-Verlag.

Vogt, A. and J. Barta (1997). The Making of Tests for Index Numbers. Heidelberg, Physica-Verlag.

Waggoner, P. E. and J. H. Ausubel (2002). "A framework for sustainability science: a renovated IPAT identity." Proceedings of the National Academy of Sciences **99**(12): 7860-7865.

Wood, R. and M. Lenzen (2006). "Zero-value problems of the logarithmic mean divisia index decomposition method." Energy Policy **34**(12): 1326-1331.

Wu, L., S. Kaneko and S. Matsuoka (2006). "Dynamics of energy-related CO2 emissions in China during 1980 to 2002: The relative importance of energy supply-side and demand-side effects." Energy Policy **34**(18): 3549-3572.

Zhang, F. Q. and B. W. Ang (2001). "Methodological issues in cross-country/region decomposition of energy and environment indicators." Energy Economics **23**(2): 179-190.

# 5 UNCERTAINTY ANALYSIS

This chapter concludes the methodological part of the thesis. After chapters on energy modelling and decomposition analysis, chapter 5 explains why it is important to consider uncertainty in MAC curves and how it can be represented.

Uncertainty analysis is a process that describes, either in quantitative or qualitative manner, the relative magnitude of uncertainty and the resultant implications for the problem assessment. The term uncertainty or the degree of certainty surrounding the value of a variable can imply anything from confidence just short of certainty to informed guesses or speculation (Schneider and Kuntz-Duriseti 2002, p. 55).

The goal of uncertainty analysis is to evaluate to what extent particular uncertainties impact upon the conclusions (Rotmans and van Asselt 2001, p. 115). This does not only concern measuring the degree to which input factors contribute to uncertainty in the outputs but includes also the model structure and the uncertainty presentation.

The consideration of uncertainty was not always regarded as helpful in policy analysis. In positivist epistemology, which assumes that authentic knowledge is only based on positive verification, for example, uncertainty is considered as something unscientific. In this context, Rotmans et al. (2001, p. 126) noted that

> "*…integrated assessment models fail to make uncertainties explicit, and to illuminate and explain the nature of the various types and sources of these uncertainties, let alone to communicate these uncertainties in sound and transparent way to decision-makers*."

It should be noted that some degree of uncertainty can prove to be irresolvable. Walker et al. (2003) describe this as uncertainty due to the inherent variability of the underlying phenomenon, while some level of uncertainty is due to the imperfection of our knowledge.

This holds also true for MAC curves. The literature review chapter (section 2.2.2) discusses the insufficient level of uncertainty representation in all types of MAC curves. Recent attempts concerning expert-based approaches have considered the influence of major inputs, such as fuel prices, to a limited extent. However, since they assess each abatement measure individually, expert-based curves cannot take into account interactions between uncertainties. While this is feasible to a limited extent in energy models, uncertainty has been rarely represented in model-based MAC curves and if it has, then it lacks the technological detail in the visualisation. In general, the typical technology-specific representation of abatement curves with the marginal cost on the ordinate and the abatement level on the abscissa does not allow for a simple way of incorporating uncertainty. This is because the order of abatement measures can change as a result of a change in input assumption so that error bars or similar techniques cannot be applied. In recent studies, several MAC curves with different assumptions are usually represented next to each other to visualise uncertainty.

Decomposition analysis (chapter 4) visualises the contribution of different abatement measures to the overall abatement effort and the uncertainty related to the reduction level. In this way it helps to identify the largest uncertain abatement measures and their interactions.

Efforts are spent on investigating uncertainty related to problems in the energy and climate change mitigation fields with the goal to incorporate a more accurate representation of uncertainties. Nevertheless, new knowledge on complex processes may reveal uncertainties that always existed but were previously unknown or were underestimated (van Asselt and Rotmans 2002). Thus, new knowledge does not necessarily reduce uncertainty, but can increase the awareness of uncertainty by improving the understanding of particular processes.

The goal of this chapter is to present appropriate methods to see how robust the findings are and explain the uncertainties relating to MAC curves. Robustness is defined as the persistence of a characteristic, in this case abatement costs, under perturbations or conditions of uncertainty.

The chapter starts with uncertainties in the field of energy modelling. This includes three parts: data uncertainty including all external variables, model uncertainty spanning model parameters, structure and equations and user uncertainty including uncertainty related to experts, analysts, uncertainty communication and understanding. The second part of the chapter focuses on methods to address uncertainty, which include sensitivity analysis, scenario analysis, uncertainty propagation and stochastic programming.

## 5.1 Uncertainties related to MAC curves

This thesis combines two methods to derive MAC curves: energy system modelling and index decomposition analysis. On the one hand, uncertainty due to index decomposition concerns the choice of a specific decomposition method that can influence the final result due to divergent approximations of the mathematical integral. Energy system modelling, on the other hand, is the basis for the calculation of MAC curves and is subject to important uncertainties. Model construction implicitly involves the choice of a model scope and the embedding of assumptions at many levels, which are subject to a possible bias by the modeller. Those assumptions propagate through the model and finally affect the model output. In the following, uncertainty is firstly classified into different types and then areas of uncertainty referring to the generation of MAC curves are discussed.

### 5.1.1 Types of uncertainty

Although, consideration of uncertainty is by now an important element in energy system modelling, there is no common typology of uncertainty. Many different typologies exists that try to categorise the nature and characteristic of uncertainties, while some of them are similar. A list with different classifications of types of uncertainty can be found in Ascough II et al. (2008, p. 387).

Possible distinctions can be made between parametric uncertainty and stochasticity. Where parametric uncertainty refers to uncertainty associated with model parameters, such as the own price demand elasticity, and stochasticity stands for natural variability, e.g. weather, in variables manifested in natural and human systems, such as the behavioural influence on energy service demand or wind speeds. It can be difficult to identify precisely what uncertainties are reducible, in particular related to human input (Ascough II et al. 2008, p. 389).

A somehow different distinction, proposed by Hirst et al. (1990), is between internal and external uncertainties. Where internal uncertainties describe the uncertainties related to the modelling parameters and external uncertainties relate to the uncertainty connected to exogenous assumptions on variables, which are beyond the system being modelled. Moreover, a different existing distinction is between short-term and long-term uncertainties. This typology is, however, of less use in the context of this thesis as it is focused on findings for the long-term.

Another possible perspective for the differentiation between different types of uncertainty is the impact of uncertainty over time (Gerking 1987, p. 193). Static uncertainties refer in this context to uncertainties that do not change or are not affected over time. Quasi-static uncertainties can be reduced in a negligible period of time compared to other decision alternatives. Finally, dynamic uncertainty describes uncertainties concerning the development of parameters that can be resolved over time.

The International Energy Agency established in the 1980s a classification of uncertainty into quantifiable and non-quantifiable. Quantifiable uncertainties encompass to a certain extent technological developments, facility lifetime and performance and the development of alternative energy. Non-quantifiable uncertainties deal with environmental considerations, major accidents, political developments and regulatory changes.

In the context of model-based decision support, Walker et al. (2003) distinguish uncertainty into the location, the level and nature of uncertainty. The context, model uncertainty, external inputs, parameter uncertainty and model outcome uncertainty are examples for the location uncertainty. The levels of uncertainty are defined into four categories ranging from determinism to total ignorance. The nature of uncertainty is divided into epistemic uncertainty, which may be reduced by more research and empirical efforts and variability uncertainty, which is due to inherent variability.

A very common and broad uncertainty typology, which summarises other typologies, is the distinction of uncertainty into variability and limited knowledge (van Asselt and Rotmans 2002, p. 78) (see also Table 5.1). Variability means that a particular process can behave in different ways, while limited knowledge expresses that knowledge with regard to a deterministic process is incomplete or uncertain. The meaning of variability can be regarded to be similar to stochasticity and external uncertainty. Sources of variability include natural processes, human behaviour, social, economic and cultural dynamics and technological surprises. In the context of energy modelling, lack of knowledge, which is equivalent to internal uncertainty (see above), refers to lack of observation or data (e.g. concerning possible future technologies), conflicting evidence and reducible and irreducible ignorance.

**Table 5.1: Uncertainty typologies according to two broad categories**

| Variability | Limited knowledge | Other |
|---|---|---|
| stochasticity | parametric uncertainty | |
| objective uncertainty | subjective uncertainty | |
| primary uncertainty | secondary uncertainty | |
| external uncertainty | internal uncertainty | |
| variability uncertainty | epistemic uncertainty | |
| | | static uncertainty, quasi-static uncertainty, dynamic uncertainty |
| | | quantifiable, non-quantifiable |

In the context of energy system modelling, an uncertainty typology is chosen that differentiates between data uncertainty, model uncertainty and user uncertainty similar to a categorisation proposed by Maier et al. (Maier et al. 2008, p. 74). As stated before, there are different existing typologies in other research areas, which include uncertainties that do not play a major role in energy modelling.

**Data uncertainty** comprises all kinds of uncertainties linked to all the input data into a model. This includes absence of information, missing data, availability of recent data, error in data and uncertainty related to the initial state of specific values. New development or breakthroughs in technology or unexpected consequences of technologies make it difficult to quantify the uncertainty profile. There exist also processes, characterised by indeterminacy or irreducible ignorance, where uncertainty cannot be described through probability distributions. Poor quality data, which is biased due to random noise or changing definitions, and measurement uncertainty can be another reason for data uncertainty (Schneider and Kuntz-Duriseti 2002, p. 56). Measurement uncertainty can refer to human errors or to scientific inaccurate methods. Rotmans et al. (2001, p. 113) described this uncertainty type as technical uncertainty, which includes next to the quality of the data, also possible simplifications and aggregations.

In natural sciences this category includes lack of measurements or measurement errors, which can be caused by the type of instrument, the quality of calibration of the instrument, errors in data reading, transmission and storage.

The next type, **model uncertainty**, refers to uncertainties relating to the model structure and in the context of this thesis also to decomposition analysis. This includes unknown functional relationships, choice of algorithm and known historical data where reasons exist to believe that the parameter structure will change. The choice of analytical tools, of the system boundaries, the level of detail and the appropriateness of the model are further aspects of this type. System boundaries concern for example the treatment of global interactions in the case of restricting the model to a specific country. Further, all the necessary relationships can be integrated in a model but only to an insufficient level of detail, so that important sources of uncertainty, such as changing wind velocities in the case of wind power, are inadequately represented. In addition, this includes the aspect of model completeness (van Asselt and Rotmans 2002, p. 82), i.e. does the model capture all the necessary relationships, does it reproduce actual behaviour, is the conceptualisation in line with established theories?

Those aspects arise since models are necessarily a simplified representation of the real system being studied. One of the key tasks in modelling is to simplify reality in so far that it is as simple as possible, but still contains the necessary relationships. Thus, model structure uncertainty arises from the use of aggregated parameters, the exclusion of variables, simplified relationships and approximations of functional forms (Ascough II et al. 2008, p. 388f).

The last type of uncertainty, which is often overlooked, is **user uncertainty**. This comprises all kind of human uncertainties involved in energy modelling: the expert providing inputs to the model, the analyst involved in using and developing the model, decision makers and the process of results communication. During the model development analysts have to make choices e.g. about data selection and model structure that are subject to biased opinion. The uncertainty of the modelling outcome, which in a next step is presented to the research community and decision makers, is dependent on the analyst's knowledge, experience and expertise. Analysts can have preferences for particular technologies, model structures, for quantitative or qualitative uncertainties and can make diverging decisions on what results to present. The risk of modelling errors can be minimised by peer-reviewing modelling efforts.

The process of communicating the results of any modelling exercise is subject to linguistic uncertainty. Aggregated uncertainty measures are usually difficult to understand for audiences unfamiliar with those concepts. Further uncertainty arises due to the fact that our natural language is vague, ambiguous and context dependent. In everyday conversation, people often refer to events or quantities with imprecise language. The precise meaning of words can change from person to person and over time (Ascough II et al. 2008, p. 390). In addition, readers often assume for themselves a possible distribution of probabilities when the authors do not state it clearly (Schneider and Kuntz-Duriseti 2002, p. 66).

The communication aspect could be improved via different forms of graphical representation. For this purpose, it is important to find a clear, uncluttered graphic style and easily understood format and make decisions about what information to display. It is important to present uncertainty in the best possible way since judgement under uncertainty is subject to common fallacies, as summarised e.g. in Tversky et al. (1974).

Whereas many sources of uncertainty, including lack of data and model structure uncertainties, are often impossible or difficult to eliminate, uncertainty due to linguistic imprecision is comparably easy to remove (Morgan et al. 1990, p. 61f).

### 5.1.2 Areas of uncertainty in respect to MAC curves

While the previous section discussed the typology of uncertainty, this part gives examples for the different types of uncertainty in relation to MAC curves. Those curves are derived with decomposition analysis from an energy system model, which relies on different categories of uncertain parameters and variables and consequently introduces itself data and model uncertainty. Different assumptions for those values can potentially significantly alter the MAC curve. This section builds upon the discussion of influencing factors of MAC curves in section 2.2.3.

**Data uncertainty**

One category of data uncertainty in an energy system model is demand-related factors. This includes the demand for energy services, which is either a direct input into the model or is determined via socioeconomic drivers, such as economic activity, population or household size. Nordhaus (1994, p. 106), for example, found the development of demand drivers to be the most important uncertainty in his energy model. Demand development is uncertain as socioeconomic drivers cannot be predicted with confidence and demand for energy services is subject to behavioural changes, e.g. thermal comfort in residential buildings. Also the willingness to adopt new technologies or energy efficiency practices, which affect so called mitigation at negative cost, is not well understood. Seasonal and daily patterns with respect to electricity or gas use are another uncertain element in this area.

Next to the demand development, demand changes between specific energy services are equally uncertain. Examples for this issue are mode changes in passenger transport between rail, bus, car and cycling or changes in freight transport between rail and road transport. Demand elasticity, or the change in the level of energy service demand due to price changes, is another uncertain factor in this category. Behavioural factors, which are modelled via technology specific hurdle rates or uptake rates are equally difficult to determine and are thus a further source of uncertainty.

A second category of uncertain data are technology parameters in an energy system model. Technologies are involved in the production, transformation and use of various energy forms, while their parameters can be distinguished into technical and financial parameters. Uncertain technical parameters include lead time, life time, the year of availability for future technologies, annual and seasonal availability, efficiency and emission factors. In this context, the emergence of entirely new technologies is highly uncertain. Economical factors are especially uncertain for evolving technologies and include investment costs, annual fixed operating and maintenance cost and variable costs. Technological innovation (or progress) and the reduction of technological costs over time due to learning are uncertain as well.

Fuel reserves, resources and prices are a third category of data uncertainty. Oil, gas, coal and uranium reserves and the corresponding production costs are highly uncertain due to limited geological knowledge, geopolitical uncertainty and political acceptability amongst others. Also the temporal availability of fossil fuels is not completely known in advance and fossil fuel prices are highly volatile. This is also a result of the choice to limit the system to one country so that fuel prices are exogenous inputs. In addition, the resources for different kinds of biomass, wind speeds, solar radiation and river discharge volumes are uncertain. This all affects different parts of the energy system, such as electricity production.

A further uncertainty category are system-wide parameters, such as the assumed discount rate, the division of the model horizon into model periods and time slices. The annual discount rate is the most important parameter in this category and significantly affects all financial parameters in the model for future years. Due to compound interest, financial parameters in distant years are much more affected by changes in the discount rate than years close to the present. There has been much discussion about the correct level of the discount rate to be applied in optimisation models, taking into account time preference, income redistribution and the utility of consumption (Schelling 1995). Since the model includes behavioural changes to a certain extent different discount rates can apply to different agents.

Discounting theories can be differentiated into a social and private perspective. The first one is an ethical approach and the second is the discount rate people actually apply in their daily decisions. Social discount rates are in general between 2-4% compared to private discount rates, which start at about 5% (AEA Energy & Environment et al. 2008, p. 18). The social discount rate sums up the pure rate of social time preference and the growth rate of per capita consumption, while the private perspective takes into consideration the market rate of return to investments (see e.g. Nordhaus 1994, p. 154; Markandya et al. 2001, p. 466; Halsnaes et al. 2007, p. 136; Stern 2007, p. 43ff).

Another uncertain factor is the emission path or $CO_2$ tax path over time. Since a MAC curve is in most cases a static snapshot of one year, the mitigation costs depend on emission restrictions in previous periods and also in later periods when the model possesses perfect foresight. Thus, the model results are influenced by the implemented $CO_2$ tax profile over time, i.e. if it is flat, growing linearly or growing exponentially, for example with the discount rate.

Finally, energy transmission and distribution capacities can be uncertain. It is not certain that electricity transmission lines can be expanded as it is necessary for the integration of renewable energy sources into the electricity grid and for an envisaged electrification of end-use energy demand.

It is not only important to consider different areas of uncertainty but as well their interactions. There exist several interactions between the different areas in the form that a change of one input datum is likely to affect another one. Examples are that discount rates tend to be higher in an environment of high economic growth or that different fossil fuel prices, such as crude oil and natural gas, are correlated. These interactions between uncertainties can be handled in a model environment if correlations among uncertainties are taken into account by the modeller when specifying uncertainty profiles for various variables. This approach requires, however, the specification of dependent probability distributions or covariance matrices, which proves to be very difficult.

Some uncertainties have not been considered as they are beyond the scope of MAC curves. This covers uncertainties about climate predictions, about impacts of climate change and uncertainties related to the effectiveness of policy instruments and possible revenue recycling. The modelling framework assumes that policy instruments are 100% effective, so that no implementation barriers are considered.

**Model uncertainty**

Not only uncertain input variables represent a source of uncertainty for the generation of MAC curves, but also the applied methodology. On the one hand, one has to mention the uncertainty introduced by relying on a specific model type, in the context of this thesis an energy system model. A linear optimisation approach is used with an objective function that maximises total producer and consumer surplus. The results from such an approach can be significantly different from other approaches, such as simulation models, non-linear approaches or different objective functions. Furthermore, the methods used to calibrate and validate the model equally fall in this category as a source of uncertainty. Additionally, relatively simple model structures, such as those used for expert-based curves, which do not possess the system character and assess each abatement measure individually have already been used. These models are not able to capture uncertainties related to interactions between abatement measures. In summary, there exist many different possible alternatives to model the relationships within the energy system, of which only one has been implemented in the model used for this thesis.

On the other hand, the applied decomposition method is a further possible source of uncertainty. Differences in methods result from the fact that each decomposition is a different approximation of the underlying curvilinear integral, whose shape is not completely known. Section 4.3.3 presented nine methods, which can be used to decompose the results of the energy system model. Section 4.3.4 presented a decomposition example for a typical application in the context of abatement curves. The similarity of decomposition methods for this example was found to be striking. Except for the relatively crude methods, Laspeyres and Paasche index, the results were found to be within a range of two percent. Nevertheless, the choice of the decomposition method is subject to the analyst's view and there exists no clearly superior alternative. Thus, decomposition analysis is a further source of uncertainty, which is, nonetheless, limited in comparison to energy system model uncertainty or the uncertainty related to input variables.

**User uncertainty**

The uncertainty related to the user covers the uncertainty related to experts providing input assumptions for a model, uncertainty in relation to the analyst that uses the model and uncertainty in results communication. Both, expert-based and model-derived abatement curves are based on expert information as inputs to their assessment. Especially, expert-based curves rely on the direct information from experts concerning the abatement cost and abatement level of individual abatement measures. This information will be biased, can have limited value and will be influenced by subjective errors, such as those discussed in the previous section 5.1.1. But also energy models are subject to uncertainty concerning data selection, while the chosen data itself can be subjective and biased in the same way as expert information described above.

The modeller is a possible additional source of uncertainty. He/she is involved in formulating relationships within the model, imposing user constraints and presenting the results. Depending on the experience and expertise of the modeller, the model can be incorrectly specified without being known to the wider audience. The last example of uncertainty in this category lies in the way results are presented. It can be influenced by imprecise language or by an unclear graphical display, as well as different values and attitudes of the analyst and the decision maker.

## 5.2 Methods to address uncertainty in energy modelling

The previous sections have explained different kinds of uncertainty and highlighted that the construction of a MAC curve is subject to deep uncertainties. Although there is a need to address uncertainty, many modelling efforts are still predominantly deterministic and the results are presented without a clear concept on the implications of uncertainties for practical policy making. Since one of the goals of this thesis is to assess the robustness of MAC curves, this section presents different methods to address uncertainty in energy modelling.

Uncertainties need to be addressed because a failure to do so invites potential unreliability of the results with a consequential loss of confidence and trust in the model's usefulness. Consideration of uncertainty can reduce uncertainty by identifying limits in the variable of interest, but also help decision makers to become aware of arguments for the flexibility of policy options in the case where uncertainties are bigger than previously assumed.

The different techniques, which are presented in this chapter, do not have to be regarded separately, but can be used in combination. Sensitivity analysis, for example, can serve as a starting point for probability-based analyses by finding the most sensitive input factors so that in a next step probability analysis can focus on those variables.

Most of the presented methods concentrate on data uncertainties, while only a few address the structure of the model itself and there are no structured approaches toward user uncertainty. Some researchers have tried to classify existing methods that address uncertainty in energy modelling. Kann et al. (2000) base their classification around the concept of stochastic dynamic optimisation. Rotmans et al. (2001, p. 120f) give an overview of methods of uncertainty analysis in terms of types of uncertainty, including sensitivity analysis, probability-based methods, scenario analysis and hedging-oriented methods. Voß (2009, p. 164) distinguishes methods for the treatment of uncertainty into those that tackle uncertainties during data collection, model building and model application. For the latter category, methods are further separated into those that look at single input variable and those that look at the general conditions.

### 5.2.1 Sensitivity analysis

The goal of sensitivity analysis is to identify those variables and parameters that have the biggest influence on the behaviour of the considered system and to quantify their influence on model outcomes. Consequently, sensitivity analysis examines the sensitivity of relationships between variables and parameters of a model and their repercussions on the solution of a problem. Saltelli et al (2000, p.3) define sensitivity analysis as the study of how the variation in the output of a model can be apportioned to different sources of variations. Sensitivity analysis can also estimate the relative importance of uncertain variables. Mechanism reduction is another possible goal for this technique, which leads to the elimination of insignificant factors from the final model.

An example for sensitivity analysis would be to study the influence of a variation of the oil price on the $CO_2$ emission level.

In most cases, single-valued sensitivity analysis, also called one-at-a-time (OAT) variation, is performed, which involves setting a single variable at different values (usually to extreme points) while holding all other variables at their previous level. In more detail, the steps of sensitivity analysis comprise the determination of the input factor and the definition of variation ranges for each input factor. Many models contain a large number of uncertain input factors that makes it impossible to vary them all. Therefore, the analyst has to limit the number of variables included in the sensitivity analysis to the most interesting variables. In general, this is based on the analyst's choice, which can be biased and therefore exclude potentially interesting factors. Further, the model is evaluated, i.e. an output range is created and lastly the influence of each input factor on the output variable assessed. Sensitivity analysis is widely used in energy modelling as an option to assess uncertainty. Examples can be found in Ha-Duong et al. (1997), Bosetti et al. (2006) and van Vuuren et al. (2007).

The simplicity of sensitivity analysis comes at the expense of several shortcomings. Like most of the other methods in this section, sensitivity analysis assumes that the model structure is correct and adequate to address the problem at hand. Specification errors are not measured. The extreme points chosen for the sensitivity analysis might not reveal the complete uncertainty involved, especially if maximum divergence in output variables lies in the interior of the range (Kann and Weyant 2000, p. 35). These values are dependent on a subjective bias of the modeller. Finally, OAT sensitivity analysis focuses on one variable, neglects mutual interactions between uncertainties in input variables and thus cannot cover the entire output spectrum (see Saltelli and Annoni 2010).

If one wants to convert a deterministic model into a probability-based one, sensitivity analysis can be helpful to select key uncertain variables and understand the robustness of the model outcome to variations in input variables. The same can be applied to stochastic programming, i.e. finding the variables that are most interesting for stochastic analysis. In contrast to probability-based methods, stochastic programming allows for the determination of optimal policies at more than one point in time.

To conclude, sensitivity analysis does nothing more and nothing less, than providing insights into the role of uncertain variables and initial values in model runs.

### 5.2.2 Scenario analysis

A scenario is a particular situation that can be described as a vector of values for each input variable (Morgan et al. 1990, p. 174). These scenarios must be a harmonised, interesting and meaningful combination of different assumptions about possible future states of the world. Scenario analysis should improve the understanding of the complex interactions of the considered system and in some cases stretch the thinking of the audience by generating unexpected combinations of possible events. Hughes (2009, p.3) summarises that scenarios are intended to improve robust future decision making, identify opportunities for intervention and strengthen consensus building.

The use of scenarios can be traced back to military planning and has been around for more than 30 years in strategic business planning (Bradfield et al. 2005). In the climate change mitigation context, the Intergovernmental Panel on Climate Change (IPCC) has used emissions scenarios as a central component of its work since 1990. In this year, the IPCC explored four emissions pathways, including a business as usual future and three policy scenarios. In 1992, the existing scenarios were updated and extended by two other scenarios to present 6 different scenarios, which considered uncertainties in economic growth, population and technology (Legget et al. 1992). These scenarios were used for the subsequent assessment reports by the IPCC.

In 2000, new scenarios were developed through one of the best-known exercise, the Special Report on Emissions Scenarios (Nakicenovic and Intergovernmental Panel on Climate Change 2000), which defined four representative scenarios for the IPCC. It defines scenarios as alternative images of how the future might unfold and characterises them as an appropriate tool to analyse how driving forces may influence future emissions outcomes and to assess associated uncertainties (Nakicenovic and Intergovernmental Panel on Climate Change 2000, p. 3). In contrast to previous efforts, the scenarios were complemented by narrative storylines of the future that should facilitate scenario interpretation. In this context, six different modelling approaches were used, each relying on similar assumptions about driving forces.

The most recent scenarios for climate change research have been developed in 2008 for the IPCC (Moss et al. 2008) and should be applied during IPCC's fifth assessment report. Four Representative Concentration Pathways will be developed in a parallel process that does not start with socioeconomic conditions but is based on radiative forcing targets (Moss et al. 2010). The four pathways can be achieved by a diverse range of socioeconomic and technological developments. An overview of international and UK low carbon scenarios can be found in Hughes et al. (2009).

Scenario building generally includes several steps. In general, the process starts with the identification of the scenario user in order to adapt the scenarios to the specific audience. The acceptance with the scenario user is increased if a scenario is grounded in the present and is then clearly linked from the present to future situations, e.g. via storylines. The latest step is usually the communication of scenarios to potential users (Hughes 2009).

A significant problem in scenario analysis is the coordination of the different input variables. The input assumptions have to be made mutually consistent so that they do not contradict themselves, e.g. assure consistency among the assumptions for different fossil fuels. In addition, they need to be as exhaustive as possible to include most uncertain states. There is a possibility that a subjective probability bias will be attached to scenarios in the absence of quantitative uncertainty analysis. Finally, a particular selection of scenarios can influence the understanding of decision makers in the way that they create a subjective likelihood of an outcome and explicitly bound the probability of the outcome. If, for example, the global population estimation in all scenarios varies between 8.7 and 11.3 billion people in 2050, this presumes that anything outside this range is very unlikely.

Scenario analysis does not only play an important role as a method of uncertainty analysis. It is also one of the few ways in which model structure uncertainty can be investigated by comparing the outputs of several models. Usually in model comparison projects, the model analyst is relieved from the task to define the most important inputs. Instead, all models are provided with broadly identical input assumptions by the organisation that performs the model comparison.

### 5.2.3 Probability-based methods

Probability-based methods are an extension of sensitivity analysis approach in the sense that a predefined number of realities of how an input variable will evolve over time is no longer given, but a probability distribution describes the indeterminacy in its future evolution. Based on the probability of an input factor, uncertainty propagation creates a distribution function of the output parameter. Thus, probability-based methods give an indication of the likelihood of outputs dependent on the likelihood attached to uncertain model inputs (Rotmans and van Asselt 2001, p. 117).

The simplest form of implementation, called Monte Carlo method, involves specifying a distribution (discrete or continuous) and a range on an input variable, e.g. the development of the demand for residential heating, and then propagating this uncertainty through to the model output. For this purpose the model is run many times via sampling from the probability distribution. Sampling means that values are drawn at random from the specified distribution. The evaluation of the resulting output distribution is the last step. This distribution is, however, only an approximation of the exact distribution. An extension of this approach is the use of joint distributions for more than one input variable.

The appeal of Monte Carlo sampling is that its computational complexity is linear in the number of uncertain input variables in contrast to discrete probability methods (Morgan et al. 1990, p. 199). Moreover, there is no need to discretise continuous distributions, since the values can be directly taken from a continuous distribution.

Concerning the sampling process, i.e. how random numbers are chosen out of a given distribution, broadly two main methods can be compared: random sampling and stratified sampling. Random sampling is also called pseudo-random because of the fact that the random numbers are machine-generated by a deterministic process and are therefore not random in a strict sense. The advantage of this method is that it produces unbiased estimates of the mean and the variance.

Of particular importance during the sampling process is not primarily the randomness of the sample but a resulting equidistribution property of data points in the distribution. This expresses the need for a better and more complete coverage of the sample space of the input factors than it is possible with random sampling. Stratified sampling can improve the coverage by dividing the input space into strata. Input values are then obtained by sampling separately from within each stratum instead of the whole distribution (Morgan et al. 1990, p. 204). A widely used method for stratified sampling is Latin Hypercube sampling (LHS).

For LHS each uncertain input variable is divided up into equiprobable intervals or strata and a single value is sampled at random from within each of these intervals according to the distribution function. This step is repeated as often as required. The division of the input space assures that the sampled data points are more evenly spread out, so that the sample from each input represents the mean and variance of the distribution more accurately. This is especially the case if the model is roughly linear and if output uncertainty is dominated by only a few input variables. Problems can occur for models that exhibit periodicity with respect to an input (Morgan et al. 1990, p. 205).

Next to the two categories discussed above, there exist also quasi-random sampling, which is characterised by an enhanced convergence rate, and importance sampling. The latter technique generates more sample points to illuminate certain aspect of special interest and fewer in other parts in the case that the analyst is more interested in some parts of the output distribution.

Although Monte Carlo analysis gives a distribution of an output variable and insights into the relative importance of different input variables, it possesses several drawbacks. Ultimately the accuracy of the outcome distribution depends on the accuracy of the probability density functions of the uncertain input variables. In most cases, neither mean nor range and probability distribution are known, which makes it very difficult to choose a meaningful distribution. Nordhaus (1994, p. 144) states that the definition of a distribution function of uncertain variables in this context sometimes resembles "fine arts more than high science". In general, it can be said that the selected range has a bigger influence compared with the assigned distribution (Saltelli et al. 2000, p. 21). This is because high impact, low probability events can be important to consider.

Another problem is the accuracy of the method. This can be addressed by increasing the sample size, which again leads to another problem. The number and dimensionality of uncertain variables can render Monte Carlo analysis impractical to use. Today's energy models rely on many uncertain input variables, which possess a large dimensionality and show mutual interactions. The PAGE2002 model, for example, has 19 unrelated variables with independent distributions. To have, on average, at least one iteration from the most unlikely quintile (5%) for all 19 variables, it would be necessary to run the model 20 trillion times (Stanton et al. 2008, p. 7). This makes it basically impossible to illuminate worst case situations in most variables at the same time.

In addition, it is not always simple to identify policy relevant variables via uncertainty propagation. An outcome variable, such as $CO_2$ emissions, can vary greatly with changes in an input variable. But this pattern can be exactly the same across policy alternatives, so that this method will not necessarily identify the policy relevant variables and parameters. An alternative is to vary certain policy-relevant parameters, such as a $CO_2$ tax or a renewable share as an additional constraint in the model.

A last problem is how to assess the correlation between different uncertain input variables and an according representation in the probability function. It is very difficult to specify joint distributions due to the unknown extent of correlations between variables. In the presence of significant interdependencies among variables, uncertainties can be grossly misrepresented if an independent distribution is specified for each variable.

Examples for an application of Monte Carlo analysis in energy modelling are the ICAM, EPPA, MERGE and PAGE model (Dowlatabadi 1998; Webster et al. 2002; Kypreos 2008; Hope 2009). In addition, the Stern Review (Stern 2007, p. 229) has been underpinned by a probabilistic model developed by Dennis Anderson. Further studies that have employed uncertainty propagation as a tool of uncertainty analysis can be found in an overview compiled by Peterson (2006, p. 14).

Another concept used in this context is rank transformation. This is a procedure where data points for all input factors are replaced with their corresponding ranks 1 (highest value) to N (lowest value). After generation, the observed outcomes are also replaced by their corresponding rank. In a next step, one is able to perform a regression analysis, where the outcome variable is the dependent variable and the input variables are the independent variables. Based on this regression a partial rank correlation coefficient can be calculated that measures the specific contribution of each uncertain input to the output uncertainty. The difference in the coefficient of determination ($R^2$) between the transformed model and the one based on raw data indicates the nonlinearity of the model. Rank transformation can be particularly useful for regression analysis in a highly nonlinear model. One example where rank transformation has been employed, is the PAGE model (Hope et al. 1993, p. 336). This method can also serve to identify conceptual errors if the estimated sensitivities possess the wrong sign (see e.g. Kleijnen 1994, p. 327). In principle, a ranking of uncertain inputs is also possible based on sensitivity analysis, but this does not enable the analyst to perform a meaningful regression analysis due to the lack of sufficient data.

A limitation to this approach is that an altered model is being studied, so that possible sensitivity measures give information about a different model. Through the rank transformation the importance of higher-order interactions are decreased at the benefit of first-order terms (Saltelli et al. 2000, p. 26). This opens up the possibility to overlook the influence of interactions in an analysis based on ranks.

### 5.2.4 Sequential decision-making under uncertainty

Sequential decision making under uncertainty differs from the previously discussed methods in the sense that optimal policies are determined at more than one point in time taking into account learning. Manne et al. (1991, p. 545) have described uncertainty propagation in optimisation models as “learn now then act” and sequential decision making in contrast as “act now then learn”. While all the input variables are known in advance for uncertainty propagation, not all information is available from the beginning of the model period during sequential decision-making so that the model has to “act” and later adapt to new information when uncertainty is resolved. It is assumed that there are one or more points in time in which policy makers make decisions to react to outcomes and that their knowledge increases with time.

Sequential decision-making under uncertainty is implemented in energy models via stochastic optimisation. Two methods can be distinguished to convert problems into solvable stochastic optimisation problems: decision tree and mean-variance modelling. The latter one is based on Markowitz’ mean-variance method (Markowitz 1952), where parameters are substituted with a distribution function weighted by a mean and a variance in a linear optimisation approach (for an example see e.g. Yu 2003).

The most common way of applying two-stage stochastic programming is via decision trees. The analyst has to define the uncertain variable(s) and define how many alternatives, i.e. branches, should be considered for the variable(s). Those alternatives are either states of the world or a new distribution with a different mean and/or with a reduced variance. In the next step, probabilities for each branch, and a period when uncertainty is resolved, have to be defined. In the case of multiple-stage stochastic programming, where uncertainty is not completely resolved at one point in time, multiple uncertainty resolution times are determined. Finally, the model is solved to obtain results on optimal decision making under uncertainty.

In this context, one can differentiate between two different sets of decisions. On the one hand, a number of decisions are taken before the resolution of uncertainty, where the period is called the first stage or hedging period. On the other hand, a number of decisions are taken after the resolution of uncertainty; the period associated with those decisions is called second stage or recourse period (Birge and Louveaux 1997, p. 52). The set of second stage decisions can be different depending on the outcome, while the set of first stage decisions cannot. During the first stage a strategy composed of contingent actions is followed that takes into account all probable outcomes and their probabilities.

The main goal of stochastic programming is to identify hedging strategies, which balance the risks of waiting with premature action (Rotmans and van Asselt 2001, p. 118). Hedging can be regarded as a strategy that builds a contingency plan and responds to opportunities and dangers as they are resolved (Kann and Weyant 2000, p. 38). This is in contrast to a strategy that only takes the average of different policies, which are optimal for different states of the world. Thus stochastic modelling can give insights additional to the comparison of several runs with a deterministic model. An illustrative example is the stochastic definition of a $CO_2$ reduction target, where the model chooses an emission path in the first stage from where it is always possible to meet all specified final targets. Deliberations include the trade-off between waiting to learn more versus higher damage or waiting to learn more versus beneficial effects from induced technological learning. In addition, stochastic programming can yield interesting results on robust technologies, i.e. those that are chosen during the first stage of the optimisation problem. Furthermore, after the resolution of uncertainty the recourse strategy can reveal interesting insights on the flexibility of the energy system if an unlikely event occurs. It could be interesting, e.g., to see what are the consequences if an investment opportunity into a low-carbon technology opens up after uncertainty is resolved.

Peterson (2006, p. 11) summarises several models, which have applied sequential decision-making under uncertainties, with Peck et al. (1993) and Manne et al. (1991) being one of the first to apply stochastic programming to an energy model.

The expected value of perfect information (EVPI) is a mathematical value and is often used in the context of stochastic programming to determine the value of having the information about the uncertain variables available from the start. More precisely the EVPI is the difference between the expected value obtained if the state of the world is known before a policy must be adopted and the expected value obtained if a single policy must be adopted and then applied across all possible states of the world. The EVPI measures the maximum amount a decision maker would be ready to pay in return for complete information about the development of the concerned uncertain variable(s) (Birge and Louveaux 1997, p. 137). Peck et al. (1993, p. 94) noted in this context that the value of information for two or more variables if treated together can be bigger than the sum of all variables at once.

Drawbacks of this concept are that the value of information depends largely on the dispersion of the distribution that is assigned to a variable, which is a subjective estimation. Usher (2011) found the EVPI to be at a maximum when uncertainty is maximised in the way that all possible outcomes have the same probability. Although the EVPI gives a precise number for the availability of information, this is based on subjective assumptions. A value of information for an individual input variable is most likely not the information decision makers are looking for. They are more interested in joint values, which are difficult to obtain due to complex calculations and correlations among variables.

The concept of sequential decision-making under uncertainty comes with several shortcomings. In general, energy modelling comprises a very large number of uncertainties, which cannot all be taken into account due to incomplete knowledge and computational limitations. As the number of branches increases exponentially with the number of uncertain inputs, the analyst needs to limit the number of uncertain variables that are considered. This makes an exhaustive representation of uncertainty impossible. In addition, stochastic modelling only assumes a few variables to be uncertain, whereas others are assumed to be fully known. Thus, results reflect the certainty associated with deterministic variables that can lead to a preference for a known technology independent of the uncertainty characterisation of stochastic variables.

Concerning the assessment of variable uncertainties, stochastic programming suffers from the same problem as uncertainty propagation. While in some cases it is possible to determine for certain variables a range, information on the distributional shape is generally not available. This makes the analyst's choice of probability determination arbitrary. Further, the extent of possible correlations among uncertain variables is not known. A survey among experts, an expert elicitation, is a possibility to obtain a meaningful uncertainty profile.

Stochastic programming using the decision tree formulation with states of the world suggests that there is one point in time in the future, where perfect information becomes available all at once. Yet, this is not the case, instead there is a continuing process of updating best estimates over time as information is developed (Peck and Teisberg 1993, p. 86). Reducing decision-making to every 20 years or so is an oversimplification of the process, since adjustments to policies are made continuously as information is updated. In addition, released information is obstructed by noise and imperfect understanding of social and technological dynamics, so that it cannot be considered to be perfect.

### 5.2.5 Model-related uncertainty methods

All of the methods presented so far deal with the treatment of data uncertainty, while none focuses on uncertainties relating to the model structure. Nevertheless, the model structure is of particular importance for the validity of the reported outcome. A model can be at best a good approximation of reality, but it can never be exact and so the treatment of data uncertainty can lead to a false confidence in the model.

One of the most frequently applied methods to treat the uncertainty in model development and its structure is the peer review of models. Usually after having finished the early stages of model development, the model is handed over to other researchers in the same area for closer inspection. A problem with this approach is that model structures end up to be very similar and possibly not optimal due to an existing consensus among experts in one field. Regardless of peer review, each model development should start by examining previous models and their critiques and hence synthesise the most useful elements into the new model.

Another approach is to compare the outcome of similar models when they are based on broadly the same input assumptions. Excluding uncertainty relating to input data, it is possible to attribute the remaining differences to the respective model structure and thereby characterise the uncertainty. A drawback of this approach is that the harmonisation of input assumptions is very often limited to only a few assumptions. The first model comparison study was undertaken by the Energy Modeling Forum in the year 1977 (Energy Modeling Forum 1977). The latest one of the Energy Modeling Forum, EMF-22, which focused on climate change mitigation, included a total of 17 models (Clarke and Weyant 2009). Other model comparison projects have been the Innovation Modeling Comparison Project (Edenhofer et al. 2006), a comparison project by the U.S. Climate Change Science Program (Clarke et al. 2007) and ADAM's Modeling Comparison Project (Edenhofer et al. 2010).

In order to address the uncertainty in relation to the choice of algorithm the modelling to generate alternatives (MGA) technique can be used. MGA uses the optimal model solution (cost minimisation for example) as a starting point and explores the surrounding feasible area via a different objective function. The purpose is to create maximally different alternatives that each lie in the vicinity of the previous optimal solution. The optimal value is relaxed by a specific margin and integrated as an upper bound into the model. The model is then run with a reformulated objective function to generate different alternatives (Brill et al. 1982, p. 222f). In this way, it is possible to account for some previously unmodelled objectives. Disadvantages are that the extent of relaxation is arbitrary and that no probabilities are attached to the alternatives as it is the case in scenario analysis. An application of this technique for the electricity sector was presented in DeCarolis (2010).

Lastly, emulation is a further technique to investigate model uncertainty. Emulation means in this context the imitation of an energy model by another one. This can be of use if one wants to emulate a large and complex model with a smaller, faster and easier to use model. Thereby one can reduce efforts needed to accomplish diverse analyses, such as energy strategies and costs of climate change mitigation. Emulation involves generally several steps of model adaptation, like the revision of the regional structure and the harmonisation of exogenous drivers and model-specific parameters. An example can be found in Mensink (2000).

### 5.2.6 Other approaches

Less common methods to treat uncertainty are mentioned in this section.

**Decision analysis** combines analytical techniques aimed at summarising available information from different sources to help policymakers assess the consequences of various decision options (Toth et al. 2001, p. 606). The goal is to extract optimal decisions starting from a set of given alternatives. An example of decision theory is the report by Willows et al. (2003). The authors present guidelines to decision makers to take account of the risk and uncertainty associated with future climate change. The decision making process is characterised as a circular and iterative process, which is divided into eight key stages, comprising problem structuring, problem analysis, decision making and post-decision action. Decision analysis does not only consider the modelling outcome but weighs uncertainty depending on how much it could affect the decision (Morgan et al. 1990, p. 197).

Another approach, which comes close to the hedging strategies approach of stochastic programming, are **minimax regret strategies**. In contrast to stochastic programming it does not maximise or minimise a certain criterion, but it minimises the maximum regret, where regret is defined as the difference between the cost of a strategy and the least cost achievable under perfect information. The results depend only on the possible states of the world and not on the likelihoods of the possible outcomes. It therefore avoids the problems associated with measuring uncertainties. An example of minimax regret strategies for emission reduction in Québec with MARKAL can be found in Loulou et al. (1999).

The **fuzzy system** approach tries to capture the imprecision associated with decision-making and represent human judgement as fuzzy rules. The boundaries between an acceptable and an unacceptable outcome are not considered as sharp, but as fuzzy. The comparison of a scenario with an objective is translated into the comparison of two fuzzy numbers. This enables the decision makers to see whether one is near or far from the criterion. An example where fuzzy decision making has been applied in the context of air pollution can be found in Fisher (2003). Problems with this approach consist in converting uncertainties into fuzzy sets (Ascough II et al. 2008, p. 391).

**Bayesian updating techniques** have also been used in the context of energy modelling. Tschang et al. (1995), for example, used a Bayesian updating procedure, where input data distributions and corresponding output observations are used to improve the quality of the input distribution. This updating process within the framework of a Monte Carlo analysis improves the knowledge of the outcomes by ensuring that the input values, which are linked to the more likely outcomes in a predefined window, are made more influential. Thus, in contrast to sequential decision-making, this technique updates uncertainty (e.g. in the form of a distribution) with new information, resulting in a conditional probability, i.e. that a value for another variable is given.

The concept of option values has also been used to model future learning in the context of climate change. A **real option** represents the right, but not the obligation, to undertake a decision, for example to emit further $CO_2$. The real value is associated with the preservation of the current climate regime. An application example for renewable power technologies can be found in Kumbaroglu et al. (2008).

**Stochastic differential equations** (SDE) allow for the classification of the propagation of uncertainty associated with the model parameters in terms of their dynamics and the magnitude of the interactions. In contrast to Monte Carlo simulations, uncertainty is assessed by numerically solving explicit equations. Ito calculus is used for the interpretation of SDEs to reformulate the system into the stochastic dynamical system. An application to an integrated assessment model can be found in Zapert et al. (1998).

## 5.3 Approach to uncertainty for MAC curves using an energy system model

Since a key aspect of this thesis is to investigate the influence of uncertainty on MAC curves, a variety of methods to address uncertainties were presented in this chapter. This section discusses the usefulness of the different approaches in the context of energy system modelling and carbon abatement cost curves.

**Data uncertainty**

Of the four above-mentioned methods, which deal with data uncertainty, it is possible to use three to examine uncertainties related to MAC curves, while uncertainty propagation is difficult to apply. In order to consider a sufficient portion of the input range for uncertainty propagation, it is necessary to run the model at least several thousand times. Since the UK MARKAL model takes about two minutes to run on a 2.1 GHz dual processor, this would require several days if not weeks to obtain useful results. An alternative would be to use a highly simplified model derived from the UK MARKAL model to run it in a probabilistic mode. This would, however, alter the model structure and therefore not only affect data uncertainty. Furthermore, one of the goals of this thesis is to incorporate technological detail into the graphical representation of a MAC curve, which would no longer be feasible with a highly simplified model.

The advantage of using stochastic programming over simple sensitivity analysis is the possibility to consider hedging strategies and robust technologies. This is associated with the difficulty of defining the number of outcomes and probabilities for different developments, such as technology costs or availability dates. Further, due to computational issues the number of parameters treated stochastically in parallel is limited and not all parameters can be treated in a stochastic way.

The easiest method to examine uncertainty without the need to specify probabilities is sensitivity analysis. It is judged to be the most effective tool in this context as it can highlight the uncertainty for abatement cost curves associated with a specific technology, fuel price, behavioural aspects or time dynamic issues. Thus, it reveals how robust the MAC curve is to a change in a specific model input. Sensitivity analysis is considered to yield relevant insights for a manageable amount of work and time involved. This is carried out in chapter 6 to 9. In order to challenge the results from the sensitivity analysis, one scenario is run with the stochastic version of the UK MARKAL model in chapter 9. This relaxes the assumption of perfect foresight and is therefore potentially an appropriate tool to reveal additional insights.

Uncertainty analysis should focus on those parameters and input variables that are important and least defensible. However, as many assumptions about the future 40 years are uncertain, but time for the analysis is limited, a judgement about the set of parameters has to be made. Table 5.2 presents the variables and parameters that will be considered within the scope of a sensitivity analysis based on the earlier discussion in section 5.1.2.

**Table 5.2: Set of uncertain variables and parameters**

| **Category** | **Specific examples** |
|---|---|
| Time-dynamic aspects | Discount rate |
| | Emission pathway / carbon tax pathway |
| Demand | Energy service demand development |
| | Own price elasticity |
| Technologies | Technological learning |
| | Technology costs |
| | Technology potential |
| Energy prices / Resource potential | Crude oil |
| | Natural Gas |
| | Coal |
| | Biomass |

Time-dynamic aspects should be examined since this has been largely neglected in previous studies and is of particular importance in a perfect foresight model. MAC curves generally only include the abatement effort during one year and consequently depend on the abatement effort in earlier and later time periods. Demand uncertainty is a next category to be studied since previous studies have found that the baseline assumptions concerning the energy service demand development can be more influential for marginal abatement costs than a mitigation target (Akimoto et al. 2004).

Technological learning, associated costs and technology potential will be included in the sensitivity analysis in order to quantify the influence of breakthroughs or failure on the MAC curve. Finally, energy prices are in the focus of much uncertainty considerations and their development as well as estimates about resource potential is particularly uncertain.

Lastly, to capture the interactions or a set of variables and form a scenario to examine the variables' combined effects on the MAC curve, it is important to treat the uncertainty originating from several input variables together. Scenarios will be considered for the parallel variation of all fossil fuel prices, of energy-service demand levels, of the cost of several energy technologies, and of various technology potentials.

**Model uncertainty**

In theory, model uncertainty can be illuminated by comparing two or more models with similar input assumptions. This thesis is based on the energy system model UK MARKAL, which is one model from the MARKAL/TIMES model family. One possibility to quantify model uncertainty is to use a different model from this model family or a completely different energy model. The model structure of other MARKAL/TIMES models is comparable to UK MARKAL as they are based on the same or a very similar model generator. The additional insights generated by using a different model from the same model family are therefore judged to be limited. The situation when using a completely different energy model is certainly different in the sense that the model structure would differ more. This would enable more insights into the influence of the model structure on the model output. Nevertheless, it is difficult to obtain such a model and it would take a significant amount of time to get familiar with the model in order to use it for the purpose of this thesis.

A literature review of other studies using energy models to derive MAC curves can help in this context to identify model-specific influences. Own results can be compared along major sources of uncertainty and uncertainty ranges with existing studies. This comparison is complicated by the fact that MAC curves are presented for varying points in time, for a specific sector and with partly very different exogenous inputs, which can account for the majority of the observed discrepancy. Differences in assumed input assumptions would dilute the influence of different model structures on the observed uncertainties.

**User uncertainty**

Of the three uncertainty types – data, model and user uncertainty – user uncertainty is certainly the most complicated to address in a structured manner. Concise language and more importantly adequate graphical illustration should help to reduce any uncertainty in communicating research results. It is important to present uncertainty in the best possible way since judgement under uncertainty is subject to common fallacies, such as anchoring to a given starting point or a subjective probability distribution. Within this thesis, model-derived MAC curves will be presented in the same way as expert-based curves. Decision makers are mostly familiar with this kind of representation, which should facilitate understanding. Representing abatement measures in this way, where the height stands for the abatement cost, the width for the abatement amount and the colour for the specific abatement measure, is intended to avoid any misunderstandings. Unfortunately, uncertainty cannot be represented in a simple manner, for example with error bars, since the ranking of abatement measures can change. Therefore each sensitivity case needs to be presented in a separate illustration.

## 5.4 References


AEA Energy & Environment, E4Tech, Metronomica, Ricardo, IEEP and CE Delft (2008). Building a UK Transport Supply-side Marginal Abatement Cost Curve. London, Committee of Climate Change.

Akimoto, K., T. Tomoda, Y. Fujii and K. Yamaji (2004). "Assessment of global warming mitigation options with integrated assessment model DNE21." Energy Economics **26**(4): 635-653.

Ascough II, J. C., H. R. Maier, J. K. Ravalico and M. W. Strudley (2008). "Future research challenges for incorporation of uncertainty in environmental and ecological decision-making." Ecological Modelling **219**(3-4): 383-399.

Birge, J. R. and F. Louveaux (1997). Introduction to stochastic programming. New York, Springer.

Bosetti, V., C. Carraro and M. Galeotti (2006). "The Dynamics of Carbon and Energy Intensity in a Model of Endogenous Technical Change." Energy Journal **27**(Endogenous Technological Change and the Economics of Atmospheric Stabilization): 191-205.

Bradfield, R., G. Wright, G. Burt, G. Cairns and K. Van Der Heijden (2005). "The origins and evolution of scenario techniques in long range business planning." Futures **37**(8): 795-812.

Brill, E. D., Jr., S.-Y. Chang and L. D. Hopkins (1982). "Modeling to Generate Alternatives: The HSJ Approach and an Illustration Using a Problem in Land Use Planning." Management Science **28**(3): 221-235.

Clarke, L., J. Edmonds, H. D. Jacoby, H. Pitcher, J. M. Reilly and R. Richels (2007). Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations. Sub-report 2.1A of Synthesis and Assessmnet Product 2.1 by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. Washington, DC., Department of Energy / Office of Biological & Environmental Research.

Clarke, L. and J. Weyant (2009). "Introduction to the EMF 22 special issue on climate change control scenarios." Energy Economics **31**(Supplement 2): S63-S63.

DeCarolis, J. F. (2010). "Using modeling to generate alternatives (MGA) to expand our thinking on energy futures." Energy Economics **In Press, Corrected Proof**.

Dowlatabadi, H. (1998). "Sensitivity of climate change mitigation estimates to assumptions about technical change." Energy Economics **20**(5-6): 473-493.

Edenhofer, O., B. Knopf, M. Leimbach and N. Bauer (2010). "ADAM's Modeling Comparison Project - Intentions and Prospects." Energy Journal **31**(Special Issue 1): 7-10.

Edenhofer, O., K. Lessmann, C. Kemfert, M. Grubb and J. Köhler (2006). "Induced Technological Change: Exploring its Implications for the Economics of Atmospheric Stabilization: Synthesis Report from the Innovation Modeling Comparison Project." Energy Journal **27**(Special Issue: Endogenous Technological Change and the Economics of Atmospheric Stabilization): 57-107.

Energy Modeling Forum (1977). Energy and the Economy. Stanford, CA, Insitute for Energy Studies Stanford University.

Fisher, B. (2003). "Fuzzy environmental decision-making: applications to air pollution." Atmospheric Environment **37**(14): 1865-1877.

Gerking, H. (1987). "Modeling of multi-stage decision-making processes in multi-period energy-models." European Journal of Operational Research **32**(2): 191-204.

Ha-Duong, M., M. J. Grubb and J. C. Hourcade (1997). "Influence of socioeconomic inertia and uncertainty on optimal CO2-emission abatement." Nature **390**(6657): 270-273.

Halsnaes, K., P. Shukla, D. Ahuja, G. Akumu, R. Beale, J. Edmonds, C. Gollier, A. Grübler, M. H. Duong, A. Markandya, M. McFarland, E. Nikitina, T. Sugiyama, A. Villavicencio and J. Zou (2007). Framing Issues. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. B. Metz, O. R. Davidson, P. R. Bosch, R. Dave and L. A. Meyer. Cambridge, UK and New York, NY, USA, Cambridge University Press.

Hirst, E. and M. Schweitzer (1990). "Electric-Utility Resource Planning and Decision-Making: The Importance of Uncertainty." Risk Analysis **10**(1): 137-146.

Hope, C. (2009). "How deep should the deep cuts be Optimal CO2 emissions over time under uncertainty." Climate Policy **9**: 3-8.

Hope, C., J. Anderson and P. Wenman (1993). "Policy analysis of the greenhouse effect : An application of the PAGE model." Energy Policy **21**(3): 327-338.

Hughes, N. (2009). Transition pathways to a low carbon economy. UKERC and E.ON UK/EPSRC Transition Pathways Project. London, King's College London.

Hughes, N., J. Mers and N. Strachan (2009). Review and Analysis of UK and International Low Carbon Energy Scenarios. UKERC and E.ON UK/EPSRC Transition Pathways Project. London, King's College London.

Kann, A. and J. Weyant (2000). "Approaches for performing uncertainty analysis in large-scale energy/economic policy models." Environmental Modeling and Assessment **5**(1): 29-46.

Kleijnen, J. P. C. (1994). Sensitivity Analysis versus Uncertainty Analysis: When to Use What? Predictability and Nonlinear Modelling in Natural Sciences and Economics. J. Grasman and G. van Straten. Dordrecht, Kluwer Academic Publishers**:** 322-333.

Kumbaroglu, G., R. Madlener and M. Demirel (2008). "A real options evaluation model for the diffusion prospects of new renewable power generation technologies." Energy Economics **30**(4): 1882-1908.

Kypreos, S. (2008). "Stabilizing global temperature change below thresholds: Monte Carlo analyses with MERGE." Computational Management Science **5**(1): 141-170.

Legget, J., W. J. Pepper and R. Swart (1992). Emissions Scenarios for IPCC: An Update. Climate Change 1992 - The Supplementary Report to the IPCC Scientific Assessment. Intergovernmental Panel on Climate Change. Cambridge, NY, USA, University of Cambridge**:** 69-96.

Loulou, R. and A. Kanudia (1999). "Minimax regret strategies for greenhouse gas abatement: methodology and application." Operations Research Letters **25**(5): 219-230.

Maier, H. R., J. C. Ascough Ii, M. Wattenbach, C. S. Renschler, W. B. Labiosa and J. K. Ravalico (2008). Uncertainty in Environmental Decision Making: Issues, Challenges and Future Directions. Environmental Modelling, Software and Decision Support: State of the Art and New Perspectives. A. J. Jakeman, A. A. Voinov, A. E. Rizzoli and S. H. Chen. Amsterdam, Elsevier.

Manne, A. S. and R. G. Richels (1991). "Buying greenhouse insurance." Energy Policy **19**(6): 543-552.

Markandya, A., K. Halsnaes, A. Lanza, Y. Matsuoka, M. Shakespeare, J. Pan, J. Shogren, R. Seroa de Motta and T. Zhang (2001). Costing Methodologies. Contribution of Working Group III to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). B. Metz, O. Davidson, R. Swart and J. Pan. Cambridge, UK, Cambridge University Press.

Markowitz, H. (1952). "Portfolio Selection." The Journal of Finance **7**(1): 77-91.

Mensink, P. G. C. (2000). Emulating a Long-Term Energy Scenario with the MERGE2 Model. Laxenburg, International Institute for Applied Systems Analysis.

Morgan, M. G., M. Henrion and M. Small (1990). Uncertainty : a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge ; New York, Cambridge University Press.

Moss, R. H., M. Babiker, S. Brinkman, E. Calvo, T. R. Carter, J. Edmonds, I. Elgizouli, S. Emori, L. Erda, K. A. Hibbard, R. Jones, M. Kainuma, J. Kelleher, J. F. Lamarque, M. R. Manning, B. Matthews, J. Meehl, L. Meyer, J. F. B. Mitchell, N. Nakicenovic, B. O'Neill, R. Pichs, K. Riahi, S. Rose, P. Runci, R. J. Stouffer, D. van Vuuren, J. Weyant, T. J. Wilbanks, J. P. van Ypersele and M. Zurek (2008). Towards New Scenarios for Analysis of Emissions, Climate Change, Impacts, and Response Strategies. Geneva, Intergovernmental Panel on Climate Change.

Moss, R. H., J. A. Edmonds, K. A. Hibbard, M. R. Manning, S. K. Rose, D. P. van Vuuren, T. R. Carter, S. Emori, M. Kainuma, T. Kram, G. A. Meehl, J. F. B. Mitchell, N. Nakicenovic, K. Riahi, S. J. Smith, R. J. Stouffer, A. M. Thomson, J. P. Weyant and T. J. Wilbanks (2010). "The next generation of scenarios for climate change research and assessment." Nature **463**(7282): 747-756.

Nakicenovic, N. and Intergovernmental Panel on Climate Change (2000). Special report on emissions scenarios : a special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge ; New York, Cambridge University Press.

Nordhaus, W. D. (1994). Managing the global commons : the economics of climate change. Cambridge, Mass., MIT Press.

Peck, S. C. and T. J. Teisberg (1993). "Global warming uncertainties and the value of information: an analysis using CETA." Resource and Energy Economics **15**(1): 71-97.

Peterson, S. (2006). "Uncertainty and economic analysis of climate change: A survey of approaches and findings." Environmental Modeling and Assessment **11**(1): 1-17.

Rotmans, J. and M. B. A. van Asselt (2001). "Uncertainty Management in Integrated Assessment Modeling: Towards a Pluralistic Approach." Environmental Monitoring and Assessment **69**(2): 101-130.

Saltelli, A. and P. Annoni (2010). "How to avoid a perfunctory sensitivity analysis." Environmental Modelling & Software **25**(12): 1508-1517.

Saltelli, A., K. Chan and E. M. Scott (2000). Sensitivity analysis. Chichester ; New York, Wiley.

Schelling, T. C. (1995). "Intergenerational discounting." Energy Policy **23**(4-5): 395-401.

Schneider, S. and K. Kuntz-Duriseti (2002). Uncertainty and Climate Change Policy. Climate Change Policy: A Survey. S. Schneider, A. Rosencranz and J. O. Niles. Washington D.C., Island Press.

Stanton, E. A., F. Ackerman and S. Kartha (2008). Inside the Integrated Assessment Models: Four Issues in Climate Economics. Somerville, MA, Stockholm Environment Institute.

Stern, N. H. (2007). The economics of climate change : the Stern review. Cambridge, UK, Cambridge University Press.

Toth, F. L., C. Carraro, J. Christensen, J. Edmonds, B. Flannery, C. Gay-Garcia, H. Lee, K. M. Meyer-Abich, E. Nikitina, A. Rahman, R. Richels, Y. Ruqiu, A. Villavicencio, Y. Wake and J. Weyant (2001). Decision-making Frameworks. Contribution of Working Group III to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). B. Metz, O. Davidson, R. Swart and J. Pan. Cambridge, UK, Cambridge University Press.

Tschang, F. T. and H. Dowlatabadi (1995). "A Bayesian technique for refining the uncertainty in global energy model forecasts." International Journal of Forecasting **11**(1): 43-61.

Tversky, A. and D. Kahneman (1974). "Judgment under Uncertainty: Heuristics and Biases." Science **185**(4157): 1124-1131.

Usher, W. (2011). Investment uncertainty under stringent UK decarbonisation targets 11th IAEE European Conference. Vilnius, Lithuania.

van Asselt, M. B. A. and J. Rotmans (2002). "Uncertainty in Integrated Assessment Modelling." Climatic Change **54**: 75-105.

van Vuuren, D., M. den Elzen, P. Lucas, B. Eickhout, B. Strengers, B. van Ruijven, S. Wonink and R. van Houdt (2007). "Stabilizing greenhouse gas concentrations at low levels: an assessment of reduction strategies and costs." Climatic Change **81**(2): 119-159.

Voß, A. (2009). Systemtechnische Planungsmethoden in Wirtschaft und Technik - Skript zur Vorlesung. Stuttgart, Institut für Energiewirtschaft und Rationelle Energieanwendung, Universität Stuttgart.

Walker, W. E., P. Harremoës, J. Rotmans, J. P. van der Sluijs, M. B. A. van Asselt, P. Janssen and M. P. K. von Krauss (2003). "Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support." Integrated Assessment **4**(1): 5 - 17.

Webster, M. D., M. Babiker, M. Mayer, J. M. Reilly, J. Harnisch, R. Hyman, M. C. Sarofim and C. Wang (2002). "Uncertainty in emissions projections for climate models." Atmospheric Environment **36**(22): 3659-3670.

Willows, R. and R. Connell (2003). Climate adaptation: Risk, uncertainty and decision-making. Oxford, UK Climate Impacts Programme.

Yu, Z. (2003). "A spatial mean-variance MIP model for energy market risk analysis." Energy Economics **25**(3): 255-268.

Zapert, R., P. S. Gaertner and J. A. Filar (1998). "Uncertainty propagation within an integrated model of climate change." Energy Economics **20**(5-6): 571-598.

# 6 ELECTRICITY SECTOR MAC CURVES

This chapter is the first results chapter and discusses the economics of carbon emissions reduction in the UK electricity sector. Chapter 7 presents MAC curves for the transport sector and Chapter 8 discusses the economics of emissions reduction in the residential sector. Chapter 9 looks at $CO_2$ emissions reduction from an energy system's perspective and uses the stochastic version of the UK MARKAL model to generate additional insights.

The electricity sector is a key element in an economy-wide decarbonisation since electricity is used in all end-use sectors and low-carbon electricity has the potential to extend to electric vehicles in transport and electric heat in buildings. In addition, the power sector is currently a major source of emissions in the UK with 210 Mt $CO_2$ in 2008 or 32% of all energy-related $CO_2$ emissions (DECC 2010). Major efforts will be necessary to bring down the average emissions from today's 540 g $CO_2$/kWh. The next two results chapters discuss MAC curves for the transport and residential sector. The service sector is not considered as the abatement options are relatively similar to the residential sector. The industry sector is, despite its importance, not considered due to the diverse structure and the difficulty to represent the abatement structure in the necessary detail.

This chapter exhibits MAC curves for the electricity sector with different input assumptions, which are derived with the UK MARKAL model and decomposition analysis. It helps to expose the technological structure behind emission mitigation and sheds light on the uncertainties related to an electricity sector MAC curve via various sensitivity cases. In this way it addresses issues related to data uncertainty (see chapter 5.1.2) in a comprehensive way. The sensitivity analysis of the electricity sector is focused on the year 2030 as an important medium-term target for emissions reduction. The CCC (2010) recommends in its fourth carbon budget report that emissions should be reduced by 60% in 2030 compared to 1990. In total, 17 scenarios, which can be differentiated into eight categories, have been performed. Table 6.1 gives an overview over the different scenarios and explains each of them. Scenarios related to path dependency, discount rates, fossil fuel prices and the demand level consider issues that are not only of importance for the electricity sector, but also for other sectors. That is why these scenarios are equally used for the discussion of the transport sector (chapter 7) and the residential sector (chapter 8). The other scenarios are on technological learning (IEP and FIRST-OF-KIND) and technological availability (NO-NUC-CCS). Further scenarios (not shown in Table 6.1) were performed concerning the price of biofuels, demand elasticity, an extended lifetime of power plants, the peak contribution of wind and tidal power and technological learning. Due to the limited insights they provide, the scenarios are not discussed in this chapter.

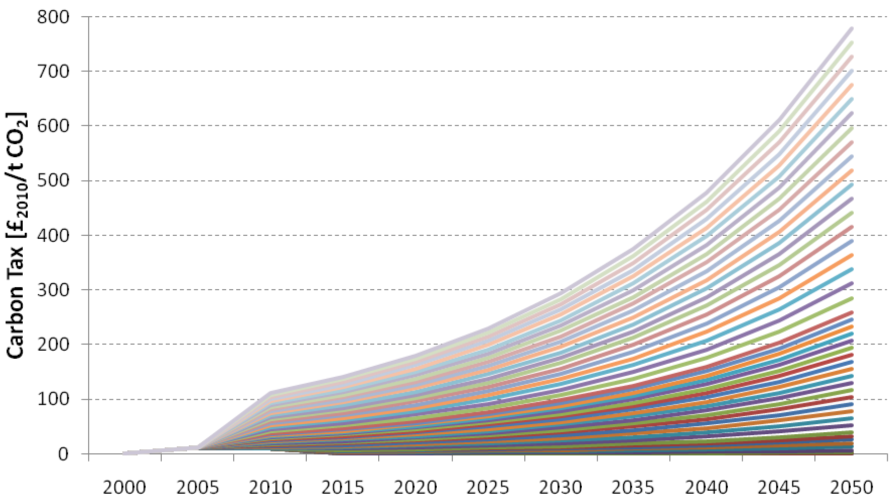
**Table 6.1: Scenario overview**

| Scenario | Category | Description |
|---|---|---|
| **REF** | *Reference case* | Carbon tax increases by 5% p.a. from 2010 |
| **ZERO-BEFORE** | *Path dependency* | Carbon tax is zero before 2030 |
| **CONST-AFTER** | *Path dependency* | Carbon tax is constant after 2030 |
| **INCR-AFTER** | *Path dependency* | Carbon tax increases with 10% p.a. from 2030 |
| **ZERO-AFTER** | *Path dependency* | Carbon tax is zero after 2030 |
| **HIGH-BEFORE** | *Path dependency* | Carbon tax is kept constant on the 2030 level from the REF scenario for the period 2015-2030 |
| **PDR10** | *Discount rate* | Hurdle rates introduced for all technologies at 10%, previously existing rates were doubled |
| **SDR** | *Discount rate* | Discount rate lowered to 3.5%, all hurdle rates, taxes and subsidies removed |
| **FF+** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 100% |
| **FF++** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 200% |
| **GAS** | *Fossil fuel price* | Costs for natural gas decreased by 50% |
| **IEP** | *Technological learning* | Investment costs increased by 200% for all CCS technologies, biomass, nuclear, tidal, wind, wave |
| **FIRST-OF-KIND** | *Technological learning* | Early investments required in order to carry out investments into CCS and nuclear from 2030 |
| **LIFE** | *Lifetime* | Reduced lifetime for coal and nuclear power plants by 10/15 years, for wind and CCGT by 5 years |
| **NO-NUC-CCS** | *Technological availabiltiy* | No investments are allowed into nuclear power plants and CCS technologies |
| **DEM+** | *Demand level* | All energy service demands increased by 20% |
| **DEM-** | *Demand level* | All energy service demands decreased by 20% |

These scenarios were chosen because discount rates, fossil fuel prices and technological learning have been identified in the literature as important influencing factors (see also chapter 2.2.3). The energy service demand level is judged to be influential as it influences the overall demand for electricity. Particular emphasis is put on the issue of path dependency as this has only been addressed in two previous studies and is judged to be a shortcoming of the way current single-year MAC curves are represented.

Each MAC curve consists of 46 different model runs with differently high system-wide $CO_2$ tax levels (see Figure 6.1), ranging from £$_{2010}$ 0 to 294/ t $CO_2$ in 2030. With respect to the year 2050 the $CO_2$ tax is first increased from one model run to the other by £5/t $CO_2$, from £30/t $CO_2$ in steps of £10/t $CO_2$ and from £200/t $CO_2$ in £20/t $CO_2$ steps. In the REF scenario the $CO_2$ tax is assumed to increase after 2010 with the model inherent discount rate of 5% p.a. The $CO_2$ tax level for the different years is calculated backwards from the target level in 2050. Up to the year 2010, the EU ETS $CO_2$ price, the climate change levy and the renewables obligation are integrated into the model. From 2010 onwards, no climate-related policies are included in order not to dilute the marginal abatement costs. Equally, no climate taxes or technology-specific subsidies are incorporated into to the model.

**Figure 6.1: Carbon tax pathway in the different model runs**




While the majority of this chapter focuses on the year 2030, at the end of this chapter a cumulative MAC curve and MAC curves for the years 2020, 2040, and 2050 are discussed. All costs are given in £ of the year 2010.

## 6.1 Description of the electricity sector in UK MARKAL

The power sector in the UK MARKAL model encompasses all the relevant power plant types and combined heat and power (CHP) plant types, distinguished into centralised, distributed and micro generation. Centralised power generation is associated with distribution and transmission losses, while decentralised generation only incurs distribution losses. In total there are 17 different CHP plants and 108 different power plants. This includes coal-fired power plants with and without biomass co-firing, coal CCS plants, oil-fired power plants, dual fuel (oil/gas) power plants, hydro plants, solid waste power plants, gas-fired power plants, gas CCS plants, nuclear power plants, biomass-fired power plants, biomass CCS plants, agricultural waste power plants, tidal technologies, wave technologies, onshore wind turbines and offshore wind turbines. The supply of electricity matches the demand for electricity from the residential, service, agriculture, industrial, upstream and transport sector accounting for international electricity trade with Ireland and France based on assumptions from the TIMES PanEU model (Blesl et al. 2010). It is assumed that a maximum of 82 PJ (23 TWh) can be imported from France and Ireland each year. The demand for electricity depends on technological and cost parameters of end-use technologies as well as on price-elastic energy service demands. The price elasticity varies for different energy service demand, so that it is e.g. higher for space heating than for electric appliances. Demand for electricity is divided into six timeslices: three characterising the season (intermediate, summer and winter) and two characterising the time of the day (day and night) for each season. Furthermore, the availability of electricity generation options during peak hours is taken into account via a peaking constraint and a reserve capacity factor is modelled to account for reserve capacity.

A number of key data parameters that are required to characterise power technologies, such as technical efficiency, capital cost, fixed and variable operating costs, lifetime or annual availability, are defined in the model. Table 6.2 provides an overview of assumptions for the most important technologies in the power sector in 2030. The assumptions change over time as costs are assumed to come down and new technologies become available. Build rate limits are given for the year 2030, though they are in general lower in earlier periods.

When interpreting the scenarios' results that are presented in the next sections it is important to take into account that they are all based on the UK MARKAL model with its particular strengths and weaknesses. Strengths of the electricity sector's representation in UK MARKAL are the technological detail and the capturing of interactions with end-use sectors. Weaknesses are the rough temporal resolution of the model, the lack of spatial distribution and demand-side management, and the negligence of endogenous technological change. The low temporal resolution does not allow for an optimal representation of load management and the integration of renewable technologies. In particular the lack of spatial detail could explain the low uptake of decentralised power generation in the model.

**Table 6.2: Assumptions for key power technologies in UK MARKAL in 2030**

| 2030 | [£=1.4€=1.8$] | Coal PF | Gas CCGT | Gas CHP | Nuclear | Coal CCS | Gas CCS |
|---|---|---|---|---|---|---|---|
| **Capital cost** | [$£_{2010}$/kW] | 1027 | 463 | 870 | 1363 | 1438 | 652 |
| **Availability** | [%] | 83% | 83% | 69% | 83% | 83% | 83% |
| **Load factor** | [%] | - | - | - | - | - | - |
| **Efficiency** | [%] | 52% | 57% | 80% | 36% | 45% | 50% |
| **Life time** | [years] | 50 | 35 | 20 | 50 | 50 | 35 |
| **Build rate limit** | [GW/5 years] | 10 | combined 12.5 | | 7.5 | combined 7.5 | |
| | | **Wind onshore** | **Wind offshore** | **Tidal (Severn barrage)** | **Hydro** | **PV** | |
| **Capital cost** | [$£_{2010}$/kW] | 682 | 1224-1944 | 1947 | 1038 | 2965 | |
| **Availability** | [%] | - | - | 23% | 37% | 10% | |
| **Load factor** | [%] | 16-44% | 36% | - | - | - | |
| **Efficiency** | [%] | - | - | - | - | - | |
| **Life time** | [years] | 25 | 25 | 120 | 40 | 30 | |
| **Build rate limit** | [GW/5 years] | combined 10 | | - | - | - | |

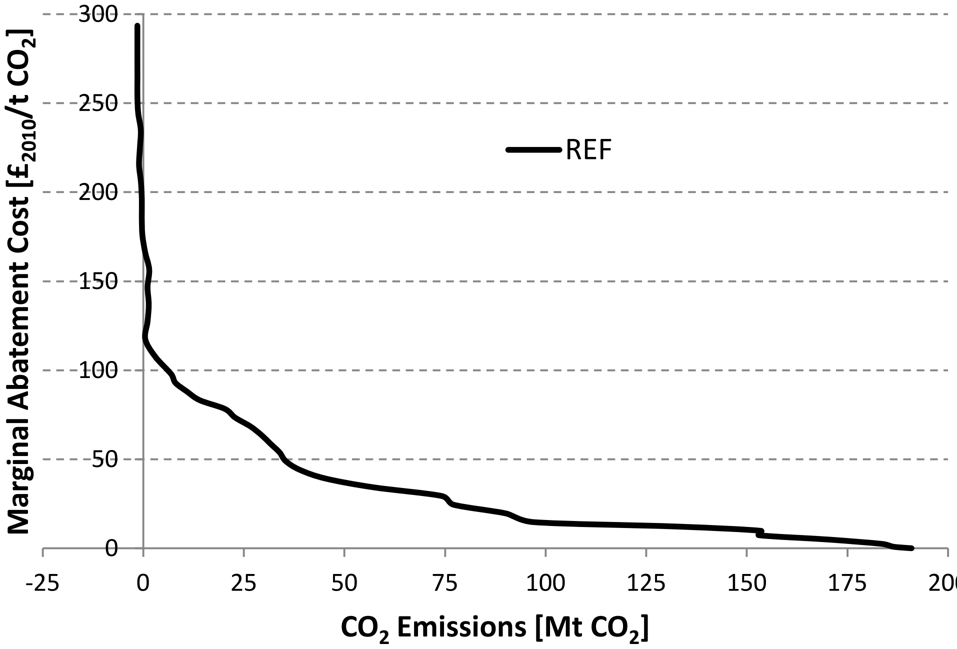
## 6.2 Reference scenario

The reference scenario (REF) describes a development of carbon emissions reduction with the standard assumptions of the UK MARKAL model as they can be found in the model documentation (Kannan et al. 2007). It does not represent the most likely development of abatement costs and potentials, but rather serves as a reference for the sensitivity analysis.

According to the model results, power sector emissions are 191 Mt $CO_2$ in 2030 in the no tax run, which compares to 204 Mt $CO_2$ in 1990 and 174 Mt $CO_2$ in 2008. Thus, emissions are expected to increase by about 10% from current levels due to higher levels of coal in the electricity mix, but to be 6% lower compared with 1990 levels. Model results indicate that total electricity supply in the UK is roughly constant over the next 20 years with 356 TWh in 2030 compared with 367 TWh in 2008.

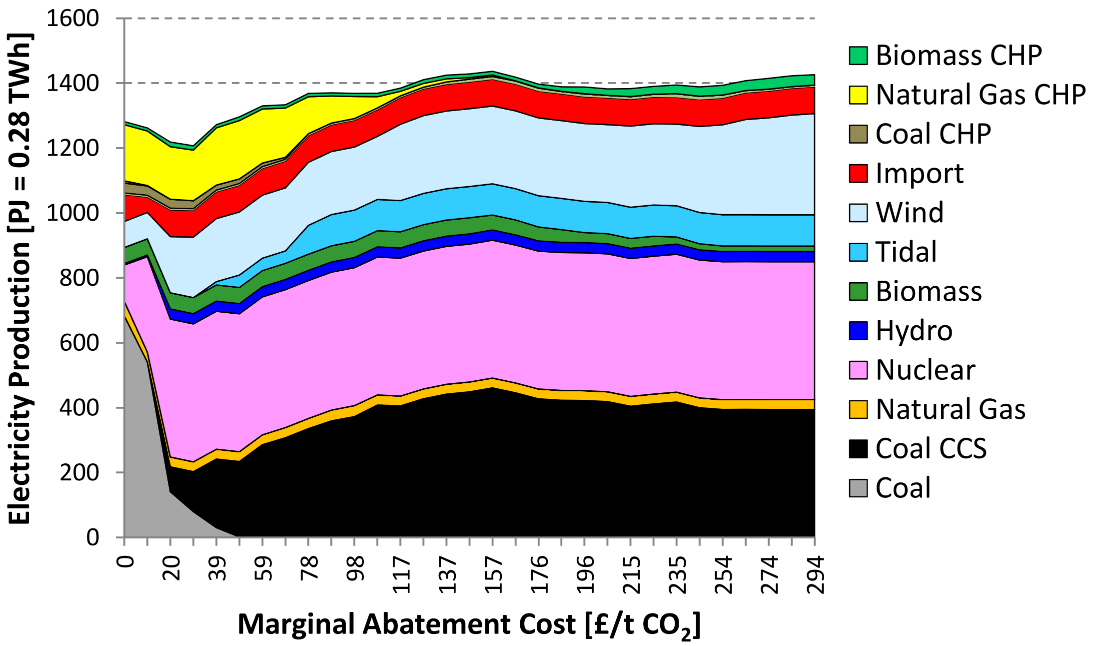
Figure 6.2 shows an emission curve for the electricity sector. In general, one can observe that power sector emissions are reduced dramatically up to £25/t $CO_2$, where the sector is decarbonised by 60% in the REF scenario. At a level of £176/t $CO_2$, all power sector emissions are abated, while emissions turn negative at higher prices. This is possible when biomass is co-fired in coal CCS power stations.

