The role of end-use energy conversion efficiency as a climate mitigation tool

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To David MacKay

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Leonardo Paoli
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Abstract

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Historically, conversion efficiency improvements have revolutionised the energy system, yet to reach climate targets, the scientific community agrees that even higher levels of energy efficiency improvement are required. When focusing on technical options there are two classes of technologies: conversion devices and passive systems. This thesis explores the role that the former can have in reducing energy demand with the aim of providing advice on the prioritisation and differentiation of policy action among these devices. The analysis is divided into three main chapters.

First, issues with data quality were identified a cause for the marginalisation of end-use efficiency measures compared to supply-side ones. For the first time, the uncertainty of end-use statistics is quantified by drawing from methods developed in the field of Material Flow Analysis using the United Kingdom as a case study. The majority (85%) of the Useful energy balance uncertainties are below an acceptable (±25%) threshold. Therefore, end-use statistics are deemed sufficiently reliable for the development of policy-relevant indicators.

Second, the technical efficiency limits for six widely used conversion devices are determined stochastically based on a combination of engineering models and review of the technical literature. The resulting limits are used to calculate the energy saving potential of each conversion device, and each design parameter for the United Kingdom. It is shown that 25% of the UK's Final energy demand could be avoided if all conversion devices reached their technical limit. On the other hand, 15% savings could be achieved by applying available technology. Nonetheless, improvement margins vary substantially among devices meaning that strategies involving different balances of R&D and technology adoption incentives are required for each technology.

Third, the International Energy Agency's Energy Technology Perspective's modelling results are used to assess the saving potential of seven conversion devices in three emission scenarios. Between 3.2% and 4.2% of cumulative energy demand between 2014 and 2060 can be saved thanks to improvements in conversion efficiency. Most savings come from improved internal combustion engines in all scenarios. Carbon emission savings from conversion efficiency are highest in the baseline scenario and lowest in the most ambitious climate scenario due to negative emissions in electricity generation nullifying the effect of improvements in electricity-using devices. No technology was found to breach the technical efficiency limit in the IEA's assessment meaning that expected efficiency improvements technically realistic. Current innovation activity in energy conversion devices is quantified by means of patent counts and it's compared to the distribution of saving potentials. It is found that innovation in air coolers and heat pumps is low when compared to the expected efficiency savings from these technologies.

The thesis results are useful for directing policy and investment priorities for conversion devices as function of the ambition of the climate scenario. The analysis of technical efficiency limits for conversion devices, help improve energy system models. The novel uncertainty method provides a powerful tool for supporting energy planning and decision making.

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Publications

The research presented in this thesis has been published as original research articles in the peer-reviewed journals and academic conferences listed below.

Journal articles

- Paoli, Leonardo, Richard C. Lupton, and Jonathan M. Cullen. "Probabilistic model allocating primary energy to end-use devices." Energy Procedia 142 (2017): 2441-2447.
- Paoli, Leonardo, Richard C. Lupton, and Jonathan M. Cullen. "Useful energy balance for the UK: An uncertainty analysis." Applied energy 228 (2018): 176-188.
- Paoli, Leonardo and Jonathan M. Cullen. "Technical limits for end-use conversion devices" Energy - *accepted–in print*

Conference presentations

- Paoli, Leonardo and Jonathan Cullen. "Global Primary to Final Energy Efficiency: range and evolution." International Conference of Industrial Ecology, Chicago 2016
- Paoli, Leonardo and Jonathan Cullen. "Visualisation and interpretation of uncertainty." International Conference of Industrial Ecology, Chicago 2016
- Paoli, Leonardo, Richard C. Lupton, and Jonathan M. Cullen. "Probabilistic model allocating primary energy to UK conversion devices" International Conference on Applied Energy, Cardiff 2018
- Paoli, Leonardo "The future of end-use energy conversion efficiency" International Conference of Industrial Ecology, Beijin 2019

Other published work during the course of the doctoral programme, not directly included in this thesis is listed below:

- Hernandez-Gonzalez, Ana , Leonardo Paoli, and Jonathan M. Cullen. “How resource-efficient is the global steel industry?.” Resources, Conservation and Recycling 133 (2018): 132-145.

- Craglia, Matteo, Leonardo Paoli, and Jonathan Cullen. "Fuel for thought: Powertrain efficiencies of British vehicles.” Energy Procedia 142 (2017): 1300-1305.

- Cazzola, Pierpaolo, Marine Gorner, Leonardo Paoli, Sacha Scheffer, Renske Schuitmaker, Jacopo Tattini, Till Bunsen, and Jacob Teter. “Global EV Outlook 2018: Towards cross-modal electrification.” International Energy Agency (2018).

- Cazzola, Pierpaolo , Sacha Scheffer, Leonardo Paoli, Matteo Craglia, Uwe Tietge and Zifei Yang “Fuel economy in major car markets- Technology and policy drivers 2015-2017”, International Energy Agency (2019)

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Nomenclature

Roman Symbols

ε	Efficacy (in lm/W)
η	Efficiency
γ	Ratio of specific heats
λ	Excess Air
ϕ	Sector to end-use allocation matrix
θ	End-use to conversion device allocation matrix
2DS	2 Degrees Scenario
AC	Air Conditioning
B2DS	Beyond 2 Degree Scenario
BAT	Best Available Technology
CCS	Carbon Capture and Storage
COP	Coefficient of Performance
CR	Compression Ratio
CRI	Colour Rendering Index
CSP	Carbon Saving Potential
CT	Colour Temperature
DOE	United States Department of Energy
EER	Energy Efficiency Rating
EPA	United States Environmental Agency
ESP	Energy Saving Potential
ETP	Energy Technology Perspectives
F	Final energy
GHG	Green House Gasses
GT	Gas Turbine
HP	Heat Pump
IAM	Integrated Assessment Model
IEA	International Energy Agency
IPC	International Patent Classification
IPCC	International Panel on Climate Change
LED	Light Emitting Diode
LHV	Lower Heating Value
OECD	Organisation for Economic Co-operation and Development
OEM	Original Equipment Manufactrers
OPR	Overall Pressure Ratio
R&D	Research and Development
RCA	Renewable Capacity Avoided
RE	Reciprocating Engine
RTS	Reference Technology Scenarios
SEER	Seasonal Energy Efficiency Rating
SI	Compression Ignition Engine
SI	Spark Ignition Engine
TEL	Technical Efficiency Limit
TIT	Turbine Inlet Temperature
UNFCCC	United Nations Framework Convention on Climate Change

Chapter 1

Introduction

1.1 Energy conversion and climate change

Our planet is plentiful in energy resources. From above, the sun provides enough energy every two and a half hours, in the form of electromagnetic radiation, to satisfy humanity's yearly 800 EJ of energy demand [1, 2]. Additionally, the sun's rays heat up the atmosphere and oceans giving rise to winds and currents which carry kinetic energy. From below, approximately 315 EJ per year of thermal energy seep up from the earth's core to its crust [3]. Meanwhile, the energy stored by organic life over millions of years, trapped in the form of fossil fuels, could, alone, power our society for centuries. If we take into account the energy contained in the nuclei of fissile elements, the potential resources exceed current levels of demand by orders of magnitude.

However, not all of these raw—or Primary—energy sources are conducive to human well being. For humans, energy is only useful if it can provide us with "services" that expand our possibility space beyond what is dictated by our natural condition. Energy services allow us: to be comfortably warm when the outside temperature is too low; to reach places at speeds unachievable with our own legs; to move objects that exceed our physical carrying capacity; to grow food at faster rates than naturally possible; and to continue activities when the sun is not shining.

From the beginning of history to the dawn of the industrial evolution, humanity accessed roughly the same amount of energy—be it in the form of food, light, or motion. Economic historians refer to this as the "photosynthesis constraint" [4, 5] referring to the limitations of conversion efficiency found in biological and natural systems: plants convert the sun's "Primary" energy into "Final" energy in the form of wood and crops with an efficiency of about 4%, while animal muscle system produce “Useful” work and tractive force with an efficiency of about 25% [6]. Therefore, for each unit of available land, the amount of useful energy, and thus the amount of energy service delivered, was limited. The importance of our ability to convert raw energy sources into useful forms—our conversion efficiency—has been paramount in human development. Nowadays, the entire energy system can be understood as a complex set of technologies and practices that bridge the gap between a world of abundant, Primary energy and the very specific forms of energy that allow humans to flourish. Hence, the vast majority of our energy system is tasked with the conversion of energy, and at the highest practical efficiency.

The ability to convert chemical energy, in the form of fossil fuels, into mechanical energy was brought about by the development of the steam engine, a technology that changed the course of history. The rapid increase in chemical-to-mechanical energy conversion observed between the 18^{th} and 19^{th} centuries (see Figure 1.1) has enabled the practical use of increasingly large quantities of energy. In fact, the average energy consumption in the UK increased from 30 GJ/capita in 1710, to 150 GJ/capita by 1900: a five-fold increase [4]. A similar long term pattern is observed for illumination, where three-order-of-magnitude increases in efficiency have lead to a large increase in light consumption (see Figure 1.2). Consensus among economic historians suggests that this large increase in energy availability enabled industrialisation and the improvements in material well-being that followed [7].

Today, technologies convert greater quantities of energy at higher efficiencies than ever before, causing the price of energy to be much lower compared to incomes [8]. Consequently, Primary Energy consumption has increased to levels as high as 300 GJ/person [9]. Since 80% of Primary energy supply comes from fossil fuels, increases in energy consumption are linked to increased in greenhouse gas (GHG) emissions that cause anthropogenic climate change [10]. Therefore, improvements in conversion efficiency that enabled increased consumption can be seen as of the key drivers of increased carbon emissions.

Warnings about the potentially disastrous consequences of climate change have been issued by the scientific community in periodic reports published by the United Nations Framework Convention on Climate Change (UNFCCC) [12]. Following these reports, most governments have subscribed to a number of agreements aiming to mitigate the effects of climate change by decreasing GHG emissions. These agreements have resulted in the introduction of new legislation and the investment in technologies to decrease our dependence on fossil fuels. As a result of these efforts, the global carbon intensity of economic activity has more than halved from 763 gCO_2/USD in 1990 to 325 gCO_2/USD in 2014 [13]. Yet, even so, absolute global CO_2 emissions continue to rise [14].

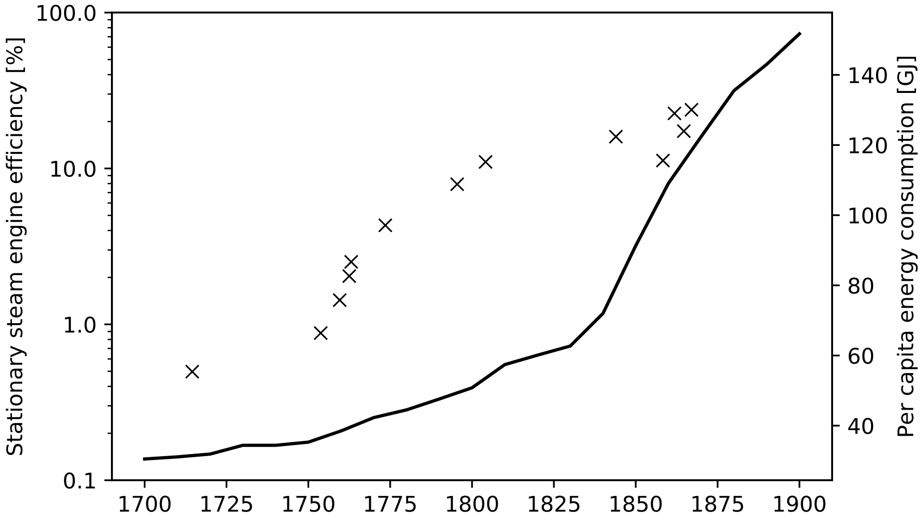

Fig. 1.1 Comparison of the evolution of stationary steam engine efficiency and per capita energy consumption from in England and Wales from 1700 to 1900. Efficiency is plotted as points on the left y-axis, consumption is shown as line plotted against the right y-axis. Efficiency data retrieved from Smil [6] while consumption data is retrieved from Warde [4].

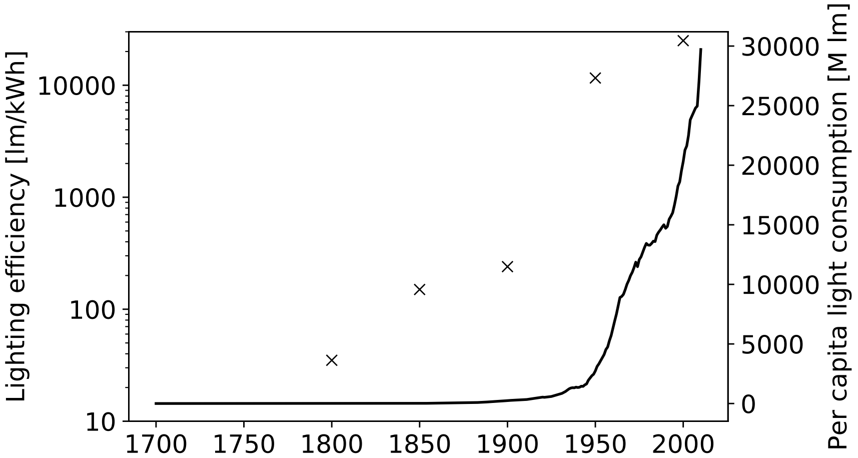

Fig. 1.2 Comparison of the consumption of light and the efficiency of lighting between 1800 and 2000 according to Fouquet and Pearson [11]. Efficiency is plotted as points on the left y-axis, consumption is shown as line plotted against the right y-axis.

As early as 1990, in the First Assessment Report (FAR), increased energy efficiency was hailed as one of the best measures to reduce emissions [15]. The relative advantages of efficiency over other options are threefold [16]. Firstly, efficiency options do not suffer from long planning and construction times associated with most electricity generation technologies, meaning that emission reductions can be achieved more quickly. Secondly, efficiency improvement is almost always accompanied by cost savings due to lower fuel requirements, meaning that the overall cost of the emission abatement is typically lower. Thirdly, many efficiency options can be implemented using known technology, and therefore carry reduced risk compared to other options. In what might appear as paradoxical given what has just been discussed, the latest Intergovernmental Panel on Climate Change (IPCC) report on global warming mitigation to 1.5 °C [17] still anticipates that energy efficiency improvements will bring about the largest emission reductions in 2050, among all mitigation measures.

As part of the Paris Agreement, most nations worldwide have pledged to "limit the increase in global average temperature to well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C " [18]. Following on from the Agreement, the scientific community has stressed the urgency of climate action at a global level by showing that a ten year delay of effective action would prevent the possibility to reach our 1.5 °C global warming goal, meaning that the need to drastically reduce emissions is no longer a long term perspective but instead an immediate challenge. Mitigation pathways to meet the climate targets developed over the past decade rely heavily on negative emissions (Biomass with Carbon and Storage (CCS) and Direct Air Capture and Storage technologies) during the second half of the century [19]. In the 1.5 °C report, four of the five pathways presented assume annual negative emissions in 2100, ranging from 5 $GtCO_2$ to 25 $GtCO_2$ [17]. To put this into perspective, total global CO_2 emissions in 1990 were 22 Gt [20]. These four pathways state that by the end of the century such large quantities of CO_2 could be safely captured and stored underground, despite the current deployment of CCS (in 2018) being three orders of magnitude lower, at 2.4 $MtCO_2$/year. While the development of CCS and other negative emission technologies is of paramount importance, it is incautious to rely so heavily on one technology that is yet to be proven at scale. The only scenario presented in the 1.5 °C report which does not rely on net negative emissions is the *Low Energy Demand* scenario, which focuses on our abilities to reduce demand for energy using currently available technologies. Energy intensity reduction measures are pushed to the extreme, resulting in an improvement rate that is 40% higher than in other scenarios and 160% higher than historical improvement rates [21, 22].

Irrespective of the specific mitigation pathway chosen, energy intensity must decrease (i.e. the efficiency of the energy system must increase) at unprecedented rates. The higher the efficiency of the energy system, the greater chance of meeting our climate goals. Technological advances will be necessary in all aspects of this complex system, and it is desirable to clearly understand the role that each advance plays in improving the energy system efficiency. Decision makers will be forced to allocate limited effort and resources to chosen policies and technologies: a task which can be streamlined if the scientific community can deliver clear guidance on how to prioritise actions to maximise emission reduction.

This thesis aims to provide evidence on the efficiency of the energy system, to enable decision makers to prioritise action for reducing CO_2 emissions and mitigating climate change. The next section describes the specific elements of energy efficiency that this thesis will target.

1.2 Defining efficiency improvements

Before any analysis of the energy system, it is necessary to define what is meant by efficiency improvements in the field of climate mitigation, and then to define specifically the term end-use conversion efficiency.

A good starting point is the renown Kaya identity [23] displayed in Equation 1.1, which identifies three main drivers of CO_2 emissions: the demand for products and services, driven by population (P) and material wealth (GDP); the efficiency with which energy is used to produce wealth; and the carbon intensity of the energy used in the economy. These drivers translate into three broad categories of measures: demand reduction, efficiency improvements, and decarbonisation.

$$\mathrm{CO_2} = \underbrace{\mathrm{P} \times \frac{GDP}{\mathrm{P}}}_{\text{Demand}} \times \underbrace{\frac{Energy}{GDP}}_{\text{Efficiency}} \times \underbrace{\frac{\mathrm{CO_2}}{Energy}}_{\text{Carbon intensity}} \tag{1.1}$$

We can decompose this identity further to distinguish between two types of efficiency, as per Equation 1.2, by introducing the concept of “Service”. Energy services represent the services demanded by society, such as thermal comfort, illumination, mobility, and sustenance [24]. They are also referred to as “activity” or “energy demand drivers”, and are quantified in units of tonnes-km, m^2 of heated space or tonnes of steel production.

$$\frac{Energy}{GDP} = \underbrace{\frac{Energy}{\text{Service}}}_{\text{Technical efficiency}} \times \underbrace{\frac{\text{Service}}{GDP}}_{\text{Structural efficiency}} \tag{1.2}$$

Structural efficiency refers to the service required to generate one unit of wealth. Structural efficiencies vary substantially across economic sectors, for example, the service required to generate one unit of wealth in heavy industries is much larger than the service required in the financial sector [25]. Decomposition analyses have shown that the change in structure of the economy, away from heavy industry and towards a service-based activities has been responsible for a large share of overall efficiency improvements (in energy per GDP) in developed economies[26–28]. However, the implications and details of climate measures targeting changes in the structure of the economy are best studied from a social science perspective rather than a technical one, and so sit outside the remit of this thesis.

Technical efficiency, refers to the energy that is required for the delivery of one unit of service and is quantified using metrics such as MJ per passenger km, for vehicles, or MJ per m^2 per year, for buildings. Unlike structural change, technical efficiency is entirely dependent on technological choices. Although consumer choice and financial considerations still affect aspects of technical efficiency improvements, technological improvement sits at the core of this efficiency driver, falling within the scope of an engineering thesis.

When looking at different technical efficiency improvements, the term “energy” must be further qualified. As shown in Figure 1.3 three types of energy can be defined according to their ability to provide energy services [29]. Energy that is extracted from the natural environment is defined as Primary energy and it includes all energy sources (e.g. crude oil, coal, hydropower and biomass, to name a few). Final energy includes all refined energy vectors that are purchased by consumers (e.g. gasoline, diesel, electricity, district heat and natural gas). Useful energy refers to energy in its final desired form (eg. thermal, kinetic, and electromagnetic energy) and is the last form of energy that is quantifiable in energy units, before the delivery of energy services. Work delivered to wheels in road transport, cool air delivered by air conditioners, and heat delivered by an industrial boiler in a manufacturing plant, are all examples of Useful Energy.

At each stage of the energy system energy is lost. Energy is lost in the conversion between Primary and Final energy, primarily in power plants for electricity generation and transmission, but significant losses also exist in oil extraction and refining. Further losses result from the conversion of Final energy into Useful energy, such as heat rejection in piston engines or stack losses in boilers. In each stage, between Primary and Final energy, and between Final and Useful energy, a fraction of the energy is lost, allowing an efficiency to be calculated.

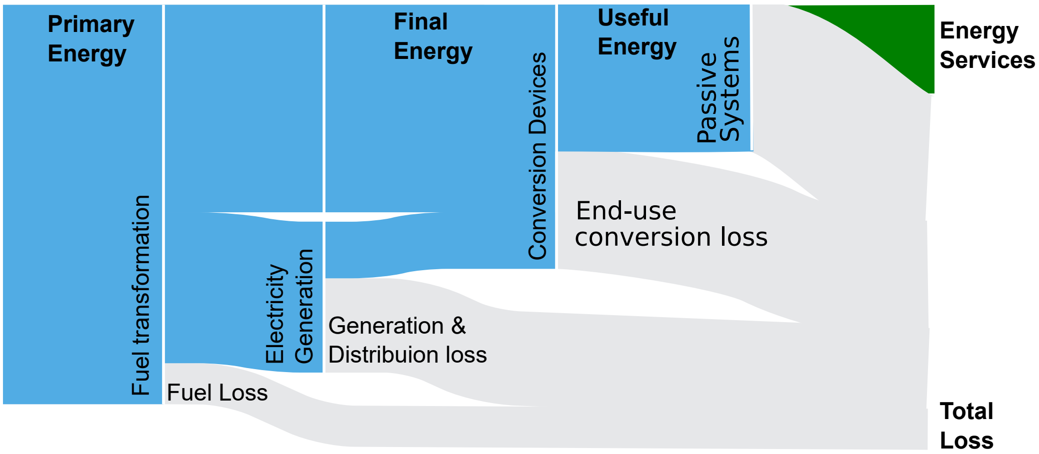

Fig. 1.3 Simplified illustration of the energy system showing energy transformation and losses from Primary energy to Energy services. Conversion devices and Passive systems are labelled to show their location along the energy transformation pathway. Adapted from [24].

In contrast, converting Useful energy to final service involves the dissipation of “all” the Useful energy, meaning a traditional efficiency measured in percentage cannot be applied. Cullen and Allwood [24] differentiated the technologies involved in energy service delivery based on whether they dissipate Useful energy to deliver services (passive systems) or whether they convert and upgrade energy resources (conversion devices). Conversion devices include power plants, refineries, engines, and boilers to name a few. Their performance is often described in terms of power output, power density and percentage efficiency. Passive systems include building shells and vehicle gliders (i.e. the vehicle without the powertrain). Their efficiency is characterised by their ability to provide the most service with the least Useful energy, measured by an array of intensity metrics, e.g. MJ_{useful}/km or $\mathrm{W/m^2}$.

Equation 1.3 shows how technical efficiency can be further decomposed as per the three broad energy categories in Figure 1.3. Energy conversion efficiency can be divided into upstream conversions (from Primary to Final energy) in power plants, refineries, and energy transmission, and end-use conversions (from Final to Useful energy) in motors and engines.

$$\frac{\text{Service}}{\text{Primary}_\text{E}} = \underbrace{\underbrace{\frac{\text{Final}_\text{E}}{\text{Primary}_\text{E}}}_{\text{Upstream efficiency}} \times \underbrace{\frac{\text{Useful}_\text{E}}{\text{Final}_\text{E}}}_{\text{End-use efficiency}}}_{\text{Conversion efficiency}} \times \underbrace{\frac{\text{Service}}{\text{Useful}_\text{E}}}_{\text{Passive system efficiency}} \tag{1.3}$$

Cullen has modelled the passive system’s practical efficiency limit and shown that most potential energy savings are found among improvements in this category of technologies.

However, improving the analysis on passive system energy efficiency requires a more nuanced analytical framework than the one offered by engineering analysis. This is because passive system efficiency is intertwined with considerations about values and consumer preferences [30]: questions like “what is the minimum size of a vehicle?” or“ what is the minimum internal winter temperature?” are not appropriately answered with an engineering approach. Contrarily, conversion efficiency is a purely technical parameter that can thus be studied using a purely techno-economic approach.

Upstream conversion efficiency refers to the efficiency of electricity generation and of fuel processing (mostly refineries), while *end-use conversion efficiency* refers to the efficiency of all those devices that convert Final energy into Useful energy (boilers, engines, motors, heat pumps etc.). Upstream technologies have historically received a disproportionately large share of research and development resources, and continue to dominate public research budgets [31]. While improvements can still be made, upstream efficiency potentials are well understood and tracked: average upstream conversion efficiencies can be computed for any country with an available energy balance [32] and, their improvement potentials and associated costs are regularly explored by energy modellers [33].

Moreover, upstream efficiency is dictated by a relatively small number of well-known technologies and processes—Brayton and Rankine cycles for electricity generation and oil cracking for refining—and is dependent on the choices of a limited number of technically literate actors, such as energy companies and utilities. In addition, as the electricity supply is decarbonised through a shift to low-carbon generation capacity, the relative impact of power generation efficiency on emissions will decrease. In summary, the role of upstream conversion efficiency as a climate mitigation tool is clearly understood.

The opposite is true for end-use conversion devices, where many different technologies are involved, devices are managed and used by a variety of users in many economic sectors, and there is little consistent reporting on their performance. Wilson et al. [34] identified “analytical intractability” as the main cause for the marginalisation of end-use technologies. This is caused by three factors: the lack of data on end-use efficiency, the lack of objective savings targets based on technical evidence, and the consequential poor modelling of end-use efficiency in energy and climate models. Altogether, this means that despite the historical revolutionary power of end-use conversion efficiency improvements, their role in emission abatement is not fully understood and warrants further investigation in this thesis.

1.3 Research goals and thesis structure

The importance of end-use conversion devices and their potential efficiency improvements as a driver of a low-carbon future, cannot be overstated. In a world of increasing urgency for climate action, it is neglectful to disregard such a key policy lever, due to "analytical intractability".

In response, this thesis aims to shed light on the current status of end-use conversion efficiency across all economic sectors and to understand the future role of each end-use conversion device and its potential for saving energy and mitigating carbon emissions. Therefore, the overall research question for this thesis is:

> **Q0: What role do different end-use energy conversion devices have in reducing energy and carbon emissions?**

This question is answered using a combination of qualitative and quantitative research methods, with a stronger focus on the latter. No experimental work is used, instead extensive use of engineering models is made. The data used to inform this thesis is retrieved from many sources including statistical offices, public product databases, academic literature, and personal communications with analysts at national and international statistical agencies. A probabilistic approach is used throughout to reflect the high level of uncertainty associated with national and global level energy assessments. Despite having such extensive system boundaries, this thesis is conducted using an engineering approach thus ensuring physical plausibility.

The structure of this thesis is as follows. Chapter 2 describes the analytical approach taken and reviews the literature to identify three research questions that will be addressed in the thesis. Chapters 3- 5 are the core analytical chapters where the methodologies used to answer the research questions and the research outcomes are outlined. Finally, Chapter 6 discusses the results of the study, provides recommendations to the main stakeholders involved in end-use energy policy, and suggests further research avenues.

Chapter 2

Literature Review

2.1 Analytical framework

In the previous section, the importance of furthering the understanding of end-use conversion efficiency and its role for emission mitigation was highlighted. The topic of energy efficiency is addressed in many different academic fields. Behavioural studies using social-practice to understand how users interact with energy technology, traditional engineering empirical studies on new technologies that aim to improve current performance, and econometric analyses finding correlations between efficiency improvements and increased energy consumption, could all be described as end-use energy efficiency studies. This thesis will attempt to answer the main research question with the tools and methods typical of an engineering approach while attempting to retain a level of analysis that is relevant to decision makers in the field of energy and technology policy. In this section, the analytical framework chosen as the foundation of this thesis is explained.

2.1.1 Passive systems and conversion devices

Technical efficiency improvement measures are normally analysed across entire sectors or entire technical systems. That is, studies analysing the energy saving potential of efficiency are traditionally either about an entire sector, i.e. the transport sector, or an entire technical system, i.e. long haul trucks. Knowledge about more specific technical components such as engines, transmission, or aerodynamic design are usually considered only within the realm of engineering studies. This body of knowledge is only indirectly linked to national or global level energy saving potential studies.

Cullen and Allwood [35–37] created a novel framework that enables the calculation of efficiency improvement potentials using a physical basis, thus explicitly connecting global energy savings to specific technical measures. To this end, they introduce the distinction between *conversion devices* and *passive systems* with the aim of facilitating the prioritisation of technical efficiency measures based on their physical energy saving potential. The two categories are described by the authors as follows.

> “[...] the term passive system is introduced here for the first time, and refers to a system to which useful energy (in the form of heat, motion, light, cooling, or sound) is delivered. Passive systems are the last technical components in each energy chain, and in contrast to conversion devices, do not convert energy into another useful form, hence the descriptor ‘passive’. Instead, useful energy is ‘lost’ from passive systems as low-grade heat, in exchange for the provision of final energy services ”

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Improvements in conversion device efficiency do not typically have any impact on the user: a more efficient engine or boiler does not affect how a user experiences transport or thermal comfort provision. On the other hand, passive systems are more closely linked to user choice and perceived comfort. Increases in passive system efficiencies in vehicles can be achieved by downsizing and lightweighting [38, 39]; both measures impact the way in which a user experiences the car. Similarly, in space heating provision, highly insulated buildings often limit users from the ability to open windows as this would alter the energy balance of the building [40].

An analysis of energy savings using this framework focuses on the technical devices and systems in the energy system (the motors, engines, boilers), rather than on economic sectors (transport, industry and buildings). The energy system is split in a series of distinct technical components that link energy sources to final energy services. The list and description of the conversion devices and passive systems that were included in the analysis is shown in Table 2.1.

This approach has been used in other studies, for example where similar analyses were performed for China [41] and for Malaysia [42] and a similar framework was also used for the global CO_2 allocation to different technical systems in the third work package of the 2014 IPCC [43].

Cullen and Allwood estimated the technical (they use the term *practical*) saving potential from passive systems [24], while for conversion devices they focus on theoretical saving

Table 2.1 List and description of the technical components used by Cullen et al. [35] to describe the energy system. On the left conversion devices are listed while passive systems are on the right.

Conversion device	Description
Motion	
Diesel engine	Compression ignition diesel engine: truck, car, ship, train, generator
Petrol engine	Spark ignition otto engine: car, generator, garden machinery (incl. two-stroke)
Aircraft engine	Turbofan, turboprop engine
Other engine	Steam or natural gas powered engine
Electric motor	AC/DC induction motor (excl. refrigeration)
Heat	
Oil burner	Oil combustion device: boiler, petrochemical cracker, chemical reactor
Biomass burner	Wood/biomass combustion device: open fire, stove, boiler
Gas burner	Gas combustion device: open fire, stove, boiler, chemical reactor
Coal burner	Coal combustion device: open-fire, stove, boiler, blast furnace, chemical reactor
Electric heater	Electric resistance heater, electric arc furnace
Heat exchanger	Direct heat application: district heat, heat from CHP
Other	
Cooler	Refrigeration, air con.: industry, commercial, residential
Light device	Lighting: tungsten, fluorescent, halogen
Electronic	Computers, televisions, portable devices

Passive system	Description
Vehicle	
Car	Light-duty vehicle: car, mini-van, SUV, pick-up
Truck	Heavy duty vehicle: urban delivery, long-haul, bus
Plane	Aircraft: jet engine, propeller
Ship	Ocean, lake and river craft: ship, barge, ferry
Train	Rail vehicle: diesel, diesel-electric, electric, steam
Factory	
Driven system	Refrigerator, air compressor, conveyor, pump
Steam system	Medium temperature application: petrochemical cracker, reaction vessel, cleaning facility
Furnace	High temperature application: blast furnace, arc furnace, smelter, oven
Building	
Hot water system	Fuel and electric immersion boilers
Heated/cooled space	Residential/commercial indoor space
Appliance	Refrigerator, cooker, washer, dryer, dishwasher, electronic devices
Illuminated space	Residential/commercial indoor space, outdoor space

potentials with an additional cursory attempt made to estimate technical limits for conversion devices, using a heuristic metric based on Finite Time Thermodynamics [37]. They also categorise energy losses according to the loss mechanism that generates them. A Sankey diagram summarising the analysis' results is shown in Figure 2.1. They show that by pushing passive systems to their technical maximum efficiency 73 % of primary energy could be avoided, with most savings found in light duty vehicles and thermal comfort in buildings where savings of over 90% were identified. For conversion devices, the theoretical savings would amount to an 89% reduction in energy demand, with biomass burners and coal power plants identified as the devices with the most promising energy saving potential. When combining the cursory estimate of the conversion device technical efficiency limit and the technical efficiency limit of the passive system, they estimate that 85% of primary energy could be avoided. This analysis was the first to compare the saving potential of all possible efficiency measures in a physically consistent way and has proven to be a useful framework for assessing efficiency measures.

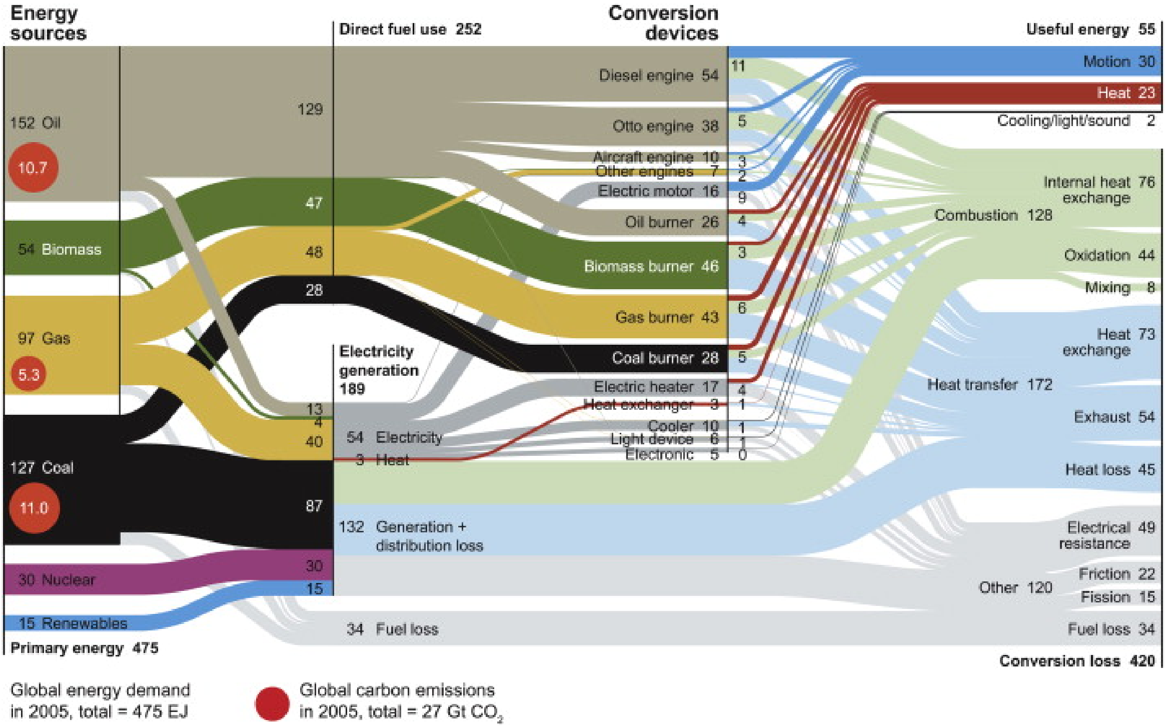


Fig. 2.1 Sankey diagram showing the global map of exergy flows and losses from source to useful energy. Taken from Cullen and Allwood [36]

2.1.2 Looking ahead: proposed research question

One of the aims of Cullen and Allwood's work was to support and stimulate decision makers to prioritise policy action among different technologies . The results of the study represent an important stepping stone in this direction especially thanks to the development of a framework that links specific engineering parameters to global emission reductions. This thesis focuses on the role of the different conversion device technologies as tools to mitigate climate change. The "role" of different end-use technologies is assessed using their energy and CO_2 emission savings potential as well as other impacts on the wider energy system. Since the focus is on conversion devices, rather than on the entire energy system, this thesis will delve deeper into methodological aspects and advance the technological detail of the framework used.

The structure of the literature review provided in this chapter it is based on four aspects of Cullen's framework that should be improved upon in order to advance this analytical framework and to make it more fit for the purpose for analysing of end-use conversion devices.

1. The study is based on the best available data on global energy end-uses available at the time. However, this data is rather unreliable (as stated by the authors' themselves) due to the lack of availability of end-use efficiency statistics at a global level. Therefore, to increase the robustness of the important results of this analysis, it is necessary to further understand the quality and uncertainties associated with end-use energy data.

2. While theoretical energy saving potentials offer an initial idea of the relative importance of different efficiency technologies, technical saving potentials are better suited to the task of prioritising action among technologies and to define upper efficiency limits in energy models. Therefore, to increase our understanding of the potential role that different end-use conversion devices could take, it is necessary to define the technical efficiency limits of conversion devices.

3. The analysis assumes an energy system structure fixed at the year 2010, meaning that the conclusions drawn do not take into account the major trends that will affect future energy systems (decreases in traditional biomass use, less coal based electricity generations etc.). Therefore, to make the results more relevant to decisionmakers, different energy futures are considered when estimating the energy saving potential associated with each end-use conversion device.

4. Describing the relative importance of the different technologies is not enough to steer decisions towards technologies with the highest potential if decision-makers are not aware of the current allocation of efforts in energy technology. Therefore, a method to quantify current innovation activity for different energy conversion devices is be developed

2.2 Quality of end-use efficiency data

The aim of this thesis is to understand the potential role of end-use conversion efficiency as a tool to mitigate carbon emissions. The first step in this analysis focuses on the availability and quality of information and on the way Final energy is used across the economy. Two types of information are required for this analysis. First, data on the quantification of the end-uses of energy, that is, how much Final energy is used to provide: space heating, space cooling, water heating, cooking, motion, material processing? Second, data on the end-use conversion efficiency is required, or in other words, information on the efficiency with which Final energy is converted into Useful energy for each end-use. Wilson et al. [34] have identified the lack of reliable and available data and indicators on energy-end uses as one of the reasons for the marginalisation of demand side measures compared to supply side ones. Therefore, the aim of this review is two-fold. Firstly, the sources and methods for end-use consumption and end-use efficiency are explored; secondly, literature on the quality of energy data and literature on methods to assess the uncertainty of energy metrics is reviewed. Sections 2.2.1 and 2.2.2 review sources of data on end-use consumption and efficiency respectively, while section 2.2.3 review uncertainty in energy system studies and in other fields.

2.2.1 End-use energy statistics

The main reason behind the the collection of end-use energy statistics by academics, statistical offices, and energy companies to better understand the drivers of energy demand. Knowing how energy is consumed is necessary in order to understand how overall demand is likely to evolve and what actions can be taken to modify such demand. Another role of end-use energy demand statistics is for the development of granular efficiency indicators such as metrics representing the space heating requirements of dwellings, measured in kWh of space heating per m^2 [44]. In general, statistical offices can justify the costs of gathering this extra data on energy end-uses by weighing the costs against the avoided costs associated with poor policy design and evaluation.

Currently, several national and international statistical offices offer national level statistics on how energy is used. In the UK, these are published annually in the UK energy consumption statistical digest [45] which is put together by the detpartment for Business, Energy, and Industrial Strategy (BEIS). This data is used for modelling purposes and to inform policy-making, as was done in the 2016 “Next steps for UK heat policy” publication to identify the extent of heat demand in the UK economy [46]. In the USA, end-use energy consumption statistics are published in the Annual Energy Outlook [47] compiled by the Energy Information Agency. They are based on three surveys, one per main sector, conducted every five years. Several other OECD countries publish regular end-use consumption statistics such as Germany [48], New Zealand [49], and Canada [50].

International organisations also provide end-use energy consumption statistics. Enerdata provides information for the 28 EU member countries using both direct national surveys and its in-house energy model (funded through the EU grant ODYSEE-MURE [51]) for countries that don't have regular surveys. The IEA publishes a yearly report on end-use energy consumption for its member countries. In 2014, 14 countries provided end-use breakdown [52] while in its 2018 edition 27 countries are reported [53]. Therefore, there is wide availability of end-use energy statistics at national and global level. However, unlike for Primary and Final energy data collection, the collection procedures and methodologies are not standardised. In the following section, the methods used to collect end use data are reviewed.

Collection methods and data quality

National statistical offices use different methodologies to estimate national level consumption statistics. Since the reliability and accuracy of end-use statistics depends on the data gathering methodology, it is important to review these methods to understand their reliability. In this section, the four types of methods are listed and for each, at least one real world example is provided.

- **Metering/Auditing** a breakdown of end-use energy can be measured directly by installing sub-metering equipment in buildings. This enables a high resolution understanding of energy use by each type of appliance and end-use. In the residential sector, these studies are conducted by selecting a sample that is representative of the housing stock both in terms of building type, geographical distribution, and inhabitant demographics. Sample sizes are usually in order of a few hundred houses, for example, in Sweden 400 household were surveyed [54] and 250 household were surveyed in the UK [55]. Data is collected on the energy use of each appliance in a household making use of electrical metering equipment (mostly wattmeters) [56]. Internal and external temperatures are also recorded for the estimation of space heating consumption. The duration of the metering period varies from one month up to one year. De Almeida et. al [57] have collected data following this methodology on the electricity consumption of 12 EU countries within the framework of the EU funded REMODECE project. Isaac et al' [58] have monitored 200 households in New Zealand for a ten year period to obtain electricity and fuel consumption data for the country's residential sector.

Gas consumption is easily retrieved from standard gas meters used for billing purposes, however, in cases where gas is used for multiple uses splitting the house-level gas consumption into cooking, hot water and space heating can be difficult. Therefore, these statistics rely either on engineering models [59] or on questionnaire based surveys [60].

In the industrial sector, this type of collection methodology is known as an energy audit, where the performance of equipment and processes are measured by visiting experts. While there are several benefits to this methodology, costs are high, meaning that the sample size and frequency of the metering are often low [61].

- **Direct Survey** End-use energy breakdowns can be estimated using a survey that directly asks for the breakdown. This method assumes that the respondents are technically literate and have access to detailed data on their energy consumption. Therefore, this methodology is only relevant to the industrial sector and possibly to buildings that employ an energy manager or an energy management system. One examples of this method is the Manufacturing Energy Consumption Survey carried out in the USA where detailed questionnaires on energy consumption are sent to a sample of 15 000 manufacturing facilities [62].

- **Engineering Models** Engineering models require information on a representative sample of buildings or of industries and a calculation method to estimate the breakdown of energy consumption. The input data requires quantitative information on building physics (e.g. U-values, floor area, type of process technology) and energy using equipment. The detail and accuracy of the physical model is constrained by the resolution of information provided by the resolution of the stock survey [63].

  This method is used for the UK residential and commercial end-use statistics. The housing model uses a bottom-up, physical, housing energy consumption model based on Standard Assessment Procedure 2009 calculations [64]. The model uses data from the English Housing Survey [65]: a stratified random sample of around 15 000 English dwellings conducted annually. For commercial buildings the allocation of energy consumption to the various end-use allocations is completed with the results of the Building Energy Efficiency Survey [66]. The survey is based on 4 084 telephone interviews and 284 site visits of non-residential buildings sampled across the UK. The engineering model estimates energy consumption by associating each area of the building to a "space type" which in turn is linked to a specific end-use consumption profile. Information about the building's space type and efficiency of equipment is determined in the phone interviews [67].

For the industrial sector, engineering models break down energy consumption by end-uses based on industrial equipment and process stock and efficiency. These models are usually not based on public surveys but instead are either informed by propriety databases [68] or by ad hoc academic studies carried out for each industrial process [69].

- **Statistical Models** This method is similar to the method described above in terms of data requirements and quality. However, instead of calculating the energy consumption based on physical relationships, a regression analysis between input variables and end-use consumption is used. The regressions are calculated using historical data [70] on energy end-uses.

  In the USA, statistical models are used to determine energy consumption for each end-use based on the Residential Energy Consumption Survey [71]. The survey collects data on the type of equipment in each household as well as on question about typical energy use (i.e. how many times a week the microwave is used). This information is then used as inputs to the statistical model. A similar methodology is used for the Chinese Residential Energy Consumption Survey [72]

  In the German Industrial Energy use survey, statistical models are used to obtain cross-cutting energy requirements such as lighting or space heating starting from available data on number of employees or floor area of industrial facilities [73].

The methods and sample sizes used to estimate the breakdown of energy end-uses have an impact on the reliability of the resulting statistics. Direct measurements, audits and surveys provide more reliable estimates since the consumption values are measured directly. However, the large time requirement and cost of each measurement mean that sample sizes are much lower, thus reducing the statistical significance of the results. Although the cost of networked sensors is decreasing rapidly, engineering and statistical models based on surveys conducted remotely or based on existing data (housing surveys) enable much larger sample sizes but at the cost of introducing modelling errors and uncertainty.

The resulting accuracy of these studies ranges from ± 10% (for national level estimates of large energy end-uses) [64] to ± 80% for sub-sector level estimates [74]. Reliability and uncertainty of the data is mentioned in most statistical documentations, yet, only few report uncertainties (or at least sampling errors) consistently. This lack of systematic uncertainty assessment undermines the robustness of the end-use statistics and of the studies using these statistics.

In this review of end-use energy consumption data collection methods, the UK stands out for the availability of data sources and for the quality of the documentation published making it an ideal subject of study.

2.2.2 End-use efficiency statistics

The review of examples of end-use energy consumption statistics and the methods employed for their collection shows that such statistics are regularly compiled across several jurisdictions and that their collection methods are deemed sufficiently reliable. The situation for end-use energy conversion efficiency is rather different. In fact, there are no systematic statistical collections of these parameters. In the past, energy agencies and scholars have estimated end-use conversion efficiency statistics in attempts to estimate Useful energy consumption. In this section the concept of Useful energy is further expanded upon and previous work on the estimation of this metric is provided.

Useful Energy

Since the 1970s, academics [75] have argued in favour of measuring Useful energy, for its use as an energy indicator. Useful energy is now used in energy demand modelling at various levels. For example, it is used at a global level in the World Energy Model [76] and at a sectoral level (industry) in the UK [77]. The metric is also often used in facility level analyses [78], especially for air conditioning systems where end-use efficiencies of different technologies have large variations [79].

However, Useful energy consumption is seldom measured directly because it would require the measurement of efficiency and consumption for each of the various energy-using devices. In addition, no monetary transaction is usually involved with the conversion from Final to Useful energy, therefore its estimation cannot be based on existing accounting practices as is the case for Final and Primary Energy [80]. Instead, Useful energy is calculated from Final energy statistics with the addition of two pieces of information: the split (or allocation) between end-use applications of energy, and information on the average conversion efficiency of each end-use application. Equation 2.1 summarises the simplest Useful energy calculation method.

$$U = F\ \phi\ \eta \tag{2.1}$$

where U is Useful energy, F is Final energy, ϕ is the allocation vector that contains information on the split of energy end-uses, and η is the average conversion efficiency.

The European statistical office (EUROSTAT) attempted to estimate Useful Energy balances for member countries in the period between 1975 and 1988 [81, 82]. The allocation of energy to various end-uses was completed for three broad sectors (Industry, Transport and Buildings) using proxy data such as surveys of energy uses, the physical form of the energy products and expert knowledge of the energy uses in each sector. The average efficiencies were determined for about 30 devices based on unspecified “studies published by energy technicians and engineers”. More recently, Useful energy accounts have been compiled at a European level [83, 84], but only for the provision of space heating and cooling.

Outside Europe, the Brazilian ministry for mines and energy commissioned Useful energy analyses for the years 1984, 1994 and 2004 [85]. These studies had two aims: first to analyse separately the structure of energy consumption and the development of energy efficiency; and second to compute the energy saving potential from improved conversion efficiency. The authors employed various government-led surveys to assess the allocation of energy to end-uses while conversion efficiencies were estimated directly by the authors (without a clear methodology). Both these studies are well documented and analyse the entire energy system, but unfortunately they have been discontinued.

De Stercke [86] compiled a database containing estimates of Useful energy and Useful exergy for 15 countries in the period between 1960 and 2009. He employed IEA data as a starting point and used estimates by Nakićenović in 1996 [87] on the split of energy consumption to the various end-uses, whenever country specific data was unavailable. Data on conversion efficiencies found by past studies was used to define an empirical exponential function relating the efficiency of various devices with GDP to fill the gaps for years and countries without available data. This study has the benefit of providing a time series of Useful energy consumption for a group of countries, however gross approximations were required to fill the large data gaps present in terms of conversion efficiency and energy end-use split.

There are currently no official Useful energy balances being published by governmental agencies. One of the reasons for this discontinuation in Europe and in Brazil is the uncertainty associated with the estimates. In fact, as early as in 1979, the statistical review of UK energy stated estimates of Useful energy were desirable, but they were not published because they were deemed too unreliable [88]. However, official statistics on the breakdown by energy end-use, one of the key ingredients for Useful energy calculation, are currently widely used and deemed sufficiently reliable, as was discussed in the previous section. However, the uncertainty of the conversion efficiency component in equation 2.1 was not discussed quantitatively in any of the reviewed studies.

Useful Exergy

One field that has expanded the concept of Useful energy is field of societal exergy analysis, which aims to characterise the energy efficiency of societies at different scales, sectoral, national and global [89]. Exergy, is a thermodynamic measure of the available work in an energy stream, and in practice, it devalues heat energy according to the temperature, following Carnot's Law. Exergy instead of energy is used because it is believed to further describe the quality of energy consumption compared to energy metrics as described by Hammond and Stapleton [90]. Ertesvaag has compiled a comparison of estimates of the overall Primary to Useful exergy efficiency for different societies and shown that they range between 10% and 30% [91]. Cullen estimated exergy efficiency at a global level and found an efficiency of 11%. Useful exergy has also been used in the field of Energy economics. Aryes [92] has explored the impact of Useful energy on economic growth in the USA claiming that the addition of Useful exergy time series can better explain economic growth compared to the traditional economic production factors of capital and labour. Brockway has used a similar approach to study the interrelations between energy consumption, exergy efficiency and economic development in the UK, USA, and China [93]. Sakai et al. [94] used an economic model where exergy efficiency accounted for explicitly to claim that thermodynamic efficiency gains have contributed to 25% of the UK's economic growth between 1971 and 2013.

Different methods are used in this field to estimate Useful Exergy and the differences are well summarised in a recent review paper by Sousa et al. [89]. Equation 2.2 describes how the total Useful exergy of a society (E_U) is calculated [95],

$$E_U = \sum F_{sfe}\ \eta_{sfe}\ \varepsilon_{sfe} \tag{2.2}$$

where η is the end-use conversion efficiency, ε is the exergy factor and F is Final energy. The index s,f,e refer respectively to the sector, fuel and end-use of energy. This equation contains one further efficiency term (ε) compared to the standard Useful energy estimation method shown in Equation 2.1. Cullen and Allwood [96] argue that better insights are available by distinguishing the technical sub-systems that form the energy system. To this end, they introduce the concept of "conversion device" and "passive system". Since conversion devices are well defined technical systems, it is easier to estimate their efficiency as well as their improvement potential [97]. According to their framework, Useful exergy is therefore better estimated as shown in equation 2.3,

$$U = \sum F_{sfd}\ \eta_{sfd}\ \varepsilon_{sfd} \tag{2.3}$$

where all symbols retain their meaning and index d refers to the conversion device undertaking the energy conversion.

The Useful energy/exergy results obtained in this field are often affected by the lack of robustness and reliability dictated by the numerous assumptions and estimates required. The following issues affect the reliability of the results.

- The allocation to end-use applications is often performed by a combination of data and educated guesses, without systematic and comparable methodology being put in place.
- The estimation of average conversion efficiencies employed are often quoted from previous work with minor adjustments made for changes over time. There is little focus on efficiency data gathering while there is a lot of reliance on expert judgement.
- The calculation of the exergy factors for each end-use requires estimates of average environmental and process conditions. However, there is very limited information on the average temperatures of the various processes.

While these issues have been recognised by members of the research community [89], there has been no attempt to quantify the uncertainty of the assumed end-use conversion efficiencies. Given the recent use of thermodynamic efficiencies in economic models made by this research community and the increasingly bold claims made on the importance of conversion efficiency, a scrutiny of the underlying efficiency data has become of paramount importance.

Energy Modelling

Another source of end-use efficiency data is found in the literature behind large energy models which require this data to simulate and forecast future energy systems. The US NEMS publishes “assumptions” documents containing the assumed performance of end-use appliances in buildings and industry. The publication “Updated Buildings Sector Appliance and Equipment Costs and Efficiency ” [98] was produced at regular intervals between 2011 and 2018. This publication includes the efficiency of most appliances and has estimates that date back to 2005. The data sources for these estimates are mostly manufacturers associations and the Office of Energy Efficiency and Renewable Energy.

Other technology rich models, such as those using the TIMES/MARKAL modelling framework need to make assumptions on end-use efficiency. In the documentation for the UK-MARKAL [99] states:

> energy services were calculated using typical efficiency of demand technologies and appliances

However, the assumed efficiencies are not shown in the documentation and this exercise is only done to calibrate the reference year of the model and is not regularly updated. The global optimisation model TIAM-UCL provides the efficiency assumptions for all assumed technologies [100]. However, again these are only provided for a base year and no information on how the values were chosen is provided.

In transport sector models, efficiency is tracked using fuel economy metrics (MPG, l/100km) which are overall equipment metrics (conversion device and passive system). Engine efficiencies are not quoted directly in the modelling literature. However, Thomas et al have attempted to quantify the average efficiency of new US vehicles sales from 2005 to 2013 [101] and in 2017 [102] by combining the fuel economy measurements with coast down data, both published by the EPA. They found that improvements in engine efficiency were occurring and estimated that in order to achieve the required targets efficiencies currently observed in hybrid vehicles are required.

Cullen and Allwood criticise the aggregation of conversion devices and passive systems into a single metric, as this hides what is often diverging trends in the individual efficiencies. Current trends in the transport sector as perfect examples for their critique. In fact, engines are increasinly more efficient, but the larger size of vehicles nearly offsets this trend. Furthermore, the technical solutions to improve efficiency in conversion devices (e.g. combustion, heat recovery) are completely different from those in the passive systems (e.g. aerodynamics, tyre friction).

2.2.3 Uncertainty in Useful energy estimates

This review shows that end-use energy consumption statistics are increasingly available and that uncertainty is often quantified, albeit with varying methodologies. On the other hand, end-use efficiency estimates are not the subject of regular estimation by government agencies (with the exception of US building sector) but rather are mostly guessed by modellers and academics. High uncertainty in the estimates is always quoted when referring to these data, however, no example of the quantification or the effective treatment of this uncertainty was found in the literature. The danger of the current practice is that end-use consumption and efficiency statistics might be used for policy analysis and formulation as if they were just as reliable as traditional (Final and Primary) energy statistics, when they might not be. In the following section, the concept of uncertainty in energy studies is explored and lessons are drawn from uncertainty treatment in the field of Material Flow Analysis.

Uncertainty in energy models

Energy models are composed various data inputs, assumptions and mathematical relationship that enable the processing of large quantities of information in a way that can support decision making. Uncertainty is present in every step of the modelling process [103]. One of the first widely used frameworks to characterise the uncertainty of environmental models was the NUSAP methodology developed by Van der Sluijs[104] which proposes to both quantify the uncertainty of each parameter but also to consider the Pedigree [105], or the data quality behind the uncertainty estimate, thus combining quantitative and qualitative approaches. Walker et al. [106] propose a taxonomy to characterise uncertainty and ease communication that is currently widely used in the academic community. They define three dimensions of uncertainty: (i) the location of uncertainty, where in the model uncertainty is present; (ii) the level of uncertainty, representing the intensity of uncertainty; (iii) and the nature of uncertainty, which distinguishes between two inherently different types of uncertainty (Figure 2.2). The nature of uncertainty is of two types, *epistemic* or *ontic* (Walker uses the term *variability* instead of *ontic* but other sources mostly uses the latter term). Epistemic uncertainty refers to the imperfection of knowledge about the true value of a parameter and can therefore be reduced by further research. Ontic uncertainty refers to the inherent variability of a process which could be physical (e.g. future weather) or social/behavioural (eg. future GDP growth).

Location				
Context	Model structure	Inputs	Parameter	Model outcome

Level				
Determinism	Statistical Uncertainty	Scenario Uncertainty	Recognized Ignorance	Total Ignorance

Nature				
Epistemic Uncertainty		Variability Uncertainty		
Reducible	Irreducible	Behavioural	Societal	Natural randomness

Fig. 2.2 Figure showing the components of the uncertainty matrix developed by Walker et. al [106]. The terms in bold represent the three dimensions of uncertainty: Location, Level and Nature. Each dimension is composed of the different categories shown in the figure.

Various levels of uncertainty assessment have been deployed in sector level analysis, including: Integrated Assessment models (IAMs), energy models, building models and transport models.

- A thorough review of uncertainty in integrated assessment models (which include energy models) was conduced by Gillingham et al [107]. They identified that parameter uncertainty is much more relevant than model uncertainty within IAMs and noted that uncertainty is routinely analysed within IAMs. Interestingly, Lemoine et. al [108] find that in IAMs policy evaluations are more sensitive to the uncertainty associated with energy technology breakthroughs and on damage functions rather than on climate uncertainty, thus confirming the importance of increasing the robustness of energy models. Yue et al. [109] reviewed uncertainty analyses in energy optimisation models. They identify four main methodologies and identify model uncertainty and input uncertainty to be often downplayed or ignored even though the literature often identifies these as important issue for the robustness of the model outputs.

- Uncertainty in the building sector is reviewed by Kacgic et. al [63] which identifies the key issue of lack of transparency in the inputs and assumptions made in physics based energy models as well as on the end-uses of energy consumption. Booth et. al [110] propose the use of a Bayesian approach to better quantify input parameter uncertainty. Both articles highlight the fact that while physical bottom-up models in the residential sector tend to be superior to economic based top-down models, they suffer from a worse treatment of uncertainties, mostly due to the large number of parameters involved. In fact, top-down residential models tend to assess uncertainty at the calibration stage [111]. One exception is found in Moret et al. [112], where the uncertainty of a technology rich bottom-up model is fully characterised through a newly developed methodology. In this study a colossal 559 uncertain parameters were identified in a model which only covered the Swiss energy system, which shows the complexity of full uncertainty characterisation in technology rich assessments. This is also one of the very few studies where conversion efficiency uncertainty is transparently quantified.
- In the transport sector, stochastic methods have been proposed and used to estimate stochastically emissions and energy consumption in a way that enables a transparent evaluation of uncertainty. Bastani et al. [113] developed a stochastic model of the US light duty fleet and identified that the parameters for which the uncertainty has a critical effect on the decision making process are: vehicle scrappage rate, annual growth of vehicle kilometres travelled, total vehicle sales, and fuel economy of ICE vehicles. More recently, Martin et al. [114] has produced a stochastic model of the UK light duty fleet taking into account detailed vehicle design parameters to project the likely consumption of the UK fleet in 2020.

A common feature of most of the literature dealing with uncertainty in energy models is that they focus on the uncertainty associated with the future state of the energy system. The uncertainty associated with the inputs to the model about the reference year are systematically ignored. Walker et al. justify this in their founding work: talking about statistical uncertainty (relevant to model input uncertainty) they say [106]

> [..] deeper forms of uncertainty supersede statistical uncertainty, and statistical uncertainty should not be accorded as much attention as other levels of uncertainty in the uncertainty analysis.

Similarly Culka [115] claims that uncertainty about the future state of the energy system is more important than the one about the current state of affairs.

> A typical energy model incorporates physical facts, for example, stocks of electricity generation capacity within system boundaries, storage capacities, electricity or gas grid infrastructure information, car stock, and the like, depending on the scope and aim of the energy model. These facts (at least for the base year or calibration) face uncertainty to a lesser extent than other assumptions. A more delicate issue are "facts" about the future.