**Figure 6.2: Emission curve for the electricity sector in United Kingdom in 2030**




The emission curve in Figure 6.2 only shows the overall emissions in the power sector, without giving any detail on the technologies and measures that are behind them. In order to judge the technological structure of the MAC curve, it is important to know the electricity mix in the REF case. As can be seen in Figure 6.3, the electricity system is dominated by coal in the case without any $CO_2$ tax. The rest of the electricity mix is made up of natural gas in the form of pure power plants and CHP plants (17%), nuclear power plants (9%), import (6%), wind (6%), biomass (4%) and coal CHP plants (2%).

**Figure 6.3: Electricity generation mix for different marginal abatement costs in 2030 (REF scenario)**



Including the results of the decomposition analysis shows which measures are responsible for the emissions reductions. Decomposition analysis is discussed in detail in chapter 4. Equation (6.1) details the decomposition employed to disaggregate changes in total electricity-related $CO_2$ emissions in this chapter:

$$\boldsymbol{CO_{2,Power}} = \boldsymbol{activity} \left( \sum_{\boldsymbol{j=technology}} \frac{\boldsymbol{activity_j}}{\boldsymbol{activity}} * \frac{\boldsymbol{fuel_j}}{\boldsymbol{activity_j}} * \frac{\boldsymbol{CO_{2,Power,j}}}{\boldsymbol{fuel_j}} \right) \tag{6.1}$$

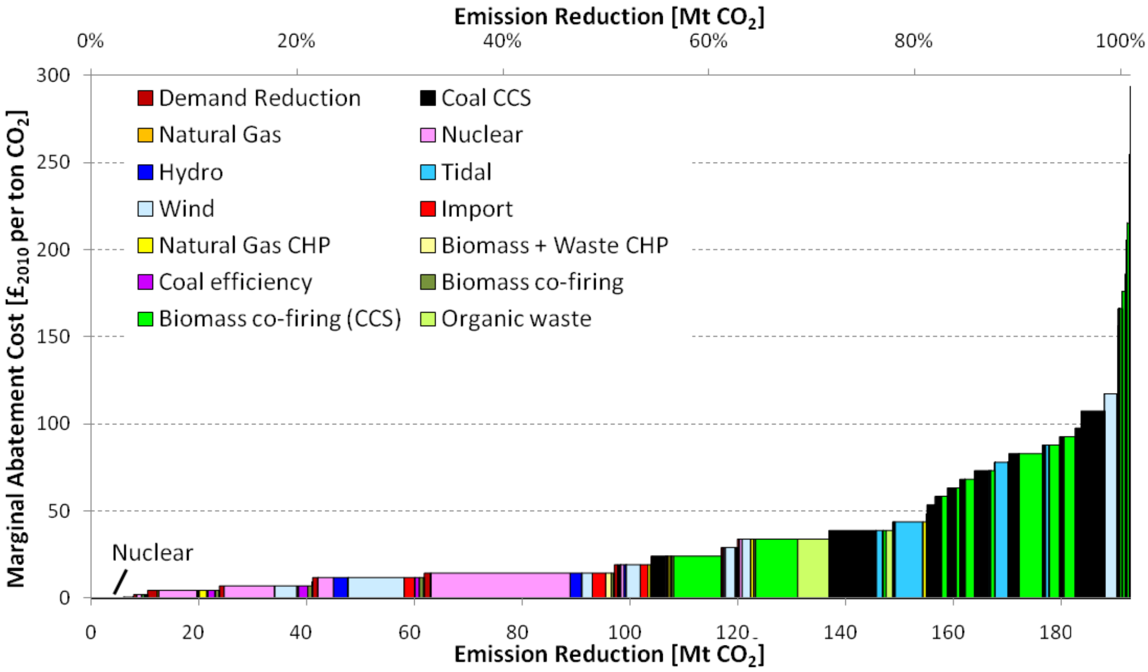
*activity* is the demand for electricity in Petajoules, $activity_j$ is the electric output of one technology type *j*, $fuel_j$ describes the amount of fuel that is necessary to realise this output with technology *j*. $CO_{2,Power,j}$ represent the amount of $CO_2$ released by the use of technology *j*. The first factor represents changes in the total demand for electricity, while the first ratio in the brackets stands for changes by power plant type in the electricity mix, for example a switch from coal to nuclear power plants or coal CCS power plants. The second ratio permits insights into fuel efficiency gains of a particular power technology and finally the third ratio describes the $CO_2$ intensity of a fuel, which can be changed for example by co-firing biomass to a coal-fired power plant.

Correspondingly, the decomposition distinguishes between demand-related influences, changes related to the structure of electricity generation, and the impact of fuel efficiency and carbon intensity. The logarithmic mean Divisia index (LMDI) is used to derive the contribution towards $CO_2$ emission of specific measures (see chapter 4).

Figure 6.4 shows that almost all abatement happens at MACs of below £100/t $CO_2$. Only 4.4 Mt $CO_2$ of emissions reduction is realised at higher $CO_2$ tax levels. Moreover, one can see that the electricity sector is entirely decarbonised at a tax of £176/t $CO_2$ and even becomes an emission sink of 1.4 Mt $CO_2$ by capturing emissions from burning biomass at higher costs.

For the interpretation of the MAC curves it should be taken into account that each bar represents the marginal mitigation measure, i.e. the measure responsible for the emissions reduction between two adjacent $CO_2$ tax runs. Because of the dynamic model character, the bars cannot be added together to form a total abatement potential for a particular attribute as is the case in conventional expert-based MAC curves. The total mitigation potential and total cost still match, but abatement potentials for a specific technology are no longer additive. This is because a mitigation measure might be cost-effective at a certain tax level, but replaced at higher tax levels by another measure. An example can be a switch from coal power plants to gas power plants at low tax levels, while gas power plants are again replaced by nuclear at higher tax levels. Existing expert-based MAC curves assume that all measures are always additive and do not replace each other. However, the applied model-based approach overcomes this significant shortcoming by accounting for interactions between mitigation measures.

**Figure 6.4: MAC curve for the REF scenario in 2030**




The technological detail reveals that nuclear power is the main technology available to reduce carbon emissions cost-effectively. Electricity generation is shifted away from coal-fired power plants to nuclear power plants from as low as £1/t $CO_2$ up to a tax level of £34/t $CO_2$, while the weighted average abatement cost for nuclear power is £12/t $CO_2$. Nuclear power does not have one single marginal abatement cost, because a system model with many input assumptions has been used to generate the MAC curve. Thus, the MAC of nuclear power is a range of costs because more than one type of nuclear power plant and a supply cost curve for uranium are implemented in UK MARKAL. In addition, nuclear power, as with all other power technologies is subject to a build rate limit. In the case of nuclear, this starts at 2.5 GW and is gradually increased in the first half of the 21st century to 10 GW per five year period. This is one of the reasons for intertemporal interactions, i.e. that the conditions in one time period influence the result in a previous or later time period. Furthermore, nuclear power competes with other low-carbon technologies that are also subject to changing economics, particularly coal CCS. The abatement cost for nuclear power is comparably low since levelised electricity generation cost of nuclear power plants are assumed to be 3.74 p/kWh (pence per kilowatt hour) in comparison to 3 p/kWh for coal IGCC plants, the main baseload technology in the REF case.

Coal CCS plays a significant role in the electricity mix from a higher tax level of £19/t $CO_2$ upwards, which is due to the higher generation cost of 4.75 p/kWh in the REF case. The higher generation cost accounts for higher capital, operating and $CO_2$ capture and storage costs. The abatement cost range for coal CCS is significantly larger than for nuclear from £19/t $CO_2$ to £147/t $CO_2$ with a weighted average of £63/t $CO_2$. Reasons are that a variety of coal CCS alternatives, such as pre-combustion and post-combustion are implemented in the model, as well as conventional coal-fired power stations with retrofit. Moreover, another power station type can co-fire biomass. This co-firing option brings in further interactions with biomass that has different characteristics and supply costs and competes with other potential users, such as biofuels in transport or as a heating fuel in the building stock.

Biomass co-firing in CCS plants is a further important mitigation option. On an energy-equivalent basis particular types of coal CCS plants are assumed to be able to co-fire up to 20% of biomass. This can make co-firing coal CCS plants a $CO_2$ emission sink, given the fact that they capture 85% of all emissions and biomass is almost carbon-free only accounting for emissions during cultivation, processing and transport. Biomass supply includes domestic sources, consisting of grassy, as well as woody energy crops and forest residues, mainly wood chips, and imports of woody biomass from overseas. The supply potential for domestic energy crops and imported biomass is assumed to be 450 PJ for each in 2030. The supply of forest residues is much more limited with 45 PJ.

Biomass co-firing is the third most important mitigation measure in the REF scenario mitigating 31 Mt $CO_2$ between £25/t $CO_2$ and £245/t $CO_2$ with a weighted average of £67/t $CO_2$. Biomass co-firing only becomes cost-effective once coal CCS power plants have been introduced. The wide abatement cost range is due to different cost steps for the different types of biomass and the competition with other end-use energy sectors for the same limited resource. A third option for the use of biomass is in solid waste combustion, where dry organic waste can be co-fired to produce electricity. Overall this abatement option is comparably limited as the potential of organic waste is limited to 112 PJ in 2030 and waste combustion makes up a small amount of overall electricity production. In total organic waste incineration accounts for 7 Mt $CO_2$ of abatement at a marginal abatement cost of £34/t $CO_2$.

Next to nuclear and coal CCS power plants, wind power represents one of the important abatement technologies in the power sector. Marginal abatement costs for wind power range from £0/t $CO_2$, as it is already included in the baseline, up to £117/t $CO_2$, while the weighted average is £25/t $CO_2$. This range includes onshore as well as offshore wind power, while the potential electricity production from offshore is far higher than from onshore wind. Onshore wind production facilities are divided into ten categories and offshore wind power into four categories with different load factors. This leads to a situation where wind categories with the highest load factors are able to compete with nuclear and coal power stations, while for some potential areas wind power has levelised generation costs of up to 5.92 p/kWh.

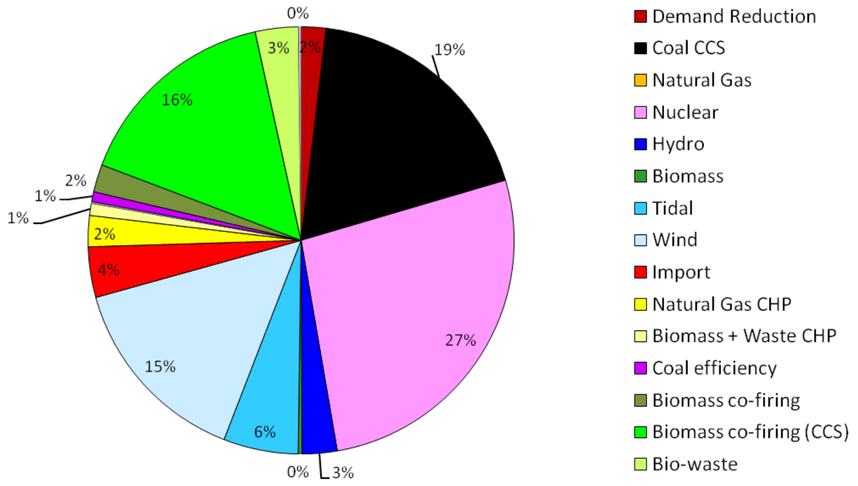
The United Kingdom possesses an important share of the known worldwide tidal stream resources. Tidal power, which uses the water flow in and out of estuaries and through straits, is therefore a potentially important mitigation option for the UK electricity sector. The levelised electricity generation costs are assumed to between 4.8 p/kWh and 5.6 p/kWh, while the biggest potential at the higher end of this cost range is attributed to the Severn estuary in southwest England. The abatement cost range is narrower than for other technologies between £39/t $CO_2$ and £88/t $CO_2$ with a weighted average of £57/t $CO_2$ because there are no interactions concerning the fuel input and not a big cost range.

Smaller abatement measures are country-wide efficiency gains in coal-fired power stations as older power stations are decommissioned earlier, which saves 1.5 Mt $CO_2$. The import of 30 PJ/a of low-carbon electricity from France helps to mitigate emissions to a limited extent. Further mitigation options are hydro power, natural gas CHP, and biomass CHP plants.

At lower carbon tax levels, changes in the price-elastic energy service demand and fuel switching contribute to emissions reduction as one of the first responses to an increasing electricity price is a demand reduction for electricity of up to 79 PJ (22 TWh). Electricity consumption is lowest at £34/t $CO_2$, but increases at higher $CO_2$ tax levels again as electricity-fuelled low-carbon technologies become cost-effective, despite a price-induced reduction in energy service demand. That is why the overall emissions reduction contribution of demand changes for electricity remains relatively small. The results only regard the power sector and should not be confounded with wider energy demand savings in the end-use sector that are much more significant (see chapter 7 and 8).

An idea of the overall contribution of different technologies and effects to emissions reduction up to the highest $CO_2$ tax of £294/t $CO_2$ in 2030, is given in Figure 6.5. It can be seen that the reduction in the demand for electricity caused by higher carbon tax levels, has a very minor (2%) contribution. Once electricity is sufficiently decarbonised, there is no motivation from an emissions reduction perspective to reduce the demand for energy services that are provided by devices relying on electricity.

**Figure 6.5: Technology-specific contribution to overall emissions reduction 192 Mt $CO_2$ (REF scenario) in 2030**

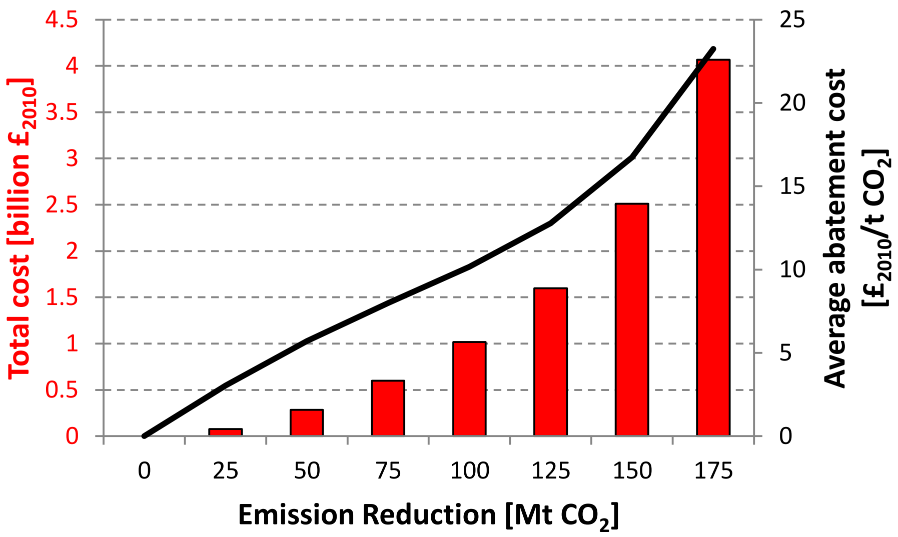



A reduction in fuel intensity (equivalent to efficiency improvement) has a minor contribution in the context of coal-fired power stations. More efficient power stations are already incorporated in the REF case as they are assumed to be cost-effective even without a $CO_2$ tax. Since structural changes dominate the power sector and power plants have a lifetime of up to 50 years, investments into efficiency upgrades will not be realised given an anticipated switch to a different technology.

The most important effects are structural changes in the electricity mix. Nuclear power is the most important mitigation measure with a share of 27% in emissions reduction followed by coal CCS with 19%. However, this share only includes the shift towards coal CCS power plants and not the additional emissions savings that are achieved by co-firing biomass, which accounts for an additional 16%. The other significant mitigation measure in the UK power sector is wind power with a contribution of 15%. Nuclear power, coal CCS (including biomass co-firing) and wind power are responsible in total for 77% of all emissions reduction.

Taking the integral under the curve in Figure 6.4 gives information about the total cost associated with emissions reduction in 2030. This does not, however, consider costs associated with carbon abatement in earlier and later time periods. Figure 6.6 indicates that total costs increase exponentially with an increasing emissions reduction target. This can be explained with the fact that the second derivative of the MAC curve is positive. Total costs in 2030 are £0.29 billion for an emissions reduction of 50 Mt of $CO_2$ emissions in the power sector and £2.51 billion for a reduction of 150 Mt $CO_2$, this corresponds to an average abatement cost of £6/ t $CO_2$ and £17/t $CO_2$ respectively.

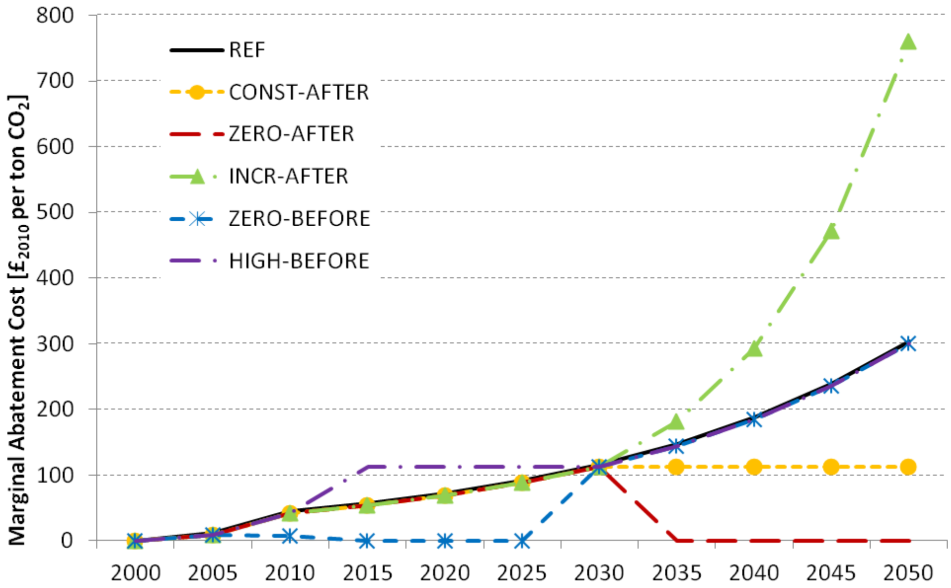
**Figure 6.6: Total abatement costs (left) and average abatement costs (right) for the electricity sector in United Kingdom in 2030**




## 6.3 Path dependency

MAC curves are generally merely a static snapshot of one year, in this case of the year 2030. Nevertheless, the abatement cost and the corresponding abatement potential of all abatement measures depends on previous abatement efforts. As the model underlying these MAC curves is a perfect foresight model, the MAC curve is also influenced by expectations about future climate change policies. Path dependency originates from technologies' lifetimes that span several model periods and build rate limits. It should be noted that UK MARKAL does not consider endogenous learning, thus there is also no induced technological change (ITC), which possibly limits the effects of path dependency. Nonetheless, in order to quantify how sensitive the MAC curve reacts to different $CO_2$ tax trajectories the $CO_2$ tax path of an annual 5% increase has been altered in five scenarios. Figure 6.7 presents the different $CO_2$ tax pathways for one model run (£113/ t $CO_2$ in 2030), where three consider different pathways after 2030, CONST-AFTER, ZERO-AFTER, INCR-AFTER, and two regard different pathways before 2030, ZERO-BEFORE, HIGH-BEFORE.

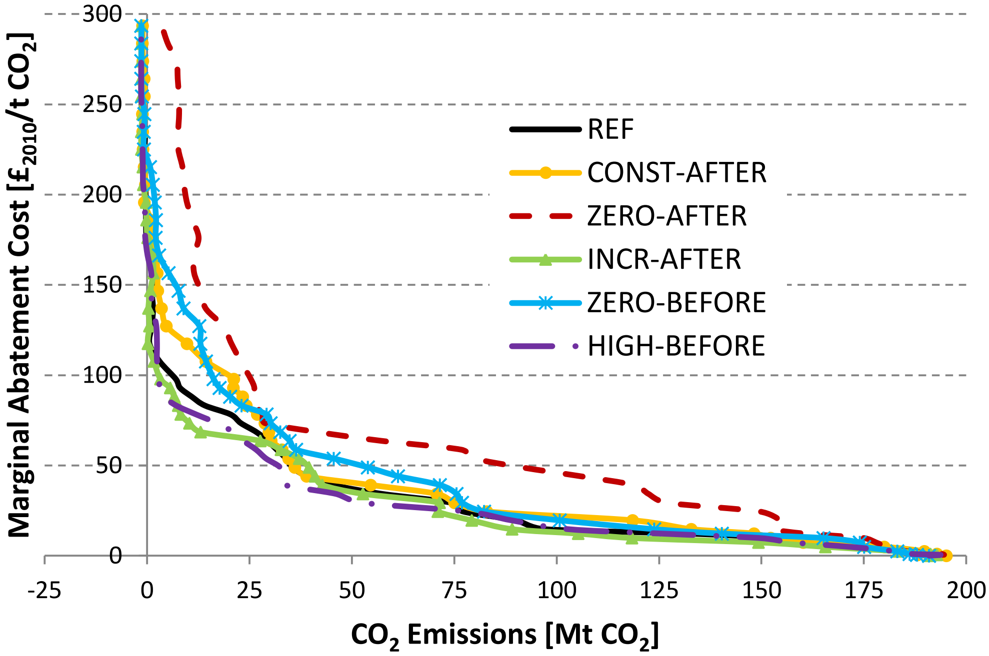
**Figure 6.7: $CO_2$ tax trajectory for different path dependency scenarios for an exemplary model run with a $CO_2$ tax of £113/ t $CO_2$ in 2030**




Although all six scenarios have the same $CO_2$ tax in 2030, they result in different MAC curves, especially for higher abatement costs (see Figure 6.8). Those scenarios with a higher $CO_2$ tax compared with the REF scenario, i.e. INCR-AFTER and HIGH-BEFORE show for the same carbon tax generally a slightly higher abatement level. This is on average 3 Mt $CO_2$ for the INCR-AFTER scenario and 2 Mt $CO_2$ for the HIGH-BEFORE scenario.

The CONST-AFTER scenario, which keeps the $CO_2$ tax constant after 2030, is similar to the REF scenario except for a range from £50/t $CO_2$ to £150/t $CO_2$, where abatement is significantly less. While the abatement potential is significantly lower for a given $CO_2$ tax in the whole tax range, but in particular from £80/t $CO_2$ in the ZERO-AFTER scenario, it is the inverse case for the ZERO-BEFORE scenario where the abatement potential is especially less up to £150/t $CO_2$. Thus, a scenario where the $CO_2$ tax is kept at zero after 2030 significantly increases the marginal abatement costs. The ZERO-BEFORE and CONST-AFTER scenario increase the abatement costs moderately for a given abatement level, while the scenarios that have a higher tax level before or after 2030 show slightly lower marginal abatement costs.

**Figure 6.8: End-use emission curve for different path dependency scenarios**




### 6.3.1 Constant $CO_2$ tax after 2030

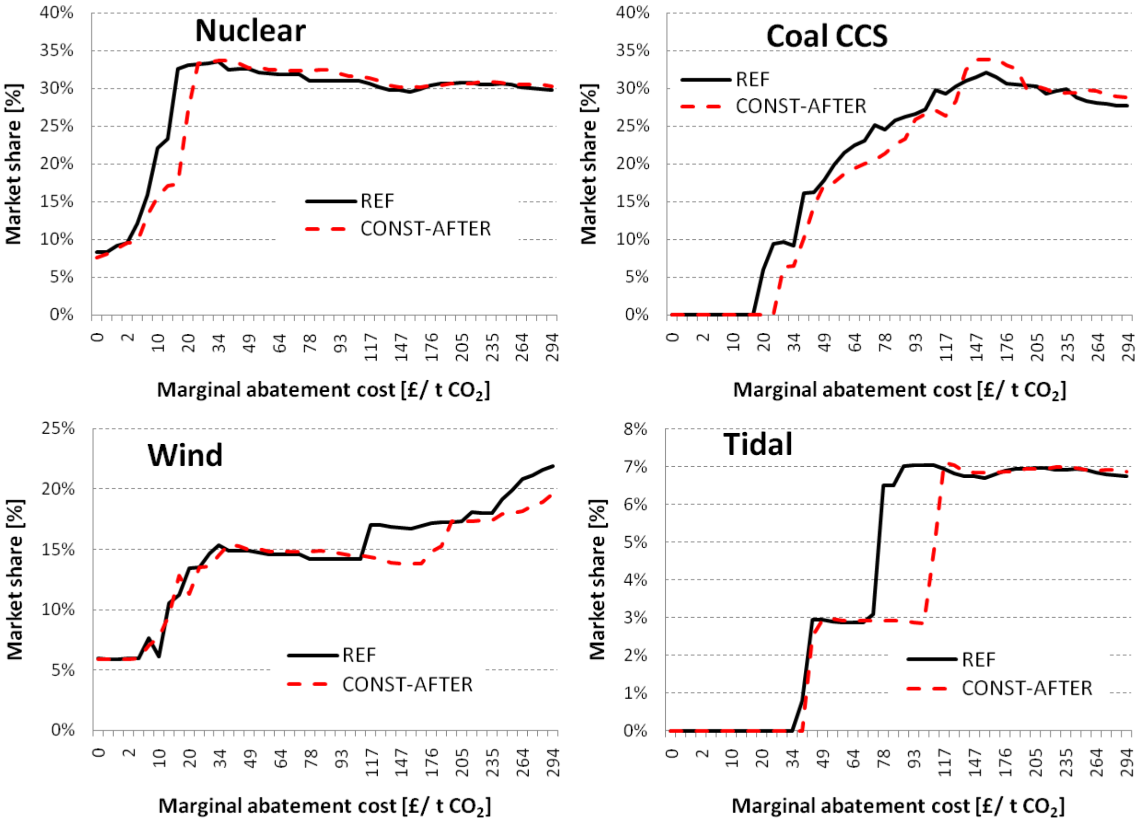
The CONST-AFTER scenario differs from the REF scenario in the way that the $CO_2$ tax no longer increases with the model inherent global discount rate of 5% p.a. after 2030, but instead stays constant at the same level as it is in 2030. Consequently, the incentive for $CO_2$ abatement is less than in the REF scenario. As expected emissions are higher in the CONST-AFTER scenario compared with the REF scenario for the same tax level.

The abatement structure of the CONST-AFTER scenario is very similar to the REF scenario concerning overall emissions reduction and the contribution of each technology. However, one can notice that low-carbon technologies require higher tax levels for the same market penetration as the model anticipates that the carbon tax will be lower in the future compared with the REF scenario. This is illustrated in Figure 6.9. One can see that nuclear power plants reach the highest market share of 33% at £24/t $CO_2$ in the CONST-AFTER scenario, while this is already the case at £15/t $CO_2$ in the REF scenario, i.e. at £9/t $CO_2$ less. For coal CCS power plants the difference in carbon tax levels for the same market share level is similar to nuclear power.

For wind power and tidal power, this situation is slightly different at higher carbon tax levels of around £100/t $CO_2$. Wind power reaches a market share of 17% only at £196/t $CO_2$ in the CONST-AFTER scenario, which is £80/t $CO_2$ higher than in the REF scenario. Similarly, tidal power reaches its highest market share of 7% at a £30/t $CO_2$

higher carbon tax. The reason for the limited expansion of wind and tidal power is that natural gas CCS power plants become cost-effective to a very limited extent in a tax window from £108/t $CO_2$ to £137/t $CO_2$. Natural gas CCS power plants can reduce emissions substantially, but still have residual emissions, so that their introduction is only cost-optimal in the case where the tax level does not increase after 2030.

**Figure 6.9: Market share for different technologies in the CONST-AFTER scenario in 2030**

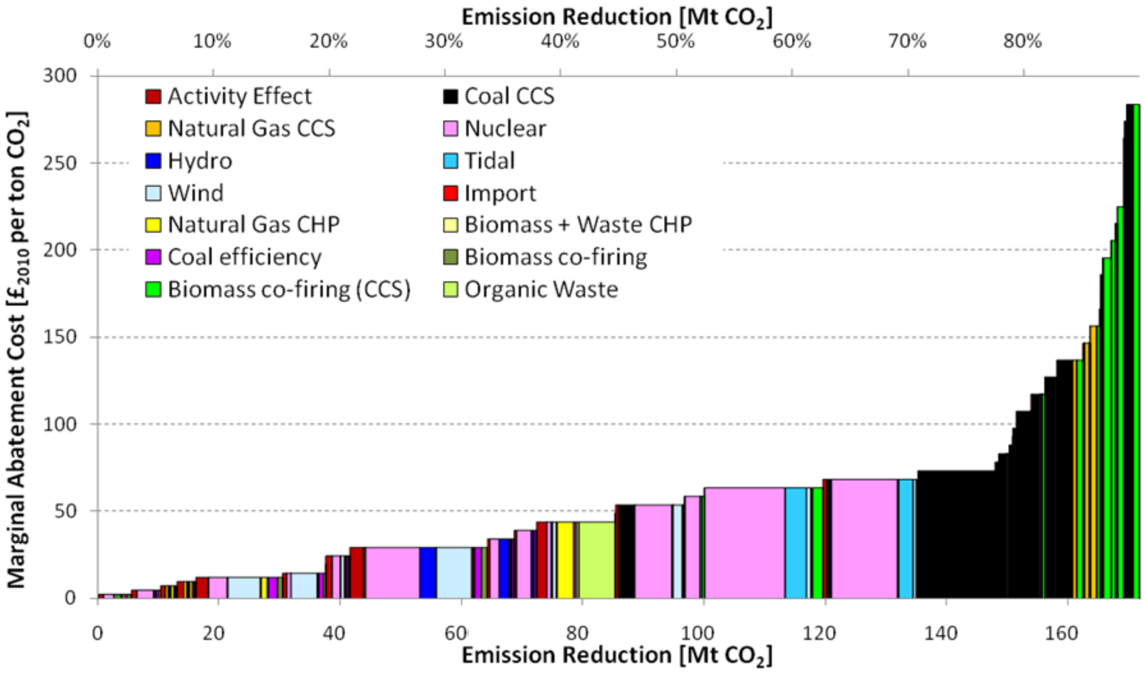



### 6.3.2 Zero $CO_2$ tax after 2030

This path dependency scenario assumes a $CO_2$ tax that drops back to zero for all model runs after 2030. This means that the incentive to shift the energy system to low carbon technologies is smaller because there is no penalty for emitting $CO_2$ after 2030. Correspondingly, one should expect less emissions reduction for the same $CO_2$ tax level. A look at Figure 6.8 confirms this supposition. Figure 6.10 reveals more insights into the technological detail of the abatement in the ZERO-AFTER scenario.

The MAC curve looks different to the extent that the bars are higher than in the REF scenario, i.e. the abatement costs are higher and the abatement structure is different. Nuclear power plants only reach their highest market share at £68/t $CO_2$, which is £53/t $CO_2$ more compared with the REF scenario. Moreover, this abatement technology abates about 9 Mt $CO_2$ more in the ZERO-AFTER scenario. Similarly, natural gas CHP plants are a viable mitigation option in the electricity sector for a wider tax range. This plant type is completely displaced from £186/t $CO_2$ upwards, which is £40/t $CO_2$ more than in the REF case.

**Figure 6.10: MAC curve for the ZERO-AFTER scenario in 2030**

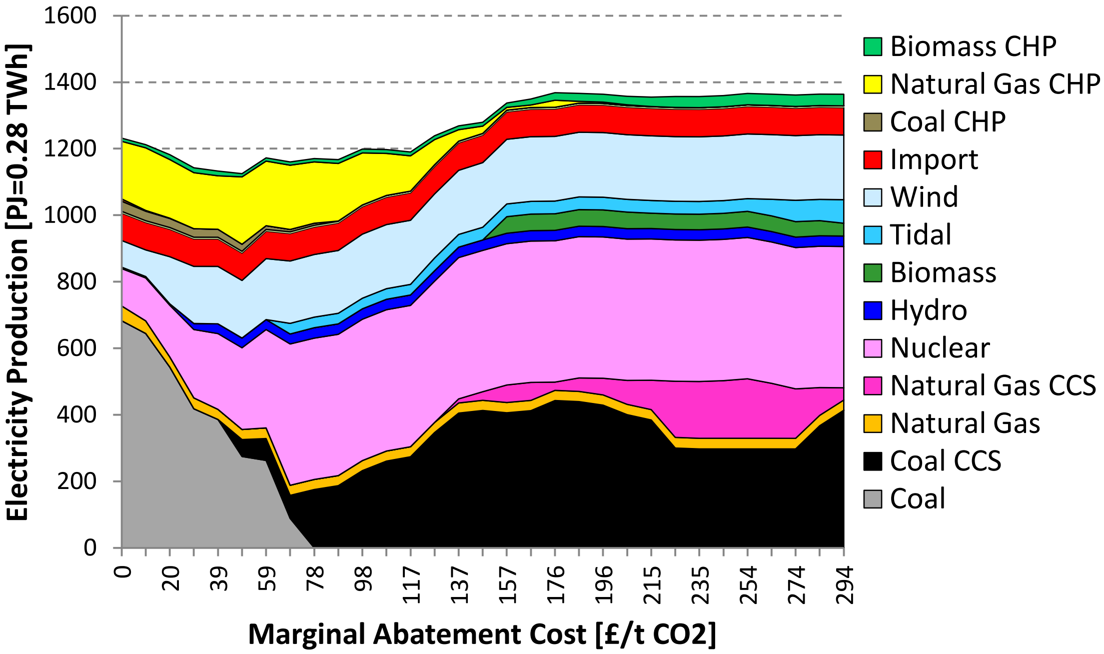



In addition, demand reduction plays a much more important role in this scenario. At £117/t $CO_2$ electricity demand is 145 PJ (40 TWh) less in the ZERO-AFTER scenario, which corresponds to 10% of total demand. This shows that demand reduction is an important abatement measure as demand is flexible and can be adapted to situations in future years where no carbon policies are pursued. Similar to the CONST-AFTER scenario, natural gas CCS becomes cost-effective for a specific tax window (£137/t $CO_2$ - £294/t $CO_2$).

In this tax window, coal CCS power plants that are not able to co-fire biomass are replaced by natural gas CCS power plants. Investments in gas CCS are only made when the model foresees $CO_2$ tax levels staying constant or decreasing because otherwise it would not be competitive in later years with coal CCS plants that co-fire biomass. This shift saves about 43% $CO_2$ as natural gas has a lower emission coefficient of 65 g/kWh compared with 115 g/kWh for coal CCS plants. The shift is illustrated in Figure 6.11.

Renewable energy sources with comparably high electricity generation costs, such as wind and tidal power, are not introduced to the market to the same extent as in the REF scenario. The reason is that these technologies are no longer competitive once there is no carbon tax after 2030. Lastly, one can see that biomass co-firing to CCS plants only plays a minor role. This can be explained with the fact that once CCS plants become cost-effective, they already co-fire biomass to the maximum extent so that the abatement potential is attributed to a structural shift towards coal CCS plants.

**Figure 6.11: Electricity generation mix for different marginal abatement costs in 2030 (ZERO-AFTER scenario)**




In conclusion, one can summarise that in this scenario the model chooses measures, such as demand reduction, efficiency gains in coal power plants, natural gas CHP, natural gas CCS and nuclear power, that can cut carbon emissions and have levelised generation costs that are close to the technologies chosen without a carbon policy.

### 6.3.3 Steep increase in $CO_2$ tax after 2030

In the INCR-AFTER scenario the $CO_2$ tax increases after 2030 by 10% annually, thus it increases with a rate that is twice as high as in the REF scenario. The shape of the MAC curve looks very similar to the REF scenario as Figure 6.8 reveals. Since the $CO_2$ tax is higher in the years after 2030, there should be an additional incentive for the model to choose low carbon technologies in 2030 in order to anticipate the additional future penalty for emitting $CO_2$.

Accordingly, coal CCS is introduced at a £13/t $CO_2$ less compared with the REF scenario. Tidal power reaches its maximum share at £10/t $CO_2$ less and nuclear at £5/t

$CO_2$ less. Apart from these minimal deviations, however, the overall abatement technologies and their contribution towards emissions reduction looks very similar. The steep increase of the $CO_2$ tax of 10% p.a. after 2030, therefore, does not present a big, additional incentive to invest in low carbon technologies already in 2030 compared to the REF scenario.

### 6.3.4 Zero $CO_2$ tax Before 2030

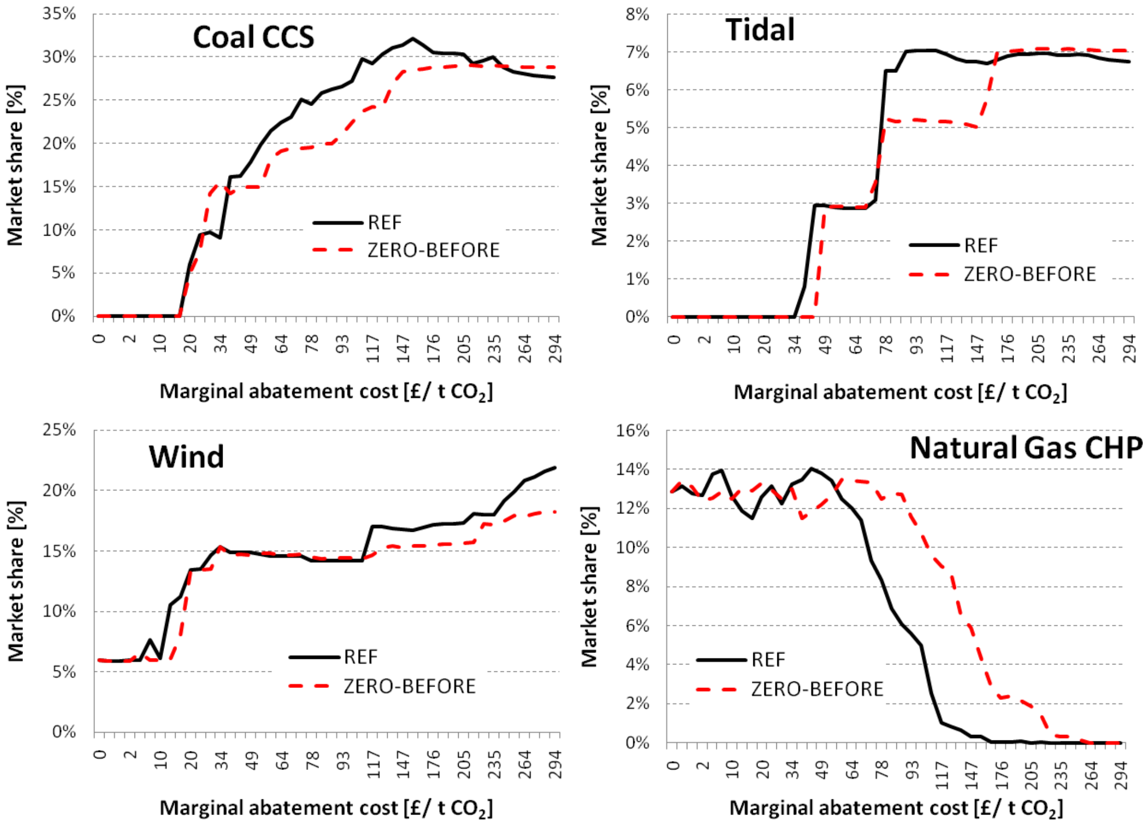
In contrast to the REF scenario, there is no $CO_2$ tax before 2030 in the ZERO-BEFORE scenario that means there exists no incentive to shift to any low-carbon technologies before 2030. As power plants have a lifetime of between 20 to 50 years, investments taken in 2010 or 2020 have consequence on the electricity mix throughout the whole first half of the 21$^{st}$ century.

The overall abatement potential of this scenario is the same as in the REF scenario, though an emissions target of 10 Mt $CO_2$ is achieved at a tax level of £135/t $CO_2$, while this is realised at a tax level of £90/t $CO_2$ in the REF scenario. This deviation can be explained with investment decisions in the time prior to 2030 that are influenced by the absence of any climate policy. Therefore, low-carbon technologies are more gradually introduced into the market as Figure 6.12 shows. The market share of coal CCS power plants in the ZERO-BEFORE scenario stays, with a few exceptions, constantly below the one in the REF scenario; the same is true for tidal power.

Wind power does not reach the same market share as in the REF scenario; they reach a maximum of 18% compared with 22% in the REF scenario. This is due to investments into less promising wind turbine sites not being realised in previous periods. This lack of investments cannot be overcome very rapidly due to yearly build constraints. As low–carbon technologies are introduced at higher tax levels, natural gas CHP plants have a bigger role as a transition technology towards a decarbonised electricity sector.

In summary, the fact that there is no $CO_2$ tax prior to 2030 represents a disincentive for the investment in low-carbon technologies so that the investment level is slightly lower in comparison to the REF scenario despite a high $CO_2$ tax in 2030 and in the following years.

**Figure 6.12: Market share for different technologies in the ZERO-BEFORE scenario in 2030**




### 6.3.5 High $CO_2$ tax from 2015

The HIGH-BEFORE scenario assumes that the $CO_2$ tax stays on a constant level from 2015 to 2030, which is the same as the $CO_2$ tax in the REF scenario in 2030, i.e. it no longer increases with the discount rate during that period but jumps in 2015 directly to the level in 2030. This means that for the period from 2015 to 2025 the $CO_2$ tax is higher than in the REF scenario and should present an additional incentive to decarbonise the energy system.

The shape of the emission curve (see Figure 6.8) looks very similar to the REF scenario. Only in a tax range from £30/t $CO_2$ to £100/t $CO_2$ is the difference in emissions reduction is noteworthy, which is 8 Mt $CO_2$ higher in the HIGH-BEFORE scenario. The overall abatement is also almost the same as in the REF scenario. A closer look at the individual abatement options reveals that this difference is mainly due to the more aggressive introduction of coal CCS power plants. The market share of coal CCS attains 31% at a tax level of £78/t $CO_2$, which is about £50/t $CO_2$ less than in the REF scenario. The economics of the other low-carbon technologies remain mainly unaffected by the higher tax level prior to 2030. Consequently, a high $CO_2$ tax from 2015 to 2030 does not alter the overall MAC curve substantially, but does accelerate the introduction of coal CCS plants.

## 6.4 Discount rate

Discount rates play an important role in determining future marginal abatement costs as they determine how future cash flows are weighted with regard to present cash flows. The higher the discount rate, the more weight is put on costs and financial gains that occur early in the project phase, relative to those incurred later. Those technologies where a large proportion of investment costs occur at the start of a project, but the benefits accrue over time, will be more economic the lower the discount rate.

In general, the research literature distinguishes between social and private discount rates. A social discount rate is used to determine whether an investment or policy is beneficial from society's perspective, i.e. whether it represents a good use of society's resources. All taxes and subsidies (except for the carbon tax necessary to generate the MAC curve) are excluded from this analysis as they are only transfers between groups in society. The discount rate is around the 3.5% rate the UK Government (HM Treasury, 2003) uses, which is based on a social time preference rate that is the sum of a rate at which future consumption is valued over present consumption and a factor accounting for changes in per capita consumption. The social discount rate is applied based on the assumption that governments can borrow at that rate if they want to incentivise capital-intensive abatement opportunities. The SDR scenario assumes such a social discount rate.

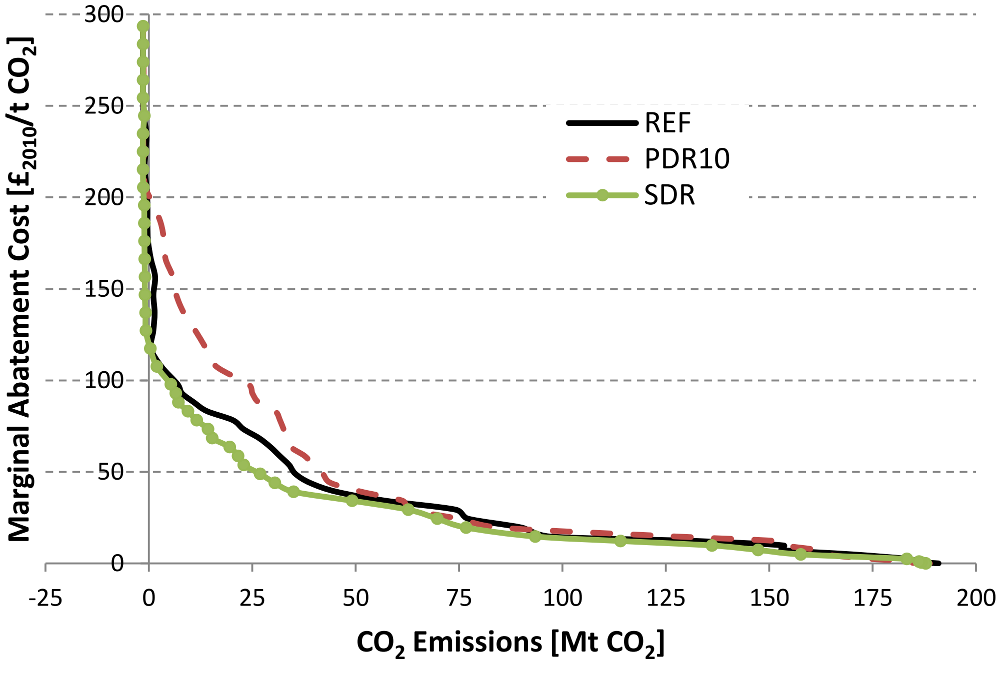
The application of a social discount rate can help to answer the question: "what should happen from a society's perspective on a least cost path?"; however, to understand what is likely to happen in reality, a private cost-benefit analysis has to be applied.

Cost calculations from a private perspective differ from society's view, not only in the discount rate applied, which must reflect the private cost of capital, but also in that taxes and subsidies are included. Moreover, project risks are specific to the investor, and will, from the investor's perspective, not be averaged out across the economy. Consequently, the investor will require a higher rate of return to justify proceeding, which is represented in the form of technology-specific hurdle rates in the UK MARKAL model. In general, individuals and companies additionally face several uncertainties.

Observed discount rates can be relatively high and differ from company to company. In their study on the costs of decarbonising electricity, the CCC (2008) gives an overview of four studies that use real discount rates for the power sector. All of the discount rates are in the range of 10-12%. The PDR10 scenario represents the perspective of a private investor, where all existing hurdle rates were doubled and a 10% hurdle rate was introduced for all technologies in the whole energy system in the case that no hurdle rate was defined. The general discount rate remains at 5%.

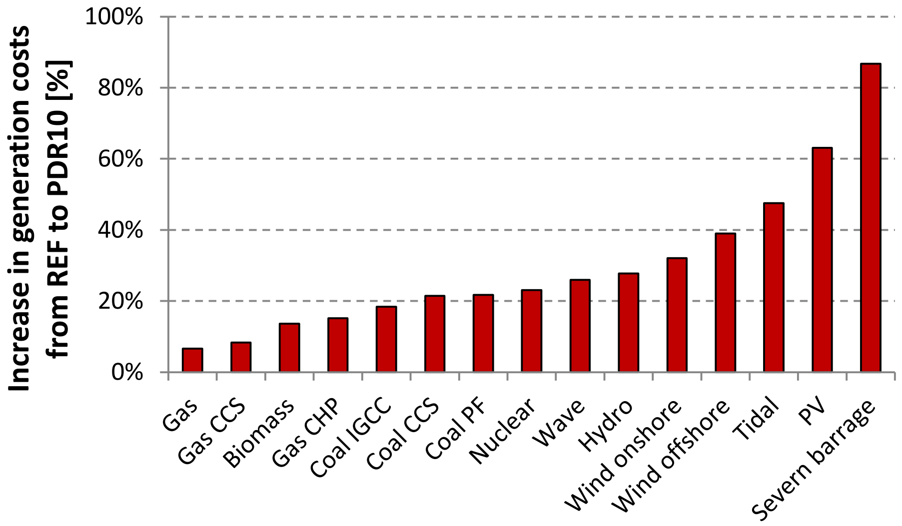
Figure 6.13 indicates that the emission curves are similar for the SDR and the REF scenario, while the emissions in the PDR10 scenario are, as expected, higher. Emissions are more slowly decreased with higher $CO_2$ taxes owing to the higher discount rate that makes low-carbon technologies less attractive. The SDR scenario shows slightly lower emissions in the case without a $CO_2$ tax due to a higher share of renewables in the electricity mix. From around £170/t $CO_2$ all three curves look very similar as the electricity system is widely decarbonised at that tax level.

**Figure 6.13: Emission curve along rising $CO_2$ abatement costs for different discount rate scenarios in 2030**



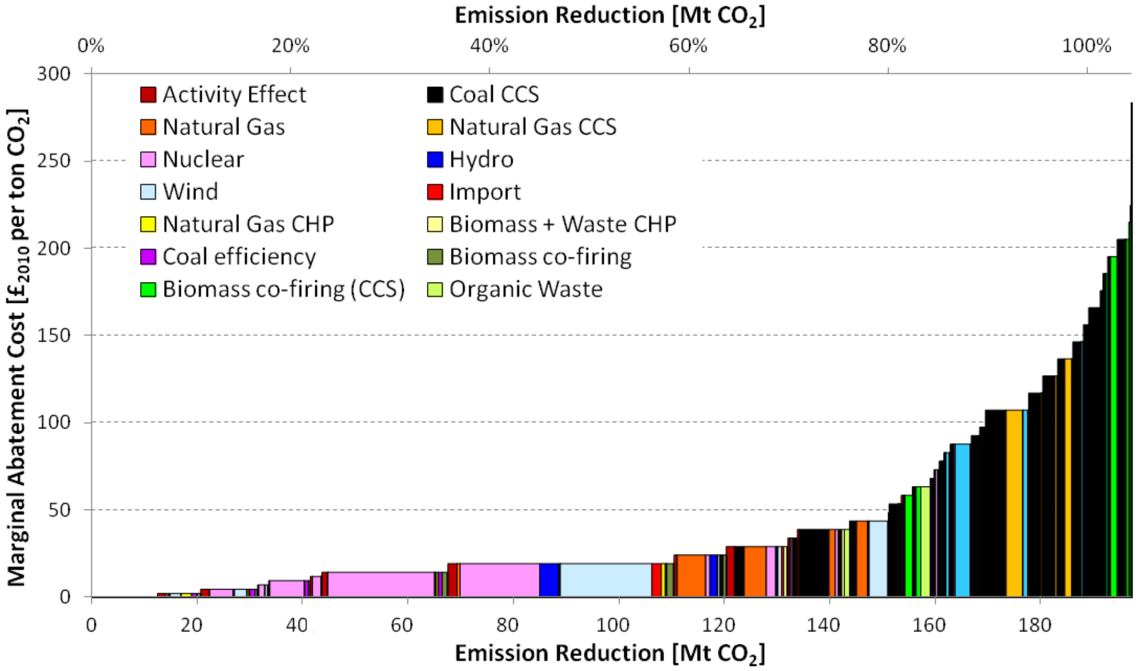

Different electricity generation technologies are affected in different ways by the doubling of the discount rate (see Figure 6.14). The generation costs in the UK MARKAL model are formed of annualised investment costs, variable operating costs, fixed operating costs, fuel costs and in the case of CCS technologies the costs for the capture, transport and storage of $CO_2$. Out of the different cost components only annualised investment costs are affected by the discount rate change. Consequently, technologies, whose generating costs are dominated by investment costs, will see their generation costs increase substantially when the discount rates is doubled. As fuel costs are responsible for a big part of the electricity generation costs in gas-fired and biomass-fired power plants, the generation costs increase only up to 15% in UK MARKAL with a change in the discount rate from 5% to 10%. Coal and nuclear plants are in a range from 18-23%, while renewable energy sources are most influenced by a higher discount rates. In summary, a higher discount rate substantially increases the generation costs of renewables, while gas- and biomass-based generation types are least affected by an increase.

**Figure 6.14: Increase in levelised electricity generation costs from the REF (5% discount rate) to the PDR 10 scenario (10% discount rate) in UK MARKAL in 2030**




The MAC curve for the PDR10 scenario (Figure 6.15), where the discount rate and the hurdle rates were increased by 100%, shows that emission abatement is more expensive than in the REF scenario. Demand reduction plays a more important role in the PDR10 scenario, where emissions reduction due to less demand is three times bigger than in the REF scenario. This is due to a higher electricity price but higher discount rates also make low-carbon, electricity-consuming end-use technologies more expensive.

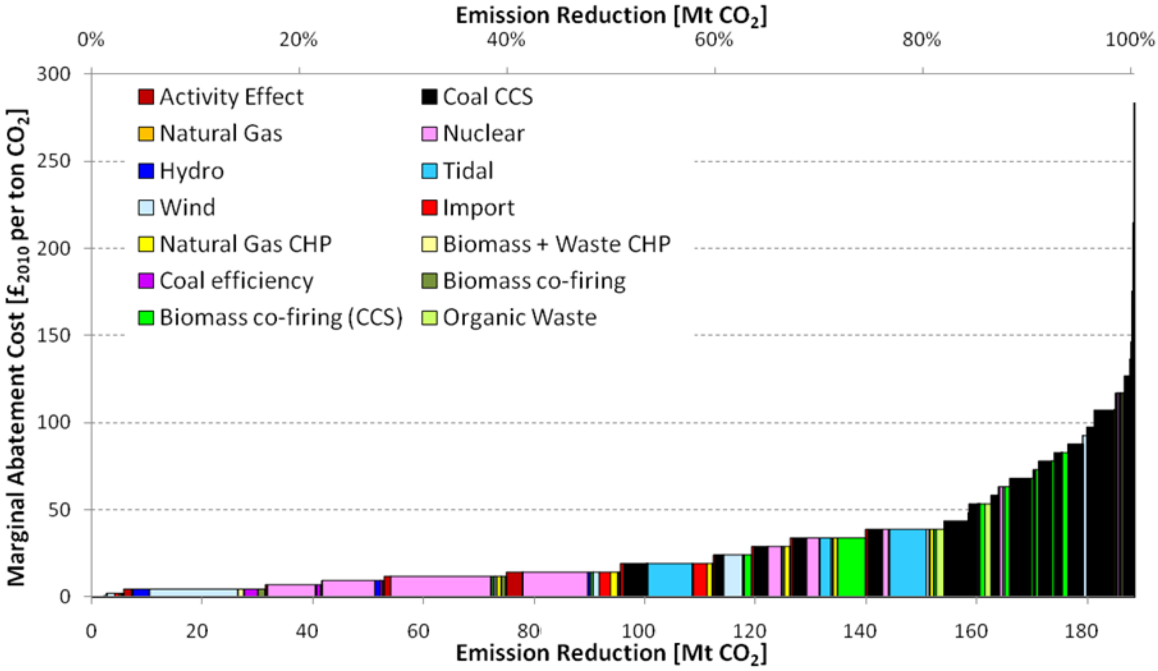
**Figure 6.15: MAC curve for the PDR10 scenario in 2030**




A further difference is that gas-fired power plants profit from the low proportion of capital cost in the levelised costs. The share of natural gas CHP plants increases up to £58/t $CO_2$. In a small tax window from £97/t $CO_2$ to £156/t $CO_2$ natural gas CCS power plants become cost-optimal by replacing a portion of conventional gas power plants and attain a market share of 5%. However, at higher tax levels they are again replaced by coal CCS power plants that can co-fire biomass. Finally, wind power requires slightly higher tax levels in order to achieve the same market share as in the REF scenario and emissions reduction from tidal power is significantly less as electricity generation costs increase by almost 90%.

The MAC curve for the SDR scenario (Figure 6.16) shows a slightly higher abatement level for the same carbon tax, explained by the lower generation costs due to the lower discount rate. Similar to the PDR10 scenario, coal CCS does not abate the same amount of $CO_2$ emissions as in the REF scenario because it is more gradually introduced so that the reference electricity generation mix is already less carbon-intensive. In contrast to that, tidal power abates almost twice as much $CO_2$ in the SDR scenario compared with the REF scenario explaining much of the difference between the two scenarios. As the generation cost of tidal power depends very much on the applied discount rate, the reduced discount rate makes tidal power more cost-effective. Similarly wind power attains the same market share as in the REF scenario at about £20/t $CO_2$ less.

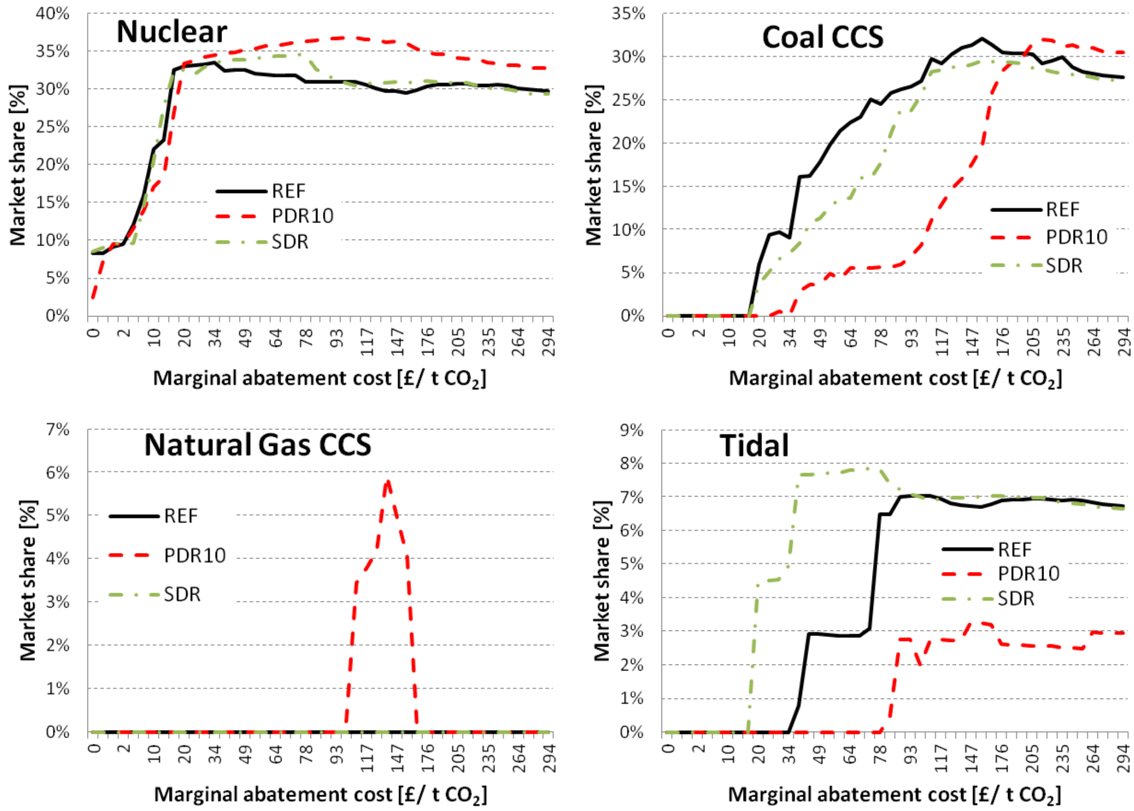
**Figure 6.16: MAC curve for the SDR scenario in 2030**




Concerning the overall contribution to emissions reduction, demand reduction plays a more important role in the PDR10 scenario with 11 Mt $CO_2$ compared to 4 Mt $CO_2$ in the REF scenario. Reasons are higher electricity prices and higher investment costs for low-carbon technologies, such as electric cars and electric heat pumps, in the end-use sectors. The share of nuclear power remains fairly constant, while the share of coal CCS in the discount rate scenarios between £20/t $CO_2$ and £150/t $CO_2$ remains below the REF scenario. This can be explained with an earlier introduction of wind and tidal power in the SDR scenario and the temporary introduction of natural gas CCS in the PDR10 scenario (see Figure 6.17).

In conclusion, the impact of changes to the discount rate is rather moderate in the electricity sector due to the fact that annualised investment costs do not make up a significant share of generation costs for key low-carbon technologies in UK MARKAL, such as coal CCS and nuclear. Further, in the higher discount rate scenario (PDR10), natural gas is used as a transition fuel and helps to mitigate emissions in the lower third of the MAC curve.

**Figure 6.17: Market share for different technologies in the discount rate scenarios in 2030**




## 6.5 Fossil fuel prices

Previous studies came to the conclusion that fossil fuel prices have a large impact on the shape of a MAC curve (see 2.4). Therefore, this subsection addresses the effect of fossil fuel prices by analysing three different fossil fuel price scenarios.

In the UK MARKAL model the fossil fuel price is mainly determined by the resource cost, which is an external input into the model. This input represents the production costs (including finding, development and direct lifting costs) and the transport costs. Other possible influencing factors on fossil fuel prices such as temporal availability, risk premium and speculation are not included in the model, but can be considered by varying the assumptions on the import price.

In contrast to the standard version of UK MARKAL, which employs stepped supply curves, the version used for this thesis assumes a single resource cost for crude oil, natural gas, hard coal, and coking coal respectively. It is assumed that a possible low-carbon strategy of the United Kingdom has no significant influence on global fossil fuel prices so that different cost steps are omitted. Normally, one would assume the UK to pursue a low-carbon strategy together with other countries, so that the demand for fossil fuels will be reduced resulting in lower prices. This was not implemented in UK MARKAL due to two aspects. Firstly, a lower fuel price would trigger non-compliant countries to consume more fossil fuels, limiting the price effect. Secondly, a cost step representation together with import shares leads to distortionary modelling effects in UK MARKAL in the form of negative shadow prices.

The development of fossil fuel prices can be found in Table 6.3, which is based on DECC's fossil fuel price assumption from 2008. To test the sensitivity of the MAC curve with respect to different fossil fuel prices, the prices were doubled in the FF+ scenario and tripled in the FF++ scenario, while the gas price was halved in the GAS scenario.

**Table 6.3: Fossil fuel prices in different scenarios**

| Scenario | Fuel | Unit | 2010 | 2015 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| | Oil | $£_{2010}$/GJ | 7.3 | 5.8 | 6.2 | 6.7 | 7.2 | 7.2 |
| **REF** | Gas | $£_{2010}$/GJ | 4.5 | 4.9 | 4.6 | 5.1 | 5.5 | 5.4 |
| | Coal | $£_{2010}$/GJ | 2.8 | 1.9 | 2.3 | 2.6 | 2.9 | 2.8 |
| | Oil | $£_{2010}$/GJ | 7.3 | 5.8 | 6.2 | 6.7 | 7.2 | 7.2 |
| **GAS** | Gas | $£_{2010}$/GJ | 4.5 | 2.5 | 2.3 | 2.6 | 2.7 | 2.7 |
| | Coal | $£_{2010}$/GJ | 2.8 | 1.9 | 2.3 | 2.6 | 2.9 | 2.8 |
| | Oil | $£_{2010}$/GJ | 7.3 | 11.6 | 12.3 | 13.4 | 14.4 | 14.4 |
| **FF+** | Gas | $£_{2010}$/GJ | 4.5 | 9.9 | 9.3 | 10.3 | 10.9 | 10.9 |
| | Coal | $£_{2010}$/GJ | 2.8 | 3.9 | 4.5 | 5.1 | 5.7 | 5.6 |
| | Oil | $£_{2010}$/GJ | 7.3 | 17.5 | 18.5 | 20.1 | 21.6 | 21.6 |
| **FF++** | Gas | $£_{2010}$/GJ | 4.5 | 14.8 | 13.9 | 15.4 | 16.4 | 16.3 |
| | Coal | $£_{2010}$/GJ | 2.8 | 5.8 | 6.8 | 7.7 | 8.6 | 8.4 |

The three fossil fuels are affected in a different way by rising $CO_2$ tax levels as they do not emit the same amount of carbon dioxide for the same unit of energy used. Table 6.4 shows how the prices for coal, oil and gas increase with a rising $CO_2$ tax.

**Table 6.4: Increase in fossil fuel prices over price in 2010 for a given $CO_2$ tax**

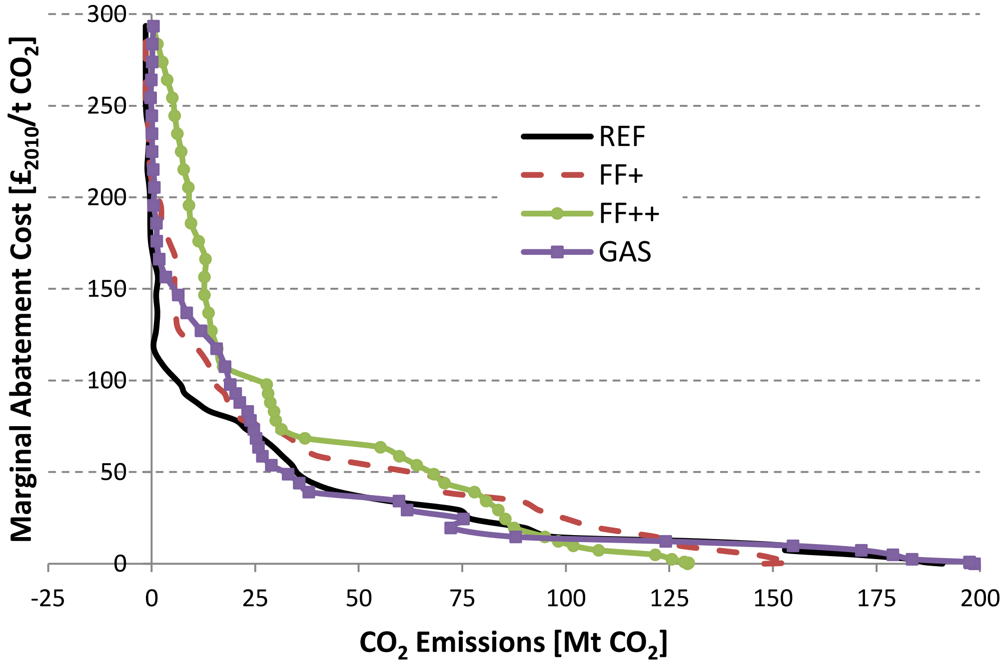
| $CO_2$ tax [£/t $CO_2$] | Hard Coal [%] | Crude Oil [%] | Natural Gas [%] |
|---|---|---|---|
| **£100** | 322% | 105% | 113% |
| **£200** | 644% | 210% | 227% |
| **£300** | 965% | 315% | 341% |

The emission curve for the different fossil fuel price scenarios are shown in Figure 6.18. The emission curves start at different baseline levels, while emissions in the REF scenario are 191 Mt $CO_2$, they are 148 Mt $CO_2$ in the FF+ scenario, 129 Mt $CO_2$ in the

FF++ scenario and 199 Mt $CO_2$ in the GAS scenario. Reasons are that more gas is used in the GAS scenario and that significantly less coal is used in the FF+ and FF++ scenarios. At a tax level of £25/t $CO_2$ emissions levels are much more aligned with each other, while there still exist differences in particular up to £75/t $CO_2$. At a tax rate of £70/t $CO_2$, the official UK central carbon price projection for 2030, the power sector would be decarbonised by between 71% and 87% compared with the baseline in 2030.

While the GAS scenario is very close to the REF scenario, the higher fossil fuel price scenarios show less abatement for an equivalent tax level. At higher $CO_2$ taxes, the emission curves look very similar, which can be explained with the increasing contribution of the $CO_2$ tax towards the total price of coal, oil and gas, which overshadows the original difference in fuel prices.

**Figure 6.18: Emission curve along rising $CO_2$ abatement costs for fossil fuel price scenarios in 2030**

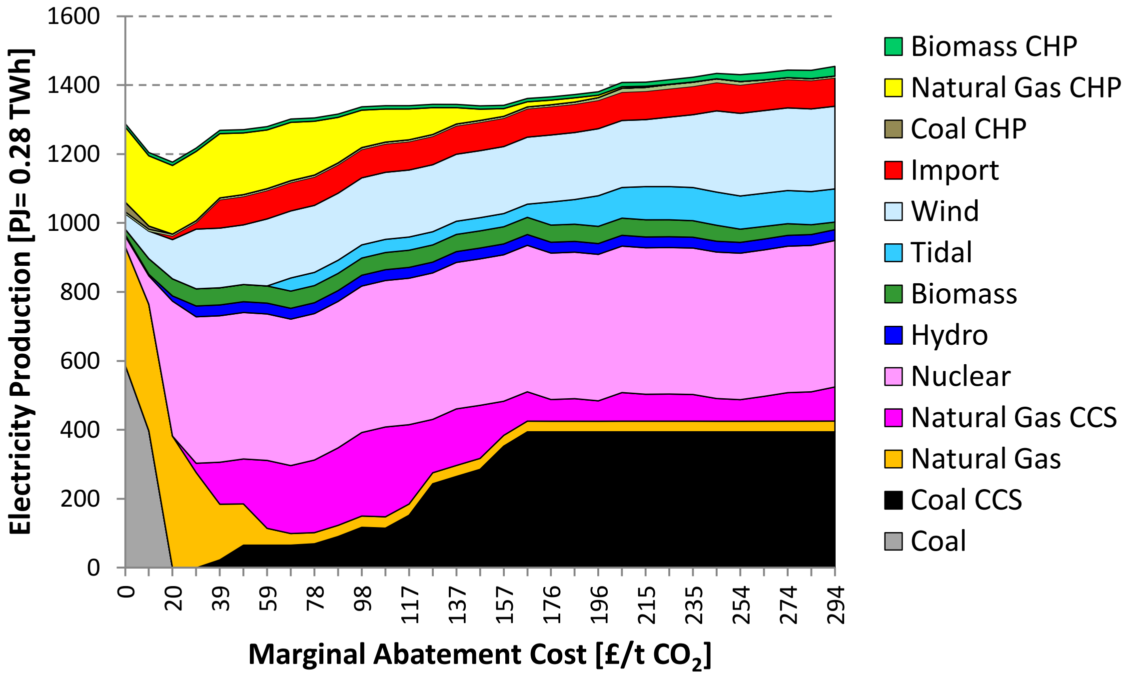



### 6.5.1 Low gas prices

This scenario assumes a gas price that will drop from current levels of £4.5/GJ to £2.5/GJ in 2015 and then stay roughly constant. In comparison to the REF scenario the price for natural gas is reduced by 50%. This is a situation observed since 2009 for Henry Hub natural gas in the United States where the gas price is below 40% of the oil price in energy equivalent terms. Such a low natural gas price could be explained by the significant and unexpected increase in the supply of unconventional gas, in particular shale gas, leading to a decoupling of gas and oil prices in the long-run.

Figure 6.18 revealed that the emissions in the power sector are about 8 Mt $CO_2$ higher without any $CO_2$ tax in the GAS scenario compared with the REF scenario. This can be explained with a higher share of gas at the expense of wind power and electricity import. The emission curves look very similar over all tax levels except for the range between £75/t $CO_2$ and £150/t $CO_2$, where emissions in the GAS scenario are a maximum 15 Mt $CO_2$ higher for the same tax level. A reason is the higher share of natural gas in the power sector (see Figure 6.19), while emissions are lower in return in the residential sector and industry. Overall, the MAC curves in both cases look very similar and are thus robust to lower gas prices.

**Figure 6.19: Electricity generation mix for different marginal abatement costs in 2030 (GAS scenario)**



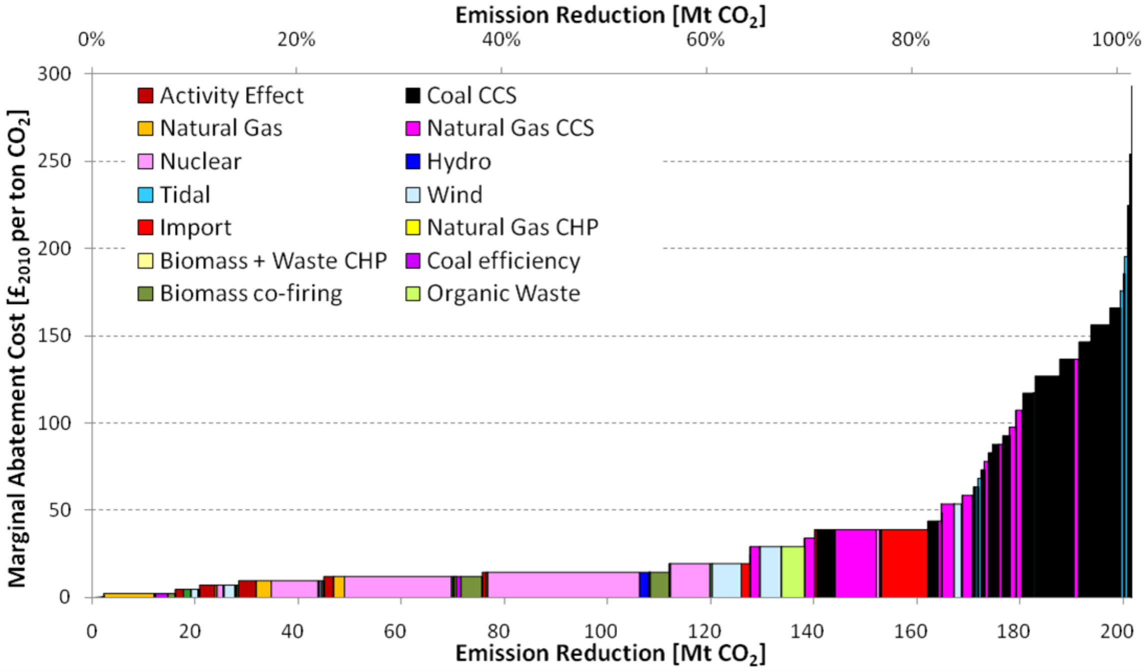

Before turning towards the MAC curve of the GAS scenario, it is interesting to examine the electricity mix at different tax levels. One can see that the baseline electricity mix is no longer dominated by coal as in the REF scenario. The share of gas-fired power plants in electricity production increases from 17% to 25%. Combined-cycle gas turbines remain an important part of the electricity mix up to £59/t $CO_2$ and natural gas CHP plants up to £157/t $CO_2$. Coal CCS plants only become cost-effective from £39/t $CO_2$, i.e. £20/t $CO_2$ more than in the REF scenario.

Gas-fired power stations with CCS enter the electricity mix at £29/t $CO_2$, while this plant type does not become cost-effective in the REF scenario. Electricity production from gas CCS plants is highest at £107/t $CO_2$ with 261 PJ (72 TWh). This carbon tax is far from the carbon tax of £70/t $CO_2$ calculated by the Government (DECC 2009) to be necessary in order to achieve an overall 80% emission cut in 2050. The levelised generation cost of coal and gas CCS plants are very similar in the REF scenario with a difference of only 0.15 p/kWh. When the gas price is halved, levelised electricity costs are 1.5 p/kWh lower for gas CCS plants so that they become cost-effective in the GAS scenario. They are replaced by coal CCS plants at higher tax levels because coal CCS plants can achieve negative emissions via biomass co-firing. Biogas is not co-fired to gas CCS plants due to the initial lack of infrastructure, limited resource potential and higher processing costs than for biomass.

Given lower gas prices, natural gas can play a significant role as a transition fuel in a decarbonisation strategy of the UK power sector in a specific tax and time window in the form of natural gas CHP plants and particularly natural gas CCS plants. At a $CO_2$ tax of £108/t $CO_2$ a maximum of 18 GW of natural gas CCS power plants are built from 2023 to 2032, while the first CCS plants are retrofitted in 2020. After this period gas CCS plants are no longer competitive with coal CCS plants and nuclear power.

The MAC curve for the GAS scenario (Figure 6.20) shows a similar uptake of nuclear power as in the REF scenario. The contribution of coal CCS plants is significantly less as gas CCS plants become an important abatement measure and coal CCS power plants with biomass co-firing account at higher tax level only for the uncaptured emissions from gas CCS plants. In addition, the weighted average abatement costs for coal CCS plants are £42/t $CO_2$ more than in the REF scenario. Biomass co-firing is not part of the MAC curve because this option is only shown when the share of biomass as an input fuel in coal CCS plants increases. When coal CCS plants become cost-effective in this scenario, they are already co-fired with the maximum amount of biomass and therefore the emissions mitigation is attributed to ‘Coal CCS’. Wind power plays a smaller role in reducing $CO_2$ emissions, while the average abatement cost remains constant.

**Figure 6.20: MAC curve in the GAS scenario in 2030**




Natural gas CCS reduces $CO_2$ emissions by 24 Mt $CO_2$ or 12% at a cost range between £29/t $CO_2$ and £137/t $CO_2$ with a weighted average of £56/t $CO_2$. Furthermore, a switch from coal-based to gas-based electricity production proves to be one of the most cost-effective mitigation options up to £20/t $CO_2$. A switch to natural gas saves in total 12 Mt $CO_2$ or 6%.

In summary, one can say that the shape of the MAC curve in the GAS scenario is robust to lower gas prices from £20/t $CO_2$ upwards with small deviations around a tax level of £100/t $CO_2$ due to intersectoral interactions. Concerning the abatement structure, a lower gas price induces investments in natural gas CCS plants that make coal CCS plants more expensive.