Uncertainty in energy data These statements are correct within the field of energy modelling and it is justified to focus on larger uncertainty sources. This lack of focus from the energy modelling community has left the analysis of uncertainty of energy statistics vastly unexplored. Macnick [116] contributed by highlighting the lack of attention given to uncertainty in energy statistics published by international organisations and stated that this might undermine the credibility of studies that employ this data. At the same time it must be said that the long established practice of Primary and Final energy accounting by governmental agencies in the developed world means that statistical differences in energy balances are always below 0.5% and that the uncertainty associated with these estimates is deemed to be less than 5% [117, 118]. As noted in section 3.1.1, the same cannot be said of end-use statistics and even less so about Useful energy statistics. Therefore, it can be concluded that the analysis of uncertainty in end-use energy statistics is a clear research gap.

Uncertainty in material flow analysis

Material Flow Analysis (MFA) is one of the core tools used in the field of Industrial Ecology. In MFA studies, the mass of material flows are tracked through a technoeconomic system which could be a country, an industry or a supply chain. Examples include the tracking of global steel flows [119], the study of all materials flowing through a specific industrial area [120], or the analysis of the supply and use of rare-earths across Europe [121]. Since MFAs do not benefit from the long history of accounting practices and methodologies available to energy studies, therefore this field pays close attention to the current material accounts and the quality of the data available. For this reason, the field has used existing theoretical frameworks and developed tools to assess the uncertainty of their methods and data sources [122].

As discussed above, uncertainty can be of two types: epistemic or aleatory. The former refers to uncertainty due to lack of knowledge about the true value of a parameter, while the latter refers to the uncertainty due to the intrinsic randomness of a phenomenon . For both energy and material accounts, uncertainty is solely epistemic since energy flows in an economy have one true value, but there is uncertainty about this value due to knowledge imperfection. Conventional (frequentist) approaches to uncertainty quantification and analysis [123] are less relevant here because they focus on repeatable processes such as measurements in experiments or survey answers. In contrast, the collection of national level energy statistics is a non-repeatable process. “Single-sample” uncertainty assessment techniques have been in use since the 1950s [124] and aim to quantify the uncertainty of a given non-repeated measurement, but depend on empirical techniques such as auxiliary calibration experiments. These have no equivalent in assessing uncertainty in national statistics, where uncertainties are quantified through techniques such as expert elicitation and pedigree matrices. Therefore, the best way to analyse the uncertainty of this type of data is through a Bayesian framework using Monte Carlo methods [125].

In a Bayesian framework, the uncertainty of a parameter is defined using probability distributions representing the degree of belief about the accuracy of that parameter. Bayesian approaches have been gaining momentum in studies that analyse the uncertainty of highly aggregated systems. For example, this theoretical framework is used in national and global level material flow analyses. Laner et al have reviewed many possible techniques for uncertainty evaluation of MFAs [122] and developed a framework for data quality evaluation and uncertainty propagation which is based on the quantification of prior knowledge using a Bayesian framework [126, 127]. Gottschalk et al [128] discussed a Bayesian approach to MFA, and Cencic and Frühwirth [129] applied this to data reconciliation for simple linear models. Lupton and Allwood have introduced a general recipe for the application of the Bayesian framework to MFA and applied it to the global steel supply chain [130]. Interestingly, also the techniques prescribed by the IPCC for GHG accounting are based on a Bayesian framework since governments are asked to provide confidence intervals for their emission estimates [131].

In summary, two lessons can be drawn from a review of MFA literature on the topic of data uncertainty. First, the best theoretical framework to quantify material and energy statistics is the Bayesian framework. Second, there are numerous methodologies available to formalise the assessment of “single-sample” uncertainty. Therefore, these two lessons need to be simultaneously applied in the assessment of the uncertainty of end-use energy statistics.

2.2.4 Research Gap

The first step towards an assessment of the future role of end-use conversion efficiency is to establish the availability of data with sufficient quality. This review has shown that Final end-use energy statistics are available to policymakers and that they are deemed sufficiently reliable. Useful energy estimates do not enjoy the same widespread use. While there have been attempts in the past to compile Useful energy accounts, the difficulty in collecting end-use conversion efficiency data has led to a discontinuation of this process. Some scholars have continued the study and development of national level end-use efficiency estimates, but these studies lack any quantification of the uncertainly associated with their estimates. The UK energy system has been the subject of numerous studies and has high quality and well documented end-use energy statistics. Yet, even for the UK, Useful energy uncertainty remains unquantified. This gap can be filled by answering the following research question:

> **Q1: What is the uncertainty of Useful energy consumption statistics in the United Kingdom?**

This review has also shown that the field of Material Flow Analysis has developed a number of techniques to quantify uncertainty for their material balances which could be applied to the study of energy balances. Therefore, it is proposed to fill this research gap by transposing some of these existing methods from the field of MFA to the one of Useful energy accounting. This question is addressed in chapter 3.

2.3 Efficiency limits and conversion devices

To quantify the impact that conversion efficiency improvement can have as a climate mitigation tool it is necessary to first understand the technical limits to efficiency improvement. This review is composed of two parts. First, different ways in which scholars have defined energy saving potentials and efficiency limits are reviewed. Second, the distinction between conversion devices and passive systems is explained in detail and subsequent uses of this framework are reviewed.

2.3.1 Energy saving potentials

An Energy Saving Potential (ESP), is the amount of energy that can be saved by increasing the current efficiency of a system to a higher target efficiency. Therefore, any energy saving potential is directly proportional to increases in efficiency. Understanding and quantifying ESPs is necessary to enable the comparison between demand side measures and supply side ones. Different ESP, can be calculated according to the target efficiency of interest. Rogner, in the 2000 UNDP World Energy Assessment report [132], provides a comprehensive definition of five type of potentials: theoretical, technical, societal, economic and market trend. A similar list of saving potentials is given by Jaffe and Stavins [133] in their 1994 article on the energy efficiency gap. A summary of the given definition of the five types of potentials is given below.

- **Theoretical potential** represents the minimum allowable use of energy for the provision of a given energy service.
- **Technical potential** represents the energy that could be saved by employing the best commercially available, or near commercially available technology, irrespective of cost considerations.
- **Societal potential** includes all energy saving measures that would make society as a whole better off. This includes the externalities linked to energy use (i.e. savings associated with a fair carbon price).
- **Economic potential** refer to the savings that could be achieved while still being profitable for firms and individuals ignoring the costs associated with externalities.
- **Market trend potential** indicates the savings that are likely to be achieved by stock turnover and substitution since new products tend to be more efficient than older ones.

Economic potential

An economic energy saving potential refers to the amount of energy that can be saved through energy efficiency improvements at a zero net cost, that is, with investments in efficiency that can be repaid through the monetary savings resulting from lower energy costs over a defined payback period. Conversely, the economic efficiency limit is the efficiency that can be reached without a net loss of financial resources.

According to neoclassical economists, economic saving potentials exists because markets deliver sub-optimal efficiency (through under-investment in efficiency technologies) due to market and behavioural failures. A market failure is an inherent fault in the market that causes it, when unregulated, to allocate resources inefficiently. Behavioural failures occur when agents fail to make rational choices (i.e. profit maximising for firms and utility-maximising for consumers) [134, 135]. The difference between the observed market driven trend in efficiency and the optimal economic efficiency is called the "energy efficiency gap" [133]. Some economists challenge this view by claiming that there are hidden costs that are not accounted for in economic analyses, which would justify the lower uptake of efficiency measures in the market [134]. Work by Rohdin and Thollander [136] and Sorrell [137] has helped to describe the mechanisms that cause sub-optimal efficiency levels. Their work includes the "hidden costs" mentioned by other economists, yet they highlight a number of market and non-market failures that warrant the existence of the efficiency gap and therefore the need for government policy to intervene. Policy actions aimed at fixing these market failures (such as mandatory energy labelling or mandatory energy audits) are therefore expected to increase overall energy efficiency at minimal costs to firms and consumers.

Yet, the level of energy efficiency that is optimal from the point of view of individual firms and consumers is often lower than the one that would maximise the welfare of society as whole. This is because energy consumption is associated to negative externalities [138]. Externalities are costs that are associated with a certain action but that are not reflected in the cost of the action [139]. Therefore, if the costs of mitigating the externalities of energy use were internalised in energy prices, higher overall energy efficiency would result [134]. The consequences of this theoretical framework mean that governments can rightfully attempt to internalise these costs to the energy price, for example by means of energy or carbon taxes, with the aim of stimulating more investment in energy efficiency.

The grey literature contains several estimates of economy-wide economic energy saving potentials estimated for each sector that have been used to inform decision makers– a list of high profile examples are shown in Table 2.2.

Table 2.2 List of recent bottom-up studies commissioned by governments with the aim of estimating energy saving potentials.

Author	Title	Year	Region	Sector	
Energy Saving Trust	Review of potential for carbon saving from residential energy efficiency	2013	UK	Residential	[140]
McKinsey	Capturing the full electricity efficiency potential of the UK	2012	UK	Power Sector	[141]
Fraunhofer ISI	Study on the energy saving potential in EU member states	2009	EU	All	
ICF International	Study on energy efficiency and energy saving potential in industry and on possible policy mechanisms	2015	EU	Industry	[142]
McKinsey	Unlocking energy efficiency in he US economy	2009	US	All except Transport	[143]
ENERGETICS	Bandwidth study on energy use and potential energy saving opportunities in US Industry	2014	US	Industry	[144]

These types of analyses are often the foundation for policy making in the field of energy efficiency since governments look for policy mechanisms that will increase efficiency while minimising the impact on the economy. In these reports, the barriers to efficiency investment are identified, and the impact of possible policies on the energy efficiency of specific sectors is quantified. Therefore, some of the most important energy efficiency policy decisions, such as energy consumption reduction targets and minimum energy performance standards [145], are based on reports that calculate the economic saving potentials.

These studies are useful for short term policy and strategic decisions since they help decision makers prioritise action that will yield incremental improvements. At the same time, the conclusions drawn from these studies can be misleading within the context of climate change mitigating policy. Policies for climate change require a long-term perspective and ambitious targets rather than incremental change, as outlined in every iteration of the IPCC's assessment report. For this reason, limiting the analysis to current economic cost structure and technology performance is not desired. History has shown that technical efficiency has rapidly increased over the past century [146, 147], and that what was considered to be Best Available Technology at one point in time can quickly become a common performance level [148]. Equally, over the long term both the economic structure and the energy system structure can change. Savings estimated by extrapolating the current energy system might never be realised – if a technology is superseded by a superior one –or be heavily underestimated, if the future improvement of a technology is underestimated.

Theoretical potential

On the other end of the spectrum to economic saving potentials are the theoretical saving potentials. These are calculated using theoretical efficiency limits which refer to maximum conversion efficiency limits, dictated by laws of physics. These limits are absolute and are defined by derivation of well proven physical laws. Examples of theoretical limits are the Betz limit [149] – concerning the maximum efficiency of wind power – and the Shockley–Queisser limit, defining the maximum efficiency of solar photovoltaics [150]. The most notorious and widely used theoretical limit is the Carnot limit, which stems from the second law of thermodynamics and determines the maximal efficiency of a heat engine operating between two temperatures (T_l,T_h) [151].

$$\eta_C = 1 - \frac{T_l}{T_h} \tag{2.4}$$

In the 1970s, the field of finite time thermodynamics has attempted to provide more "realistic" efficiency limits compared to the Carnot efficiency by removing the infinite process time embedded in reversible processes [152]. This technique has been used to study several engineering processes such as heat engines and refrigeration cycles [153–156]. One of the main outputs of this field is the introduction of the Curzon–Ahlborn efficiency (η_{CA}) [157] which defines the efficiency of a Carnot engine operating at maximum power output between to reservoirs at T_l and T_h as

$$\eta_{CA} = 1 - \sqrt{\frac{T_l}{T_h}} \tag{2.5}$$

Since the Curzon–Ahlborn efficiency is always lower than the Carnot efficiency some authors have misunderstood the use of this efficiency as a more realistic efficiency limit. Two recent examples of this include Muratori et al. [33] who use it to define the long term efficiency limits of power plants, and Cullen who uses it as a heuristic for the estimation of the technical efficiency limits of conversion devices [97]. This misunderstanding has been the cause of academic debate in the past [158]. In this debate, Chen et al. [159] drafted a concise explanation of the meaning of the Curzon–Ahlborn efficiency:

> the Curzon–Ahlborn efficiency is not the maximum efficiency of a heat engine but determines the lower bound on the optimal efficiency of a heat engine affected by finite rate heat transfer. [...] It is, thus, obvious that although the efficiencies of real heat engines cannot attain the Carnot efficiency, it is possible, and is often desirable, for the efficiencies to exceed the respective maximum power efficiencies.

Therefore, while the field of finite time thermodynamics offers clean models, with analytical solutions, of conversion efficiencies for several heat engines and thermodynamic cycles, it cannot be used to gain further insights on the theoretical limits of efficiency.

The field of Societal Exergy Analysis uses thermodynamic limits (Carnot) to estimate saving potentials. For example, Van Gool [160] and Hammond [161, 162] use exergy efficiency of a given process or economic sector to define an Improvement Potential which compares the current efficiency with an ideal irreversible state, represented by an exergy efficiency of unity. Therefore, the improvement potential represents the theoretical energy gains that could be obtained if all processes were operating at Carnot efficiency (for the assumed temperature levels). This approach was also used by Cullen and Allwood [97] to study the saving potential for conversion devices with the aim of prioritising action in efficiency improvements. This approach has the benefits of being transparent (as long as all assumed temperature levels are stated) and simple to implement. However, the issue of using theoretical limits to assess saving potentials is that it ignores well known loss mechanisms that make it impossible to reach the theoretical limits, for example friction losses and finite temperature heat transfer. This has two implications: firstly, the resulting saving potentials are known *a priori* to be unreachable; secondly, the analysis lacks the technological granularity needed to assess the feasibility of reaching the theoretical limit for each technology. The exploration and application of technical limits – which include practical considerations and known unavoidable energy losses – can avoid these problems.

Technical Potential

There is no shared definition of the concept of technical efficiency limit in the energy literature. However, two broad understandings of the technical efficiency limit (and therefore of the technical energy saving potential) can be identified.

In the mainstream energy efficiency literature, technical efficiency limits and technical saving potentials are defined in opposition to economic limits and savings. That is, technical efficiency limits include measures that are not cost effective. This definition is used in relation to electric motors [163], building insulation [164], and space heat demand [165]. In all of these articles, and in the wider energy efficiency literature, much attention is paid to the dynamics of energy efficiency improvements which depend on factors such as: stock turnover rates, product lifecycles, and efficient product uptake rate. These parameters are important to decision makers because they can be directly affected by regulations such as minimum energy performance standards, scrappage schemes, or energy labelling. System wide studies looking at technical potentials are less common. Letschert et al. [166] estimate the savings associated with the introduction of the most aggressive minimum energy performance standard possible in four major economies. They assume that by 2015 only the appliances with the currently best available technology can be sold and estimate that such a measure would lower energy demand by 20% compared to business as useful by 2030. The authors refer to this energy saving as a technical energy saving. However, this approach does not take into account the fact that by 2030 technologies allowing for even higher efficiencies could become available.

In research stemming from the Societal Exergy Analysis (SEA) literature, technical efficiency limits are defined in opposition to theoretical efficiency limits. Hammond [162] describes the technical limit to efficiency savings as the savings that can be achieved "*in practice*". Similarly Cullen talks about the technical potential as setting a "*target based on practical design and material limitations*" [35]. Therefore, if theoretical limits are unreachable, technical limits are reachable through technical innovation. Recent examples of this conception of the technical limit are rare. In work by Beaudreau and Lightfoot [167], authors attempt to understand the physical limitations to R&D outcomes and their impact on the limits to economic growth. To this end, they define values of efficiency beyond which further R&D efforts would not enable further gains and define the technical limits for several end-use energy technologies. The main drawback of their approach is the lack of a consistent methodology and theoretical framework to define the efficiency limit, thus the resulting estimates are purely a result of the author's expert opinion. An interesting framework to define technical efficiency limits is provided in the *Bandwidth Study on Energy Use and Potential Energy Saving Opportunities* [144]. Here, a distinction is made between two types of technical potential: the Current ESP and the R&D ESP. The former refers to the energy savings that can be achieved by complete adoption of best available technologies. The latter refers to the energy that could be saved by the deployment of all technology currently under research, which is always higher than the former because R&D activity can push the boundaries of what is currently available. In addition, this study also defines for each industrial process a "thermodynamic minimum" energy demand which can be understood as the theoretical limit. The study uses this insightful framework to define different type of saving potentials, which enables decisionmakers to visualise different levels of possible ambition, both now and accounting for future development, and to quantify the difference between the potential gains of regulation and those stemming from further R&D.

Within the context of climate change mitigation policy all possible technical efficiency improvement measures should be accounted for. Limiting the assessments to the current level of efficiency and performance results in the underestimation of the role of end-use measures. In the academic and grey literature much attention has been given to the dynamics of technical energy efficiency improvement while the maximum level of efficiency that is technically reachable has not been carefully assessed.

2.3.2 Research Gap

This literature review has shown that there are at least three ways to define efficiency limits and energy saving potentials. Among the three, the technical limits are the most informative for long term perspectives which are required in the context of climate change, yet they are those for which there the literature is least dense. Additionally, it was shown how Cullen's technique of categorising technical efficiency options into those affecting conversion devices and passive systems separately can provide some useful insights as well as provide a coherent physical basis for the estimation of energy saving potentials.

	Economic	Technical	Theoretical
Entire Sector	Gray literature Efficiency policy support	Efficiency policy support	Field of societal exergy analysis
Passive systems	Gap	Cullen and Allwood 2010	Not applicable
Conversion devices	Technology specific literature	**Gap (this study)**	Cullen and Allwood 2010 Finite time thermodynamics

Fig. 2.3 Types of energy saving potentials compared with with different disaggregation levels of technical efficiency measures. The matrix shows that there is a gap in the literature concerning the technical saving potentials of conversion devices and the economic saving potentials from passive systems. All other combinations have at least some literature covering the topic.

The information gathered in the review is summarised in Figure 2.3, where is clear that the main research gaps exist in passive system economic saving potential and in conversion device technical saving potentials. While topic of economic saving potentials of passive systems is very important due to the already identified magnitude of the technical saving potentials, this gap will not be addressed in this thesis because it would require extensive socio-economic analyses which are considered outside the scope of the thesis. Conversely, the estimation of the technical saving potential for conversion devices requires a purely engineering approach. In light of the discussion presented in Chapter 1, it is more important to focus on end-use conversion devices than upstream conversion devices because of their technological diversity and because their efficiency will always have an important effect on the energy consumption and CO_2 emissions. Therefore, the research question that can be formulated to fill this research gap is as follows

> **Q2: What are the technical efficiency limits of end-use energy conversion devices?**

2.4 Future of conversion device efficiency

As seen in Section 2.1 the saving potentials of different conversion devices was quantified by Cullen and Allwood. However, their analysis was limited by a reliance on theoretical limits and it used the global energy system in 2010 as a reference to calculate the energy saving potential. Two improvements to this analysis are proposed here. First, realising energy and carbon savings depends not only on the improvement of device efficiency, but in addition, on changes to the structure of the energy system itself. Therefore, to analyse and understand the future of conversion efficiency, it is necessary to take into account the possible changes in the energy system. Second, the prioritisation of actions to address climate change includes investments in Research and Development (R&D) which should be aligned to the saving potential of each technology. Therefore, it is required to provide a metric for current R&D efforts in energy efficiency. This section provides an overview of how different fields extend their analyses into the future, then the main energy models are reviewed to identify how end-use conversion efficiency is characterised.

2.4.1 Future energy system scenarios

The field of Life Cycle Assessements (LCA) attempts to measure the environmental impact of a given choice or technology through a life cycle accounting methodology with the aim of facilitating decision making [168] . This field is faced with a similar problem to the one faced in this thesis: How to quantify future environmental impacts when these are dependent on the future structure of the energy and production system? The main solution adopted by the LCA community is the use of scenarios to explore different possible future systems [169]. Authors in this field, update some key variables of their life cycle inventories (such as carbon intensity of the grid and of material inputs) to reflect the future state of the energy system. This has resulted in a specific type of LCA, the “prospective LCA” [170], which is an LCA where the analysed products and processes are set in a future system. This type of study was used to asses emerging technologies such as bioenergy [171], electric mobility [172], and metal production [173] among other things. The latest trend in this field is to move away from ad-hoc scenarios and to make use of scenarios recognised by the academic community to increase transparency. For example, Mendoza et. al [172] have approached the issue of uncertainty about the future energy system by conducting the LCA study for several possible scenarios among the share socioeconomic pathways which were modelled using an integrated assessment model.

The use of scenarios has always been the preferred way to explore future energy systems in the context of climate change, because it avoids any implication that the future is known. A good definition of a scenario was provided by Moss et al. [174]: "Emissions scenarios for climate change research are not forecasts or predictions, but reflect expert judgments regarding plausible future emissions based on research into socioeconomic, environmental, and technological trends". Therefore, scenarios are used to quantify uncertainty about future energy systems by defining the extremes of the range of possible emissions outcomes. A good summary of the history of climate change scenarios is provided by Girod [175]. The first set of IPCC emission scenarios, the SA90, were developed in 1990 [176] they were then followed by the IS92 scenarios [177] in 1992, and then by the SERS in 2000 [178]. The scenarios used in the Firth Assessment report are the Representative Concentration Pathways [179] while the latest set of scenarios are the five Shared Socioeconomic Pathways [180, 181]. Each scenario has its own narrative on variables such as demographics, economic development, social preferences and technical innovation. At a UK level, one of the latest set of influential scenarios are the three "Transition Pathways" that explore different future transitions to a low-carbon economy where each scenario is consistent with a given world view [182]. In these scenarios all factors affecting the energy system, from governance structures, to technical solutions are modelled and analysed with much greater detail than is possible in global scenarios [183, 184]. Given the global scale of climate change, it is preferred to focus on global scenarios.

The main critique that has been been put forward against the use of scenarios for decision making for climate change, is the lack of characterisation of their probability [185]. That is, each emission scenario is considered equally likely even though some scenarios are extreme while others are more moderate and thus most likely. Some authors have therefore attempted to develop analyses where each scenario was associated with a probability distribution, and where results such as cumulative emissions, mean temperature rise, and sea level rise were presented as random variables [186]. However, this approach has not been followed through, one reason for this is the difficulty to gain expert consensus on the likelihood of different futures. Therefore, the scenario approach, which enables each decision maker to individually assess the likely hood that that scenario is the current preferred method to explore future energy systems and will be used in this thesis.

Conversion efficiency in Integrated Assessment Models

One of the main tools to explore the impacts of different scenarios in the field of climate change mitigation is the use of Integrated Assessment Models (IAM). These models are composed of four main modules: an economy model, and energy module, a land-use model, and a climate model [187].

Bottom-up and top-down models are the two broad classes of energy models which, taken to the extreme, have a radically different approach. The former tend to be developed and preferred by scholars and analysts with an engineering background, while the latter tend to be preferred by economists. Several descriptions of the two approaches exist in the literature, but Böhringer and Rutherford [188] provide a succinct and clear definition:

> Bottom-up energy system models are partial equilibrium representations of the energy sector. They feature a large number of discrete energy technologies to capture substitution of energy vectors on the Primary and Final energy level, process substitution, or efficiency improvements. Such models often neglect the macroeconomic impact of energy policies. Bottom-up energy system models are typically cast as optimization problems which compute the least-cost combination of energy system activities to meet a given demand for final energy or energy services subject to technical restrictions and energy policy constraints.
>
> Top-down models adopt an economy-wide perspective taking into account initial market distortions, pecuniary spillovers, and income effects for various economic agents such as households or government. Endogeneity in economic responses to policy shocks typically comes at the expense of specific sectoral or technological details. Conventional top-down models of energy-economy interactions have a limited representation of the energy system. Energy transformation processes are characterized by smooth production functions which capture local substitution (transformation) possibilities through constant elasticities of substitution (transformation). As a consequence, top-down models usually lack detail on current and future technological options which may be relevant for an appropriate assessment of energy policy proposals. In addition, top-down models may not assure fundamental physical restrictions such as the conservation of matter and energy.

While there have been continuous efforts to close the gap between these two modelling approaches [189], the distinction remains useful to this day to classify different types of models on the basis on their predominant modelling philosophy.

Several IAMs have been used in the latest IPCC assessment report, however only twelve are used commonly and have a comparable documentation. Among these, Pauiliuk et al. [190]

have identified the five most technology-rich models. Since the aim of this study is to explore the evolution of end-use conversion technology, only these models will be assessed.

Table 2.3 List of five technology rich IAMs commonly used in the climate modelling community. The models are categorised based on whether they are explicitly about Useful energy consumption, end-use conversion efficiency technology, and on whether they include endogenous conversion efficiency improvements.

Model	Final to Useful	Building categories	Industry categories	Transport tech. detail	Endogenous efficiency	Rreferences
IMAGE	yes	Heating, Cooling, Other	Cement, Steel, Other	Medium	endogenous	[191–193]
MESSAGE	yes	Heating, Other	Heat, Other	Low	unknown	[194, 195]
GCAM	yes	Heating, Cooling, Appliances, Other	Cement, Fertiliser, Other	High	exogenous	[196–198]
AIM-CGE	yes	all end-uses	Cement and cross cutting techs.	High	endogenous	[199, 200]
REMIND	no	Heating, Other	no	Low	endogenous	[201]

REMIND is a traditional top-down model as it does not model explicitly useful energy and its conversion into final energy demand. Instead, it uses linear production functions which yield an energy demand as a function of economic and demographic variables. The efficiency parameters are not linked to specific technologies but are instead used to calibrate the model and enable it to reflect previously observed shifts from solid fuels to gaseous and then to electricity. For transport, three powertrain technologies are included (ICE, BEV, FCEV). AIM-CGE comes in two forms, one where it behaves like a pure top-down model, and another where it is explicit about most end-uses and technologies involved.

In the other three models, final to useful energy conversion is explicitly modelled for each combination of fuel and end-use, even though usually only heating is modelled explicitly (except for GCAM, which also models cooling demand). For the transport sector, the three models have varying degrees of complexity. CGAM has a full characterisation of possible transport technologies, both for freight and passenger transport. IMAGE has full technological details for passengers, but not for freight and it does not model hybrid vehicles explicitly. MESSAGE takes mostly a top down approach to transport which is modelled only through fuel switching, price elasticities, and user defined constraints. In these models, industry, is either treated as an aggregate sector, or each energy intensive module has its own model.

In most models, conversion efficiency parameter can vary endogenously in response to specific fuel price increase or as a function of economic growth. In IMAGE and REWIND, both an autonomous and price induced efficiency improvement are included. In MESSAGE it is not clear how the end-use efficiency improvements are modelled, while in GCAM efficiency of end use equipment is modelled exogenously following past US trends.

This review suggests that the technical granularity of end use efficiencies in IAMs has improved since it was described by Cullen et al. [96] in 2010. However, these models are not deemed suitable for the assessment of the future of conversion efficiency for two reasons. Firstly, one of the recurring critiques of IAMs is their lack of comprehensive documentation, long development times, and their broad scope [202]. Without extensive documentation it is difficult to properly assess the underlying assumptions about conversion efficiency. Secondly, efficiency parameters are not modelled explicitly as technologies but only as conversion routes which often contain several conversion devices (e.g. Heat pumps and resistance heater for electrical-to-thermal energy). Thirdly, the publicly available modelling results are only broken down to broad demand sectors –Industry, Transport, Buildings – which make it difficult to associate energy consumption to specific devices. Therefore, models that are limited to the energy sector that have a higher technological granularity and a bottom-up modelling approach should be investigated.

Treatment of efficiency in bottom-up engineering models

When looking at technology rich scenarios, the highest level of granularity is found in national or regional models. These models focus on the energy sector and do not model explicitly other sectors of the economy. Bhattacharyya provides a review of such models [203], and Hall reviews all models used in the UK [204]. Three notable national energy models used for decision making are: the National Energy Model System (NEMS) [205] used for the USA, the Price-Induced Market Equilibrium System (PRIMES)[206] used in the EU, and the UK MARKAL [207] used in the UK. These models employ different modelling techniques to explore the environmental impact and associated costs of energy policies as well as to assess different energy system scenarios. While the granularity of these models is sufficiently high to assess the impact of conversion efficiency in different scenarios, their limited geographical scope means that they cannot be used for a global assessment of technical efficiency measures.

The World Energy Council compiled a list of global energy system models that have been used recently to explore energy futures [208]. In Table 2.4 the main global models are listed and assessed according to a series of parameters that are necessary to the analysis of future of conversion devices: the model should be bottom-up and technology rich, it should provide detailed results and documentation, and ideally it should be widely used by the scientific community.

Table 2.4 List of recent energy system model runs published by private and governmental institution. The models are classified according to the type of modelling approach, hybrid models are classified according to their most widely used approach. The number of studies scenarios includes alternative cases which only explore different GDP growths or energy prices. The models are classified to to have available results and documentation if results are available in tabular formats and if a methodology document exists. The climate scenarios indicate whether the models considered are in line with the respective climate targets.

Institution	Report title	Type	Scenarios	Available results	Documentation	Climate scenarios		
						2 °C	1.5 °C	
Governmental								
WEC	World Energy Scenarios to 2060	bottom up	3	no	no	yes	no	[209, 210]
EIA	International Energy Outlook	top down	1	yes	yes	no	no	[211, 212]
IEA	World Energy Outlook 2018	bottom up	3	yes	yes	yes	no	[213, 214]
IEA	Energy Technology Perspectives 2017	bottom up	3	yes	yes	yes	yes	[215]
IEEJ	Outlook to 2050	top down	2	no	no	yes	no	[216, 217]
IRENA	Perspective for energy Transition	bottom up	1	no	yes	yes	no	[218]
Private								
BP	Energy Outlook to 2040	bottom up	4	yes	no	yes	no	[219]
Exxon	Outlook for energy : a view to 2040	bottom up	2	yes	no	yes	no	[220]
Enerdata	Global Energy Scenarios to 2040	bottom up	3	no	yes	yes	no	[221, 222]
DNV GL	Energy Transition Outlook	top down	1	yes	no	no	no	[223]
Shell	New Lens Scenarios to 2100	top down	2	no	no	no	no	[224, 225]
Equinor	Energy Perspectives to 2050	top down	3	yes	no	yes	no	[226]

The scenarios research listed in Figure 2.4 are created by both governmental and private sources. Private organisations are less likely to provide results and documentation as well as to take into consideration climate scenarios. They also tend to create one scenario that provides a single view of the most likely outcome, rather then exploring the possibility space. Furthermore, many private organisation scenarios assess the impact of different socioeconomic futures (i.e. GDP growth, level of globalisation, demographics) rather than different climate action pathways.

Among the governmental institutions, all provide climate scenarios with the exception of the US government's EIA, which only provides a reference case scenario which is varied to test for different GDP growth possibilities. Among these energy models, the IEA's publications appear to be the best suited for the analysis because they use bottom up models, they explore climate scenarios, and they provide numerical results and documentation. Among the two models, the IEA's Energy Technology Perspective (ETP) is deemed more appropriate for this analysis for two reasons. Firstly, the published results are more detailed than for the alternative World Energy Outlook and the documentation focuses more on technological aspects of the energy system. Second, the ETP publication provides an estimate for a scenario that is consistent with the 1.5 °C target and this scenarios was included in the recent UNFCCC 1.5 °C Global Warming report [17].

The IEA's ETP scenarios are based on the ETP model which is formed of three energy demand models (buildings, transport, and industry) and an energy supply model. The supply model is a technology rich, least-cost optimisation model based on the TIMES modelling framework [227]. In the latest edition of the ETP report (2017), three scenarios were used: the Reference Technology Scenario (RTS), a scenario that only takes into account current climate action pledges; the 2 degree scenario, in line with a 50% chance of keeping warming at 2 °C by 2100 (2DS) ; and the below 2 degree scenario, in line with a warming of 1.75 °C by the end of the century (B2DS). The difference among the scenarios is purely in terms of energy technology choices, as key parameters such as GDP and population growth are kept constant. Efficiency measures are considered the largest (40%) contributors to the difference in emissions between the RTS and the 2DS, and between the 2DS and B2DS [228]. This key role of efficiency has been reiterated by the IEA in several reports and in ad-hoc publications [229]. Despite the pivotal role of efficiency measures in meeting climate targets the contributions of efficiency are only analysed at a sectoral level and the gains are not allocated to the different technologies involved, making it difficult to prioritise action. The IEA's approach is understandable given the breadth of their analysis. However, there is room to deepen the analysis of these modelling results by applying Cullen's framework and to assess the future role of each energy conversion device in this bottom-up technology rich model.

2.4.2 Comparing energy saving potentials with innovation activity

The purpose of taking into account different future energy systems in the analysis of end-use energy conversion is also to operationalise energy saving potential results. That is, to make the results more meaningful such that they can be used when making decisions about end-use efficiency technologies. Since one of the main policy levers to increase energy efficiency is research and development, the saving potential results should be benchmarked against current innovation activity. Such a comparison can provide decision makers in the field of energy and innovation policy with guidance when allocating their budgets. In this section, the literature is reviewed to identify the most suitable metric to quantify innovation activity.

Quantifying innovation activity

Innovation activity can be quantified using three types of metrics: input metrics, output metrics, and outcome metrics [230]. Input metrics quantify the resources (capital and labour) allocated to research and development activity, these include but are not limited to: public and private R&D budgets or the number of scientists and engineers engaged in R&D. Output metrics measure the direct output of research activity examples are: number of peer-reviewed publications, number of patents or the number of technologies commercialised. Outcome metrics quantify the results of research activity for example by measures of market penetration (of a given new energy technology), of learning rates, or of economic benefits.

Energy technology research budgets

Public funding is allocated to energy research in all industrialised countries [231] with the purpose of improving the energy system across all dimensions through increased energy affordability, availability and sustainability. The private sector also engages in energy technology research however data on these activities is scarce and often proprietary. On the other hand, public R&D budgets and portfolios are publicly available therefore innovation budget metrics are mostly limited to the public sector.

Grubler and Rihai have used this type of data to compare the current research portfolios with the expected carbon saving potentials for a number of IAMs [31]. They use the end-of-century cumulative GHG emission reduction of each technology category to determine the innovation “needs” and compare it with the current and historical R&D budgets published yearly by the IEA. They observe that there is a clear mismatch between the two portfolios: 60% of carbon savings are expected to come from energy efficiency while only 13% of the global energy technology R&D budget is allocated to this same category; conversely, nuclear energy accounts for 8.5% of expected savings but receives 39% of the research budget. The main outcome of their study was to identify a large mismatch between research budgets and climate technology needs with a strong preference for research on energy supply. Wilson et. al have corroborated this conclusion by analysing an even wider set of research inputs, including technology roadmaps and research strategy work plans, and showed that end-use efficiency research is marginalised compared to supply side research [34]. At a regional level, Pezzutto et al. [232] have compared the saving potential of heating and cooling in buildings with the EU’s energy research budget and concluded that this sector receives only 7% of the funding budget while accounting for 75% of the saving potential. Rosen [233] completed a similar analysis for Ontario (Canada) and the US, comparing energy research funding with the energy and exergy saving potentials at a sectoral level (buildings, industry, transportation, utilities). Funding data was taken from just one specific energy research funding program (enersearch) for Canada, and energy data from his own 1987 analysis. The saving potential is calculated in exergy terms and Rosen concludes that energy research funding is allocated according to the energy saving potential rather than the exergy saving potential. This is the only study that appears to find a correlation between saving potentials and research budgets, however it uses outdated information and its analysis is aggregated at the sectoral level and therefore provides no guidance innovation activity at an individual technology level.

While R&D budget data can be useful to study these broad technology classes, it is not suitable to compare innovation activity occurring in end-use efficiency technologies because the data is not sufficiently granular. Energy efficiency is a single category in the IEA’s database and while sub-categories for efficiency in the various economic sectors exist, most of the data is found in the “other efficiency” category. In addition, one of the reasons explaining the relatively low public budget in efficiency technology is that much of the innovation is conducted within the private sector since efficiency technologies tend to be closer to commercialisation than other energy technologies [230].

Energy technology patent counts

Patent counts is a widely used metric to assess innovation. A patent is an intellectual property right granted for an invention in the the technical field by a patent office, hence giving the owners the right to exclude others from the industrial exploitation of the patented invention for a defined number of years [234].

The use of patent data to quantify innovation has two important drawbacks in quantifying innovation activity compared to input metrics: first, not all innovation can be patented and patents are not always the best way to protect intellectual property meaning that different technological fields can have different patenting rates. Second, not all patented innovations end up becoming marketable products hence there is a mismatch between patents and real innovation. Despite this, patent counts have been widely used to understand innovation dynamics because they retain a strong link to relevant innovation and because of the availability of granular data which allows detailed analyses [235]. In addition, by measuring innovation by using patent counts, private sector innovation efforts are accounted for and this is especially important when analysing end-use energy technologies. Data on patent counts is classified using the International Patent Codes (IPC) which define the technologies being affected by each patent. The OECD publishes patent counts from the United States Patent and Trademark Office database (USPTO) and the European Patent Office (EPO) grouped by IPC class [236]. By accessing the databases directly, it is possible to perform patent counts up to granular technology classes (IPC sub-groups).

Albino et al. [237] review a number of previous studies that use patent counts to understand the dynamics of innovation in energy technologies such as electric vehicles, solar photovoltaic, and hydrogen production. They also used patent count data to trace the history of major energy technology developments between 1971 and 2010 in the United States Patent and Trademark Office database. They show that patent count trends can be explained by major energy technology innovation programs, private initiatives, and historical events . They filter the data for “high impact” patents, defined as patents with several forward citations to avoid counting patents that have not had a significant impact on the economy.

Girod et al. explore the link between energy efficiency policies in buildings and innovation in efficient technology using patent counts from the EPO as a metric for innovation. They find a correlation between the two variables using an econometric framework, especially for financial subsidies to efficiency technologies and for energy labels. Their analysis is aided by the fact that the EPO “tags” technologies that have a positive impact on emission reduction. Costantini et. al [238] perform a similar analysis with the patent database and find similar results. However they use very granular IPC classifications in addition to keyword search to define which efficiency technology is affected by the patent. Work by Noally et al. [239] focused on innovation in energy efficiency technology in the building sector in the Netherlands. The authors use granular patent counts from the national patent office and the European Patent Office to track the evolution and identify the main actors of innovation in the building sector. Their results show the predominance of innovation in lighting and boiler technologies in the Netherlands and identify the links between environmental policy and increased innovation. In subsequent work, the same authors quantify this relationship through an econometric model and find that a 10% increase in minimum wall-insulation requirements is accompanied by a 3% increase in patents in building energy efficiency [240].

This review shows that patent counts have been used in the literature to assess the dynamics of innovation and to compare innovation activity for different technologies. Therefore patent counts can be used as an alternative, more granular, metric to assess the suitability of current research activity for climate goals instead of R&D budgets

2.4.3 Research gaps

The aim of this thesis is to understand the role of different end-use conversion technologies as tools to mitigate carbon emissions and to prioritise action on the different available technology options. Energy system scenarios are the best tool to analyse the future role of energy technology. There are a large number of energy models using an even larger set of scenarios and in all of these efficiency improvements are modelled. However, only Cullen and Allwood have assessed the energy saving potentials purely from conversion efficiency improvements. There are two gaps in their approach. First, the energy saving potentials were estimated using a static picture of conversion chains and technology types. Second, the saving potentials of each technology are not benchmarked against any metric of current policy action or innovation. These gaps can be addressed by the following research questions.

> **Q3.1: How is the technical saving potential of different end-use conversion technologies expected to vary in different climate scenarios?**

> **Q3.2: What is the current energy technology innovation activity taking place in different conversion devices and how does it compare with their expected saving potential?**

Chapter 3

Uncertainty of end-use energy statistics

In Chapter 2 it was shown that the quantification of the reliability of end-use energy statistics is a necessary first step to analyse the future role of end-use conversion efficiency: knowing the current picture in detail is required before one can make any statements about the future. Furthermore, the end-use energy data can be divided between end-use consumption and end-use efficiency data and the best way to quantify the quality of this data is by assessing its uncertainty within a Bayesian framework as done in the MFA for similar tasks. The Useful energy metric is used to combine end-use consumption and efficiency data to better understand energy demand since it is much closer to the end-user demand than final or primary energy. The quantification of the uncertainty of Useful energy demand is expected to show that despite their lower perceived reliability, compared to Primary and Final energy statistics, end-use statistics can be successfully used for modelling and even policymaking. The UK is used as a case study because of its accessible documentation and wealth of literature studies focusing on the UK as shown in Chapter 2.

This chapter aims achieving two objectives: (a) to provide a methodology to estimate the uncertainty of Useful energy calculations, and (b) to test this methodology with the application to the United Kingdom's energy system. In section 3.1 the methodology developed to estimate Useful Energy consumption and its associated uncertainty is explained in detail. In section the Useful energy balance of the UK and its uncertainty are displayed, while section 3.3 offers a discussion of the results.

3.1 Methods

This section outlines the methods used for this study in three parts. First, the general methodology to disaggregate Final energy consumption and to compute Useful Energy is presented and specific terminology is introduced. Second, the uncertainty quantification techniques and the probabilistic model is described. Third, the data sources used to analyse the UK's Useful energy consumption and its uncertainty are listed. This methodology was developed in conjunction with Dr Richard Lupton, the co-author of one of the journal articles published during the course of the doctoral programme.

3.1.1 Useful Energy Calculation

Useful energy is calculated by multiplying Final energy consumption by the end-use conversion efficiency (η). Final energy can be disaggregated in terms of energy carrier f (eg. coal, electricity etc.), sector s (eg. industry, residential), end-use e (heating, lighting etc.), and device d (eg. electric motor, boiler etc.). Hence, Useful energy is calculated for each combination of f,s, e, and d using equation 3.1.

$$U_{fsed} = F_{fsed} \quad \eta_{fsed} \tag{3.1}$$

Standard energy balances provide Final energy consumption statistics disaggregated in terms of of energy carriers and sectors ($F_{f,s}$). Therefore, two allocation matrices ϕ and θ are needed before the Useful energy calculation can be made. Matrix ϕ allocates Final energy of each fuel to each end-use application. For example, ϕ can specify that coal in the residential sector is used for space heat and for hot water with respective shares of 80% and 20%. Matrix θ allocates Final energy to the specific conversion device used for each end-use. For example it could specifying that 40% of oil used for mechanical energy in road transport is converted in petrol engines and 60% in diesel engines. Equation 3.2 summarises the relationship, where the superscripts indicate that there is a matrix for each of the indicated categories.

$$F_{fsed} = F_{fs} \quad \phi_{fs}^{(e)} \quad \theta_{fse}^{(d)} \tag{3.2}$$

In the following sections, the choice of categories used for this framework is explained.

Final Energy (F_{fs})

National energy balances (most of which are published by the IEA [241]) containing data on Final energy consumption split by economic sectors and by energy carriers are used to define F_{fs}. Fuels in the IEA energy balances are classified according to their fuel of origin. This is not conducive to an allocation of fuels to different end-uses and conversion devices since the use of a fuel depends on its final form, not on it's origin. Thereofore, fuels are classified according to their physical state. For instance, Blast Furnace Gas is originally classified as a "coal product" while in the chosen classification system it is classified as "gas". The following categories are used: Liquid fuels, Gas, Coal, Solid Biomass and Waste, Electricity and District Heat (DH).

The end-use sector classification used by the IEA is retained as it is commonly used across all energy studies. The only change made to the classification is the grouping of three sub-sectors, namely Agriculture, Fishing, and Forestry into a single category named AFF. Therefore the final list of sectors is as follows: Industry, Residential, Services, Agriculture/Fishing/Forestry(AFF), Road Transport, Rail Transport, Navigation, Aviation, and Pipeline Transport.

Sectors to End-use ($\phi_{fs}^{(e)}$)

Energy end-use statistics are used to define the ϕ_{fs}^{e} matrix which allocates Final energy to the various end-uses. To define this matrix, a coherent definition of end-use categories is required. End-use statistics are compiled at a sectoral level thus the categories employed are often sector specific. A cross-sectoral analysis requires comparable end-use categories for all sectors, while still being sufficiently specific about the end-use of energy. Since these two requirements are often at odds, a judgement is required in the defining the end-use categories employed. The German Energy Statistics Office provides a good starting point, as it employs end-use categories that facilitate a compromise between the two needs [242]. Table 3.1 lists and describes the nine end-use categories employed in this study. The only modification of the German definition is the split of the "Process Heat" category in "Process Heat – Direct" and "Process Heat - Indirect". This separation is performed to separate energy that is used in boilers and steam generators from energy used to heat products directly (thus including both material processing in Industry and cooking in the residential sector).

Table 3.1 List of end-use categories used to classify end-uses for all sectors

End Use Category	Description
Process Heat - Direct	Energy applied directly for material processing (cooking, blast furnace, etc.)
Process Heat - Indirect	Energy delivered through an intermediate mean, usually steam.
Space Heat	Energy used to maintain comfortable temperature inside buildings
Hot Water	Energy used to increase water temperature for hygiene and comfort
Space Cooling	Energy used to maintain a comfortable temperature inside buildings
Process Cooling	Energy used to decrease the temperature of materials below ambient (refrigeration)
Mechanical	Energy used to deliver Useful work (pumping, motion etc.)
Illumination	Energy used to the illumination of buildings and streets.
Information, Communication, Entertainment	Energy used for computing power, and for communication and control.

End-use to Conversion Device ($\theta_{fse}^{(d)}$)

The allocation matrix $\theta_{fse}^{(d)}$ describes the share of energy converted in a specific devices for a given combination of sector, energy carrier and end-use. The definition and classification of "energy conversion devices" used in this study is based on the work by Cullen and Allwood [97], with only one modification. They distinguish four types of burners based on the type of fuel they use. While there are technical differences between these categories, there are further differences between the mode of combustion, that is, on whether the combustion occurs within a boiler or directly on the product to be heated. This is because the efficiency of the boiler depends on both the combustion efficiency and the heat exchanger design; while for direct combustion, only the former matters. Since the framework used in this analysis enables the distinction of energy flows by fuel, it is best to classify the devices only on their technical differences: direct combustion versus indirect combustion. Table 3.2 lists and describes the conversion devices employed in this study.

Table 3.2 Description of conversion device categories and mapping with categories used for conversion devices TEL estimation

Device Category	Description and Examples
Chemical to Work	
Spark Ignition Engine (SI)	Engine based on Otto cycle, where charge is ignited by a spark (light duty vehicles, lawn mowers)
Diesel Engine (CI)	Engines following the Diesel cycle, where the charge is autoignited due to compression. (Heavy duty vehicles, sea vessels, agricultural equipment)
Gas Turbine (GT)	Device following the Bryton cycle with axial turbomachinery. (gas pipeline compressors, mechanical drive in industry)
Jet Engine (JE)	Gas turbine used to provide thrust to aircrafts.
Chemical to Thermal	
Burner (BU)	Device where combustion products are used to deliver the energy service directly. (gas hobs, blast furnace)
Boiler (BO)	Device used to transfer the heat of combustion to water, acting either as a heat transfer fluid for space heating and process heating, or as direct sanitary water heating.
Electrical to Work	
Electric Motor (EM)	Device generating shaft work from electrical energy through the interaction of magnetic fields. The most common design being the induction motor.
Electrical to Thermal	
Electric Heater (EH)	Device converting heat from Joule effect to deliver an energy service directly (electric hobs, electric arc furnace)
Cooler (CO)	Device converting electricity to thermal energy in the form of coolth. (residential fridge, air conditioner, gas separation)
Electrical to Electromagnetic	
Light Device (LD)	Device converting electrical energy into light (LED, incandescent light bulb)
Other	Other electricity using devices where energy is not converted into quantifiable other forms before delivery of energy services. (computers, mobile phone, televisions)

Conversion Efficiency (η_{fsed})

The conversion efficiency of each device must represent the average efficiency for a device using a given energy carrier, in a given sector, to deliver a specific energy service. The definition of efficiency depends on the system boundary definition chosen, that is, whether it includes the entire conversion system or only the conversion device. Taking the example of a motor system used for ventilation, the efficiency of the motor is the ratio of electricity input to rotational shaft power output, while the efficiency of the system is the ratio of electrical input to the energy of the displaced air. In this thesis, the boundary is limited to the first form of energy in the Useful form, thus to the conversion device. This choice is dictated by a will to limit resolution of the technologies considered and due to limitation in data about the specific uses (water pumping, ventilation, space heating, oven heating) of Useful energy. Therefore, the output from the conversion devices is classified in five Useful Energy categories: Motion, Heating, Cooling, Illumination, Information.

3.1.2 Uncertainty analysis

Three steps are used to assess the uncertainty of end-use energy statistics. First, the uncertainty associated with each term of equations 3.1 and 3.2 is quantified and described. Second, a probabilistic model linking each input matrix to the Useful energy estimate is defined. Third, the uncertainty is propagated in the model to assess the uncertainty of the Useful energy consumption.

Uncertainty Estimation

Epistemic uncertainty is routinely quantified in various fields such as engineering modelling [243], scientific computing [244], and safety assessments [245]. Two widely used methods for uncertainty quantification are expert elicitation and the pedigree matrix. Expert elicitation techniques are designed to formally interview experts in the field who possess in depth knowledge of the parameter being studied. This method is often used in risk assessment and in technological forecasting studies [246]. The pedigree matrix technique enables the consistent quantification of uncertainty of the available data according to its source by assessing the data source against multiple quality dimensions. This method is mostly used in Life Cycle Assessments [247] and in MFAs [127]. In addition to these primary methods used in academia, statistical agencies can provide confidence intervals or uncertainty ranges for their published statistics.

In this study uncertainty is defined as the probability associated with two times the coefficient of variation, in accordance with the IPCC guidelines. This definition enables the uncertainty (Y) to be intuitively expressed as a percentage range (e.g. ±Y%).

Energy Balance Information on the uncertainty of energy statistics is rarely provided by national and international statistical offices. Therefore, an alternative must be found to estimate the variance of each fuel-sector combination in $F_{f,s}$. Fortunately, an alternative can be found looking at GHG inventories. The 2006 IPCC guidelines on GHG inventories [131] advise Annex I countries to perform uncertainty analyses on their emissions. Since most emissions are due to fossil fuel combustion in the energy system, this data can be used to inform the uncertainty of energy statistics. These uncertainties are estimated by staff working in the reporting institution or by appropriate experts, for each energy carrier in each sector. Emission uncertainties are the combination of *emission activity*, which represents the physical quantity of fuel burnt, and of the carbon *emission factor* which represents how much CO_{2eq} is emitted by the combustion of one physical unit of fuel. The carbon emission factors are related to the heating values of the fuels since both are a function of the fuel's chemical composition, and sometimes emission factors are calculated from calorific value data [248]. Therefore, it is assumed that the uncertainty of the calorific value is equivalent to that of the emission factor. Calorific values are easier to calculate than emission factors and are measured more often due to contractual needs. Hence the assumption is deemed conservative. The activity (A) and the emission factor (EF) probability density functions are combined to determine the overall emission intensity uncertainty (Y_e), as shown in equation 3.3

$$Y_e = \frac{\sqrt{\mathrm{Var}\,[A+EF]}}{\mathrm{Exp}\,[A+EF]} \tag{3.3}$$

Knowing the probability distributions which describes these uncertainties it is possible to determine the probability density function of aggregated fuel categories. The uncertainty is assumed to follow a lognormal distribution as that is the most suitable distribution for non-negative random variables [249]. For electricity, the uncertainty in consumption derives from measurement error, since electricity networks must always balance. Therefore a value of 0.5% is appropriate since this is the standard for electricity meters in the EU [250]. For district heating, an uncertainty of 3% is assumed since it represents typical metering accuracies [251].

Allocations to end-uses and devices Energy end-use statistics collected using the categories outlined in section 3.1.1 result in an allocation vector of proportions α_e for each energy carrier and each sector, such that

$$\sum_e \alpha_e = 1 \tag{3.4}$$

Statistical agencies rarely provide uncertainty estimates for their published values, and when they do, it is a single value . However, most end-use energy data is sourced from energy consumption models which provide interpretation and quantification of uncertainty in their input parameters and in their outputs. When there is a lack of official figures, it is necessary to make use of expert judgement for the quantification of the uncertainty (Y) for each allocation based on information on the models used to determine the allocation.

Describing the uncertainty of an allocation is, perhaps surprisingly, not straightforward. For example, assume we have 100 MJ of energy split into three parts of 80%, 17% and 3%. What is the meaning of a 10% "uncertainty"? Intuitively, it is expected that all shares vary by 10%. That is, the biggest from 72 to 88 MJ, the middle one from 15 to 19 MJ and the smallest from 2.7 to 3.3 MJ. However, this is not possible. To see why, consider that the smallest share reduces to the minimum expected, from 3 MJ to 2.7 MJ. The other two shares must increase by a total of 0.3 MJ. Even if all of this increase went to the 80 MJ share, that would still be only a variation of 0.3 / 80 = 0.4%: much less than the expected variation. Conversely, if the largest share were to increase by 10% the corresponding change in the smaller shares would be bigger than expected.

Because it is not possible to have “10% uncertainty" on all parts of the allocation, a choice about how to interpret the uncertainty must be made. At the same time, there is no information about the specific probability distributions describing the allocations, or their covariance (i.e. which part would increase if another part decreases). In this thesis the Dirichlet distribution is used to describe uncertain allocations because it naturally represents allocations that add up to 100%, and because it has a simple parameterisation in terms of the mean shares and a "concentration parameter" determining the level of uncertainty. We consider the following rules for the interpretation of a “10% uncertainty" relative to different “reference parts": (**a**) 8 percentage points (pp) on 80% ,(**b**) 1.7pp on 17%, (**c**) 0.3pp on 3%.

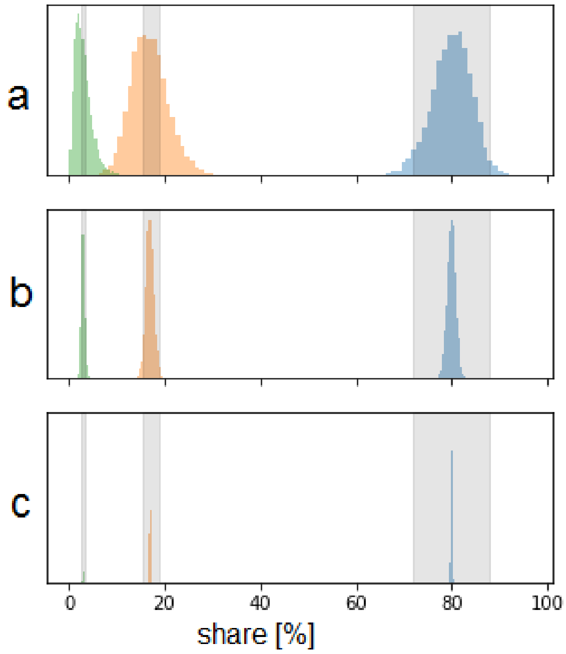


Fig. 3.1 Comparison of probability distributions from a Dirichlet distribution with input parameters α_e=[0.8 0.17 0.03] using three different interpretations for an uncertainty of 10%. In cases **a**, **b**, and **c** the 10% relative uncertainty is applied is applied respectively to the smallest, mid and largest input parameters. The shaded bands show the ± 10% range relative to each share which is in line with the most intuitive interpretation of uncertainty.

Figure 3.1 compares the results of these rules to the expected outcome – 10% variations in the size of the output parts. Unsurprisingly, the expected uncertainty range is observed for the reference part whose uncertainty was specified: **a** has the expected range for the first part, **b** for the second part, etc. But this example shows that parts smaller than the reference part have greater than expected uncertainty, while parts bigger than the reference part have smaller than expected uncertainty. Because bigger parts have a bigger influence on the overall results, it is better to exaggerate the uncertainty of small parts than it is to deny the uncertainty of large parts. We therefore use rule **a**: adjust the distribution to match the uncertainty in the largest part to the specified value. This approach is followed for both the allocation of Final energy to end-uses, and for the allocation from end-uses to conversion devices. A more formal explanation of the equations used is shown in Appendix B.

Conversion efficiencies Data on the average efficiency of conversion devices is seldom found in either official statistics or academic literature. When no information is available, average efficiencies must be estimated using other sources. These include: technical equipment surveys, device performance databases; and device performance data found in manufacturer's catalogues. Whenever possible and appropriate performance data is collected for a large number of conversion devices. This data is analysed to obtain a range of efficiency values as well as to determine the major trends that influence a device's efficiency (e.g. power rating, technology type).

The uncertainty of the efficiency estimate is quantified using two parameters: the quality of the underlying data (which quantifies the magnitude of the uncertainty) and the quality of the central estimate (which determines the probability distribution is used). Therefore, for each estimate the range of possible values and the probability distribution across that range needs to be defined.

Data quality is assessed in a consistent way using a pedigree matrix similar to the one used by Laner et al [127] for Material Flow Analysis. The data is assessed using five qualitative indicators: Reliability, Completeness, Geographical Correlation, Temporal correlation, Other correlation. The score obtained by each data point is used to determine the magnitude of the uncertainty of each estimate. The definition of each indicator, as well as the qualitative aspect associated with each score are show in in Table 3.3, while the values associated with each score are shown in Table 3.4.

Table 3.4 Values associated with each score in the pedigree matrix.

Score	*1*	*2*	*3*	*4*
Reliability	0.1	0.2	0.5	0.7
Completeness	0	0.1	0.2	0.3
Geo. Corr	0	0.05	0.1	0.15
Temp. Corr	0	0.05	0.1	0.15

Since efficiency values are bound between zero and one, and because the range of efficiencies can be either small or large depending on the technology, the uncertainty is defined as a fraction of the efficiency range (R) for each technology as seen in equation 3.5.

$$\beta = R \sum_i s_i \tag{3.5}$$

where β is the uncertainty parameter for each efficiency, R is the performance range for a given technology, s is pedigree matrix score for that technology and the index i refers to each indicator.

Table 3.3 Pedigree matrix employed to assess the data quality of the national average energy efficiencies. The lower the score value the higher the quality of the data.

Indicator	Definition	Score: 1	Score: 2	Score: 3	Score: 4
Reliability	Focus on the data source: documentation of data generation, e.g., assessment of sampling method, verification methods, reviewing processes.	Methodology of efficiency data measurement is well documented and consistent, peer-reviewed data.	Methodology of efficiency data generation is described, but not fully transparent; no verification.	Methodology not comprehensively described, but principle of data generation is clear; no verification.	Methodology of data generation unknown, no documentation available.
Completeness	Composition data set is assessed. Possible over- or underestimation is assessed.	Data includes all types of relevant conversion devices.	Data includes main types of relevant conversion devices.	Data includes partially main types of conversion devices. certainty of data gaps.	Only fragmented data available; important conversion device types are missing.
Temporal correlation	Congruence of the available data and the ideal date with respect to time reference.	Value relates to the right time period.	Deviation of value 1 to 5 years.	Deviation of value 5 to 10 years.	Deviation more than 10 years.
Geographical correlation	Congruence of the available data and the ideal data with respect to geographical reference.	Value relates to the studied region.	Value relates to similar socioeconomical region (GDP, consumption pattern).	Socioeconomically slightly different region.	Socioeconomically very different region.
Other correlation	Congruence of the available data and the ideal data with respect to technology, product, etc.	Value relates to the same conversion device	Values relate to similar conversion device technology	Data deviates from conversion device of interest, but rough correlations can be established based on experience or data.	Values deviate strongly from conversion device of interest, with correlations being vague and speculative.