### 6.5.2 High fossil fuel prices

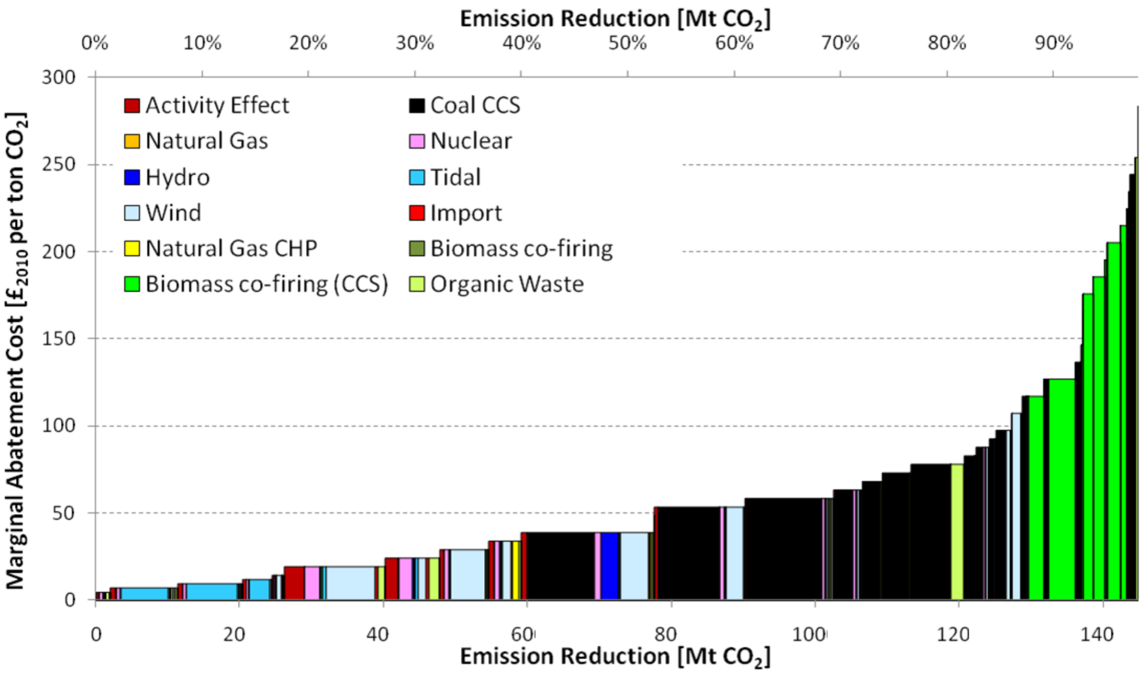
The FF+ scenario differs from the REF scenario in the way that the price for hard coal, coking coal, natural gas, crude oil and refined products were increased by 100% from 2015 onwards. This corresponds to a scenario where global fossil fuel prices increase, for example, due to a significant demand increase from Asian countries or due to the absence of sufficient investments that limit the supply of energy carriers.

Emissions without a carbon tax are 148 Mt $CO_2$ in the FF+ scenario, i.e. 43 Mt $CO_2$ less than in the REF scenario. This is caused by a lower share of coal in the electricity mix and natural gas CHP plants that are completely replaced by nuclear power plants (28%

generation share), wind power (13% generation share), tidal power (3% generation share) and hydro power (2% generation share). As low-carbon alternatives have already been integrated in this scenario without a carbon tax, the electricity sector decarbonises slower with increasing tax levels compared with the REF scenario. Both curves intersect at £13/t $CO_2$ from where on emission abatement in the FF+ scenario is associated with slightly higher costs. This is due to the fact that an important abatement option, coal CCS plants, becomes more expensive due to higher fuel costs. In addition, wind power, nuclear power and CCS plants are constrained by build rate limits. From a tax level of £50/t $CO_2$, which is expected to be at the lower end of what is needed to achieve the legally required emission cuts, the emission curve for the REF and FF+ scenario diverge by a maximum of 11 Mt $CO_2$.

Figure 6.21 illustrates the MAC curve for the FF+ scenario. The curve looks very different from the REF scenario as it only covers 149 Mt of $CO_2$ emissions reduction due to significant emissions savings already in the baseline development. Nuclear power does not play a significant role in the MAC curve with only 9% due to the fact that a significant share of electricity production comes from nuclear power plants at £0/t $CO_2$.

**Figure 6.21: MAC curve in the FF+ scenario in 2030**




The relative contribution of coal CCS as a mitigation option is significantly higher with 33%, but also the absolute emissions reduction is higher at 47 Mt $CO_2$. Due to the higher coal prices the weighted average abatement cost of coal CCS plants increases to £71/t $CO_2$ (£8/t $CO_2$ higher than in the REF scenario). Co-firing of biomass into coal

CCS plants is substantially more expensive with a weighted average abatement cost of £160/t $CO_2$. This can be explained with the higher costs for coal CCS, but also with the same limited amount of biomass being used at lower carbon tax rates in competing biomass power and CHP plants. The high fossil fuel prices decrease the marginal abatement cost of wind power, which makes up a significant share of the electricity mix in the baseline development, while abatement cost of tidal power come down to a weighted average of £11/t $CO_2$. Lastly, a higher reduction in the demand for electricity caused by higher prices leads to a higher share of demand-related emissions savings of 9% (14 Mt $CO_2$).

Summing up, higher fossil fuel prices shift the start point of the MAC curve and lead to a slower decarbonisation of the electricity sector due to higher cost for electricity from coal CCS plants. Marginal abatement costs of renewable energy sources, such as wind and tidal power, are significantly lower due to the higher fossil fuel prices. Overall, both MAC curves, once accounted for baseline differences, look very similar, which holds especially true for the range of likely carbon tax levels in 2030.

### 6.5.3 Very high fossil fuel prices

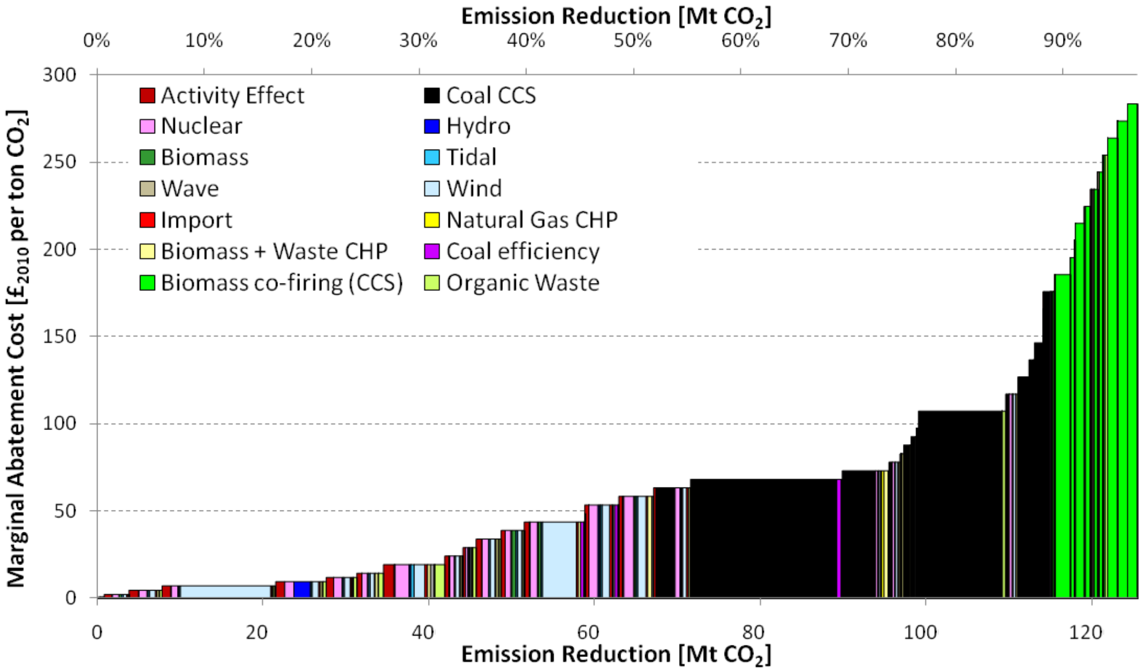
In the FF++ scenario all fossil fuel prices are increased by 200% compared to the REF scenario. Such a substantial price increase could be explained with supply shocks comparably to those in the 1970s. This scenario assumes extremely high fossil fuel prices with oil prices being above $\$_{2010}$ 220 per barrel for decades. Hence it is all the more interesting to see how robust the MAC curve reacts to such extreme assumptions.

Emissions without a carbon tax are 62 Mt $CO_2$ lower compared with the REF scenario and 19 Mt $CO_2$ lower than in the FF+ scenario. This can be explained with an even lower share of coal in the electricity mix of only 20%. The reduced electricity production from coal is made up by biomass power and CHP plants, tidal power and wind power with a market share of 12%, 6%, and 17% respectively. Since many abatement options are already implemented without a carbon tax, further decarbonisation of the power sector requires, similar to the FF+ scenario, higher marginal abatement costs than the REF scenario. For a given carbon tax, carbon abatement remains less in the FF++ scenario compared with the REF scenario from £24/t $CO_2$ upwards with a maximum difference of 30 Mt $CO_2$ for the same carbon tax. This difference is reduced to 16 Mt $CO_2$ for a range of more likely carbon tax levels in

2030 of £50/t $CO_2$ to £150/t $CO_2$. Thus, even a substantial threefold increase of fossil fuel prices changes the emissions level for a given carbon tax by a maximum of 30 Mt $CO_2$ or by 16% in relation to baseline emissions.

As many low-carbon technologies are part of the baseline development, the MAC curve in the FF++ scenario (see Figure 6.22) covers only 129 Mt $CO_2$ of emissions reduction and its structure looks very different. The abatement potential of nuclear power plants is more limited compared to the REF scenario. Nuclear power already makes up 29% of the electricity mix without a carbon tax. Caused by very high fuel prices, wind power is a substantial part of the baseline development, while the installation of further wind capacity contributes 20% or 26 Mt $CO_2$ to emissions abatement. Tidal power does not show up in the MAC curve as it is already a part of the electricity mix at the start of the MAC curve.

**Figure 6.22: MAC curve in the FF++ scenario in 2030**




The most important abatement measure are coal CCS power plants with 31%. Owing to the significantly higher coal price, the abatement costs for coal CCS are in a range from £64/t $CO_2$ to £176/t $CO_2$ with a weighted average of £87/t $CO_2$. This is significantly higher than in the REF scenario with the average being £24/t $CO_2$ higher. Consequently, a 200% increase in fossil fuel prices means that a threefold increase in the carbon tax would be necessary to make a first application of the coal CCS technology cost-effective. The co-firing of biomass is equally more expensive with a weighted average abatement cost of £234/t $CO_2$, more than three times more than in the REF scenario.

This can be explained with a significantly higher amount of biomass being used in biomass CHP plants and for heating purposes in the residential and service sector that have repercussions on the use of biomass as a co-firing fuel.

Lastly, it is interesting to note that wave power becomes cost-effective at £235/t $CO_2$. But as it represents only 3% of overall electricity production, the abatement potential remains rather limited with 0.5 Mt $CO_2$. With high fossil fuel prices, electricity prices are also higher compared with the REF scenario so that overall demand for electricity is lower and demand changes contribute 9% towards overall emissions reduction.

To summarise, the increase of fossil fuel prices has a significant effect on technology-specific MACs with tidal power and wind power having significantly lower marginal abatement costs. On the other hand, coal CCS with biomass co-firing becomes significantly more expensive as fuel prices triple. The shape of the MAC curve proves to be robust to an extreme increase in fuel prices, where the difference to the REF scenario in a range of likely carbon taxes for the year 2030 of £35/t $CO_2$ to £105/t $CO_2$ is on average 21 Mt $CO_2$, thus only 11% with respect to baseline emissions in the REF scenario.

## 6.6 Technology learning

As well as the influence of fuel prices, the influence of technology learning on mitigation costs has been studied several times in the past and is in the focus of this subsection. Table 6.2 presented the cost assumptions on key technologies in the electricity sector for the year 2030. These assumptions, in particular assumptions on investment costs, are subject to many uncertainties and therefore highly uncertain in itself. The first commercial application of the European Pressurised Reactor in Finland, was several years behind schedule and was 50% over the initially planned budget in 2009 (Kanter 2009). The uncertainties are even bigger for technologies that do not have commercial applications. That is why the IEP (Increased Electricity Price) scenario studies the consequences of a variation in investment cost assumptions. In this scenario the specific investment costs for all CCS technologies, biomass, nuclear, wind, tidal and wave technologies are increased by 200%. A comparison of specific investment costs in both scenario is given in Table 6.5.

**Table 6.5: Specific investment cost for power plants (REF, IEP= Increased Electricity Price)**

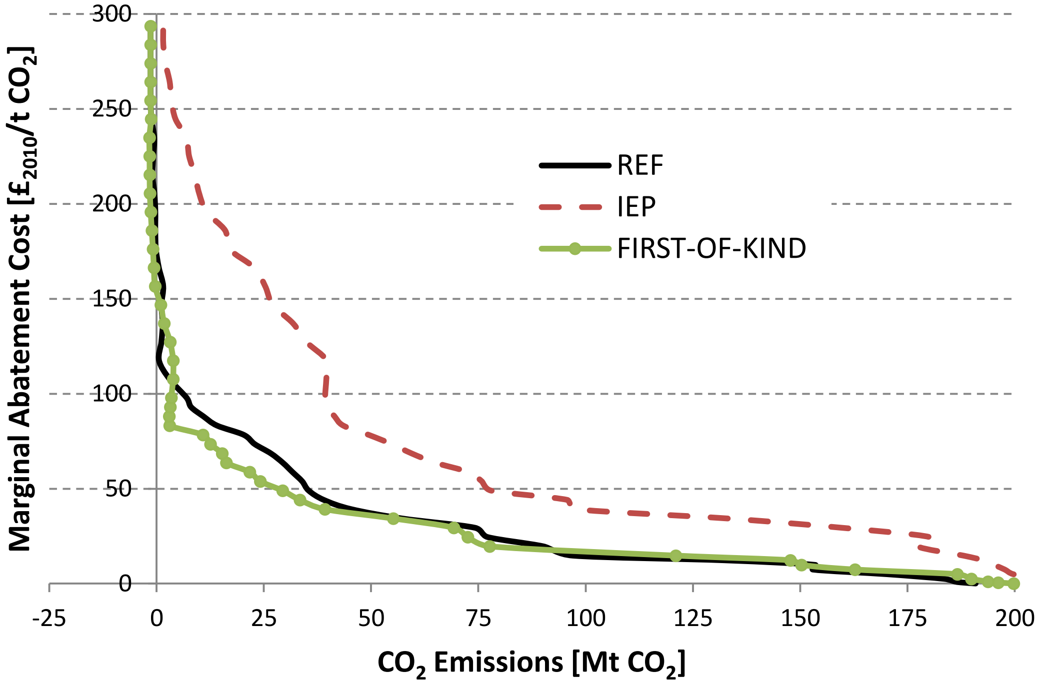
| **Technology** | **Specific investment cost [£$_{2000}$/kW]** | |
|---|---|---|
| | BASE | IEP |
| **Coal CCS** | 1,225 | 3,676 |
| **Gas CCS** | 652 | 1,955 |
| **Biomass CCS** | 2,940 | 8,820 |
| **Biomass** | 1,038 - 2,364 | 3,115 - 7,091 |
| **Nuclear** | 1,363 - 2,318 | 4,089 - 6,955 |
| **Wind Onshore** | 681 | 2,044 |
| **Wind Offshore** | 1,281 - 1,944 | 3,847 - 5,833 |
| **Tidal** | 1,887 - 1,947 | 5,662 - 5,841 |
| **Wave** | 2,553 - 3,933 | 7,659 - 11,799 |

Technological learning in this scenario is merely interpreted as changing exogenously given investment costs over time. This is certainly a crude way of dealing with technological learning as it does not consider endogenous technological learning (ETL) via learning curves. However, learning curves are considered to be inappropriate to use here because in a global context the UK's cumulative investment would be a poor indicator for technological learning.

The FIRST-OF-KIND scenario addresses ETL to a certain extent by requiring the model to invest in a more expensive 1$^{st}$ of a kind technology in early years in order to access a cheaper n$^{th}$ of a kind technology in later years. The reason behind this constraint is that specific technology costs can only be driven down if investment is carried out in a more expensive early version of that technology. This constraint has been implemented for all CCS and nuclear technologies: the model needs to invest in more expensive versions between 2013 and 2022 in order to be able to invest in cheaper versions from 2028 to 2050. For each unit of capacity in 2013-2022, the model can build four to six units in 2028-2050. A comparable ratio for the expansion of nuclear electrical capacity in the UK was below four in the second half of the 21$^{st}$ century.

The emissions curve for the IEP scenario (Figure 6.23) shows a higher baseline emission level, which is 19 Mt $CO_2$ above the REF scenario. This is due to a lower share of nuclear power plants and wind power as they become less competitive due to their increased investment costs. Over the whole tax range, the IEP cost curve is above the REF curve with a difference of about £15/t $CO_2$ for the same emission level at the beginning of the MAC curve, which increases up to £100/t $CO_2$ for lower emission targets. The emission curve for the FIRST-OF-KIND scenario looks very similar to the REF scenario from tax levels of £10/t $CO_2$, although the FIRST-OF-KIND curve indicates cheaper abatement despite an additional constraint on technology learning.

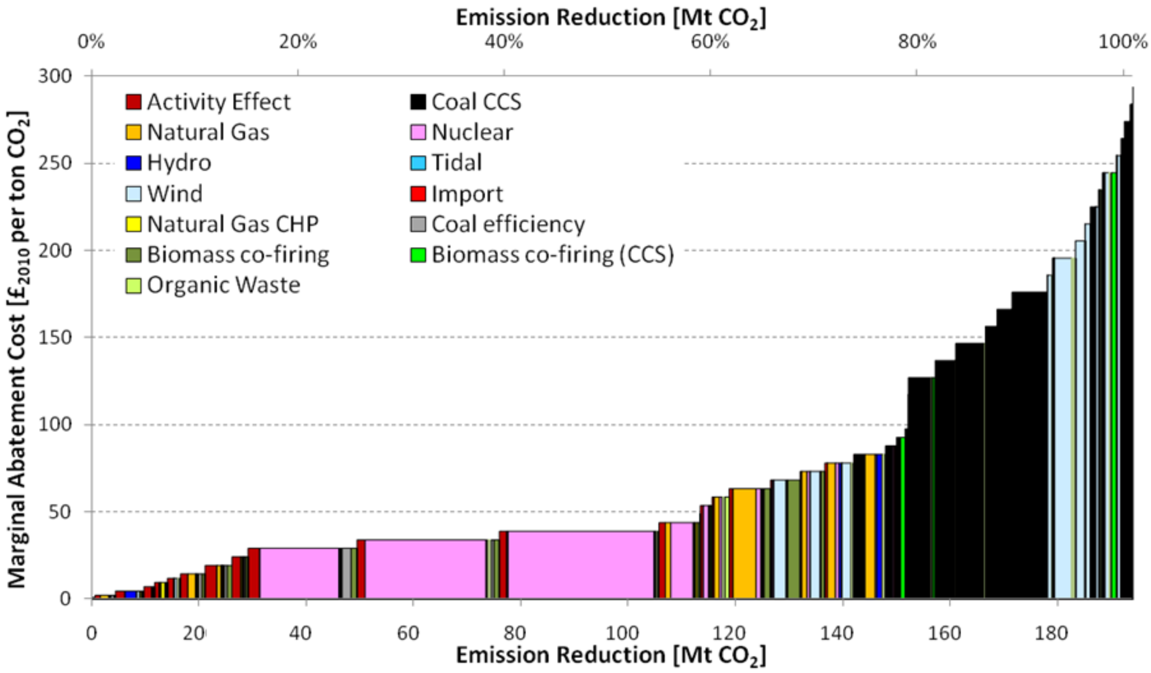
**Figure 6.23: Emission curve along rising $CO_2$ abatement costs for the IEP and FIRST-OF-KIND scenario in 2030**




This surprising finding can be explained with the perfect foresight characteristic of the model, which anticipates the need to invest early in nuclear and CCS technology in order to be able to invest in cheaper versions in later years. The consequence is that, compared to the REF scenario, investments in CCS and nuclear are significantly higher prior to 2030, which leads to lower emission for a given $CO_2$ tax level in the FIRST-OF-KIND scenario. However, the emission curve for the year 2030 does not represent the dynamic issues introduced by this constraint that makes abatement more expensive in later years. In 2050, the emissions level is on average 12 Mt $CO_2$ higher in the FIRST-OF-KIND scenario compared with the REF scenario for a given tax level.

The MAC curve for the IEP scenario (Figure 6.24) shows that the main low-carbon technologies, such as coal CCS, nuclear, and wind power, are significantly more expensive. This is well illustrated in Figure 6.26, which depicts the market share of four technologies in the electricity sector. Weighted MACs for nuclear power are £39/t $CO_2$, which is £27/t $CO_2$ above the value in the REF scenario. Similarly, the weighted average abatement cost for coal CCS is at £158/t $CO_2$ or £94/t $CO_2$ higher than in the REF scenario, while the weighted average abatement cost is £138/t $CO_2$ for wind power or £113/t $CO_2$ higher than in the REF scenario. Thus, the average abatement cost for those three technologies increases by between 2.2 and 5.5 times.

**Figure 6.24: MAC curve for the IEP scenario in 2030**



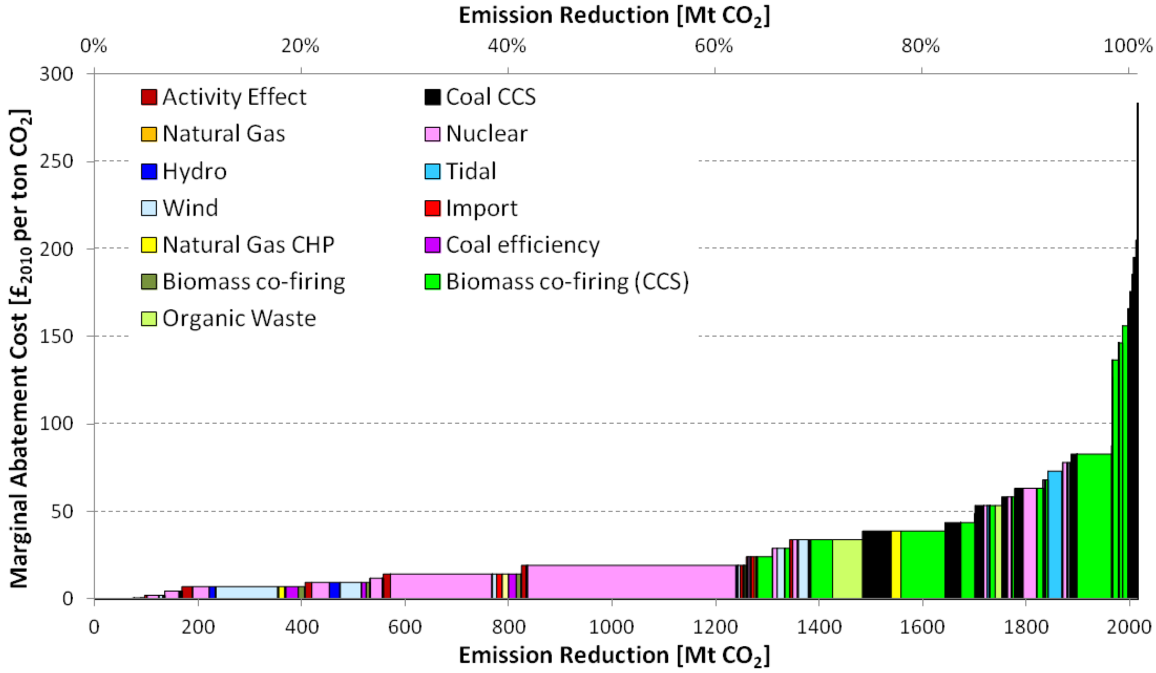

As an important share of wind power only becomes available at very high $CO_2$ tax levels in the REF scenario, the 200% increase of the capital costs makes this even costlier, so that some wind power sites no longer become cost-effective up to the highest tax level of £294/t $CO_2$ (see Figure 6.26). Tidal power is even more affected by the 200% increase in investment costs, i.e. it is no longer cost-optimal over the whole range of the applied carbon tax.

As low carbon technologies are much more gradually introduced into the market other measures partially compensate for this. Overall electricity demand is lower due to the higher electricity prices so that the contribution of demand reduction in the IEP scenario is four times as high as in the REF scenario. Due to the higher carbon intensity of electricity, electricity production is on average 7% lower compared with the REF scenario.

Natural gas power plants are a mitigation measure in the MAC curve, in particular from £40/t $CO_2$ to £80/t $CO_2$. In this tax range, natural gas increases its market share from around 5% to 20% and displaces the remaining coal-fired power plants. Thus, natural gas helps to mitigate 21 Mt $CO_2$ up to £80/t $CO_2$, but at higher carbon tax levels it is replaced by coal power plants with CCS. Finally, nuclear power mitigates about 50% more emissions in the IEP scenario due to the fact that it attains a higher market share, because other technologies need an even higher carbon tax to be introduced to the market.

The MAC curve for the FIRST-OF-KIND scenario (Figure 6.25) indicates that the abatement from nuclear is on average almost £7/t $CO_2$ more expensive due to the required investment into early technology versions. In contrast to that, abatement costs for coal CCS are slightly cheaper as more investment is required prior to 2030 to reach the anticipated capacity targets at the end of the model horizon. A look at the total contribution towards emissions reduction in the FIRST-OF-KIND scenario reveals that nuclear power is more dominant than in the REF scenario, making up 44% of total emissions abatement.

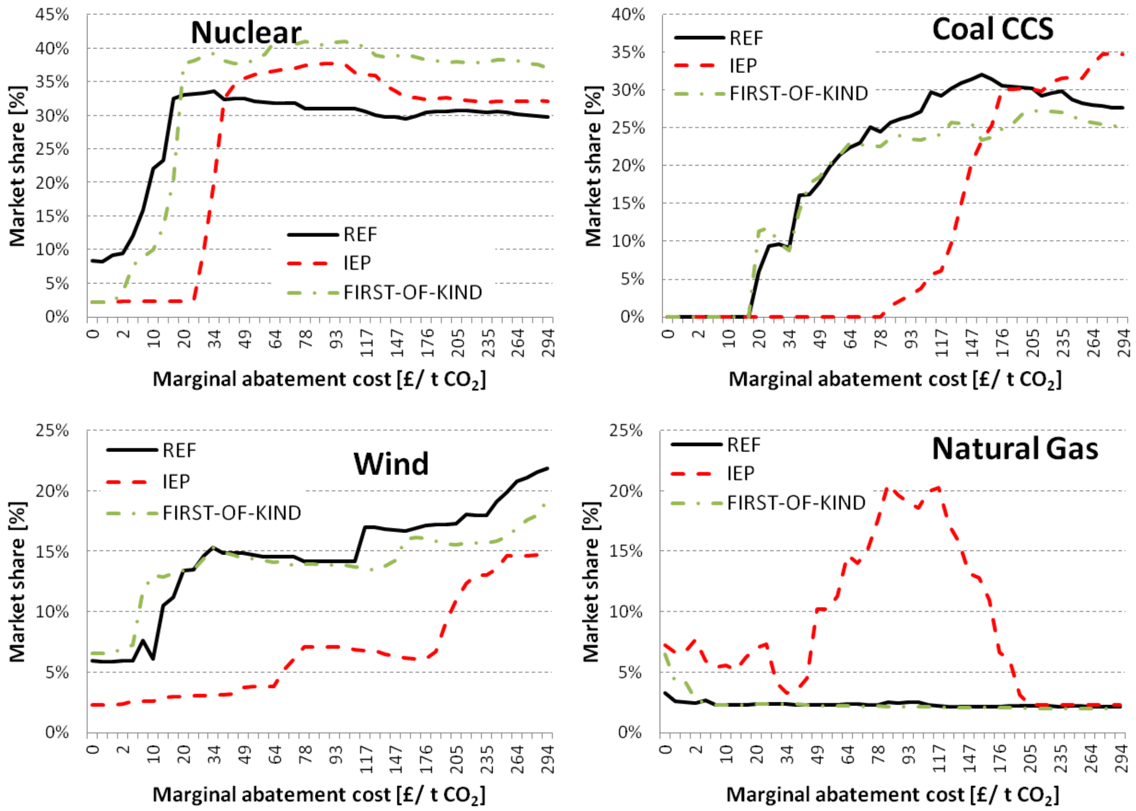
**Figure 6.25: MAC curve for the FIRST-OF-KIND scenario in 2030**




The market shares (Figure 6.26) confirm that nuclear becomes more dominant, while the market share of coal CCS stays lower than in the REF scenario at high tax levels. Thus, the requirement to invest into early technologies is a larger disincentive for the CCS technologies than for nuclear over the whole model horizon.

In summary, one can conclude that the 200% increase in investment costs for low-carbon technologies has a significant effect on the MAC curve by shifting it significantly upwards. The higher costs of the IEP scenario can equally be expressed in terms of total cost associated with emissions mitigation. In order to achieve a 10 Mt $CO_2$ emission target (200 Mt $CO_2$ emissions reduction) for the UK electricity sector, the total costs in 2030 are £11.1 billion or 143% more compared with the REF scenario. The FIST-OF-KIND scenario shows lower abatement cost for a given tax level over most of the tax range owing to required early investments into nuclear and CCS. The curve for the year 2030 does, however, not show that abatement becomes more expensive towards the end of the model horizon.

**Figure 6.26: Market share for different technologies in the IEP and FIRST-OF-KIND scenario in 2030**

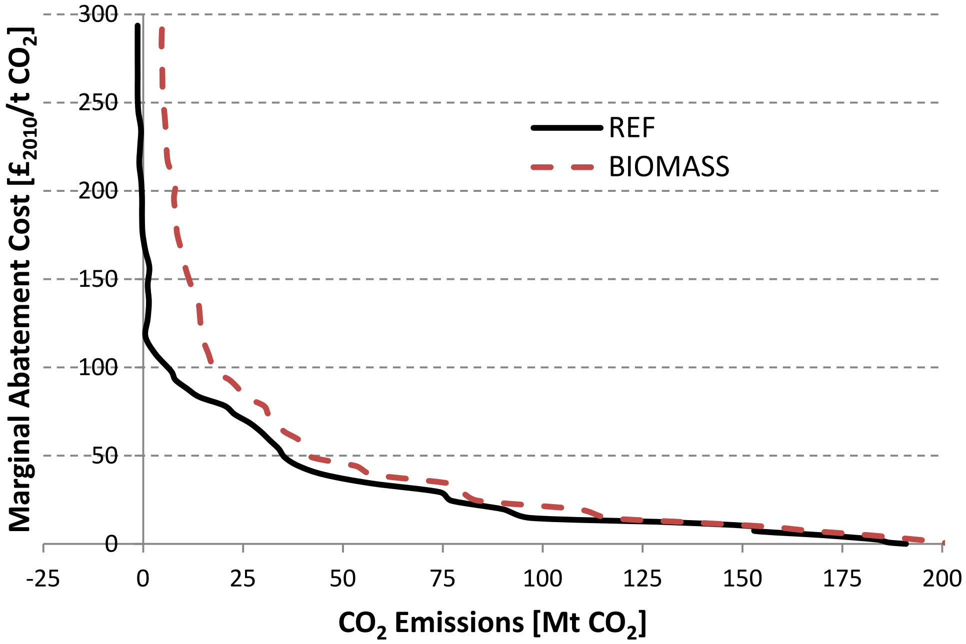



## 6.7 Biomass availability

As the previous scenarios have shown, biomass plays a considerable role in decarbonising the UK energy system and in particular the power sector, mainly in the form of biomass co-firing to coal power plants. The majority of the biomass is imported, while there are significant uncertainties as to whether the required quantity can be provided. In addition, domestic biomass availability is uncertain due to land-use competition with forest-based industries and the food industry.

Consequently, the BIOMASS scenario investigates how sensitive the power sector MAC curve is to the assumptions on biomass availability. Therefore, domestic biomass resources have been reduced by 50% for all types of biomass. Moreover, no imports of biomass of any kind are allowed in this scenario. Figure 6.27 shows that the emission curve for the BIOMASS scenario is different to the REF to the extent that the mitigation potential remains behind the one in the REF scenario for a given carbon tax. The average difference between both curves is 10 Mt $CO_2$.

**Figure 6.27: Emission curve along rising $CO_2$ abatement costs for the BIOMASS scenario in 2030**




In the REF scenario biomass is used as a low-carbon fuel in biomass CHP and power plants and at higher carbon tax levels as a substitute for coal in unabated and CCS plants. In the BIOMASS scenario, significantly less biomass is available to be used in the power sector due to the imposed restrictions. The consequence is that 63% less biomass is used in the power sector compared with the REF scenario, so that less biomass is co-fired in coal CCS power plants. As a consequence the emission intensity produced from this generation type remains positive and does not act as an emission sink. Furthermore, electricity production from coal CCS power plants is less than in the REF scenario, which is compensated for by a lower electricity demand and higher production from gas-fired power plants up to £150/t $CO_2$.

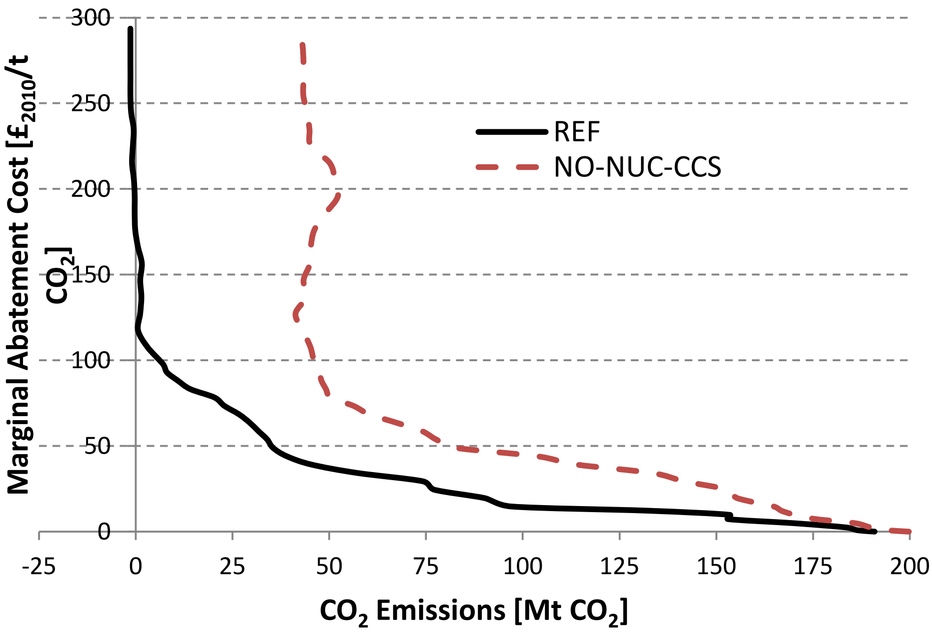
Summarising, the use of biomass represents a key abatement measure for the UK power sector, especially at higher $CO_2$ tax levels in combination with coal CCS. Reducing domestic biomass production and allowing no imports results in an emissions increase of roughly 10 Mt $CO_2$.

## 6.8 Availability of technologies

Nuclear power and carbon capture and storage technologies, in particular in combination with coal-fired power plants, have been indentified from the previous analysis to be the key mitigation technologies in the power sector. Both technologies are responsible for 62% of all emissions reduction in the REF scenario. The NO-NUC-CCS scenario tests the reliance of the power sector decarbonisation on both technologies and the influence on abatement costs. Accordingly, no new investments are allowed in this scenario into nuclear and any CCS technologies, including coal CCS, gas CCS and biomass CCS power plants.

The emission curve (Figure 6.31) illustrates that carbon abatement is a lot more expensive without any new investments in nuclear and CCS technologies. Baseline $CO_2$ emissions are 9 Mt above the reference scenario due to less electricity production from nuclear reactors, which is compensated by a higher electricity production from natural gas and coal power plants. The difference between both curves is striking as an emission target of 100 Mt $CO_2$ is achieved at £15/t $CO_2$ in the REF scenario, but only at £45/t $CO_2$ in the NO-NUC-CCS scenario.

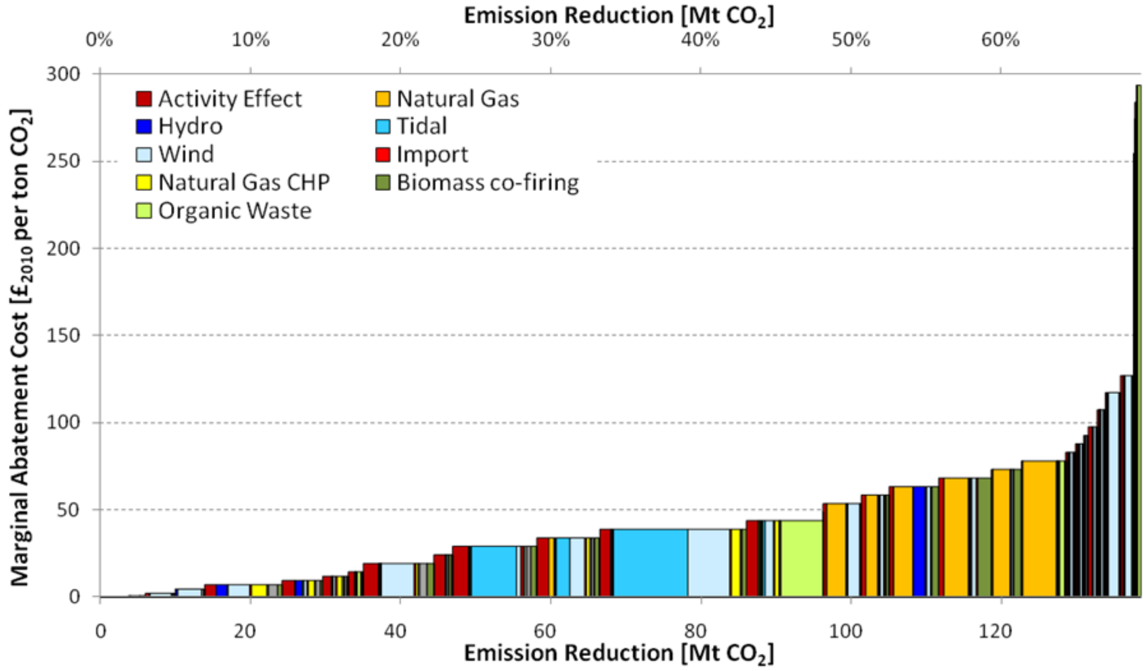
**Figure 6.28: Emission curve along rising $CO_2$ abatement costs for the NO-NUC-CCS scenario in 2030**




Furthermore, $CO_2$ emissions do not drop below 41 Mt $CO_2$, but stay constantly around that level from a carbon tax of £120/t $CO_2$ upwards. At £200/t $CO_2$, emissions in the power sector increase again to 52 Mt $CO_2$ despite a rising carbon tax. This is an immediate effect of a rising electricity production from gas-fired power plants. The additional electricity is used in the transport sector for battery cars and in the service and residential sector for space heating via heat pumps. The overall system-wide emission levels decrease with an increasing carbon tax but due to intersectoral interactions emissions increase in the electricity sector.

Since coal CCS and nuclear power are no longer available to reduce emissions, the technologically detailed MAC curve (Figure 6.29) looks markedly different from the reference case. Electricity demand is significantly lower with up to 320 PJ (89 TWh) less than in the reference scenario (see also Figure 6.30) so that demand reduction contributes 12% to overall emissions reduction.

**Figure 6.29: MAC curve for the NO-NUC-CCS scenario in 2030**

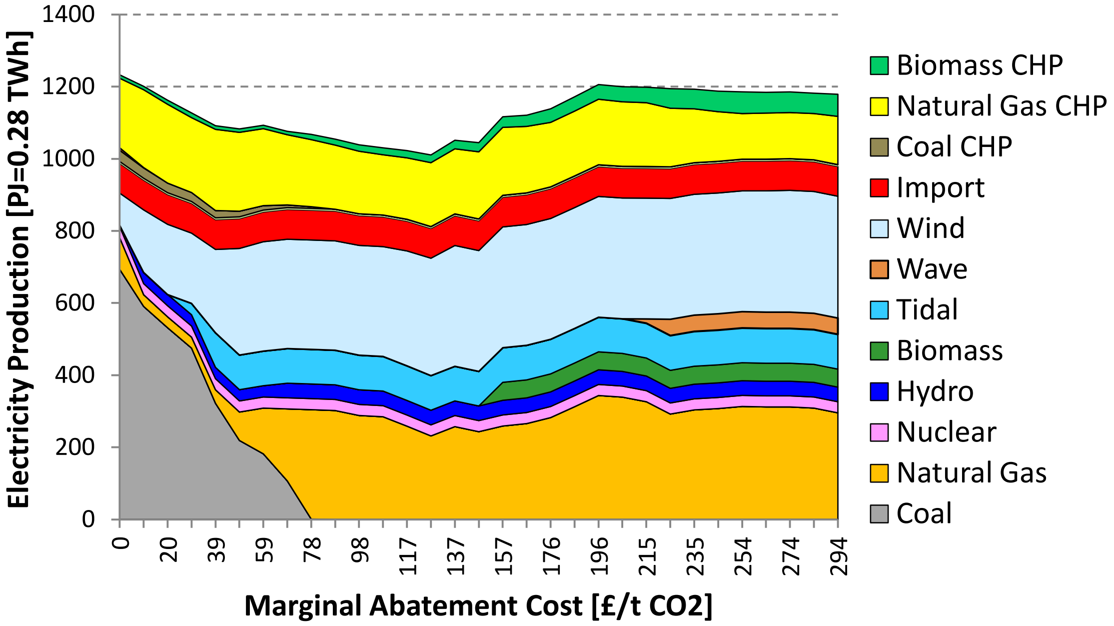



The most important technology that compensates for nuclear and coal CCS is wind power. This renewable energy source reduces emissions by 47 Mt $CO_2$ with a weighted average of £41/t $CO_2$, which is about £14/t $CO_2$ higher compared with the REF scenario. This can be mainly explained with previously unprofitable sites for wind turbines being installed due to the absence of other mitigation technologies. Less profitable wind categories have a lower load factor and are assumed to contribute less to electricity production during peak times in UK MARKAL and therefore require more backup capacity. However, a system with a significant amount of intermittent renewable capacity cannot be modelled to the best possible extent in UK MARKAL due to the limited temporal detail.

Tidal power is another low-carbon option that generates more electricity than in the REF scenario in order to make up for less electricity from nuclear and coal CCS plants. A further mitigation measure with an increased mitigation contribution is co-firing of biomass to coal power plants. This is one of the most cost-effective mitigation measures and starts from £5/t $CO_2$. Nevertheless, at a tax of £78/t $CO_2$ all coal-fired power plants are phased out and replaced by other generation types. Moreover, wave power becomes cost-optimal to introduce at £215/t $CO_2$.

As these technologies cannot fully replace nuclear and coal CCS power plants, natural gas plays an important role since emissions from natural gas are roughly half compared to those from coal. From £50/t $CO_2$ natural gas power plants replace coal power plants. Electricity production from natural gas remains in the electricity mix at a relatively constant level of around 25% for the whole range of the MAC curve due to high costs associated with zero carbon technologies and an already exhausted potential for wind and tidal power.

**Figure 6.30: Electricity generation mix for different marginal abatement costs in 2030 (NO-NUC-CCS scenario)**

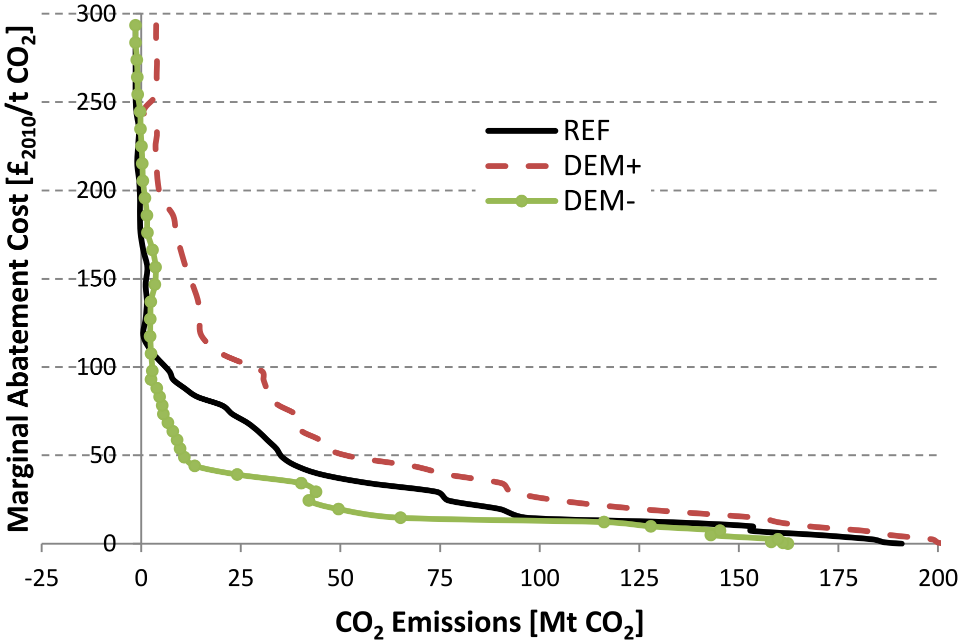



In summary, wind, tidal, wave and hydro power compensate partially for coal CCS and nuclear power. However, these technologies are not able to replace the whole electricity generation from the two key mitigation technologies. Consequently, natural gas makes up a significant portion of the electricity mix emitting a significant amount of $CO_2$ even at tax levels up to £300/t $CO_2$.

## 6.9 Demand development

Next to factors that are specific to the electricity sector, the mitigation structure is equally influenced by the demand development for energy services that influence the consumption of electricity. The most important demand services consuming electricity are industrial demand for motor drive and high temperature, which consume about 30% of all electricity. Other important energy service demands in terms of electricity use are electric appliances, residential heating and finally lighting in the service and residential sector. Forecasting the demand for the different energy services, such as travel, space heating, industrial energy use, is far from being certain. For this reason two scenarios were created to test the robustness to varying levels of demand. Energy service demands were increased by 20% in the DEM+ scenario and decreased by 20% in the DEM- scenario. Figure 6.31 shows the emission curves of the different demand scenarios.

**Figure 6.31: Emission curve along rising $CO_2$ abatement costs for different demand scenarios in 2030**




It is reasonable that the emission curve is shifted to the right with an increased demand level and to the left with a decreased demand level. More interesting to investigate is whether this demand level change brings about changes in the technological structure or affects abatement costs. Without any carbon policy in place the emissions level in the DEM+ scenario is about 6% higher than in the REF scenario, while it is 15% less in the DEM- scenario despite the fact that electricity consumption is almost exactly 20% less in the DEM- scenario and 20% more in the DEM+ scenario. The lower increase in the DEM+ is due to the fact that mainly wind, nuclear power and natural gas CHP plants serve the increased electricity demand. In the DEM- scenario the electricity generation from coal power plants only decreases by 11% compared to an overall decrease in electricity production of 20% so that the carbon intensity of electricity increases.

The biggest difference between both DEM emission curves is around a tax level of £50/t $CO_2$ where 11 Mt $CO_2$ remain in the DEM- scenario and 54 Mt $CO_2$ in the DEM+ scenario. While the electricity sector is almost completely decarbonised from £100/t $CO_2$ in the DEM- scenario, emissions in the DEM+ do not fall below 4 Mt $CO_2$ due to the limited availability of biomass that can be co-fired to coal CCS plants. A look at both technologically detailed MAC curves (Figure 6.32 and Figure 6.33) reveals some insights into the technologies affected by the changes in energy-service demand.

**Figure 6.32: MAC curve for the DEM+ scenario in 2030**

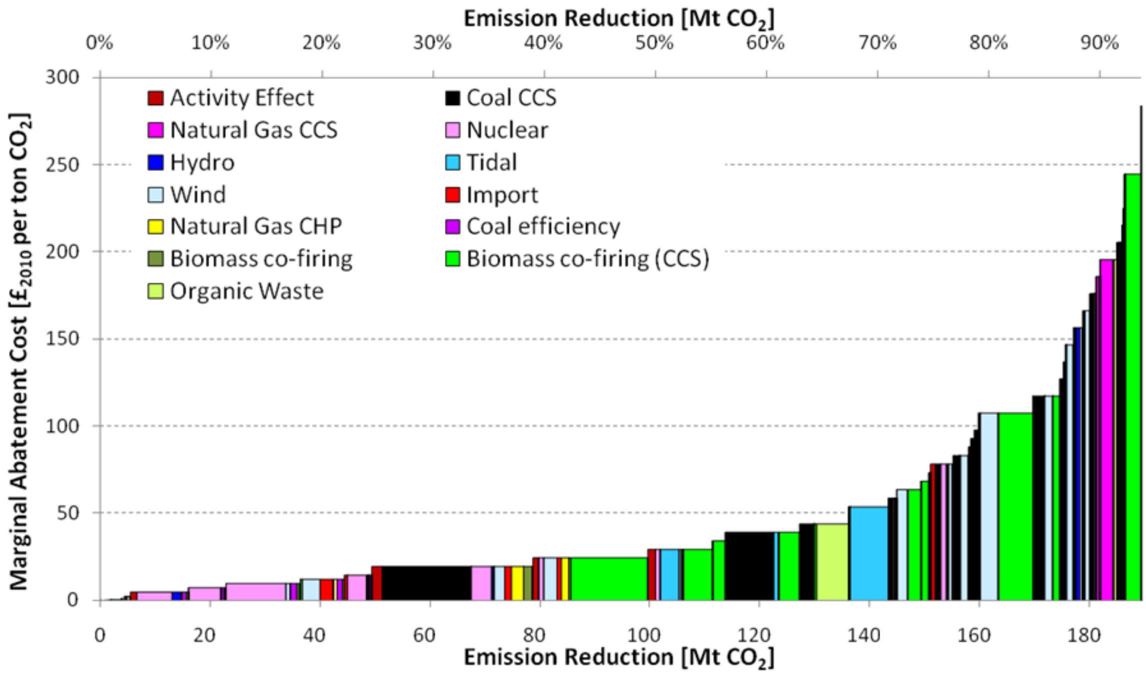
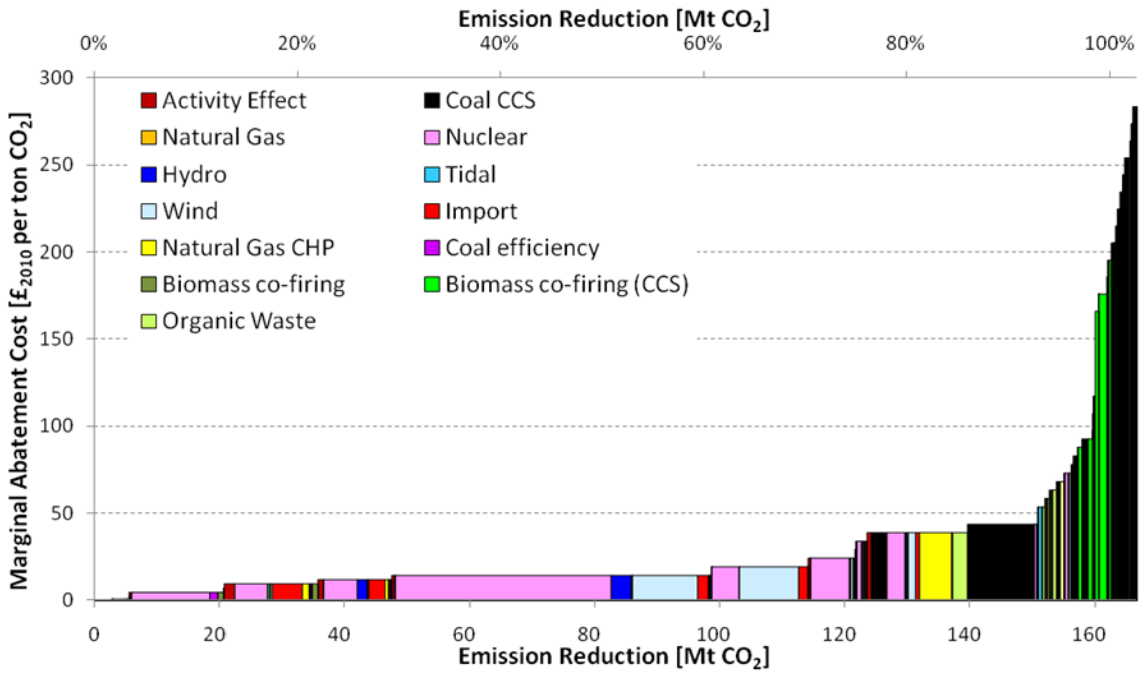



**Figure 6.33: MAC curve for the DEM- scenario in 2030**



One can observe in the DEM+ scenario that the contribution from nuclear power and wind power is reduced compared to the REF scenario due to an increased production from nuclear and wind in the baseline. The role of coal CCS is more important than in the REF scenario as the reference carbon intensity is higher when coal CCS is introduced. Coal CCS is introduced to the market at a lower carbon tax with the average abatement cost being slightly lower at £55/t $CO_2$ compared with £63/t $CO_2$. The same holds true for the co-firing of biomass to coal CCS power plant, where average abatement cost is equally slightly lower with £58/t $CO_2$.

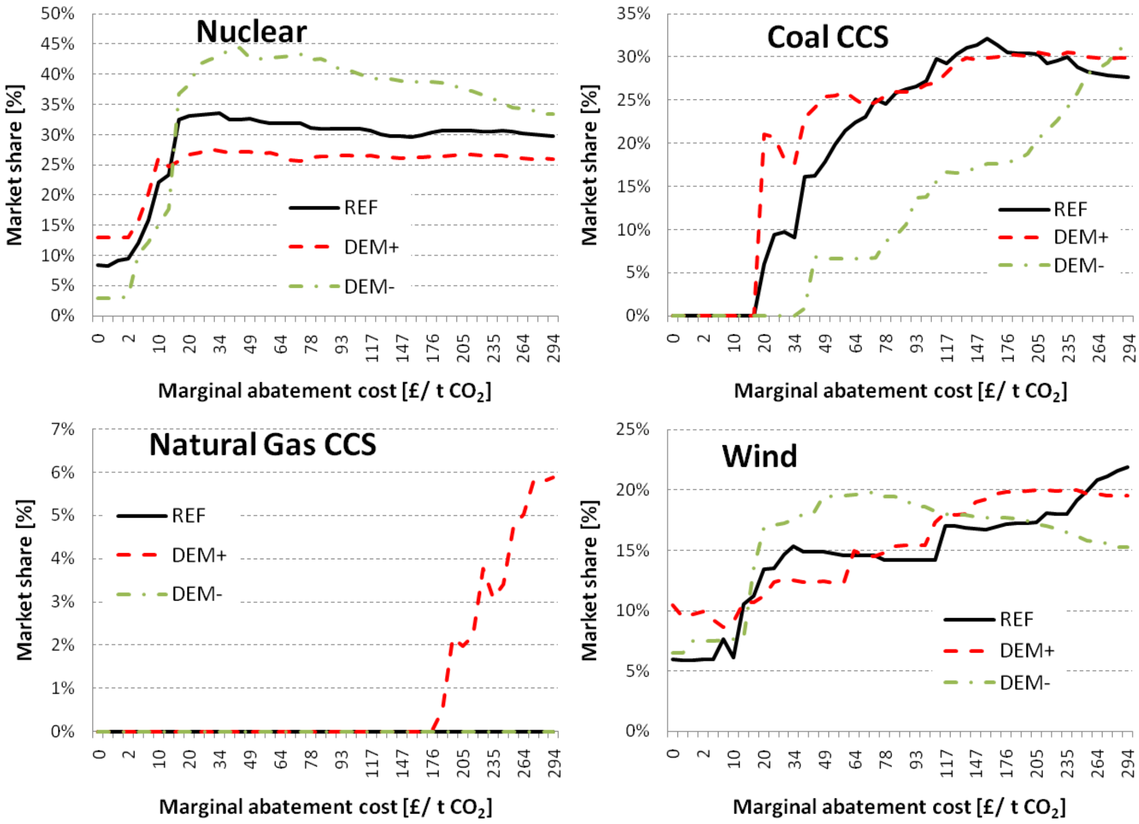
Total electricity generation from coal CCS power plants at the end of the MAC curve is 24% higher in the DEM+ scenario than in the REF scenario, which leads to the emission factor from all coal CCS power plants being higher due to a limited availability of woody biomass to be co-fired. The emission factor from coal CCS power plants is -3 g $CO_2$/kWh in the DEM+ scenario, while it is -17 g $CO_2$/kWh in the REF scenario. As a consequence it becomes cost-optimal from £176/t $CO_2$ to replace coal CCS plants, which only use coal as an input fuel, by gas CCS power plants because this generation type emits about 50% less $CO_2$ (see Figure 6.34).

In contrast to the DEM+ scenario, the DEM- scenario requires less total electricity production. While electricity production from nuclear power plants is the same in all three scenarios from a tax level of £25/t $CO_2$ upwards, the share is significantly higher in the DEM- scenario as a result of the lower total electricity demand.

As the electricity generated from coal-fired power plants can be almost completely replaced by nuclear power plants at a tax of £40/t $CO_2$ in the DEM- scenario, there is less of an incentive to introduce coal CCS plants at those tax levels. Coal CCS is more gradually introduced with increasing carbon tax levels as it can act as an emission sink. Consequently, the abatement costs for coal CCS increase to a weighted average of £89/t $CO_2$, which is 40% higher than in the REF scenario. The contribution from other mitigation measures looks very similar with the exception of the contribution from electricity demand reduction, which is higher.

Concluding, one can say that coal CCS is most affected by the change in the demand level, while it becomes cost-effective to invest in natural gas CCS plants in the DEM+ scenario at very high carbon tax levels.

**Figure 6.34: Market share for different technologies in the demand scenarios in 2030**




## 6.10 Summary

17 carbon cost curves of the UK electricity sector were presented in this chapter to illustrate the uncertainties involved in assessing marginal abatement costs and corresponding abatement potentials. The scenarios as a whole answer the initial questions asked in chapter 1 referring to the contribution of abatement measures to emissions reduction, the influencing factors of the MAC curve, and the interaction of measures. Furthermore, they address the sensitivity to changes in input parameters raised in chapter 5.

The discussion in this chapter has identified coal CCS and nuclear as the key technologies for a decarbonisation of the UK electricity sector in the 21st century. Under the assumptions of the UK MARKAL model in the REF scenario nuclear power is one of the cheapest abatement options with average abatement costs of £12/t $CO_2$. Coal CCS is more expensive compared to nuclear power becoming cost-effective from £19/t $CO_2$. Nevertheless, coal CCS power plants have proved to be robust throughout the different scenarios in particular due to the possibility of co-firing biomass. This mechanism allows coal CCS plants to act as carbon sinks when enough biomass is co-fired. Co-firing biomass has an average abatement cost of £67/t $CO_2$.

While nuclear power is responsible for 27% of emissions reduction in the REF scenario, coal CCS including biomass co-firing represents 35% of all emissions reduction. The importance of both technologies is emphasised by the significant limitation of abatement once investments in CCS and nuclear technologies are not allowed. A further mitigation option that proves to be robust throughout the different scenarios is wind power, which contributes about 15% to the overall emissions reduction. Other smaller mitigation measures are tidal power, low-carbon electricity imports, hydro power, natural gas CHP plants and organic waste incineration.

The uncertainties related to a decarbonisation of the electricity sectors have also been quantified. Table 6.6 summarises the influence of the seven different categories on the shape of the MAC and its technological structure, i.e. the ordering and contribution of mitigation options, into strong, medium, and weak. This difference is made because there exist scenarios where the emission curves do not indicate major differences but are made up of different abatement measures. The classification into strong (+), medium (o), and weak (-) cannot be completely objective. However, concerning the influence on the shape, the classification indicates how strongly the scenario deviates from the reference scenario, in particular in a likely tax range in 2030 of £35/t $CO_2$ to £105/t $CO_2$, with weak indicating a deviation in emissions of up to 5%, medium between 5% and 20%, and strong more than 20% in terms of baseline emissions.

**Table 6.6: Influence of the change in different model assumptions on MAC curve: strong (+), medium (o), weak (-)**

| Category | Influence | |
|---|---|---|
| | Shape | Structure |
| Path dependency | o | o |
| Technological learning | o | o |
| Discount rate | - | o |
| Life time | - | - |
| Technological availability | + | + |
| Fossil fuel price | - | + |
| Demand level | o | o |

The scenario analysis has pointed out that the uncertainty around the availability of nuclear power and CCS has a significant influence on the shape and structure of the power sector MAC curve. The choice of the discount rate has a very limited influence but affects the ordering of mitigation measures. A variation of fossil fuel prices also has a limited influence on the MAC curve, in particular in the range of the expected carbon tax level in 2030, but alters the ranking and importance of mitigation technologies.

Uncertainty related to path dependency, technological learning and the demand level has a medium influence on the MAC curve's shape and the ordering of abatement measures.

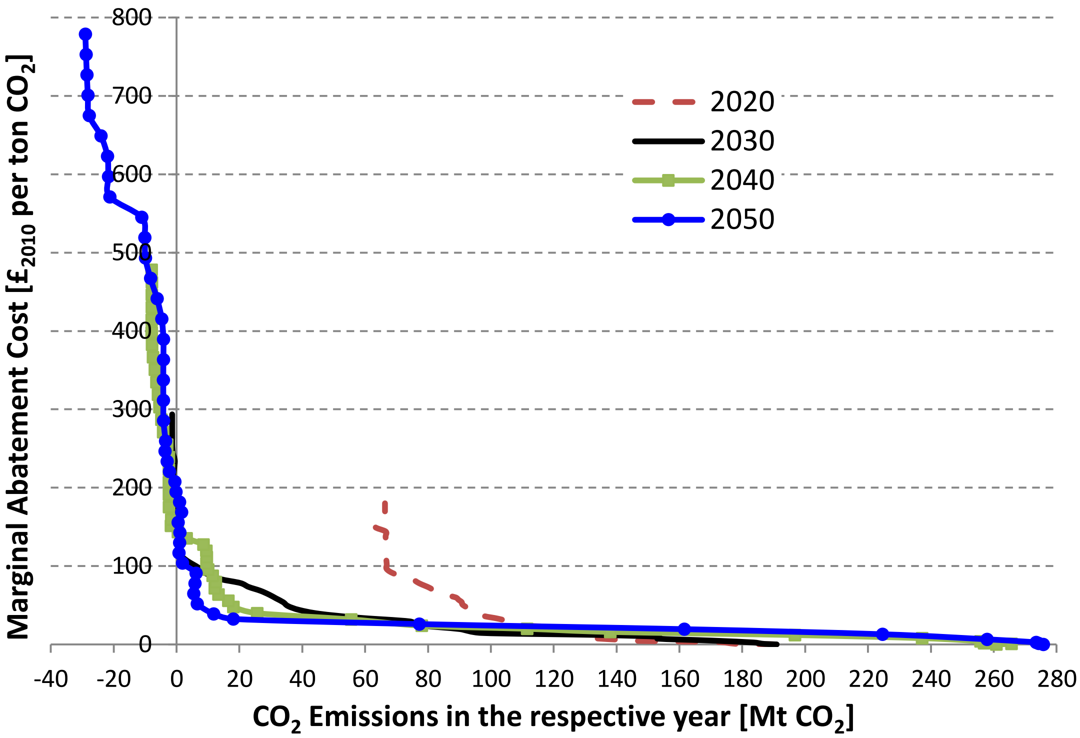
Finally, interactions between mitigation measures is one of the points of interest of this thesis. The electricity sector has a pivotal role to play in the decarbonisation of the whole energy system because it is already used in all energy demand sectors and has the potential to contribute to the reduction of $CO_2$ emissions by switching to battery vehicles in the transport sector or to heat pumps for space heating in the built environment. A change in fossil fuel prices does not affect the overall shape of the MAC curve, but has an influence on the mix of mitigation measures with renewables becoming relatively cheaper compared to fossil fuel-based alternatives. On a technology level, one can notice interactions between gas and coal CCS power plants as well as the use of biomass in the electricity sector and the generating capacity of coal CCS. This can be explained with the fact that the majority of biomass is co-fired in coal CCS power plants. In scenarios with a lower gas price, a higher discount rate or a high level of energy demand, natural gas becomes an important transition fuel used in CHP plants and in combination with CCS.

## 6.11 MAC curves for the year 2020, 2040 and 2050

The previous scenarios have focused on the year 2030, as an important milestone for medium-term emissions reduction goals. In order to get a broader picture of emissions reduction during the first half of this century, this section presents MAC curves for the year 2020, 2040, 2050 and finally a cumulative emissions reduction curve.

In order to compare the different MAC curves, Figure 6.35 compares the emissions associated with different $CO_2$ tax levels in each of the four representative years. This representation accounts for different baseline emissions. In order to ensure a clearer representation of the emission curves, the illustration shows only carbon tax levels up to £200/t $CO_2$, although the carbon tax goes up to almost £800/t $CO_2$ in 2050. The baseline $CO_2$ emissions increase with time from 191 Mt $CO_2$ in 2020 to 261 Mt $CO_2$ in 2040 and 276 Mt $CO_2$ in 2050. This can be explained with an increasing electricity generation, which is dominated by coal-fired power plants.

**Figure 6.35: Emission curve along rising $CO_2$ abatement costs for the REF scenarios in different years**

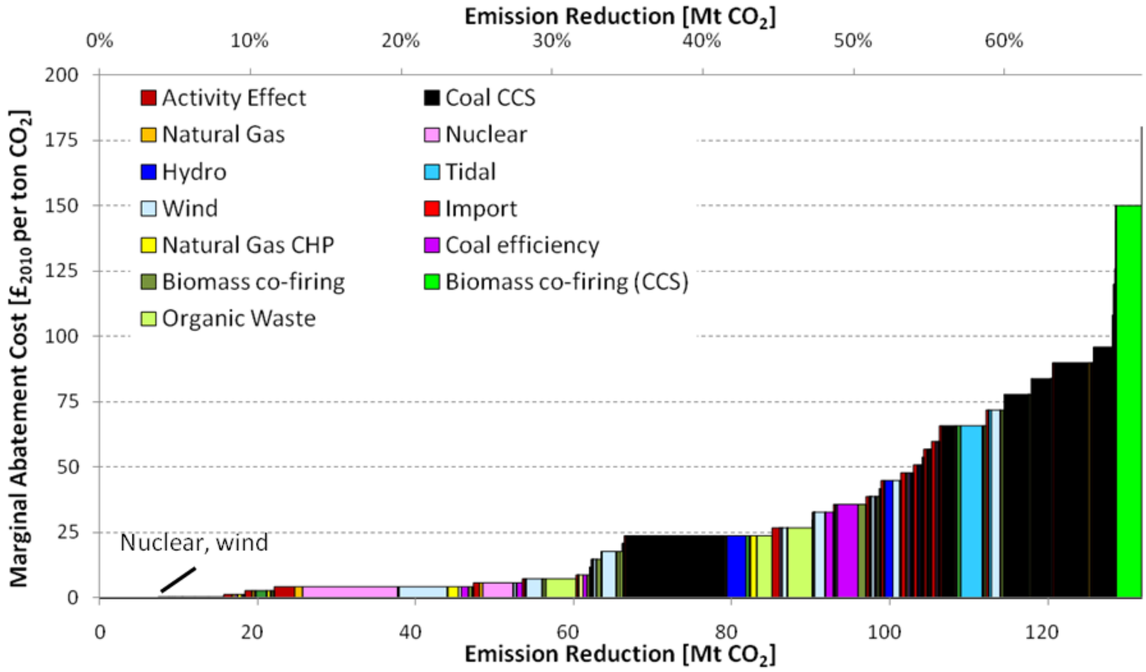



All emission curves assume that the $CO_2$ tax increases from 2010 with the model-inherent discount rate of 5% p.a. This explains why the emission curve stops at a tax level of £180/t $CO_2$ in 2020 and at £779/t $CO_2$ in 2050. A $CO_2$ tax higher than £180/t $CO_2$ in the UK in 2020 is deemed unrealistic, given the current carbon policies for the electricity sector being equivalent to a carbon tax of less than £20/t $CO_2$. Different carbon tax pathways over time would affect the MAC curve, whereby a MAC curve in 2020 would be less affected than a MAC curve in the year 2050 (see also section 6.2)

The emission curve for the year 2020 reaches a plateau from £96/t $CO_2$ at 66 Mt $CO_2$, below which emissions do not fall. Many coal-fired and gas-fired power plants have not reached the end of their life time at this point meaning it would entail high sunk costs to replace them with low-carbon alternatives. Furthermore, new power plants cannot be built so quickly due to lead times involved and the limited time period of less than ten years up to 2020. At a tax level of £40/t $CO_2$ the electricity sector is more than 90% decarbonised in the year 2040 and 2050 indicating the low-cost abatement potential. The difference with respect to the emission curves is limited for the years 2040 and 2050, while it is comparably large for the years 2020 and 2030. It is also apparent that emissions turn negative at £151/t $CO_2$ in 2040 and at £195/t $CO_2$ in 2050 due to biomass-co-firing to coal power plants and biomass CCS plants.

The electricity mix in the year 2020 without a carbon tax is dominated by natural gas (37%), coal (33%), nuclear (11%) and natural gas CHP plants (8%). Figure 6.36 shows that nuclear, wind power and a reduction in the demand for electricity are low-cost options to reduce $CO_2$ emissions in the power sector in 2020. Electricity demand is up to 6% lower in the presence of a carbon tax compared to the case without one and thus an important abatement measure. Nuclear power has an average abatement cost of £10/t $CO_2$, while it is £23/t $CO_2$ for wind power.

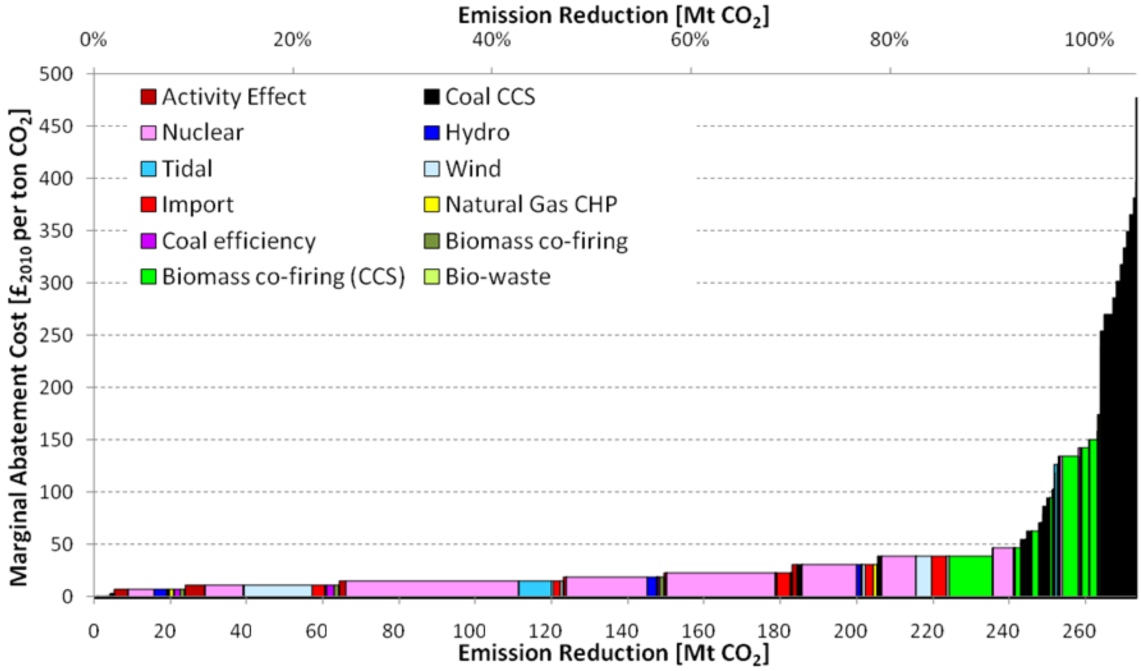
**Figure 6.36: MAC curve for REF scenario in 2020**




The most important abatement measure is coal CCS, which is responsible for 27% of all emissions abatement in 2020. Though, this abatement option is significantly more expensive with abatement costs ranging from £24/t $CO_2$ to £96/t $CO_2$ and an average abatement cost of £58/t $CO_2$. The mentioned abatement options are complemented by biomass power plants, tidal power, biomass co-firing and organic waste incineration.

The MAC curve for the year 2040 (Figure 6.37) looks very different from the one in the year 2020 due to the different mix in the baseline case and the higher flexibility concerning the abatement measures. The power sector is dominated by coal power plants (75%) with nuclear, biomass, wind and natural gas making up the rest of the electricity generation. A look at the MAC curve for the year 2040 reveals that nuclear power is the dominant mitigation measure where more than half of all emissions reduction can be attributed to nuclear power. This electricity generation type increases its share in the electricity mix up to a carbon tax of £48/t $CO_2$. In a similar range as nuclear power, wind power becomes cost-effective to contribute to emissions reduction.

**Figure 6.37: MAC curve for REF scenario in 2040**

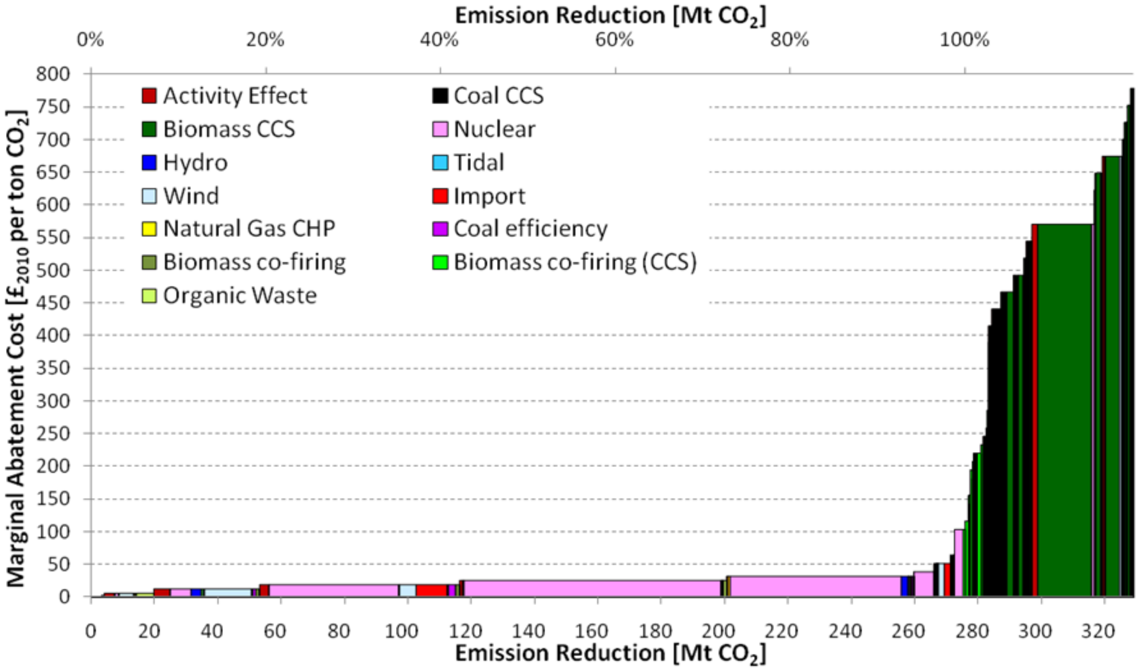



A further important mitigation technology is coal CCS in particular in combination with biomass co-firing. Coal CCS power plants require a significantly higher carbon tax of at least £32/t $CO_2$ to become cost-effective, while co-firing to coal CCS plants starts from £40/t $CO_2$. Coal CCS power plants contribute towards emission mitigation also at much higher tax levels owing to interactions with other mitigation measures, with other sectors, and due to intertemporal interactions.

Turning to 2050, the electricity sector without a $CO_2$ tax is still dominated by coal-fired power plants as in previous time periods. Coal-fired power plants make up 76% of the electricity mix, while nuclear power plants account for 5%, tidal for 4%, natural gas CHP plants for 3%, and wind for 3%.

Similar to the MAC curve in 2040 up to £39/t $CO_2$, the MAC curve in 2050 is dominated by a switch to nuclear power (see Figure 6.38). This option abates 59% of all emission in the power sector. In the same way, wind power and coal CCS are two further important abatement technologies in 2050. In contrast to earlier years, biomass CCS power plants are an option that plays a significant role in the MAC curve for the year 2050. This abatement option reduces emissions by 30 Mt $CO_2$ storing emissions of biomass underground and thereby acting as a $CO_2$ sink. Nevertheless, this option is relatively expensive and becomes cost-effective only at a tax level of £467/t $CO_2$, with an average abatement cost of £596/t $CO_2$.

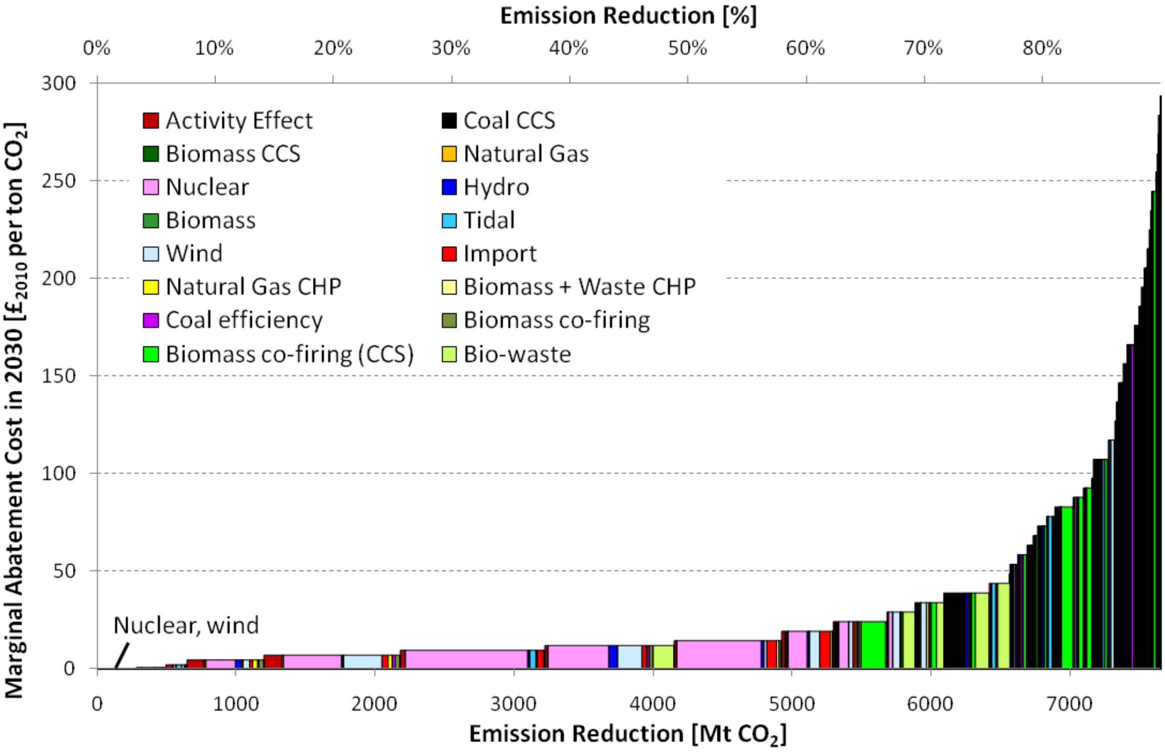
**Figure 6.38: MAC curve for REF scenario in 2050**




All of the MAC curves that have been presented so far in this chapter are designed for the cumulative emissions of one single year, e.g. 2030. This is the standard way of displaying MAC curves. In order to address the static character of a usual MAC curve and take into account intertemporal interactions, Figure 6.39 presents a cumulative power sector MAC curve for the period from 2010-2050. The y-axis represents the $CO_2$ tax level in 2030, which is however not constant through time but increases with the discount rate of 5%, so that the tax level is lower prior to 2030 and higher thereafter.