Once the uncertainty (β) of the estimate is quantified, a probability density function is selected to represent the distribution of the uncertainty. The distribution is chosen according to the quality of the central estimate.

- *Uniform distribution*: if there is no information available to provide a central estimate of the average efficiency. The difference between the lower and upper bound of the distribution is equal to β.
- *Triangular distribution*: if there is sufficient information to provide a central estimate of the efficiency. The expected value of the distribution is set to the central estimate; while difference between the upper and lower bound is β
- *Normal distribution*: If a reliable central estimate for the average efficiency is available. The expected value of the distribution is the central estimate, while the standard deviation is $\frac{\beta}{4}$.

Uncertainty Propagation

The uncertainty is propagated through the model using a Monte Carlo simulation technique. The simulation is implemented using a Python and a MatLab script, using 5000 samples drawn from each of the probability distributions and then multiplied together to obtain a sample of estimates for Useful energy. The value of 5000 was chosen to provide numerical stability to the resulting distributions without excessive computational effort.

3.2 UK Data Sources

In this section, the sources of data used to calculate the Useful energy consumption of the UK are described. The method followed is summarised in Figure 3.2.

3.2.1 Energy Balance

The 2013 Eurostat energy balance for the UK [252] is used for the analysis because the Department for Business, Energy and Industrial Strategy (BEIS) does not publish a disaggregated balance. Data on the uncertainty associated with each of the fuels is retrieved from the 2016 GHG inventory report [253], while an explanation of the methodology use to compile the data is found in a 1998 Department for Environment, Food & Rural Affairs (DEFRA) report [248]. The uncertainty of liquid and gaseous biofuels is assumed to be the same as their fossil equivalents, since their reporting follows similar centralised practices [254]. Solid biomass consumption in the energy sector and industry is assumed to have the same uncertainty as coal, since it is reported by similar organisations. The DEFRA documentation reports that solid biomass statistics in the residential scetor are very uncertain, therefore it is assigned an uncertainty of 50%.

3.2.2 End-use allocation

In this section the models and techniques used by the UK statistical office to estimate the allocation of Final energy to the different end-uses are described. In light of this information, the ucertainty parameter for these allocations is defined for each sector.

Residential

The quantification of the energy used for each end-use application within dwellings is provided by the Cambridge Housing Model [64]. It is a bottom-up, physical, housing energy consumption model based on Standard Assessment Procedure 2009 calculations – the government agreed procedures to establish compliance with building regulations. The model uses data from the English Housing Survey [65]: a stratified random sample of around 15 000 English dwellings conducted annually. Each building in the survey is modelled and its energy consumption estimated, the results are then scaled and weighted by dwelling type and dwelling age, to represent national level values. The end-use applications modelled are:

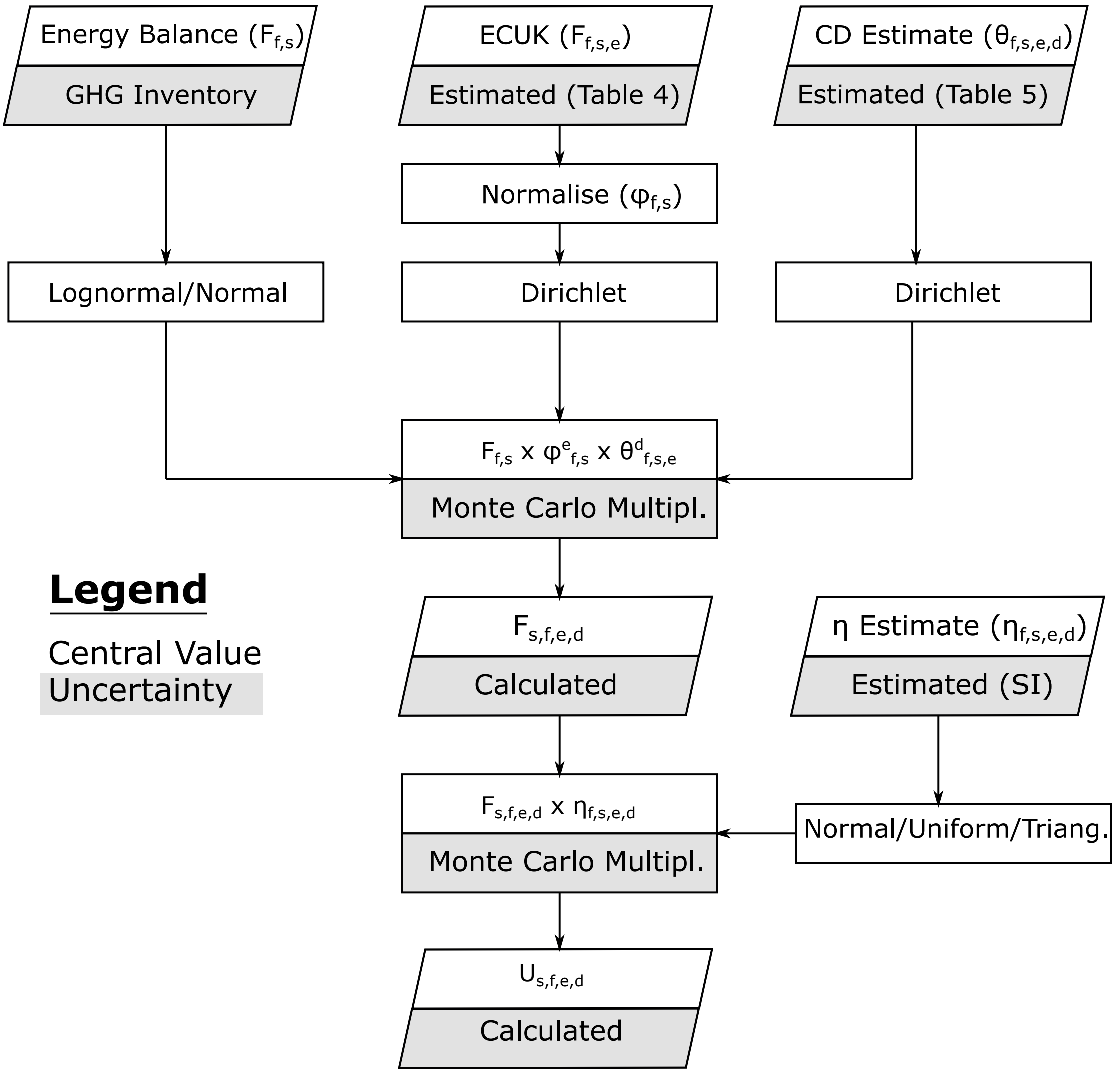


Fig. 3.2 Flowchart summarising the steps taken to calculate the Useful energy demand of the UK and its uncertainty, from data sources to results. The text shaded in grey refers to the uncertainty of the data, described in the transparent boxes. The text in brackets indicates where the assumptions are found in the text. The abbreviations used are the following. ECUK:Energy Consumption UK, CD: Conversion Device, SI: Supporting Information.

Space Heating - Main, Space Heating - Secondary, Water Heating, Space Cooling, Lighting, Electrical Appliances, Cooking, Pumps and Fans.

In addition, for the consumption of electricity in UK dwelling a better data source is available. In 2010 a measurement campaign was conducted with the aim of understanding how electricity is used in UK homes. Electricity meters were installed in a stratified sample of 251 homes [55]. Electricity use is classified in the following categories: Cold Appliances, Cooking, Lighting, Audiovisual, ICT, Washing/Drying, Heating, Water Heating, Other, Not known. The uncertainty in the estimate is due to a share of "not-known" energy consumption, a sampling error (about 6%) and a measurement error (about 2%).

Two uncertainty and sensitivity analyses have been performed on the CHM model by its authors [255, 256]. The authors estimate the uncertainty in the model's input parameters, which they define using expert judgement and estimates found in the literature. A uniform probability distribution is used with values ranging from 1% for wind speed to 50% for wall U-values. The input uncertainties are propagated using a Monte Carlo simulation. The result of the analysis is only published for the entire energy demand of the UK residential sector. In the 2016 version of the ECUK data [257], there is a note about the end-use results which states that

> The breakdown of energy by final use is based on modelling, and this is subject to uncertainty from housing data, behavioural data, climate data and building physics assumptions. The proportions used in the breakdown could vary by as much as 18%.

This text is interpreted as a relative uncertainty of 18% on the largest share of each allocation vector. This interpretation is very conservative since the resulting uncertainties for other end-uses will be higher than the 18% specified. This estimate does not take into account the higher resolution data available for electricity consumption as there is no metion of it in the published end-use statistics.

Commercial Services and Public

The allocation of energy consumption to the various end-use allocations in the commercial and public sector is done with the results of the Building Energy Efficiency Survey [66]. The survey is based on 4084 telephone interviews and 284 site visits of non-residential buildings sampled across the UK. The model estimates energy consumption by associating each area of the building to a "space type" which in turn is linked to a specific end-use consumption profile.

Information about the building's space type and efficiency of equipment is determined in the phone interviews [67].

The results of the model have been peer reviewed by a group of researchers at UCL [258]. They compared the output for the BEES model to their own, in-house building energy model. The allocation of energy to end-uses was checked by running both models on two samples of office spaces. However, no formal uncertainty analysis was performed on this model.

In the literature, there are estimates of uncertainties associated with non-residential building simulations in the UK [259–261], but no estimate of the uncertainty for the end-uses of energy in the buildings was found since most studies focus on the uncertainty associated with the total energy consumption of buildings and even then uncertainty analyses are rare [262].

For this study, the uncertainty of end-uses in the service and commercial sectors is assumed to be 20% for the largest share. This is in line with the differences observed between the BEES model and the UCL model for office spaces [258]

Industry

The industrial breakdown is based on the non-domestic Energy and Emissions Model, which uses a survey last conducted in 2000 [263].

Industrial end-uses of energy are provided in the following categories: Drying/Separation, Motors, Compressed Air, Lighting, Refrigeration, Space Heating, Other. Very few details are known about the surveys and methodologies used to determine these end-use application of energy in the industrial sector in the UK. One recent study by the Fraunhofer ISI [264] aimed at quantifying the energy used for heating and cooling in the EU industry, quotes an uncertainty value of 25% for its estimates which has been agreed upon by various practitioners. This will be used as the uncertainty of the largest share for the industrial allocation vector.

Agriculture, Fishing and Forestry

The data for the end-use allocation in Agriculture is extracted from a report by the University of Warwick [265]. The allocation is not based on a survey, but rather on expert judgement. An assessment of the uncertainty in these estimates would require a formal interview with the experts that conducted the study. Such efforts are not warranted by the low share of energy consumed in this sector. An uncertainty of 25%, as for industry, is assumed.

Table 3.5 summarises the uncertainty value associated with each end-use allocation used in this study.

Table 3.5 Summary of the uncertainty associated with each end-use allocation vector estimated by the author. Further details about the rationale underpinning the values is found in Section 1 of the Supporting Information

Sector	**Uncertainty**
Residential	18%
Service and Commercial	20%
Industrial	25%
Agriculture, Forestry, and Fishing	25%

3.2.3 Allocation to Devices

For the majority of flows, only one device is associated with a given sector, fuel, end-use combination. For example, only the “Electric Heater" can deliver residential process heat using electricity (i.e. cooking stoves). There are four instances, listed in Table 3.6, where further allocations are required. In all cases, the ambiguity arises because more than one type of internal combustion engine can be used to deliver mechanical energy from fossil fuels. The energy balance distinguishes between Diesel Fuel, Gasoline Fuel and Type A Jet fuel. This distinction is sufficient to make most of the required allocations. Liquid fuel used in Industry, is split between gas turbines and diesel engines according to the global sales of Diesels and Gas Turbines for mechanical drive obtained from "Diesel and Gas Turbine Worldwide" [266]. Gas use in industry is assumed to be either used in spark ignition gas engines or gas turbines, with a strong predominance of the latter technology. Liquid fuel in the service sector is split equally among diesel and spark ignition.

For device allocation based on the specific fuels retrieved from the energy balance, the Final energy uncertainties retrieved from the GHG inventories are used. For those based on broader estimates, a value of 20% is deemed reasonable.

Table 3.6 Combinations of sector, fuel and end-use which require further allocations to determine the share of energy used by a specific device. The Uncertainty column indicates the uncertainty associated with the allocation.

Sector	Fuel	End-use	Gas Turbine	Diesel Engine	Spark Ignition Engine	Uncertainty
Industry	Gas	Mechanical	75%		25%	20%
Industry	Liquid fuel	Mechanical	30%	60%		20%
Road	Liquid fuel	Mechanical		63%	37%	1.2%
Aviation	Liquid fuel	Mechanical	99.5%		0.50%	5%
Services	Liquid fuel	Mechanical		50%	50%	20%

3.2.4 Conversion Efficiencies

Average values for the conversion efficiency of each device category in the UK in 2013 is sought. Data is sourced from both national and international databases and catalogues. Whenever possible, official governmental figures are used. For residential boilers, data retrieved from the Product Characteristic Database is used [267], while for industrial boilers a combination of data from Energy Technology System Analysis Partnership [268] and an Ecodesign on Industrial boilers [269] are used. Engines in light duty vehicles, efficiencies estimated by Craglia et. al [270] based on EPA dynamometer test results applied to UK vehicles is used. For Heavy duty vehicles and shipping, data from EPA test procedures is used [271]. For jet engines, data from NASA [272] and from the stock of American Commercial Aircrafts is used [273]. For electric motors, coolers and lighting, data from the UK energy consumption statistics was used [45]. Conversion efficiency estimates vary sector by sector, reflecting the different type of equipment used in each sector. Table A.1 in appendix A, lists the efficiency range found for each device in each sector and the assumed probability distribution.

3.3 Results

3.3.1 Useful Energy Balance

The energy flow through the UK, is modelled to obtain estimates of Useful energy consumption with the results shown in Table 3.8 as a Useful energy balance.

In Figure 3.4 a Sankey diagram mapping UK energy flows from Final to Useful energy is shown. The Final energy consumption was 5.8 EJ y^{-1} (1 EJ = 10^{12} MJ) while a Useful energy consumption of 3.9 EJ y^{-1} was estimated. Hence the average conversion efficiency is of 67%. The largest Useful energy category is Heating, which accounts for 64% of total Useful energy consumption while Motion is the second most used form of Useful energy consumption, accounting for 22%. The transport sector is the one that consumes most Final energy (2.2 EJ) while the Residential sector consumes most Useful energy (1.6 EJ).

Figure 3.3 shows the contributions of Final and Useful energy, by conversion devices, to sectors. The lower contribution of the transport sector in terms of Useful energy consumption is because mechanical energy has the lowest conversion efficiencies compared to other Useful energy categories. Motion is provided with an average conversion efficiency of 34% while the same value for heating is 90%. These results are well in line with existing literature and previous Useful energy balances compiled for the UK [161, 82].

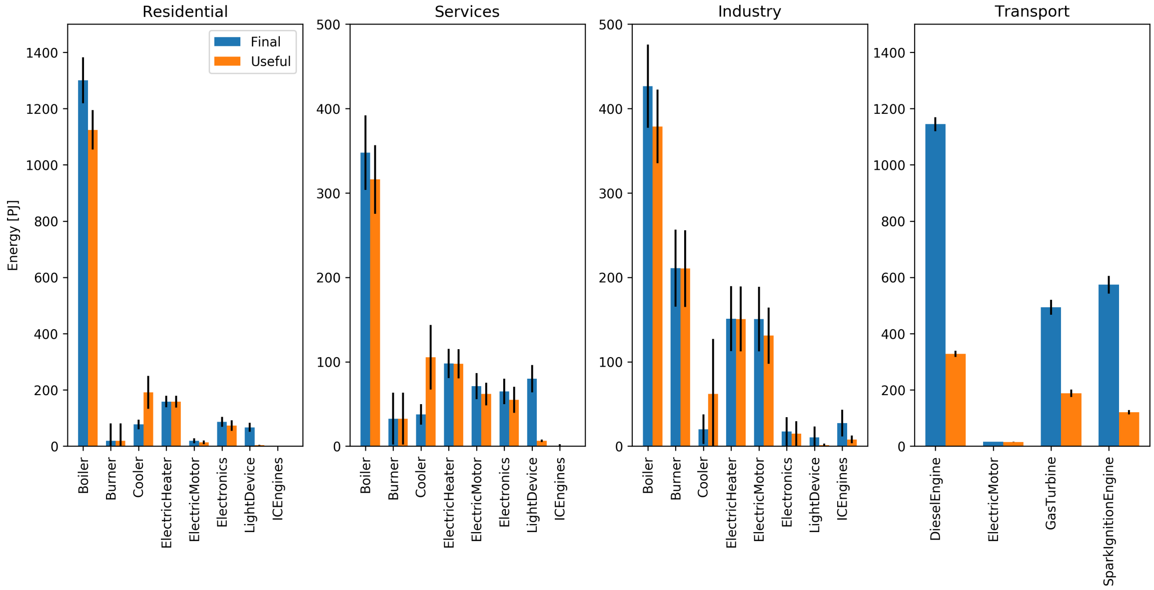


Fig. 3.3 Final and Useful energy consumed and produced by each end-use conversion device in each sector. The error bars indicate the range of two standard deviations. Useful energy bars are lower than Final energy bars because of conversion losses (except for cooling, where efficiencies ≥ 1 are observed). The magnitude of the error bars shows that there is not always enough information to rank end-use consumption because the uncertainty is larger than the differences between estimated consumption figures

Table 3.7 shows the average conversion efficiencies for each sector and each end-use category. It can be observed that the provision of cooling has the highest Final to Useful efficiencies as well as the highest uncertainties. Uncertainties are higher for the delivery of Motion than for Heating. The data collected enables comparisons in the rate of change of average conversion device efficiencies against historical results [81]. For example, lighting efficiency has increased from 6% in 1978 to 10% in 2013, thanks to the development of new lighting technologies and their comparatively fast market penetration. Also the efficiency of space heat delivery has increased from 64% to 83%, mainly thanks to the substitution of oil and coal for natural gas and electricity. On the other hand, there seems to have been a very small increase average petrol engine efficiency and the average efficiency of electric motors has decreased. For petrol engines, that is linked to a higher technological development emphasis placed on increased power and reduced cost instead than on efficiency [274]. While for electric motors, the most likely driver for this trend can be found in the much higher share of smaller motors (thus less efficient) used nowadays compared to 1978 [275].

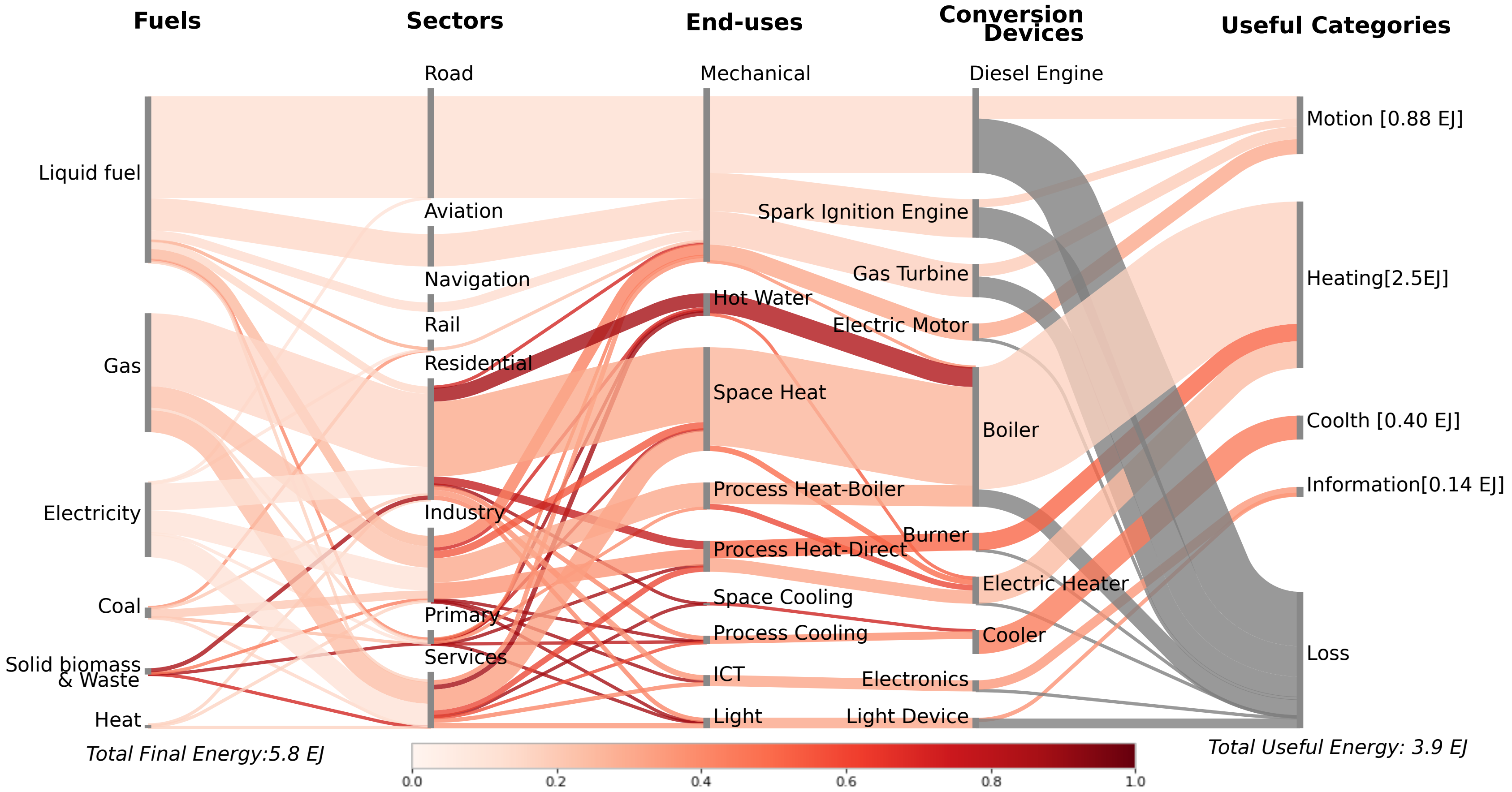


Fig. 3.4 Sankey diagram representing the energy data and uncertainty used in this study. The width of the lines represents the quantity of energy (in PJ, where 1 PJ = 10^9 MJ) while the intensity of the colour represents the uncertainty of each flow from 0 to 1, where 1 represents the maximum uncertainty of 350%. The first four layers are loss-less because they show only allocations, losses are only incurred in the stage between conversion devices and Useful energy categories.

Table 3.7 Average conversion efficiencies from Final to Useful Energy for each sector, aggregated by Useful energy category

	Cooling	Heating	Illumination	Information	Mechanical
Industry	309% ± 347%	94.2% ± 1%	13% ± 2%	85% ± 27%	83.8% ± 3%
AFF	311% ± 345%	89.2% ± 1%	13% ± 2%		60.5% ± 3%
Residential	248% ± 104%	88.3% ± 1%	6% ± 2%	84.8% ± 26%	74% ± 5%
Services	289% ± 77%	93.6% ± 3%	8% ± 2%	84.9% ± 26%	86.9% ± 3%
Aviation					38% ± 3%
Navigation					39% ± 3%
Rail					72.7% ± 3%
Road					25.1% ± 1%

3.3.2 Uncertainty Analysis

The analysis shows that there is great variability in the uncertainty associated with energy statistics. Final energy statistics found on the energy balance have mostly low uncertainties ($\leq$ 5%) with the exception of Biomass and Waste for which there are higher uncertainties (around 30%). Figure 3.3 show the magnitude and uncertainty of the Final energy consumption, and of the Useful energy output from each conversion device. Boilers, have the lowest uncertainty (around 7%) while the output of light devices has the highest (126%) because of higher technical variability (from incandescent to LED) and because of more uncertain allocation.

One clear trend is that smaller energy quantities are more uncertain than larger ones. For example in Industry, Useful energy for illumination has an uncertainty of 126% while Useful energy for heating has an uncertainty of 6%. Higher level of aggregation are also linked to lower uncertainty, therefore entire sector uncertainties are lower than those associated with a specific device. This is an expected result as uncorrelated uncertainties become smaller when aggregating results.

The uncertainty generation is highest in the allocation of Final energy to end-uses. The uncertainty associated with Final energy consumption in a sector for each fuel varies between 0.5 % and 55% with a median uncertainty of 5%. While the uncertainty associated with Final energy consumed for each end-use in each sector ranges between 1.5% and 120% with a median uncertainty of 34%. Similar uncertainties are observed for Useful energy estimates broken down by sector and end-use, with only a slightly higher median uncertainty.

It is important to note that the results of this uncertainty analysis are as valid as the assumptions outlined in the methodology section and do not include the “modelling” uncertainty which is associated with the assumptions made. However, the analysis has aimed to be conservative throughout, to avoid being overconfident about the uncertainty of the results.

Table 3.8 Useful energy balance [PJ] for the UK in 2013. Values are expressed for each sector and energy carrier combination and contain an uncertainty estimate.

Sector	Energy Carrier	Cool	Heat	Illumination	Information	Motion
AFF	Coal		0.2±11%			
	Electricity	6.7±79%	3.9±37%	0.2±69%		5.6±25%
	Gas		39±4%			
	Liquid fuel		5.6±76%			6.9±35%
	S. Bio. & Waste		5.5±57%			
	Total	6.7±79%	54±10%	0.19±69%	0±0%	12±22%
Industry	Coal		119±8%			
	Electricity	61.9±105%	151±25%	1.3±126%	15±98%	131±25%
	Gas		281±7%			5.2±111%
	Heat		30.8±6%			
	Liquid fuel		139±11%			2.6±108%
	S. Bio. & Waste		19.4±26%			
	Total	61±105%	739±6%	1.33±126%	14±98%	138 ±24%
Residential	Coal		24.6±7%			
	Electricity	191±31%	158±13%	4±28%	73.6±26%	14±48%
	Gas		971±4%			
	Heat		2.2±5%			
	Liquid fuel		98±3%			
	S. Bio. & Waste		47.8±59%			
	Total	191±31%	1302±4%	4.0±28%	73.6±26%	14±48%
Services	Coal		0.7±5%			
	Electricity	105.2±36%	97.8±18%	6.4±23%	55.1±28%	61.9±22%
	Gas		305±11%			
	Heat		16.7±5%			
	Liquid fuel	0.1±415%	24±6%			0.1±209%
	S. Bio. & Waste		1.9±48%			
	Total	105±36%	446±8%	6.4±23%	55±28%	62±22%
Aviation	Liquid fuel					188±6%
Navigation	Liquid fuel					55.2±4%
Rail	Electricity					14.9±2%
	Liquid fuel					9.5±16%
Road	Electricity					0.1±6%
	Liquid fuel					384±3%

3.4 Discussion

This chapter provides a methodology to quantitatively assess the uncertainty associated with end use-energy statistics and updates data on the efficiency of conversion devices. The Useful energy balance of the United Kingdom in 2013 was calculated and its uncertainty quantified for the first time.

3.4.1 Useful Energy Balance

The differences between the Final and Useful energy balances are similar to those observed in previous studies of the UK in national [90], European [95], and global studies [86]. There are two main considerations shown by the analysis. First, the provision of mechanical energy (mostly for transport) has the highest improvement potential in terms of Final to Useful efficiency as its efficiency is low and it has increased only marginally since 1978. Policies to help bridge this gap are already in place in most jurisdictions [276], but are evidently not sufficiently stringent to stimulate the adoption of available technologies such as cylinder deactivation or Atkinson cycle engines [277]. Second, the industrial sector is the most efficient sector because it tends to use the largest (and thus most efficient devices) and relies more than any other sector on direct combustion, which has a 100% first law efficiency. While Primary energy consumption lies outside the boundaries of this analysis, it is important to note that Primary to Useful efficiency is different from the Final to Useful efficiency. For example, while electric motors display a very high Final to Useful efficiency, their Primary to Final efficiency can be on par with the one of Diesel engines (further details can be found in Cullen et. al [97]).

The energy conversion efficiency values used in this analysis of UK energy flows, have been revised based on the latest efficiency data from tested conversion devices. This update was long due in the literature and it enables the assessment of some long term trends by comparing the results with values used by Eurostat in the 1970s [81]. At the same time, Table 3.7 shows that there is considerable variation in the uncertainty associated with efficiency: showing efficiency values with a confidence interval should be standard practice, and any claim of year on year variation should at least be checked for statistical significance.

From the conversion efficiency data collection procedure, it was observed that device efficiencies do not show large year on year variations but they do change over longer time periods, albeit with different rates. Data on devices with short lifetimes and fast technological progress (e.g. light bulbs) must be updated with higher frequencies compared to devices that have long lifetimes and slower technological progress (i.e. industrial boilers or jet engines).

The present study is a snapshot view of the Useful energy balance of the UK because the focus of the study was on the development an uncertainty quantification framework. It is recognised, that the full benefit of Useful energy accounting are found in consistent time series and in comparisons between countries.

3.4.2 Uncertainty Analysis

The results from the uncertainty analysis show three broad trends. First, end-use application with smaller shares of energy have higher uncertainty. This results from the nature of the distribution used to model the uncertainty of the allocation vector, and because at parity of absolute uncertainty, smaller shares will have higher relative uncertainties. Second, results with a higher level of aggregation have lower uncertainty, because the uncertainties are assumed to be uncorrelated they decrease in magnitude for aggregated value, thus reflecting the intuition that we are more confident about aggregated values than detailed breakdowns of data. Third, the main source of uncertainty is found in the allocation to end-use applications. It was previously thought that both end-use allocation and efficiency values contributed to the uncertainty of Useful energy estimates, however this study has shown that the key element that results in uncertainty is the allocation to end-use applications. One of the reasons for the higher uncertainty of the allocation to end-uses is the fact that practitioners are reluctant to quantify uncertainty while compiling national level statistics and thus only very conservative assumptions can be made about these values.

The interpretation of the uncertainty results is facilitated by defining an acceptability threshold, and conveniently statistical offices often define a range of acceptable uncertainty for national surveys. For example, the UK's Annual Survey of Hours and Earnings considers acceptable uncertainty values between 20% and 40% [278]. In a study by Eurostat, examples of acceptability thresholds for uncertainty were found between 10% and 33% [279], while the American Community Survey, considers values with uncertainties up to 24% as "reliable" [280]. Using these examples as guidelines, Useful energy estimates with uncertainties below 25% are deemed sufficiently reliable. Table 3.8 shows that Useful energy estimates for the provision of Heating in all sectors (with the exception of Heating from biomass) and of Mechanical energy in the Transport sector are sufficiently reliable; these sectors account for 85% of total Useful energy consumption. Therefore, the development of policy-relevant indicators based on Useful energy estimates are warranted by sufficient data quality. All other Useful energy categories are too uncertain to be deemed acceptable for policymaking. Therefore, although the uncertainty of Useful energy estimates is higher than Final energy statistics, this study shows that most Useful energy estimates are reliable. Statistical offices only need to focus on reducing the uncertainty in a small number of Useful energy categories to expand the scope of Useful energy statistics available to develop indicators to be used in policymaking.

In the specific case of the UK, an improvement of the industrial end-use energy statistics would have the greatest impact on the reliability of Useful energy accounting with the smallest effort. This could be achieved by an energy end-use application survey for the Industrial sector. A possible practical solution would be to adopt the survey methodology used for the US Manufacturing Energy Consumption Survey [62], where the energy managers of a sample of industrial facilities report on the end-use applications of their energy consumption.

At a global level, the advent of the *Smart Grid* vision in buildings, and of the *Internet of Things* paradigm in the manufacturing sector are likely to increase the quantity and quality of metered end-use consumption data for energy statistics. In particular, new developments in metering and sensing technology, such as the Non Intrusive Appliance Load Monitoring [281], smart plugs [282], and natural gas sensors [283], enable consumers to be aware of their energy consumption. The decreasing costs of sensing and data processing technology (which are at the basis of the Industry 4.0 revolution [284]) mean that an increasing share of energy consumption will be monitored. These new developments mean that increasing quantities of data on the end-uses of energy will become available in the near future. It is recommended that statistical offices make use of these new tools for their data collection protocols as this would bridge the gap between the reliability of supply and demand side statistics. This is expected to facilitate the deployment of more detailed policies on the end-uses of energy and thus reduce the imbalance between supply and demand side policy action.

Chapter 4

Technical efficiency limits

Knowing the maximum technically achievable performance of a technology is the first step required in an assessment of its potential benefits. In the case of energy conversion devices, understanding the maximum efficiency that each technology can reach is necessary to estimate their energy saving potential and thus their role in climate mitigation. In previous work, Cullen had estimated the theoretical limits of energy conversion devices at a global level and calculated the saving of each device with the aim of prioritising policy and R&D action [24]. However, as explained in Chapter 2, the theoretical limits are not a sufficiently representative metric to estimate an achievable saving potential while the technical efficiency limits provide more relevant information. Policy and R&D action in end-use conversion efficiency are very different in terms of the stakeholders and costs involved. The potential savings from these two broad classes of measures has never been quantified for conversion devices nor for most energy technologies, meaning that policymakers might not be informed correctly regarding the relative importance of action targeting market deployment of current technology versus investment in the improvement of technology. In addition, studies conducted at conversion device level are certainly pertinent to help direct policy action but R&D agenda setting would benefit from more specific guidance on which technical parameters are more promising for potential efficiency gains.

This chapter has two aims. First, it provides a novel methodology to develop a robust engineering assessment of the technical efficiency limit of each device. Second, it estimates the energy saving potential associated with each device and with each technical parameter, drawing on the detailed case study of end-use conversion efficiency presented in chapter 3. The chapter is structured as follows. Section 4.1 outlines the methodology developed to estimate the TEL using a probabilistic approach. Section 4.2 contains the detailed analysis of each conversion device, including a description of the physical models developed and the rationale behind the definition of the TEL. Section 4.3 displays the results regarding the energy saving potential of each conversion device applied to UK end-use energy data, while section 4.4 contains a discussion of results.

4.1 Methods

There is no established methodology to determine the Technical efficiency limit of conversion devices. In this section, the methods used to establish the TEL of each device and to calculate the saving potential of each technology is presented.

4.1.1 Technical efficiency limit

There are innumerable types and variations of machines that transform energy to more useful forms and there is no unique way to classify and categorise these technologies. The device classification is the same as the one presented in chapter 3 (Table 3.2)

In the literature the term “technical efficiency limit” (TEL) is used to refer to an array of meanings. In economic assessments of energy efficiency, it refers to the efficiency level that would be achieved without market distortions [133], while in techno-economic assessments, it often refers to the efficiency of the best available technologies [132]. In this study, the technical efficiency limit of each device is defined as the steady-state conversion efficiency that can be achieved while taking into consideration unavoidable energy losses, but ignoring economic considerations. The estimated TEL considers factors such as the properties of materials, unavoidable friction losses and non-ideal thermodynamic cycles. Economic factors and manufacturing constraints are ignored because these aspects are contingent to the present techno-economic situation and are subject to change. Examples of these trends include, the evolution of the minimum feature size that can be economically manufactured [285] in electronic components and the increase in thermal properties of materials [286] in jet engines.

As is often the case in engineering design, there are trade offs between performance parameters, therefore increases in energy efficiency can be accompanied by decreases in other parameters such as power density (kW/m^3 or kW/kg). When defining the TEL, it is important to ensure only options that affect these other parameters marginally, this is particularly important for the transport sector where power density is crucial.

The efficiency limit is estimated only for conversion devices that share the same limitations and function. In particular, the distinction between SI and CI engines is irrelevant for the estimation of the efficiency limit because distinction is only existent due to contingent economic and technological conditions, SI engines are used because they can deliver work with a high power density, low cost and respect emission regulations, while sacrificing efficiency compared to CI engines. However, when estimating the efficiency limit, a device that produces shaft work from chemical energy with a high power density is all that is required and the distinction between SI and CI becomes redundant. The efficiency limit is not estimated for device categories that produce thermal energy directly, the electric heater and burner, because their energy conversion efficiency is already of unity and cannot increase. Therefore, the TEL is estimated for six conversion device categories: Reciprocating Engine, Jet Engine, Boiler, Electric Motor, Cooler, and Light devices. The limit is estimated stochastically to avoid any overconfidence in the results. This approach has already been followed in the literature, for example by Martin et. al [114], Yan et al. [287], and Baker et. al [288]. Since there is no agreed methodology in the literature to estimate the TEL, two methods are presented below and either one or the other is applied to each conversion device.

Method A –*Parametric model*: a physical model (f) of the conversion device is developed to relate the conversion efficiency (η) to a limited number of key performance parameters (for example α and β).

$$\eta = f(\alpha, \beta) \tag{4.1}$$

The optimal value of each parameter (α^*, β^*) is estimated after a thorough literature review taking into account only unavoidable physical limitations to the optimal value of the parameter. For example, when considering the maximum combustion temperature in a gas turbine, the limiting factor is the activation of endothermic dissociation reactions rather than the melting temperature of current materials. In most cases, there are a range of opinions and values found in the literature, therefore to minimise the consequences of subjective judgement, the optimal parameters are defined as a uniform probability distribution which encompasses the values found in the literature. Such that

$$\alpha^* \sim \text{Uniform}(\alpha^*_{min}, \alpha^*_{max}) \tag{4.2}$$

$$\beta^* \sim \text{Uniform}(\beta^*_{min}, \beta^*_{max}) \tag{4.3}$$

Using a stochastic approach enables a more explicit assessment of the uncertainty associated with the results and helps mitigate overconfidence in the results. The parameters are then fed into the physical model to obtain a probability distribution of the Technical Efficiency Limit as seen in equation 4.4

$$\eta_{TEL} = f(\alpha^*, \beta^*) \tag{4.4}$$

Method B –*Loss reduction method*: the main loss mechanisms for the conversion device are defined and characterised. Then, the magnitude of each loss mechanism (l) in the current best available technology is quantified by means of a literature review. The reduction potential of each loss mechanisms (ΔL) is then estimated by relating it to a specific advance in the conversion device technology. The TEL (η_{TEL}) is then calculated using equation 4.5

$$\eta_{TEL} = \eta_{BAT} + \sum_{l} L_l \Delta L_l \tag{4.5}$$

where L_l is the share of the input lost due to a specific loss mechanism l. The quantification of the reduction potential refers to the reduction that could be achieved by the best possible technical solution, disregarding economic considerations. For example, the reduction potential of iron losses in electric motors should take into account the use of amorphous metals, despite their currently high cost. The loss reduction potentials are estimated as a uniform probability distribution that represents different values found in the literature and the degree of uncertainty of each reduction potential, such that

$$\Delta L \sim \text{Uniform}\left(\Delta L_{min}, \Delta L_{max}\right) \tag{4.6}$$

They are then combined to obtain the technical efficiency limit of the device which is itself a probability distribution.

The parametric model methodology (Method A) is preferred and, whenever possible, this method is used. However, for some devices, physical modelling is prohibitively complex due to a large number of design parameters or due to the presence of important complex interactions that require computationally intensive models (such as computational fluid dynamics or finite element analysis). For these cases, the loss reduction methodology is employed as an alternative physical basis for the technical efficiency limit. A summary of the methodology and the steps taken to model each conversion device is shown in the flowchart in Figure 4.1.

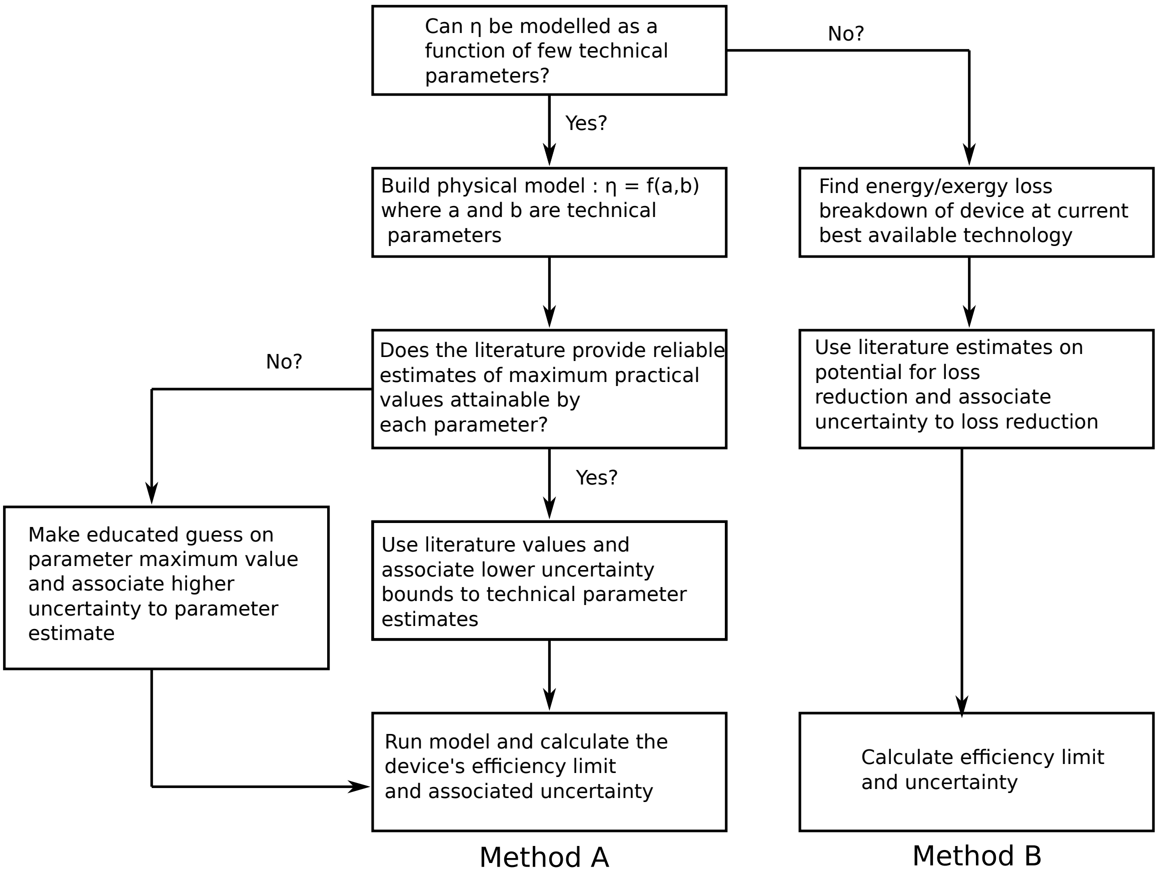


Fig. 4.1 Flow chart showing the decisions and steps taken to determine the technical efficiency limits following both methodologies.

To reduce the number of parameters studied and the complexity of the models, efficiency at steady state and rated power operation is modelled by default. This simplification is acceptable for most conversion devices either because they operate mostly at constant load, or because their performance degrades only marginally for variable load. One important exception is for reciprocating engines used in light duty vehicles, where the highly variable load and the strong correlation of efficiency with load conditions, means that the average efficiency varies significantly from the constant load efficiency [289]. Therefore, for road transport, both the current efficiencies and the TEL are estimated for engines operating over a typical drive cycle.

Methods A and B were used on roughly the same number of devices: gas turbines (including Jet Engines), boilers, and coolers were analysed using method A; reciprocating engines, electric motors, and light devices were analysed with method B. Section 4.2 provides a full analysis of each conversion device including all relevant references and a description of the models used.

4.1.2 Current efficiency

To operationalise the TEL (η_{TEL}), it is necessary to know what is the current status of conversion efficiencies for each device categories. The current status of efficiency is defined using two values, the average efficiency (η_{avg}) and the best available efficiency (η_{BAT}):

- *Average efficiency* represents the typical value of conversion efficiency for a given device. The average efficiencies for the UK have been estimated stochastically in Chapter 3. The probability distributions for average efficiencies represent the 90% confidence range of the estimate.

- *BAT efficiency* represents the highest efficiency of each device that is available in the market. The BAT is established through desk research focused on searching product catalogues. The BAT is is modelled as a deterministic value rather than as a probability density because its value is well defined. η_{BAT} is always higher than η_{ave} but it can be either equal or slightly higher than the upper bound of the current efficiency range. That is because the range of current efficiencies should represent the 90th percentile range, while η_{BAT} might represent a niche technology. The BAT efficiencies are a function of the sector in which the device is used, therefore different BAT efficiencies are defined for different sectors. In addition to determining the value of BAT efficiency for each device, it is important to understand thanks to which technical improvements, that efficiency is reached. If the TEL of a device is found using Method A, then a device that reaches the BAT efficiency is modelled as a function of the key design parameters identified. If the TEL is found using Method B, then the loss breakdown a device operating at BAT efficiency needs to be defined.

Figure 4.2 depicts the relationship between the three efficiencies that are defined for each device. As explained in the above section, η_{TEL} and η_{avg} are defined as a probability distributions, while the η_{BAT} is a deterministic value.

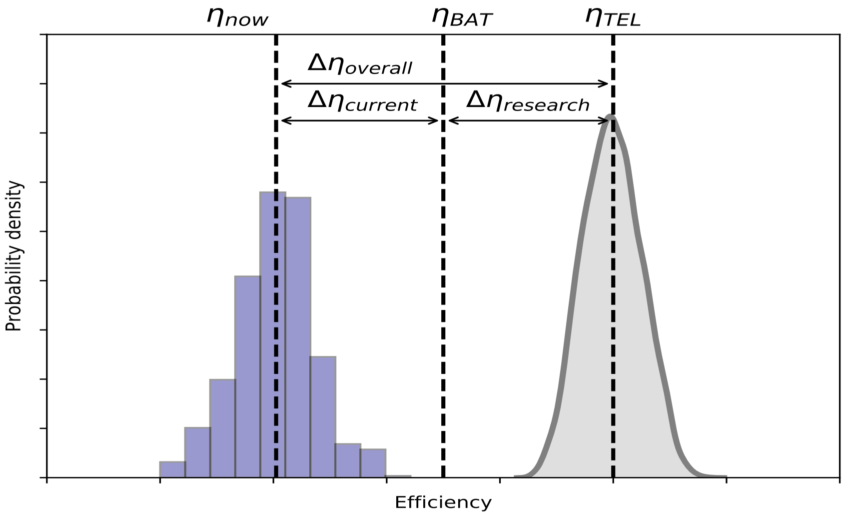


Fig. 4.2 Diagram showing the conceptual difference between current efficiency (η_{now}), best available efficiency (η_{BAT}), and the technical efficiency limit (η_{TEL}). Current efficiency is understood as a probability density function based on data. The TEL is understood as a probability density function representing the uncertainty of the models and parameters used in its estimation.

The analysis uses first law efficiencies, rather than second law efficiencies as done in the Societal Exergy Analysis literature, because energy first law efficiency better captures Useful energy defined as the last stage of quantifiable energy before the delivery of an energy service. This is best exemplified by the case of the residential boiler, where the first law efficiency is around unity, while the second law efficiency is around 15%. The lower value of the second law efficiency reflects the use of that high quality energy to deliver low temperature heat, however, for space heating it is this low temperature (30-80 C°) heat that is required, rather than work. The energy balance is built using the lower heating value (also known as the net calorific value) of fuels so all efficiencies are calculated on this basis.

4.1.3 Energy saving potential estimation

In order to put the TELs into context, it is important to calculate the energy saving potential associated with the technically maximum efficiency that each device can reach. Given the very high technical granularity of this analysis, it is possible to link individual technical parameters within devices to their potential savings at a national level. This ability is used to calculate two saving potentials, one related to the improvement of current efficiency to BAT efficiency and one between BAT and TEL. The first represents the potential savings without any further R&D action, while the second represents savings associated only with

R&D efforts. The latter potential can be further be disaggregated into the potential for each technical parameter improvement.

More in detail, The Energy Saving Potential (ESP) is a measure of the energy associated with the quantity of Final energy that would be saved if each conversion device was operated at a target efficiency. The computation of ESP requires knowledge on the energy throughput (E_d) of each conversion device (d) as well as the current (η_d^1) and target efficiency (η_d^2). The throughput of each conversion device in the UK is taken from the results of Chapter 3. This means that the quantity of final energy input in each device is defined as probability distribution which represents the uncertainty of the estimate. Equation 4.7 shows the formula used for the calculation of the ESP in its general form

$$\mathrm{ESP}_d = E_d\left(1 - \frac{\eta_d^1}{\eta_d^2}\right) \tag{4.7}$$

With the information on energy efficiency available, three ESPs can be defined. First, the overall ESP (ESP_o), represents the savings associated with moving from current efficiency to the TEL ($\eta_d^1 = \eta_{avg}; \eta_d^2 = \eta_{TEL}$). Second, the current ESP (ESP_c) which represents the savings associated with moving current efficiency to BAT efficiency ($\eta_d^1 = \eta_{avg}; \eta_d^2 = \eta_{BAT}$). Third, the research ESP (ESP_r) which represents the savings associated with moving from BAT efficiency to TEL ($\eta_d^1 = \eta_{BAT}; \eta_d^2 = \eta_{TEL}$). All of these saving potentials are calculated at the most granular level (for each combination of fuel, sector, end-use and device) and then aggregated to present the savings at a sectoral, device, and country level.

The ESP_r is broken down for each technical parameter and loss reduction mechanism identified. In this case the ESP_{rp} measures the potential savings associated with the improvement of a given parameter p from its BAT level to the level identified for the calculation of the TEL. The potential is calculated by first estimating the efficiency associated with a given parameter (η_p), assuming that all other parameters remain equal. The saving potential is calculated following equation 4.9

$$\Delta\eta_p = \eta_{BAT} - \eta_p \tag{4.8}$$

$$\mathrm{ESP}_{rp} = E_d\left(1 - \frac{\eta_{BAT}}{\eta_{BAT} + \Delta\eta_p}\right) \tag{4.9}$$

For all the above mentioned measures, a Carbon Saving Potential (CSP) is calculated for each device (d) and fuel (f) combination using equation 4.10

$$\mathrm{CSP}_d = c_f \, E_{df} \left(1 - \frac{\eta^1_{df}}{\eta^2_{df}} \right) \tag{4.10}$$

where c_f is the carbon emission per unit energy (gCO$_2$/MJ) associated with each fuel. Carbon emission factors are taken from the UK government official emission factors for the year 2013 [290]. The savings for each parameter are also aggregated in broader "engineering research fields" to provide a first order estimate of the role of each of these fields in improving conversion efficiency.

All the saving potentials are calculated using a Monte Carlo method taking 5000 random samples from each distribution using the NumPy package [291] in Python.

4.2 Defining the Technical efficiency limits

In this section an analysis aiming to establish the TEL for each device is presented. The structure of the analysis is as follows. First, the technology is characterised, then the device specific efficiency measure is defined, then the key design parameters are identified and literature relevant to the estimation of the technical limit is presented. The assessment methodology is chosen and the physical model or the loss distribution models are presented. Then for each technical parameter a limiting value is defined based on physical laws or on specific technical literature recommendations. Finally, the TEL for the device is established and if possible, compared to previous literature estimates.

4.2.1 Gas Turbines

Description

Gas turbines convert chemical energy into work by means of the Brayton cycle, shown in figure 4.3. A simple cycle gas turbine (GT) is composed of: a compressor, which continuously compresses gasses from ambient condition to high pressure; a burner, where fuel is added to raise the temperature of the compressed air; an expander (turbine), where gases are continuously expanded to a lower pressure. The expansion work generated is larger than the work required for the compression, resulting in a power output [292]. A defining characteristic for GTs is the processes of compression, heat addition and expansions, which all occur continuously and simultaneously in different locations.

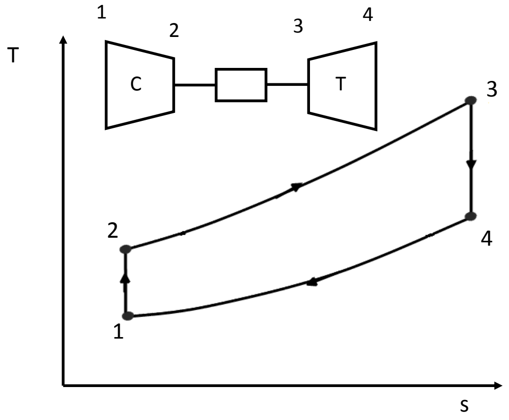


Fig. 4.3 T-s diagram of ideal air standard Brayton Cycle and layout of simple cycle gas turbine

Characterisation

Gas turbines have four applications: jet-propulsion, power generation, industrial use and microturbines. In jet engines, the work generated is converted to kinetic energy which is used to propel the aircraft. Technology developed for aircraft propulsion has been translated for land-based applications in what are called aeroderivative (AD) gas turbines. Aeroderivatives are used in industry for mechanical drive and in situ power generation [293]. For power generation, large devices known as Heavy Duty (HD) gas turbines, are operated in combined cycle (CCGT) to maximise efficiency[292].

Efficiency measure

The efficiency measure for gas turbine is defined trivially as the ratio between input chemical energy (measured LHV terms) and shaft work output.

$$\eta = \frac{\dot{W}}{\dot{m}\mathrm{LHV}} \tag{4.11}$$

Key Parameters

Four key parameters affecting GT efficiency are identified and in this section they are described and quantified.

Turbine Inlet Temperature: Exact values of TIT are seldom published in the open literature. Mitsubishi claims to have reached a TIT of 1873 K in it's latest J-series turbine [294], and while no specific value was found for Western manufacturers, temperatures around 1700 K were achieved by GE in in its HA series in the early 2000s [295]. Manufacturers design GTs with TITs that range from 1200 K to 1700 K since there is demand also for GTs with low TIT due to their lower costs.

Blade Cooling: Current TITs are only achievable thanks to blade cooling technology. Cooling can either be internal, with up to 30% of the air being bled off form the compressor to the turbine blades; or external, with externally sourced steam used to cool the blades. Blade cooling maintains blades below their metallurgical limit, while allowing the combustion gasses to exceed that temperature. The metallurgical limit of even the most advanced single crystal alloys is in the order of 1300 K. Since neither compression nor expansion are isentropic, internal cooling decreases both the specific power and efficiency of the cycle [296].

Politropic Efficiency: At GE, a polytropic efficiency of 92% for axial compressors was achieved as early as 1947 according to L Smith [297], however the design was impractical for real world applications. Subsequent designs show efficiencies that range from 86% to 91%. The polytropic efficiency a GE aeroderivative gas turbine, the LMS6000, was estimated to be 91% and 90% for the compressor and the turbine respectively [298]. It is understood that similarly high values are found in heavy duty turbines.

Pressure Ratio: The overall pressure ratio ranges from 12 to 37 for single cycle land based machines but can be as high as 60 for jet engines, for example, Rolls Royce Trent 1000 has an OPR of 52 [299]. The reason for this discrepancy between jet engines and power generation machines is that the inlet air is much colder at cruise altitude and hence higher OPRs can be used without rising the compressor temperature beyond its limits.

Efficiency Limits

Literature estimates

Two studies focusing on establishing the ultimate performance of gas turbines were identified. The first was published in 1993 by Chiesa et al [300], they establish the performance of the gas turbine based on a detailed thermodynamic model. Their “Ultimate high-temperature situation” scenario provides two temperature (and thus efficiency) values, one assuming full oxidation and the other assuming frozen equilibrium compositions. The actual temperature and efficiency value is within these boundaries and it depends on the reaction kinetics that would occur in the combustor under such conditions. For all of their scenarios, the authors do not specify a maximum pressure ratio but rather provide results as a function of it.

The second article was published in 2005 by Willckok et al [296] and focuses on the effect of cooling technology on the efficiency of gas turbines. The calculations are based on a computer code written by the same authors. They calculate the ultimate efficiency for an uncooled turbine as a function of TIT ranging between 1400 K and 2200 K, and with a pressure ratio ranging between 25 and 60. While the authors do not specify the maximum efficiency that can be achieved under these conditions, a global maximum appears in the graph for TITs and pressure ratios beyond the specified range.

The calculated ultimate efficiencies and design parameters used in these studies are summarised in table 4.1.

Table 4.1 Summary of GT efficiency limit values found in the literature

	Chiesa et al.	Wilcock et al.
Turbine Inlet Temperature	2250 - 2361 K	2200K
Pressure Ratio	120	70
Compressor Polytropic Efficiency	90.6%	92.5%
Turbine Polytropic Efficiency	93.1%	92.5%
Thermal Efficiency	53-56%	56-57%

Physical model

Since the efficiency of GTs can be reliably modelled as a function of a limited number of parameters, a 0D thermodynamic model is developed to understand the efficiency limits using methodology A. From the air-standard Brayton cycle, one can derive an expression for efficiency that is solely a function of the pressure ratio. The pressure ratio is defined as the ratio between the compressor exit pressure and the inlet pressure.

$$r = P_2/P_1 \tag{4.12}$$

$$\eta = 1 - \left(\frac{1}{r}\right)^{\frac{\gamma-1}{\gamma}} \tag{4.13}$$

As can be seen in Figure 4.4, the theoretical efficiency increases slowly with pressure ratio. The specific power, on the other hand, is a function of both the TIT and the pressure ratio.

In the ideal Brayton cycle, the compression and expansion process are assumed to be isentropic. In real machines, where entropy is generated in both processes. The increase in entropy is normally quantified using the concept of *isentropic efficiency* which is defined as the ratio between the real difference in temperature over the ideal difference in temperature. The level of entropy generation is also a function of pressure ratio [292], and for this reason the concept of *polytropic efficiency* is commonly used. This efficiency is defined as the the isentropic efficiency of an elemental stage in the process such that the efficiency stays constant throughout. In practice, the polytropic efficiency is a good measure of the efficiency of a certain component design, irrespective of the number of stages involved, or of the pressure ratio. Compression and expansion processes is modelled as follows

$$\frac{T_2}{T_1} = \left[\frac{P_2}{P_1}\right]^{\alpha_c} \qquad \frac{T_4}{T_3} = \left[\frac{P_4}{P_3}\right]^{\alpha_t}$$

$$\alpha_c = \frac{\gamma - 1}{\eta_{pc}\gamma} \qquad \alpha_t = \eta_{pc}\frac{\gamma - 1}{\gamma} \tag{4.14}$$

where η_{pc} and η_{pt} are the compressor and turbine polytropic efficiency respectively, and γ is the ratio of specific heats.

Higher polytropic efficiency leads to higher overall cycle efficiency since deviations from ideal conditions contribute to a decrease of net power output for the same heat input. This effect is shown in figure 4.4.

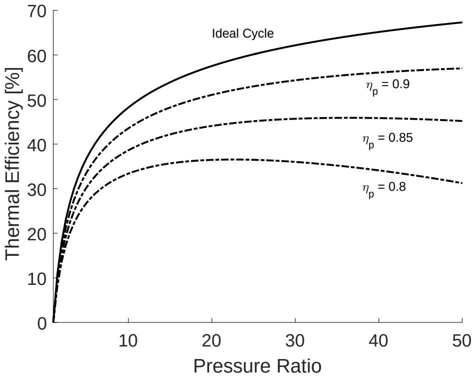


Fig. 4.4 Relationship between efficiency and pressure ratio for air standard Bryton Cycle. η_p represents isentropic efficiency for compressor and turbine.T_2 = 1500 K, λ = 1.4

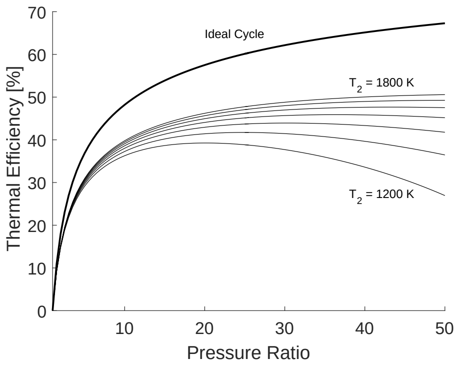


Fig. 4.5 Relationship between efficiency and pressure ratio for air standard Brayton Cycle for different values of turbine inlet temperature (T_2). $\eta_c = \eta_t = 0.9$, $\lambda = 1.4$

In a real machine, the thermal properties of the working fluid change after combustion. The heat capacity of the gases are computed at the entry and exit of the compressor and of the turbine using the Candera thermodynamics package [301]

If the irreversabilities of the compression and expansion processes are considered, the cycle efficiency is also a function of the turbine entry temperature T_3. The expression for efficiency and specific power are given by

$$\eta = \frac{T_3\left(1 - r^{\alpha_t}\right) - T_1\left(r^{\alpha_c} - 1\right)}{T_3 - T_1 r^{\alpha_c}} \tag{4.15}$$

$$\frac{\dot{W}}{\dot{m}} = cp_g T_3\left(1 - r^{\alpha_t}\right) - cp_a T_1\left(r^{\alpha_c} - 1\right) \tag{4.16}$$

Figure 4.5 shows that higher TIT and r result in higher cycle efficiency. The efficiency increases with TIT because the relative effects of the irreversibilities becomes smaller as the ratio of positive turbine work over negative compression work increases [293]. For lower values of TIT and η_p efficiency reaches a peak for compression ratio values around 40, while for higher values there is no peak.