Within the 40 years, emissions in the REF scenario are 8.5 Gt $CO_2$, which corresponds to 216 Mt $CO_2$ per year for the UK power sector. The MAC curve indicates that emissions reduction is comparably inexpensive in the power sector, where half of all cumulative emissions can be abated with a $CO_2$ tax of £15/t $CO_2$ in 2030 (assuming a tax that increases with 5% per year). Similar to the MAC curve in 2030, nuclear power plays the most important role in decarbonising the power sector with a share of 39% in all emissions reduction. The share of nuclear is higher than in 2030 because nuclear can be deployed earlier than coal CCS power plants and nuclear power plants are assumed to be less expensive. From 2040 onwards, the role of coal CCS power stations is diminished owing to the introduction of biomass CCS plants that can act as important carbon sinks. Accordingly the share of coal CCS power plants in overall emissions reduction is 16% (including biomass co-firing) and 2% for biomass CCS plants. Wind proves to be an equally important mitigation option with 11% of emissions reduction.

**Figure 6.39: Cumulative emission curve along rising $CO_2$ abatement costs for the REF scenario**




This overview of abatement costs and potentials at different points in time has shown that emissions reduction is more flexible in later periods compared with earlier ones. In 2020, demand reduction is one of the important measures reducing $CO_2$ emissions, whereas technology options, such as nuclear and biomass CCS, dominate abatement in 2040 and 2050.

## 6.12 References

Blesl, M., T. Kober, D. Bruchof and R. Kuder (2010). "Effects of climate and energy policy related measures and targets on the future structure of the European energy system in 2020 and beyond." Energy Policy **38**(10): 6278-6292.

CCC (2008). The Costs of Decarbonising Electricity Generation - Technical Appendix to Chapter 5. London, Committee on Climate Change.

CCC (2010). The Fourth Carbon Budget - Reducing emissions through the 2020s. London, Committee on Climate Change.

DECC (2009). Carbon Valuation in UK Policy Appraisal: A Revised Approach. London, Department of Energy and Climate Change.

DECC (2010). Provisional 2009 results for UK greenhouse gas emissions and progress towards targets. London, Department of Energy and Climate Change.

Kannan, R., N. Strachan, N. Balta-Ozkan and S. Pye. (2007). "UK MARKAL model documentation." Retrieved November 18th 2010, from www.ukerc.ac.uk.

Kanter, J. (2009). In Finland, Nuclear Renaissance Runs into Trouble. The New York Times. New York.

# 7 TRANSPORT SECTOR MAC CURVES

This chapter is the second results chapter and discusses the economics of carbon emissions reduction in the UK transport sector. It exhibits MAC curves with different input assumptions, which are derived with the UK MARKAL model and decomposition analysis. This chapter helps to expose the technological structure behind emissions mitigation and sheds light on the uncertainties related to a transport MAC curve via various sensitivity cases. The sensitivity analysis of the transport sector is focused on the year 2030 as an important medium-term target for emissions reduction. In total, 20 scenarios, which can be differentiated into ten categories, have been performed. 13 scenarios are the same as those used in the previous chapter on electricity sector MAC curves. These include the categories path dependency (only one scenario is added), discount rate, electricity cost, fossil fuel price, and demand level. In addition, technology learning in the transport sector is studied in two scenarios. Moreover, two scenarios cover transport-specific aspects: the role of battery vehicles and the potential of biofuels. Lastly, the demand elasticity for transport-related energy services is varied to quantify uncertainty around this input factor. Table 7.1 gives an overview of the different scenarios and explains each one in turn. Each MAC curve consists of 46 different model runs with system-wide $CO_2$ taxes, ranging from £$_{2010}$ 0 to 294/ t $CO_2$ in 2030. In the reference scenario (REF) the $CO_2$ tax is assumed to increase from 2010 with the model inherent discount rate of 5% p.a.

At the end of this chapter a cumulative MAC curve and MAC curves for the years 2020, 2040, and 2050 are discussed. All costs are given in £ of the year 2010.

**Table 7.1: Scenario overview**

| Scenario | Category | Description |
|---|---|---|
| **REF** | *Reference* | Carbon tax increases by 5% p.a. from 2010 |
| **ZERO-BEFORE** | *Path dependency* | Carbon tax is zero before 2030 |
| **CONST-AFTER** | *Path dependency* | Carbon tax is constant after 2030 |
| **INCR-AFTER** | *Path dependency* | Carbon tax increases with 10% p.a. from 2030 |
| **ZERO-AFTER** | *Path dependency* | Carbon tax is zero after 2030 |
| **HIGH-BEFORE** | *Path dependency* | Carbon tax is kept constant on the 2030 level from the REF scenario for the period 2015-2030 |
| **2030** | *Path dependency* | Model horizon is limited to 2030 instead of 2050 |
| **ITL** | *Technological learning* | Annual technological learning rates increased by 30%-50% |
| **DTL** | *Technological learning* | Annual technological learning rates decreased by 25%-30% |
| **PDR10** | *Discount rate* | Hurdle rates introduced for all technologies at 10%, previously existing rates were doubled |
| **SDR** | *Discount rate* | Discount rate lowered to 3.5%, all hurdle rates, taxes and subsidies removed |
| **BATTERY** | *Battery potential* | Limited market share of electric vehicles to 15% for cars and buses |
| **IEP** | *Electricity cost* | Investment costs increased by 200% for all CCS technologies, biomass, nuclear, tidal, wind, wave |
| **FF+** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 100% |
| **FF++** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 200% |
| **BIOFUEL** | *Biofuel potential* | Biomass costs halved, biomass space & water heating in buildings limited to 4% of total market |
| **ELAST+** | *Demand elasticity* | All demand elasticities increased by 50% |
| **ELAST-** | *Demand elasticity* | All demand elasticities decreased by 50% |
| **DEM+** | *Demand level* | All energy service demands increased by 20% |
| **DEM-** | *Demand level* | All energy service demands decreased by 20% |

## 7.1 Description of the transport sector in UK MARKAL

In the transport sector of the UK MARKAL model, energy service demands, measured in billion vehicle kilometres, are included for various modes of transport: air travel, car travel, bus travel, heavy goods vehicles (HGV), light goods vehicle (LGV), rail transport and two-wheeler. In line with current $CO_2$ accounting, international shipping and aviation are not considered in the model for this thesis. Energy service demand levels up to 2050 are estimated based on projections from the Department for Transport. More detail can be found in the model documentation (Kannan et al. 2007).

In addition, the model has a number of fuel distribution networks to track fuel use by mode of transport: petrol, diesel, biofuels, hydrogen and electricity. To meet the different transport energy service demands, a number of vehicle technologies are integrated in the model. These include internal combustion engine (ICE) vehicles, hybrid vehicles, plug-in vehicles, battery vehicles, E85 vehicles (flexible-fuel vehicles that can run on up to 85% ethanol in the fuel mix), methanol vehicles and hydrogen vehicles. Hydrogen vehicles are distinguished into vehicles with an internal combustion engine and those with a fuel cell.

A number of key parameters that are required to characterise the transport vehicle technologies, such as technical efficiency of a vehicle, capital cost, operating cost, vehicle lifetime or annual kilometrages, are defined in the model. Transport technologies are exogenously assumed to become more efficient over time (see also 7.4). Hurdle rates are implemented for new technologies to account for technology-specific risks. They are 10% for hydrogen vehicles, 7.5% for battery, methanol, hybrid, as well as plug-in hybrid vehicles, and 12.5% for battery and hydrogen two-wheelers.

Concerning railway travel, the model takes account of track electrification where capacity exceeds existing electrification. Current fuel duties for the use of petrol and diesel are included in the UK MARKAL model and are assumed to stay the same over the first half of the 21$^{st}$ century in constant prices.

The strengths of the UK MARKAL's representation of the transport sector include the technological detail and taking account of intersectoral interactions, in particular related to the use of electricity and biomass. Limits of the model are that it does not allow for variations in load factors (i.e. how many passengers use a vehicle), it does not allow for speed reduction and does not capture efficiency options explicitly, such as downsizing, start-stop-control or low-resistance tyres. This has consequences on the contribution of efficiency gains for emissions reduction.

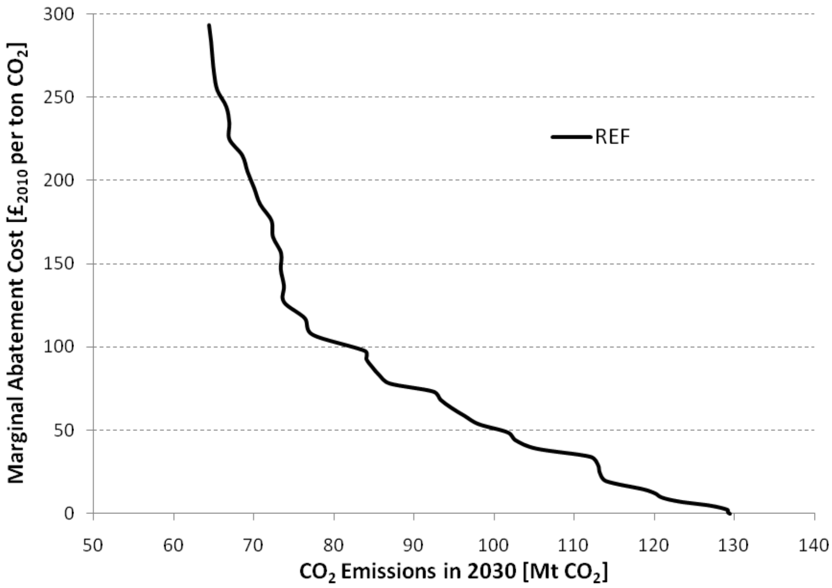
Furthermore, the model does not include walking or cycling as transport modes and does not allow for modal changes. Induced technological change is not included in the model, so that effects of path dependency may be underestimated. The model does not possess any spatial detail, which together with the lack of modal changes can affect the contribution of demand changes in decarbonising the transport sector. Lastly, the crude temporal resolution simplifies interactions with the electricity sector, e.g. when charging a battery vehicle.

## 7.2 Reference scenario

The REF scenario describes a development of carbon emissions reduction with the standard assumptions of the UK MARKAL model.

In the following analysis of the transport sector, emissions have been attributed from an end-user perspective, i.e. emissions resulting from the generation of electricity that is consumed in the transport sector are assigned to the transport sector. According to the model results, transport emissions (excluding international shipping and aviation) from an end-use perspective are 130 Mt $CO_2$ in 2030 in the REF scenario, which compares to 134 Mt $CO_2$ in 1990. Figure 7.1 shows an emission curve for the transport sector from an end-use perspective.

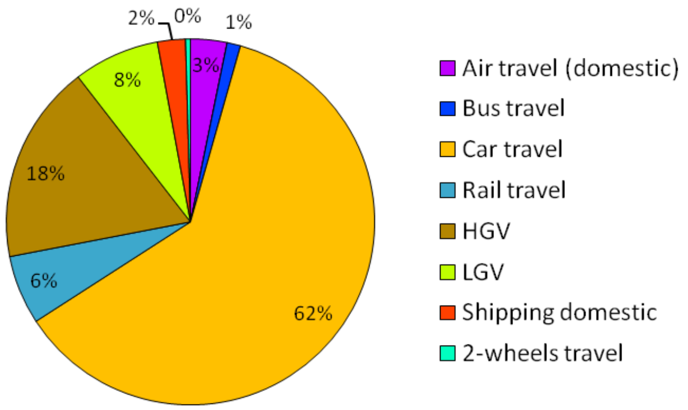
**Figure 7.1: End-use emission curve for the transport sector in United Kingdom in 2030**




At a price of £100/t $CO_2$ emissions are reduced by 50 Mt $CO_2$ to a level of 80 Mt $CO_2$ and from then on more gradually to 65 Mt $CO_2$. This representation does not only allow insights into the emissions reduction from a baseline, but also to put the absolute emissions into perspective. At some points of the curve, emissions increase despite increasing $CO_2$ tax levels due to interactions with other sectors and intertemporal interactions, i.e. it is more cost-effective to reduce emissions in other sectors or other time periods.

130 Mt $CO_2$ emissions in the reference case at no $CO_2$ tax originate from different transport modes (Figure 7.2). As the majority of all travel is done via cars, this transport mode is responsible for 62% of all end-use transport emissions in 2030. The second most important source of $CO_2$ emissions are heavy goods vehicles (HGVs) with 18%, followed by light goods vehicles (LGVs) with 8% and rail travel with 6% of all transport emissions. Minor contributions come from domestic aviation (3%), domestic shipping (2%), bus (1%) and two-wheelers (<1%). Correspondingly, one can expect to see predominantly emissions reduction measures associated with those transport modes that emit the most $CO_2$, i.e. cars, HGVs and LGVs. The numbers for aviation and shipping would change significantly with international emissions included, since in 2008 emissions from international aviation were 14 times greater than those from domestic aviation, while the corresponding ratio is 1.25 for shipping.

**Figure 7.2: $CO_2$ emissions from different transport modes in United Kingdom in 2030**




In order to judge the technological structure of the MAC curve it is important to know what propulsion systems are used for the different transport modes in the reference case. Without any $CO_2$ price in the REF case, the transport sector is characterised by cars that rely on petrol/diesel ICE vehicles and petrol hybrids (46%) and the vast majority of buses with diesel hybrid engines. A small proportion of buses (12%) are vehicles equipped with a battery. The large majority of LGV as well as HGV are also propelled by diesel hybrid engines. 7% of all rail travel does not use electricity, but relies on diesel as a fuel.

Including the results of the decomposition analysis shows which measures are responsible for the emissions reductions (see chapter 4). Equation (7.1) details the decomposition employed to disaggregate changes in total transport $CO_2$ emissions in this chapter:

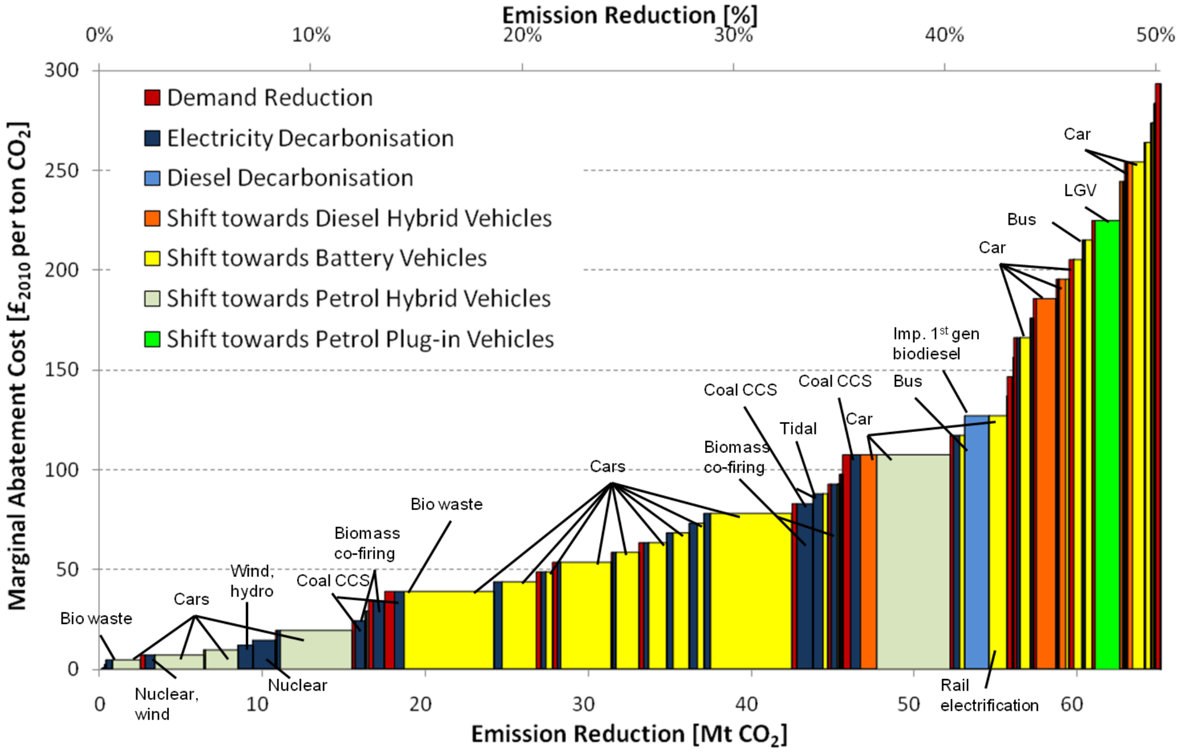
$$CO_{2,Transport} = \sum_{i=trsp\ mode} activity_i \left( \sum_{j=technology} \frac{activity_{i,j}}{activity_i} * \frac{fuel_{i,j}}{activity_{i,j}} * \frac{CO_{2\ i,j}}{fuel_{i,j}} \right) \tag{7.1}$$

*activity*$_i$ stands for the demand level of transport mode $i$ in billion vehicle kilometres. *activity*$_{i,j}$ represents the demand level satisfied by technology $j$ for transport mode $i$, while *fuel*$_{i,j}$ indicates the amount of fuel in PJ used for technology $j$ to satisfy demand of transport mode $i$. Lastly, $CO_{2\ i,j}$ is the amount of $CO_2$ in kt emitted by technology $j$ while satisfying demand of transport mode $i$. Correspondingly, the decomposition distinguishes between demand-related influences, structural changes, and the impact of fuel efficiency and carbon intensity.

Demand-related factors describe a change in the demand for energy services and structural changes mean a change from one technology to another, e.g. a switch from petrol ICE cars to hydrogen fuel cell cars. Fuel efficiency influences relate to improvements in the fuel that is used for a specific distance and carbon intensity effects describes a change in the carbon content of a fuel, e.g. by blending biodiesel into diesel or by reducing the carbon intensity of electricity. The logarithmic mean Divisia index (LMDI) is used to derive the contribution towards $CO_2$ emission of specific measures (see also chapter 4).

Figure 7.3 shows that structural shifts and the decarbonisation of fuels are responsible for the majority of emissions reductions in the central scenario. Energy-service demand reduction due to higher costs for energy service demands represents a constant but minor contribution. The demand contribution is limited due to structural changes that keep the price for energy service demand relatively constant, especially for cars. Nevertheless, alternative technologies are limited for aviation, shipping and HGV, so that these transport modes show a disproportionately high demand reduction. In addition, one can distinguish two major trends in the MAC curve.

**Figure 7.3: Transport MAC curve for the REF scenario in 2030**

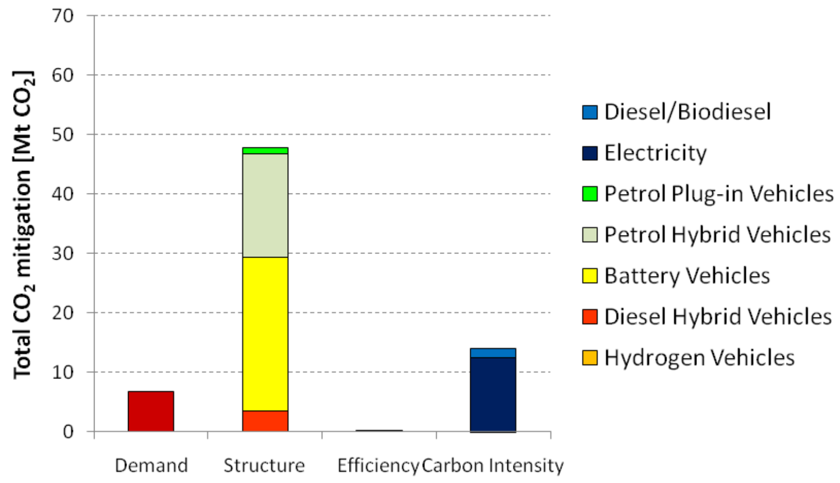



Firstly, the predominant trend in the transport sector is the electrification of most of the transport modes. The cheapest option to reduce transport emissions is the switch from conventional petrol cars towards petrol-electric hybrid cars as they are more efficient and consume less fuel. Mainly in a range from £40/t $CO_2$ and £80/t $CO_2$, battery cars become cost-effective and make up 43% of all cars. This trend is accompanied by a decarbonisation of electricity. It is an important condition since electricity is used as an energy input for almost all trains, for slightly more than 10% of all buses and from £40/t $CO_2$ a significant proportion of cars. Up to £40/t $CO_2$ electricity is decarbonised by 80% compared to £0/t $CO_2$ in 2030. At a higher tax of around £225/t $CO_2$, LGVs partly shift to petrol plug-in vehicles and thereby reduce $CO_2$ emissions via a higher consumption of electricity rather than petrol.

A second trend concerns cars and LGV consuming diesel. Diesel begins to be slightly decarbonised (by 5%) around £125/t $CO_2$ due to a higher share of imported first generation biodiesel in the diesel mix. The decarbonisation of this secondary energy carrier via the increase of the share of biodiesel reduces $CO_2$ emissions from transport modes relying on diesel, i.e. bus, car, LGV and HGV. At the upper end of the MAC curve, conventional diesel cars are displaced by diesel hybrid cars in a range from £100 to £250. Diesel hybrid cars are at a higher cost level in the MAC curve compared with petrol hybrids because the additional investment cost of diesel hybrids compared with diesel ICE cars is higher than the additional cost of petrol hybrids compared with petrol ICE cars. This is based on the reasoning that at present most hybrid vehicles are petrol vehicles, so it is assumed that technology costs can be more rapidly reduced for petrol hybrids than for diesel hybrids. Even a small difference in investment cost premiums is important, since the level of the $CO_2$ tax determines the fuel price that is crucial in determining how long it takes to compensate for the premium through reduced fuel costs. Currently about 70% of the diesel and petrol price consists of fuel taxes, and the crude oil price makes up only a relatively small part. Consequently, the mitigation costs of hybrid vehicles are very sensitive to the underlying assumptions, not only to investment costs, but also to hurdle rates and efficiency advantages.

An idea of the overall contribution of different technologies and effects up to the highest $CO_2$ tax of £294/t $CO_2$ in 2030, is given in Figure 7.4, which summarises the results for $CO_2$ emissions reduction due to demand changes, structural shifts, efficiency improvements, and carbon intensity reductions.

**Figure 7.4: Total decomposition of transport MAC (REF) for the UK in 2030**



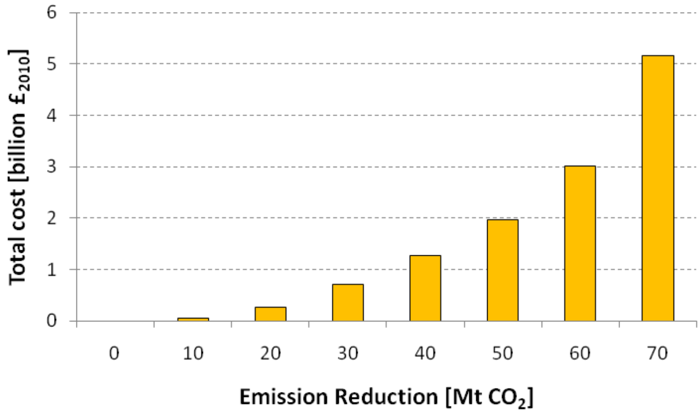

The reduction in the demand for energy services, caused by higher prices, has a minor (10%) but constant contribution. However, this finding is dependent on the specified price elasticity of energy service demands, as will become clear in the sensitivity cases. A reduction in fuel intensity [PJ/billion v.km] (equivalent to efficiency improvement) does not contribute to emissions reductions in the transport sector. This means that a carbon tax does not present an incentive for efficiency gains in addition to those present in the baseline without any carbon tax. Significant efficiency improvements are already incorporated in the reference case as they are assumed to be cost-effective without a $CO_2$ tax; in consequence, cost-effective, additional efficiency gains are relatively small and affect only a limited portion of the entire vehicle fleet. More importantly, since structural changes dominate the transport sector and since road vehicles have an average life time of 7 to 15 years, investments into more efficient vehicles are not realised over time because of an anticipated switch to a different technology. Another reason for the small role of efficiency improvements is the poor treatment of efficiency options in the model so that the fuel intensity effect could change under an alternate model type (see 7.1).

Within UK MARKAL, the most important effects for carbon reduction are structural changes and the decarbonisation of electricity and diesel. 70% of total carbon reduction originates from structural changes in the central case. This is shared between battery vehicles (38%), petrol hybrid vehicles (25%), diesel hybrid vehicles (5%), and petrol hybrid vehicles (2%). The decarbonisation of fuels contributes 20% towards $CO_2$ emissions reduction. Only a small proportion (2%) comes from a higher share of biodiesel due to the fact that it is more cost-effective to use the available biomass resources in the power sector and in buildings for space and water heating.

This stresses the importance of the supply sectors and the corresponding decarbonisation of secondary energy carriers in order to achieve mitigation targets for the transport sector. Structural changes and a reduction of carbon intensive electricity are pivotal to a decarbonisation of the transport sector, where structural changes are in general preceded by a decarbonisation of the concerned energy carrier.

Taking the integral under the curve in Figure 7.3 gives information about the total cost associated with emissions reduction in the UK transport sector in 2030. This does not, however, consider the costs associated with carbon abatement in earlier and later time periods. Figure 7.5 indicates that total costs increase exponentially with an increasing emissions reduction target. Total abatement costs in 2030 are £1.96 billion for an emissions reduction of 50 Mt of transport-related $CO_2$ emissions and £5.17 billion for a reduction of 70 Mt $CO_2$, this corresponds to an average abatement cost of £39/ t $CO_2$ and £74/t $CO_2$ respectively.

**Figure 7.5: Total abatement cost for the transport sector in United Kingdom in 2030**



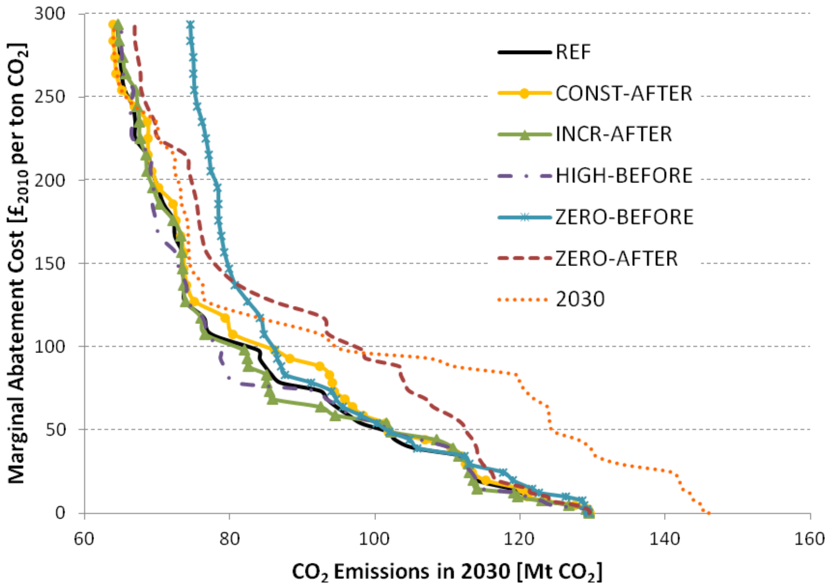

## 7.3 Path dependency

Five scenarios presented in this section correspond exactly to those presented in chapter 6 for the electricity sector. In addition, the 2030 scenario is presented, where the model is run until 2030 instead of 2050. Three scenarios consider different pathways after 2030, CONST-AFTER, ZERO-AFTER, INCR-AFTER, and two regard different pathways before 2030, ZERO-BEFORE, HIGH-BEFORE (see also Figure 6.7).

Although all seven scenarios have the same $CO_2$ tax in 2030, they result in different MAC curves, especially for higher abatement costs (see Figure 7.6). Those scenarios with a higher $CO_2$ tax compared with the REF scenario, i.e. INCR-AFTER and HIGH-BEFORE show for the same carbon price generally a slightly higher abatement level. The CONST-AFTER scenario, which keeps the $CO_2$ tax constant after 2030, shows only a very limited divergence from the REF scenario.

The emission curves for all three scenarios look very similar to the REF emission curve, where, for a given $CO_2$ tax, the biggest difference in the abatement potential is 9%. The picture looks different for the scenarios where the $CO_2$ tax is kept at zero before or after 2030, which significantly increases the marginal abatement costs. While the abatement potential is significantly lower for a given $CO_2$ tax up to £150/t $CO_2$ in the ZERO-AFTER scenario, it is the inverse case for the ZERO-BEFORE scenario where the abatement potential is less from around £100/t $CO_2$ onwards. In the 2030 scenario, the emission level is on average 22 Mt $CO_2$ above the REF scenario up to £127/t $CO_2$ and at higher tax levels very similar to the reference case.

Figure 7.6: End-use emission curve for different path dependency scenarios



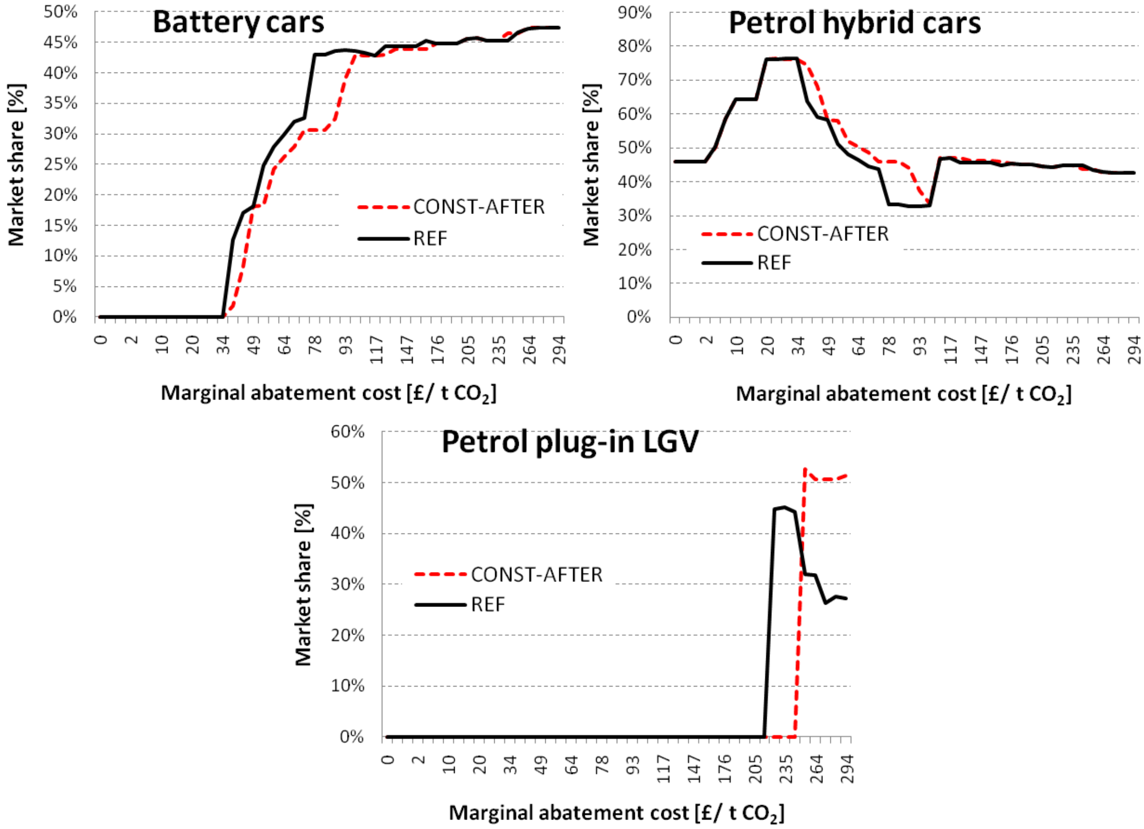

### 7.3.1 Constant $CO_2$ tax after 2030

In the CONST-AFTER scenario the $CO_2$ tax stays constant after 2030 at the same level as it is in 2030. Thus, the incentive for $CO_2$ abatement is less than in the REF scenario as the $CO_2$ tax no longer increases after 2030. Consequently the MAC curve can be expected to be steeper compared with the reference case.

It turns out that the results look very similar and that the constant $CO_2$ tax after 2030 has only a small cost-increasing effect. Figure 7.7 reveals that the abatement cost is slightly higher for certain technologies in the CONST-AFTER scenario, i.e. £5-25/t $CO_2$ more for battery cars, £15/t $CO_2$ more for diesel hybrid cars and £29/t $CO_2$ more for LGVs. The share of battery cars does not increase significantly above a market share of 43% because battery cars are only cost-effective a few years before 2030, but replacing all cars would take at least twelve years.

Petrol plug-in LGVs become cost-effective in the CONST-AFTER scenario at a higher cost level of £254/t $CO_2$ because petrol plug-in LGVs are used during the whole model horizon after 2030 and only partially replaced by diesel plug-in LGVs in 2050. In contrast to this, hydrogen becomes an important fuel for LGVs in the REF scenario from around £250/t $CO_2$ on in later model periods, so that petrol plug-in LGVs are introduced earlier, but to a smaller extent compared to the CONST-AFTER scenario as the technology replacement is anticipated. The market share of petrol plug-in LGVs in the CONST-AFTER scenario is not reduced with rising marginal abatement cost as no hydrogen vehicles become cost-effective in later periods.

**Figure 7.7: Market share for different technologies in the CONST-AFTER scenario in 2030**

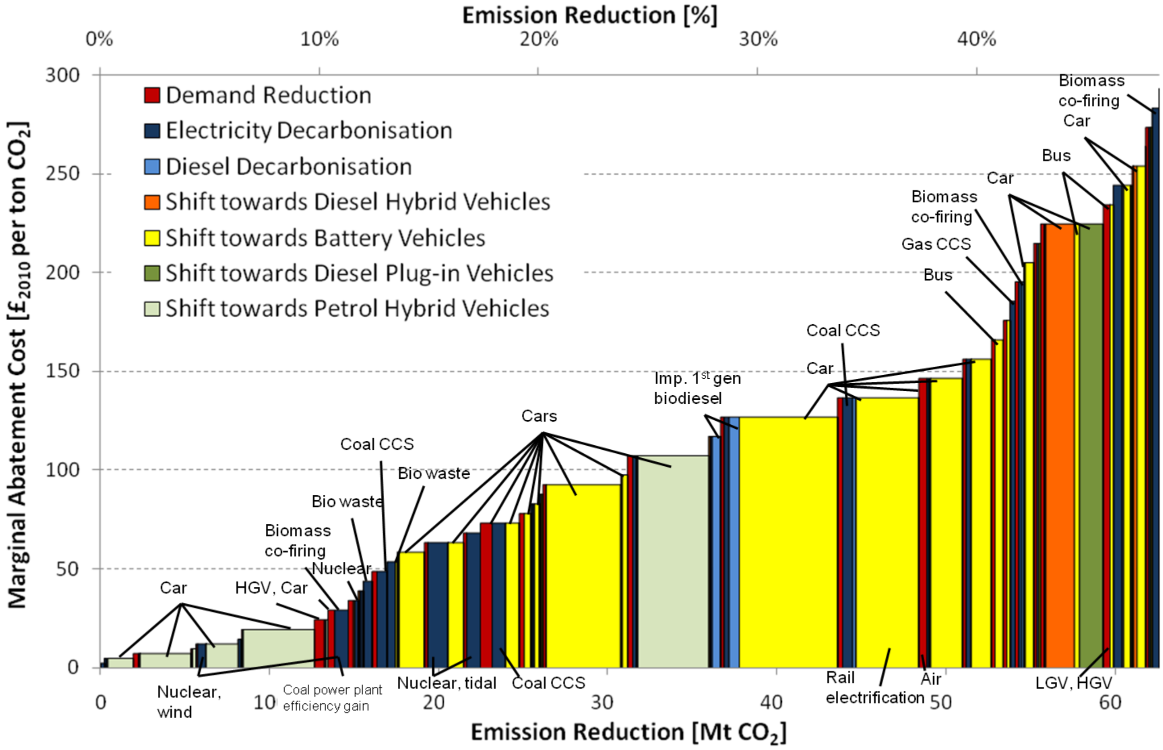



Petrol hybrid cars are the cheapest abatement option and up to £34/t $CO_2$ their market share increases to 76% in compensation for petrol ICE cars (see Figure 7.7). From this $CO_2$ tax level on, the market share declines steadily up to £98/t $CO_2$ as battery cars take over the market share. This decline is slower in the CONST-AFTER scenario due to the fact that the introduction of battery cars happens at higher cost levels. A last increase in market share can be observed at £108/t $CO_2$, where all remaining petrol ICE cars are replaced by petrol hybrid cars. A reason for the later introduction of battery cars is that the $CO_2$ tax does not increase as rapidly as in the REF scenario after 2030, which leads to a situation where electricity is not decarbonised to the same extent.

### 7.3.2 Zero $CO_2$ tax after 2030

This path dependency scenario assumes a $CO_2$ tax that drops back to zero for all model runs after 2030. This means that there is no penalty for emitting $CO_2$ after 2030. Correspondingly, one should expect less emissions reductions for the same $CO_2$ tax level. A look at Figure 7.6 and Figure 7.8 reveals that the ZERO-AFTER scenario is up to £50/t $CO_2$ more expensive compared with the REF scenario and in total results in 2.5 Mt $CO_2$ less abatement.

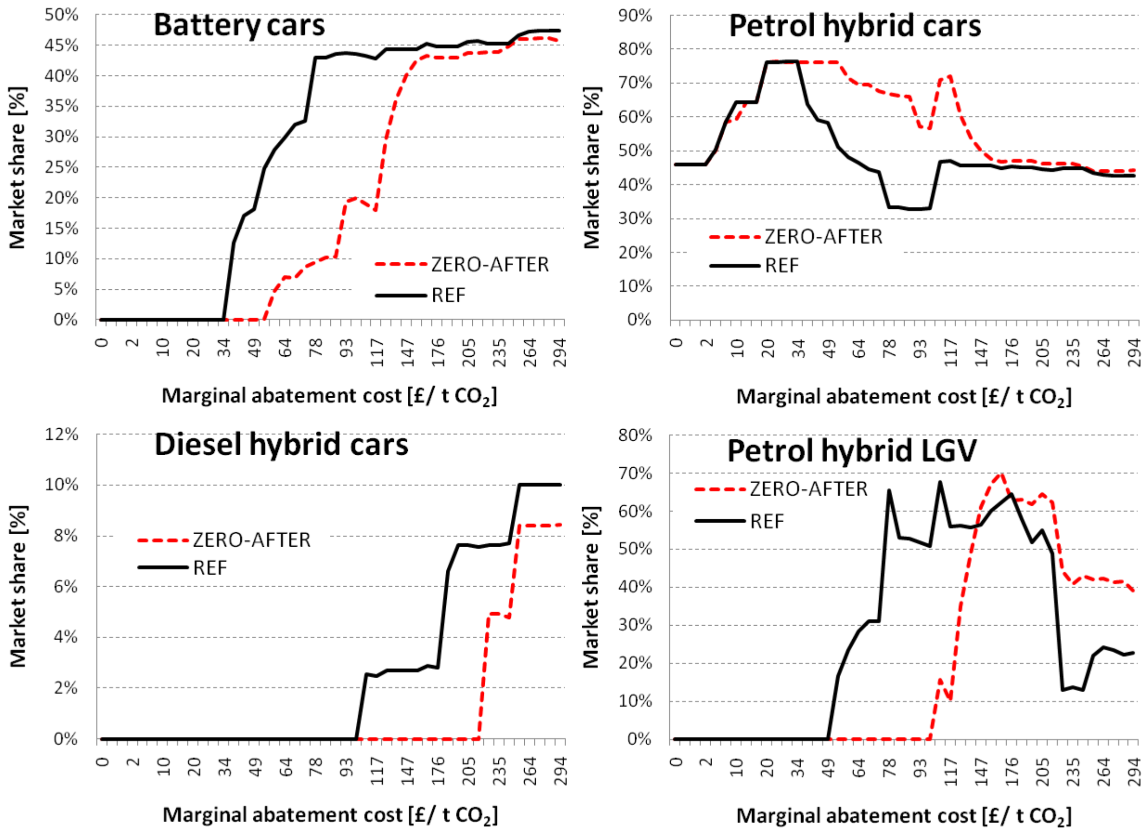
**Figure 7.8: MAC curve for the ZERO-AFTER scenario in 2030**




The MAC curve in the ZERO-AFTER scenario (Figure 7.8) indicates that mitigation technologies, such as petrol and diesel hybrid cars, and battery cars are introduced to the market at higher marginal abatement costs. It is also interesting to note that the whole MAC curve only includes technological mitigation measures relating to cars and buses, i.e. there are no structural changes within LGVs. Petrol plug-in LGVs do not become cost-effective up to £294/t $CO_2$, while petrol hybrid LGVs need a carbon tax that is £54/t $CO_2$ higher than in the REF scenario to enter the market. In anticipation of the $CO_2$ tax disappearing after 2030, the model does not choose petrol plug-in LGVs. The abatement potential from diesel hybrid cars is less compared with the REF scenario because diesel plug-in cars become cost-effective at £225/t $CO_2$ (see Figure 7.8). This additional abatement technology is introduced in 2030 as since no other low-carbon technologies are needed after 2030 and plug-in vehicles can consume electricity and refined products.

From Figure 7.9 it can be seen that abatement options need an even higher $CO_2$ tax to become cost-effective than in the CONST-AFTER scenario. Battery cars, for example, reach their full potential at £157/ t $CO_2$, which is £78/ t $CO_2$ more than in the REF scenario. As battery cars are later introduced into the market, the decrease of the share of petrol hybrid cars is less accentuated in the CONST-AFTER scenario.

**Figure 7.9: Market share for different technologies in the ZERO-AFTER scenario in 2030**




### 7.3.3 Steep increase in $CO_2$ tax after 2030

In the INCR-AFTER scenario the $CO_2$ tax increases after 2030 by 10% annually, thus the $CO_2$ tax increases with a rate that is twice as high as in the REF scenario. The shape of the MAC curve looks very similar to the REF scenario as Figure 7.6 reveals. Since the $CO_2$ tax is higher following 2030, there is an additional incentive for the model to choose low carbon technologies in 2030 in order to anticipate the future additional penalty for emitting $CO_2$. Therefore, a few mitigation technologies figure at lower cost levels on the MAC curve, e.g. battery cars reach their highest market share of 43% at £10/t $CO_2$ less, battery buses significantly increase their market penetration at £29/t $CO_2$ less and plug-in LGVs enter the market as well at £29/t $CO_2$ less.

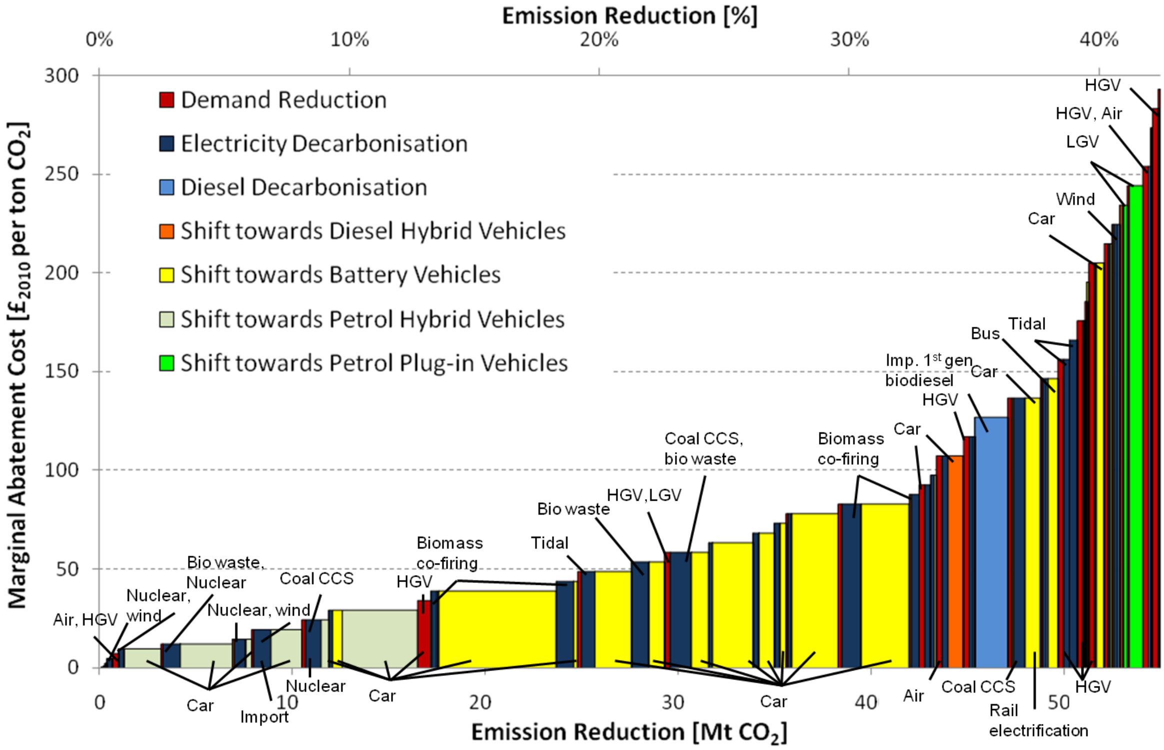
The steep increase of the $CO_2$ tax of 10% p.a. after 2030 presents an additional incentive to invest in a few low carbon technologies in 2030 compared to the REF scenario. Overall, the influence of this additional increase of the later $CO_2$ tax is limited.

### 7.3.4 Zero $CO_2$ tax before 2030

In contrast to the REF scenario, there is no $CO_2$ tax before 2030 in the ZERO-BEFORE scenario. There is no incentive to shift to any low-carbon technologies before 2030. This is important since road vehicles have a lifetime of 7 to 15 years, while aircrafts, ships and trains have a lifetime of up to 40 years. Even if investments are taken into low-carbon technologies in 2030, there will be still conventional technologies present in 2030 due to earlier long-lasting investments.

Figure 7.6 and Figure 7.10 show that the overall MAC curve for the transport sector looks very similar to the REF scenario up to £70/t $CO_2$, but then starts to diverge in the sense that less $CO_2$ is reduced so that at £294/t $CO_2$ 10 Mt $CO_2$ are unabated compared to the REF scenario. The contribution of electricity decarbonisation is higher with a share of 26% compared to 18% in the REF scenario, since the switch to battery cars happens at approximately the same cost level, but electricity gets decarbonised at slightly higher cost levels (see Figure 7.11).

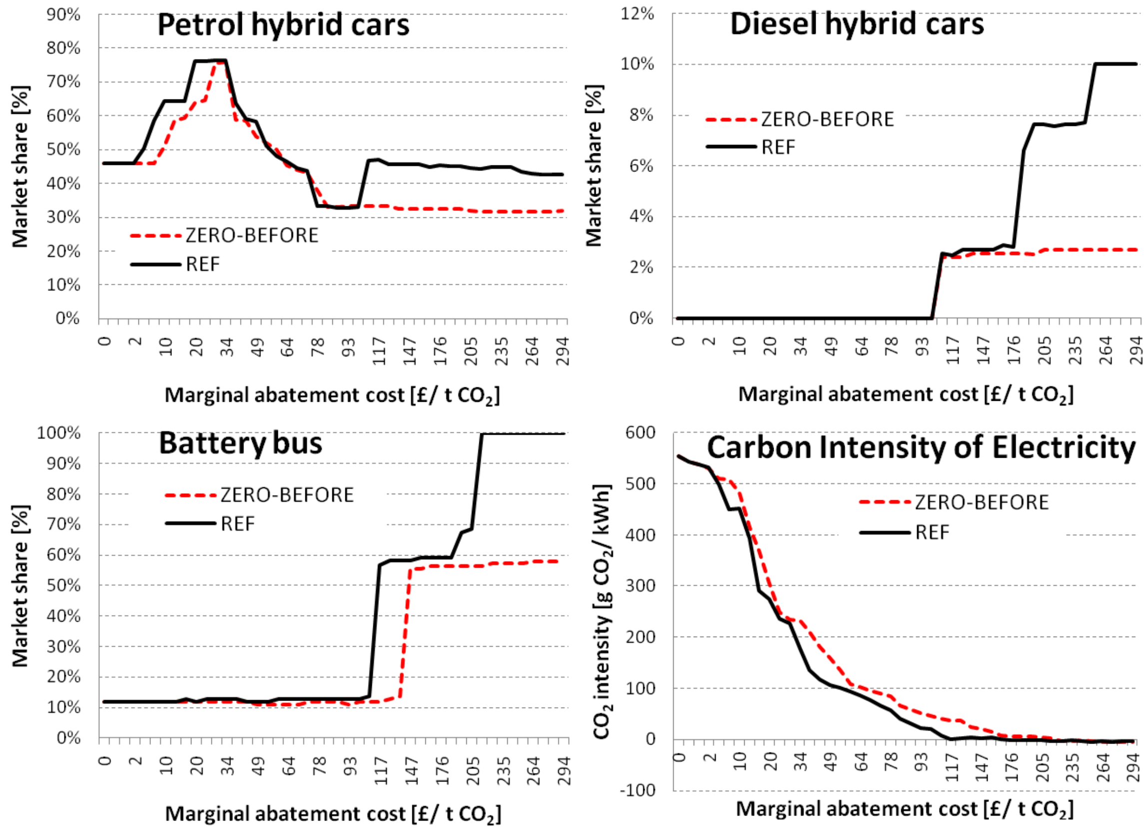
**Figure 7.10: MAC curve for the ZERO-BEFORE scenario in 2030**




The abatement potential is lower in the ZERO-BEFORE scenario compared with the REF scenario because several low-carbon technologies remain significantly behind their market penetration in the REF scenario. This is particularly the case for petrol hybrid cars, diesel hybrid cars and battery buses (see Figure 7.11). A reason for the lower market share of diesel hybrid vehicles is that in the model no investments are realised for this vehicle type before 2030 so that diesel ICE cars retain a significant market share. Similarly, the model does not invest in petrol hybrid cars until 2025, while this is already the case in 2020 for the REF scenario.

In summary, the fact that there is no $CO_2$ tax prior to 2030 represents a significant disincentive for the investment in low-carbon technologies. The investment level is therefore lower in comparison to the REF scenario despite a high $CO_2$ tax in 2030 and in subsequent years.

**Figure 7.11: Market share for different technologies and carbon intensity of electricity (bottom right) in the ZERO-BEFORE scenario in 2030**




### 7.3.5 High $CO_2$ tax from 2015

The HIGH-BEFORE scenario assumes that the $CO_2$ tax stays at a constant level from 2015 to 2030, which is the same as the $CO_2$ tax in the REF scenario in 2030. The shape of the emission curve (see Figure 7.6), as well as the MAC curve, looks very similar to the REF scenario. The overall abatement is also almost the same as in the scenario with a constantly rising $CO_2$ tax. Looking specifically at the mitigation measures reveals that petrol ICE cars are completely replaced by petrol hybrid and battery cars at a cost level of £78/t $CO_2$, thus at £30/t $CO_2$ less. Similarly, electric buses become cost-effective at

£50/t $CO_2$ less compared with the REF scenario. For other mitigation options the abatement potential and the marginal abatement cost level is comparable.

A high $CO_2$ tax that is higher for two periods can lead in specific cases to a reduction of marginal abatement costs, but does not alter the overall MAC curve substantially. Thus, the MAC curve is more affected by lower carbon tax pathways than by higher carbon taxes owing to the already high tax level in the reference case.

### 7.3.6 Model horizon limited to 2030

In the 2030 scenario, the model is only run until 2030 so that expectations about the development of the energy system beyond 2030 do not play a role. The results in the 2030 scenario diverge significantly from the other path dependency scenarios in the transport sector. In the other sectors that have been studied, there exists almost no difference between the 2030 scenario and the REF scenario so that results are only presented for the transport sector.

Figure 7.6 showed that emissions are substantially higher up to £127/t $CO_2$ owing to a change in the model horizon to 2030. At £0/t $CO_2$ petrol hybrid cars are not cost-effective so that the emissions level is 16 Mt $CO_2$ higher. Petrol hybrid cars become cost-effective at £30/t $CO_2$, while they are already part of the vehicle mix without a $CO_2$ policy in the REF scenario. Similarly, the abatement costs associated with battery cars are £30/t $CO_2$ higher than in the REF scenario, i.e. battery cars are introduced to the market from £70/t $CO_2$.

The model no longer expects fuel prices to moderately increase in the years after 2030 as it is assumed in the REF scenario because the model is only run until 2030. Since abatement costs of petrol hybrid cars are very sensitive to the underlying assumptions, abatement costs increase by more than £30/t $CO_2$ compared with the REF scenario. The situation is similar for battery cars. In summary, an optimisation up to 2030 leads to substantially higher abatement costs up to a $CO_2$ tax of £127/t $CO_2$ compared to all other path dependency scenarios.

## 7.4 Technology learning

Technology learning rates are a static, exogenous input to the UK MARKAL model. Since learning rates are uncertain and become more uncertain the further one projects trends into the future, a sensitivity analysis is performed around the assumptions concerning learning in the transport sector. Learning rates concerning capital costs have been increased in one scenario, Increased Technology learning (ITL) and decreased in a second scenario, Decreased Technology learning (DTL). The investment costs are detailed in Table 7.2.

**Table 7.2: Investment cost in different scenarios for constant 2010 efficiency levels (ITL= Increased Technology learning, DTL= Decreased Technology learning) [£$_{2000}$ per vehicle]**

| BUS | Battery | Diesel ICE | Hydrogen ICE | Hydrogen FC | Methanol FC | Hybrid diesel |
|---|---|---|---|---|---|---|
| **2010** Base | 190,806 | 137,388 | 157,117 | 229,901 | 238,943 | 155,501 |
| **2030** Base | 147,548 | 121,972 | 89,733 | 101,779 | 109,567 | 95,555 |
| **2030** ITL | 129,536 | 114,894 | 67,388 | 72,343 | 79,087 | 74,561 |
| **2030** DTL | 159,451 | 126,415 | 106,337 | 130,689 | 139,147 | 110,726 |

| CAR | Battery | Diesel ICE | E85 | Hydrogen ICE | Methanol ICE | Gasoline ICE | Hydrogen FC |
|---|---|---|---|---|---|---|---|
| **2010** Base | 30,160 | 12,283 | 11,346 | 17,705 | 14,124 | 11,234 | 114,481 |
| **2030** Base | 16,452 | 11,425 | 10,508 | 9,285 | 11,449 | 10,410 | 30,759 |
| **2030** ITL | 13,385 | 10,881 | 10,008 | 7,016 | 10,471 | 9,916 | 19,162 |
| **2030** DTL | 18,587 | 11,764 | 10,819 | 10,950 | 12,077 | 10,718 | 40,526 |

| | Methanol FC | Hybrid diesel | Hybrid E85 | Hybrid gasoline | Plug-in diesel | Plug-in gasoline |
|---|---|---|---|---|---|---|
| **2010** Base | 42,603 | 15,871 | 14,338 | 14,104 | 20,983 | 19,429 |
| **2030** Base | 15,044 | 10,658 | 9,629 | 9,478 | 14,028 | 12,402 |
| **2030** ITL | 10,733 | 8,706 | 7,866 | 7,744 | 11,409 | 9,850 |
| **2030** DTL | 19,742 | 12,021 | 10,860 | 10,688 | 15,852 | 14,213 |

| HGV | Diesel ICE | Hydrogen ICE | Hydrogen FC | Hybrid diesel |
|---|---|---|---|---|
| **2010** Base | 54,656 | 83,270 | 237,333 | 58,376 |
| **2030** Base | 47,799 | 50,431 | 74,406 | 45,430 |
| **2030** ITL | 44,681 | 39,027 | 51,508 | 40,024 |
| **2030** DTL | 49,766 | 58,709 | 100,350 | 48,997 |

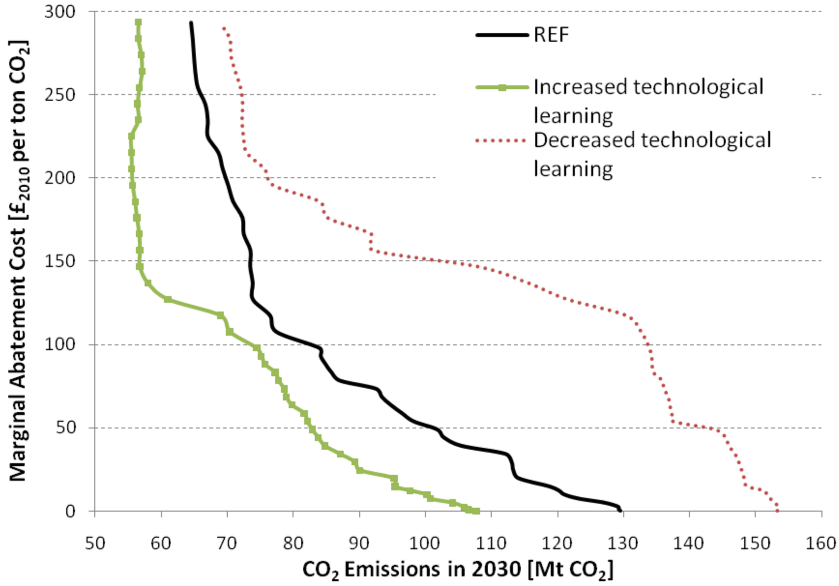
| LGV | Battery | Diesel ICE | E85 | Hydrogen ICE | Methanol ICE | Gasoline ICE |
|---|---|---|---|---|---|---|
| **2010** Base | 48,255 | 13,593 | 14,607 | 20,254 | 15,629 | 12,469 |
| **2030** Base | 29,926 | 12,336 | 13,259 | 10,760 | 12,372 | 11,369 |
| **2030** ITL | 23,425 | 11,750 | 12,631 | 7,775 | 10,994 | 10,855 |
| **2030** DTL | 34,595 | 12,701 | 13,651 | 13,039 | 13,275 | 11,689 |

| | Hydrogen FC | Methanol FC | Hybrid diesel | Hybrid gasoline | plug-in diesel | plug-in gasoline |
|---|---|---|---|---|---|---|
| **2010** Base | 44,132 | 43,667 | 16,391 | 16,316 | 20,945 | 19,992 |
| **2030** Base | 12,511 | 16,821 | 11,009 | 10,922 | 15,522 | 14,156 |
| **2030** ITL | 11,002 | 14,926 | 8,994 | 8,906 | 13,334 | 11,879 |
| **2030** DTL | 17,400 | 22,652 | 12,417 | 12,331 | 16,993 | 15,713 |

The investment costs in Table 7.2 do not account for efficiency gains that occur over time, i.e. efficiency levels are kept constant at the 2010 level in order to make the investment costs comparable. Standard ICE vehicles are 7% to 12% cheaper in 2030 than in 2010 in the REF scenario, up to 18% cheaper in the ITL scenario and only 4% to 9% cheaper in the DTL scenario. The learning rates for less mature technologies are significantly higher. Investment costs for hybrid cars are about 33% lower in 2030 compared to 2010 in the REF scenario, 46% lower in the ITL scenario and 24% lower in the DTL. The corresponding figures for battery cars are 45% in the REF scenario, 56% in the ITL scenario and 38% in the DTL scenario. Low carbon technologies are on average 39% cheaper in 2030 compared with 2010 in the REF scenario; this increases to 50% in the ITL scenario and decreases to 31% in the DTL scenario.

The emission curves in Figure 7.12 show that both scenario curves look very different from the REF scenario. The DTL scenario shows emission of 153 Mt $CO_2$ without any $CO_2$ tax, which corresponds to an additional 24 Mt $CO_2$ in comparison with the REF scenario. This can be mainly explained by the fact that no petrol hybrid cars and no diesel hybrid LGVs are part of the market in the £0/t $CO_2$ run, but the market is dominated by petrol ICE LGVs. The difference is biggest at £108/t $CO_2$ with 55 Mt $CO_2$, but is reduced once battery cars become cost-effective to 4 Mt at £294/t $CO_2$.

**Figure 7.12: Emission curve along rising $CO_2$ abatement costs for different technology learning scenarios in 2030**




For the ITL scenario the situation is reversed, where emissions reduction is 22 Mt higher without any $CO_2$ tax. The reasons are a 45% market share of battery cars compared to 0% in the REF scenario and diesel hybrid vehicles are at 10% market share, while they were not cost-effective in the REF scenario.

The MAC curve for the DTL scenario (Figure 7.13) looks very different from the REF scenario to the extent that up to £50/t $CO_2$ only 7 Mt of emissions abatement are realised. A lower carbon intensity of electricity used for railway transport and energy-service demand reduction save emissions. Demand reduction contributes 30% towards $CO_2$ emissions reduction up to an abatement cost of £40/t $CO_2$. The cheapest technological abatement options are diesel hybrid LGVs at £50/t $CO_2$. Battery cars are responsible for the major share of the emissions reduction, although they reach the full abatement potential at £176/t $CO_2$ due to increased investment costs, i.e. around £100/t $CO_2$ more than in the REF scenario. While diesel hybrid cars do not become cost-effective below £294/t $CO_2$ in the DTL scenario, petrol hybrid cars enter the market at almost £200/t $CO_2$ (see also Figure 7.15)

**Figure 7.13: MAC curve for the DTL scenario in 2030**

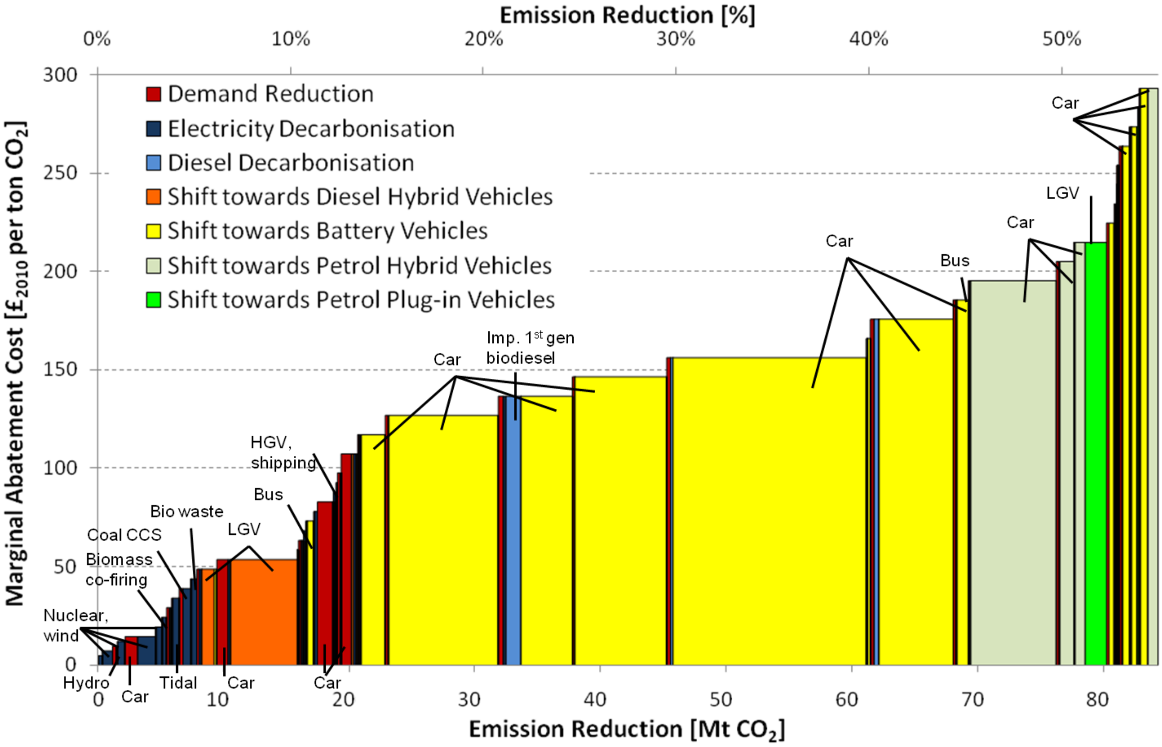
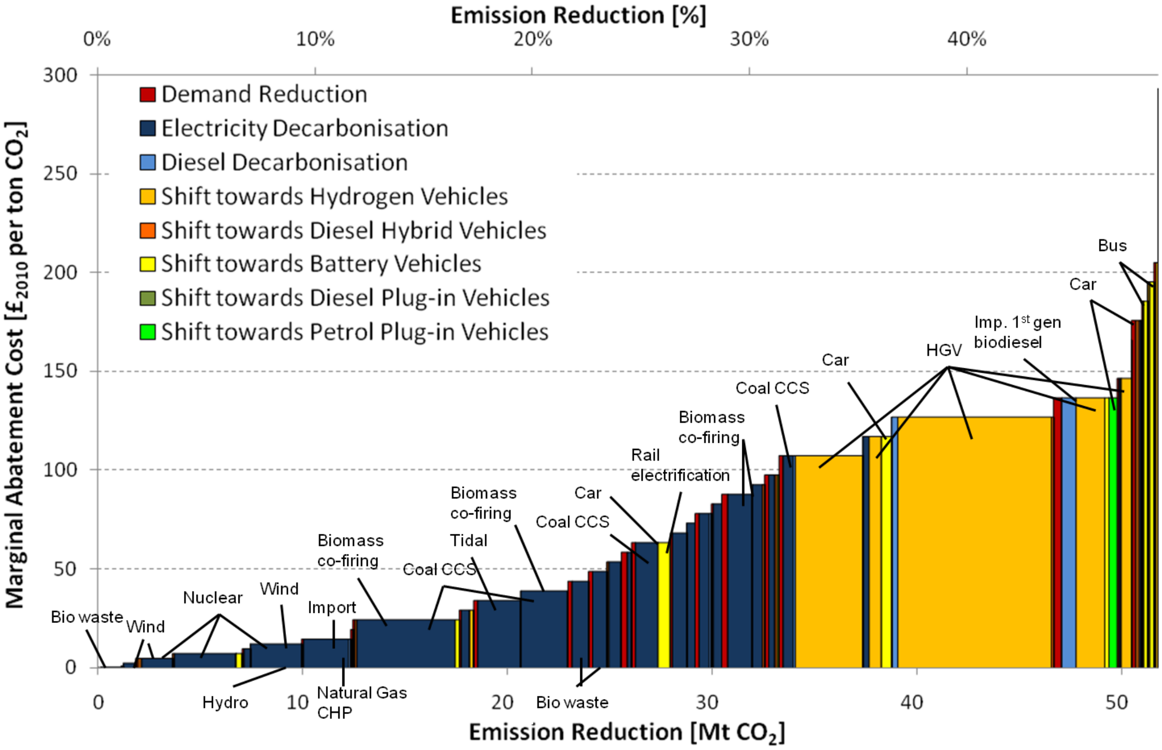



**Figure 7.14: MAC curve for the ITL scenario in 2030**

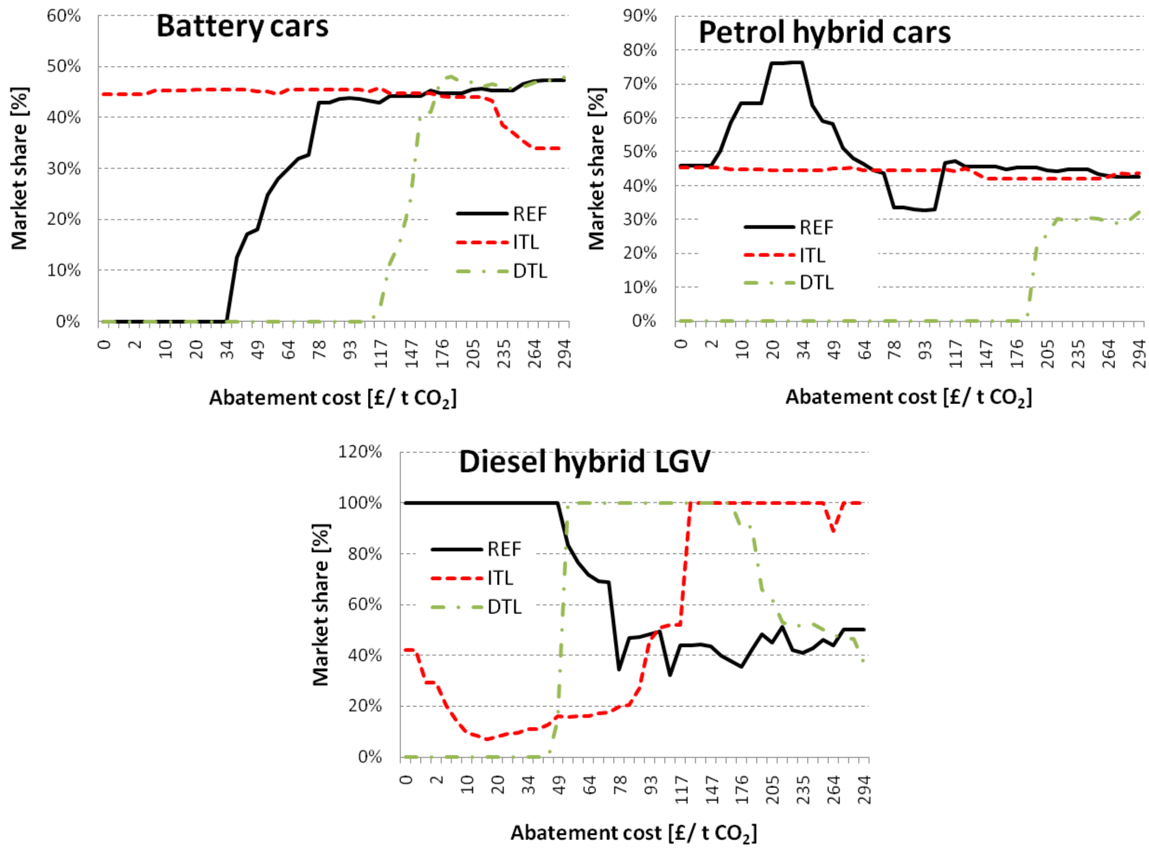


The MAC curve for the ITL scenario (Figure 7.14) does not contain any petrol hybrid, diesel hybrid vehicles and virtually no abatement from battery cars, which are assumed to be cost-effective without any $CO_2$ tax as a result of the higher technology learning.

Since a significant portion of cars rely on electricity as an energy carrier, the cheapest abatement option on the MAC curve up to £100/t $CO_2$ is to reduce the carbon intensity of electricity, so that the contribution of an electricity decarbonisation towards overall reduction in transport-related $CO_2$ emissions in the ITL scenario is substantial with 59% (see also Figure 7.16).

Hydrogen is 90% decarbonised at £30/t $CO_2$ via the use of CCS plants using coal as a fuel, so that hydrogen fuel cell HGVs become cost-effective from £104/t $CO_2$ and 75% of all HGVs are powered by hydrogen at £296/t $CO_2$. Two-wheelers also partially switch to hydrogen as a fuel, but the effect on emissions remains very limited due to the limited amount of emission in the £0/t $CO_2$ case. Taking a deeper look at specific technologies reveals that the share of battery cars decreases in the ITL scenario from £225/t $CO_2$ in anticipation of a higher share of hydrogen cars in the future (Figure 7.15).

**Figure 7.15: Market share for different technologies in the DTL and ITL scenarios in 2030**



Petrol hybrid cars have a steady market share of 45% since they are more cost-effective than petrol ICE cars and are not influenced by a fluctuating battery car market share as battery vehicles are already cost-effective without any $CO_2$ tax. Finally, the share of diesel hybrid LGVs is very different between the learning scenarios because the cost difference in comparison with petrol hybrid LGVs is minimal so that small changes in the fuel cost can result in large swings of market shares.

The total composition of $CO_2$ emissions reduction looks very different from one learning scenario to the other. Due to a large share of battery cars, the ITL scenario is dominated by electricity decarbonisation and structural shifts towards hydrogen HGVs, which reduce emissions by 15 Mt $CO_2$. The emissions reduction in the DTL scenario is far greater because emissions are higher without a $CO_2$ tax. The composition is dominated by battery vehicles and petrol hybrid cars and less by electricity decarbonisation since a higher use of battery cars is preceded by a decarbonisation of electricity. Finally, the contribution of demand reduction is double in the DTL scenario compared to the ITL scenario due to more expensive low-carbon technologies.

**Figure 7.16: Total decomposition of transport MAC (ITL & DTL scenario) for the UK in 2030**

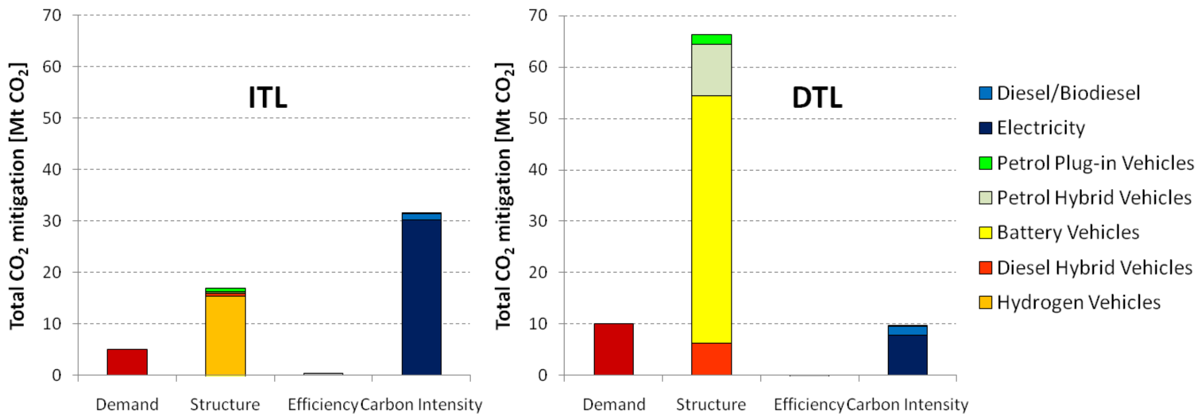
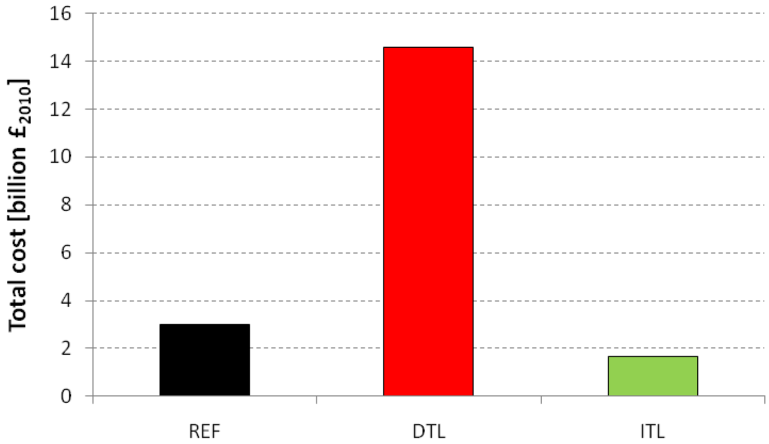



Figure 7.17 illustrates the total costs, in contrast to the marginal costs, in 2030 associated with an emission target of 70 Mt $CO_2$, which corresponds to an emissions reduction of 60 Mt $CO_2$ (REF), 38 Mt $CO_2$ (ITL), and 83 Mt $CO_2$ (DTL). According to the MAC curves based on the model runs, such an emission target can be achieved at a $CO_2$ tax of £205/t $CO_2$ in the REF scenario, £117/t $CO_2$ for the ITL scenario, and £294/t $CO_2$ for the DTL scenario. The total cost to reduce transport-related emissions to 70 Mt $CO_2$ is about £3 billion in the REF scenario, while it is £1.6 billion in the ITL scenario and £14.6 billion in the DTL scenario. This means that achieving the same target is 480% more expensive in the DTL scenario compared with the REF scenario and 45%

less expensive in the ITL scenario. This illustrates the large uncertainties related to assumptions concerning technology learning.

**Figure 7.17: Total cost in 2030 to achieve an emission target of 70 Mt $CO_2$**

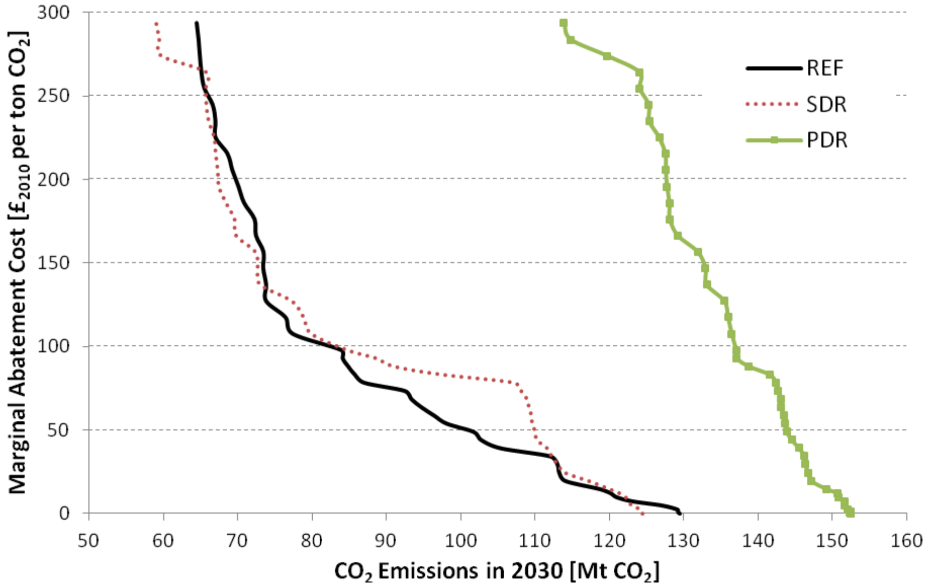



## 7.5 Discount rate

The two scenarios presented in this section, PDR10 and SDR, correspond exactly to those presented in chapter 6 for the electricity sector. In a MAC curve study for the CCC (AEA Energy & Environment et al. 2008, p. 18), discount rates were assumed to be 7% for passenger cars. The PDR10 scenario represents the perspective of a private investor, where the discount rate and the technological hurdle rates were doubled with respect to the REF scenario, although both are separate and do not have to increase accordingly. The PDR10 scenario assumes comparably high technological hurdle rates of 10% in general and of 20% for hydrogen vehicles and 15% for hybrid, plug-in and battery cars, which account for technology-specific uncertainties. In the SDR scenario a social discount rate of 3.5% is employed and all fuel duties and hurdle rates removed.

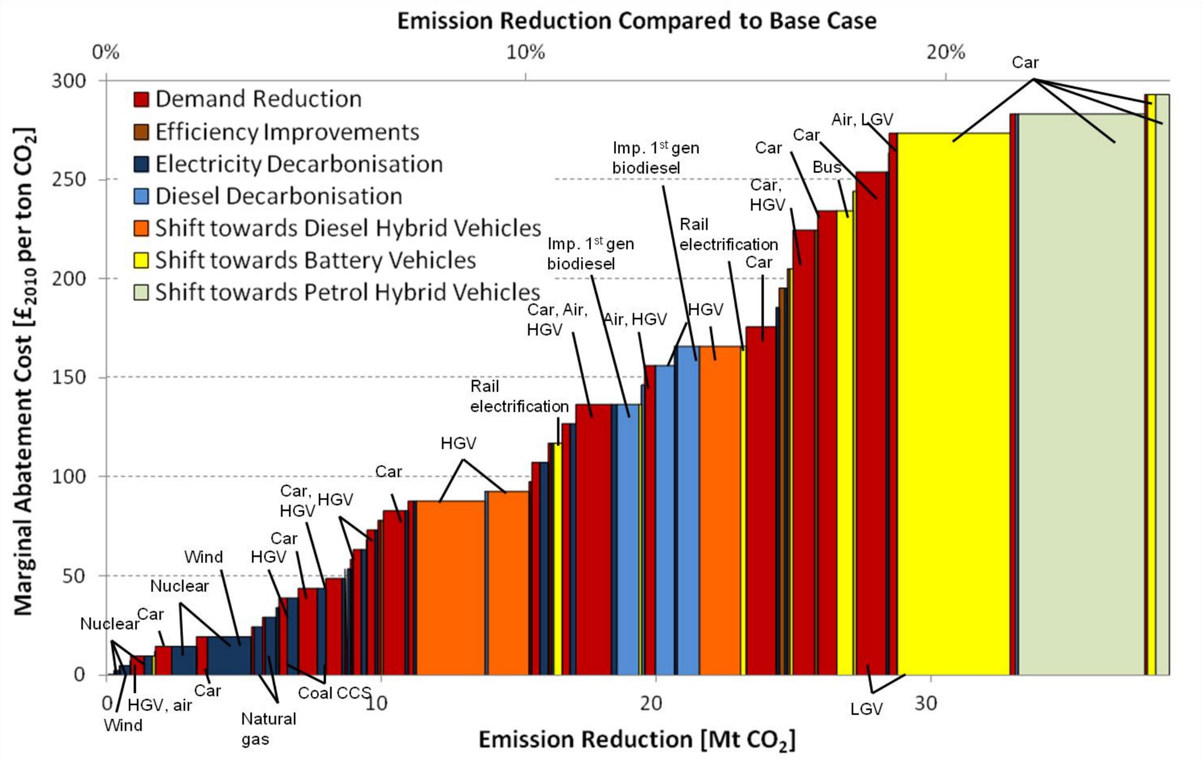
Figure 7.18 indicates that the emission curves are similar for the SDR and the REF scenario, while the emissions in the PDR10 scenario are a lot higher. They are 23 Mt $CO_2$ higher without a $CO_2$ tax since no petrol hybrid cars and electric buses are introduced to the market. Emissions are only very slowly decreased with higher $CO_2$ tax levels owing to the higher discount rate and hurdle rates that penalise low-carbon technologies. The SDR scenario shows slightly lower emissions in the case without a $CO_2$ tax because the market share of petrol hybrid cars is 30 percentage points higher. In other respects the emission curves of the REF scenario and the SDR scenario look relatively similar, though the SDR scenario shows more abatement potential at very high $CO_2$ taxes, where hydrogen vehicles become cost-effective.

**Figure 7.18: Emission curve along rising $CO_2$ abatement costs for different discount rate scenarios in 2030**




The MAC curve for the PDR scenario (Figure 7.19) shows that technological alternatives are very expensive. Hence, demand reduction plays an important role especially up to £250/t $CO_2$ with 13 Mt $CO_2$ emission reduction. The same holds true for the decarbonisation of diesel, though at a much smaller scale.

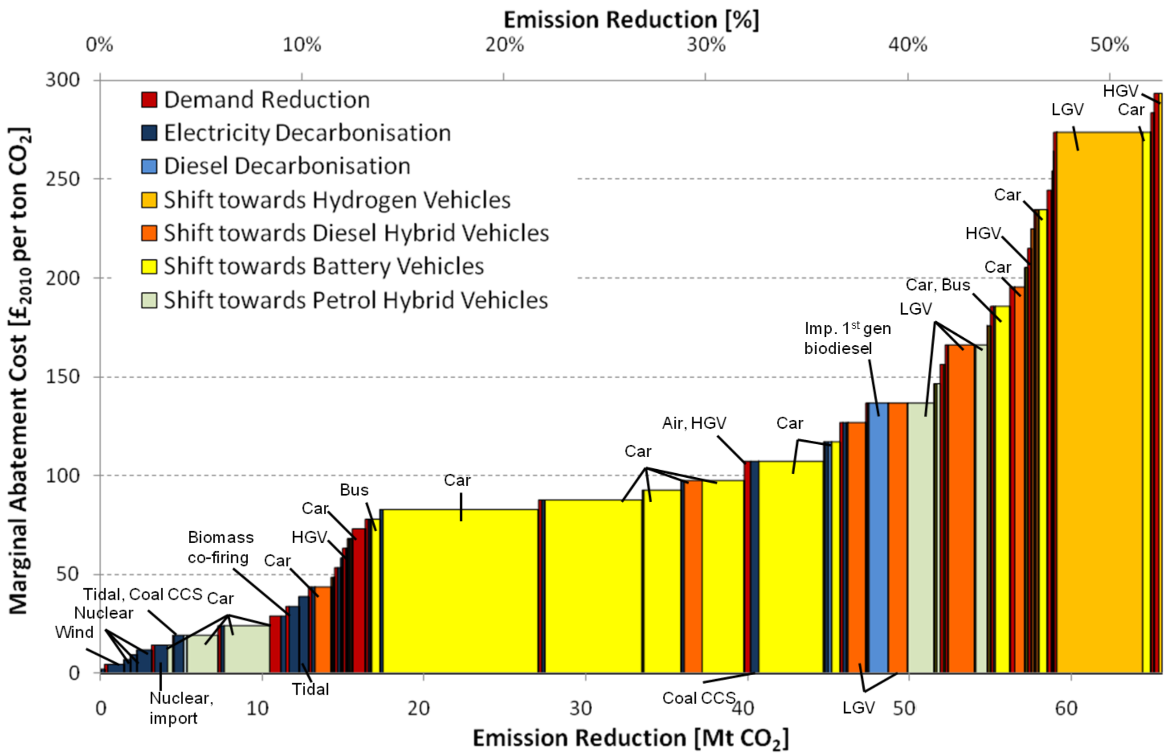
**Figure 7.19: MAC curve for the PDR10 scenario in 2030**



Taking a look at technological shifts reveals that increasing the hurdle rate for electric cars from 7.5% to 15% raises the marginal abatement cost of battery cars by almost £200/t $CO_2$. While petrol hybrid cars are cost-effective at £0/t $CO_2$ in the REF scenario, they are only cost-effective at a tax of £284/t $CO_2$. Diesel hybrid HGVs are cost-optimal at £0/t $CO_2$ in the REF scenario but not in the PDR10 scenario. The marginal abatement cost for this technology is increased to £85/t $CO_2$ to £166/t $CO_2$. This highlights the sensitivity of hybrid vehicles to the underlying assumptions concerning the discount rate, investment cost mark-up and efficiency gain.

The MAC curve for the scenario with a social discount rate looks very different from the PDR10 MAC curve (see Figure 7.20). There are two effects that counteract each other: on the one hand, low-carbon technologies save less fuel costs in the SDR scenario due to lower prices for petrol and diesel (taxes are removed). On the other hand, the investment cost premium for abatement technologies is less as there are no technological hurdle rates and the overall discount rate is lower at 3.5%. Differences in operating and maintenance costs, which include insurance, are comparably small and do not influence the overall result.

**Figure 7.20: MAC curve for the SDR scenario in 2030**

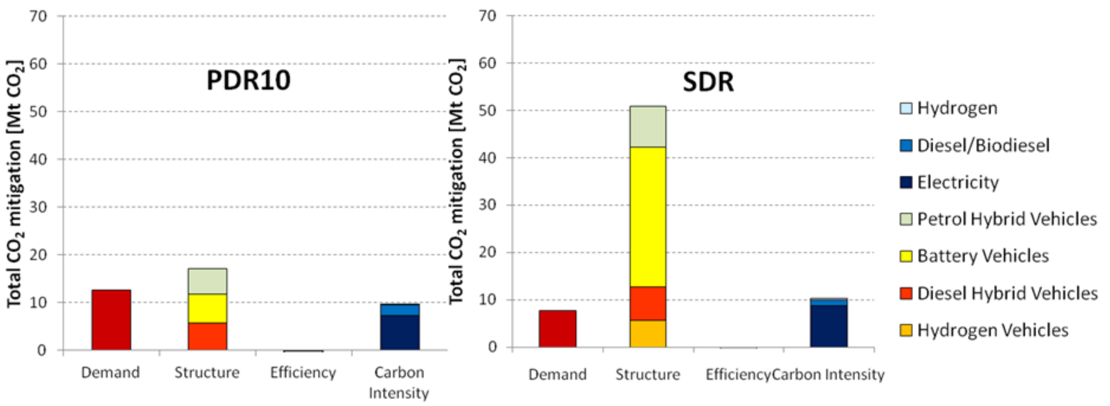



The MAC curve for the SDR scenario shows a lower abatement cost level for diesel hybrid cars of around £70/t $CO_2$ because there is no longer a 7.5% hurdle rate on the hybrid technology. Thus, the investment cost disadvantage is roughly halved, while the fuel cost advantage is reduced, although not to the same extent. Consequently, and similarly to petrol hybrid cars, the reduction in the investment annuity outweighs the reduced fuel saving. Furthermore, it is interesting to note that battery cars need a £44/t $CO_2$ higher tax in order to become cost-effective, because the investment cost disadvantage is not sufficiently reduced to offset the loss in fuel savings. Lastly, hydrogen fuel cell vehicles show up on the MAC curve at a very high $CO_2$ tax of £274/t $CO_2$ because they no longer have a technological hurdle rate of 10% and thus account for 6 Mt of $CO_2$ abatement (see Figure 7.21). While the emissions curves for the SDR and the REF scenario look relatively similar, the technologically detailed MAC curves are different.

Concerning the overall contribution to emissions reductions (Figure 7.21), demand reduction plays a much more important role in the PDR10 scenario, with 33% compared to 12% in the SDR scenario, due to a lack of low-priced technological alternatives. This is expressed in the overall contribution of structural shifts within the transport sector, which represents an emissions reduction of 17 Mt $CO_2$ in the PDR10 scenario and almost three times that amount in the SDR scenario.

The difference in the emission curve between the SDR and the PDR10 scenario is reflected in the total cost needed to achieve an emission target of 110 Mt $CO_2$ in 2030, which is £0.3 billion in the REF scenario, £0.4 billion in the SDR scenario and £7 billion in the PDR10 scenario. In summary, from a risk-averse private investor's perspective (PDR10), the same target for transport-related emissions of 110 Mt $CO_2$ is 17 times more expensive to achieve compared with a situation where the hurdle rates are half in the REF scenario.

**Figure 7.21: Total decomposition of transport MAC (PDR10 & SDR scenario) for the UK in 2030**

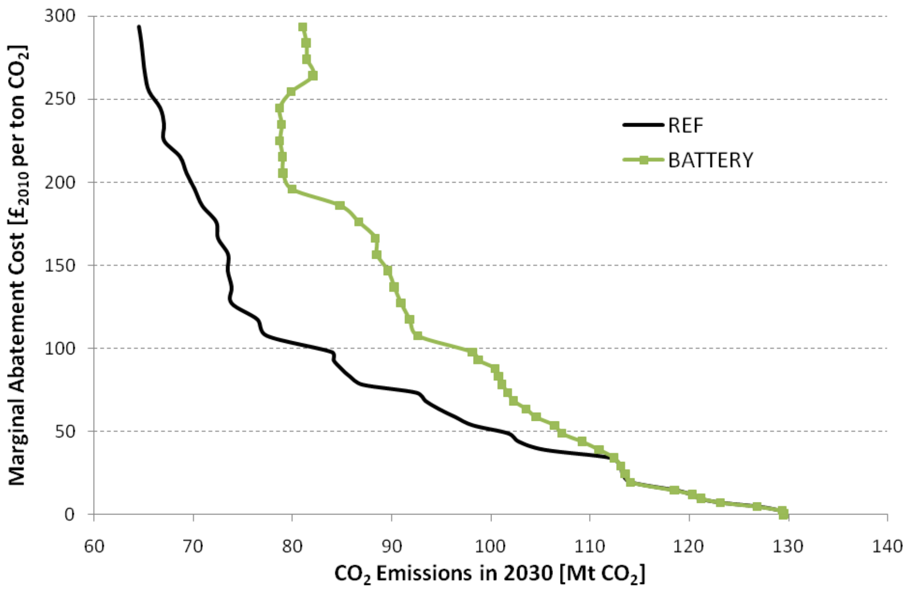


## 7.6 Market potential of battery vehicles

Battery vehicles play an important role in decarbonising the whole transport sector. Structural shifts towards electric vehicles represent 38% of all transport-related emissions reduction and the decarbonisation of electricity represents 18%. Consequently, more than half of the abatement in the transport sector is related to the electrification of transport. The BATTERY scenario tests how sensitive abatement potentials and related marginal abatement costs in the transport sector are to a limited market share of battery cars and buses. In the REF scenario battery cars and electric buses reach a maximum market share of 45% and 100% respectively at a high $CO_2$ tax levels. In both cases the market share is limited to 15% in the BATTERY scenario to see which other technologies compensate for this limited abatement potential.

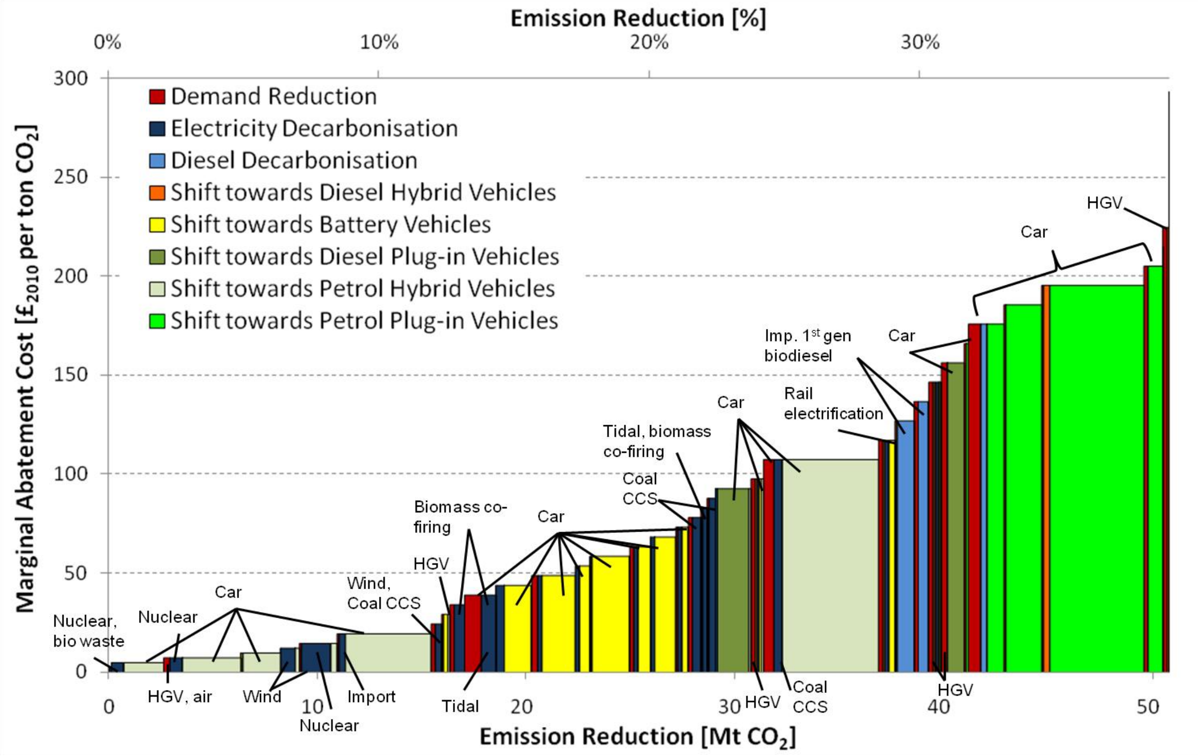
The emission curve (Figure 7.22) looks exactly the same as the REF scenario, up to £34/t $CO_2$. Subsequently, emissions abatement remains lower than in the REF scenario owing to the limited potential for battery vehicles and emissions grow from £245/t $CO_2$ to £264/t $CO_2$ despite a rising $CO_2$ tax. This is due to both intertemporal adjustments between model periods, but principally due to interactions with other end-use sectors. In this case, emissions increase by 3.4 Mt $CO_2$ in the transport sector due to a declining share of plug-in cars, but emissions are reduced to a bigger extent in the residential sector where electricity is used for space heating and displaces fossil fuel based heating.

**Figure 7.22: Emission curve along rising $CO_2$ abatement costs for the BATTERY scenarios in 2030**




The MAC curve for the BATTERY scenario (Figure 7.23) looks different in that the abatement potential for battery cars is limited and other technologies in the form of petrol plug-in, petrol hybrid and diesel plug-in vehicles compensate for the limited abatement potential of battery vehicles. Petrol plug-in cars become cost-effective at £176/t $CO_2$ and diesel plug-in vehicles at £93/t $CO_2$, while they are not a part of the MAC curve in the REF scenario.

**Figure 7.23: MAC curve for the BATTERY scenario in 2030**




Furthermore, the abatement potential of diesel hybrid cars is limited as they are partially replaced by diesel plug-in cars. The abatement potential is also higher for petrol hybrid cars because they are not replaced as quickly by battery cars as in the REF scenario; their market share remains at 64% at the end of the MAC curve in contrast to 43% in the REF scenario (see Figure 7.24). Interestingly, plug-in cars, which can rely on refined oil products and electricity, enter the vehicle pool, but their market share declines at higher $CO_2$ taxes again owing to a more efficient use of electricity in the residential sector.

**Figure 7.24: Market share for different technologies in the BATTERY scenario in 2030**

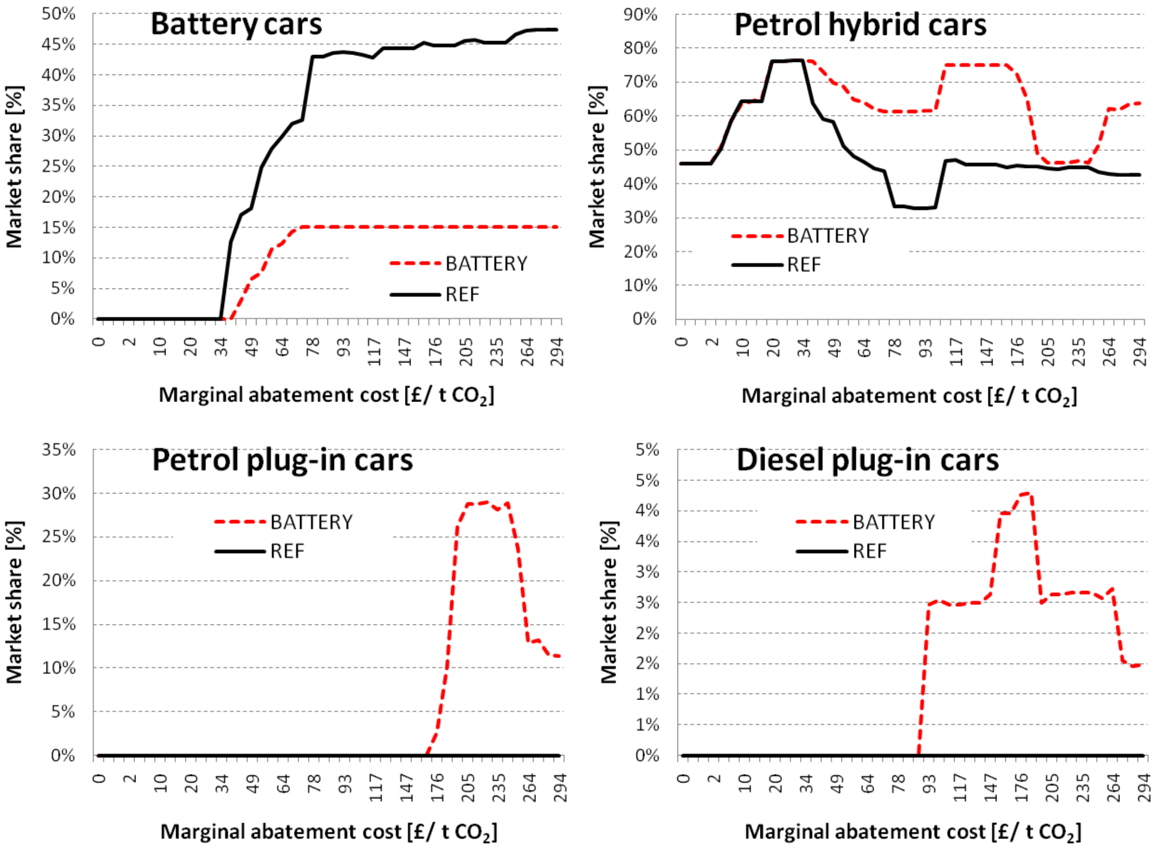
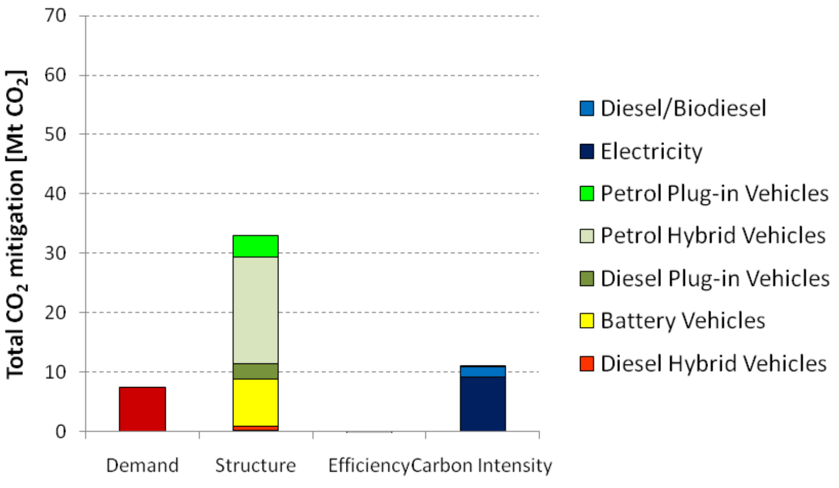



Figure 7.25 indicates that in the BATTERY scenario the overall contribution to emissions reductions of battery vehicles falls to only 8 Mt $CO_2$ or 16% of the total emissions reduction. Diesel plug-in vehicles can fill this gap by reducing emissions by 3 Mt $CO_2$, and petrol plug-in vehicles by 4 Mt $CO_2$. Since the market share of petrol hybrid cars remains higher in the BATTERY scenario, total abatement due to petrol hybrid vehicles is a little higher at 18 Mt $CO_2$.

**Figure 7.25: Total decomposition of transport MAC (BATTERY scenario) for the UK in 2030**



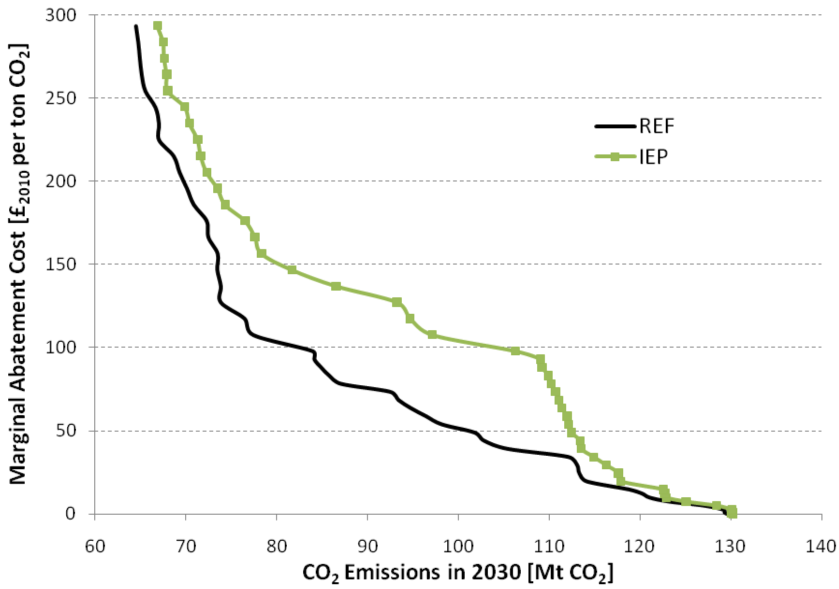
In summary, the limited abatement potential of battery buses and cars is in part compensated by plug-in vehicles and a higher share of petrol hybrid cars, but this is associated with significantly higher marginal abatement costs compared to the REF scenario. To reduce transport-related emissions to 80 Mt $CO_2$ in 2030 requires a $CO_2$ tax of £200/t $CO_2$, which is double the level in the REF scenario.

## 7.7 Cost of electricity

The electrification of the transport sector does not only depend on the availability and cost level of electric vehicles, but also on the cost of electricity. Electricity is decarbonised through structural shifts mainly to nuclear power plants, coal CCS and wind power. The IEP (Increased Electricity Price) scenario examines the sensitivity of the MAC curve to more expensive electricity. It is equivalent to the one used in chapter 6, where specific investment costs are increased by 200% (Table 6.5).

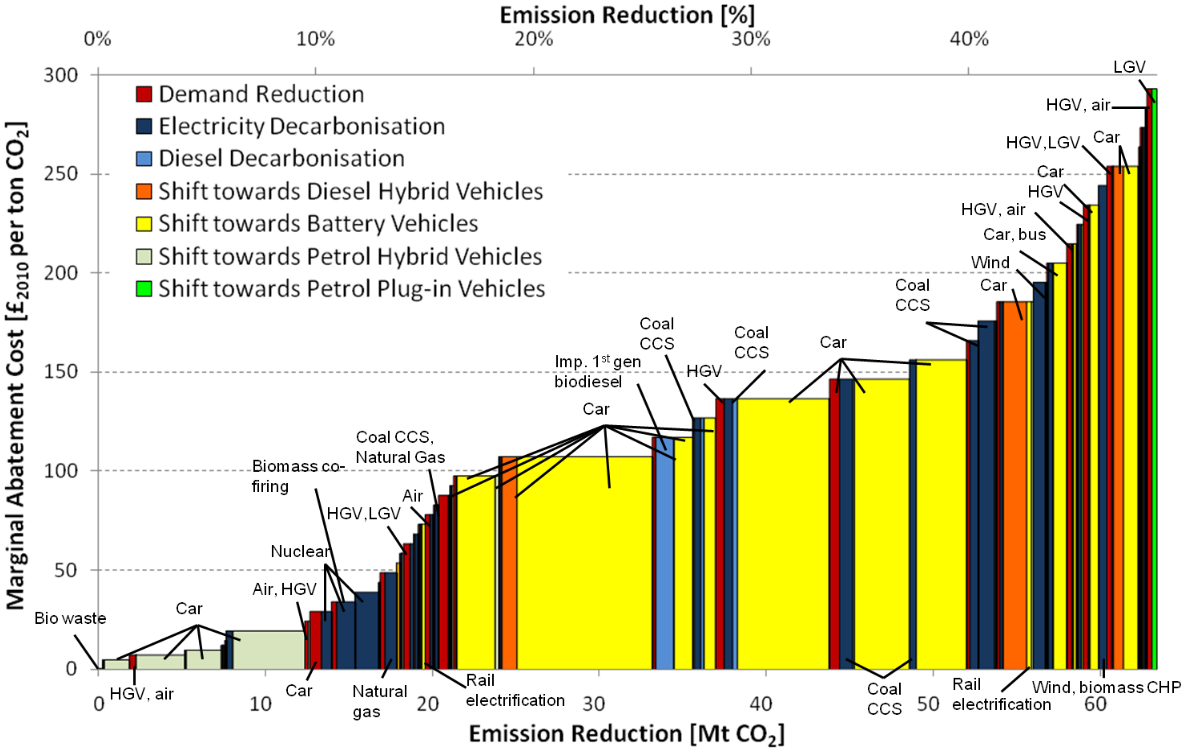
The emissions curve for the IEP scenario (Figure 7.26) looks similar to the REF scenario up to a tax level of £34/t $CO_2$. From then on the emissions reduction curve is shifted to the right due to more expensive electricity. The difference is greatest at £93/t $CO_2$; in the REF case 25 Mt $CO_2$ have already been abated via battery cars, while this technology is still not cost-effective in the IEP scenario. The difference is reduced to 2 Mt $CO_2$ at a price of £294/t $CO_2$ once battery vehicles have entered the market.

**Figure 7.26: Emission curve along rising $CO_2$ abatement costs for the IEP scenario in 2030**




The MAC curve for the IEP scenario (Figure 7.27) looks not particularly different from the REF scenario in the sense that battery cars dominate the abatement curve, though at higher carbon tax levels. Petrol hybrids, diesel hybrids, electricity decarbonisation and demand reduction play a comparable role. Only petrol plug-in LGVs do not show the same abatement potential, as a result of higher electricity prices, so that the full abatement potential is achieved at marginal costs above £300/t $CO_2$.

**Figure 7.27: MAC curve for the IEP scenario in 2030**




A look at the carbon intensity of electricity at different points on the MAC curve reveals that the carbon intensity at £0/t $CO_2$ is higher in the IEP scenario with 607g $CO_2$/kWh (52g $CO_2$/kWh more than in the REF scenario). This is an immediate result of the increased investment costs for low-carbon technologies. To reach the same carbon intensity of electricity, the IEP scenario first requires an additional £24/t $CO_2$ compared with the REF scenario to achieve 500 g $CO_2$/kWh and then increases to £79/t $CO_2$ at 100g $CO_2$/kWh.

**Figure 7.28: Emission intensity of electricity along rising $CO_2$ abatement costs for the IEP scenario in 2030**

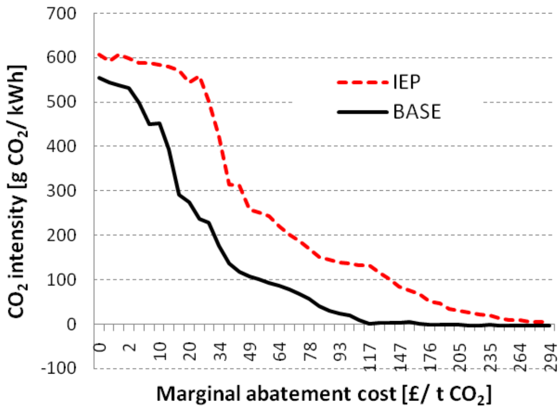
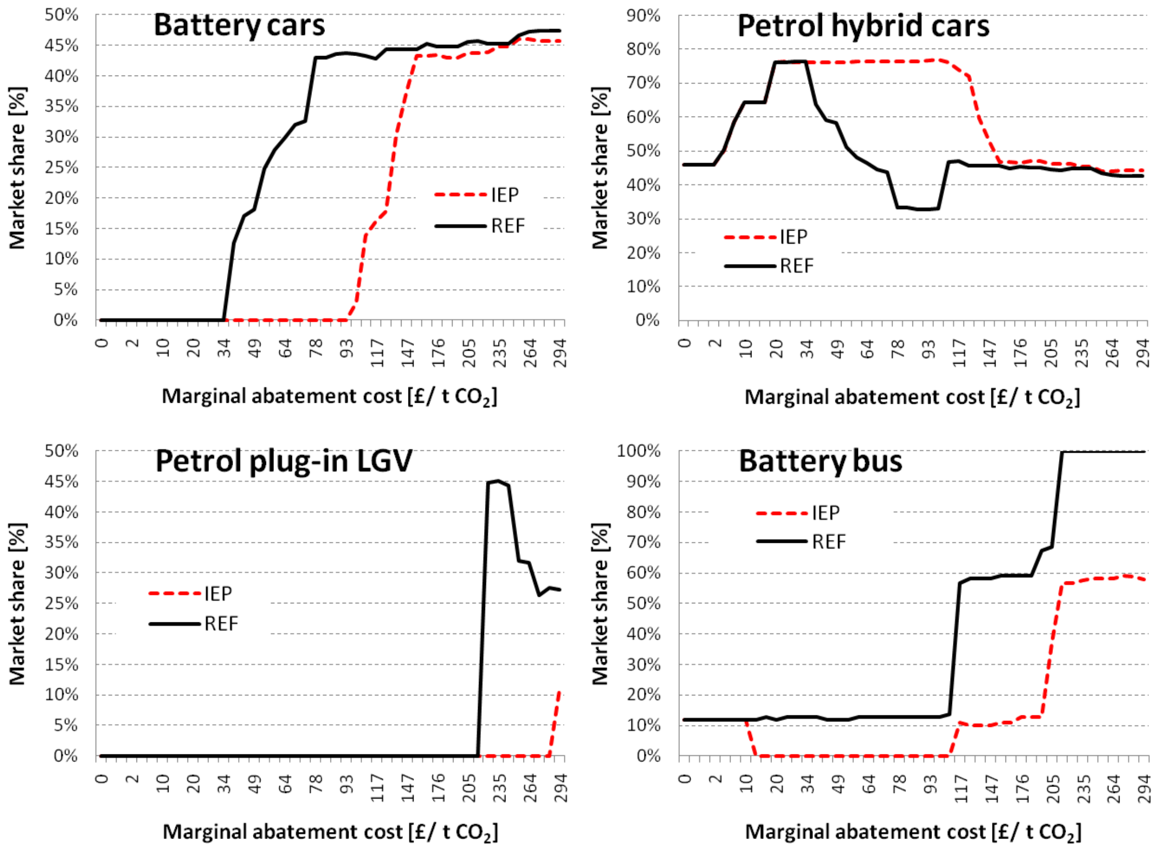



Figure 7.29 illustrates the market share of several low-carbon technologies in the transport sector when electricity is more expensively decarbonised. Consequently, technologies that rely on electricity enter the market later than in the REF scenario; battery cars need a £59/t $CO_2$ higher $CO_2$ tax to become cost-effective and petrol plug-in LGVs a mark-up of £68/t $CO_2$.

**Figure 7.29: Market share for different technologies in the IEP scenario in 2030**



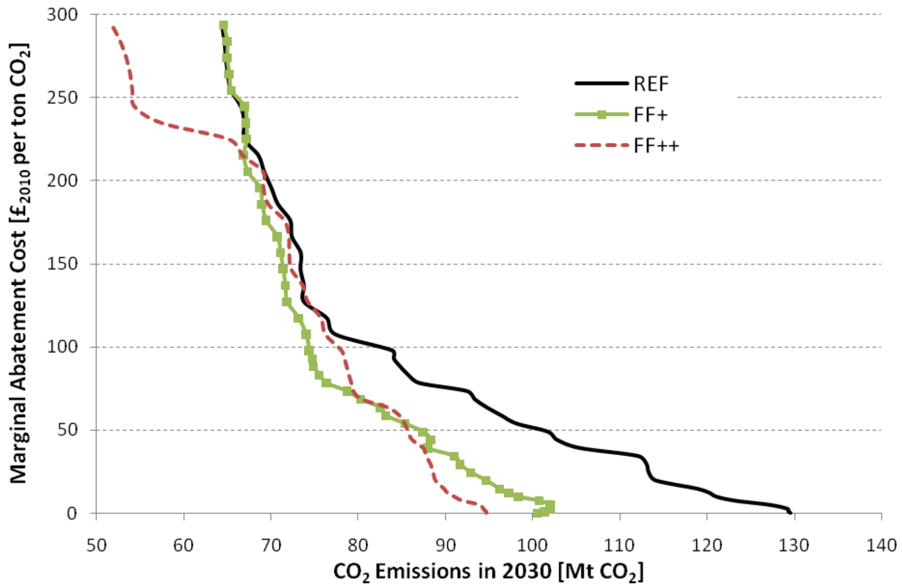

In contrast to the REF scenario, the market share of petrol hybrid cars remains at around 75% up to £117/t $CO_2$ and only decreases with the introduction of battery cars. Battery buses do not penetrate the market to the same extent as in the REF scenario with a rising $CO_2$ tax due to more carbon-intensive electricity.

## 7.8 Fossil fuel prices

The scenarios presented in this section, FF+ and FF++, are the same as in chapter 6, i.e. fossil fuel prices are increased by 100% in the FF+ scenario and by 200% in the FF++ scenario. The fossil fuel price assumptions can be found in Table 6.3. The GAS scenario is not presented in this context since natural gas is barely used in the transport sector.

The emissions curve for the different fossil fuel price scenarios (Figure 7.30) reveals that emissions are very different in the case without a $CO_2$ tax in the fossil fuel scenarios, but look very similar from £100/t $CO_2$. From £235/t $CO_2$ the emission pathway of the FF++ scenario diverge from the two others; here, more emissions are abated as hydrogen fuel cell HGVs become cost-effective. The similarity of the curves at higher $CO_2$ taxes can be explained by the increasing contribution of the $CO_2$ tax towards the total price of diesel and petrol, which overshadows the original difference in fuel prices.

**Figure 7.30: Emission curve along rising $CO_2$ abatement costs for fossil fuel price scenarios in 2030**




The emissions are significantly less in the scenario with higher fuel prices than in the REF scenario (29 Mt $CO_2$ in the FF+ scenario and 35 Mt in the FF++ scenario) due to a higher market share of battery cars of 43% in both fossil fuel price scenarios and a higher share of battery buses. The emissions in the FF++ scenario are even lower than in the FF+ scenario as the model chooses a higher share of diesel hybrid cars.

Figure 7.31 and Figure 7.32 depict the MAC curves for both fossil fuel price scenarios. Compared with the REF scenario the decarbonisation of diesel by around 5% is significantly cheaper in the FF+ scenario at £10/t $CO_2$ and is already realised at a £0/t $CO_2$ tax in the FF++ scenario. The MAC curve of the FF+ scenario involves greater electricity decarbonisation compared to the REF scenario because low-carbon technologies, which use electricity, are already introduced to the market and consume more electricity.

**Figure 7.31: MAC curve for the FF+ scenario in 2030**

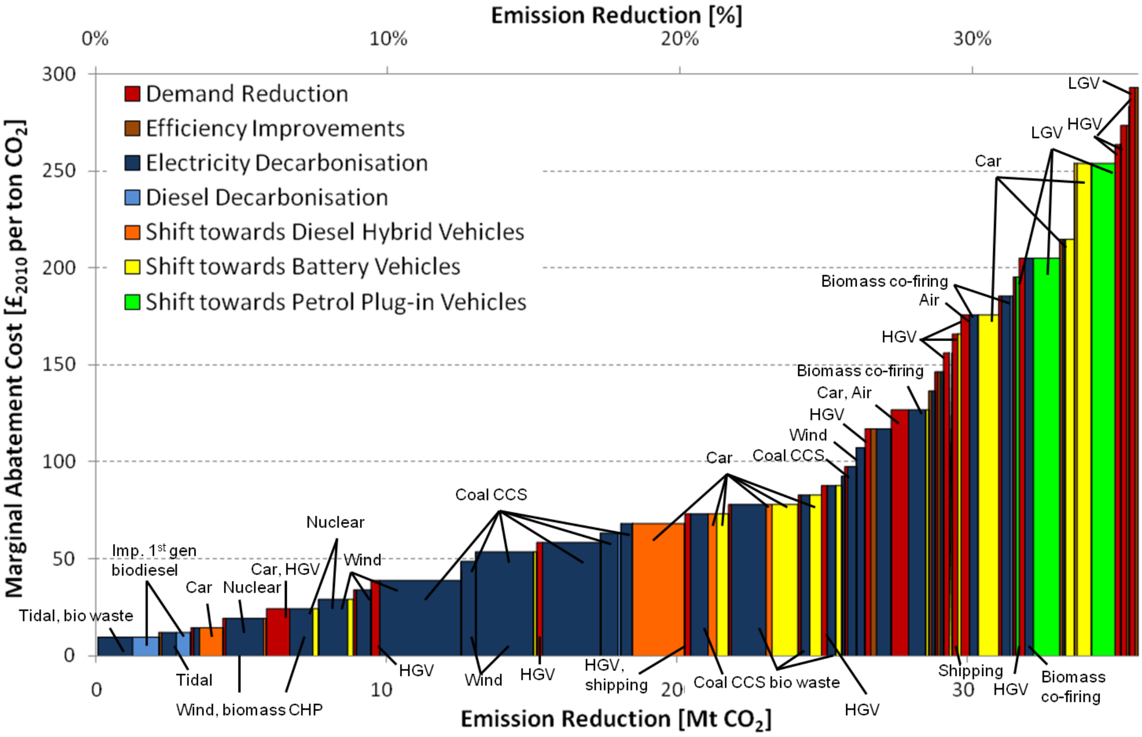
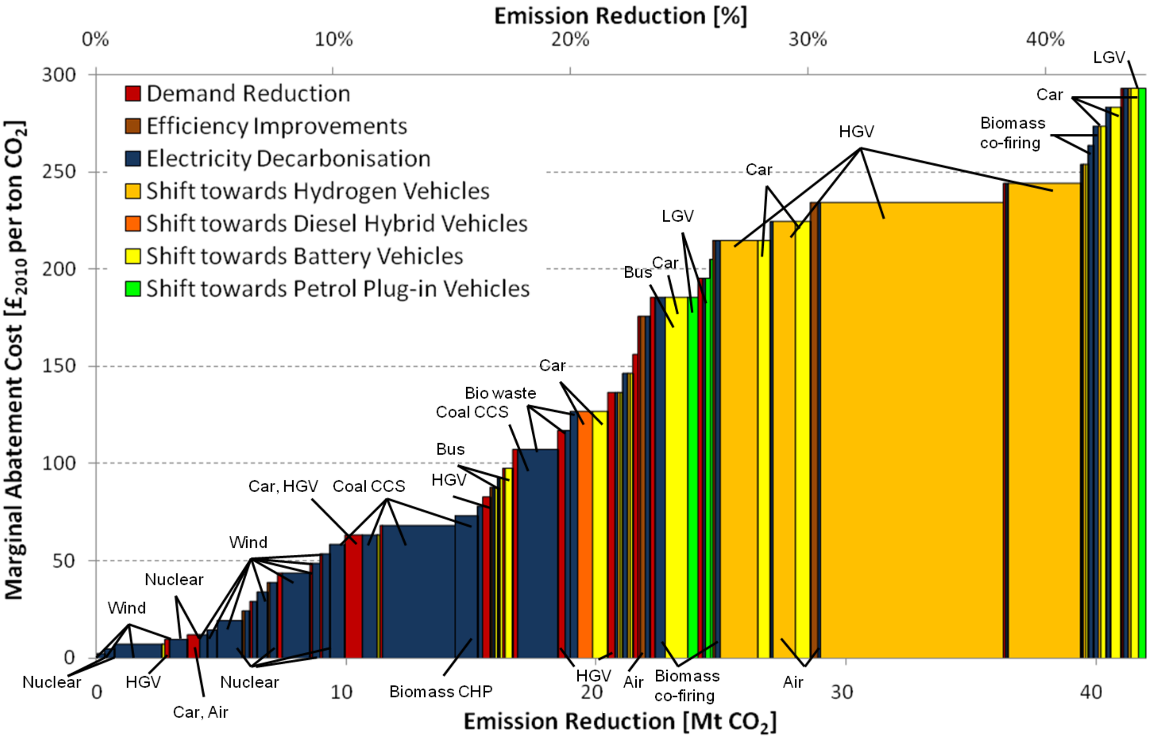


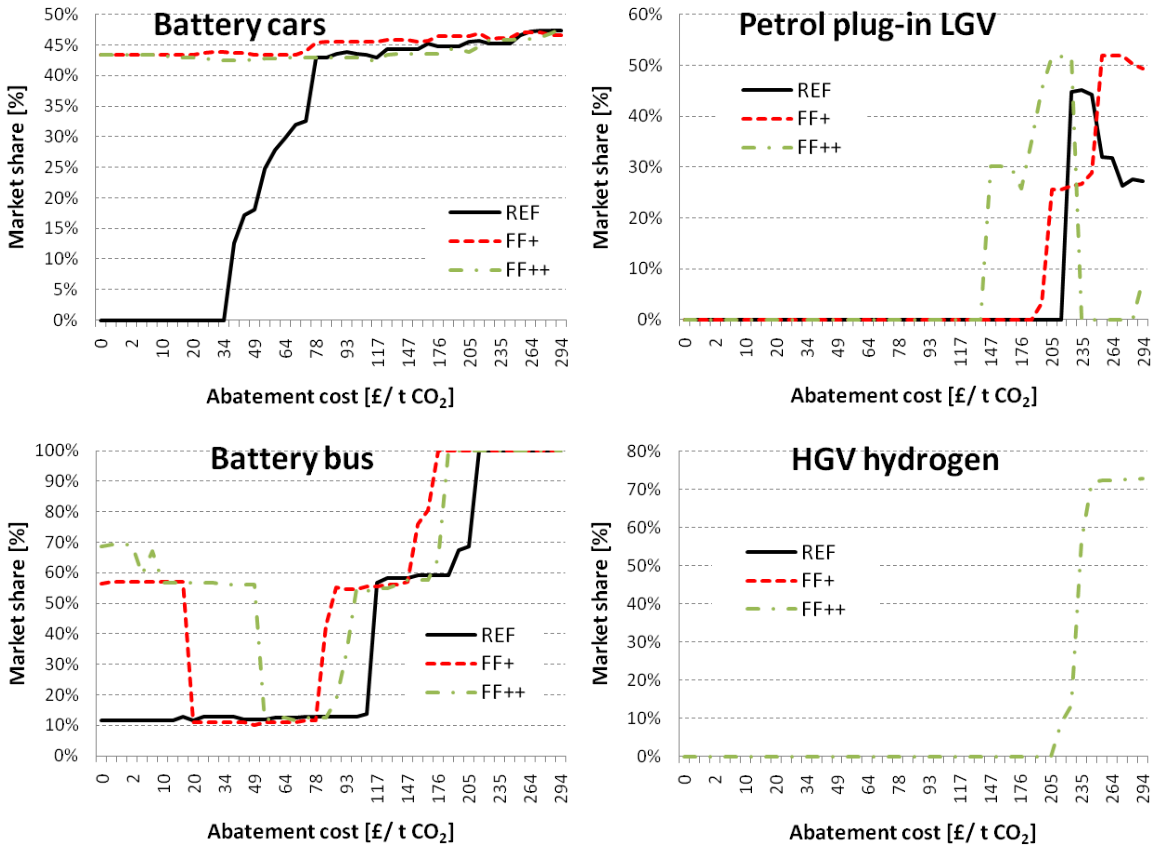

**Figure 7.32: MAC curve for the FF++ scenario in 2030**



Furthermore, there are no petrol hybrids and only a very limited amount of battery cars in the FF+ MAC curve as they are already part of the technology mix in the no carbon tax run. Diesel hybrid cars are more cost-effective in the FF+ scenario and achieve the full abatement potential at £78/t $CO_2$, while it is £254/t $CO_2$ in the REF scenario. Plug-in LGVs are roughly £29/t $CO_2$ cheaper in the FF+ scenario.

Up to £100/t $CO_2$, the MAC curve of the FF++ scenario (Figure 7.32) is characterised by electricity decarbonisation and demand reduction. One reason is most technologies that show up in the REF scenario MAC curve are cost-effective in the FF++ scenario. The important difference in the FF++ scenario is that hydrogen fuel cell HGVs play an important role in the further decarbonisation of the transport sector. While it is not cost-effective to use hydrogen HGVs in the REF scenario and the FF+ scenario, the additional fossil fuel price increase causes this vehicle type to enter the market between £215/t $CO_2$ and £245/t $CO_2$ in the FF++ scenario (see also Figure 7.33).

**Figure 7.33: Market share for different technologies in the battery scenario in 2030**




A closer look at the technologies' market share shows that the market share of battery cars is relatively constant over the whole MAC curve in the fossil fuel scenarios. The market share of petrol hybrid cars (not depicted in Figure 7.33) is stable at 45% during the whole $CO_2$ tax range. Petrol plug-in LGVs achieve a higher market share in the FF+ scenario of up to 50% replacing petrol hybrid LGVs.

The FF++ scenario shows a different pattern; here, petrol plug-in LGVs reach their highest market share at £215/t $CO_2$ and then decline to 0% at £215/t $CO_2$. This can be explained firstly by the model anticipating that hydrogen vehicles become cost-effective in later periods and secondly by diesel becoming slightly cheaper, despite a higher $CO_2$ tax, due to relatively fixed refinery output ratios.

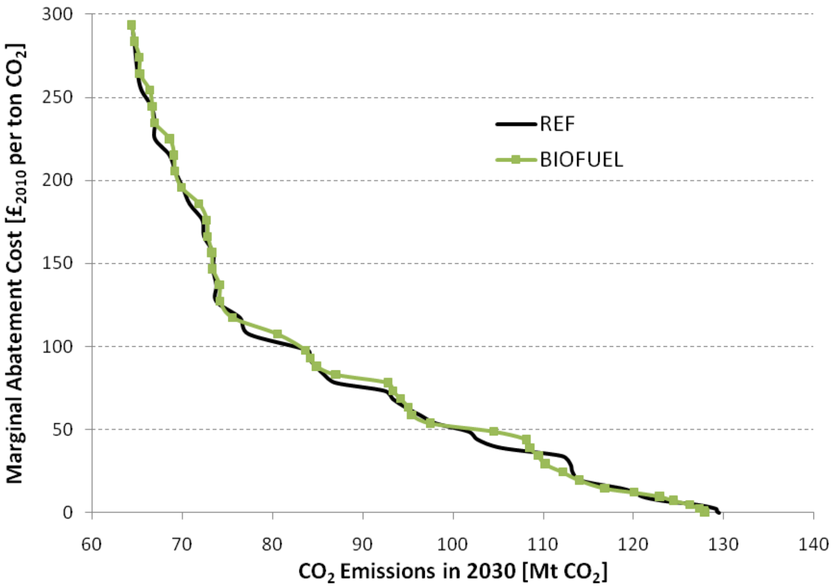
The market share for battery buses in the fossil fuel price scenario starts between 56% and 69% and drops back to 12% for a specific range of $CO_2$ tax levels. This is a result of diesel hybrid buses becoming cheaper than battery buses in this range as electricity prices increase more than the price for diesel up to £80-90/t $CO_2$.

## 7.9 Availability and price of biofuels

Biofuels are potentially an important abatement option through the displacement of conventional carbon emitting fossil fuels. As all climate policies are excluded from the model, EU legislation including the Renewable Energy Directive, setting out a mandatory biofuel share, is not considered in the model. Biofuels contribute only 2% in the REF scenario to emissions abatement in the transport sector. Different types of biomass are instead used in the power sector and are used in the residential sector for space and water heating. In contrast to previous UK MARKAL model versions, the version used in this thesis maps indirect emissions that occur during domestic biomass cultivation, processing and transport. However, those indirect emissions are relatively small and are only a small fraction of emissions from fossil fuels (maximum 5%). In the BIOFUEL scenario the upper limit of biomass for direct space and water heating in the residential and service sector (excluding district heating) was lowered from 25% to 4%. Consequently, more biomass is available to be transformed into biodiesel, methanol or ethanol for the transport sector. In addition, the import costs and domestic cultivation costs were halved for all biomass types used to produce biofuel. The BIOFUEL scenario was created to test the sensitivity of the MAC curve to cheaper and more available biofuels.

Figure 7.34 shows that the emission curve for the BIOFUEL scenario is very similar to the REF scenario. On average the emissions differ by 1.2% between the BIOFUEL and the REF scenario for a given $CO_2$ tax. The emissions are slightly lower due to a lower carbon intensity of electricity, which can be explained by lower costs for biomass. The technologically detailed MAC curve reveals that the abatement from biofuels in the BIOFUEL scenario is 0.3 Mt $CO_2$ higher owing to a higher share of imported biodiesel. In addition, the blending of biodiesel already happens at between £10-29/t $CO_2$, which is significantly less than in the REF scenario. Other changes are very limited: the MACs of battery cars and petrol plug-in LGVs are increased by £10/t $CO_2$.

**Figure 7.34: Emission curve along rising $CO_2$ abatement costs for the BIOFUEL scenarios in 2030**




The very limited consequences of a higher availability and reduced price of biomass on transport-related $CO_2$ emissions are observed because biofuels are simply too expensive to compete with other decarbonisation pathways, in particular the electrification of the transport sector, although there is almost no competition from other sectors (residential, service) for the same biomass resources. This situation would change dramatically once current subsidies and policy mandates are taken into account.

## 7.10 Price elasticity of demand

The price elasticity of demand indicates the responsiveness of the quantity demanded of a service or a good to a change in its price. Price elasticities are in general negative as it is assumed that the demand for a service will decrease if its price increases and vice versa. All energy service demands in UK MARKAL are assumed to be price elastic, to have a different elasticity depending on the direction of the price change and to have an upper and a lower limit for the maximum change of demand.

While there have been studies to analyse the price elasticity of final energy carriers, such as diesel or petrol, it is difficult to identify the correct level of demand elasticity of an energy service demand (see e.g. Anandarajah and Kesicki 2010). Therefore, the price elasticity of all energy service demands was varied by +50% in the ELAST+ scenario and by -50% in the ELAST- scenario to illustrate the sensitivity of the MAC curve to different levels of demand elasticity. Table 7.3 gives an overview of the demand elasticities for increasing prices.

**Table 7.3: Price elasticity of demand for increasing prices of transport modes**

| Scenario | Air | Bus | Car | Rail | HGV | LGV | 2-wheel |
|---|---|---|---|---|---|---|---|
| **BASE** | -0.19 | -0.19 | -0.27 | -0.12 | -0.31 | -0.31 | -0.21 |
| **ELAST+** | -0.28 | -0.28 | -0.41 | -0.18 | -0.46 | -0.46 | -0.31 |
| **ELAST-** | -0.09 | -0.09 | -0.14 | -0.06 | -0.15 | -0.15 | -0.10 |

The only input parameter that was changed was the price elasticity of demand, which should have an influence on the demand contribution towards overall $CO_2$ emissions reductions. It is assumed in UK MARKAL that energy-service demands can only be reduced by a maximum of 25% meaning that it is deemed unrealistic that energy services would be more flexible than this. The overall contribution of energy service demand reduction to $CO_2$ emissions reductions in the REF case is limited with 6.6 Mt $CO_2$ (10%). Accordingly, neither the emissions curves (see Figure 7.35), nor the technology structure, nor the technology-specific marginal abatement costs differ significantly in the elasticity scenarios. As can be expected, the emissions reduction is higher in the ELAST+ and lower in the ELAST- scenario.

**Figure 7.35: Emission curve along rising $CO_2$ abatement costs for different demand elasticity scenarios in 2030**

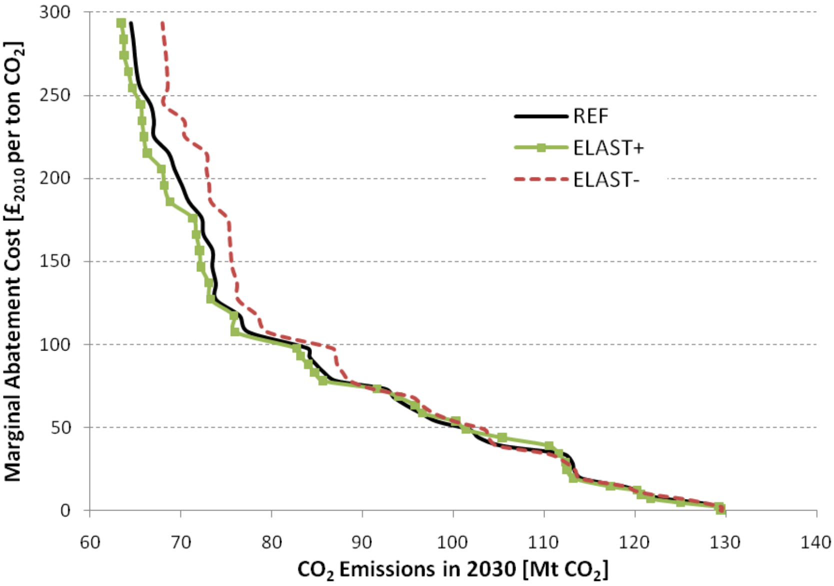
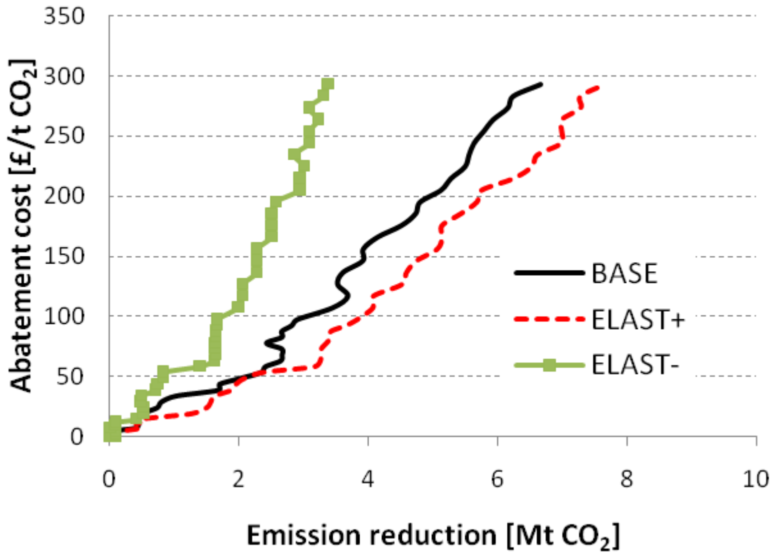


Figure 7.36 illustrates how the demand contribution changes with an increasing $CO_2$ tax in terms of $CO_2$ emissions reductions. The contribution is sensitive to the applied demand elasticity; the contribution is reduced to 3 Mt $CO_2$ (5%) in the ELAST- scenario and increased to 8 Mt $CO_2$ (11%) in the ELAST+ scenario. The level of emissions reduction does not increase proportionally in the ELAST+ scenario since, for some energy services, at high $CO_2$ taxes the demand reduction approaches the lower limit of energy service demand, where the model allows no more demand reduction. Although demand reduction is sensitive to the assumed elasticity, the overall contribution is limited to only a few Mt $CO_2$ owing to the low contribution in the REF scenario.

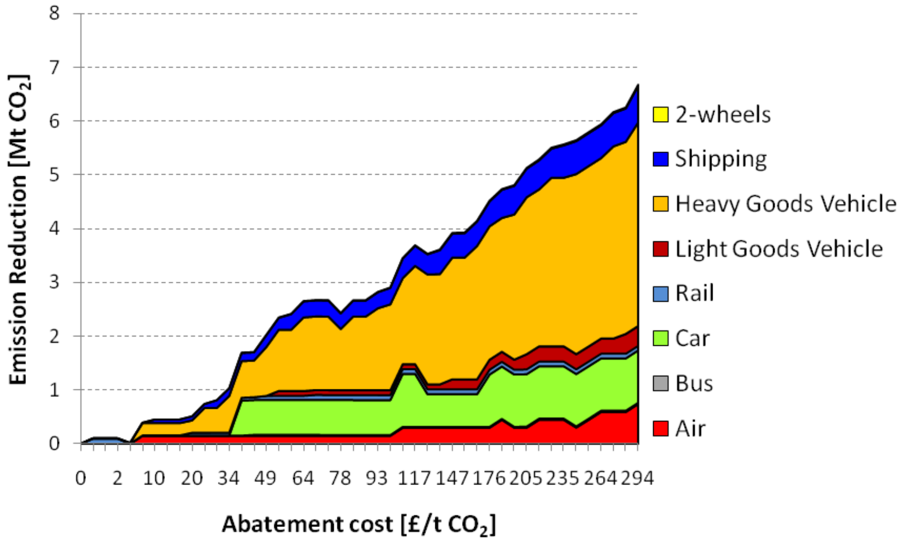
**Figure 7.36: Emissions reduction due to demand reduction for different demand elasticity scenarios in 2030**




From Figure 7.37 one can see that the biggest contribution towards $CO_2$ reduction from demand reduction comes from HGVs (57%), followed by cars (15%), air travel (11%) and shipping (10%). This is  surprising since cars emit by far the most $CO_2$ emissions, while domestic air and shipping are responsible for 7% (together) and HGVs are responsible for 22% of all emissions.

This can be explained with more expensive decarbonisation options for HGVs, which include hydrogen and biodiesel. Therefore, demand reduction remains the last option in UK MARKAL as the price for HGV travel increases significantly. The same holds true for aviation and shipping where the technology options are limited. In contrast, low-carbon technologies are available for cars, buses and LGVs that keep the transport costs comparably low.

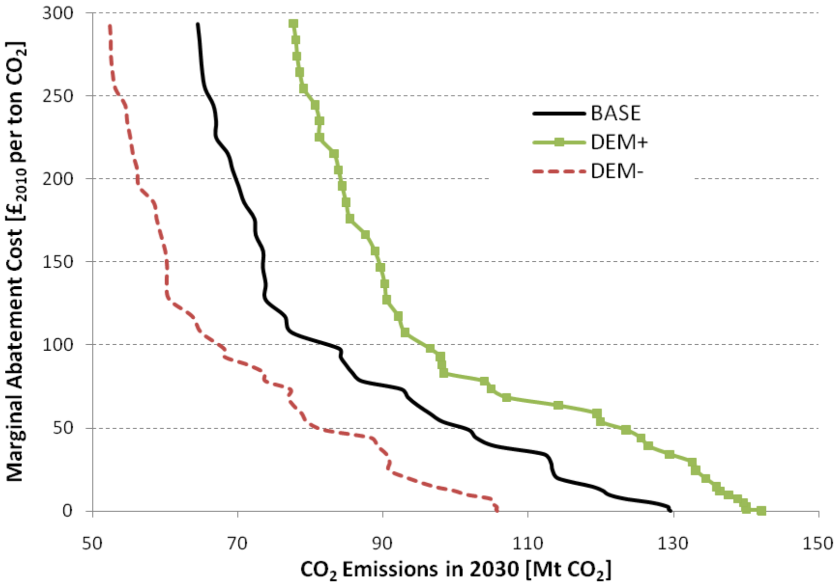
**Figure 7.37: Contribution of different transport modes' demand reduction towards $CO_2$ emissions reduction scenarios in 2030**




## 7.11 Demand development

Not only the price elasticity of demand is uncertain, but also the overall demand development. The energy service demand of the eight transport modes is assumed to increase from 2010 to 2030 on average by 29% in the REF scenario, with domestic air travel increases by 68%, bus by 31%, car by 34%, HGV by 30%, LGV by 48%, two-wheelers by 19%, rail by 31%, and domestic shipping by 10% (Kannan et al. 2007). As the demand development is uncertain, all energy service demands were increased by 20% in the DEM+ scenario and decreased by 20% in the DEM- scenario- equivalent to the demand scenarios in chapter 6. Figure 7.38 shows the emission curves of the different demand scenarios.

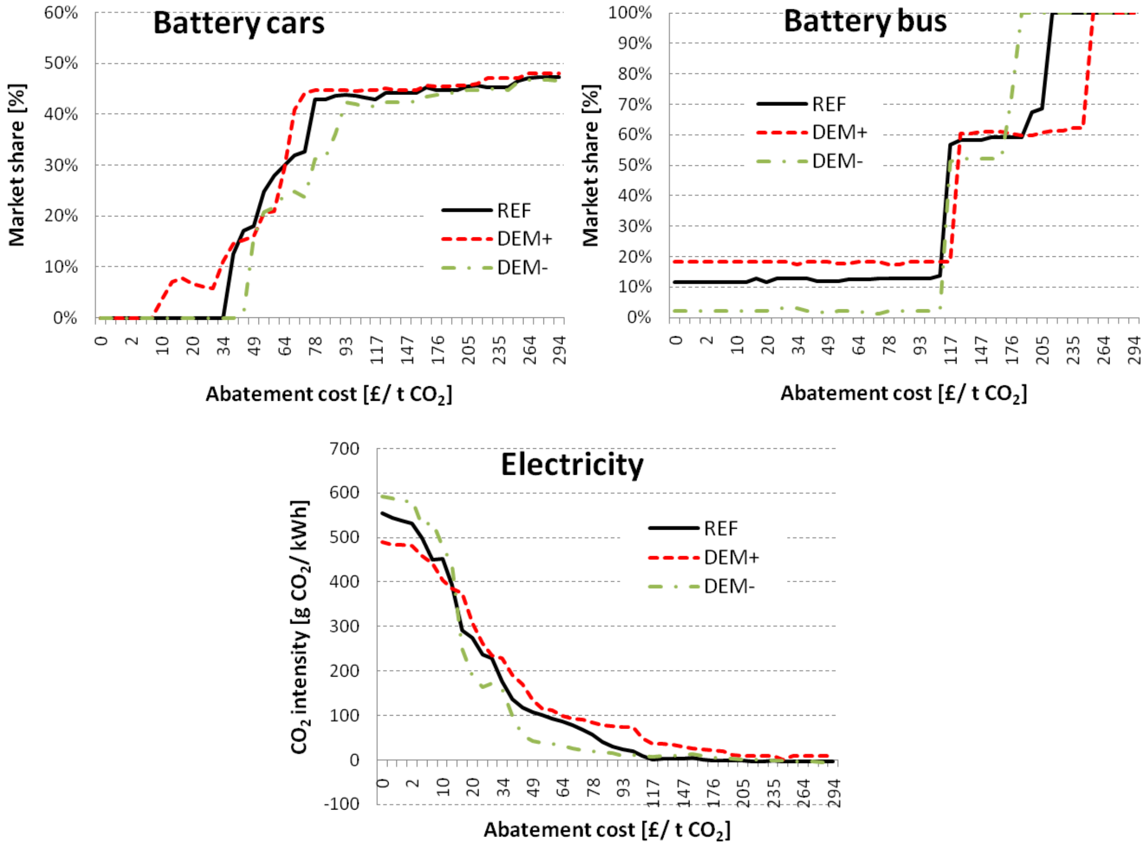
**Figure 7.38: Emission curve along rising $CO_2$ abatement costs for different demand scenarios in 2030**




The emission curves are shifted to the right with an increased demand level and to the left with a decrease in demand. Without a $CO_2$ tax the emission level is approximately 20% less in the DEM- scenario, but is only 10% higher in the DEM+ scenario, despite an increase in all energy service demands by 20%. The reason for this is a higher share of petrol hybrid cars in the DEM+ scenario and a lower carbon intensity of electricity. The share of petrol hybrid cars is higher because this technology is very sensitive to changes in the framing conditions. In this case, the petrol price increases slightly in the DEM+ scenario (by 2.5%), which triggers the model to increase the market share of petrol hybrid cars from 46% to 72%.

The decarbonisation of electricity does not follow the same pathway in all three scenarios, but differs to the extent that the carbon intensity of electricity is first higher in the DEM-, but then, at a tax level of £20/t $CO_2$, drops below the one for the REF and DEM+ scenario (see Figure 7.39 and chapter 6.9). This development leads to battery cars entering the market already at £10/t $CO_2$ in the DEM+ scenario, while this happens at £39/t $CO_2$ in the REF scenario and £44/t $CO_2$ in the DEM- scenario. Similarly electric buses have a lower market share in the DEM- scenario at £0/t $CO_2$ compared with the REF scenario, but a higher share at £186/t $CO_2$. This pattern does equally reflect the different decarbonisation pathways of electricity in both scenarios.

**Figure 7.39: Market share for different technologies in the demand scenarios in 2030 and emission intensity of electricity (bottom)**




## 7.12 Summary

This chapter has presented 20 scenarios for possible MAC curves of the UK transport sector to illustrate the uncertainties involved in assessing marginal abatement costs and corresponding abatement potentials. This sections summarises the results in the light of the initial questions asked in chapter 1, concerning the contribution of abatement measures to emissions reduction, the influencing factors, and the interaction of measures.

There are several abatement measures that are robust to different assumptions and show a significant abatement potential in the majority of the performed scenarios. This includes price-related reduction of energy service demand, which abates between 3 and 8 Mt $CO_2$ in the transport sector. Since the transport sector consumes a significant amount of electricity (particularly trains, but in some scenarios also electric vehicles), transport-related emissions can be reduced if the carbon intensity of electricity is reduced. The decarbonisation of the power sector proves to be one of the most important conditions for the decarbonisation of the transport sector and contributes 18% to overall abatement of transport-related emissions in the REF scenario. From a technological perspective, petrol hybrid, diesel hybrid, petrol plug-in and battery vehicles prove to be essential to reduce carbon emissions in the transport sector. As car travel is responsible for the biggest share of transport emissions, petrol hybrid cars, diesel hybrid cars and especially battery cars possess the largest abatement potential. In particular, hybrid technologies and battery technologies are key technologies in the transport sector.

The REF scenario was compared with 19 scenarios, grouped into nine categories, under different assumptions in order to quantify the uncertainties related to emissions reduction in the transport sector. Table 7.4 summarises the influence of the different categories on the overall shape of the MAC curve and its technological structure. The analysis of the scenarios has highlighted the parameters that have a significant influence on abatement costs and potential. This includes uncertainty around technology learning, the choice of the discount rate, and the deployment of battery vehicles. It has also highlighted that uncertainty related to demand elasticity has a significant effect on the share of demand reduction in overall emissions reduction but, as the overall contribution of demand reduction to emissions mitigation is low, the effect on total emissions is limited. Changes to biomass availability and costs have, as well as changes to fossil fuel prices, only a limited effect. For very high fossil fuel prices, the MAC curve changes due to the introduction of HGV vehicles. While the influence of fossil fuel prices on the emission curve is limited, the contribution of specific measures is very different. Changing the tax path and increasing the cost of electricity has a medium influence on the MAC curve in general, while the effect on specific abatement measures can be relatively strong.

**Table 7.4: Influence of the change in different model assumptions on MAC curve: strong (+), medium (o), weak (-)**

| Category | Influence | |
|---|---|---|
| | Shape | Structure |
| Path dependency | o | o |
| Technological learning | + | + |
| Discount rate | + | + |
| Battery potential | + | + |
| Electricity cost | o | o |
| Fossil fuel price | -/o | + |
| Biofuel potential | - | - |
| Demand elasticity | - | - |
| Demand level | o | - |

The last point to address is the interactions between abatement measures. Within the transport sector, this chapter has highlighted the sensitivity of hybrid technologies to assumptions on discount rates, investment costs, fuel costs and efficiencies. Minor changes in the price for diesel or petrol can cause significant changes in the cost-effectiveness of hybrid technologies. Although biofuels play only a minor role in the decarbonisation of the transport sector, the marginal abatement costs of biofuel are sensitive to assumptions on fossil fuel prices. Furthermore, interactions occur between the use of biomass in the transport sector, the power sector and for heating in the residential and service sectors. The most visible interactions occur with the electricity sector, since electricity has a key role in reducing carbon emissions in the transport sector. The scenarios in the categories electricity cost, fossil fuel price, and demand level show clearly that the carbon intensity of electricity has a strong influence on the cost-efficiency of transport abatement technologies.

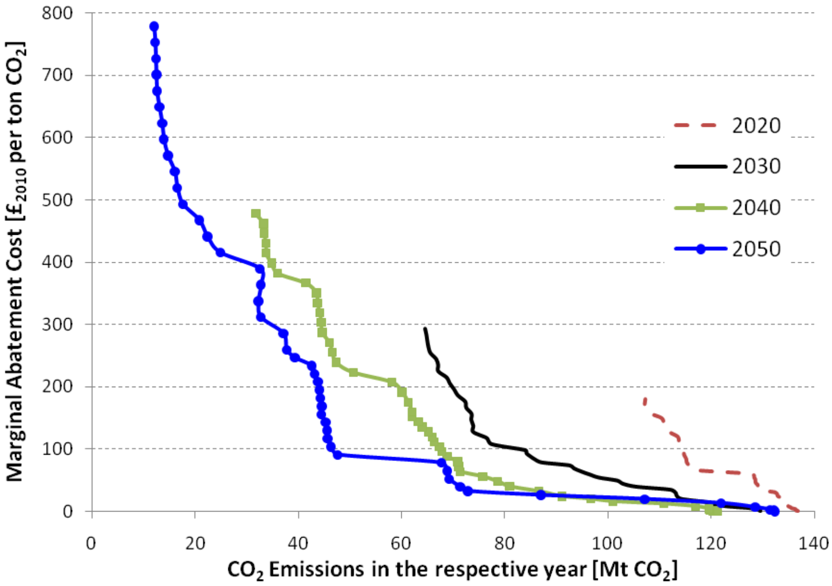
All the conclusions are subject to the choice of model employed, so that the interactions could be different if another model were employed, particularly one that addresses the shortcomings of the UK MARKAL model (see 7.1).

## 7.13 MAC curves for 2020, 2040 and 2050

In order to get a broader picture of emissions reduction during the first half of this century, this section does not focus on 2030 but presents MAC curves for the year 2020, 2040, and 2050 as well as a cumulative MAC curve.

Figure 7.40 presents the emissions associated with different $CO_2$ tax levels in each of the four representative years. The emissions level at a $CO_2$ tax of £0/t $CO_2$ is relatively similar, ranging from 120Mt $CO_2$ to 137 Mt $CO_2$ per year. Two trends counteract each other: firstly, emissions increase over time due to an increasing demand for transport services and secondly, emissions decrease as, over time, low-carbon technologies are introduced to the market as they become comparably cheaper. Emissions are higher in 2020 because no petrol hybrid cars are cost-effective at £0/t $CO_2$. In 2040, emissions are lower than in 2030, since battery vehicles gain a significant market share, while they are at 132 Mt $CO_2$ in 2050, i.e. similar to the emissions level in 2030. A high share of battery cars and plug-in LGVs explains the stable emissions level despite a rise in demand for transport services.

**Figure 7.40: Emission curve along rising $CO_2$ abatement costs for the REF scenarios in different years**

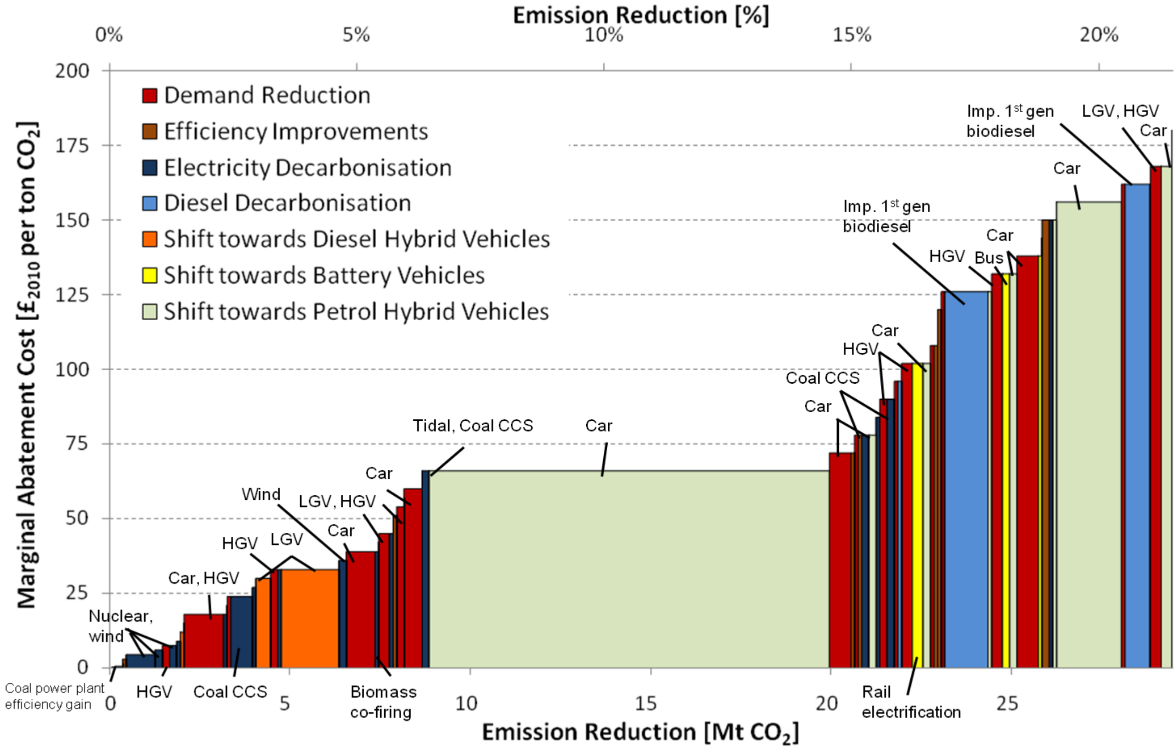



An underlying assumption for all emissions reduction curves is that the $CO_2$ tax increases from 2010 with the model-inherent discount rate of 5% p.a. This explains why the emissions reduction curve ends at tax levels of £180/t $CO_2$ in 2020 and at £779/t $CO_2$ in 2050.