Efficiency limit estimation

In this section the rationale behind the estimated limit value of each of the key performance parameters is explained and the range of values summarised.

Turbine inlet temperature The temperature at the entrance of the turbine has historically been considered the main driver of improved gas turbine performance and considerable resources have been devoted to the improvement of this parameter. As can be seen in figure 4.6, there has been a continuous increase in TIT over the past fifty years, driven both by improvements in material properties and by the introduction of cooling technology. Macchi et al. have estimated the historical improvement rate to be 12 K/yr in TIT and of 3 K/yr in metallurgical temperature resistance in the period from 1950 to 1990 [300, 302]. However, in recent years the rate of increase has decreased.

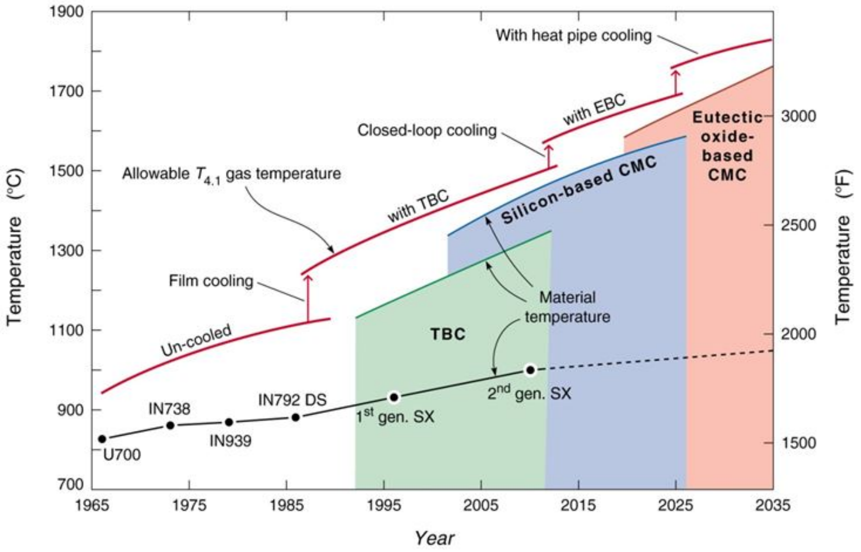


Fig. 4.6 Historical trend of turbine inlet temperature and metallurgical limit for jet engines estimated by the Wadley Research Group at Virginia Tech [286]

Estimates of future TIT by the Wadley Research Group and by Macchi et al. [300] agree on a practical limit of about 2075 K. Increases will be be mainly driven by improvements in cooling technology and ceramic based coatings [286]. Further increases in the TIT would lead to increased predominance of dissociation reaction which, would reduce the overall efficiency of the device. In this study the technical limit for TIT is considered to vary between 1900 and 2100 K to keep the estimate conservative.

Polytropic efficiency Smith has shown that very high levels of polytropic efficiency were already achieved in the 1940s at GE [297]. The engine, however, had mechanical stability problems, that made it practically un-useable. Turbomachinery efficiency is not limited by design options, but by a network of mechanical interactions. Wilcock and Joung [296], in an article dedicated to estimating maximum turbomachinery efficiency, state that the practical maximum polytropic efficiency is 92.5%.

Hall et al. estimated the breakdown of losses by mechanisms and the maximum efficiency limits of axial turbomachinery [303, 304]. The authors followed Denton's framework based on entropy generation as a metric for losses [305]. Their purpose was to obtain an upper limit of component efficiency and hence ignored any losses that they deemed removable through improved blade design, including shock losses and three-dimensional effect losses. The loss mechanism models used are all two-dimensional and are based on a small number of design parameters such as inlet Reynolds Number, Aspect Ratio hub to tip ratio etc. Their models were used to optimise blade design to obtain the highest possible polytropic stage efficiency within physical constraints. Both the relative importance of each loss mechanism and the maximum polytropic efficiency vary depending on the flow conditions encountered at each stage. For example, in compressors an efficiency of 96.1% for the first stage and 93.1% for the last stage were obtained. The difference was caused by the increased relevance of tip leakage losses in the very small last blade of the compressor. For the turbine, they obtained a maximum stage efficiency of 97.2%, however this ignores the entropy generation caused by the heat transfer to the cooling flow. Given this information, the technical limit for polytropic efficiency is assumed in the 93% - 95% range for turbines and 90%-93% for compressors.

Cooling technology There is no physical reason to believe that cooling will continue to be necessary in advanced gas turbines constructed with ceramic and ceramic composite materials. Therefore for the technical efficiency limit, no blade cooling is considered.

Overall Pressure Ratio Achieving a high OPR has three main barriers. First, a high OPR requires more compressor stages, or higher stage loading. Second, the size of the last compressor stage becomes increasingly small and inefficient as the OPR is increased. Third, the compressor exit gas become increasingly hot. The literature indicates that the limiting parameter in compressor design is the compressor discharge temperature. Cumpsty states that the limiting temperature is currently 875 K and he predicts that this could be pushed by a further 100 K by employing titanium based alloys in compressor stages [306]. On the other hand, second generation single crystal temperature limit is 1270 K [286]. By taking these two temperatures as a range of upper compressor discharge temperature and rearranging equation 4.14, the maximum OPR is expected to range between 80-100.

Table 4.2 Summary of key parameter and efficiency limit for Gas Turbines

Device	Current Efficiency	Parameters			Efficiency limit
Jet Engine	37-41 %	TIT	1900-2100	K	59-62%
		CR	80-100	-	
		η_c	92-93	%	%
		η_t	93-95	%	

Comparison with Literature

The estimate for the TEL is slightly higher than the one found in other parametric studies of gas turbines. The lowest bound of the TEL is similar to the highest efficiency reported in the literature. It is believed that there are two main reasons for the discrepancy, they are attributable to the polytropic efficiency estimates and to the complexity of the model used. This study accounts for improvements in the tubomachinery polyropic efficiency such that they might go beyond 92%, a value that is taken as the maximum efficiency in most study. Moreover, the models found in the literature take into account the dissociation reactions that occur at very high temperature, while the model used in this study does not.

4.2.2 Jet Engine

Description

Jet engines are devices using a gas turbine for converting chemical energy into work in the form of kinetic energy of a stream of air. The change of momentum of the air jet is used to propel the aircraft forwards.

Characterisation

There are three main designs of jet engine turboprop, turbofan and turbojet, which differ in the design by-pass ratio: the share of air which is not passed through the combustor. Turboprops are used for small aircraft that fly at low Mach numbers, turbofans are used for most commercial flight applications while turbojets are only used for military applications. The turbofan design has the highest bypass ratio and efficiency of all [292]. Jet engines are rated by thrust rather than by power, and to convert from one to another flight conditions must be assumed.

Efficiency measure

The overall efficiency of Jet Engine is defined as the ratio between the input chemical energy (in LHV terms) and the produced kinetic energy.

$$\eta_o = \frac{\Delta \dot{E}_k}{\dot{m}_f LHV} \tag{4.17}$$

However, the aviation industry uses different definitions of efficiency the thrust specific fuel consumption (tsfc), which needs to be manipulated in order to obtain an efficiency value in the desired form

The tsfc is a measure of the efficiency of the engine computed as the mass flow of fuel required to generate one unit of thrust. This measure can be used to understand the overall engine efficiency by making a few assumptions using the following equation, where V is the cruise speed and LHV is the fuel's lower heating value.

$$\eta_o = \frac{V}{tsfc\mathrm{LHV}} \tag{4.18}$$

Key Parameters

Thermal Efficiency The thermal efficiency is only dependent on the core design, which has the design of a gas turbine, and has already been discussed in section 4.2.1. The main difference in the design parameters, the core of jet engines and land based gas turbine are the inlet conditions. At cruise conditions at 10 600 m (35 000 ft), the standard atmospheric conditions are: T = 216 K and P = 0.226 bar [307].

Transfer Efficiency The transfer efficiency represents the efficiency with which the work generated by the core can be turned in kinetic energy. Most of the losses incurred in this process, are due to the pressure loss of the bypass flow on the nacelle wall as well as other internal entropy generation mechanisms [308]. According to Rollys Royce engineers, current state of the art engines are designed with transfer efficiencies of 85% [309].

Propulsive Efficiency The propulsive efficiency is a function of the engine's architecture and can be expressed as

$$\eta_{propulsive} = \frac{2V}{V+V_J} \tag{4.19}$$

where V_J is the jet velocity. If all of the engine's power is transferred to a jet, then that would result in a high velocity jet. On the other hand, by using a fraction of the core's power to run a fan with a much lower pressure ratio but much larger air flow rate, it is possible to lower the jet velocity and thus increase the propulsive efficiency. Current high bypass ratio designs reach values up to 10, as in the GE90. This value translate to propulsive efficiencies of about 80% [309].

Efficiency Limits

Literature estimates

Parker in a 2006 review of jet engine technologies [310], states that there is a 30% improvement potential between the high bypass ratio engines from the early 2000s and the theoretical limit. He states that the theoretical limit of propulsive efficiency is 92.5%, which the propulsive efficiency of open rotor technology. He also states that the practical limit to thermal efficiency is 55% while the theoretical limit is 60%. The first can be reached within NO_x limitations, while the latter represents the efficiency of stoichiometric combustion temperature, ultimate aerodynamic efficiency and pressure ratios above 80. Therefore according to Parker, the technical efficiency limit of jet engines is 55.5%.

In an initial assessment of Open Rotor technology [311], NASA presented engine design simulation results for an advanced geared open rotor engine. Even though there is no mention of this being an engine designed at the technical limits, the design characteristics encompass all of the available technologies. Their simulation yields a tsfc of 11.1 g/kNs which is equivalent to an overall efficiency of 50.6%.

Physical model

The physical model of the jet engine is based on the model described for gas turbines in section 4.2.1. In addition, other kinetic energy losses, described as the propulsive and transfer efficiency, are added to better represent the device.

The overall efficiency of the engine is composed of the core's thermal efficiency, the efficiency with which mechanical energy is transferred to kinetic energy and the engine's propulsive efficiency.

$$\eta_{overall} = \eta_{thermal} \times \eta_{transfer} \times \eta_{propulsive}$$

$$= \frac{E_{core}}{E_{fuel}} \times \frac{E_{jets} - E_{inlet}}{E_{core}} \times \frac{FV}{E_{jets} - E_{inlet}}$$

where E is the energy, F is the thrust and V is the cruise velocity.

Efficiency limit estimation

The efficiency limit is estimated using methodology A. The rationale and references behind each estimation are presented in this section.

Thermal Efficiency Estimates by Rolls Royce indicate that the maximum achievable core thermal efficiency is 60% [312]. Using the model developed for gas turbines, it is possible to provide a separate estimate the efficiency limit of the core. By assuming, a pressure ratio of 100 and ambient conditions at cruise, the Gas Turbine model yields a maximum technical limit of 62%.

Propulsive efficiency As the BPR increases, so does the size and drag of the nacelle. Therefore BPR levels higher than 17.5 will not to be achievable because of the increased nacelle drag [313]. However, higher bypass ratios and hence propulsive efficiencies can be achieved with open rotor technology. Rolls Royce foresees that their open rotor technology under development is likely to achieve values of propulsive efficiency around 90% at 0.8 Mach [309]. On the other hand, in an article published by GE engineers the propulsive efficiency estimate for open rotors is 95% [314].

Transfer Efficiency An open rotor configuration would result in higher transfer efficiency because the losses incurred due to friction between the air flow and the nacelle would be reduced, as only one side of the flow would be in contact with the nacelle. However, no estimate of the transfer efficiency that would be achieved by an open rotor design was found in the literature. It is assumed that the limit lies between 90% and 95% considering that the open rotor design would halve the surface area in contact with the air flow thus halving the losses compared to today's 85% transfer efficiency.

The assumption described above are used to estimate efficiency limit of jet engines. Table 4.3 includes a summary of the assumptions and their estimated variability.

Table 4.3 Summary of key parameter and efficiency limit for Jet engines,

Device	Current Efficiency	Parameters			Efficiency limit
Jet Engine	37-41 %	TIT	1900-2100	K	
		CR	80-100	-	
		η_c	92-93	%	54-58 %
		η_t	93-95	%	10.6-9.9 g/kWs
		η_{TR}	90-95	%	
		η_{PR}	90-95	%	

Comparison with the literature

The upper bound of the overall efficiency estimate is in line with the theoretical efficiency limit defined by engineers at Rolls Royce which estimate a maximum thermal efficiency of 60% and a maximum propulsive efficiency of 95% [309]. On the other hand, other estimates found in the literature propose thermal efficiency between 50% and 55% which are only slightly lower than the thermal efficiency found in this study. The most likely reason for the discrepancy is that in other studies in the literature additional parameters such as noise and NO_x production are considered in the model

4.2.3 Boilers

Description

Burners are conversion devices that transform the chemical energy of fuel into useful heat. Hot combustion products are used to increase the temperature of water or to generate steam. A boiler is defined as the combination of the burner and heat exchanger producing hot water or steam as output.

Characterisation

Boilers are used in several applications spanning all economic sectors, fuels and sizes. A common way to differentiate boilers is according to their function.

Residential Boilers These are mainly water heaters used to provide low grade heat for domestic use: heating system and hot water provision. Their rated capacity is normally below 35 kW and they can be fired with all types of fossil fuels. Each unit is used to provide heating to a single household and is controlled by the occupier. Residential heaters are bought off the shelf from boiler manufacturers.

Commercial Boilers Are either water heaters used to provide heating to commercial buildings such as office space or retail space. Their nominal capacity is usually between 35 kW and 500 kW. They can be bought off the shelf from boiler manufacturers or be custom built.

Efficiency measure

The efficiency of a boiler is calculated as the thermal energy output divided by the chemical energy input.

$$\eta = \frac{\dot{Q}}{\dot{m}\,\mathrm{LHV}} \tag{4.20}$$

As the chemical energy content of energy carriers is based on the lower heating value of the fuels in most energy balances, the latent energy of the combustion products is not considered in the heating value [151]. Therefore, if a boiler can recover the latent energy of water vapour, then its efficiency can in exceed unity.

Key parameters

Four key parameters determining the efficiency of boilers are identified.

Excess Air (λ): Higher λ, leads to lower efficiency because more air needs to be heated up for the same amount of fuel. Values of $\lambda \leq 1$ would yield incomplete combustion and hence lower efficiency. While full combustion of the products could in theory be achieved for $\lambda = 1$, in practice more air is used to make sure that the fuel undergoes complete combustion [315]. Typical boilers are designed with λ ranging form 1.25 to 1.5 [316]. There is a trade off between achieving full combustion and minimising the amount of air that needs to be fed in the boiler. Advances in combustor design (staged combustion) and combustion science (premixed flames) enable the design of boilers with lower values of λ.

Heat exchanger effectiveness (ΔT) : Larger heat exchanger surface areas, and higher heat transfer coefficients, mean that there is a smaller difference between the water return temperature and the flue gasses. The design ΔT is established on economic grounds as there is no technical parameter limiting the quantity of heat transfer [317]. Test data from condensing boilers [318], suggest that for current residential boilers ΔT ranges between 8°C and 12 °C.

Water Return Temperature (T$_{wr}$) : the return water temperature determines how much heat can be extracted from the combustion products. Standard wall radiator heating systems are designed with return water temperatures of about 60 °C [319]. In a floor heating system it would be around 30 °C [316]. For condensation to occur, water return temperatures below 58 °C are required. For space heating, this parameter depends on the design of the wider heating system rather than on the boiler design. For hot water provision in buildings, the inlet temperature is always at ambient temperature (15°C). The main technical challenge associated with low return water temperatures, and thus with condensing operation, is the use of corrosion resistant materials for the condensing section of the heat exchanger.

Heat loss : A share of the heat generated by combustion will not be transferred to the water but rather to the environment mostly due to radiative heat transfer. Heat losses account for up to 2% of the boiler power rating for residential applications [316]. Industrial boilers have much lower surface area to volume ratio, hence losses range between 0.5% and 1%.

Efficiency Limits

Literature estimates

No estimates of technical efficiency limits of boilers have been found in the literature.

Physical model

A steady-state model of a boiler can be defined using a limited number of parameters by applying energy conservation equation. Figure 4.7 shows the diagram followed to develop the model.

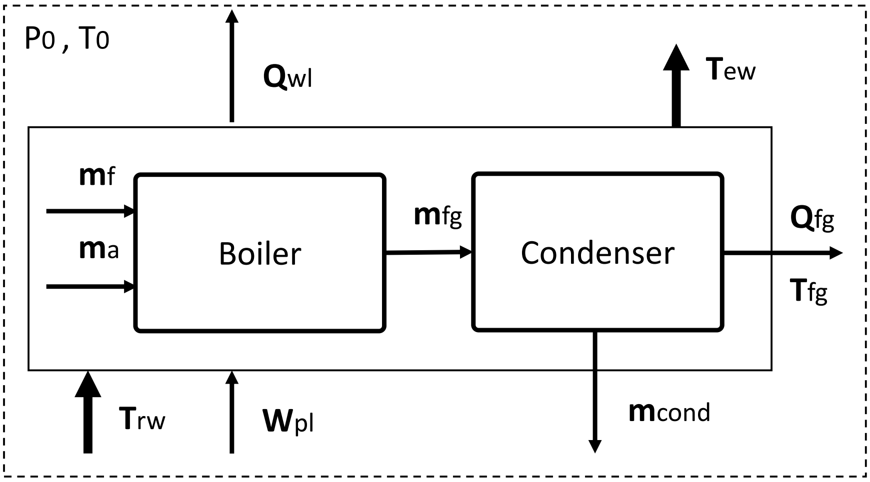


Fig. 4.7 Diagram of a water heater. Air and fuel enter the burner where combustion occurs. The combustion products are then passed through an heat exchanger where they are cooled while water is heated up

The model used follows the methodology developed by Kuck [320]. Complete oxidation of the fuel with dry air is as follows.

$$\begin{aligned} \mathrm{C_xH_y} + \lambda\ a_{stoich}\,(0.21\mathrm{O_2} + 0.79\mathrm{N_2}) = \\ x\,\mathrm{CO_2} + y/2\ \mathrm{H_2O} + (\lambda - 1)(x - y/4)\ \mathrm{O_2} + 0.79\ \lambda a_{stoich}\ \mathrm{N_2} \end{aligned}$$

To calculate the share of dry gasses in the flue gasses (n_w), it is assumed that the gasses exit the boiler in a saturated condition. The saturated partial pressure of water in air is found using the Arden Buck equation [321].

$$n_w = 6.1121 \exp\left(\left(18.678 - \frac{T_{fg}}{234.5}\right)\left(\frac{T_{fg}}{257.14 + T_{fg}}\right)\right) \tag{4.21}$$

The molar flow of condensate is calculated as the difference in water between the combustion products and the moles of water that can be carried by the flue gas at T_{fg}.

$$n_{cond} = y/2 - n_w \tag{4.22}$$

The theoretical minimum temperature that the flue gas can reach is the water return temperature (T_{rw}), which could only be achieved by an infinite heat transfer area. In practice there will be a difference in temperature between the flue gas and the water return temperature.

$$T_{fg} = T_{wr} + \Delta T \tag{4.23}$$

This difference in temperature is a function of the effectiveness of the heat exchanger employed.

The molar enthalpy of the flue gas, condensate and input air is respectively

$$h_{fg} = n_{dry} cp_{dry} T_{fg} + n_w (H_{vap} + T_{fg} cp_{w(g)}) \tag{4.24}$$

$$h_{con} = n_{con} cp_{w(l)} T_{fg} \tag{4.25}$$

$$h_a = n_a cp_a T_a \tag{4.26}$$

In addition, a share of the input will be lost to the environment due to radiative heat transfer. The heat loss share (L) is defines as:

$$L = \frac{Q_{loss}}{m_f \mathrm{LHV}} \tag{4.27}$$

Therefore, the efficiency of the boiler can be defined by applying energy conservation and is expressed in the following formula.

$$\eta = 1 - \tfrac{h_{fg} + h_{con} - h_a}{m_f \mathrm{LHV}} - L \tag{4.28}$$

Figure 4.8 shows how the efficiency of the boiler is a function of λ and the flue gas temperature.

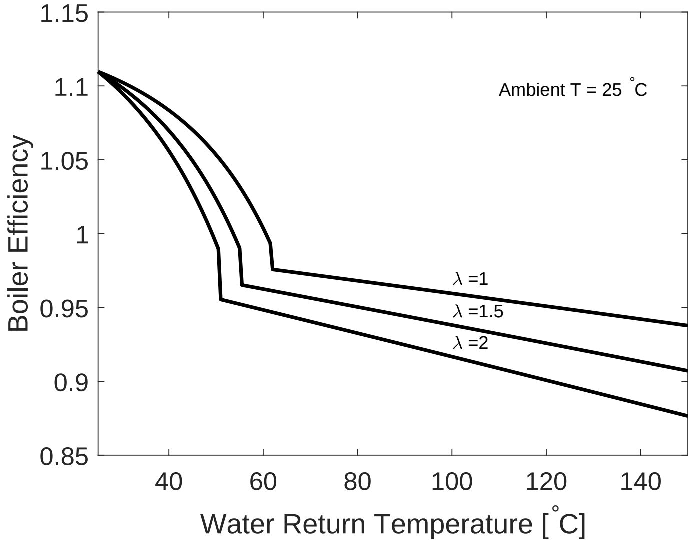


Fig. 4.8 Efficiency of boiler for different values of λ and T$_{fg}$, with L=0

Efficiency limit estimation

The efficiency limit for boilers is estimated by applying methodology A. In this section the rationale behind the choice of the limiting value of each key performance parameter is explained.

Excess Air (λ): Improved fuel/air mixing reduces excess air requirements. Premixed flames have better mixing than diffusion flames and much research has been directed towards maximising fuel mixing in order to avoid high temperature zones and thus minimise NO_x formation [151]. The lowest air to fuel ratio found in the literature related to boilers was 1.1 [315]. This was achieved in the Super Boiler program of the US DOE through a multi stage pre-mixed burner. The efficiency limit is estimated to range between 1.01 and 1.1.

Heat exchanger effectiveness (ΔT) : Higher heat transfer can achieved by either by increasing the heat transfer rate by employing grooved firetubes and optimising fin design or by increasing the overall area of the heat exchanger. Both measures can increases pressure losses and auxiliary energy requirements. It is estimated that heat transfer can increase by 30% without increasing auxiliary energy requirements. This increase in heat transfer would reduce the ΔT by the same proportion, therefore the limit of ΔT is assumed to range between 5 C° and 8 C°.

Water Return Temperature ($T_{w}r$) : For space heating applications, the lowest practical return temperature is 30 C° (range 28-34 C°) which is representative of a modern floor heating system. For water heating, a return temperature of 15 °C equivalent to ambient conditions, is assumed. For industrial applications, mostly dedicated to steam generation, it is difficult to establish a return water temperature as it depends on whether the steam is generated in a closed cycle or on whether it is generated from fresh water. Since most boilers operate in closed circuits, the return water temperature is assumed to range between 60 ° and 90 C°.

Heat Loss (L) : The share of heat lost to the environment due to radiation is dependent on the thickness of insulation applied to the device. It is assumed that a doubling of current levels of insulation would still be practical, therefore heat losses can account for 0.5-1% of the boiler's rating in residential boilers and 0.25-0.5% for industrial boilers.

The assumed values for each parameter and the resulting efficiencies are shown in Table 4.4

Table 4.4 Summary of key parameter maximum values and resulting efficiency limit

Sector	Current Efficiency	Parameters			Efficiency Limit
		λ	1.01-1.1	-	
Residential and		Δ T	6-9	C°	
Commercial	85-93%	Tw$_{in}$	28-35	C°	105-107 %
		Heat Loss	0.5-0.1	%	
		λ	1.01-1.1	-	
		Δ T	6-9	C°	94-96 %
Industrial	80-86%	Tw$_{in}$	60-90	C°	
		Heat Loss	0.25-0.5	%	

Comparison with literature

Since there is no literature estimate for the efficiency limit of boilers, this comparison cannot be done.

4.2.4 Cooler

Description

Characterisation

In most applications, cooling is provided by a vapour compression cycle [151]. A cooler is formed of four main components, an evaporator, a condenser, a compressor and an expansion valve.

Work is added to the cycle by shaft work in the compressor which is powered by an electric motor as shown in Figure 4.10. The output is thermal energy in the form of cooling. The largest use of these devices is in buildings for air conditioning and refrigeration. In the industrial sector coolers are used for process cooling.

Efficiency measure

The efficiency of coolers is customarily called the Energy Efficiency Rating (EER) which is defined as useful output energy over work input (equation 4.29)

$$\mathrm{EER} = \frac{Q_{out}}{P_{in}} \tag{4.29}$$

The theoretical EER of a cooler is a function of the temperature of the heat sink and of the heat source, according to equation 4.30

$$\mathrm{EER}_{\mathrm{Carnot}} = \frac{T_H}{T_H - T_C} \tag{4.30}$$

Since the heat source/sink temperature varies in time, a seasonal EER (SEER) is often calculated to represent the typical average performance of a device throughout the year in a given region. Different standards exist to perform this calculation. In the EU, the EN 14825 standard [322] is followed to calculate a SEER. In this study the European EER metric is used to quantify the efficiency of coolers. Therefore EER is measured for a cooler that keeps a room at a constant temperature of 20 C° while the outside air temperature is at 35 C°. This is considered the full power condition for the cooler and therefore represents the lowest EER that could occur in typical European climates.

Figure 4.9 shows that the range of EER for coolers available for purchase in the EU is between 2 and 6 with a mode 3.2 when considering the devices available on the market.

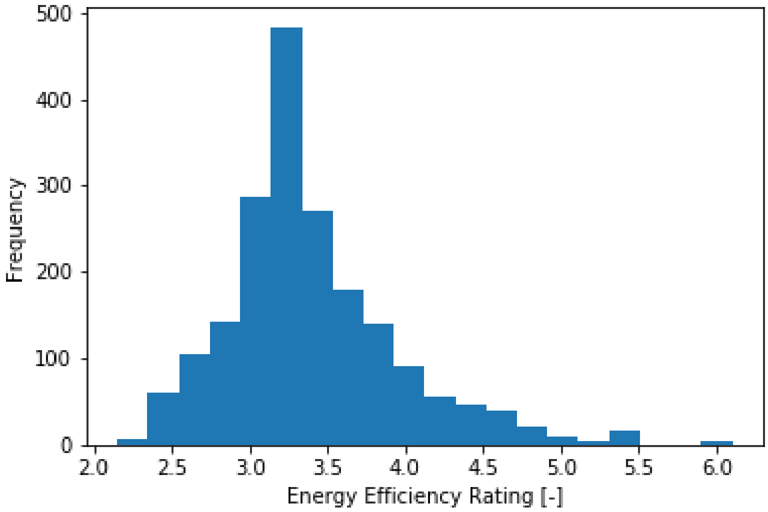


Fig. 4.9 Histogram showing the range of EER (outside temperature 35C°, inside temperature 20C°) for air conditioners available in the EU market, based on the Eurovent database [323] containing data on 1967 tested devices.

Key parameters

The practical maximum EER of a cooling device depends mostly on three parameters. The refrigerant used, the heat exchanger effectiveness, and the compressor performance.

Refrigerant: The thermo-physical properties of the refrigerant determine the maximum efficiency of a vapour compression cycle. However, the choice of refrigerant is dictated factors such as safety (toxicity and flammability), ozone depletion and global warming potential. Their use is heavily regulated in most countries [324]. The highest cycle efficiency is provided by R717 (NH_4), however, due to its toxicity, its limited to the industrial sector. For applications in buildings, the most efficient, non-ozone depleting, refrigerant is R134a [325].

Heat exchanger: The effectiveness of the heat exchanger can be quantified by the pinch temperature, that is, the minimum temperature difference between the two fluids. For air conditioners, the evaporator temperature difference is particularly important since a large temperature difference is needed to provide enough cooling power using air as a heat transfer fluid. The smaller the temperature difference, the higher the EER (as shown in Figure 4.11), however this also requires a larger or more effective heat exchanger. Typical evaporator temperature differences range between 15 C° and 8 C°, with the lowest value being associated with BAT efficiency.

Compressor efficiency: The compressor efficiency is the isentropic efficiency of the compression, which is directly proportional to the EER of the device. Isentropic efficiency values for refrigeration cycles are seldom published by OEMs. Brown et al. [326] estimates that η_i can reach values of up to 80% for low pressure ratios. Van Gerner et al. [327] have reviewed a number of high performance compressors to be used in space applications, and found the highest efficiency to be 70.3% with most compressors having values ranging around 60%-65%.