The emission curves indicate that higher reductions can be achieved in later years compared with earlier years since technology learning reduces the costs of low-carbon technologies, so that they become cheaper compared with conventional technologies. As a result the difference in emissions curves for the year 2020 and 2030 is comparatively large, while it is relatively small for the years 2040 and 2050.

In 2020, all buses are equipped with a diesel hybrid engine, while cars rely almost exclusively on ICEs. Diesel hybrid vehicles make up the entire HGV pool, while half of the LGVs are hybrid vehicles and the other half ICEs. Figure 7.41 shows which abatement measures are responsible for emissions reductions in 2020. The switch to petrol hybrid cars, mainly at £66/t $CO_2$ represents the most important abatement measure in 2020 and is responsible for 51% of all emissions abatement up to £180/t $CO_2$. A technological abatement measure that contributes less at a lower cost level is the switch from diesel ICE to hybrid vehicles at £30/t $CO_2$. Moreover, the introduction of battery buses helps to reduce emissions only slightly by 0.35 Mt $CO_2$.

**Figure 7.41: MAC curve for REF scenario in 2020**

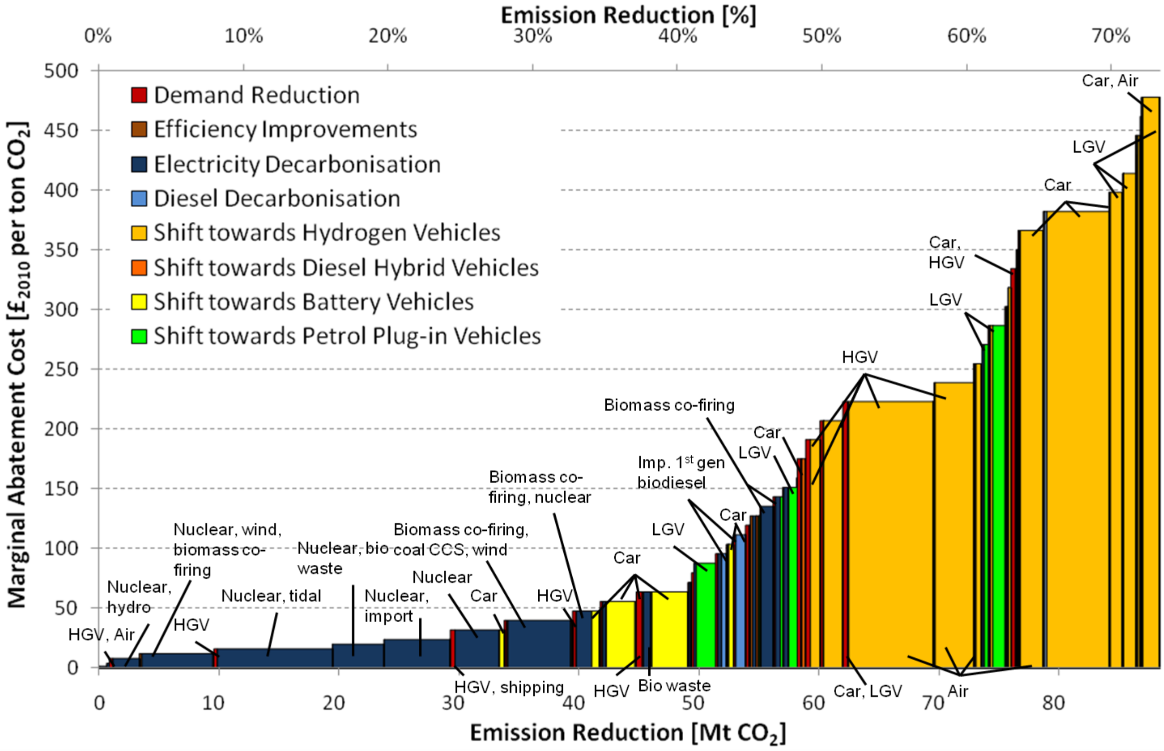



Compared to 2030, demand reduction plays a significantly bigger role in $CO_2$ emissions reductions with an overall share of 23% compared with 10% in 2030. This is due to a lower availability of cost-effective low-carbon technologies. The blend-in of biodiesel into conventional diesel helps to reduce emissions by 2 Mt $CO_2$, which is 7% higher than in 2030.

The MAC curve for the year 2040 already looks very different from the one in 2020 and 2030 (see Figure 7.42), owing to the different technological structure in 2040 at the start of the MAC curve. All buses and 43% of cars are electric vehicles, while 54% of the cars are petrol hybrid vehicles and the rest diesel ICE vehicles. HGVs rely entirely on diesel hybrid engines, whereas half the LGVs have a diesel hybrid engine and the other half a petrol hybrid engine.

The technologically detailed MAC curve reveals that up to £50/t $CO_2$, the decarbonisation of electricity is almost exclusively responsible for abatement in transport-related emissions. In total, the abatement share of a reduction in the carbon intensity of electricity is 50% over the total MAC curve. As cars, buses and trains consume a significant amount of electricity, reducing the carbon intensity of electricity from 640 g $CO_2$/kWh represents a significant abatement lever.

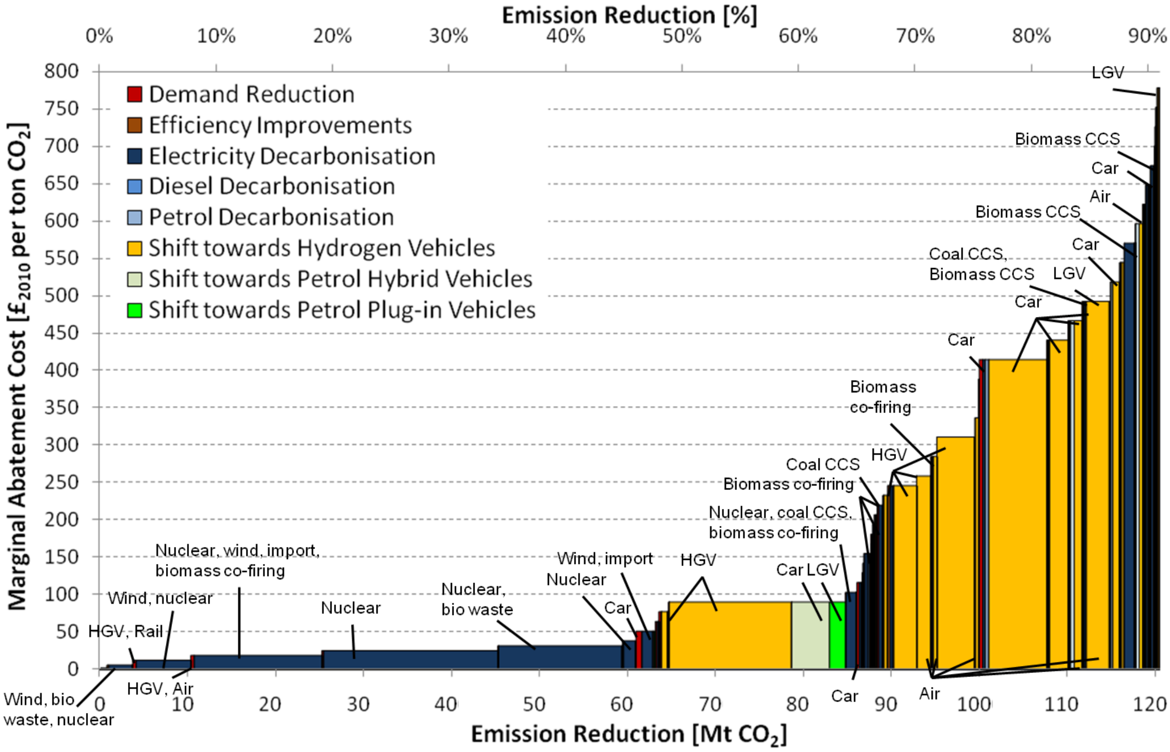
**Figure 7.42: MAC curve for REF scenario in 2040**




The other half of the abatement potential comes principally from technology shifts, since demand reduction contributes only 7% towards emissions reductions, although in total this is more than in 2030. The most important technology is hydrogen vehicles, since they are able to reduce emissions by 26 Mt $CO_2$ up to a tax level of £478/t $CO_2$. Different transport modes use hydrogen vehicles at different tax levels. While fuel cell hydrogen HGVs become cost-effective at £190/t $CO_2$, aircrafts shift to hydrogen as a fuel from £220/t $CO_2$, hydrogen ICE cars are introduced at a tax of £367/t $CO_2$ and hydrogen fuel cell LGVs at a $CO_2$ tax of almost £400/t $CO_2$. The different abatement cost levels can be explained with different technology costs, but also with different infrastructure costs that are related to hydrogen distribution for the different transport modes. The decarbonisation of hydrogen, a separate mitigation measure, is not part of the MAC curve because when hydrogen is first consumed in the transport sector it is produced from CCS plants, i.e. it is low-carbon. Further abatement technologies are battery cars, which increase their market share at £56/t $CO_2$, and petrol plug-in LGVs.

The MAC curve for the year 2050 is presented as the last MAC curve for one year in Figure 7.43. The technological structure without a $CO_2$ tax is similar to 2040. Electric vehicles make up the entire bus market, while the share of electric cars is 63%. A quarter of all cars are petrol hybrid cars and 12% are still petrol ICE cars. HGVs rely entirely on diesel hybrid vehicles, while the LGV market is shared almost equally between petrol hybrid and petrol plug-in vehicles and only a small portion of LGVs are diesel hybrids.

**Figure 7.43: MAC curve for REF scenario in 2050**

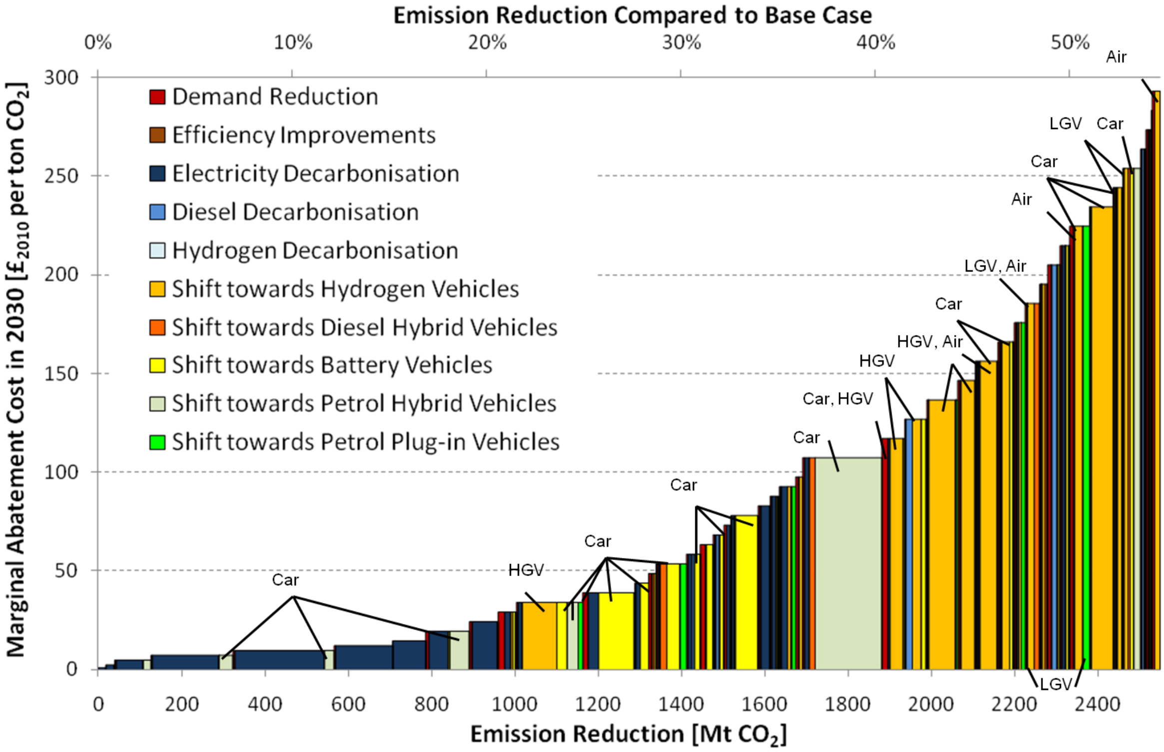



The technology structure of emissions abatement looks similar in 2050 compared with 2040; 63 Mt $CO_2$ are abated up to £52/t $CO_2$ by decarbonising the electricity used for buses, cars, LGVs and trains. The reduction in the carbon intensity of electricity is even more important in 2050 than in 2040 with 58% of overall emissions reductions. The most important abatement technology is again hydrogen vehicles. A switch towards hydrogen as an input fuel starts at £78/t $CO_2$ for HGVs, at £260/t $CO_2$ for aircrafts, at £363/t $CO_2$ for LGVs and at £415/t $CO_2$ for cars. Petrol hybrid cars and petrol plug-in LGVs play a smaller role in decarbonising the transport sector in 2050. Due to the higher availability of low-carbon technologies at lower costs, the share of demand reduction is 4%, i.e. less than in previous years.

All the MAC curves that have been presented so far in this chapter are designed for the cumulative emissions of one single year, e.g. 2030. This is the standard way of displaying MAC curves. Nonetheless, emissions abatement and the respective marginal abatement costs are dependent on earlier abatement action and expectation about future carbon policies, i.e. they are path-dependent.

To address this issue Figure 7.44 shows a cumulative MAC curve for 36 years from 2015 to 2050. The y-axis displays the $CO_2$ tax level in 2030, but as the tax increases with 5% p.a. this is not the tax level in previous years. A $CO_2$ tax of £116/t $CO_2$ in 2020, for example, translates into a tax of £188/t $CO_2$ in 2030, £407/t $CO_2$ in 2040, and £500/t $CO_2$ in 2050. A cumulative MAC curve can address questions related to intertemporal interactions by bringing information of the single MAC curves together into one. The cumulative emissions are 4.6 Mt $CO_2$ for transport-related emissions from 2015 to 2050.

**Figure 7.44: Cumulative MAC curve for REF scenario (2015-2050)**




Emissions can be reduced up to a carbon tax of £78/t $CO_2$ in 2050 by 1 Gt or 22% mainly by decarbonising electricity used in the transport sector and by switching to low-carbon vehicle types, such as petrol hybrid and battery vehicles in early model periods up to 2030. At higher tax levels the emissions reduction is more gradual so that cumulative emissions can be halved to 2.3 Gt at a tax level of £571/t $CO_2$ in 2050. This is predominantly achieved by shifting towards hydrogen vehicles from 2040 onwards, but also by switching to petrol hybrid vehicles in 2020 and by using petrol plug-in vehicles in particular from 2030 to 2040.

In summary, the abatement potential in 2020 is relatively low compared to later years and demand reduction as well as petrol hybrid cars are the dominant abatement measures. In 2040 and 2050 the decarbonisation of electricity plays a key role as many more vehicles rely on electricity than in 2030. In addition, hydrogen becomes cost-effective at higher carbon tax levels in 2040 and 2050 for use in HGV, LGV, cars and aircrafts.

## 7.14 References

AEA Energy & Environment, E4Tech, Metronomica, Ricardo, IEEP and CE Delft (2008). Building a UK Transport Supply-side Marginal Abatement Cost Curve. London, Committee of Climate Change.

Anandarajah, G. and F. Kesicki (2010). Global Climate Change Mitigation: What is the Role of Demand Reduction. International Association for Energy Economics 11th European Conference. Vilnius, Lithuania.

Kannan, R., N. Strachan, N. Balta-Ozkan and S. Pye. (2007). "UK MARKAL model documentation." Retrieved November 18th 2010, from www.ukerc.ac.uk.

# 8 RESIDENTIAL SECTOR MAC CURVES

This chapter is the third results chapter and discusses the economics of carbon emissions reduction in the UK residential sector. Similar to the two previous chapters on the power and transport sectors, this chapter presents a sensitivity analysis for MAC curves based on the UK MARKAL model and decomposition analysis. By changing different input assumptions of the model, the goal of this chapter is to lay open the key drivers for uncertainty of a residential MAC curve.

As in the previous results chapter, the analysis focuses on the year 2030 as an important medium-target for a transition to a low-carbon society. At the end of this chapter a cumulative MAC curve and MAC curves for the years 2020, 2040, and 2050 are discussed. The sensitivity analysis encompasses 19 scenarios that can be divided into eight categories. 16 scenarios are presented in this chapter that where already used in the previous chapters. In addition to this, a scenario (CONSERV) with high hurdle rates for conservation measures reflects uncertainties around implicit discount rates for those investments, while a another scenario (HEAT PUMP) investigates the consequences of a higher potential for the deployment of heat pumps. ELAST++ tests the sensitivity of a residential sector MAC curve concerning the extent of possible price-induced demand changes. The supply cost for space and water heating, by far the biggest demand categories in the domestic sector, are dominated by fuel costs so that capital costs have a very minor influence. That is why it is deemed uninteresting to present a scenario on varying degrees of technology learning. Table 8.1 gives an overview of the different scenarios and gives a short description of each one. Each MAC curve consists of 46 different model runs with system-wide $CO_2$ taxes, ranging from £$_{2010}$ 0 to 294/ t $CO_2$ in 2030. All costs are given in £ of the year 2010.

**Table 8.1: Scenario overview**

| Scenario | Category | Description |
|---|---|---|
| **REF** | *Reference case* | Carbon tax increases by 5% p.a. from 2010 |
| **ZERO-BEFORE** | *Path dependency* | Carbon tax is zero before 2030 |
| **CONST-AFTER** | *Path dependency* | Carbon tax is constant after 2030 |
| **INCR-AFTER** | *Path dependency* | Carbon tax increases with 10% p.a. from 2030 |
| **ZERO-AFTER** | *Path dependency* | Carbon tax is zero after 2030 |
| **HIGH-BEFORE** | *Path dependency* | Carbon tax is kept constant on the 2030 level from the REF scenario for the period 2015-2030 |
| **PDR10** | *Discount rate* | Hurdle rates introduced for all technologies at 10%, previously existing rates were doubled |
| **SDR** | *Discount rate* | Discount rate lowered to 3.5%, all hurdle rates, taxes and subsidies removed |
| **CONSERV** | *Discount rate* | Hurdle rates for conservation measures increased to 50% |
| **FF+** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 100% |
| **FF++** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 200% |
| **GAS** | *Fossil fuel price* | Costs for natural gas decreased by 50% |
| **IEP** | *Electricity Cost* | Investment costs increased by 200% for all CCS technologies, biomass, nuclear, tidal, wind, wave |
| **HEAT PUMP** | *Technological availabiltiy* | Upper bound for heat pumps increased from 39 PJ/year to 117 PJ/year |
| **ELAST+** | *Demand elasticity* | All demand elasticities increased by 50% |
| **ELAST++** | *Demand elasticity* | All demand elasticities increased by 50% and maximum demand change increased to 50% |
| **ELAST-** | *Demand elasticity* | All demand elasticities decreased by 50% |
| **DEM+** | *Demand level* | All energy service demands increased by 20% |
| **DEM-** | *Demand level* | All energy service demands decreased by 20% |

## 8.1 Description of the residential sector in UK MARKAL

In the residential sector of the UK MARKAL model, energy service demands include space heating, hot water, lighting, space cooling, other electrical appliances, cooking and refrigeration. Cooking is again subdivided into hob and oven, while refrigeration is divided into refrigerators, fridge freezer, chest freezer and upright freezer. The demand for cooking and refrigeration is defined in million units, which is translated into a final energy demand given an efficiency and user pattern, whereas it is in Petajoules for all other residential energy demand services. To account for seasonal differences in the demand for energy services, a seasonal profile is implemented along the six timeslices in UK MARKAL (see chapter 3.3.2) for cooking, cooling, electrical appliances, space heating, hot water and lighting.

Energy service demand levels for future periods are based on assumptions for the total number of houses from the Department of Trade and Industry (DTI), which is expected to be 35.6 million in 2050. In order to calculate the number of new houses an average annual house demolition rate of 0.08 % is assumed. All energy service demands are specified separately for two dwelling types: new and existing houses (see also Kannan et al. 2007).

Next to end-use efficiency options, such as condensing boilers, UK MARKAL considers various conservation measures to reduce residential energy consumption. This covers a total of 15 conservation measures, including loft insulation, hot water cylinder insulation, double glazing and efficient lighting. In order to account for non-financial costs related to the investment in conservation measures, these measures have a hurdle rate of 8.75%. A precise number is hard to justify given the wide range of empirical estimates. This is a reason why the influence of an increased hurdle rate is studied in the CONSERV scenario.

Technological alternatives for end-use devices are wide-ranging for space heating and hot water. They consist of oil-fired, coal-fired, gas-fired, coke-fired, wood-fired boilers, biomass pellet boilers, electric heat pumps, district heating and solar water heaters. These technologies are specified via parameters for capital costs, operating costs, lifetime and efficiency. Wood-fired boilers are limited to 25% of all households to account for fuel storage restrictions and prohibitive transport costs over long distances.

The strengths of UK MARKAL's representation of the residential sector include the technological detail and taking account of system-wide interactions with the heat, electricity and upstream, including biomass, sectors. A systems perspectives avoids relying on exogenously given $CO_2$ intensities for heat and electricity as is the case in most current housing stock models. The latter models usually represent the housing stock in much more detail than UK MARKAL, differentiating according to dwelling type and age. However, the use of two dwelling types is justified on the grounds that the impact of the dwelling type on $CO_2$ emissions is small (see Johnston et al. 2005). For a detailed comparison of UK MARKAL and UK housing stock models, see Kannan and Strachan (2009), and for a review of building stock models, see Kavgic et al (2010).

Shortcomings of the residential sector in UK MARKAL include a lack of temporal and spatial detail. UK MARKAL differentiates between seasons and day and night, but is not able to represent peak hours in detail, which again limits the representation of demand side management (DSM) and neglects its contribution to emission mitigation. Taking account of DSM could limit the need for peak electric capacity. Moreover, due to the lack of spatial detail, the district heating network cannot be adequately represented nor can the spatial availability of biomass be described. This can underestimate the true marginal abatement costs of these technologies.

In addition, internal heat gain from lighting or other devices is not considered so that consequences of more efficient appliances on the need for space heat are neglected. As more and more energy-efficient appliances are installed over time, the disregard of internal heat gain can lead to an underestimation of the need for space heat and therefore, to a limited extent, underestimate the costs associated with emissions reduction. The BREHOMES model (Shorrock and Dunster 1997), a housing stock model, addresses this problem by quantifying the effects of lighting and appliances on space heating.

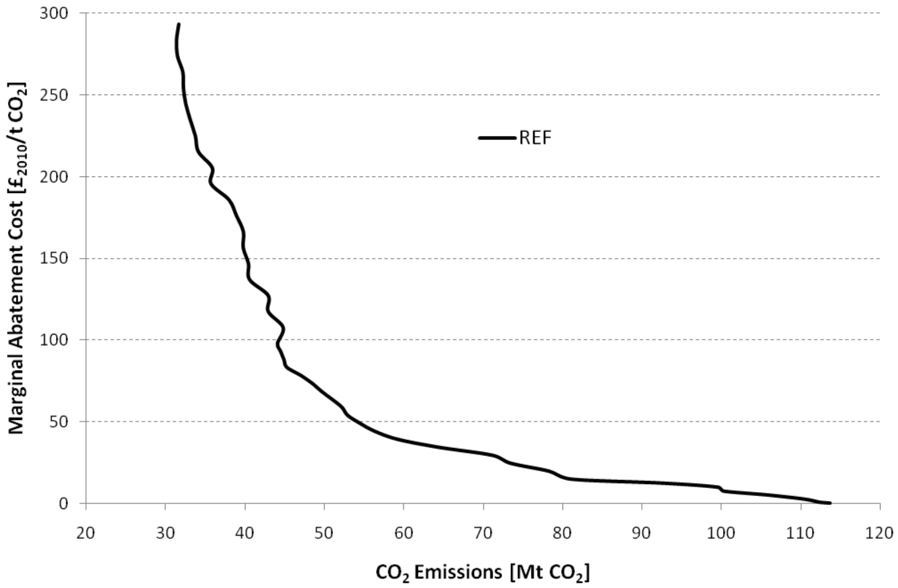
Another weakness of the model concerns the representation of household size, human behaviour and choice of preferences. Although market rigidities and non-financial factors are partly captured via technology specific hurdle rates and user constraints, it is not possible to characterise the adoption of energy-saving measures accurately. Occupant behaviour is hard to describe in economic terms and can differ widely between households so that the magnitude and the direction of the influence on MAC curves, when addressing this issue, is not quantifiable. In the past, bottom-up statistical approaches, mainly relying on regression analysis, have been used to include occupant behaviour into domestic energy models (see Swan and Ugursal 2009).

## 8.2 Reference scenario

The reference (REF) scenario describes a development of carbon emissions reduction with the standard assumptions of the UK MARKAL model (see sections 6.1, 7.1, and 8.1).

Emissions in the residential sector have been attributed from an end-user perspective, i.e. emissions resulting from electricity and heat generation are assigned to the residential sector according to the amounts consumed. The model results indicate that end-use emissions from the residential sector are 114 Mt $CO_2$ in 2030 in the REF scenario, which compares to 156 Mt $CO_2$ in 1990. This large drop in emissions is the result of basically all solid-fuel heating being phased out and the use of oil-fired boilers reduced by about 50% from current levels. Furthermore considerable efficiency gains, the implementation of conservation measures and a shift from gas as a heating fuel towards biomass and district heat explain the drop in emissions. Figure 8.1 shows an emission curve for the residential sector in 2030.

**Figure 8.1: End-use emission curve for the residential sector in United Kingdom in 2030**

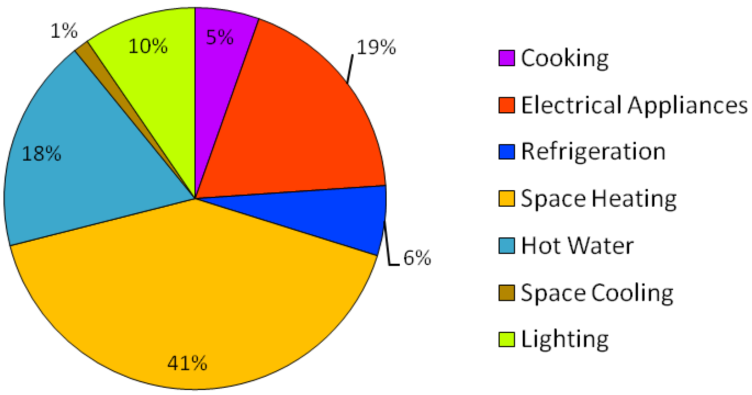



At a price of £50/t $CO_2$ emissions are reduced by 68 Mt $CO_2$ to a level of 46 Mt $CO_2$ and from then on more gradually to 31 Mt $CO_2$. So even at considerable $CO_2$ tax levels, there remain residual emissions in the residential sector. In some places the curve reverts despite increasing $CO_2$ tax levels due to interactions with other sectors, mainly electricity and heat, and intertemporal interactions, i.e. it is more cost-effective to reduce emissions in other time periods.

The emissions in the REF scenario without any carbon policy originate from different demand types. This is mainly influenced by the energy consumed for the specific service. In terms of energy consumption space heating and hot water are responsible for 81% of all useful energy consumed in the residential sector in 2030 according to model results. Eight percent of residential energy service demand originates from electrical appliances, four percent from lighting, four percent from cooking, and two percent from refrigeration. Accordingly, the majority of $CO_2$ emissions (59%) can be attributed to space heating and hot water. All the energy services that exclusively use electricity have a larger share in $CO_2$ emissions than in energy use because electricity generation in 2030 under no carbon policy is coal-dominated and a part of space heating and hot water is provided by burning biomass.

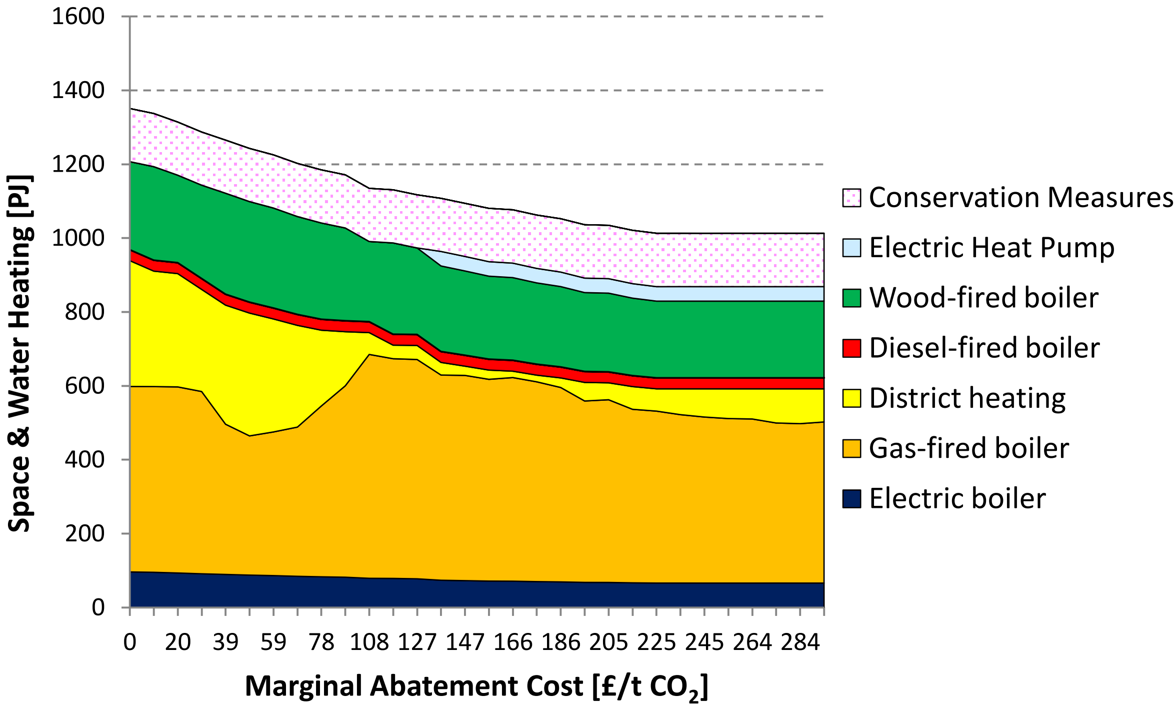
Correspondingly, one can expect to see emissions reduction predominantly from fuel switching related to space and water heating and a decarbonisation of heat and electricity. Emissions related to electric appliances, refrigeration, space cooling, lighting and, to some extent, cooking can mainly be reduced by decarbonising electricity. At higher carbon intensity levels of electricity, energy efficiency measures and demand changes represent additional means to reduce emissions in these demand categories.

**Figure 8.2: $CO_2$ emissions from different residential energy service demands in the United Kingdom in 2030 (REF scenario)**




As the flexibility for fuel switching is mainly given with respect to devices for space heating and hot water, Figure 8.3 represents how much various technologies contribute to meeting the demand for space heating and hot water. Actual demand for space and water heating is reduced through the implementation of conservation measures, which reduce energy service demand by roughly 10% or 144 PJ. Heating demand is dominated by gas-fired boilers with 42%, followed by district heating (28%) and wood-fired boilers (20%). The majority of the biomass used in the residential sector is imported, but a significant share is provided by domestic sources, such as industrial wood by-products, domestic woody energy crops, and forest residues. The costs for biomass resources, their processing and transport are based on Jablonski et al. (2009). Figure 8.3 equally shows that the main trade-off is between gas and district heat for heating purposes.

**Figure 8.3: Technology mix for space & water heating in the REF scenario**




Including the results of the decomposition analysis shows which measures are responsible for the emissions reductions (see chapter 4). Equation (8.1) details the decomposition employed to disaggregate changes in total residential $CO_2$ emissions in this chapter:

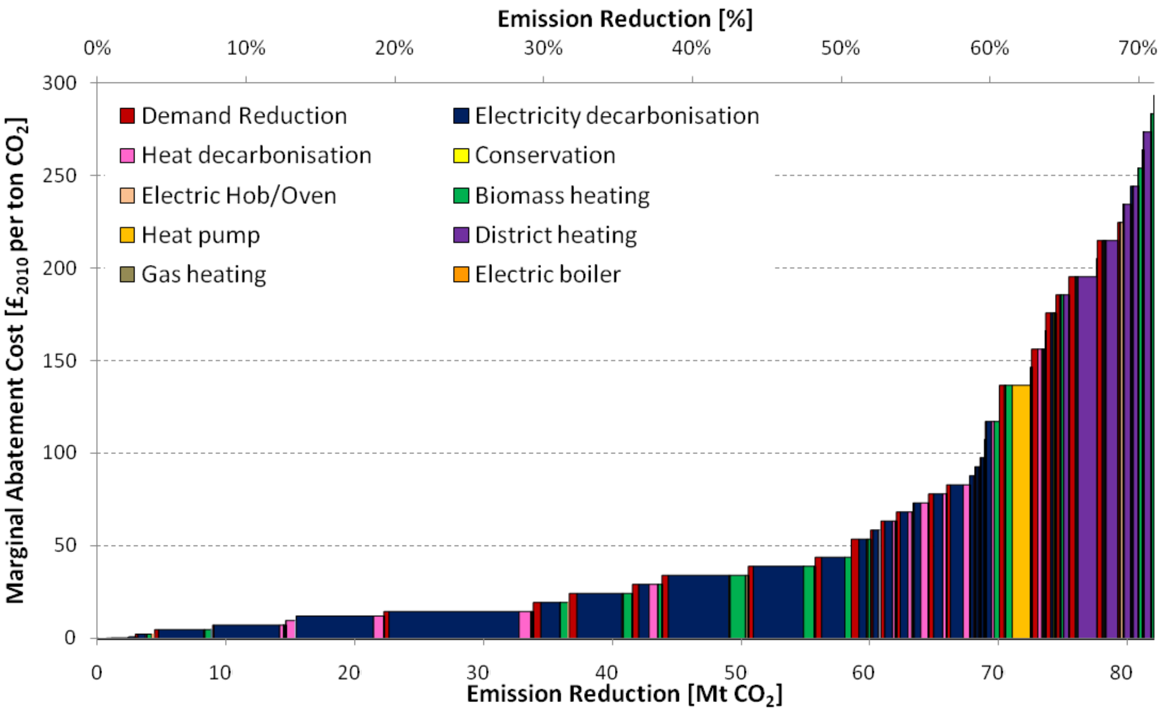
$$CO_{2,Residential} = \sum_{i=dem\ type} activity_i \left( \sum_{j=technology} \frac{activity_{i,j}}{activity_i} * \frac{fuel_{i,j}}{activity_{i,j}} * \frac{CO_{2\ i,j}}{fuel_{i,j}} \right) \qquad (8.1)$$

$activity_i$ stands for the energy service demand level of demand type $i$ in PJ or million units depending on the demand. $activity_{i,j}$ represents the demand level satisfied by technology $j$ for demand type $i$, while $fuel_{i,j}$ indicates the amount of fuel in PJ used for technology $j$ to satisfy demand of demand type $i$. Lastly, $CO_{2\ i,j}$ is the amount of $CO_2$ in kt emitted by technology $j$ while satisfying demand $i$. Correspondingly, the decomposition distinguishes between demand-related influences, structural changes, and the impact of fuel efficiency and carbon intensity.

Demand-related factors describe changes in the overall demand for energy services, such as lighting or space heating, while structural changes describe a change from one end-use technology to another, for example from a gas-fired boiler to district heating. In the decomposition analysis, conservation measures are classified as a structural change, because they are an alternative way to meet the demand for domestic heating. Fuel efficiency changes relate to less fuel being used in the same boiler type, e.g. by switching to a condensing boiler. Carbon intensity effects describe changes in the carbon content of one unit of fuel, i.e. the decarbonisation of electricity or heat. The logarithmic mean Divisia index (LMDI) is used to derive the contribution towards $CO_2$ emissions reduction of specific measures (see also chapter 4).

Figure 8.4 shows that the MAC curve in the REF scenario is dominated by the decarbonisation of secondary energy carriers, heat and electricity. As the carbon tax level increases electricity and heat are the most cost-effective options to decrease emissions in the residential sector, especially up to £40/t $CO_2$. Structural changes, including switches between different end-use technologies and conservation measures, occur only with respect to the demand for space heating and hot water and remain very limited. Demand reduction due to higher prices has a constant contribution along rising $CO_2$ tax levels. Efficiency improvements are already incorporated into the baseline development. Increasing carbon tax levels do not cause further efficiency improvements in the residential sector. One reason is that the energy carriers have already a low carbon intensity, so that the impact of efficiency improvements is limited. Another reason can also be the less detailed representation of efficiency options.

**Figure 8.4: Residential MAC curve for the REF scenario in 2030**



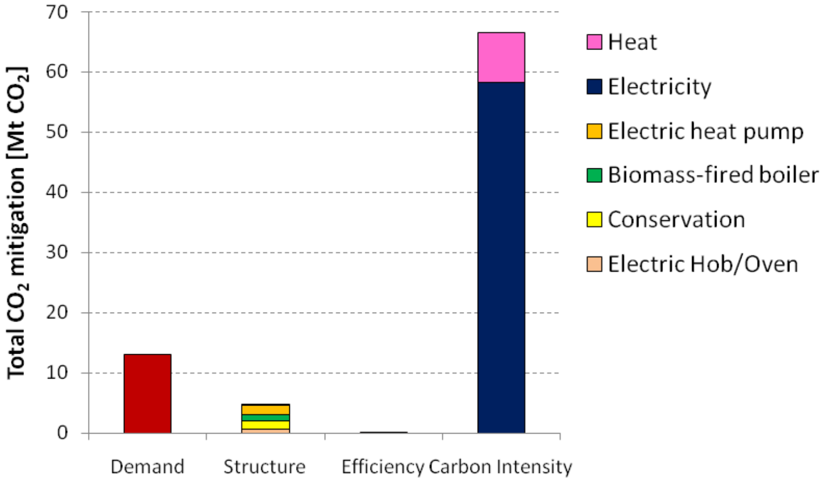

In the base case without any carbon policies the contribution of electricity decarbonisation is dominant up to £110/t $CO_2$. Except for water and space heating, the other energy service demands rely almost entirely on electricity. Electricity makes up

24% of all energy consumed in the residential sector. Since electricity can be decarbonised at lower cost than most end-use energy sectors (see chapter 6), it is an obvious way to reduce end-use emissions in the residential sector. Furthermore, at £0/t $CO_2$, a significant share of hot water and space heating is provided via district heat. Up to £80/t $CO_2$, a reduction in the $CO_2$ intensity of heat equally contributes to emissions mitigation. This mainly happens through the phasing out of CHP plants based on solid fossil fuels, which are replaced by solid biomass. This emphasises the importance of decarbonising energy carriers for emissions reduction in the residential sector.

Apart from the decarbonisation of heat and electricity, price-induced demand reduction plays a smaller, but important contribution to emissions reduction (see Figure 8.5). At a carbon tax of £200/t $CO_2$ in 2030, demand for space & water heating is reduced by 24% in UK MARKAL. Electricity prices increase significantly by 50% from £0/t $CO_2$ to £294/t $CO_2$ in the residential sector, though this is still significantly less than other fuels such as natural gas, where the price more than trebles.

It is interesting to see that structural change in the residential sector, e.g. from gas-fired boilers to electric heating or wood-fired boilers, play a minor role contributing only 4% to overall emissions reduction (see Figure 8.5). This is in contrast to the findings for the transport sector, which, however, relies heavily on carbon intensive oil products.

**Figure 8.5: Total decomposition of residential MAC (REF) for the UK in 2030**




At £137/t $CO_2$, electric heat pumps for space heating become cost-effective and replace part of the gas-fired boilers. At carbon tax levels up to £50/t $CO_2$, the share of biomass heating increases and is responsible for some emissions reduction. From around £180/t

$CO_2$, a shift towards district heating contributes to emissions reduction as heat production at this tax level comes from landfill and biomass CHP plants.

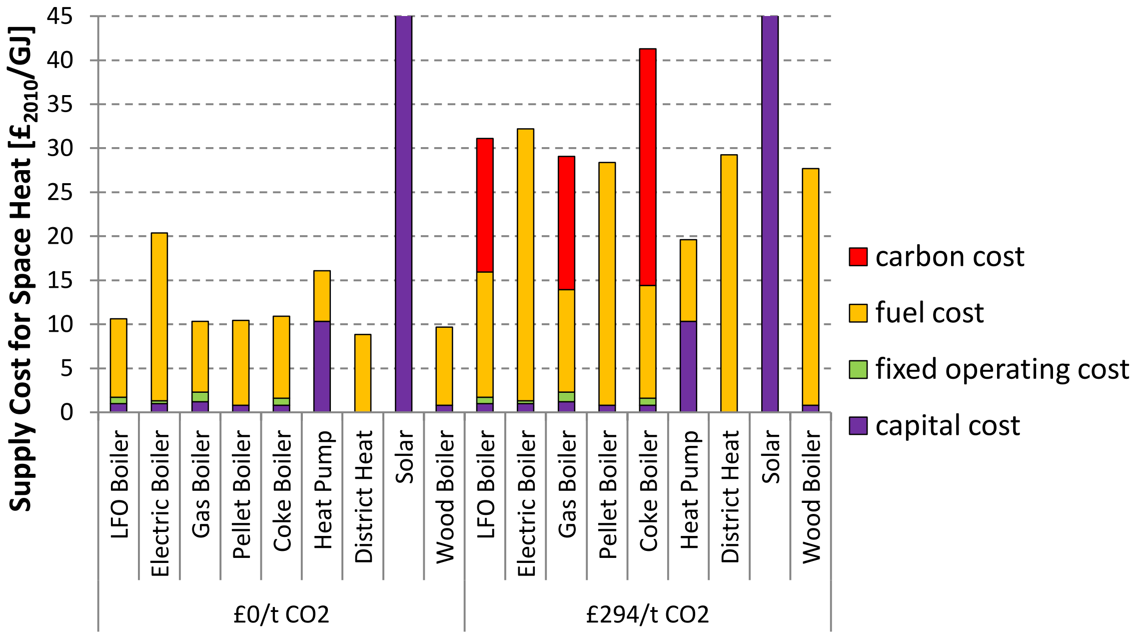
There are mainly two reasons for the lack of fuel switching in the residential sector: first, the fuel mix for space heating and hot water is expected to already change substantially from today to 2030 without any climate policy, secondly, there is no further economic incentive to change from gas-dominated heating to low-carbon alternatives.

In 2008, natural gas made up 82% of all fuels used for space and water heating in the UK, with electricity (8%), oil (8%) and solid fuels (2%) making up the rest. This is expected to change dramatically in a cost-optimal, perfect foresight setting without any climate policy intervention. Figure 8.3 shows that wood-fired boilers gain 20% of the market share, and district heating increases massively to 28% of all residential heating. Heat is mainly generated from natural gas CHP plants. Summarising, in the absence of any climate policy, emissions for residential heating are expected to fall substantially via a shift towards wood-fired boilers and district heating.

With significant change in the structural composition of heat provision already occurring at £0/t $CO_2$, replacing natural gas remains the only major possibility to reduce emissions further concerning domestic heating. Thus, the benchmark is a gas-fired boiler and only options that can provide cheaper space heat will be chosen by the model. One would expect to see alternatives to a gas boiler becoming cost-effective with an increasing financial penalty for burning gas, but this is not the case (see Figure 8.6).

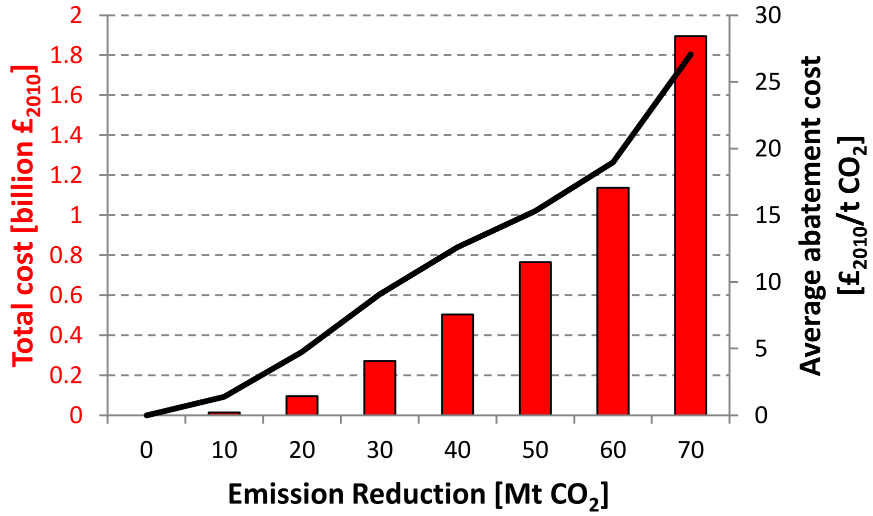
Although the cost for providing space heat with a gas-fired boiler increases from £10/GJ to £29/GJ from one end of the MAC curve to the other, only heat pumps are significantly cheaper at the highest carbon tax. In the model it is assumed that the potential for heat pumps is limited due to physical constraints (see 8.7), so that their contribution towards emission mitigation is also limited. Only wood and pellet boilers are slightly cheaper compared to gas boilers by 2% and 5% respectively. The reason for the similar cost level is that not only the gas price increases significantly but also the price for other fuels and since fuel costs dominate overall costs this is reflected in the supply cost. While the cost for natural gas increases by 233% from £0/t $CO_2$ to £294/t $CO_2$, electricity cost increases by 62%, light fuel oil (LFO) by 229%, pellets by 186%, district heat by 230% and wood by 203%. The price jump for wood and pellets can be explained with a constrained supply that meets soaring demand from the power, heat, residential, service and to some extent the transport sector.

**Figure 8.6: Costs of providing space heat for various technologies in 2030**




Lastly, when one takes the integral under the curve in Figure 8.4, information can be obtained on the total cost to reduce emissions in the residential sector in 2030 (Figure 8.7). This only refers to direct costs in the year 2030 and does not consider any earlier costs nor welfare implications. Total costs increase exponentially with an increasing emissions reduction target and are £1.9 billion for an emissions reduction of 70 Mt, which corresponds to an average abatement cost of £27/t $CO_2$.

**Figure 8.7: Total abatement cost for the residential sector in the United Kingdom in 2030**

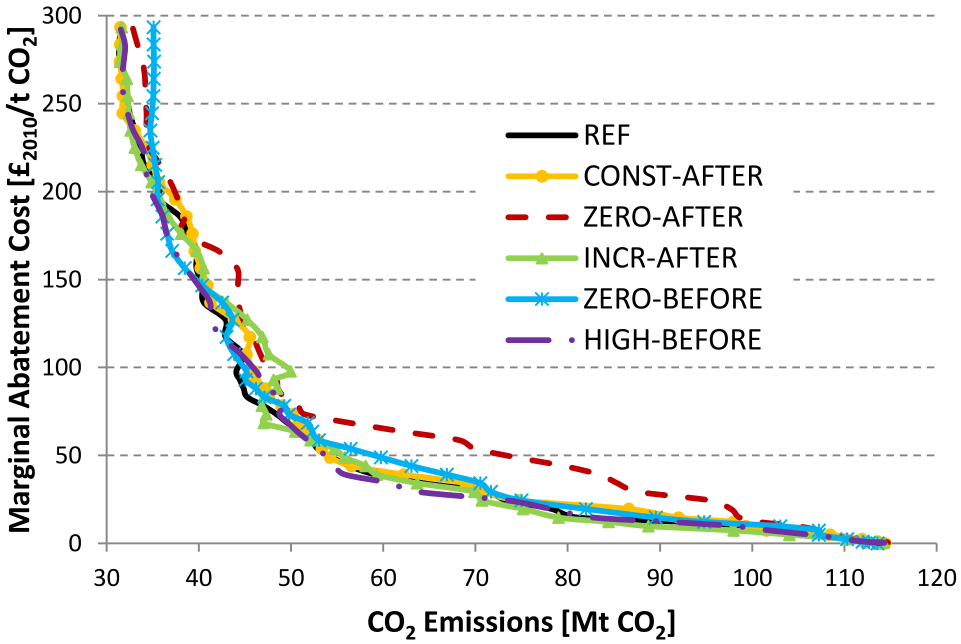


## 8.3 Path dependency

The five scenarios presented in this section correspond exactly to those presented in chapter 6. Three scenarios consider different pathways after 2030, CONST-AFTER, ZERO-AFTER, INCR-AFTER, and two regard different pathways before 2030, ZERO-BEFORE, HIGH-BEFORE (see also Figure 6.7).

Although all six scenarios have the same $CO_2$ tax in 2030, they result in different MAC curves, especially for higher abatement costs (see Figure 8.8). Those scenarios with a higher $CO_2$ tax compared with the REF scenario, i.e. INCR-AFTER and HIGH-BEFORE show for the same carbon price a slightly higher abatement level. The CONST-AFTER scenario, which keeps the $CO_2$ tax constant after 2030, shows only a very limited divergence from the REF scenario. The emission curves for all three mentioned scenarios look very similar to the REF emission curve, where, for a given $CO_2$ tax, the biggest difference in the abatement potential is 10%. The scenarios where the $CO_2$ tax is kept at zero before or after 2030 significantly increase the marginal abatement costs. While the abatement potential is significantly lower for a given $CO_2$ tax up to £80/t $CO_2$ in the ZERO-AFTER scenario, it is the inverse case for the ZERO-BEFORE scenario where the abatement potential is less from around £200/t $CO_2$ on.

**Figure 8.8: End-use emission curve for different path dependency scenarios**




When interpreting the path dependency scenarios, it should be considered that UK MARKAL is a perfect foresight model and does not include endogenous technology learning (ETL). The latter characteristic can limit the influence of a variation in the carbon tax pathway.

### 8.3.1 Constant $CO_2$ tax after 2030

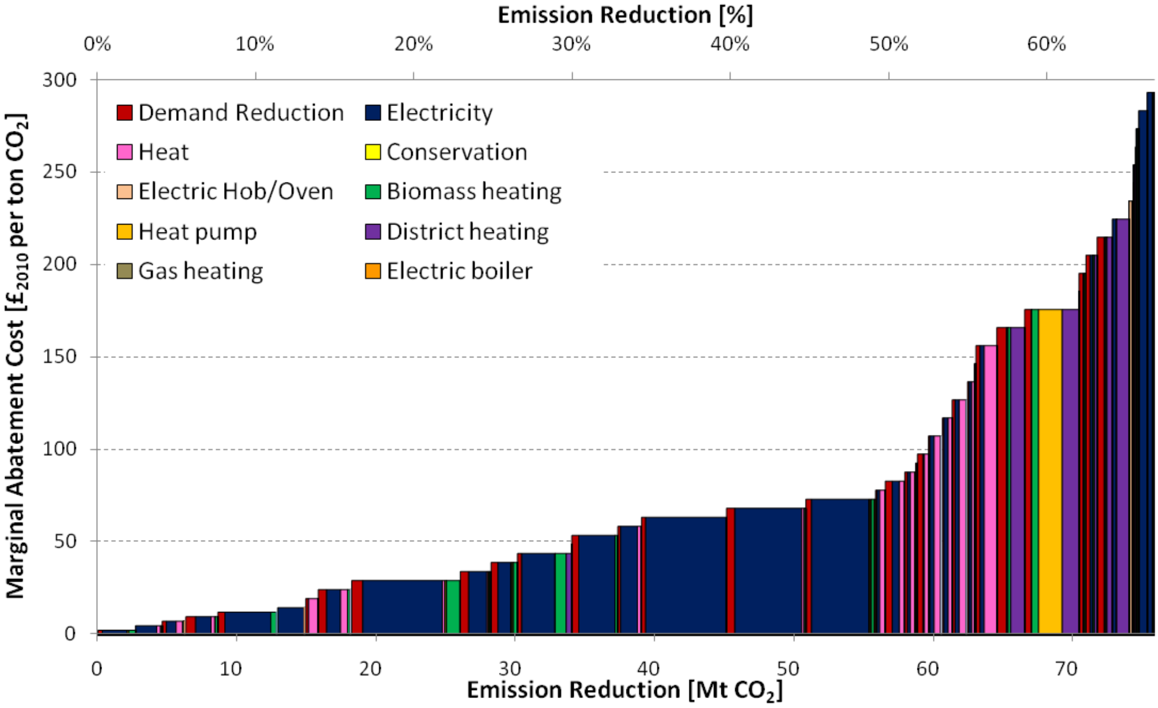
In contrast to the REF scenario, the CONST-AFTER scenario assumes a carbon tax that stays constant after 2030 and does not increase anymore. Therefore, the incentive to reduce emissions is less than in the REF scenario as the $CO_2$ tax in future periods will be lower. Consequently, one can expect the MAC curve to be at least to some extent steeper.

It turns out that the resulting MAC curve looks very similar to the MAC curve in the REF scenario. The cost-increasing effect is very small with on average 1 Mt $CO_2$. The biggest difference is in a range from £80/t $CO_2$ to £120/t $CO_2$ as heat and electricity are decarbonised more gradually. Furthermore, biomass-fired boilers contribute slightly less towards overall emissions reduction. Summarising, the influence of a constant carbon tax is very limited.

### 8.3.2 Zero $CO_2$ tax after 2030

This path dependency scenario assumes a $CO_2$ tax that drops back to zero for all model runs past 2030. After 2030 there is no incentive to shift the energy system to low carbon technologies because there is no emission tax anymore. Correspondingly, all investments into low-carbon technologies in 2030 and before will be stranded assets in an environment without a climate policy after 2030. Therefore, one can expect to see less abatement for the same carbon tax level, which is confirmed by Figure 8.8 and Figure 8.9. Especially up to £40/t $CO_2$, the MAC curve of the ZERO-AFTER scenario differs significantly from the REF scenario by 12 Mt/ $CO_2$ on average. At increasing tax levels, both MAC curves converge again.

**Figure 8.9: MAC curve for the ZERO-AFTER scenario in 2030**




A look at Figure 8.9 reveals that abatement is significantly less at £50/t $CO_2$. While almost 60 Mt $CO_2$ are abated in the REF scenario, it is less than 40 Mt $CO_2$ in the ZERO-AFTER scenario. Electricity is decarbonised more gradually, which has consequences for emissions abatement in the residential sector. The same holds true for heat decarbonisation, which occurs from £80/t $CO_2$ to £150/t $CO_2$, thus at tax levels that are more than £50/t $CO_2$ above the REF scenario.

The contribution from demand reduction towards emissions reduction is increased by 14% to make up for the lesser contribution from structural changes and the decarbonisation of electricity. Demand is assumed to react relatively flexibly to price changes so that demand reduction is preferred in this scenario over structural changes. When the carbon tax drops to zero, demand can adapt quickly, while earlier low carbon technologies would be stranded assets after 2030.

As the overall contribution of technological changes is already limited in the REF scenario, the differences are as well limited on an absolute scale. The most significant change is that heat pumps become cost efficient at £166/t $CO_2$, which is £30/t $CO_2$ higher than in the REF scenario.

### 8.3.3 Steep increase in $CO_2$ tax after 2030

In the INCR-AFTER scenario the $CO_2$ tax increases after 2030 by 10% annually, thus the $CO_2$ tax increases at a rate that is twice as high as in the REF scenario. The shape of the MAC curve looks very similar to the REF scenario as Figure 8.8 reveals. The higher $CO_2$ tax after 2030 should represent an additional incentive in 2030 to choose low carbon technologies in order to anticipate the future stricter climate policy.

A comparison of the INCR-AFTER and REF emission curves reveals that the emissions in the INCR-AFTER scenario are marginally lower than the REF scenario with an exception from £70/t $CO_2$ to £140/t $CO_2$. From £70/t $CO_2$ to around £100/t $CO_2$, the emissions in the residential sector increase despite a rising carbon tax due to biomass and district heat being substituted by gas as a heating fuel. Despite increasing emissions from the residential sector, system-wide emissions decrease due to the decarbonisation of the electricity sector, which uses more biomass. This shift happens amongst other reasons because the higher carbon price in the future makes an electrification of residential heating more economical in later years. The consequence for residential emissions is that biomass is diverted from residential heating to electricity generation.

Although the steep increase of the $CO_2$ tax after 2030 does not generally have a big influence on the MAC curve, around £100/t $CO_2$ the emissions increase despite a rising $CO_2$ tax as a result of intersectoral interactions.

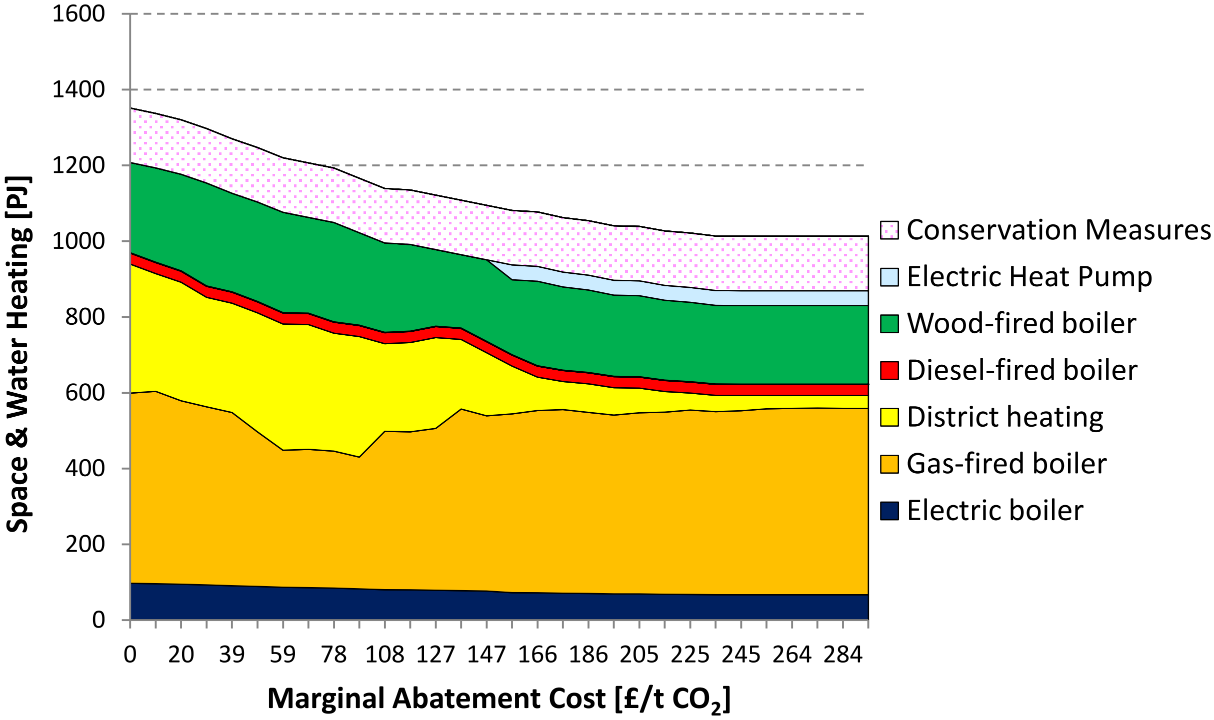
### 8.3.4 Zero $CO_2$ tax before 2030

In contrast to the REF scenario, there is no $CO_2$ tax before 2030 in the ZERO-BEFORE scenario. Consequently, there is no incentive to shift to any low-carbon technology before 2030 unless it is economic to do so without a carbon policy. This lack of incentive has consequences for the year 2030 as the devices used in the residential sector, such as boilers, fridges or ovens have an average lifetime ranging from 14 to 20 years. Thus, investments would need to be taken in the absence of any climate policy prior to 2030 in order to address a substantial carbon tax in 2030.

Figure 8.8 indicates that the overall MAC curve in the REF and the ZERO-BEFORE scenario are similar. The biggest divergence can be identified up to £50/t $CO_2$ and above £260/t $CO_2$. This divergence in curves is found to be smaller in comparison with the corresponding curves for the transport sector, which can be explained by the lesser importance of technological change in the residential sector.

Instead of a MAC curve, Figure 8.10 displays the technology mix for space and water heating in order to explain the differences between both curves. The reasons for the difference at low carbon tax levels can be found in the electricity sector where the carbon intensity of electricity is higher for a given tax level in the ZERO-BEFORE scenario compared with the REF scenario. The investment in biomass CHP for heat provision is less in the ZERO-BEFORE as it is not cost-optimal in the absence of a carbon tax. Comparable to the ZERO-AFTER scenario, electric heat pumps become cost efficient at a tax level that is £20/t $CO_2$ higher than in the REF scenario. Between £140/t $CO_2$ and £190/t $CO_2$, the emission curve in the ZERO-BEFORE scenario is even to the left of the REF scenario due to a higher share of district heating. This option is not as quickly replaced by gas-fired boilers as is the case in the reference scenario.

**Figure 8.10: Technology mix for space & water heating in the ZERO-BEFORE scenario**




In summary, the fact that there is no $CO_2$ tax prior to 2030 represents a disincentive for the investment in low-carbon technologies resulting in slightly less abatement for a given carbon tax. The influence is less compared with the transport sector because emissions reduction is dominated by electricity and heat decarbonisation and demand-related factors, but less by fuel switching.

### 8.3.5 High $CO_2$ tax from 2015

The HIGH-BEFORE scenario assumes that the $CO_2$ tax stays on a high, constant level from 2015 to 2030, which is the same as the $CO_2$ tax in the REF scenario in 2030. This means that for the period from 2015 to 2025 the $CO_2$ tax is higher than in the REF scenario and should present an additional incentive to decarbonise the energy system.

However, this additional incentive proves to be weak when one compares both emission curves in Figure 8.8. The emission curve in the HIGH-BEFORE scenario indicates more abatement at around £40/t $CO_2$ due to an earlier shift to gas boilers away from district heat from fossil fuels. The next difference is around £117/t $CO_2$ where heat pumps become cost-effective and biomass-based district heating is introduced at slightly lower tax levels compared with the reference scenario.

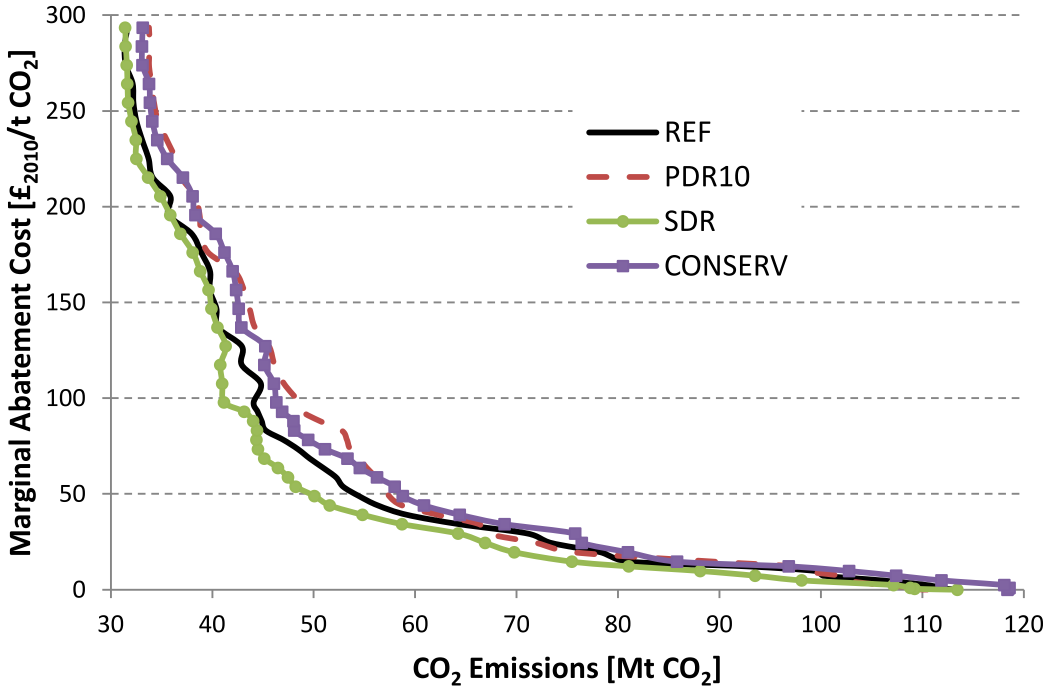
Consequently, a $CO_2$ tax that is higher for two periods can lead in specific cases to a reduction of marginal abatement costs, but does not alter the overall MAC curve substantially. Similarly to the transport sector, the MAC curve seems to be more affected by lower carbon tax pathways than by higher carbon taxes owing to the already high tax level in the reference case.

## 8.4 Discount rate

The two scenarios presented in this section, PDR10 and SDR, correspond exactly to those presented in chapter 6 and 7 for the electricity sector. In addition, a new scenario CONSERV tests the influence of a 50% hurdle rate for conservation measures in the residential sector. This should reflect the high implicit discount rate reflecting market barriers, uncertainties and technology-specific risks (see also DeCanio 1993; Jaffe and Stavins 1994). In a study for the Department of Environment, Food and Rural Affairs (Enviros Consulting Ltd 2006), a discount rate of 7% was used for the domestic sector. The CCC commissioned a study (Pye et al. 2008) that applied a discount rate of 7.5%, 8.5% and a social discount rate. The most recent study from the CCC (Weiner 2009) varied discount rates between 3.5% and 100% to study the effect on the emissions reduction potential. The PDR10 scenario represents the perspective of a private investor, where the technological hurdle rates for conservation measures and electric heat pumps were doubled with respect to the REF scenario to 17.5% and a 10% hurdle rate was introduced for all other technologies. The PDR10 scenario assumes a general discount rate of 5%. In the SDR scenario a social discount rate of 3.5% is employed and all taxes (except for the carbon tax needed to generate the MAC curve) and hurdle rates removed.

Similar to the power sector and in contrast to the transport sector, Figure 8.11 indicates that the emission curves for the different discount rate scenarios are similar. The biggest difference to the REF scenario is found in the emission curve for the PDR10 scenario in the middle part of the emission curve. Nevertheless, the maximum difference is only 8 Mt $CO_2$ for a given tax level. The emissions in the CONSERV scenario are 3 Mt $CO_2$ above the level in the REF scenario in the absence of any carbon tax. This difference decreases with an increasing $CO_2$ tax as gradually more and more conservation measures become cost-effective. The SDR scenario indicates emission mitigation to be higher from a social perspective up to £70/t $CO_2$.

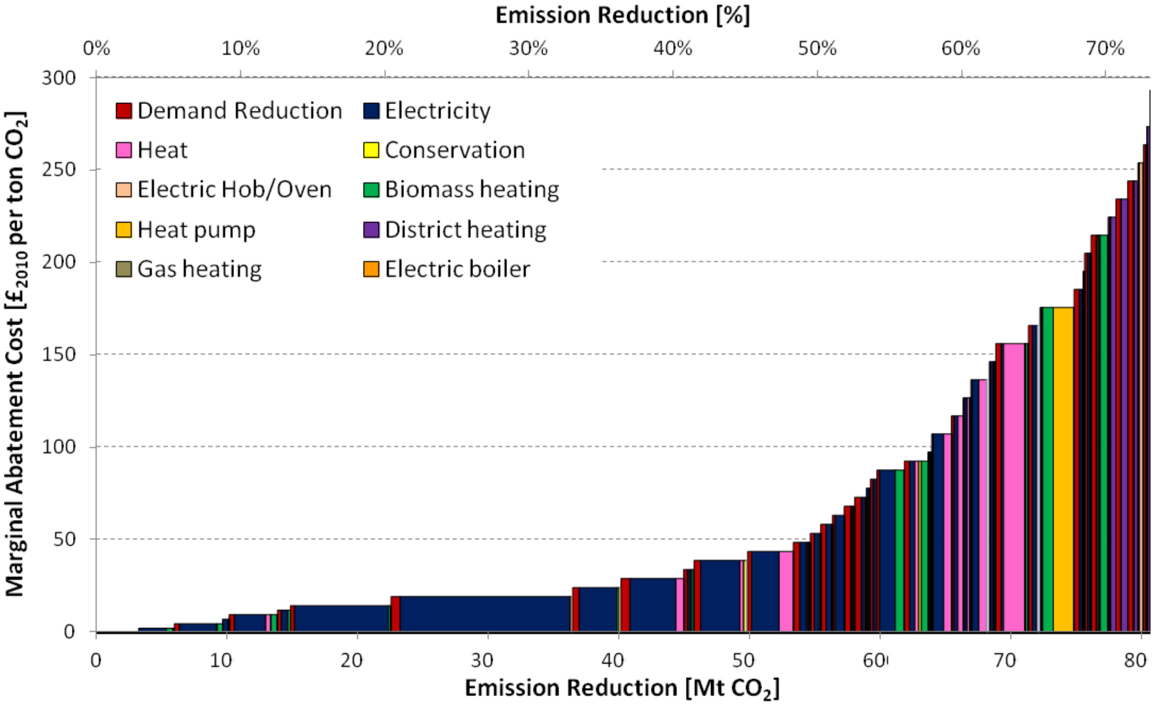
**Figure 8.11: Emission curve along rising $CO_2$ abatement costs for different discount rate scenarios in 2030**




As fuel switching plays a minor role in the REF MAC curve, a change in the discount rate, which affects annualised investment costs, has a limited impact. However, structural changes contribute significantly less to emissions reduction in the PDR10 scenario relative to the REF scenario, while the contribution from price-induced demand change is higher by 6%. One can see an upward shift in marginal abatement costs for the decarbonisation of heat and electricity owing to the increase in discount rates. At higher tax levels, a decarbonisation of district heat and a limited shift to biomass-fired boilers are responsible for most of the emissions reduction from £100/t $CO_2$ upwards

Heat pumps become cost-effective at £176/t $CO_2$, representing a mark-up of £40/t $CO_2$ compared with the REF scenario. The higher discount and hurdle rates also affect the cost-efficiency of conservation measures. These measures reduce energy service demand by only 112 PJ in the PDR10 scenario in the base case, which is 31 PJ less than in the REF scenario. However, at £40/t $CO_2$ loft insulation and at £107/t $CO_2$ solid wall insulation become cost-effective, reducing overall demand for space heating and $CO_2$ emissions by almost 2 Mt $CO_2$.

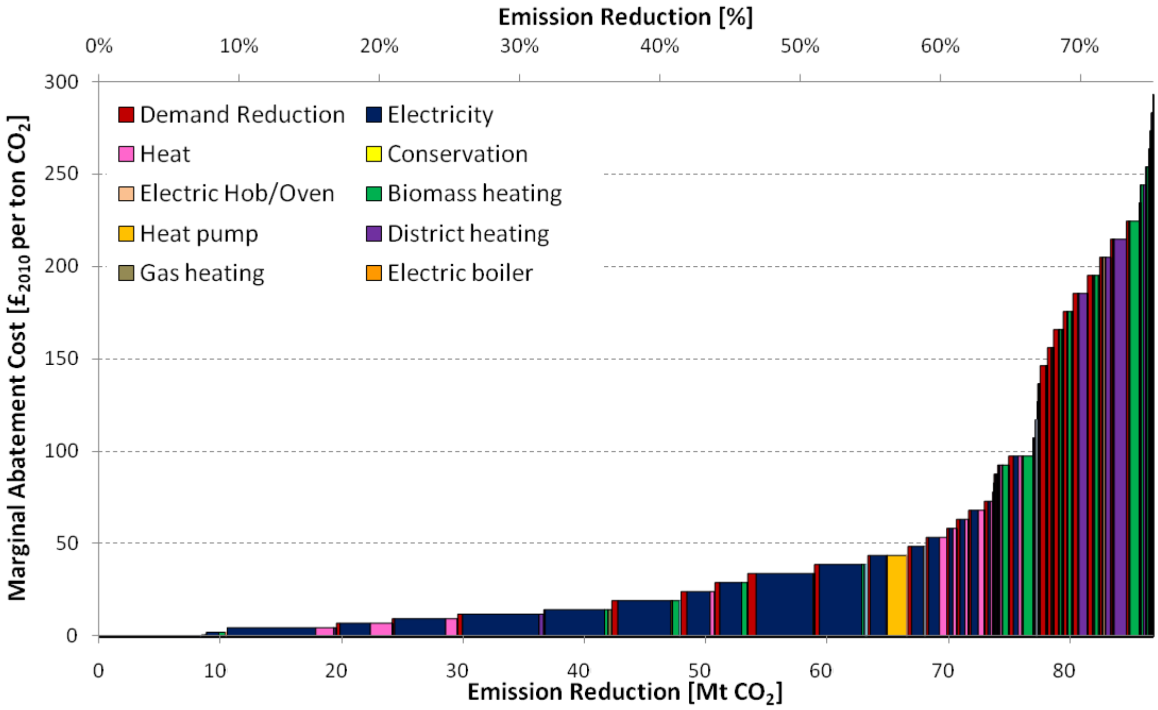
**Figure 8.12: MAC curve for the PDR10 scenario in 2030**




The MAC curve for the SDR scenario (Figure 8.13) looks in general rather similar to the REF scenario despite a few differences. Taxes and subsidies do not play an important role in the domestic sector in the UK, so they do not substantially affect the mitigation cost. A change of the discount rate influences the annualised investment cost, which make up only a very small part of the cost to provide an energy service, such as space heat. The cost is much more determined by the fuel cost. Nevertheless, conservation measures and heat pumps are an exception to this where the capital cost has a strong influence on the final cost for space heating. That is why heat pumps become cost efficient at £44/t $CO_2$, which is almost £100/t $CO_2$ less compared with the REF scenario.

However, the lower discount rate has an influence on the heat and power sector where it reduces the cost of low-carbon alternatives compared to fossil-fuel based generation. Consequently, almost all of the emissions reduction associated with the decarbonisation of heat and electricity is already realised at £80/t $CO_2$. A partial shift towards district heating and wood-boilers for space and water heating characterises the MAC curve above £160/t $CO_2$.

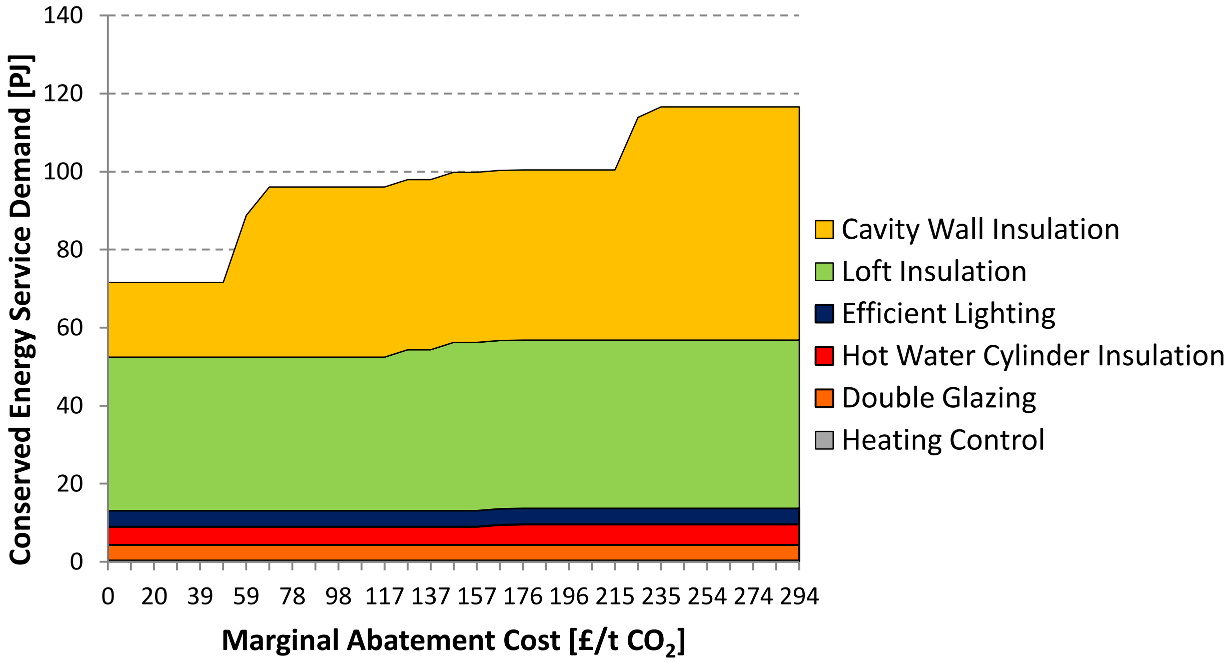
**Figure 8.13: MAC curve for the SDR scenario in 2030**




The last scenario in this category is the CONSERV scenario, which looks especially at conservation measures. As mentioned above the uptake of conservation measures in the domestic sector has been slower than predicted by economic conditions in the past. Market barriers and market failures in the form of information failures, costs associated with the installation of energy efficiency measures, financing hurdles, inertia and agency issues explain the gradual implementation of such measures (Sutherland 1991; Jaffe and Stavins 1994). Approximating market barriers and market failures via increased hurdle rates is sub-optimal but it is one of the few options in an optimisation model.

As the change in the discount rate concerns merely conservation measures, which contribute around 2% towards emissions reduction in the REF scenario, the CONSERV MAC curve looks very similar to the REF scenario. Nevertheless, the contribution from conservation measures looks different due to the high specific discount rate. In the case without any carbon policy, conservation measures reduce the demand for residential energy services by 67 PJ in the CONSERV scenario compared with 144 PJ in the REF scenario. Thus, less than 50% of the amount of conservation measures is realised with a 50% hurdle rate instead of 8.75%. Figure 8.14 displays the uptake of conservation measures along increasing carbon tax levels and shows that the saved energy related to cavity wall insulation is significantly influenced by the higher discount rates.

**Figure 8.14: Uptake of conservation measures in the domestic sector in the CONSERV scenario in 2030**




The saved energy due to cavity wall insulation more than triples over the whole range of carbon tax levels from 19 PJ to 60 PJ. While the contribution from loft insulation increases as well, the conservation potential for efficient lighting, hot water cylinder insulation, double glazing and heating control is already completely exhausted at £0/t $CO_2$. One can also note the total reduction in energy service demand amounts to 116 PJ, which is 20% less compared with the contribution in the REF scenario at no carbon tax.

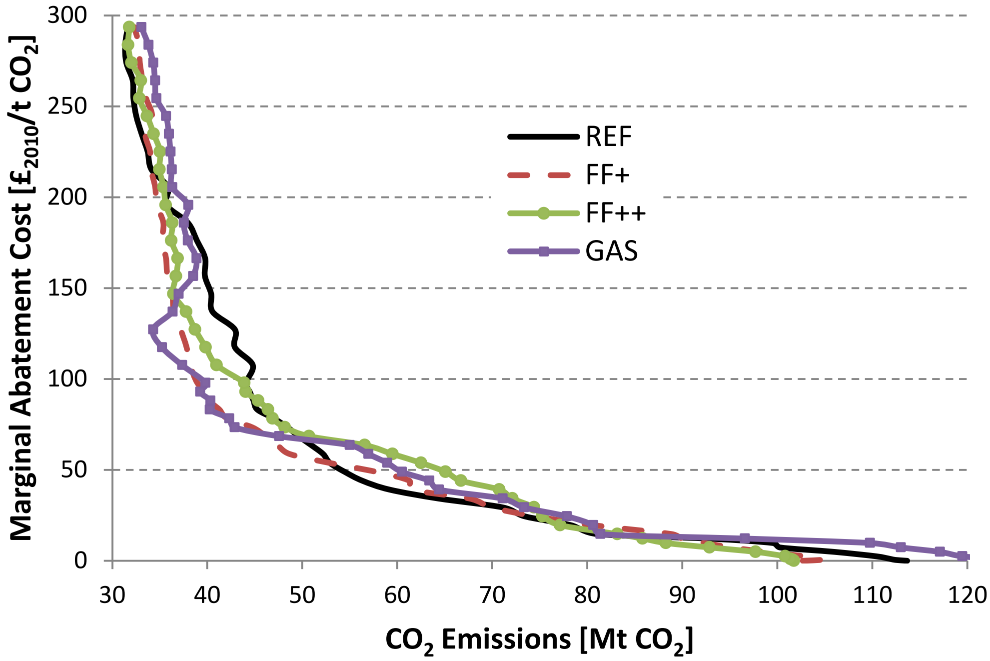
Overall, the increase in the hurdle rate for conservation measures to 50% reduces the amount of saved energy significantly. However, as the contribution from conservation measures towards emissions reduction is rather limited in the REF scenario over the carbon tax range, the change undertaken in the CONSERV scenario does not alter the shape of the MAC curve.

## 8.5 Fossil fuel prices

The scenarios presented in this section, GAS, FF+ and FF++, are the same as in chapter 6, i.e. fossil fuel prices are increased by 100% in the FF+ scenario and by 200% in the FF++ scenario, while natural gas prices are reduced by 50% in the GAS scenario. The fossil fuel price assumptions can be found in Table 6.3.

The emission curve for the different fossil fuel price scenarios (Figure 8.15) reveals that the difference between the scenarios is rather limited with an exception in the range from £60/t $CO_2$ to £130/t $CO_2$, where the abatement potential varies a little more. At very high $CO_2$ tax levels all four emission curves converge as the fuel price differences are overshadowed by the carbon tax. The baseline emissions are different to the extent that they increase by 11% in the GAS scenario, they are 10% lower in the FF+ scenario and 11% lower in the FF++ scenario. These results for the residential sector confirm the results from the power sector, namely that the MAC curve is relatively robust to fossil fuel price changes.

**Figure 8.15: Emission curve along rising $CO_2$ abatement costs for the fossil fuel price scenarios in 2030**



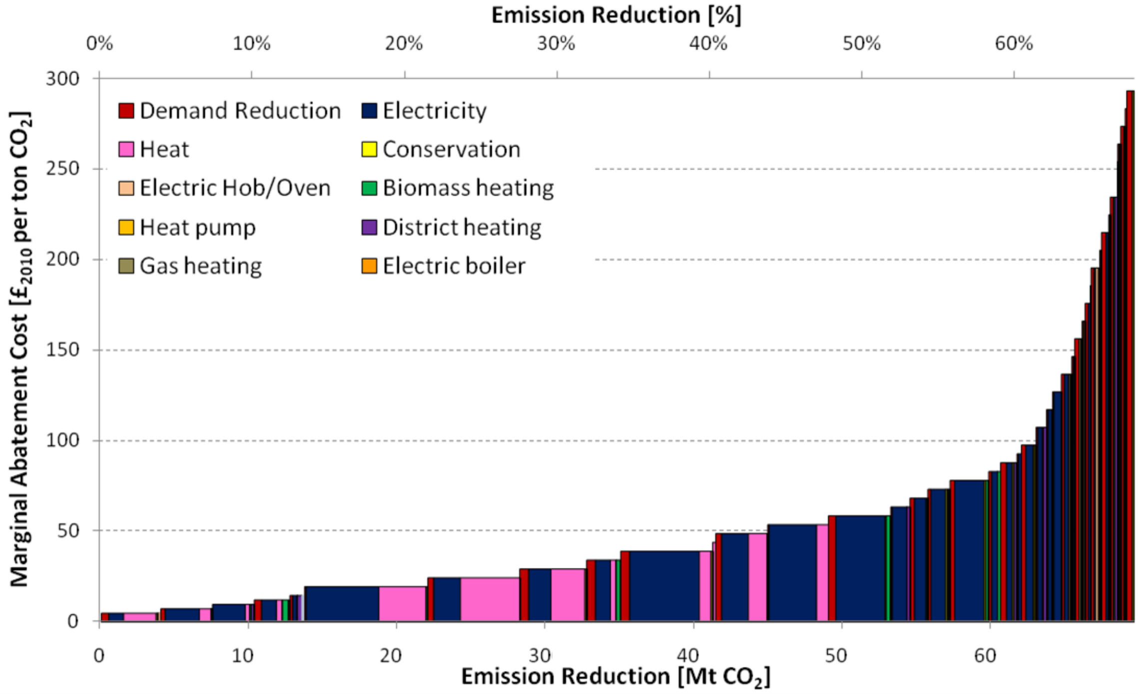

The emissions are 11 Mt $CO_2$ less in the FF+ scenario without any carbon tax compared with the REF scenario. The reasons are that the carbon intensity of electricity is 21% less than in the REF scenario and 23% more biomass is used for space and water heating.

In contrast to this, the carbon intensity of heat is significantly higher in the FF+ scenario without any carbon tax. The reason is a shift from natural gas CHP plants towards CHP plants fired by solid fossil fuels. It is economic to do so despite a price increase in all fossil fuels by 100%. Accordingly, there is a big potential to save $CO_2$ emissions by shifting towards less $CO_2$ intensive heat production technology (see Figure 8.16). With increasing $CO_2$ tax levels heat production is more and more shifted towards natural gas and above all solid biomass as a fuel input. As a consequence the contribution from heat decarbonisation in terms of $CO_2$ emissions reduction increases to 19 Mt $CO_2$.

Since biomass boilers contribute 23% more towards space heating and hot water at the start of the MAC curve in the FF+ scenario compared with the REF scenario, the further contribution in the MAC curve is minimal. Interesting to note, however, is that heat pumps are cost-effective without any carbon policy in the case where fossil fuel prices have been increased by 100%. Overall, the shape of the MAC curve looks very similar to the REF scenario, though heat decarbonisation plays a much more important role due to large role of solid fossil fuels at £0/t $CO_2$.

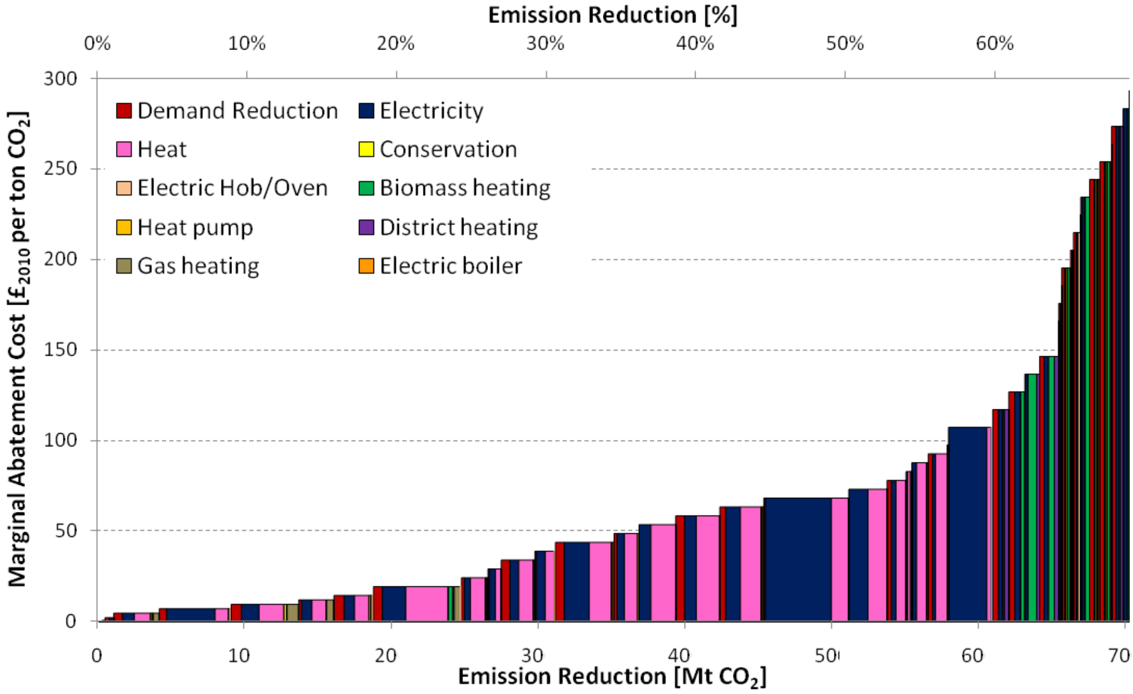
Figure 8.16 and Figure 8.17 depict the MAC curves for both fossil fuel price scenarios. Both curves look very similar with heat decarbonisation being much more important in the FF+ and FF++ scenario than in the REF scenario.

**Figure 8.16: MAC curve for the FF+ scenario in 2030**




The contribution of electricity decarbonisation in the FF++ scenario is even less compared to the FF+ scenario due to the fact that electricity generation is less carbon intensive at £0/t $CO_2$ with 274 g $CO_2$/kWh compared to 510 g $CO_2$/kWh in the REF scenario. On the other hand, similarly to the FF+ scenario, heat is much more carbon-intensive without any carbon constraints and only from £20/t $CO_2$ solid biomass takes over as the dominant fuel in heat production.

**Figure 8.17: MAC curve for the FF++ scenario in 2030**



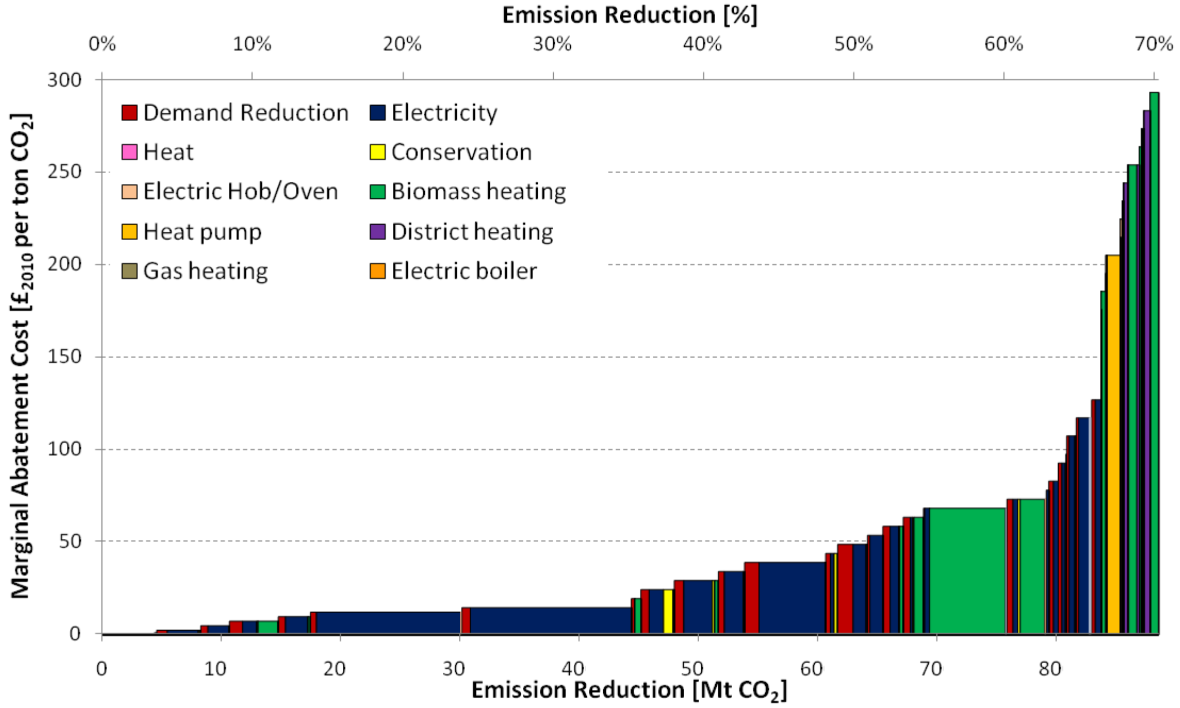

In this way, heat decarbonisation contributes almost as much towards $CO_2$ emissions reduction as electricity with 26 Mt $CO_2$ in the domestic sector. In the baseline of the FF++ scenario, district heat supplies 28% more space heat than in the REF scenario. Together with an increased reliance on biomass, the share of gas-fired boilers in space heating and hot water is reduced to 26%. Up to around £100/t $CO_2$, the share of gas-fired boilers increases at the expense of district heat. Figure 8.17 displays that a shift from carbon-intensive heat towards gas saves $CO_2$ emissions up to £20/t $CO_2$. Similar to the FF+ scenario, electric heat pumps are cost-effective even in the absence of any carbon policies.

In the FF+ and FF++ scenario, natural gas is the dominant fuel within the whole carbon tax range despite drastically increased fossil fuel prices. Possible low-carbon alternatives, such as pellets and biomass, become more expensive as the demand from the electricity sector and heat sector increases (driven by a growing demand in the industry and service sector), while supply is constrained. While the potential for electric heat pumps is limited, electric heating and boilers, as well as solar water heaters are expensive compared to gas-fired boilers in the REF scenario and cannot close this cost gap in the FF+ and FF++ scenarios.

Instead of rising fossil fuel prices, the GAS scenario looks at a decoupling of the oil and gas price, where gas prices fall over the next 20 years. This scenario assumes gas prices that are 50% below the values in the REF scenario from 2015 on. The MAC curve for the GAS scenario does not reveal that the fuel mix for space and water heating looks different compared to the REF scenario. Unsurprisingly, gas-fired boilers increase their share in providing space heating and hot water to 55%, but also district heating supplies more heat in the GAS scenario. The reason for this is cheaper heat generation from natural gas CHP plants.

The MAC curve for the GAS scenario (Figure 8.18) indicates a bigger contribution from a shift towards biomass-fired boilers as it is less dominant compared with the REF scenario at £0/t $CO_2$. An increasing space heat supply from biomass-fired boilers reduces carbon emissions by 7 Mt $CO_2$ over the whole MAC curve. With increasing carbon tax levels, the demand for space and water heating is more and more satisfied by biomass-fired boilers instead of district heating, while the share of gas-fired boilers remains almost constant.

**Figure 8.18: MAC curve for the GAS scenario in 2030**



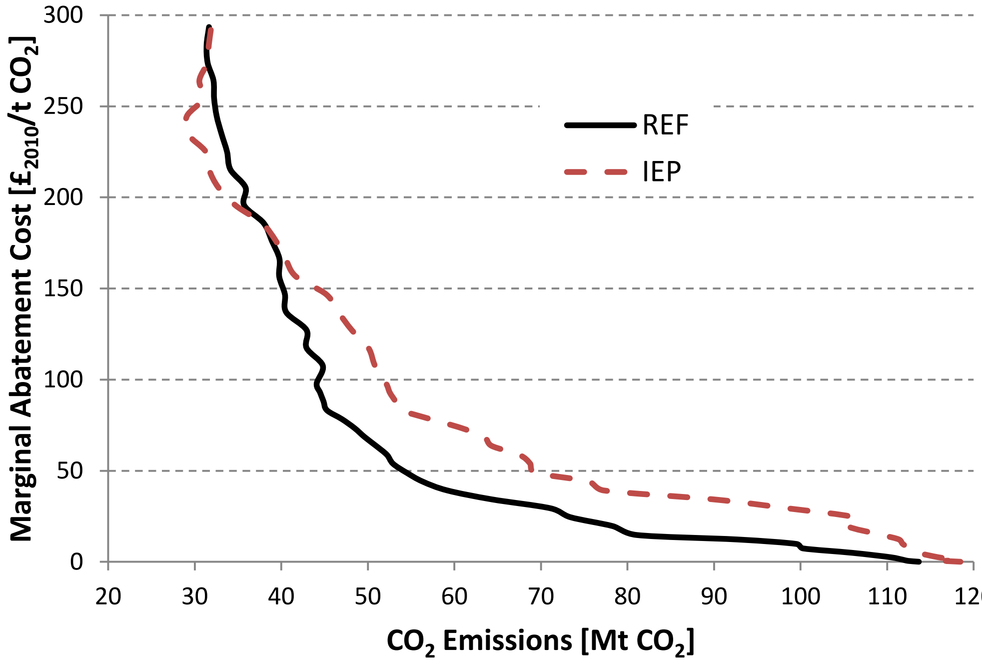

Due to the lower gas price, energy conservation does not contribute to the same extent to a reduction in the demand for domestic energy services. However, energy conservation requires higher carbon tax levels to become cost-optimal. Furthermore, it is economically optimal to introduce heat pumps into the market at £205/t $CO_2$, i.e. at £69/t $CO_2$ more than in the REF scenario. Finally, due to cheaper energy services in the baseline without a carbon policy, the contribution from demand reduction is higher, since prices increase relatively more, and reaches a total of 16 Mt $CO_2$.

## 8.6 Cost of electricity

The previous scenarios have shown that the decarbonisation of electricity plays a very important role for the reduction of emissions related to the residential sector. In total 71% of all emissions reduction in the REF scenario is attributable to a reduction of the carbon intensity of electricity. The IEP (Increased Electricity Price) scenario tests the sensitivity of the MAC curve to a significantly higher electricity price. This scenario is exactly the same as the IEP scenario presented in chapter 7.7, i.e. investment costs for key abatement technologies in the electricity sector are assumed to be 200% higher (see Table 6.5).

Figure 8.19 contrasts the emission curve for the IEP scenario with the one from the REF scenario. The emissions in the IEP scenario are 5 Mt $CO_2$ higher at £0/t $CO_2$ because electricity is 9% more carbon intensive. Up to £70/t $CO_2$, the emissions in the IEP scenario are significantly above the REF scenario with on average 16 Mt $CO_2$ for a given carbon tax mainly due to the higher $CO_2$ intensity of electricity.

**Figure 8.19: Emission curve along rising $CO_2$ abatement costs for the IEP scenario in 2030**

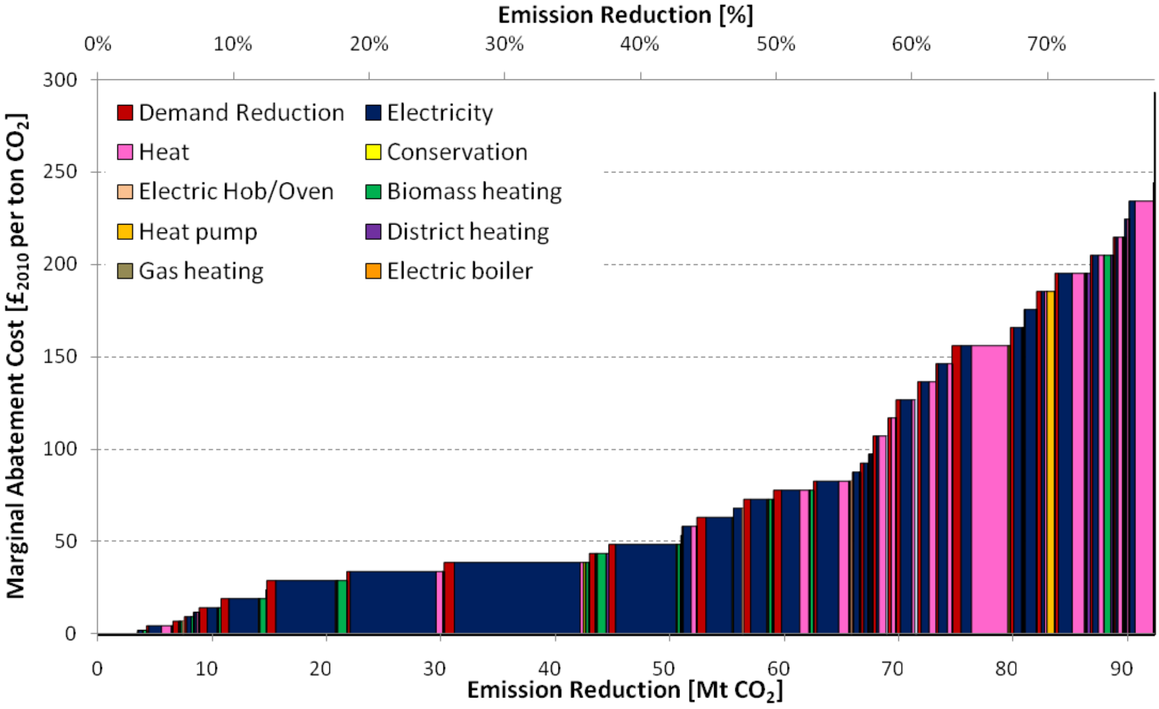



The emissions gap between both scenarios is closed at £176/t $CO_2$, while emissions are even below the REF scenario from £200/t $CO_2$ to £260/t $CO_2$. This is despite the fact that the carbon intensity of electricity is still higher in the IEP scenario compared with the REF scenario. The reason is rather that district heat contributes 25% towards space and water heating in the IEP scenario, while it is 8% in the REF scenario at that tax level. District heating is less carbon intensive than heating with natural gas because it is based on natural gas and biomass CHP plants. However, at higher carbon tax levels it is no longer cost-optimal to have natural gas CHP plants as the electricity sector shifts to low-carbon alternatives. This has consequences for heat generation, which is reduced at higher carbon tax levels and replaced by natural gas for space heating and hot water.

The MAC curve for the IEP scenario (Figure 8.20) reveals that the abatement potential is very limited up to £15/t $CO_2$ due to the increased cost to produce electricity. Nevertheless, the contribution of decarbonising electricity is relatively similar to the REF scenario albeit at higher abatement cost. The emissions reduction attributable to a lower carbon intensity of heat is higher compared with the REF scenario because district heating based on natural gas and biomass CHPs is not replaced by natural gas for space and water heating as is the case in the REF scenario.

The consequence of higher electricity prices is that price-induced demand reduction is more important for the reduction of carbon emissions. In total, demand reduction contributes 23% more towards emissions reduction. Finally, due to the higher price of electricity, the introduction of heat pumps becomes cost-optimal at £176/t $CO_2$, i.e. at £40/t $CO_2$ more compared with the REF scenario.

**Figure 8.20: MAC curve for the IEP scenario in 2030**

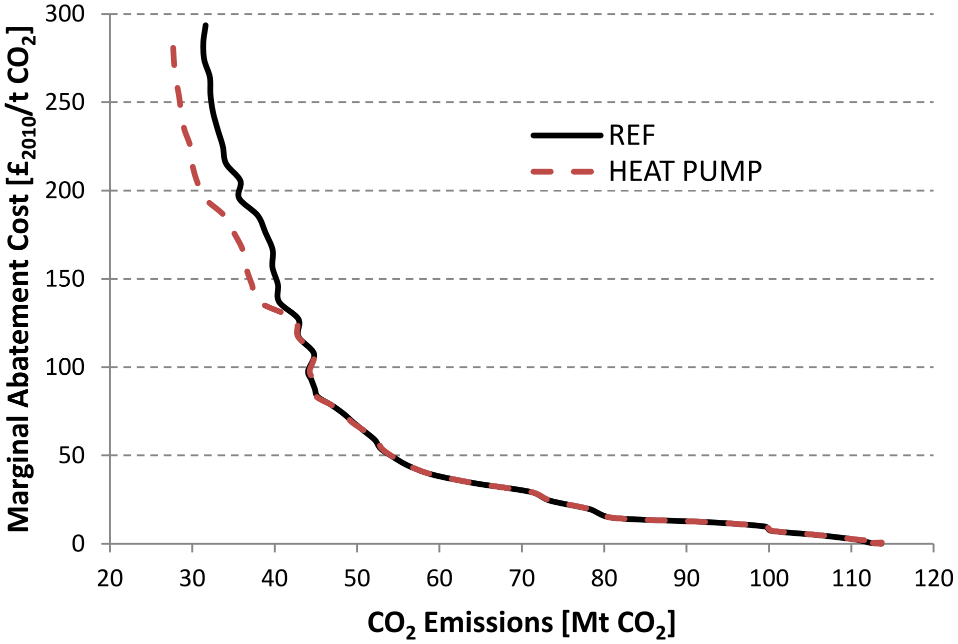


## 8.7 Market potential of electric heat pumps

In the REF scenario it is conservatively assumed that the potential of heat pumps in the domestic sector is limited to 39 PJ per year or 4% of all dwellings. This upper bound on the use of heat pumps reflects the limited potential for the installation of air source and ground source heat pumps in the UK domestic building stock. Instead of a gas-fired boiler, heat pumps need to be installed outside a house and require plenty of space to get the necessary air flow. The potential for ground source heat pumps is limited as it requires suitable conditions for a ground loop. Furthermore, heat pumps work more efficiently when underfloor heating systems are installed and when the house is well insulated because of lower water temperatures needed. The HEAT PUMP scenario assumes a bigger potential for heat pumps in the residential sector and studies the impact on the MAC curve of raising the limit by 200% from 39 PJ to 117 PJ, which is similar to the values assumed in a report for the CCC (Radov et al. 2010).

The emission curve (Figure 8.21) looks exactly the same up to £137/t $CO_2$ as in the REF scenario, but once heat pumps become cost-effective the market share of heat pumps increases more in the HEAT PUMP scenario than in the REF scenario. Subsequently, emissions are lower in the HEAT PUMP scenario by roughly 4 Mt $CO_2$ at carbon tax levels above £137/t $CO_2$.

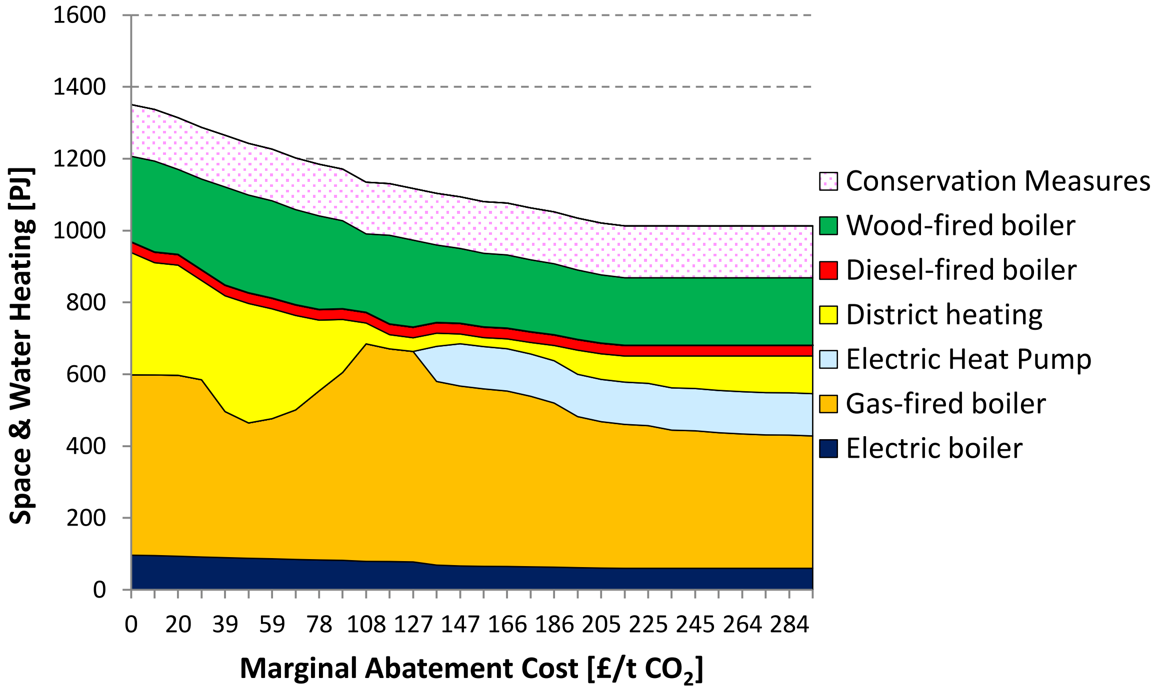
**Figure 8.21: Emission curve along rising $CO_2$ abatement costs for the HEAT PUMP scenario in 2030**



The MAC curve for the HEAT PUMP scenario only shows limited differences to the REF scenario from £137/t $CO_2$. However, technology mix for space heating and hot water (Figure 8.22) reveals that heat pumps make up a bigger share of the overall demand for space heat and hot water once they are cost-effective compared with the REF scenario. The bigger contribution from heat pumps replaces gas-fired boilers, but also a small part of wood-fired boilers. This type of biomass is used in the power sector to generate electricity.

Overall the higher potential for heat pumps has a minor influence on the shape and structure of the residential MAC curve. In the power sector, the additional electricity is mainly provided by coal CCS power plants.

**Figure 8.22: Technology mix for space & water heating in the HEAT PUMP scenario**

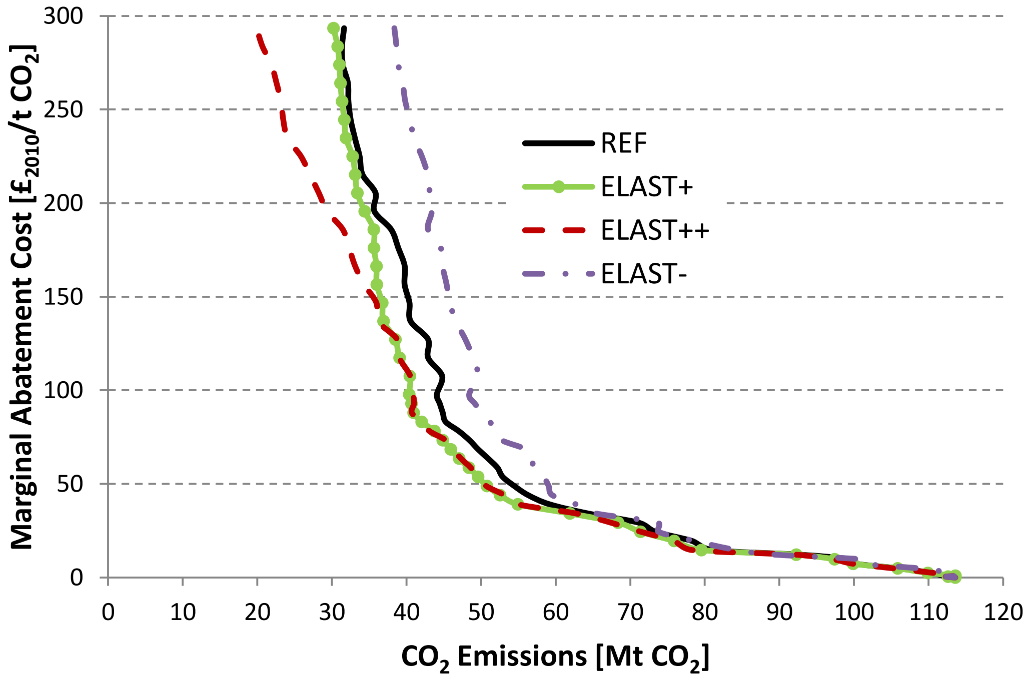



## 8.8 Demand elasticity

End-use demand reacts to changes in underlying prices. However, the extent of those changes, or the price elasticity of demand, is hard to observe empirically and remains therefore an uncertain value. This section presents three scenarios, which test the influence of changes in the demand elasticity on a MAC curve for the domestic sector. ELAST- and ELAST+ are exactly the same as in the transport chapter, where demand elasticities were increased by 50% and decreased by 50% respectively. To test the influence of the maximum change in the demand level of 25%, this limit was increased from 25% to 50% for all energy service demand types in the ELAST++ scenario, while demand elasticity was kept the same as in the ELAST+ scenario. Consequently, the ELAST++ scenario studies the maximum contribution of demand reduction towards emissions reduction.

The emission curves in Figure 8.23 show that varying the demand elasticity influences the cost of emissions abatement. While emissions reduction is more expensive in the ELAST- scenario, it is slightly less expensive in the ELAST+ and significantly less expensive in the ELAST++ scenario at high tax levels. Differences between emission curves start to appear from £20/t $CO_2$ and widen with higher carbon tax levels in the ELAST++ and ELAST- scenario. The difference between the ELAST+ and the REF scenario narrows down from £130/t $CO_2$ because at this tax level the energy service demands for space heating and hot water are decreased by 25% and are not allowed to decrease further. This is different in the ELAST++ scenario where the energy service demand for space heating and hot water are decreased by up to 40% from the reference level at £0/t $CO_2$.

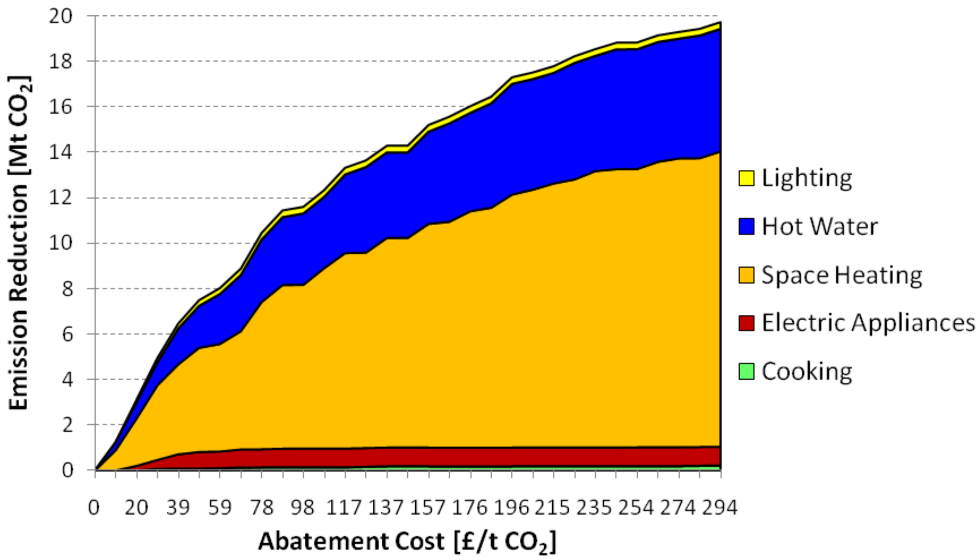
**Figure 8.23: Emission curve along rising $CO_2$ abatement costs for different demand elasticity scenarios in 2030**




Overall, the contribution from demand reduction varies from 8 Mt $CO_2$ emissions saving in the ELAST- scenario to 20 Mt $CO_2$ in the ELAST++ scenario, with 13 Mt $CO_2$ in the REF scenario and 14 Mt $CO_2$ in the ELAST+ scenario. While the contribution from demand reduction is very different for the four scenarios, the contribution from other mitigation measures remains almost unchanged.

A closer look at the source of the emissions reduction in the ELAST++ scenario (Figure 8.24) reveals that those energy services that rely mainly on electricity, such as lighting, electric appliances, cooling, refrigeration and cooking, are not reduced significantly. Demand reduction in space heating contributes 13 Mt $CO_2$ towards emissions reduction, while a reduced demand for hot water results in 5 Mt $CO_2$ of emissions abatement. This breakup corresponds to the energy service demand level in PJ at £0/t $CO_2$ of both services.

**Figure 8.24: Contribution of different energy service's demand reduction towards $CO_2$ emissions reduction scenarios in 2030 in the ELAST++ scenario**




Summing up, differences in demand elasticities are reflected in the MAC curve from £20/t $CO_2$ on, while the contribution from demand changes is in the range from 8 to 20 Mt $CO_2$. In addition, the limit on the maximum change in energy service demand imposed in UK MARKAL plays an important role in the residential sector. Relaxing this constraint can increases the contribution from demand reduction.

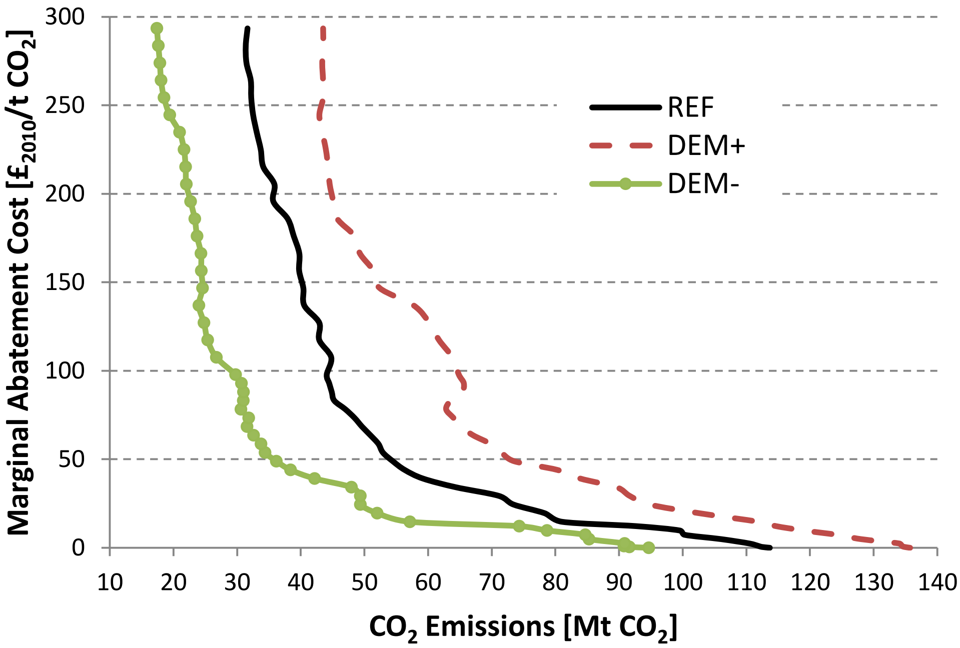
## 8.9 Demand development

The overall demand development for energy services in the whole energy system and the domestic sector depends on many uncertain factors such as population growth, economic growth, and behavioural patterns. The energy service demand in the UK is assumed to increase from 2010 to 2030 by the following rates in the REF scenario: 18% for cooking, electrical appliances, refrigeration, and lighting, 200% for cooling, and

11% for space heating and hot water. Since the demand for those energy services is uncertain, all energy service demands were increased by 20% in the DEM+ scenario and decreased by 20% in the DEM- scenario, in the same way as in chapter 6 and 7.

Figure 8.25 shows the emission curve for both demand scenarios in comparison to the REF scenario. One can see that the DEM+ curve is shifted to the right and the DEM- curve to the left according to the increased/decreased demand level. In the baseline, the emissions increase roughly by 20% in the DEM+ scenario reflecting the demand increase, while emissions in the DEM- scenario decrease by 17%. The reason is that the share of gas boilers and the carbon intensity of electricity is higher in the DEM- scenario.

**Figure 8.25: Emission curve along rising $CO_2$ abatement costs for different demand scenarios in 2030**

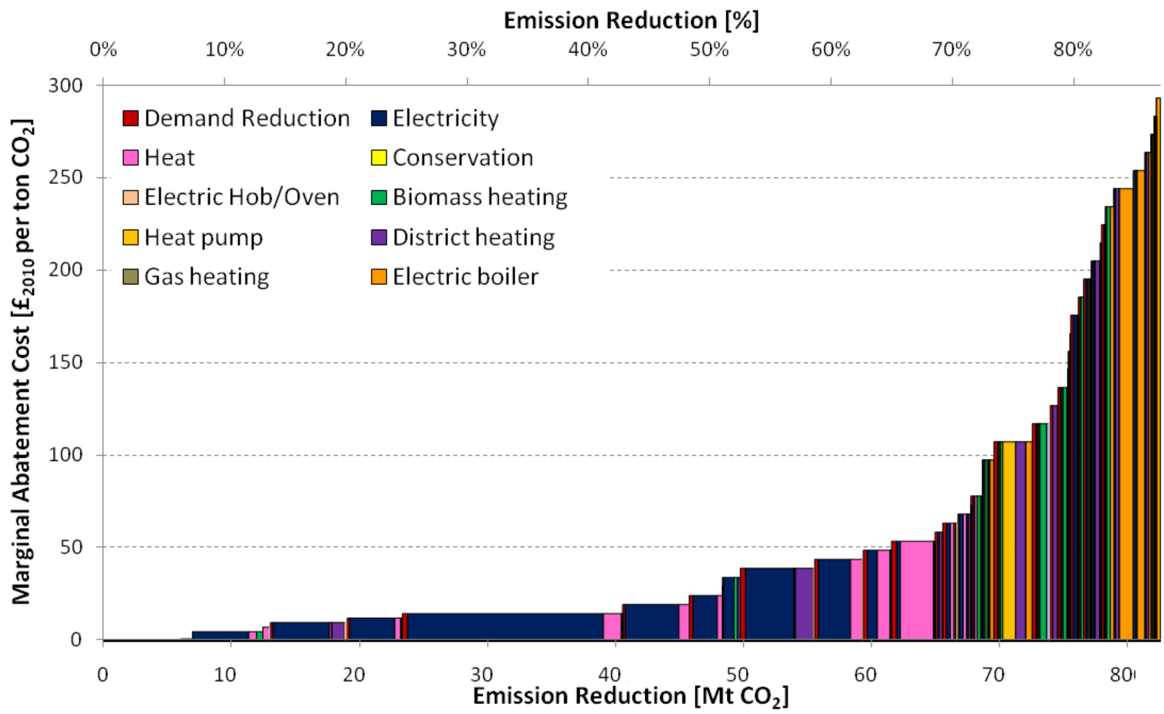



The initial difference of both demand scenario emission curves with respect to the reference case are overcome at tax levels that are higher than £30/t $CO_2$, after which the difference narrows down. This is due to more biomass being used for space heating and hot water in the DEM+ scenario and more district heating in the DEM- scenario. In the DEM+ scenario emissions increase from £78/t $CO_2$ to £93/t $CO_2$ as a consequence of a shift from biomass to natural gas as a fuel for heating. This is due to intersectoral interactions as imported biomass is no longer used for residential heating but converted into pyrolysis oil to be used in industry.

While the technological structure of the DEM+ MAC curve looks relatively similar to the REF scenario, there are some differences in the DEM- scenario, which can be seen in Figure 8.26. In contrast to the REF scenario, the share of district heating is not declining with rising carbon tax levels, but stays rather constant at 20% market share for space heating and hot water. As district heat gets decarbonised with increasing $CO_2$ tax levels by shifting gradually to biomass CHP plants, the contribution from heat decarbonisation is higher in the DEM- scenario than in the REF scenario.

Not only the carbon intensity of electricity is lower in the DEM- scenario but the price for electricity as well. At a carbon tax of £250/t $CO_2$, the electricity price in the DEM- scenario is 20% below the level in the REF scenario due to less electricity production being based on fossil fuels. Electric boilers are not significantly more expensive in the REF scenario at high carbon tax levels (see Figure 8.6), so that a significant drop in the electricity price makes them cost-effective. Consequently, the market share of electric boilers increases from £250/t $CO_2$ and thus saves roughly 3 Mt $CO_2$. Lastly, electric heat pumps also profit from a lower electricity price and become cost-effective at £30/t $CO_2$ less compared with the REF scenario.

**Figure 8.26: MAC curve for the DEM- scenario in 2030**




In general, the change in demand levels has some limited effects on the composition of emissions reduction in the DEM- scenario, while the effects are virtually non-existent in the DEM+ scenario. Although not directly comparable, it is interesting to note that a change in energy service demand by ±20% in 2030 has the biggest effect on the emission curve among all scenarios presented in this chapter.

## 8.10 Summary

19 scenarios for the UK domestic sector were presented in this chapter to illustrate the uncertainties involved in assessing marginal abatement costs and corresponding abatement potentials. Based on the discussion of the different, the results can be summarised in the light of the initial questions asked in chapter 1 concerning the contribution of abatement measures to emissions reduction, the influencing factors, and the interaction of measures:

In contrast to other sectors, it is apparent that structural changes, i.e. changes concerning the pool of end-use devices in the residential sector, do not contribute significantly towards emissions reduction. The only exceptions are heat pumps that become cost effective from £137/t $CO_2$ in the REF scenario and to a very limited extent wood-fired boilers. When fossil fuel prices are increased, heat pumps are cost-effective without any carbon policy. Once conservative assumptions on the deployment potential for heat pumps are relaxed, heat pumps can be an important mitigation measure in the domestic sector.

The limited structural change is due to the fact that there are only a few alternatives in the domestic sector for many energy service demands, such as refrigeration, lighting, cooling or electrical appliances, which all rely on electricity. Nevertheless, substantial structural change is expected without any carbon policies with respect to space heating and hot water. Under the assumptions and structure of the UK MARKAL model cost-effective energy conservation measures are taken up in the absence of any carbon policy. Moreover, wood-fired boilers and district heating are expected to supply almost half of all the energy needed for space heating and hot water, i.e. increasing substantially from current levels. Biomass plays an important role in all scenarios over the whole range of carbon tax levels, while the contribution of district heating depends much more on the scenario definition. Issues that could affect the described scenario are the significant air pollution caused by biomass combustion and the long lead time of district heat systems.

In all scenarios the decarbonisation of electricity plays a pivotal role to reduce emissions in the residential sector. The share of electricity decarbonisation in overall emissions reduction reaches 70% in the reference scenario, while the contribution from decarbonising heat is more limited at 10%. Finally, energy conservation, especially with respect to space heating, reduces energy consumption by around 10% in the baseline and thereby contributes towards emissions reduction. Price-induced demand reduction for energy services is relatively robust across the scenarios and contributes around 16% towards total emissions reduction. The results indicate the demand reduction is a flexible option under path dependency, which can be implemented in the near term. Due to the decarbonisation of heat and electricity at low carbon tax levels, the incentive for demand reduction or efficiency improvements at higher tax levels is significantly reduced.

A second purpose of the presented sensitivity analysis is to single out the most important influencing factors related to emissions reduction in the residential sector. Table 8.2 summarises the influence of the different categories on the overall shape of the MAC curve and its composition. In general, one can say that the influence of changes to the assumptions in the different scenarios is much less compared with the transport sector due to the predominant influence of decarbonising electricity and heat.

The MAC curve for the domestic sector is barely influenced by changes to the carbon tax pathway because structural changes are negligible and heat and electricity production is fairly flexible. Structural changes are limited because natural gas boilers are cost-effective even at high carbon tax levels (see section 8.2). Nevertheless, the abatement costs of individual abatement technologies, such as heat pumps, can vary depending on the path dependency scenario. Similarly, the discount rate scenarios do not have a significant influence.

More interestingly, the fossil fuel price scenarios show, despite the dominance of natural gas as a heating fuel, a very limited influence concerning the shape of the MAC curve. The composition of abatement differs as heat decarbonisation is more important in the FF+ and FF++ scenario and biomass replaces natural gas in the GAS scenario. Since the majority of emissions abatement depends on electricity, higher electricity prices (IEP scenario) have a noticeable effect and favour district heat from CHP plants. Heat pumps can play an important role as an abatement measure, yet their potential is assumed to be limited in 2030. Changing the demand elasticity and the limits on the maximum change in demand reduction alters the shape of the MAC curve, while the structure remains very similar. The most important influence of all scenarios can be attributed to changes in the demand for energy services that equally have an influence on the composition of MAC curves, particularly when demand levels are reduced.

**Table 8.2: Influence of the change in different model assumptions on MAC curve: strong (+), medium (o), weak (-)**

| Category | Influence | |
|---|---|---|
| | Shape | Structure |
| Path dependency | - | - |
| Discount rate | - | - |
| Fossil fuel price | - | o |
| Electricity Cost | o | o |
| Technological availability | - | - |
| Demand elasticity | o | - |
| Demand level | + | o/- |

The last point to address are the interactions of abatement measures. In the domestic sector, the analysis has pointed out that the fuel mix used for space heating and hot water is fairly robust to changes in assumptions with the exception of district heat, heat pumps and to some extent biomass. Particularly, the marginal abatement costs of heat pumps are very sensitive to a change in discount rates, fossil fuel prices or carbon tax pathways.

On a system-wide level there are major interactions with the upstream, heat and electricity sector. Particularly, the cost-efficiency of combined heat and power plants influences the abatement structure in the residential sector. In most cases district heat is provided either by natural gas CHP plants or biomass CHP plants that are only cost-optimal if there is a demand for district heat and if they are competitive with other low-carbon options in the electricity sector. Furthermore, the residential sector is dependent on the carbon intensity of electricity, which became obvious in the IEP scenario. Finally, the previous discussion showed that biomass can be diverted from wood-fired boilers in the residential sector to the electricity sector for co-firing or to the industrial sector for heating purposes.

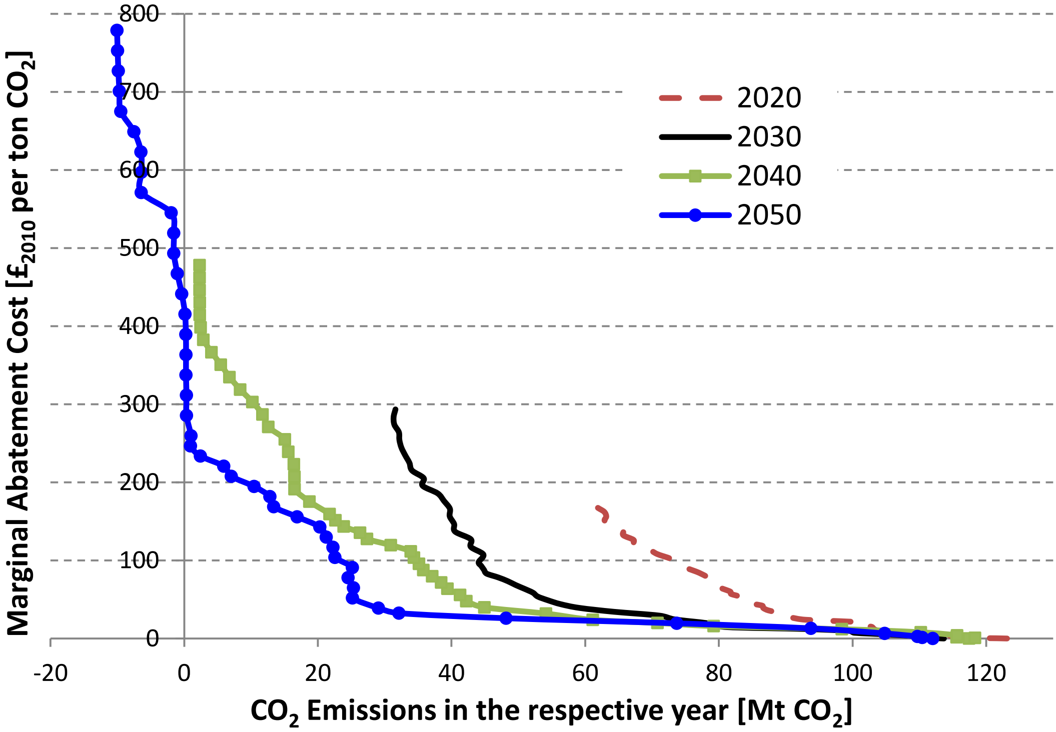
While the applied method and model focus are novel, all conclusions are subject to the input data and model structure of the employed model, so that interactions could be different if another model had been employed that addresses the shortcomings of the UK MARKAL model (see 8.1).

## 8.11 MAC curves for 2020, 2040 and 2050

The previous scenarios have all focused on the year 2030, an important year for medium-term emissions reduction goals. In order to obtain a broader picture of emission mitigation during the first half of this century, this section presents MAC curves for the years 2020, 2040, 2050 and finally a cumulative emissions reduction curve covering the time period 2015-2050.

In order to compare the different MAC curves, Figure 8.27 compares the emissions associated with different $CO_2$ tax levels in each of the four representative years. The emissions level at a $CO_2$ tax of £0/t $CO_2$ are relatively similar in a range from 112 Mt $CO_2$ to 123 Mt $CO_2$ per year. Similar to the transport sector, two trends counteract each other: on the one hand, emissions increase over time due to an increasing demand for residential energy services and an increasing carbon intensity of electricity. On the other hand, emissions decrease over time due to the fact that end-use devices become more efficient and significantly more biomass is used for heating purposes. Emissions are higher in 2020 because a lot more natural gas is used for space heating and hot water at £0/t $CO_2$. In 2040 and 2050, emissions are close to the level in 2030 due to the counteracting trends described above.

**Figure 8.27: Emission curve along rising $CO_2$ abatement costs for the REF scenarios in different years**

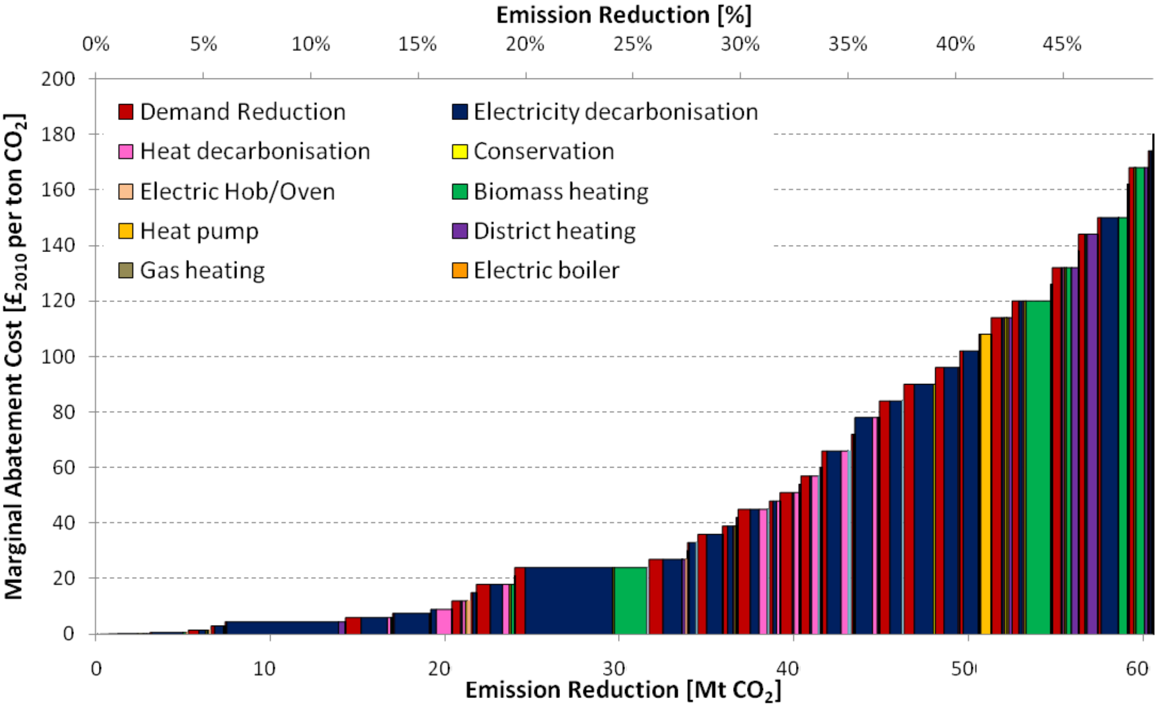


The emission curves indicate that a higher reduction amount can be achieved in later years compared with earlier years since the system has more flexibility especially in terms of low-carbon electricity, which represents a key factor for the domestic sector. Furthermore, while the year 2020 is influenced by current heating equipment and other installations, this is less the case for later years, such as 2040 and 2050. The potential for the decarbonisation of electricity is a lot higher towards the middle of the 21$^{st}$ century due to the availability and cost reduction in biomass CCS and coal CCS power plants. The emission curve for the year 2050 becomes negative above £440/t $CO_2$ because electricity becomes the predominant energy carrier for the domestic sector (crowding out remaining natural gas) and negative carbon intensity of electricity is reflected in the end-use emission curve.

For the year 2020, according to the UK MARKAL model results, it is cost-effective to change the fuel mix for heating substantially. The share of natural gas would go down from 82% in 2008 to 60% in 2020 with wood-fired boilers and district heat making up most of the rest. Figure 8.28 displays the MAC curve for the year 2020 and shows what measures are responsible for emissions reduction. As with the MAC curve for the year 2030, the importance of decarbonising electricity is visible. It is especially important at low carbon tax levels and contributes 58% towards emissions reduction. The decarbonisation of heat via a switch towards biomass CHP plants reduces emissions only to a limited extent, whereas the overall use of district heating decreases with increasing tax levels.

Next to electricity and heat, a structural change from gas-fired boilers towards wood-fired boilers contributes to end-use emissions in the residential sector at £24/t $CO_2$. However, due to intersectoral interactions with the electricity sector and industry, the share of biomass decreases within a medium tax range. Heat pumps become cost-effective at a tax level of £176/t $CO_2$, while the emissions reduction associated with this technology remains limited due to the restrained deployment potential. Comparable to the transport sector, price-induced demand reduction plays a bigger role in 2020 than in later periods. Demand reduction is responsible for 28% of all emissions reduction due to the limited availability of cost-effective low-carbon technologies and particularly due to the fact that decarbonisation of electricity is more limited and more costly compared with 2030.

**Figure 8.28: MAC curve for REF scenario in 2020**

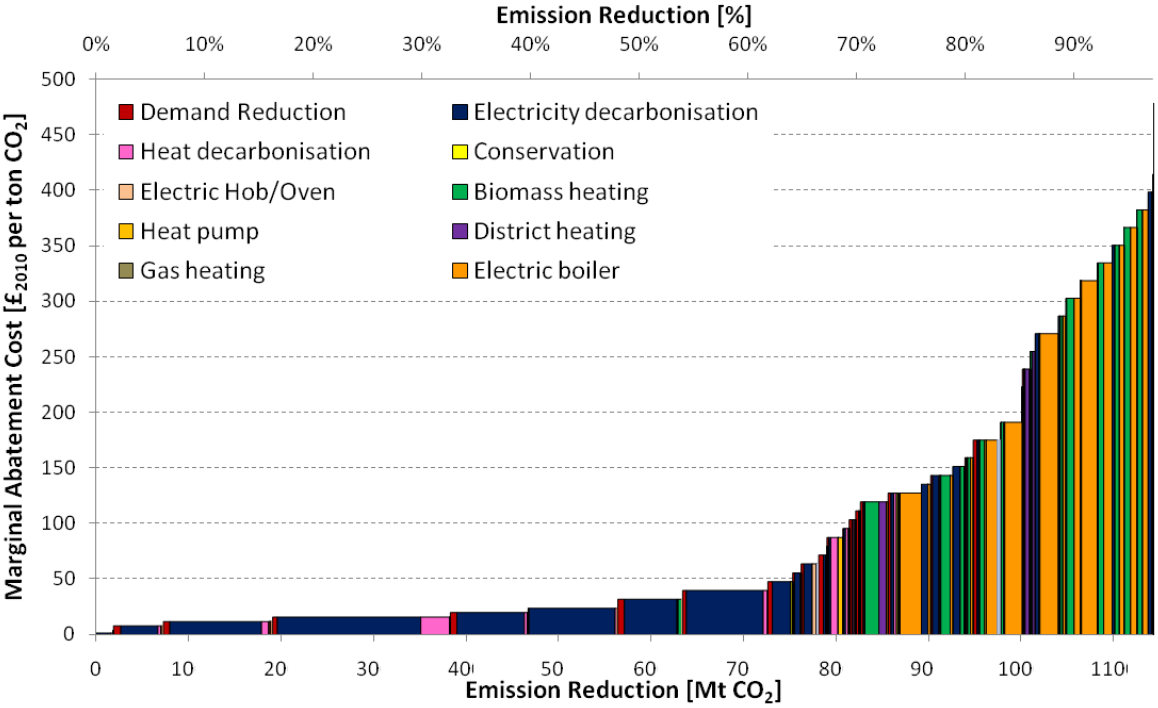



The composition of the MAC curve for the year 2040 (see Figure 8.29) looks very different from the one in 2020 and 2030. Residential heating at £0/t $CO_2$ is mainly characterised by biomass (40%) and natural gas (35%) heating. The MAC curve shows that more than 60 Mt $CO_2$ can be saved in all residential end-use emissions in the domestic sector up to £40/t $CO_2$ by decarbonising electricity.

With the greater flexibility in the electricity sector and a lower carbon intensity, the role of structural changes in the residential sector increases. In particular a switch towards electricity for space heating and hot water gains in importance from £120/t $CO_2$ up to £380/t $CO_2$ and saves about 15 Mt $CO_2$. Heat pumps are cost-effective at £80/t $CO_2$, but do not have a big impact on $CO_2$ emissions due to the assumption that their deployment will be limited. In a case where this constraint was relaxed, one would see a substantially higher contribution from heat pumps, which would replace electric boilers. This would also require a lower carbon tax level and thereby reduce the overall mitigation costs. Biomass-fired boilers also contribute to emissions reduction but to a much lesser extent than electric boilers.

Lastly, the overall importance of price-induced demand reduction is significantly less than it is in 2030 and 2020. It is responsible for less than 10 Mt $CO_2$ or 8%. The reason is that the incentive for demand reduction is non-existent if the energy services are met by zero- or low-carbon fuels.

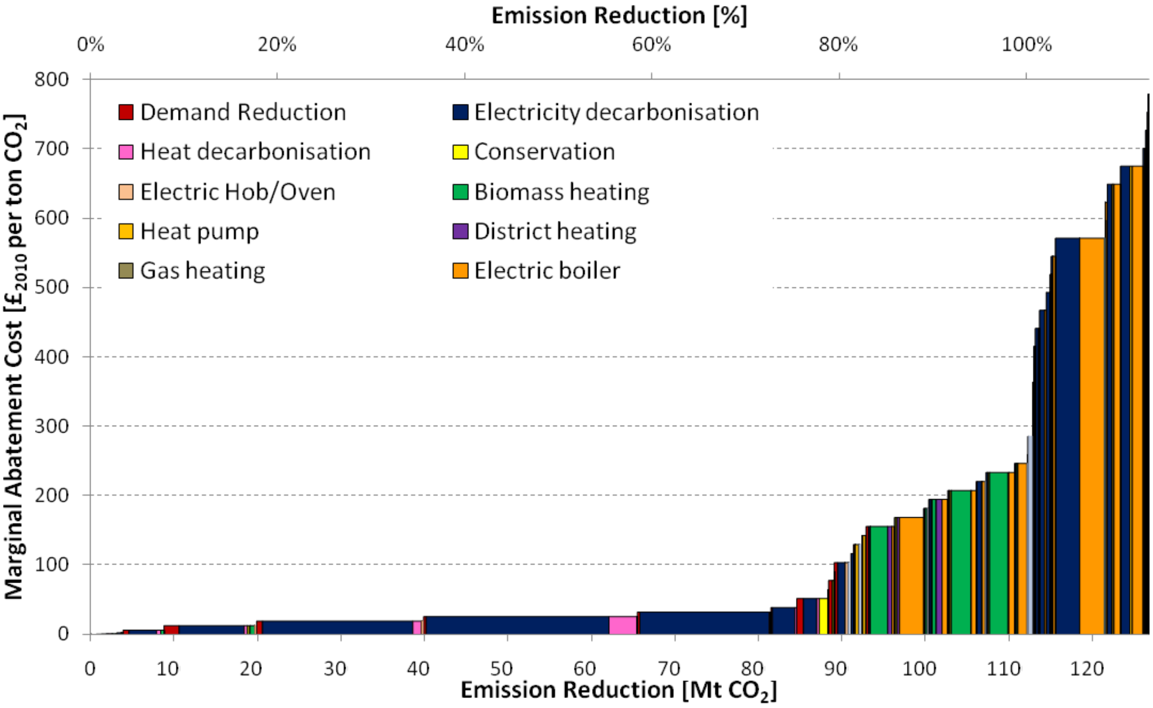
Figure 8.29: MAC curve for REF scenario in 2040




Another ten years on, the MAC curve for the year 2050 (Figure 8.30) is dominated by the same trend as the one in 2040, namely an electrification of the domestic sector. The decarbonisation of electricity is dominant up £60/t $CO_2$ and saves around 70 Mt $CO_2$. The following part of the MAC curve, £80/t $CO_2$ to £220/t $CO_2$ is characterised by a shift away from natural gas as a heating fuel towards electric boilers and biomass in particular for space heating. Similar to the MAC curve for the year 2040, electricity becomes completely decarbonised, which leads to a situation where all fossil fuel based heating is replaced by electric boilers.

In the next section of the MAC curve, from £415/t $CO_2$ upwards the carbon intensity of electricity becomes negative. This leads to indirect emissions reduction in the residential sector but also to biomass shifted completely from the residential sector towards electricity generation. Thus, biomass is no longer used as a heating fuel, but rather as an input for electricity generation, which is then again used in electric boilers to provide space heat and hot water. Structural changes are more important than in 2030 with 22% of overall emissions reduction, while the contribution from demand reduction is less on an absolute level compared to all other years and contributes only 6% to emissions reduction.

**Figure 8.30: MAC curve for REF scenario in 2050**

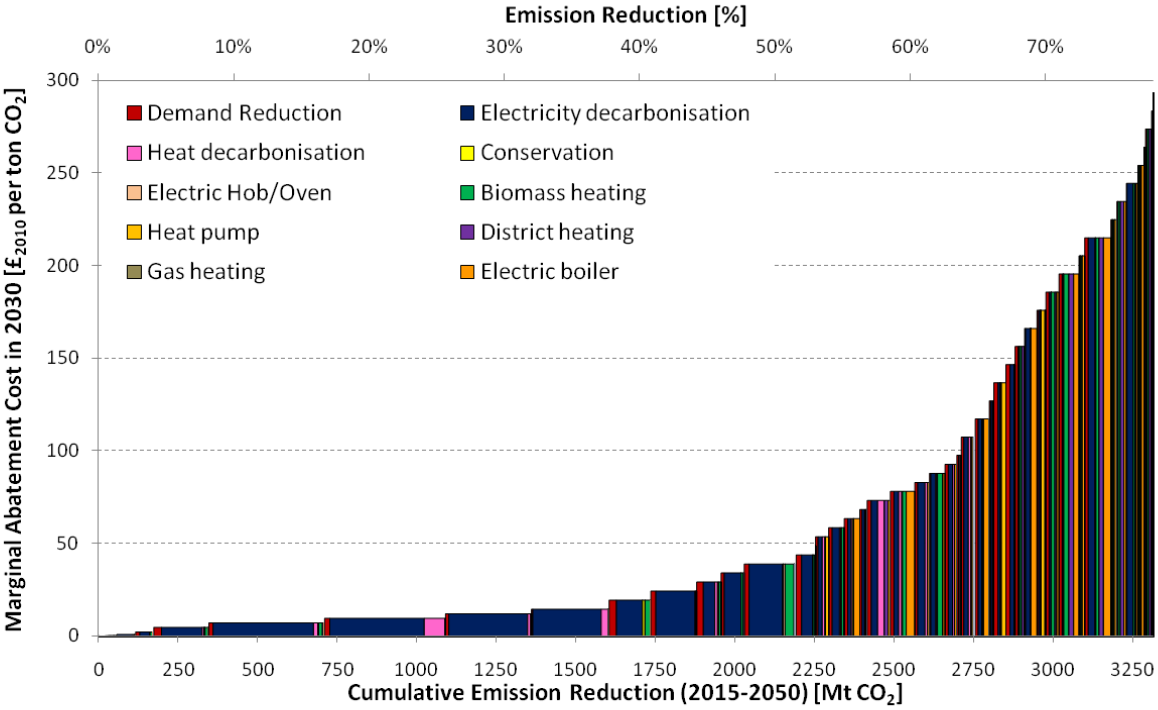



All the MAC curves presented so far in this chapter are designed for one single year, e.g. 2030. To address the issue that emissions abatement depends on earlier actions and expectations about future carbon policies, Figure 8.31 shows a cumulative MAC curve for 36 years from 2015 to 2050. This cumulative MAC curve does not include earlier years as it is not expected that a significant carbon tax will be introduced prior to 2015 and thus the emissions are stable in any model run. The y-axis displays the $CO_2$ tax level in 2030, but as the tax increases with 5% p.a. this is not the tax level in previous or later years.

A cumulative MAC curve can address questions related to intertemporal interactions by bringing information of the single MAC curves together into one. Single-year MAC curves are subject to intertemporal interactions, e.g. that abatement is shifted to later time periods, but a cumulative MAC curve captures those effects as it covers 36 years. The cumulative emissions are 4.2 Gt $CO_2$ for end use emissions from the domestic sector for the period 2015 to 2050.

Figure 8.31 reveals that low-cost emissions reduction originates mainly in the electricity sector. Overall the decarbonisation of electricity is the most important measure with 64% to reduce end-use emissions in the domestic sector. From £50/t $CO_2$ in 2030, biomass heating and electric boilers become more important. Nevertheless, even at high carbon tax levels the decarbonisation of heat and electricity play a significant role. Overall structural changes in the domestic sector are more important for emissions mitigation than price induced demand reduction, which is responsible for 13% of all emissions reduction.

**Figure 8.31: Cumulative MAC curve for REF scenario (2015-2050)**




Summarising, in all periods the abatement potential in end-use residential sector emissions is dominated by electricity decarbonisation. While natural gas has an important market share even at high $CO_2$ tax levels up to 2030, in later years electric heating via electric boilers and heat pumps becomes cost-effective and replaces natural gas heating.

## 8.12 References


DeCanio, S. J. (1993). "Barriers within firms to energy-efficient investments." Energy Policy **21**(9): 906-914.

Enviros Consulting Ltd (2006). Review and development of carbon dioxide abatement curves for available technologies as part of the Energy Efficiency Innovation Review. Department for the Environment Food and Rural Affairs. London.

Jablonski, S., C. Brand, A. Pantaleo, M. Perry, A. Bauen and N. Strachan (2009). Review of bioenergy in the UK MARKAL Energy System Model - MARKAL WORKING PAPER 1. TSEC Biosys. London.

Jaffe, A. B. and R. N. Stavins (1994). "The energy paradox and the diffusion of conservation technology." Resource and Energy Economics **16**(2): 91-122.

Johnston, D., R. Lowe and M. Bell (2005). "An exploration of the technical feasibility of achieving CO2 emission reductions in excess of 60% within the UK housing stock by the year 2050." Energy Policy **33**(13): 1643-1659.

Kannan, R. and N. Strachan (2009). "Modelling the UK residential energy sector under long-term decarbonisation scenarios: Comparison between energy systems and sectoral modelling approaches." Applied Energy **86**(4): 416-428.

Kannan, R., N. Strachan, N. Balta-Ozkan and S. Pye. (2007). "UK MARKAL model documentation." Retrieved November 18th 2010, from www.ukerc.ac.uk.

Kavgic, M., A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic and M. Djurovic-Petrovic (2010). "A review of bottom-up building stock models for energy consumption in the residential sector." Building and Environment **45**(7): 1683-1697.

Pye, S., K. Fletcher, A. Gardiner, T. Angelini, J. Greenleaf, T. Wiley and H. Haydock (2008). Review and update of UK abatement costs curves for the industrial, domestic and non-domestic sectors. Didcot, AEA Energy & Environment.

Radov, D., P. Klevnas, M. Lindovska, M. Adu-Ebid, N. Barker, J. Stambaugh and K. Fletcher (2010). Decarbonising Heat: Low-Carbon Heat Scenarios for the 2020s. London, NERA Economic Consulting.

Shorrock, L. D. and J. E. Dunster (1997). "The physically-based model BREHOMES and its use in deriving scenarios for the energy use and carbon dioxide emissions of the UK housing stock." Energy Policy **25**(12): 1027-1037.

Sutherland, R. J. (1991). "Market barriers to energy-efficiency investments." Energy Journal **12**(3): 15.

Swan, L. G. and V. I. Ugursal (2009). "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques." Renewable and Sustainable Energy Reviews **13**(8): 1819-1835.

Weiner, M. (2009). Energy Use in Buildings and Industry: Technical Appendix. London, Committee on Climate Change.

# 9 SYSTEM-WIDE MAC CURVES AND STOCHASTICITY

The previous results chapters looked at abatement costs and potentials at the sectoral level of the energy system. Chapter 6 dealt with the power sector, chapter 7 provided insights into abatement costs for the transport sector and chapter 8 looked into more detail at the residential sector. This chapter takes a broader look and presents MAC curves on a system-wide level, i.e. it considers all energy-related $CO_2$ emissions in the United Kingdom. This helps to put the results of the individual sectors into perspective with the whole system and can single out the most important influencing factors on a system-wide MAC curve.

In addition, this chapter presents results of the stochastic model version of the UK MARKAL model for one particular scenario. This model version removes the perfect foresight characteristic of the deterministic version. Since the stochastic version is implemented as a two-stage stochastic model, diverse developments of one or several model parameters can be introduced after one certain point in time by defining different likelihoods to more than one possible outcome. The hedging and recourse strategies in a stochastic model offer additional insights that cannot be captured by a sensitivity analysis.

## 9.1 System-wide MAC curves

As in the previous results chapter, the analysis focuses on the year 2030 as an important medium-target for a transition to a low-carbon society. Similar to the previous three results chapters, the sensitivity analysis encompasses 18 scenarios that can be divided into seven categories. The choice of the different scenarios is based on existing research on the influencing factors of MAC curves (see section 2.4) and the identification of gaps in existing research. All scenarios were presented in previous chapters. For each scenario, the sectoral MAC curves are compared with system-wide results to see if there are any differences.

Table 9.1 gives an overview of the different scenarios and describes each one briefly. Each MAC curve consists of 46 different model runs with system-wide $CO_2$ taxes, ranging from $£_{2010}$ 0 to 294/ t $CO_2$ in 2030. In the REF scenario the $CO_2$ tax is assumed to increase from 2010 with the model inherent discount rate of 5% p.a. All costs are given in £ of the year 2010.

**Table 9.1: Scenario overview**

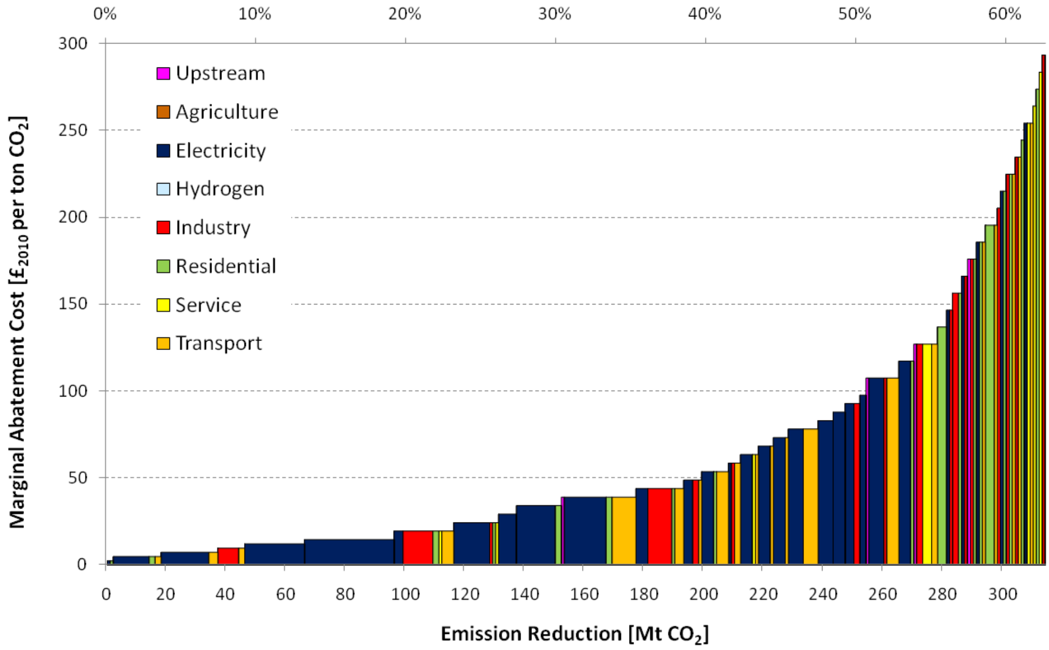
| Scenario | Category | Description |
|---|---|---|
| **REF** | *Reference case* | Carbon tax increases by 5% p.a. from 2010 |
| **ZERO-BEFORE** | *Path dependency* | Carbon tax is zero before 2030 |
| **CONST-AFTER** | *Path dependency* | Carbon tax is constant after 2030 |
| **INCR-AFTER** | *Path dependency* | Carbon tax increases with 10% p.a. from 2030 |
| **ZERO-AFTER** | *Path dependency* | Carbon tax is zero after 2030 |
| **HIGH-BEFORE** | *Path dependency* | Carbon tax is kept constant on the 2030 level from the REF scenario for the period 2015-2030 |
| **PDR10** | *Discount rate* | Hurdle rates introduced for all technologies at 10%, previously existing rates were doubled |
| **SDR** | *Discount rate* | Discount rate lowered to 3.5%, all hurdle rates, taxes and subsidies removed |
| **FF+** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 100% |
| **FF++** | *Fossil fuel price* | Costs for coal, coking coal, oil, refined products and natural gas increased by 200% |
| **GAS** | *Fossil fuel price* | Costs for natural gas decreased by 50% |
| **NO-NUC-CCS** | *Technological issues* | No investments are allowed into nuclear power plants and CCS technologies |
| **NO-BIOMASS** | *Technological issues* | No biomass/biofuel imports allowed, domestic biomass production reduced by 50% |
| **IEP** | *Technological issues* | Investment costs increased by 200% for all CCS technologies, biomass, nuclear, tidal, wind, wave |
| **ELAST+** | *Demand elasticity* | All demand elasticities increased by 50% |
| **ELAST-** | *Demand elasticity* | All demand elasticities decreased by 50% |
| **DEM+** | *Demand level* | All energy service demands increased by 20% |
| **DEM-** | *Demand level* | All energy service demands decreased by 20% |

### 9.1.1 Reference scenario

The reference (REF) scenario describes a development of carbon emissions reduction with the standard assumptions of the UK MARKAL model (Kannan et al. 2007). The assumptions in this reference scenario are exactly the same as in the previous three chapters.

Figure 9.1 depicts a MAC curve for the whole energy system and singles out the contribution of each sector towards emissions reduction in 2030. The height of each bar represents the marginal abatement cost, while the width represents the emissions abatement. All emissions associated with the use of electricity are summarised in the electricity sector, i.e. in this representation electricity savings in an end-use sector are accounted for in the electricity sector. Model results indicate that total energy-related $CO_2$ emissions are 502 Mt $CO_2$ without any $CO_2$ policy. In the model run with the highest implemented $CO_2$ tax of £294/t $CO_2$ emissions are reduced to 187 Mt $CO_2$. In order to achieve a 60% emission cut with respect to 1990, as recommended by the CCC (2010), the central carbon projection of the UK Government is £70/t $CO_2$ in 2030. At this tax level emissions reduction would be 226 Mt $CO_2$, which corresponds to an emission level of 276 Mt $CO_2$.

**Figure 9.1 : MAC curve for the United Kingdom in 2030**



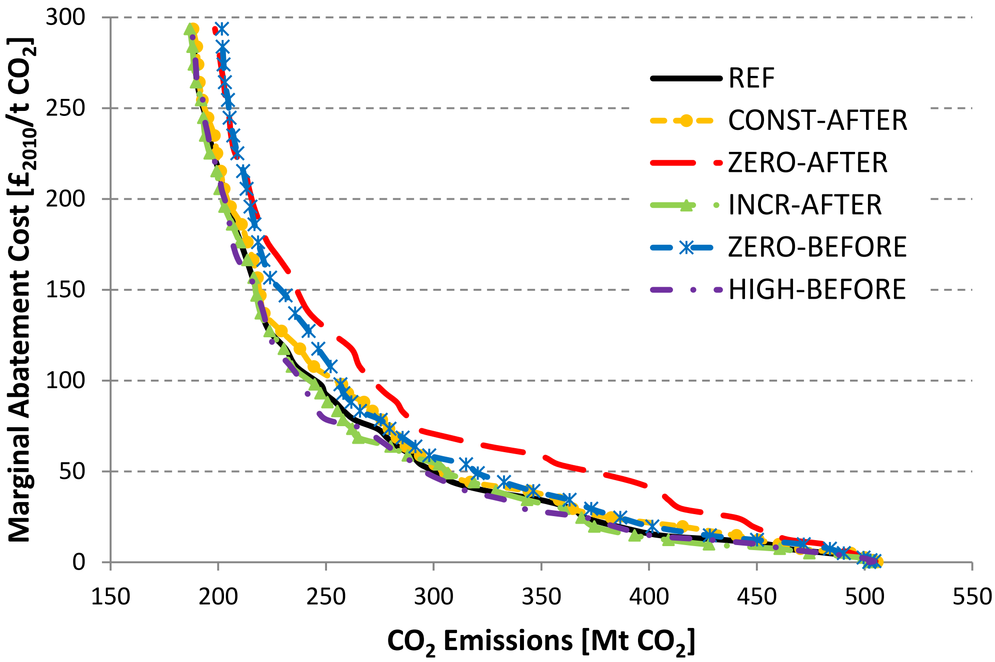

In 2030, most of the low-cost abatement potential can be found in the electricity sector, which accounts for almost 44% of all $CO_2$ emissions, followed by the transport sector with 24%, industry with 9% and the residential sector with 7%. It is apparent that there are some low-cost abatement options in industry, transport and the residential sector, but the contribution of these end-use sectors is only dominant from around £100/t $CO_2$ upwards. Abatement measures that are cost-effective in 2030, e.g. building insulation, are integrated in the £0/t $CO_2$ model run, so that they do not show up in Figure 9.1.

### 9.1.2 Path dependency

MAC curves are in most cases merely a static snapshot of one year, in this case the year 2030. Nevertheless, the abatement cost and the corresponding abatement potential of all abatement measures depends on previous abatement efforts and on uncertain expectations of future developments due to technology vintaging and technologies' long economic lifetimes. As the model underlying these MAC curves is a perfect foresight model, the MAC curve is, in addition, influenced by future climate change policies. It should be noted that UK MARKAL does not consider endogenous learning and consequently also no induced technological change (ITC), which possibly limits the effects of path dependency. Had ITC been incorporated in UK MARKAL, the model would probably focus on fewer key abatement technologies, whose investment costs would be driven down quicker than assumed without ITC. Comparably there would also be technologies whose costs would be higher than without ITC as they would not be developed to the same extent. Therefore, one could expect to see lower abatement costs for some technologies and higher for others with corresponding changes in the abatement potential.

In order to quantify the sensitivity of the MAC curve response to different $CO_2$ tax trajectories, the $CO_2$ tax path of an annual 5% increase has been altered in five scenarios (see Figure 6.7). Although all six scenarios have the same $CO_2$ tax in 2030, they result in different MAC curves, especially for higher abatement costs (see Figure 9.2).

**Figure 9.2: Emission curve for different path dependency scenarios**




The scenarios with a higher $CO_2$ tax compared with the REF scenario, i.e. INCR-AFTER and HIGH-BEFORE show a slightly higher abatement level for the same carbon tax. This is on average 3 Mt $CO_2$ for the INCR-AFTER scenario and 4 Mt $CO_2$

for the HIGH-BEFORE scenario (both less than a percent in terms of baseline emissions). The only exception is around £10/t $CO_2$ for the INCR-AFTER scenario, where the difference to the REF scenario is up to 28 Mt $CO_2$.

The CONST-AFTER scenario, which keeps the $CO_2$ tax constant after 2030, is similar to the REF scenario except for a range from £10/t $CO_2$ to £100/t $CO_2$, where abatement is less. This can be explained by the model no longer expecting the $CO_2$ tax level to rise, so that incentives to invest in low-carbon technologies are smaller. The abatement potential is significantly lower for a given $CO_2$ tax in the whole tax range in the ZERO-AFTER scenario, in particular up to £70/t $CO_2$. It is the inverse case for the ZERO-BEFORE scenario where the abatement potential is particularly lower between £10/t $CO_2$ and £50/t $CO_2$. In the ZERO-AFTER scenario the model has a smaller incentive to switch to low-carbon technologies because these will become stranded assets when the carbon tax drops back to zero. In the ZERO-BEFORE scenario the model has no incentive to invest in low-carbon technologies prior to 2030, which increases marginal costs especially at low emission targets. In this case the model needs to invest into low-carbon technologies before 2030 due the technology lifetimes of up to several decades.

Thus, the MAC curve looks particularly different for the scenario where the $CO_2$ tax is kept at zero after 2030, which increases the marginal abatement costs. This is mainly driven by the electricity sector, where coal CCS power plants contribute less to electricity generation. The ZERO-BEFORE and CONST-AFTER scenarios slightly increase the abatement costs for a given abatement level, while the scenarios that have a higher tax level before or after 2030 show marginally lower abatement costs. In general, one can say that a change in the carbon tax pathway has a bigger influence in the transport sector than in the residential sector. The reason being that abatement in the residential sector is dominated by electricity decarbonisation and in the transport sector by structural changes to electric vehicles. This becomes clear in the ZERO-BEFORE scenario, where the lack of a carbon tax prior to 2030 represents a substantial disincentive for investments in electric vehicles at tax levels higher than £100/t $CO_2$.

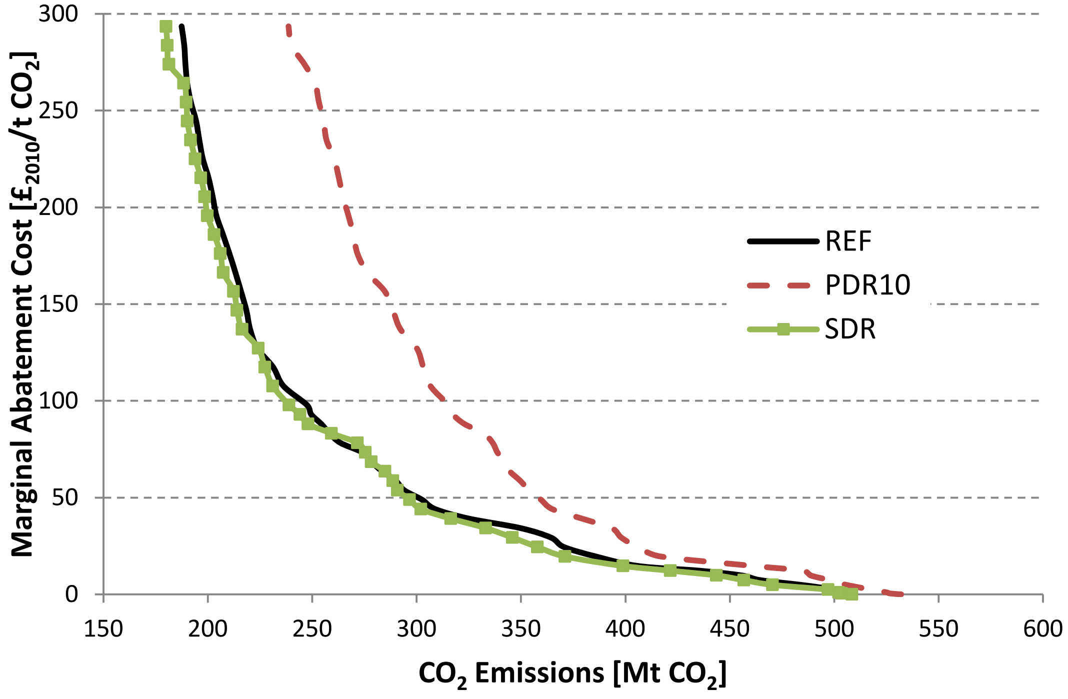
### 9.1.3 Discount rate

In the same way as in the previous chapter, two different discount rate scenarios are presented based on the concept of social discount rates, a SDR scenario, and private discount rates, PDR10 scenario. The SDR scenario assumes a social discount rate of

3.5%, where additionally all technology-specific hurdle rates are removed. The PDR10 scenario represents the perspective of a private investor, where a technological hurdle rate of 10% was introduced for all technologies and existing technological hurdle rates were doubled with respect to the REF scenario. The PDR10 scenario assumes a general discount rate of 5% as is the case in the REF scenario. Observed technology-specific discount rates can be relatively high and are assumed to be up to 17.5% in the transport sector, 17.5% in the residential sector and 12% in industry in the PRIMES energy system model (Hendriks et al. 2001, p. A2), which is widely used by EU institutions. These increased hurdle rates should not be seen as a change in pure time preference, but rather as a measure of uncertainty involved when investing in low-carbon technologies.

Figure 9.3 indicates that the MAC curve in the SDR scenario is very similar to the REF scenario, while the PDR10 MAC curve is significantly different in that substantially fewer emissions are abated for the same given $CO_2$ tax.

**Figure 9.3: Emission curve for different discount rate scenarios**




The SDR is only marginally shifted to the left from the REF scenario because two effects counteract each other. On the one hand, low-carbon technologies save less fuel costs in the SDR scenario. This is due to lower fuel prices as taxes and fuel duties were removed. On the other hand, the investment cost premium for abatement technologies over conventional technologies is less as there are no technological hurdle rates and the overall discount rate is lower at 3.5%. Differences in operating and maintenance costs, which include insurance, are comparably small and do not influence the overall result.

The picture looks very different for the PDR10 scenario. The increased hurdle rates put more weight on the investment costs that are in general significantly higher for low-carbon technologies particularly in the transport sector, such as battery cars or energy-efficiency measures in the residential sector. A hurdle rate of 10% is not particularly high given the fact that empirical research (see e.g. Hausman 1979) showed that discount rates in the residential can be a multiple of that rate, in particular for low-income households. Comparing the influence of a change in the hurdle rates for different sectors, one can notice that a hurdle rate change has a major influence on the transport MAC curve, while the abatement costs do not change to the same extent in the power sector and transport sector. While levelised electricity generation costs increase up to 40% for major abatement technologies for an increase in the discount rate from 5% to 10%, they barely influence technologies in the residential sector as fuel costs are predominant. In contrast, initial investment costs are decisive in determining the price for transport services.

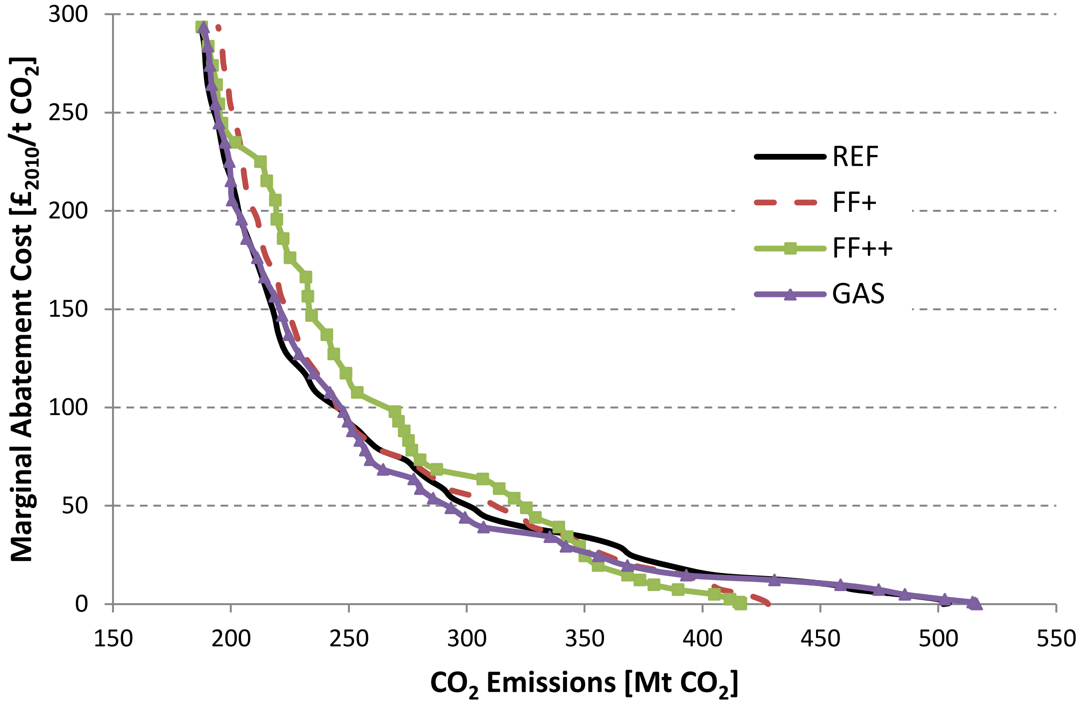
### 9.1.4 Fossil fuel price

Fossil fuel prices are an exogenous input to the UK MARKAL model because it is assumed that the UK is a price taker for coal, natural gas and crude oil. This reason is that the UK's share of global GDP is 2.5% and declining in the future. Three scenarios with different assumptions on the level of fossil fuel prices test the sensitivity of abatement costs to this input factor.

In the GAS scenario, the gas price alone is reduced by 50%. While the gas price is about 75% of the oil price on an energy-equivalent basis in the REF scenario, it is only 38% in the GAS scenario. The FF+ scenario corresponds to a situation where all fossil fuel prices are increased by 100%. In the last scenario, FF++, the fossil fuel prices are increased by 200% over the whole first half of the 21$^{st}$ century equivalent to long-lasting supply shocks seen in the 1970s. The assumptions concerning the fossil fuel prices are detailed in Table 6.3.

Intuitively, one should expect to see the MAC curves of the high fossil fuel price scenarios to be shifted to the left as renewable energy sources should become cheaper compared with their fossil fuel alternatives. Yet, Figure 9.4 reveals a very different picture. As expected the baseline emission levels without any carbon policy are lower for higher fossil fuel prices, while emissions levels at higher carbon tax levels are more similar.

**Figure 9.4: Emission curve for different fossil fuel price scenarios**




At £0/t $CO_2$, emissions are 3% higher in the GAS scenario as natural gas crowds out some renewables in the power sector. Emissions in the FF+ scenario and the FF++ scenario are 15% and 17% less respectively, owing to a higher renewable share in electricity production and less consumption of fossil fuel in the end-use sectors. Those initial differences are more or less overcome at a carbon tax level of £30/t $CO_2$ and do not diverge significantly afterwards. One can observe that the emission curve for the FF++ scenario indicates less abatement for a given carbon tax in a range from £70/t $CO_2$ to £230/t $CO_2$. The maximum deviation is 15 Mt $CO_2$ or 5% at a carbon tax level of £70/t $CO_2$ in 2030, the official carbon price assumed to be necessary to drive down UK's carbon emissions by 80% in 2050. Those findings indicate that the shape of the MAC curve is robust even to extreme fossil fuel price changes.

There is not one but rather a set of reasons that explain the robustness. One reason is that at high carbon tax levels, differences in fuel prices are overshadowed by the price increase due to the carbon tax (see Table 9.2). Fuel costs for a coal-fired power station double at a $CO_2$ tax of £28/t $CO_2$, while this is the case at £100/t $CO_2$ for a gas-fired power plant. Consequently, with an increasing $CO_2$ tax the differences in fossil fuel production costs are outweighed by the tax level. Furthermore, the UK transport sector is currently characterised by fuel duties that make up approximately 75% of the price that the consumer faces at the petrol station. This means that any relative change in fossil fuel prices will be lower once final consumer prices are considered.

**Table 9.2: Increase in fossil fuel prices over price in 2010 for a given $CO_2$ tax**

| $CO_2$ tax [£/t $CO_2$] | Hard Coal [%] | Crude Oil [%] | Natural Gas [%] |
|---|---|---|---|
| **£100** | 322% | 105% | 113% |
| **£200** | 644% | 210% | 227% |
| **£300** | 965% | 315% | 341% |

On the one hand, higher fossil fuel prices induce investment into renewable energy sources at lower carbon tax levels as they become cheaper compared to fossil fuel based alternatives. On the other hand, higher prices increase the fuel cost of coal CCS power plants, which, next to nuclear power, is one of the key abatement technologies in the power sector. Thus, an increase in fossil fuel costs, renders a low-carbon technology, namely coal CCS, significantly more expensive. Lastly, the energy system, including power sector and end-use sectors, is not reliant on one abatement option, but has several zero-carbon technologies with moderate abatement costs that can compensate for other abatement technologies. A look at the sectoral MAC curves reveals that the influence of changing fossil fuel prices is stronger in the transport sector than in other sectors as it is very much dependent on refined products. The residential sector is less affected by increased fossil fuel prices as alternatives to natural gas become also more expensive due to a higher demand, mainly from the power sector.

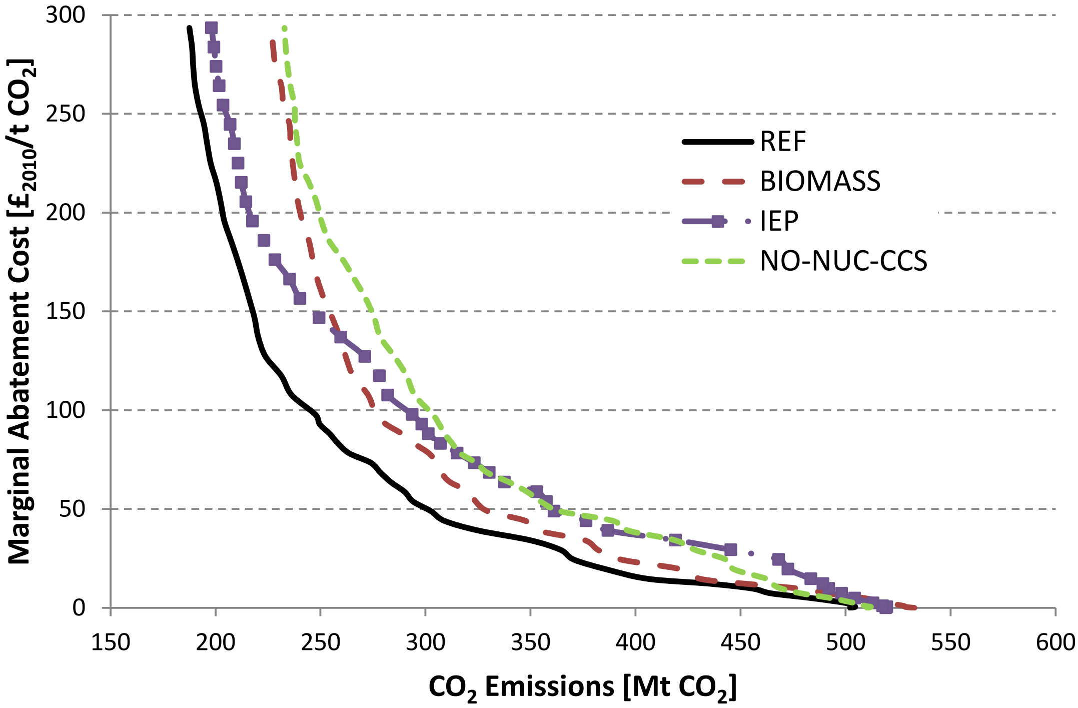
### 9.1.5 Technological issues

A technologically-detailed energy system model represents a good tool to study influences of changes to key abatement technologies or fuels. Therefore, three scenarios are presented in this section. In the BIOMASS scenario, no biomass imports are allowed and domestic biomass potential is reduced by half. This should test the reliance of the decarbonisation of the UK energy system on biomass imports and domestic biomass production. The IEP (Increased Electricity Price) scenario is the same as in the previous chapters, where investment costs of all main low-carbon power plants were increased by 200% (see Table 6.5). This scenario therefore assumes a very pessimistic development of investment costs associated with low-carbon technologies.

The last scenario called NO-NUC-CCS does not allow any new investments into nuclear power plants or carbon capture and storage (CCS) technologies. Nuclear power plants and CCS mainly in combination with coal-fired power plants are responsible for the vast majority of emissions reduction in the power sector. Given the rising hostility to nuclear power after the events in Japan and questions about the security of $CO_2$ storage, this scenario quantifies the influence of eliminating both technologies as mitigation options.

A look at Figure 9.5 shows that all three scenarios are different from the REF scenario and that the technology changes show a much bigger impact than the fossil fuel price changes. At a $CO_2$ tax of £70/t $CO_2$, the difference in emissions is 19% for the IEP scenario, 18% for the NO-NUC-CCS scenario and 11% for the BIOMASS scenario.

**Figure 9.5: Emission curve for different technology scenarios**




The difference in emissions between the BIOMASS and the REF scenario is on average 32 Mt $CO_2$ for a given tax level, while this difference increases slightly with rising carbon prices. Biomass is a mitigation option in the transport sector in the form of biofuels, in the residential sector as wood for space heating and in the power sector in biomass CHP plants. However the primary biomass use is as a co-firing option to conventional coal power plants or coal CCS power plants. Removing this option significantly increases the abatement costs, especially at higher tax levels, as co-firing biomass to coal CCS plants only becomes economically viable at high carbon prices. As the contribution of biofuels towards emissions reduction is limited in the transport sector in the REF scenario, a limited availability of biomass does not alter the transport MAC curve.

The IEP scenario is also characterised by higher MACs compared with the REF scenario. The electricity sector is a key element in an economy-wide decarbonisation due to the fact that electricity is used in all end-use sectors and low-carbon electricity has the potential to extend to further energy services. Trebling the investment costs leads to significantly higher electricity prices because annualised investment costs are responsible for a significant share of the generation costs of low-carbon technologies. Nevertheless, the difference in abated emissions decreases with rising carbon tax levels, in particular from £150/t $CO_2$. This can be explained by natural gas playing a major role up to this tax level in the IEP scenario as other technologies are not yet cost competitive owing to the increased investment costs. At higher carbon tax levels, wind power and coal CCS in combination with biomass co-firing is introduced to the market, which then narrows the difference. The influence of higher electricity prices is similar in all the studied sectors as electricity is a key decarbonisation option in the transport sector and the residential sector.

Lastly, the NO-NUC-CCS shows how important nuclear power and CCS technologies are for a cost-effective decarbonisation of the UK energy system. This becomes apparent from £15/t $CO_2$ and shows the highest deviation from the REF scenario of all technology scenarios presented in this section. In the REF scenario, the two mitigation options, nuclear power and coal CCS with biomass co-firing, are responsible for reducing more than 60% of all emissions from the power sector. Natural gas power and CHP plants as well as more generation from wind, tidal and wave compensate partially for the lack of nuclear and CCS. However, this cannot entirely compensate for the shortfall so that marginal abatement costs substantially increase in this scenario.

The significance of the non-availability of one or two key abatement technologies becomes clear when one considers total abatement costs. The total abatement costs in 2030 to attain the CCC goal of reducing emissions by 60% in 2030 with respect to 1990 are £6 billion in the REF scenario, £8 billion in the BIOMASS scenario, £11 billion in the IEP scenario and £10 billion in the NO-NUC-CCS scenario.

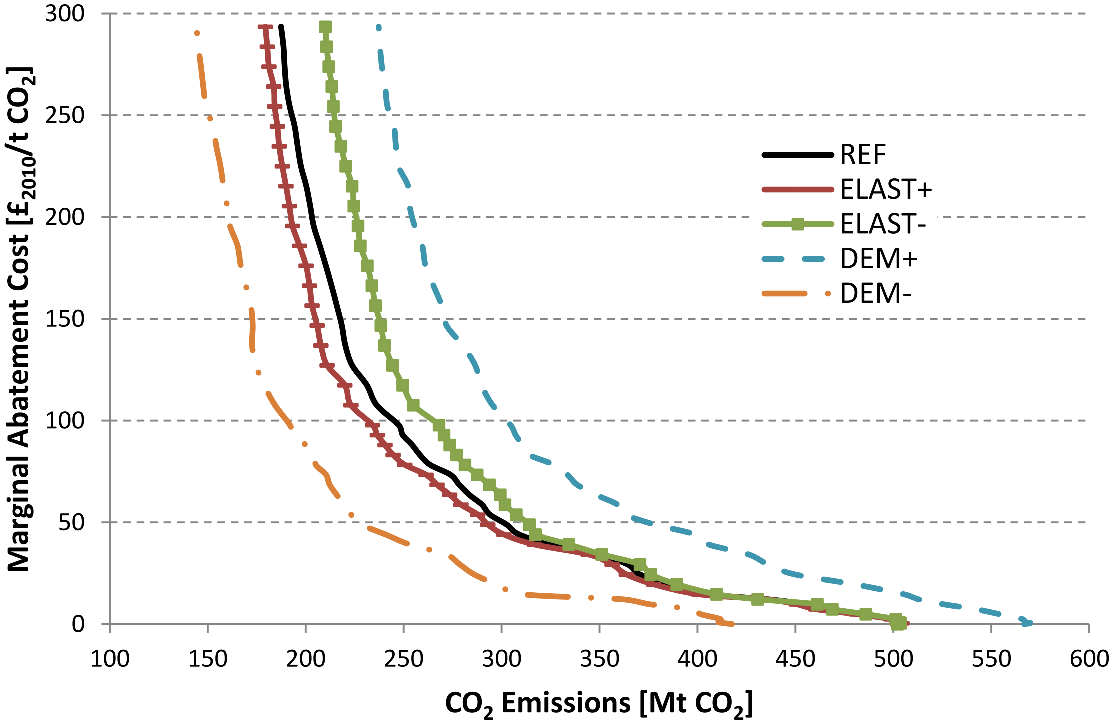
### 9.1.6 Demand related factors

This section looks at the influence of demand-related factors. Not only technological issues and fossil fuel price developments are far from certain, but the demand level and demand responses to rising energy service prices can neither be predicted for the year 2030. This is due to the uncertain development of drivers of energy demand, such as population or GDP. Therefore, all energy service demands in the UK MARKAL model were increased by 20% in the DEM+ scenario and decreased by 20% in the DEM- scenario.

Two further scenarios study the impact of the price elasticity of demand, which indicates the responsiveness of the quantity demanded of a service or a good to a change in its price. Price elasticities are in general negative as it is assumed that the demand for a service will decrease if its price increases and vice versa. All energy service demands in UK MARKAL are assumed to be price elastic, to have a different elasticity depending on the direction of the price change and have an upper and a lower limit for the maximum change of demand (generally +/- 25%). While it is comparably easy to study the past price elasticity of final energy carriers, such as diesel or petrol, it is difficult to identify the correct level of the demand elasticity of an energy service demand, such as driving or heating. Estimating energy service demand levels in the transport sector is complicated as demand for each mode needs to be assessed individually given that no modal shifts are allowed. Therefore, the price elasticity of all energy service demands was varied by +50% in the ELAST+ scenario and by -50% in the ELAST- scenario to illustrate the sensitivity of the MAC curve to different levels of demand elasticity. Figure 9.6 shows the MAC curves for the different scenarios.

One can see that emissions are higher in the DEM+ scenario, while they are lower in the DEM- scenario in accordance with increased/decreased levels of demand. However, the full change in demand is not entirely reflected in the emissions level due to structural changes in the power sector at the lower end of the MAC curve. This is no longer true at the upper end of the curve. Since there are build constraints and limited resources implemented in the energy model, the carbon intensity of electricity increases in the DEM+ scenario compared with the REF scenario, while cheap coal-fired power plants play a bigger role in the DEM- scenario. Varying the energy service demand by 20% in 2030 has the biggest impact on the presented MAC curves, except for the PDR10 scenario. The impact of demand level changes on sectoral MAC curves are fairly similar across the studied sectors.

**Figure 9.6: Emission curve for different technology scenarios**




The influence due to changes in the price elasticity of demand are a lot more limited but not negligible. Overall the deviation of the ELAST- MAC curve is larger than the one from the ELAST+ scenario. This is due to price responses of demand already playing an important role in the REF scenario and when the elasticity increases, several energy service demands hit the lower floor as defined in the model, where demand levels are assumed not to fall anymore.

### 9.1.7 Summary

Against existing literature, the sensitivity analysis has provided insights that are summarised in Table 9.3. Earlier findings concerning the influence of intertemporal interactions, i.e. the carbon pathway, can be confirmed. High carbon tax levels from 2015 onwards reduce marginal abatement costs noticeably as well as expectations about future high carbon taxes. The effect due to path dependency is not as significant as indicated in previous studies, which can be explained with the absence of endogenous technology learning in UK MARKAL. In regard to discount rates, a shift from the reference case to a social discount rate was not found to have a significant impact. This is in contrast to earlier research for the UK transport sector. Increasing the discount rate from 5% to 10% was found to have a major impact, the largest of all sensitivity cases.

In contrast to earlier research on the influence of changes in fossil fuel prices, the results of this chapter show that higher fuel prices, as well as lower prices, have a very limited influence on the shape of the MAC curve, particularly in comparison to other analysed factors. MAC curves are thus judged to be relatively robust to changing fossil fuel prices. Changes to key abatement technologies show that nuclear power and CCS power plants are essential for a cost-effective abatement of carbon emissions in the UK energy system, although this does not consider political uncertainty in regard to these technologies. The same holds true for the import and the domestic production of biomass, which can significantly raise the abatement costs. The influence of a very significant increase in power plants' capital costs was found to be moderate. Lastly, while demand elasticity scenarios were found to have only a limited influence, the impact of demand changes is important and should not be underestimated especially as energy demand developments cannot be forecasted reliably.

**Table 9.3: Influence of the change in different factors on MAC curve: strong (+), medium (o), weak (-)**

| Category | Influence |
|---|---|
| Path dependency | o |
| Discount rate | + |
| Fossil fuel price | - |
| Technological issues | o/+ |
| Demand elasticity | - |
| Demand level | + |

In summary, the results indicate the strong influence of discount rates and technology-specific factors, which seems to be underestimated in current research. On the other hand, the MAC curve was found to be robust to changing fossil fuel prices.

## 9.2 Stochasticity

Uncertainty involved in MAC curves has so far been studied by varying specific parameters in the UK MARKAL model via a sensitivity analysis. This section adds to the previous sensitivity analysis by considering another means of studying uncertainty: stochastic programming.

### 9.2.1 Stochastic UK MARKAL

Stochastic programming is implemented as a two-stage problem; it provides information prior to the resolution of uncertainty and for the period after uncertainty has been resolved. In comparison to sensitivity analysis, stochastic modelling can provide answers about hedging strategies. This means that the model takes into account all possible outcomes of the second stage together with their attached probability and optimises the energy system. This reveals more insights compared to a sensitivity analysis involving several deterministic model runs because the model hedges against different outcomes at the same time. Furthermore, in the second stage, recourse strategies can reveal information on how flexible the energy system reacts to changing information. This can also quantify the influence on abatement costs when cost or technological parameters turn out to be different to what was expected. For a more thorough discussion on stochastic modelling as a mean of studying uncertainty, please refer to chapter 5.2.4. More information on the mathematical background of the stochastic variant of MARKAL can be found in chapter 3.3.4.

In the following stochastic scenario, the resolution time, i.e. the period when all uncertainties are resolved, is set to 2025. As the focus is still on the year 2030, this means that the following discussion is centred on the recourse strategy of the stochastic problem and gives answers to the question of how flexibly the energy system reacts to a change in information. Nevertheless, MAC curves will also be presented for other years in order to discuss the dynamic issues involved when using stochastic programming.

While up to 2025 there is only one hedging strategy, the model has five years (corresponding to one model period) to react to the resolved uncertainty up to the year 2030. The results of the stochastic model runs are in each case compared to the deterministic equivalents.

Stochastic runs were performed for multiple scenarios, but results are only presented for one scenario, where the availability of biomass is limited. This scenario was judged most interesting as variable resource availability was found to have more influence on a MAC curve than a change in commodity prices or technology costs.

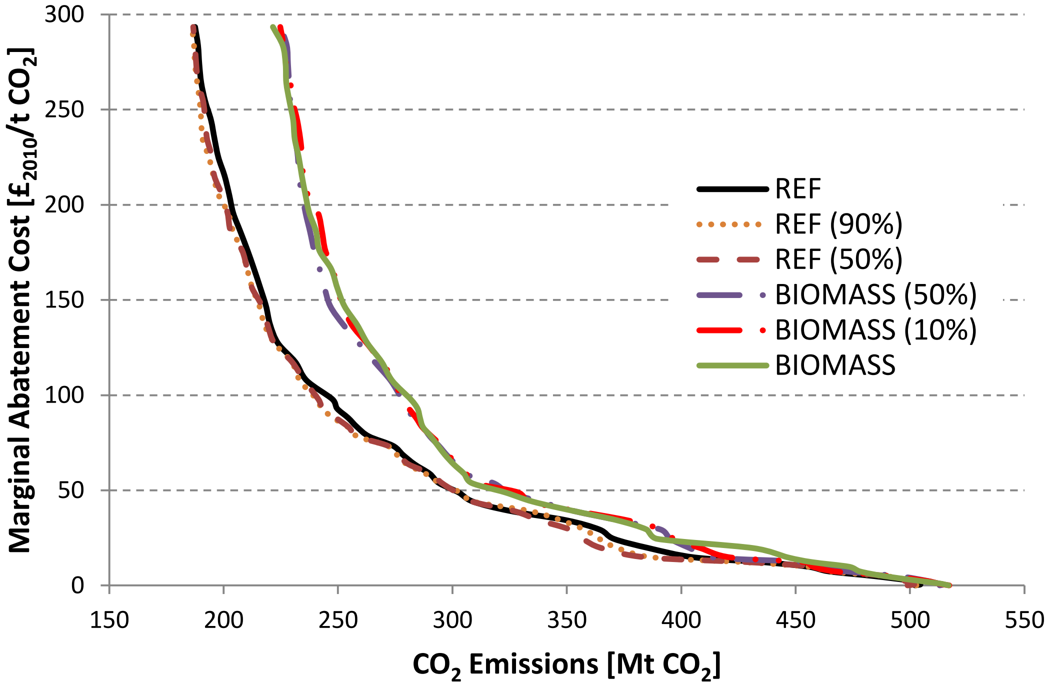
### 9.2.2 Biomass availability

This scenario studies the influence of a reduced level of biomass availability on MAC curves. It corresponds to the BIOMASS scenario presented in chapter 6, i.e. no biomass imports are allowed and domestic biomass production is reduced by 50% after 2025. Such a scenario can be explained with resistance to land-use change, i.e. diverting land from its original use in the food and wood-based industries to an energy use. Due to restrictions in implementing the scenario constraints in the stochastic version of UK MARKAL, the constraints were reformulated to apply for each biomass type individually so that there can be slight deviation from the scenario presented in chapter 6.

Figure 9.7 compares the emission curves for the deterministic REF and BIOMASS scenario with the stochastic scenario paths in 2030. One stochastic scenario gives both outcomes the same probability, while in the second stochastic scenario it is more likely (90%) that biomass will be available as defined in the REF scenario and unlikely that biomass availability will be limited (10%).

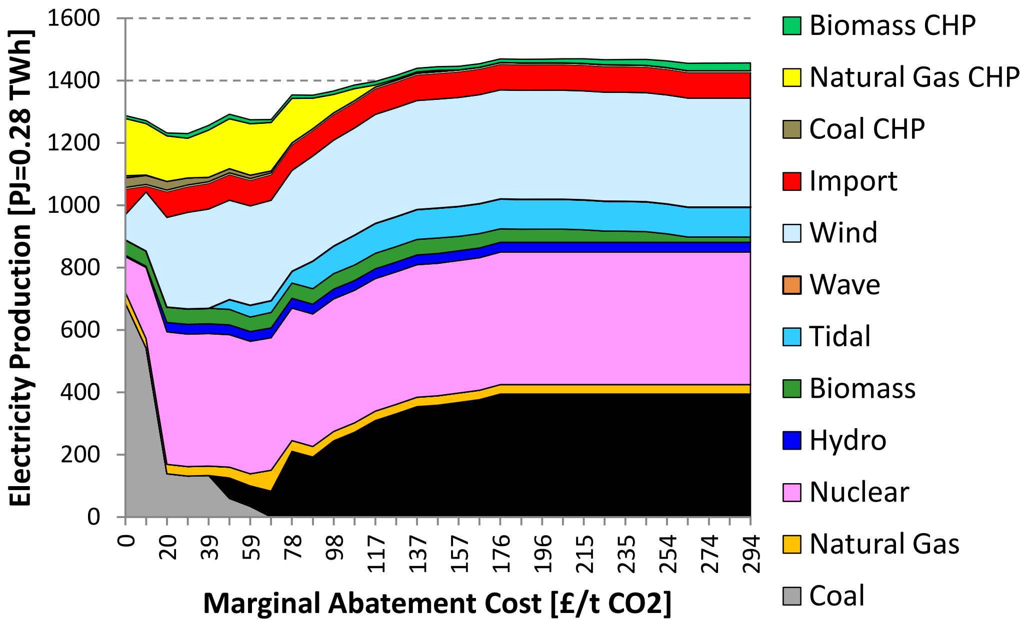
The comparison of the emission curves reveals that the limited availability of biomass (BIOMASS scenario) makes emissions reduction more expensive, which is equal to an emission curve that is shifted to the right. This is particularly the case at tax levels higher than £75/t $CO_2$ due to the fact that biomass is not available in the power sector as a co-firing fuel for coal CCS plants. Concerning the stochastic runs, they are very close to the respective deterministic scenario, although they indicate slightly more abatement for a given carbon tax level. On average abatement in the stochastic run REF (50%) is 3 Mt $CO_2$ higher for a given carbon tax compared to the deterministic run, while the equivalent number is 2 Mt $CO_2$ in the BIOMASS (50%) case. The uncertainty over biomass availability prompts the model to hedge against the case that biomass is not available. This has consequences for the year 2030 where emission levels are a little lower over the studied tax range in the stochastic runs as the model makes up for suboptimal choices in the hedging period.

**Figure 9.7 : Emission curves for the deterministic and stochastic (dashed) BIOMASS scenario in 2030**




A more detailed look at the sectoral level reveals what causes the difference in the deterministic and stochastic runs. Only the 50%/50% stochastic scenario is discussed in more detail as the findings for the 90%/10% scenario are very similar. In the REF (50%) stochastic run, coal-fired power stations are completely replaced at a carbon tax of £63/t $CO_2$ (£10/t $CO_2$ more than in the REF scenario) (see Figure 9.8). However, they are replaced by nuclear power stations instead of coal CCS as is the case in the deterministic run. The reason for this is the uncertainty concerning the availability of biomass for co-firing in coal CCS plants up to 2025, which makes investments in nuclear power plants more attractive. It is also interesting that a shift from coal to natural gas saves some emissions at around £70/t $CO_2$, while coal CCS replaces conventional coal at this tax level in the REF scenario. Overall, this leads to slightly lower emissions.

**Figure 9.8 : Electricity generation mix for different marginal abatement costs in 2030 (REF (50%) scenario)**

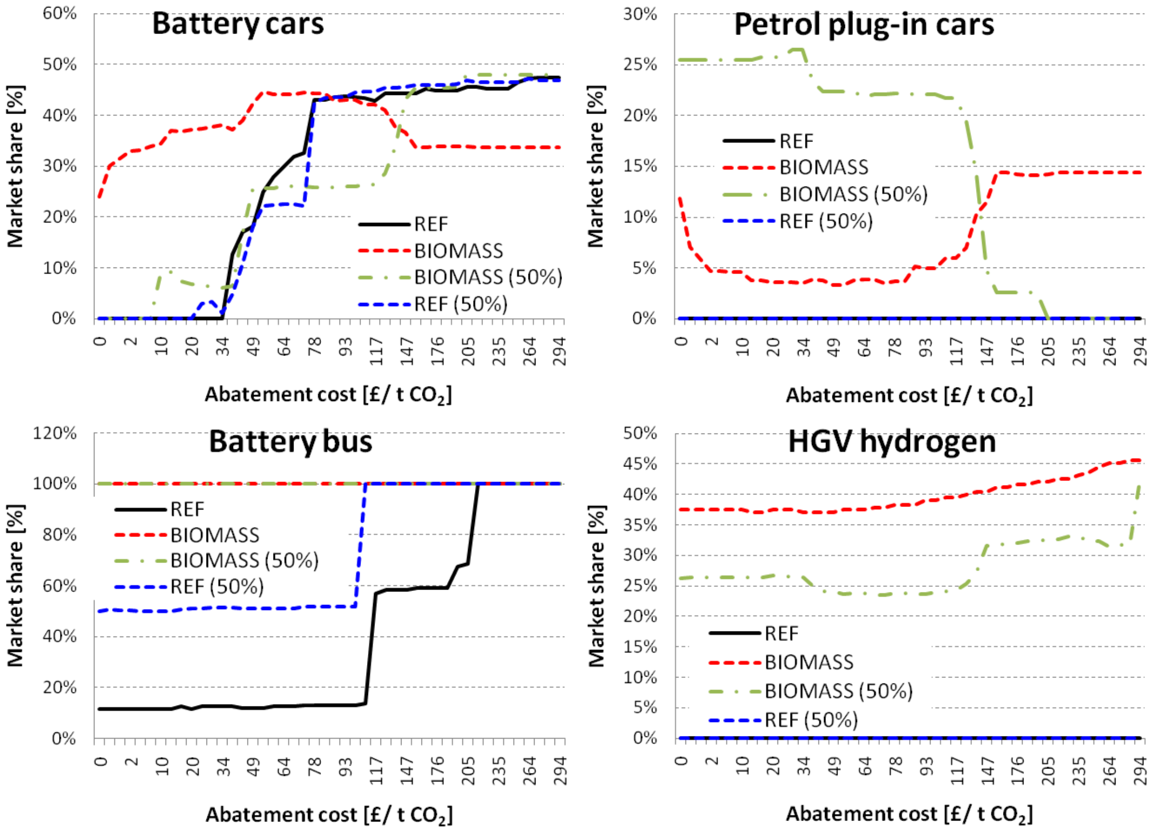



The differences in the other sectors are more limited. While there are no significant differences between the stochastic REF (50%) scenario and the REF scenario in the residential sector, the main difference in the transport sector is that the market share of battery buses is significantly higher. Battery buses make up half of all buses as electricity is about 9% cheaper in the REF (50%) scenario compared with the REF scenario.

Turning towards the other stochastic BIOMASS (50%) scenario, it differs from the REF (50%) scenario to the extent that the market share of coal CCS power plants is less due to the very limited availability of biomass for co-firing. All in all, the electricity mix looks very similar to the BIOMASS scenario presented in chapter 6. The only major difference is that total electricity production is about 9% less when compared with the deterministic scenario, explained by the uncertainty over the potential for low-carbon electricity. However, the situation in the transport sector and the residential sector looks very different. The important difference between both stochastic scenarios in 2030 is that no biomass is used for domestic space and water heating in the BIOMASS (50%) scenario as a result of the fact that no biomass imports are allowed and domestic production is restricted.

With emissions reduction significantly less in the residential sector, the transport sector takes up a higher share of emissions reduction in the BIOMASS (50%) scenario compared with the REF (50%) scenario. Without biofuels as a mitigation measure and electricity being slightly cheaper due to a lower share of coal CCS (with biomass co-firing), all buses run on electric engines in the BIOMASS (50%) scenario in the absence of any climate policy (see Figure 9.9).

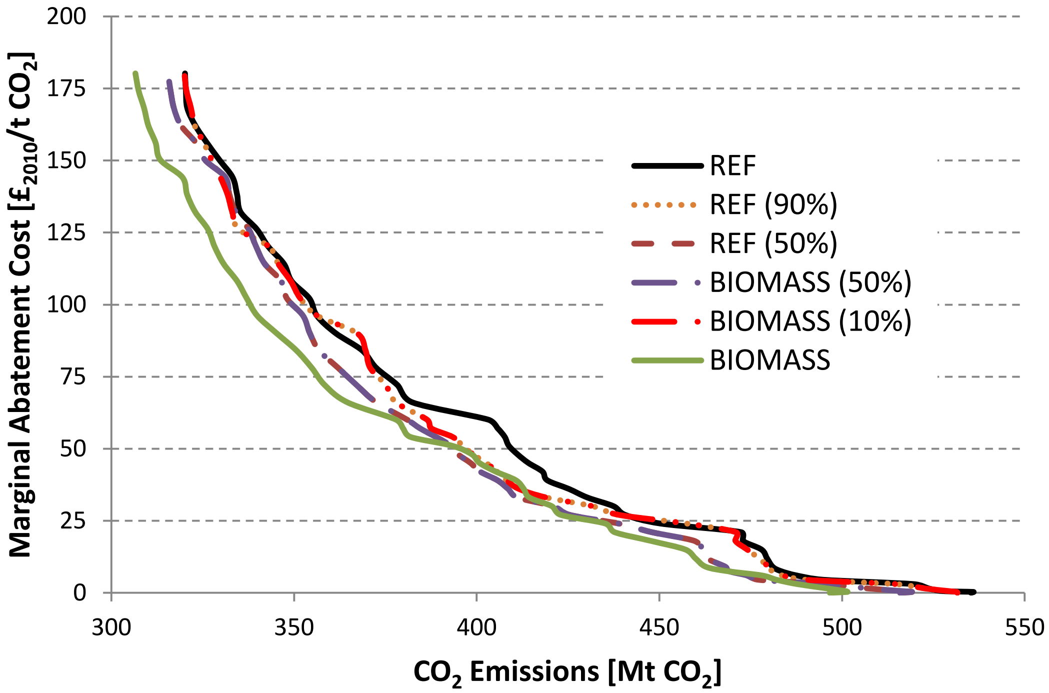
**Figure 9.9: Market share for different technologies in the biomass scenarios in 2030**




Petrol plug-in cars have a dominant role with a market share of 20% and above up to £127/t $CO_2$ when they are replaced by battery cars. Plug-in cars can be powered by electricity as well as by liquid fuels so that they represent a hedging option when petrol and electricity prices are uncertain. Petrol plug-in cars only attain such an important market share in the stochastic runs, while the market share is significantly lower in the deterministic model runs. Lastly, hydrogen-fuelled HGVs reach a market share of up to 40% in the BIOMASS (50%) scenario as this vehicle type is introduced several years earlier compared to the REF (50%) scenario.

Moving beyond the year 2030 can give more insights on the dynamic issues affecting MAC curves. Instead of looking at the recourse strategy, a MAC curve for the year 2020, i.e. 5 years (or one model period) prior to uncertainty resolution, reveals insights on the abatement costs in the hedging period (see Figure 9.10).

**Figure 9.10 : Emission curves for the deterministic and stochastic (dashed) BIOMASS scenario in 2020**

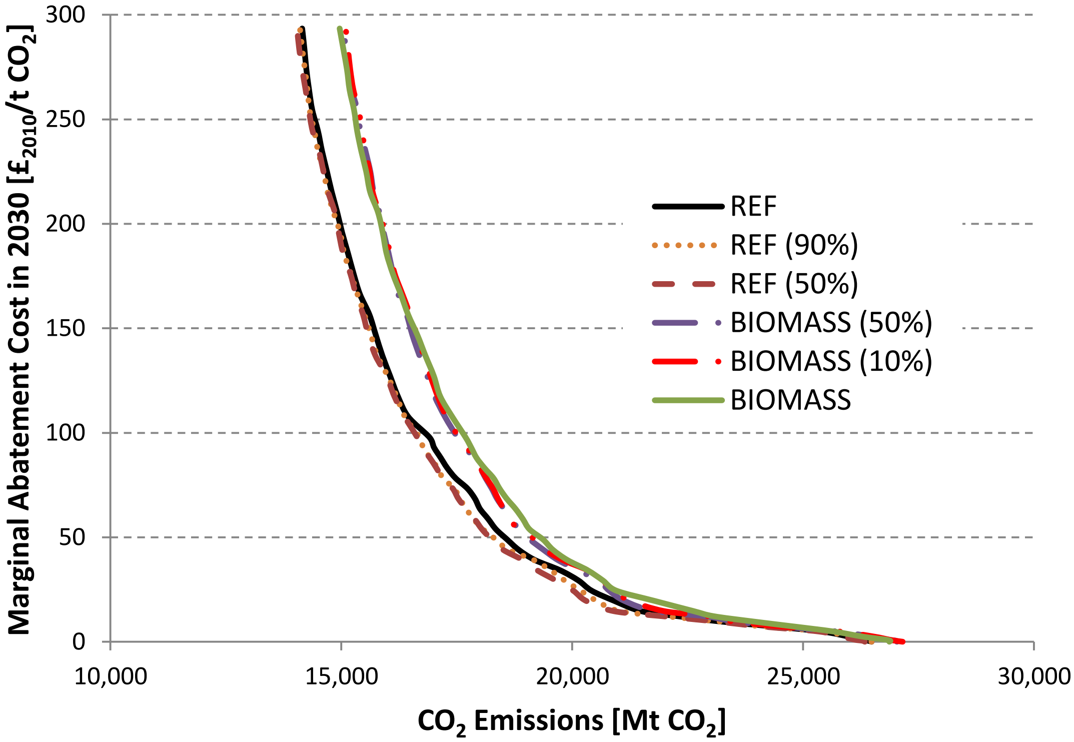



Looking only at Figure 9.10 without considering the broader context of the stochastic scenario, one could come to the conclusion that uncertainty about biomass availability in the future reduces present abatement costs. This is indicated by the stochastic MAC curves being shifted to the left of the MAC curve in the REF scenario over most of the tax range. However, this neglects the difference between the scenarios in terms of abatement in later periods. The reason for this apparently counterintuitive result is that the model anticipates the possibility of limited biomass in the future and hedges against this event by abating more $CO_2$ emissions for a given tax level in the short term in the stochastic scenarios compared to the REF scenario.

MAC curves for years after 2030 indicate, similarly to the curve in 2030, that abatement is slightly cheaper in the stochastic scenarios when compared to the deterministic equivalent. This is because in the stochastic scenarios the model makes up for the $CO_2$ that was emitted in excess of the deterministic scenarios during the hedging period.

A cumulative emission curve (Figure 9.11) over the whole model horizon shows that the stochastic MAC curves are very similar to the deterministic equivalents. The difference between the stochastic and deterministic emissions level is never more than 1.7%, which indicates that differences even out over the model horizon.

**Figure 9.11 : Cumulative emission curves for the deterministic and stochastic (dashed) BIOMASS scenario (2000-2050)**




### 9.2.3 Summary

One stochastic scenario was presented in this section that dealt with the future availability of biomass. In 2030, five years after uncertainty has been resolved, results in both stochastic cases indicate that the costs for emissions reduction are very similar to the deterministic equivalent but generally slightly cheaper. The reason is that the model hedges against the uncertainty in the time prior to the resolution of uncertainty. However, in terms of overall system costs the deterministic scenarios are always cheaper than the stochastic ones. In the hedging period, the marginal abatement costs associated with an emissions reduction amount are either higher than both scenarios or in between them.

On a technology level, it can be concluded that coal CCS power plants are strongly affected by the stochastic characterisation due to the uncertain biomass availability. A lower production of electricity from coal CCS again affects nuclear and wind power. Abatement in the transport sector is the most affected due to the reliance on cheap electricity for transport electrification in the REF scenario.

Varying the probabilities for the two states of the world does not change the shape of the MAC curve in the recourse period. In the hedging period, where the stochastic MAC curves are between the two deterministic curves, different probabilities matter more. Higher probabilities for the REF scenario shift the MAC curve towards the curve for the deterministic REF scenario. Delaying the point in time when uncertainty is resolved leads to more expensive abatement in the hedging period as biomass will be available for longer and therefore there exists a lower incentive to abate in early periods. However, there is almost no difference concerning MAC curves in the recourse strategy when changing the resolution time.

Finally, the differences in the stochastic variants (varying probabilities and the uncertainty resolution period) as well as differences in comparison to the deterministic runs are limited. Reasons are that the uncertain parameter must be very influential in order for the stochastic model version to reveal insights. Biomass availability is one of the most important factors and affects the MAC curve significantly, but it does not change the circumstances completely. Furthermore, the model can adapt relatively quickly to the changing availability of biomass as it does not need big infrastructure investments. Thirdly, in contrast to strict emissions targets, varying carbon tax levels are used to calculate the MAC curve, which leaves the model much more freedom to react to changing input assumptions. Lastly, with a discount rate of 5% and assuming constant costs the recourse period accounts for less than 25% of the energy system costs over the whole model horizon if uncertainty is resolved in 2025. This explains why decisions in the recourse strategy are less important compared to the hedging period.

## 9.3 References


Committee on Climate Change (2010). The Fourth Carbon Budget - Reducing emissions through the 2020s. London.

Hausman, J. A. (1979). "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." The Bell Journal of Economics **10**(1): 33-54.

Hendriks, C., D. De Jager, K. Blok, J. de Beer, J. Harnisch, S. Joosen, D. Phylipsen, M. Kerssemeeckers, C. Byers, M. Patel, J. Bates, C. Brand, P. Davison, A. Haworth and N. Hill (2001). Economic Evaluation of Sectoral Emission Reduction Objectives for Climate Change - Bottom-up Analysis of emission Reduction Potentials and Costs for Greenhouse Gases in the EU. Utrecht, The Netherlands, ECOFYS Energy and Environment, AEA Technology Environment.

Kannan, R., N. Strachan, N. Balta-Ozkan and S. Pye. (2007). "UK MARKAL model documentation." Retrieved November 18th 2010, from www.ukerc.ac.uk.

# 10 CONCLUSIONS

This thesis presented results that were generated from a new methodological approach towards MAC curves. While energy system modelling and decomposition were applied separately in the past, it is the first time that a technology-rich bottom-up energy system model, and decomposition analysis are combined to attribute abatement potentials to abatement measures in a MAC curve. In addition, uncertainty analysis in the form of sensitivity and stochastic analysis was used to test the robustness of the findings. The benefits of this approach are that it incorporates the advantages of a system-wide model approach, while bringing in the technological detail into MAC curves usually attained through expert judgments. In contrast to model-based mitigation wedges, the methodology presented in this thesis allows insights on marginal abatement costs and is theoretically sound as well as transparent (see 2.2.2.3).

With the new approach it is possible to avoid inconsistencies in the base case assumptions and to reflect intertemporal, as well as intersectoral interactions in the energy system. Intertemporal interactions refer to an optimal abatement over time, while intersectoral interactions capture trade-offs between different sectors, for example between the residential and the electricity sector. A model framework is not only a good tool to establish a consistent reference development as a baseline for emissions reduction and avoid double counting, but it also allows to consider uncertainty by changing input factors to the model.

The remainder of this final chapter provides an overview of the main findings of the thesis, and thus answers the three research questions posed in the introductory chapter. The limits of this thesis are also addressed and interesting ways of future research are highlighted.

## 10.1 Main findings

### 10.1.1 Abatement measures

The sensitivity analysis, which was carried out on a sectoral level for the power sector, transport sector and residential sector, identified the most important measures for a transition to a low-carbon society in the UK. The decomposition analysis distinguishes between four broad categories: demand-related changes, efficiency improvements, structural switches from one technology to another, and decarbonisation of energy carriers.

From today to the year 2030, the focus of this study, many measures are expected to become cost-effective without any carbon policies in place and therefore do not figure on the MAC curve. This includes electric hybrid technologies for several transport modes, such as cars, buses and HGVs. Moreover, in the optimisation framework of the UK MARKAL model, it is assumed that conservation measures will be carried out in a major share of existing dwellings and biomass as well as district heating will gain in importance as heating fuels. These results reflect the optimal setting in the employed model under perfect foresight and do not mirror what can be expected to happen in reality. In order to overcome market barriers and realise the abatement potential related to efficiency improvements, policy makers would need to set in place dedicated policies.

The MAC curve results for the end-use sectors, households and transport, showed that price-induced demand reduction is a flexible abatement measure that can reduce $CO_2$ emissions relatively early at comparably low cost. Demand reduction accounts for about 10% of all emissions reduction in the transport sector, whereas the respective share is 16% in the residential sector in the reference scenario. While the emissions reductions caused by reduced demand do not attain the same level as structural changes, they are still important in a cost-effective, system-wide emissions reduction. Demand reduction happens over the whole range of $CO_2$ tax levels, though the contribution at high tax levels, in particular above £200/t $CO_2$, is low. At these higher tax levels, most energy demand services are met by energy carriers that are (almost) completely decarbonised, such as electricity, heat or biomass. Consequently, demand reduction does not reduce $CO_2$ emissions any further if the energy service is met by $CO_2$-free energy carriers. Since uncertainty surrounding demand elasticity is particularly large, results can only be an approximation, but they point out the important role that price-induced demand reduction can play.

The analysis of the end-use sectors has shown that the decarbonisation of electricity plays a pivotal role in reducing emissions in the whole energy system. While this holds true to a limited extent for heat and the blending of biodiesel, electricity plays by far the most important role. In the transport sector, the use of battery and plug-in vehicles depends on low-carbon electricity, whereas in the residential sector heat pumps only become cost-effective once electricity is sufficiently decarbonised.

In order to achieve this major decarbonisation of electricity, the analysis in chapter 6 has shown that a few technologies are responsible for the lion's share of abatement in the power sector: coal CCS with biomass co-firing, nuclear power, and wind power. Nuclear power is the single most important abatement technology in the power sector as it is responsible for 27% of emissions abatement in the reference scenario. The other important abatement measure in the power sector is coal-fired power plants in combination with CCS. While coal CCS power plants become cost-effective from £19/t $CO_2$ in 2030 in the reference scenario, the option to co-fire biomass and thereby achieve negative net emissions is cost-optimal from £25/t $CO_2$. If both abatement measures, coal CCS power plants and biomass co-firing, are taken together, they are responsible for 35% of overall emissions reduction in the power sector. The third most important mitigation measure is wind power, being responsible for 15% of overall emissions reduction in the power sector in the reference scenario. In contrast to some mitigation measures in the end-use sectors, the average abatement costs for the three technologies are relatively low, ranging from £12/t $CO_2$ to £67/t $CO_2$ in the reference scenario, although this depends strongly on the underlying assumptions. Minor abatement measures are tidal energy, electricity imports, hydro power, and biomass power plants.

For policy making the results indicate that measures needs to be put in place to reduce the carbon intensity of electricity because this is a precondition for further abatement in other sectors. With the dominant role of nuclear and CCS technologies, implementation hurdles, public attitudes and spatial issues concerning carbon storage need to be carefully considered by policy makers.

The abatement structure in the transport sector is characterised by the increasing importance of electricity as an energy carrier. The decarbonisation of electricity and the shift towards electric cars and busses are responsible for almost 60% of all emissions reductions in the transport sector. Up to £35/t $CO_2$, petrol hybrid vehicles are important as a means to reduce emissions, but at higher tax levels they are replaced by battery vehicles. The only transport mode where electricity is not the most cost-effective solution is HGVs where hydrogen is the main alternative to fossil fuels. Nevertheless, HGVs fuelled by hydrogen only become cost-optimal at very high abatement costs in

2030 of above £300/t $CO_2$ in the reference scenario. Since an electrification of the transport sector is a robust finding across all scenarios, policy makers need to address infrastructure issues, and put in place support policies to transform the model results into reality.

As many energy services in the domestic household rely on electricity, such as lighting, appliances, cooling, refrigeration, and cooking, decarbonising electricity is by far the most important measure to reduce residential emissions with a share of 70%. In the absence of any carbon policy, the residential sector is subject to significant change because it is cost-optimal: an important share of households implement conservation measures, while biomass boilers and district heating become important options for space and water heating with a market share of 20% and 28% respectively. Overall structural change over the tax range from £0/t $CO_2$ to £294/t $CO_2$ is fairly limited in the residential sector compared to the transport sector, but heat pumps can play an important role to reduce emissions depending on their assumed penetration potential. The above findings once again demonstrate the importance of decarbonising electricity not only for the transport sector but also for domestic buildings.

These results can be helpful indications for policy-makers in many different ways. On the one hand the most important technologies for a cost-effective emissions abatement were identified so that the development of these technologies can be supported by policy instruments. On the other hand, the MAC curve can be a first point of reference for the emissions reduction that can result from a carbon tax or what the resulting carbon price would be if a cap-and-trade scheme is established.

### 10.1.2 Influencing factors

It is not only interesting to note what the most important mitigation measures are, but also how important their contribution towards emissions reduction is and what the biggest influencing factors are. As the sensitivity cases are not directly comparable to each other, it is not always straightforward to compare the impact of one factor to another.

The results of the sensitivity analysis indicate that the non-availability of specific technologies can make emissions abatement significantly more expensive and has therefore a significant influence on the MAC curve. If no investments into nuclear power or CCS technologies are allowed, e.g. due to public opposition, marginal abatement costs are greatly increased. This is because both technologies are essential for a cost-effective decarbonisation of electricity and low-carbon electricity is essential for system-wide emissions reduction. If only one of the technologies is not available as a mitigation option then the other can compensate to some extent for this, so that changes to the MAC curve remain limited. Battery vehicles in the transport sector play a similar role in so far as no other technology can compensate for this technology without significantly increasing marginal abatement costs. While hybrid and plug-in vehicles achieve some emissions mitigation, they are not able to reach the same emissions reduction levels at comparable costs. Technological learning was found to have a substantial influence on the MAC curve in sectors where capital cost determine a big part of the final supply cost of an energy service. This is the case in the transport sector, while the results in the power sector are more mixed as investment costs have a greater influence on generation costs for some technologies, e.g. wind, tidal, hydro, and less for others, e.g. gas-fired power stations. The residential sector is almost unaffected by varying levels of technological learning as fuel prices make up most of the price of energy services.

Demand for energy services was identified to be one of the major influencing factors on a MAC curve. Compared to the other sensitivity cases, a demand change by +/- 20% was found to have the biggest influence on the shape of the MAC curve. This is plausible because more demand for energy services is roughly equivalent to more emissions that need to be reduced. Yet, uncertainty related to demand development is often overlooked despite its important impact.

Another factor with a big influence on a system-wide level, but particularly in the transport sector, is the choice of the discount rate. While most existing MAC curves are derived based on a social discount rate, actual decisions are taken by companies and individuals that face higher discount rates. The level of the discount rate affects the annualised investment costs that play a particularly important role in the transport sector. As this cost element is rather small in the residential sector, the impacts are more limited.

It is not only interesting to see what are the factors that have the biggest impact on a MAC curve, but also to see where the shape of the MAC curve proves to be rather robust despite important changes in underlying assumptions. One of the important findings of this thesis is that the variation of fuel prices (not only fossil fuels, but also biofuels) has an important influence on specific abatement measures, but a very minor impact on the overall shape of a MAC curve. This holds true on a system-wide level, but also for each individual sector. Different fossil fuel price levels affect the abatement potential, but also the reference emission level. This means that higher fossil fuel prices reduce reference level emissions, but at the same time they also reduce the abatement potential and vice versa. While the shape of a MAC curve is usually not much affected, the mix of abatement measure can be strongly affected by different fossil fuel prices with many abatement measures becoming cost-effective in the absence of any carbon policy or becoming significantly cheaper. Nevertheless, mitigation measures that rely on fossil fuels, such as coal CCS or natural gas CCS, become more expensive with rising fossil fuel prices.

Path dependency was found to have a limited influence on a MAC curve. While specific technologies are affected by different carbon tax pathways, the more general influence on the MAC curve proved to be relatively limited. A factor that keeps the influence of path dependency small is that the UK MARKAL model does not incorporate endogenous technological learning as this is very difficult to implement in a national model for technologies that are subject to global developments. Lastly, varying the assumptions on the demand elasticity can significantly affect the contribution from demand reduction. In addition, the constraint that limits the maximum demand change from a reference level was found to be important in the residential sector. However, since the contribution from demand reduction in the reference scenario is limited, changing this amount does not result in a major shift of the MAC curve.

Carrying out a sensitivity analysis helps to see how robust findings are and what uncertain drivers decision-makers must be aware of when relying on such tools. When assessing the resulting price of a cap-and-trade scheme, for example, the sensitivity analysis can give a range of values for the resulting permit price instead of relying on an uncertain central value. Among the tested sensitivities, the results indicate which ones had a bigger impact than others so that more research can be stimulated in those areas in order to obtain a better understanding.

### 10.1.3 Interactions

An energy model that covers the whole energy system was used for this thesis. Therefore it allows one to draw conclusions about interactions both between mitigation measures and between sectors.

Electricity is at the centre of most interactions. Electricity is a critical element for a path towards a low-carbon energy system since the residential sector, service sector and industry already rely significantly on electricity as a secondary energy carrier. Furthermore, it has the potential to reduce emissions in the transport sector by switching from internal combustion engines to electric engines. In addition, heating via electric boilers or heat pumps represents an opportunity to reduce the dominance of gas heating in the domestic sector and reduce emissions. The sensitivity analysis has shown that higher electricity generation costs of low-carbon technologies or constraints on transmission lines have consequences in the whole energy system meaning that emissions abatement becomes more expensive in almost all end-use sectors. While some technologies, such as hybrid cars in the transport sector or wood boilers in the residential sector, can compensate to a limited extent for the non-availability of low-carbon electricity, this significantly increases marginal abatement costs and limits the overall reduction potential.

The analysis of the results revealed that changes to underlying assumptions of the UK MARKAL model result in interaction of abatement measures that rely on biomass. This energy carrier is used in various sectors to reduce emissions: in the residential and service sector for space heating and hot water, in the power sector mainly for co-firing into coal CCS power plants and, to a limited extent, as biofuels in the transport sector. If biomass resources turn out to be significantly less than assumed in the reference scenario, this increases abatement costs significantly not only in the residential sector, but also in the power sector. In the residential sector, biomass can either be used directly via wood boilers to provide space heat or indirectly to generate electricity and then provide heat via heat pumps or electric boilers. Interactions between both options become in particular apparent in later model periods.

The implications of this study for decision-makers are that electricity decarbonisation is a pre-condition for a decarbonisation of the whole energy system. Therefore, the power sector must be a focus of climate policy as it is not only comparably cost-effective to carry out abatement, but also essential. Concerning biomass, it is very important to continue and strengthen research with regards to the potential and costs as the analysis has shown that it is an important and versatile mitigation option.

## 10.2 Limitations of the study

While the chosen approach for this thesis has many advantages since it considers abatement from a systems perspective, integrates uncertainty and presents technological detail, it also has a few limitations. These weaknesses, the ways in which they affect the final results and how they have been mitigated is discussed in the following section.

The advantage of taking into account interactions between mitigation measures comes at the expense of a clear and easy interpretation of the MAC curve. While the abatement potential of abatement measures can be added up in conventional expert-based MAC curves as the individual reduction potential is assessed in isolation, this is no longer the case with the MAC curves presented in this thesis. This MAC curve only presents the 'marginal' mitigation measure while technologies can be replaced along rising tax levels. Consequently, there is a trade-off to be made between accuracy in terms of methodology and ease of communication. In order to alleviate this problem, other illustrations can be used to present additional information. This can take the form of graphs showing the market share of technologies over the $CO_2$ tax range or cumulated abatement potentials up to a specified tax level.

In addition, all cost-effective mitigation measure are taken up in the baseline owing to the optimisation character of the model so that they do no longer figure in the MAC curve. Conventional expert-based MAC curves, however, can display such measures with negative abatement costs. On the one hand, displaying negative abatement cost options shows clearly what measures are no-regret measures in financial terms and they are not hidden in the baseline. On the other hand, displaying negative abatement cost potential can be misleading as the potential is limited in reality by market barriers, market failures and technological constraints.

Given these shortcomings associated with all MAC curves in terms of methodology and ease of interpretation, questions arise concerning the usefulness of MAC curves. One could for example present information directly from the underlying model. However, the still existing simplicity of a MAC curve, pulling together essential information to present the economics of emissions mitigation in one illustration, outweighs the difficulties associated with this concept. Extracting and interpreting important information from model scenarios can be harder for decision makers compared with technologically detailed MAC curves. Other model-specific shortcomings are discussed in the following.

The UK MARKAL model does not represent short-term dynamics of the electricity sector or the household sectors. This lack of temporal detail concerns mostly the use and trade of electricity, where peak demand is only approximated and the daily load curve is not implemented in detail. This has consequences in the way that fluctuating electricity generation from wind cannot be optimally accounted for. Furthermore, demand-side management in the residential sector or in industry is not a mitigation option due to the lack of temporal detail. Since the model covers the whole energy system, only six timeslices are implemented, which differentiate between different seasons and day and night. In addition, the model allows only a limited contribution of intermittent renewable energy sources to peak electricity supply. Since demand-side management is not available as a mitigation measure, this could lead to a slight overestimation of abatement costs.

Similar to the lack of temporal detail, UK MARKAL does not possess any explicit spatial detail. This means that transmission and distribution networks for electricity, hydrogen or heat are not represented in any geographical detail. This lack of spatial detail is addressed by including average transmission losses and infrastructure costs, as well as distribution costs for the different energy carriers. In addition, the UK MARKAL model is limited to the United Kingdom, i.e. the influence of international energy trade on carbon abatement can only be approximated. It is hard to assess what consequences the lack of spatial detail has for a MAC curve as costs can be underestimated in some cases and overestimated in others.

Another difficult aspect to represent in an optimisation model is human behaviour or the representation of non-market costs. While the model maximises consumer and producer surplus in economic terms, behaviour is influenced by more than just economics. Market barriers and market failures have been extensively studied in the context of the slow uptake of conservation measures in the residential sector. Information failure, split incentives, difficult access to capital, and a low priority for energy matters are examples of non-financial aspects influencing energy-related investments. The influence of behaviour is not only apparent in the residential sector, but also in the transport sector. Occupancy rates, i.e. how many persons are transported in a car, are hard to estimate, as well as the speed level and consequently fuel consumption. As speed is not represented in the model, the effects related to a reduction of speed limits, for example, cannot be quantified. Moreover, an individual's decision to buy a car is mainly influenced by characteristics that are unrelated to fuel consumption. Consequently trends towards bigger cars are not compatible with the optimisation objective of the model. Technological hurdle rates are implemented in the transport and residential sector to capture some of those market barriers. Although it is acknowledged that this is imperfect, it is one of only a very few approaches to capture behaviour in an optimisation model. However, the lack of behavioural detail can lead to marginal abatement costs being underestimated and abatement potentials being overestimated.

Ancillary benefits and costs of carbon reduction are not included in the calculation of abatement costs as the focus of the thesis is on $CO_2$ emissions reduction. Beneficial side-effects of carbon emissions reduction, such as a reduction of other greenhouse gases or in air pollution, an increase in energy security or a reduction of fuel poverty, are not accounted for when optimising the energy system. Including ancillary benefits in the cost calculation would lead to lower abatement costs. Ancillary costs, such as an increase in air pollution through a higher use of biomass can lead to higher abatement costs.

Since the focus of UK MARKAL is to capture the interactions in the whole energy system, detailed issues, such as the lack of storage restricting the use of biomass boilers, the limited range of battery cars or internal heat gains in buildings, are not represented. As it is not possible to implement such issues in detail, they are approximated e.g. via constraints on the market share of technologies to account for their limited market potential. Omitting some of the detailed aspects in relation to the implementation of low-carbon technologies can possibly overestimate their contribution towards emissions abatement.

The decomposition of the MAC curve showed that the contribution from energy efficiency improvements is very limited. One reason for this is that many improvements to energy efficiency are implemented in the absence of any carbon policy so that they do not show up on the MAC curve. The other reason is that energy efficiency, in particular in the transport sector, is not well modelled. Start-stop systems, downsizing or low resistance tyres, are all possible abatement measures, which could lower overall abatement costs if considered in UK MARKAL.

While the model accounts for the own-price elasticity of demand, it does not account for cross-price elasticities and therefore does not account for modal changes in the transport sector. These can take the form of changes from road travel to rail travel or to walking or cycling. Excluding modal changes in the transport sector excludes other mitigation options, since people can be induced by high fuel prices to cover short distance travel by foot or bicycle and change for longer distances from car to train. This can lead to an overestimation of the costs of abating $CO_2$ emissions in the transport sector.

The UK MARKAL model includes fuel duties in the transport sector, but all carbon-related taxes, such as the Renewable Obligations, EU ETS or feed-in-tariffs are excluded from the model. Carbon taxes, direct and indirect subsidies were excluded from the model in order to obtain undiluted estimates for the marginal abatement costs. In the same way it does not track any subsidies for coal mining or indirect subsidies for nuclear power, e.g. for waste handling or an implicit insurance for nuclear risks. It is very hard to quantify the effects of including direct and indirect subsidies on a MAC curve since they affect various technologies in different ways.

The employed optimisation possesses perfect foresight for the whole model horizon. This means that the model knows in early model periods what mitigation measures will be available in later model periods and what the carbon tax level will be. The perfect foresight character was addressed by presenting a few results with the stochastic variant of UK MARKAL. This model version offsets perfect foresight to some extent by introducing uncertainty about a certain set of input parameters or model constraints, which is resolved at a later stage during the model horizon. The perfect foresight characteristic can lead to an underestimation of marginal abatement costs.

Finally, the model relies on external assumptions for technological learning. Thus, technological learning happens through time and it is not dependent on previous investments. This is very difficult to implement as most of the energy technologies are influenced by international trends and not exclusively by investments taken in the UK. This issue of learning was addressed to some extent by implementing a 1$^{st}$ of kind vs. n$^{th}$ of a kind constraint (see chapter 6.6), which requires early investment into a technology in order to be able to invest in later cheaper versions of that technology. Again, it is hard to assess the influence on a MAC curve of not having endogenous technological change in the model. Most likely, the costs for some technologies will be overestimated and for some underestimated because in the case of endogenous technology learning the model would focus on a handful of technologies and reduce costs further along the learning curve than for others. This would have corresponding consequences for the abatement potential.

## 10.3 Future Research

The results have shown that the research method used in this thesis has many advantages over existing research based on the individual assessment of mitigation measures. It is therefore recommended that future research on MAC curves, aimed at helping decision-makers, should focus on MAC curves derived from systems models. This approach can much better quantify marginal abatement costs or emissions potentials when market-based instruments are considered. Nevertheless, given the limitations of this thesis described above, there are opportunities to extend the existing research and to address some open questions, which still remain unanswered.

One future research avenue would be simply to improve the way that UK MARKAL addresses the weaknesses identified. This can involve a better representation of non-market costs and temporal/spatial detail, an improved modelling of efficiency options or enabling modal shifts in the transport sector. Future research can also integrate other greenhouse gases, such as methane or nitrous oxide, in an energy system model to obtain a more complete picture of emissions mitigation. In the same way, one could also enlarge the scope beyond the energy system and include agricultural or industrial greenhouse gas emissions.

Furthermore, one can use another technology detailed energy model in combination with decomposition analysis. The results presented here depend on the model structure of UK MARKAL. Therefore, it would be interesting to see to what extent the results would differ if another model was used to derive MAC curves. Other models would also offer the possibility to implement endogenous technological learning, which means that one would no longer have to rely on exogenous assumptions for technology learning. On the other hand, the analyst would be confronted with the problem to adequately determine a cluster of technologies, a start value for the technology cost and a learning rate. In order to avoid the problem of investing only in one technology, the analyst also would have to define realistic growth constraints.

To overcome perfect foresight, a myopic model version can be used that only allows foresight of a few model periods. This would be a more realistic way of representing decision making that gives more emphasis to the near term. Moreover, as this study is focused on the UK, the proposed methodology could be applied to other countries or on a global scale.

It would also be interesting to use a different decomposition technique or decomposition formula to test how the results would vary. On the one hand, the uncertainty resulting from using different decomposition techniques was shown to be minimal in chapter 4. This has been emphasised by undertaking many model runs for each MAC curve to keep the differences in emissions levels and therefore a potential residual as small as possible. On the other hand, the decomposition formula was chosen according to the standard in existing decomposition research and according to the four broad categories of emissions reduction: demand reduction, technology switches, efficiency improvements, and carbon intensity improvements. Nevertheless, a different decomposition formula with differently determined structural and intensity effects can give a different perspective on the results, though the main message would not change.

Finally, sensitivity analysis and stochastic analysis, which were applied in this thesis, are only two forms to quantify the impact of uncertainty on MAC curves. In order to attach probabilities to different outcomes, one could theoretically use a probabilistic assessment via Monte Carlo analysis to draw conclusions about the probability density of abatement potentials and related costs. To carry out a probabilistic assessment, one would have to use a smaller, less data-intensive model. The complexity of the UK MARKAL model does not allow probabilistic analyses as it would take weeks to run the model in order to obtain meaningful insights. Another possibility would be to use more sophisticated stochastic modelling, .e.g. in the way that more than two states of the world are considered or that multi-stage stochastic modelling is used. This could represent decision-making more realistically as uncertainty is not completely resolved at one moment.