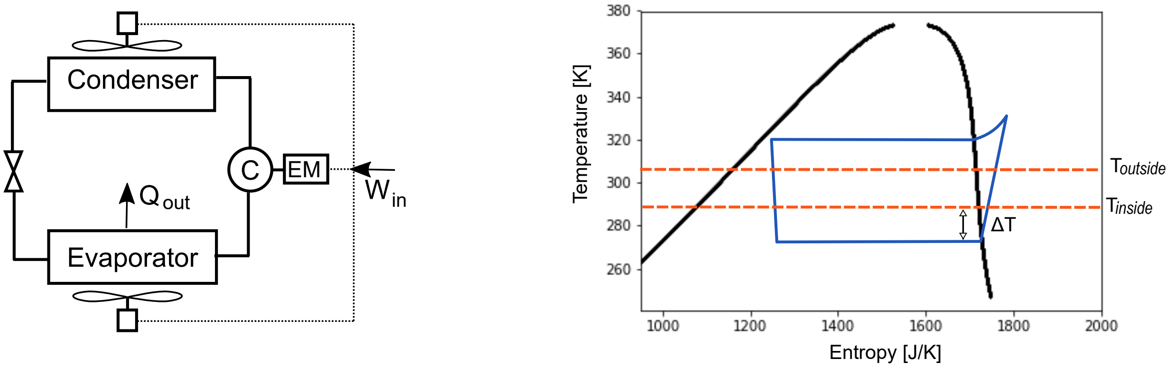


Fig. 4.10 Diagram showing the components of a vapour compressor cycle and the definition of the Temperature difference between evaporator and ambient air.

Efficiency Limits

While currently the only technology used to provide cooling at a large scale is the vapour compression cycle, other technologies have been proposed. Brown and Domanski have reviewed these technologies and assessed their potential on a number of performance parameters such as the possible temperature lift and efficiency [328]. They conclude that the only alternative technology that might compete with the vapour compression cycle is magnetic refrigeration. Proponents of this technology have speculated that, if a number of technical barriers are overcome [329], it might reach an exergetic efficiency of 65% which is higher than current vapour compression BAT which is around 50% [330]. Since even in the best scenario, the efficiency of magnetic refrigeration is not much higher than current vapour compression and since it does not present other major benefits for residential applications, it is deemed better to focus the analysis on improvements of the incumbent vapour compression cycle.

The limits are estimated using methodology A.

Literature Estimates

There are no estimates of the technical efficiency limit of vapor compression cycles.

Physical model

The thermodynamic simulation of the vapour compression cycle was adapted from a freely available code developed by Bell, the methodology employed is extensively described in the program's documentation [331] . The thermodynamic properties of refrigerants are based on the CoolProp package [332]. The refrigerant side heat transfer coefficients are calculated using the Shah correlation [333], while the air side heat transfer coefficients are calculated based on Colburn j factor [334]. The friction factors of two phase flow is estimated using the Lockheat-Martinelli correlation [335]

The model calculates the EER of a vapour compression cycle based on a number of parameters. The air-side heat exchanger is modelled as a finned coil with Louvered fins - the parameters are defined in [331]. The cycle is calculated by fixing : the design heat output (Q_o), the evaporator superheat (T_s), and the condenser minimum temperature differential (ΔT). The model is run iteratively until the desired output and the desired superheat (temperature above condensation) are reached. The pressure losses are treated in a simplified form by only accounting for the pressure losses in the evaporator and accounting for them only at the end of the cycle rather than in each component. The model is run for different cross sectional air flow velocities with values ranging between 1 and 4 m/s. The velocity that yields the highest energy efficiency is then picked. The model is validated by comparing the EER and air flow of AC units from product catalogues.

The effect of the two key parameters, η_p and ΔT are shown in Figure 4.11, where it is clear that the two parameters are linearly correlated with the EER.

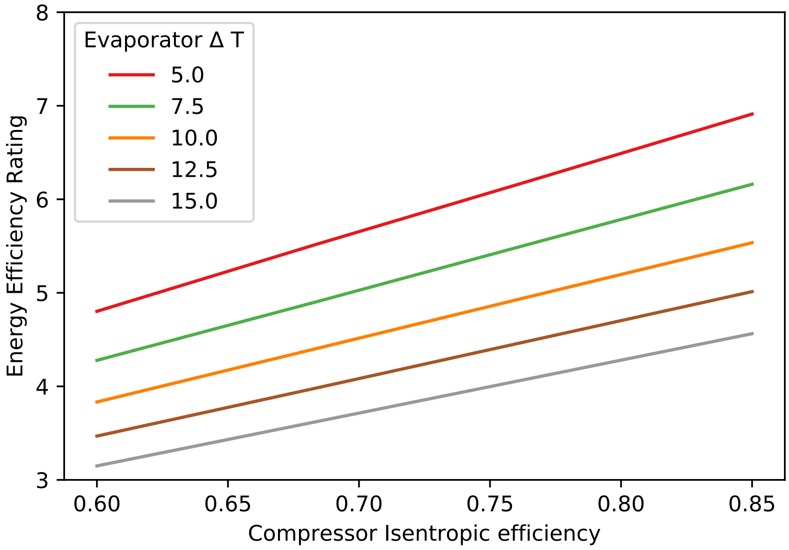


Fig. 4.11 Modelled effect of compressor isentropic efficiency and evaporator temperature difference on cooler's EER.

The EER is calculated at a high power setting which coincides with the lowest efficiency of the device. A better representation of the average conversion efficiency is the SEER. The model's EER results are converted to SEER by means of a linear model that is trained on the Eurovent database which contains both EER and SEER values for air conditioning units. Figure 4.12 shows a scatter plot of the EER and SEER values for the database as well as the linear model employed for the conversion.

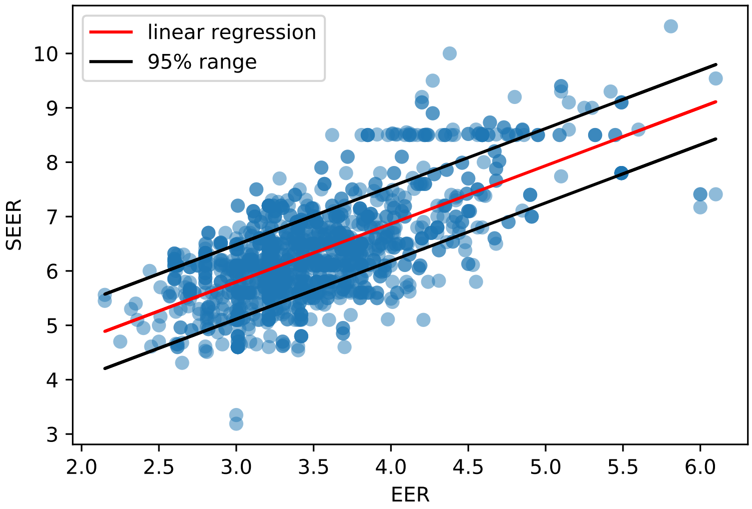


Fig. 4.12 Scatter showing the SEER and EER values for the Eurovent database as well as the linear regression model that fits the data

Efficiency limit estimation

The values estimated using a thermodynamic model based on the key performance parameters identified.

Refrigerant: Given the multitude of factors affecting the choice of refrigerant in practical applications, it is decided not to vary the refrigerant for the practical limit case. Therefore, the practical efficiency limit will be established assuming that R134a is used.

Heat exchanger : There is no technical limit for the minimum temperature difference since any ΔT can be achieved with appropriate heat exchanger design. The only practical limitation would be the decrease in power density of the device since a larger heat exchanger would be necessary for the same power output. It is assumed that the limit for ΔT ranges between 5 C° and 3 C° which would represent more than 50% reduction compared to current BAT.

Compressor efficiency : While current compressors used in refrigeration cycles are mostly reciprocating or scroll compressors, there is no technical reason preventing them from using a turbomachinery design [336, 337]. The section on gas turbines contains the rationale used to determine a maximum polytropic efficiency of 95% for axial turbomachinery. However given the low flow rates, radial turbomachinery is used instead of axial designs. In addition, the very small scale of compressor required for refrigeration applications means that efficiency is lowered further - mostly due to the lower Reynolds number of the flow [338]. Simulated maximum values of 85% polytropic efficiency for radial compressors are found in the literature [339]. Therefore, this value will be used for this application. The compressor efficiency, however, include the efficiency of the electric motor. The efficiency limit of electric motors is discussed in section 4.2.8, and for a power output of around 1kW is 96%.

One development that would increase the efficiency of the vapour compression cycle is the substitution of the throttling valve for an expander capable of extracting work from the expansion [340]. This practice is already being done for some very large scale chillers using water (or brine) as a heat source [341]. The main technical barrier for this practice is dealing with a two-phase flow in the expansion device. However, this can be overcome by specialised designs [342]. This option is nonetheless not considered practical at a residential scale. If the expanding device is mechanically coupled to the compressor, the rotational speed and thus the operating range is greatly reduced. On the other hand, if the work extracted from the expanding device is delivered to a generator, the additional equipment would not be practical to fit in a residential scale unit. Therefore, this option is only considered for industrial scale devices.

To calculate the efficiency limit, both the heat exchanger area and the compressor efficiency parameters are brought to their maximum, defined in the previous section. For a given heat exchanger duct area and compressor efficiency the heat exchanger is optimised to maximise the efficiency by varying: the tube diameter, the number of fins, the distance between tubes, and the air velocity. The results of this operation are considered the efficiency limit for building-scale devices.

Industrial devices are not modelled with as much detail because they are less common and because they are custom built for their specific use case. It is assumed that their practical limit is for a Carnot efficiency of 0.85 which can be achieved by a combination of larger heat exchangers and more efficient compressors (even though at that scale the room for improvement is lower). In addition to these measures, industrial heat pumps can also benefit from work recuperation from the gas expansion by adding two-phase expanders. The efficiency limit results are summarised in Table 4.6

Table 4.5 Summary of parameter and efficiency limits for air coolers.

Device	Current efficiency (SEER)	Parameter		Efficiency Limit (SEER)
Air Cooler	6	η_c	80%-85%	8.5-11.5
		ΔT	3-6 K	

4.2.5 Heat pumps

As mentioned in the previous section, heat pumps use the same components as an air cooler. The difference lies only in the operating mode and the energy service provided: they provide space heating instead of space cooling.

Efficiency measure

The efficiency of heat pumps is measured using the Coefficient of Performance (COP) that is defined as a standard efficiency, useful heat output over electrical energy input, and is equivalent to the EER for air coolers. The COP has a strong correlation with the temperature of the heat source and the heat sink, therefore it is usually defined at a standard temperature. In the EU, temperatures used for nominal rating are defined in the EN 14511 standard[343]: hot water temperature 35 °C and an outside air temperature of 7 °C.

Efficiency limit estimation

The efficiency limit is estimated using the same physical model and the same limiting parameters defined for the air cooler in section 4.2.4. The physical model is modified such that the evaporator and the condenser sub-modules are switched around. An air-to-water heat pump is considered for the efficiency calculation because this type of technology is the most likely to be widely used since it does not require the large land area needed for geothermal heat pumps.

Table 4.6 Summary of parameter and efficiency limits for heat pumps for space heating.

Device	Current efficiency (COP)	Parameter		Efficiency Limit (COP)
Heat pump	3.0	η_c	80%-85%	5.9-6.3
		ΔT	3-6 K	

4.2.6 Light Devices

Description

Light devices convert an energy input into electromagnetic radiation within a specific wavelength range: the visible light range. The input energy can be either chemical– in the case of candles or kerosene lamps– or electrical, in the case of LEDs and incandescent light bulbs.

Characterisation

There are currently many technologies available to generate light from electricity. The incandescent, compact fluorescent (CFL), halogen, sodium and Light Emitting Diode (LED) light bulbs. These technologies vary in terms of both efficiency and lighting quality.

Light quality can be quantified using two indicators: Colour Rendering Index (CRI) and the colour temperature (CT). CRI ranges from 0 to 100 and determines the perceived quality of colours compared to solar white light. Values above 80 CRI are needed as a minimum for indoor lighting applications. CT is a measure of the chromaticity of white light, humans tend to prefer lower colour temperatures (i.e. red light) [344].

Incandescent, CFL and halogen light devices are all characterised by relatively lower efficiency compared to LEDs and sodium lamps. Sodium lamps can reach very high efficacy values. However, their light quality is much lower than the other technologies and is therefore mostly relegated to outdoor and industrial applications.

The one technology that delivers high efficiency and high quality light is the LED. Moreover, the LED doesn't have intrinsically low luminous efficiency and its quality can be designed to deliver any light quality. For this reason the LED technology is regarded as the benchmark technology for light devices.

Efficiency measure

The simplest definition of efficiency for a light device is the ratio of electromagnetic energy output over the electrical input. However, this definition is not sufficient because the human eye is sensible only to light with wavelength between 400 nm and 700 nm. Moreover, the intensity of each wavelength varies according to a Gaussian distribution, known as the photoptic luminosity function (v). Therefore the efficiency of light devices is the product of two efficiencies, the electrical to radiation efficiency (η_e) and the spectral efficacy (ε_s)

expressed in lumens per watt (lm/w), where the watt refers to the energy of radiation. The total efficiency of a light device is an efficacy (ε), as it is expressed in units of lumens per watt of input electrical energy.

$$\varepsilon = \eta_e \, \varepsilon_s \tag{4.31}$$

The spectral efficacy is calculated as the convolution of the emitted radiation with the photopic luminosity function over the visible wavelength(λ)

$$\varepsilon_s = \int_0^\infty \phi_r v(\lambda) d\lambda \tag{4.32}$$

The distribution of the emitted radiation determine the overall efficacy, CRI, and CT of the light device. These properties are independent of the electrical-to-radiation efficiency. In fact, η_e is not a good indicator for lighting efficiency. For example, in incandescent lights, η_e is close to 100%, however, the emitted radiation is mostly outside of visible spectrum, meaning that the overall efficacy is limited to around 15 lm/W [345].

Therefore, the metric of overall efficacy is used in this study to define the efficiency of light devices even though it is not a dimensionless energy conversion efficiency.

Key Parameters

LEDs are semiconductor devices that use the electroluminescence mechanism to convert electrical energy into light. The properties of the semiconductors used determine the wavelength (thus the colour) of the light. Current white light LEDs are phosphor coated (pc-LED) meaning that they are composed of a very efficient blue “pump” LED which feeds into a phosphor layer which in turn emits the remaining wavelengths necessary to achieve white light. White light can also be achieved by colour mixing (cm-LED) LEDs of different colours to achieve white light.

The efficiency of LEDs is dependent on the following four lumped parameters

Spectral efficacy The spectral efficiency determines how much of the emitted radiation is percieved as white light by the human eye. The radiation emitted from current LEDs can achieve spectral efficacy values of around 280-320 lm/W with acceptable levels of CRI and CT [345].

Driver efficiency As electrical power in stationary applications is delivered as Alternating Current while LEDs required Direct Current, losses are incurred in the transformation process. These losses depend on the quality of the current inverters employed.

Photon efficiency Photon losses are incurred in the generation of photons from the electrons in the semi-conductor bands. This is a lumped parameter which includes a number of loss mechanisms: internal quantum losses, electrical losses, extraction losses, phosphor losses and Stockes' losses [346]. These are a function of the LED design and of the chosen semiconductor material and manufacturing quality. Phosphor coated LEDs inherently incur more losses than color-mixing LEDs because they have two extra loss mechanisms (phosphor and Stockes'losses) which occur to transform the blue light into white light.

Optical efficiency Optical losses occur because a share of the produced radiation is not emitted from the device but is absorbed by the device packaging and thermal management components. The optical efficiency is a function of luminaire architecture.

Efficiency limits

The efficiency limits for LEDs found in the literature are reviewed and presented in this section. A parametric model of LED performance cannot be generated using few parameters given the complexities of semiconductor physics, therefore the loss reduction method (Methodology B) is used for the estimation of the efficiency limits. The LED literature customarily refers to mechanism efficiencies rather than losses, therefore the same terminology is used in this section, however the two concepts are interchangeable.

Literature Estimates

In the academic and grey literature, there are a number of predictions of the technical maximum efficiency achievable by LEDs and they are shown in Table 4.7. Not all estimates use the definition of "technical efficiency limit" used in this article as economic constraints are taken into consideration in some estimates, nonetheless it provides a good picture of where expert opinion stands on this issue.

Table 4.7 Estimate of technical maximum efficiency of LED lighting in lm/W

Author	Year of estimate	Color-mixing?	min	max	
R Haitz	2010	not specified	200	200	[347]
Y Tsao	2010	not specified	200	250	[347]
US DOE	2017	yes	215	283	[348]
E Bretschneider	2007	yes	150	200	[349]
DIAL	2016	no	200	250	[350]
Pimputkar et al	2009	not specified	280	280	[344]

Efficiency Limit estimation

The key loss mechanisms in LEDs are normally referred to as efficiencies which are combined, following equation 4.33, to estimate the overall LED efficacy.

$$\varepsilon = \eta_d \, \eta_{\mathrm{WPE}} \, \eta_o \, \varepsilon_s \tag{4.33}$$

The technical efficiency limit is estimated by combining the range of maximum values found in the literature for each of the loss mechanisms.

Spectral Efficacy (ε_s): The maximum spectral efficacy of white light is difficult to establish because it is highly dependent on the light quality [351]. For multi-source LEDs, the DOE believes the maximum efficacy is 414 lm/W [348]. Hatiz et al quote a technical limit of 400 [347], while Murphy [345] quotes a maximum of 348 lm/W. All these values represent what could be achieved while maintaining a CRI of 80. To keep the analysis as conservative as possible, the entire range mentioned in the literature is taken into account for as the technical limit.

Driver Efficiency (η_d): There is no physical limit to the efficiency of AC to DC conversion. The US DOE has a long term goal of AC/DC conversion for LED luminaires of 95% [348]. The efficiency limit is assumed to range between 92% and 97%.

Wall Plug Efficiency(η_{WPE}): The theoretical efficiency limit of η_{WPE} is a function of temperature, current density, power intensity (W/cm^2) and semiconductor design [352, 353].

To achieve LED characteristics typical of space lighting LEDs (~100 W/cm^2, ~50 A/cm^2), David et al. estimate that the theoretical limit is 105%. The value is above 1 because the LED acts as heat pump and draws energy from the environment, at very low voltages and current densities, laboratory scale devices with efficiencies up to 230% have been sucesfully tested [354]. Xue has proposed to build a prototype LED with η_{WPE} = 100% for high current densities [355] in the coming years. It is assumed that the technical limit for commercial LEDs is in line with the efficiency of the current laboratory scale light devices, therefore the efficiency is assumed to range between 90% and 100%.

Optical Efficiency (η_o): The theoretical maximum optical efficiency level is 100%. The US DOE has a long term goal of 90% [348] for commercial LED applications. A range of 90% to 95% is considered as the technical limit.

Each of the four sub-efficiencies is modelled as a uniform distribution limited by the values shown in Table 4.8.

Table 4.8 Summary of the assumed efficiency limits of each parameter and the resulting LED efficiency

Device	Parameter	Efficiency Limits	Device Efficiency Limits
LED	η_d	92%-97%	284-350 lm/W
	η_{WPE}	90%-100%	
	η_o	90%-95%	
	ε_s	348 lm/W -414 lm/W	

Comparison with the literature

The resulting efficiency limit estimate has a central value of 301 lm/W with a standard deviation of 24 lm/W. This result is higher than all those seen in Table 4.7. There are two reasons that explain this. Firstly, for the estimates in the literature, the technical limit was still referred to commercial LEDs for which there would be a market, therefore those are in fact economic efficiency limits. Secondly, many of literature estimates were made in the period 2007-2011, when commercial LEDs still did not match the performance of halogens and CFCs because of poor η_{WPE} (around 20%) combined with poor colour quality, and technologies such as color-mixing LEDs were not taken into consideration. The estimate provided in this study approaches the theoretical limit of η_{WPE} while still taking into consideration some unavoidable losses, therefore this is considered a better characterisation of the technical limit of LED efficacy.

4.2.7 Reciprocating Engines

Description

Reciprocating engines (RE) are ubiquitous conversion devices used to convert chemical energy into mechanical energy. They can follow a number of thermodynamic cycles: the Otto cycle, the Diesel Cycle, the Atkinson cycle and the Miller Cycle. Their defining characteristic is that work extraction and compression is done by means of a reciprocating piston. Therefore the various steps of the cycle take place in the same volume, but at different points in time.

Characterisation

REs can be divided between those following the Diesel cycle (also known as compression ignition) and those that follow the Otto cycle (also known as spark ignition). Diesel engines are used in many sectors. In the transportation sector they power a large share of the shipping sector, all non-electrified rail, all virtually heavy and light duty road vehicles. In addition, Diesel engines are used as prime movers and power generators in industrial applications.

Spark ignition engines are mostly used for the light duty vehicle fleet, where the alternative Atkinson and Miller cycle are found in some instances. Small and mobile RE are used in appliances or pumps are also often spark ignition engines.

Efficiency measure

The simplest expression for the theoretical efficiency of a RE is the one derived from the air-standard Otto cycle.

$$\eta_{otto} = 1 - \frac{1}{r^{\gamma-1}} \tag{4.34}$$

where r is the compression ratio and γ is the ratio of specific heats. The air standard model is a poor approximation of real SI engines: the predicted efficiency for a spark ignition engine with r=10 is around 60% while real engines operate at efficiencies between 20% and 30%. Another measure is the indicated efficiency η_i which is calculated from an indicator diagram and accounts for heat losses and changes in γ. While the overall efficiency of engines that takes into account all loss mechanisms, defined as mechanical energy output over chemical energy input, is referred to as the break thermal efficiency (η_{bte}) [274].

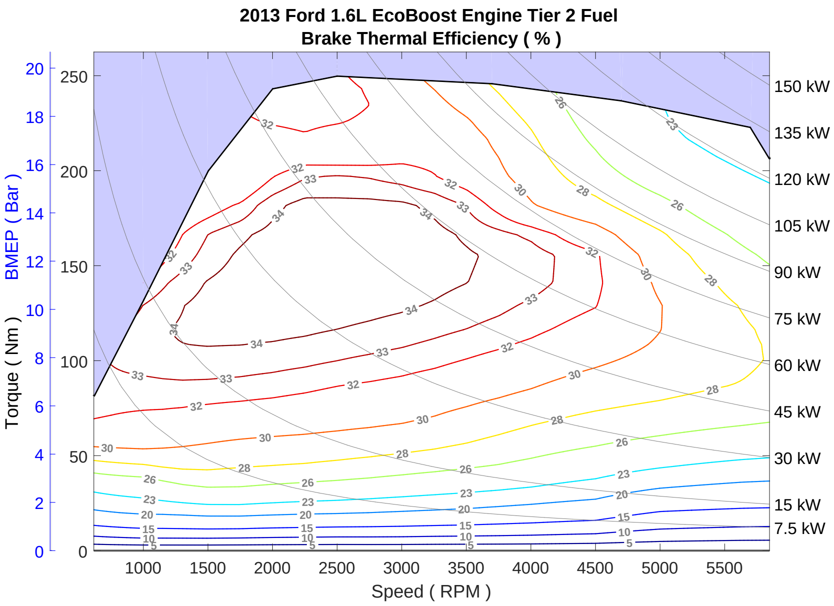


Fig. 4.13 Engine map of the 2013 Ford 1.6L ecoboost engine measured in a laboratory. Efficiency is shown as a contour line: peak efficiency is much higher than average efficiency at driving conditions

The efficiency of REs is very sensitive to the operating conditions of the engine, that is, it depends on the engine speed and torque as can be seen by the engine map shown in Figure 4.13. The efficiency of engines therefore depends largely on how it is operated and on the type of loads it experiences. For this reason, in order to maximise comparability across sectors and use cases, the estimation of the efficiency limit will focus on peak efficiency.

A key parameter for engine design is the air intake per stroke and in recent years there have been major advancements through the developments of superchargers and turbochargers. Air intake is excluded from the parametric efficiency model because this parameter is related to power density rather than to efficiency directly. At the same time it's important to acknowledge that air intake has an indirect impact on efficiency through the design practice downsizing: lower cylinder volume required for same nominal power output thanks to forced aspiration. Smaller engines in turn allow for higher efficiency at lower torque and rpm, thus increasing the overall operation efficiency of the engine [356]. However, since in this thesis only peak efficiency is considered, this effect is not included in the model.

Key Parameters

Compression Ratio The compression ratio is defined as the ratio between the bottom centre dead volume and the top dead centre volume. Higher values of r are associated with higher theoretical efficiencies (as seen in equation 4.34) and real world efficiency. Its values are limited by the auto ignition of the fuel/air mixture in spark ignition engines (a phenomenon known as knock). For compression ignition engines, r is limited by the design consequences of higher peak pressures. An important aspect is that to sustain higher pressures thicker and heavier engine components are required, thus reducing the power density and the inertia of the engine. Typical values of automobile SI engines compression ratios are 10-12, with some engines reaching 15 [357]. For CI engines, typical values range from 16 to 21. Previous research has shown that in the period between 2000 and 2011 average compression ratios have decreased for Diesel engines in light duty applications [114], this is mostly due to concerns over pollutant emissions. On the other hand, CR has been on the rise for SI engines [358, 114], while heavy duty CI engine research efforts are focusing on increasing the CR [359, 360].

γ The ratio of specific heats depends on the combustion temperature and on the air/to fuel ratio of the charge. Leaner combustion leads to higher γ [361, 362] and hence to higher efficiency. The limit to lean combustion is the flammability limit of the charge: if the mixture is too lean it might not ignite as desired [274]. Current SI engines operate with slightly lean combustion or at stochiometric values. CI engines operate at leaner combustion conditions with some engines reaching values of 0.6 [363].

Cylinder Heat Transfer During the combustion of the fuel and air mixture, the charge reaches very high temperatures, therefore a share of the heat is transferred through the cylinder walls into the environment. To maintain physical integrity, the engine block is kept within acceptable temperature ranges by a cooling system. This further increases the heat transfer losses. In current designs, approximately 25% of the input energy is lost due to heat transfer losses [274].

Mechanical losses A share of the work produced by the engine is expended to overcome the friction in cylinders, to pump in and out the air and combustion products, and to power auxiliaries (such as cooling pumps and fans). Friction in the engine is generated by the piston sliding against the cylinder walls, the crankshaft rotation, and the valve train system. These losses account for only a small percentage of total input energy when the engine is operating at optimal conditions, however they become significant when engines are operating at part load [364].

Efficiency Limits

Previous Work

In this section four methods to estimate the efficiency limits of internal combustion engines found in the literature are described.

Finite Time Thermodynamics The field of finite time thermodynamics has defined efficiency of reciprocating engines by determining the efficiency at maximum power output. Curto et al. state that: “Although real heat engines are complex devices, realistic upper bounds can be placed on the power output and efficiency performance using relatively simple thermodynamic models”[365]. However, publications in this field rarely quote explicitly maximum levels of efficiency. They describe models but then always use the same performance parameter assumption that are described in articles from the 1990s such as in references [366, 367].

One of the earlier articles shows mathematically that there are practical boundaries to the power and efficiency of an Otto Cycle that depend on the irreversibility of combustion and on the heat transfer from cylinder to engine wall [368]. Three parameters are used to describe the model of a reciprocating engine. The first there are constants that describe the average temperature rates, the second describe the irreversibility of combustion and heat transfer, the third describe the piston friction [369]. The loss factors include several of physical processes and it’s therefore difficult to obtain the required constants and parameters for real life engines as a function of design parameters. [370, 371].

US DOE Colloquium on Engine Efficiency In 2010, a group of 29 experts were invited by the DOE to discuss the theoretical and practical efficiency limits of internal combustion engines [372]. The aim of the colloquium was to review the current state of engine technology, to agree on theoretical and practical efficiency limits, and to recommend long term R&D investments for the DOE.

Their definition of “ideal” efficiency limit is: “ maximum brake thermal efficiency that could be achieved with current architecture is about 60%, assuming cost is not a constraint ” This definition is in line with the definition of technical limit employed in this thesis. Two inherent processes prevent higher efficiencies are quoted: the exergy destruction due to unrestrained combustion (20%-25%) and then the Carnot efficiency of the combustion products (20%-25%). The report states that there was a good consensus in the colloquium regarding this limit.

According to the experts, different engine architectures coupled with heat recovery systems, can yield higher efficiencies. There was less consensus on the ideal efficiency limit of other engine architectures, but no estimate went beyond 85%. The experts noted that higher engine efficiency tends to go hand in hand with lower power density.

Oak Ridge National Lab Estimate A group of researchers at the Oak ridge national lab attempted to estimate the efficiency improvement potential of a Diesel engine by estimating the maximum reduction of each exergy loss mechanism [373]. The main difficulty of this approach is that a decrease in exergy loss from one mechanism does not directly translate into work output improvement. The exergy is translated downstream to other forms. For example, a decrease in cylinder heat transfer losses leads to both increased work output and increased exhaust losses. The authors have used engineering judgement and advice from industry to establish the translation of the losses to downstream mechanisms. Their analysis was performed in the light of what was said at the colloquium mentioned above.

Table 4.9 shows the assumptions that have been made by the authors to estimate the efficiency improvement potential of light duty Diesel engines. While their analysis does not consider revolutionary engine design, it does include a waste heat recovery option (such as an Organic Rankine Cycle). The results of their analysis shows that the partial load efficiency could be improved from 25.9% to 41.8% while the full load efficiency could improve from 42.3% to 51.1%.

Table 4.9 Adapted Table from Edwards et al. [373] showing the assumed loss reduction potential for a vehicle Diesel engine.

Loss Category	Reduction Goal
Friction and accessory losses	50%
Pumping losses	30%
Heat and coolant loss	30%
Exhaust loss	20%
Combustion loss	50%
Turbocharger loss	50%

The authors highlight that their estimate is in line with the consensus reached in the colloquium, that is, a maximum efficiency of 60%. They justify the lower value by saying that real engines must be designed with additional constraints such as durability and reliability, which is not the case for the experimental engines that most colloquium participants were used to.

Simulation Liu et al. [374] have used a commercial software for engine simulation to investigate the “potential of efficiency limits for internal combustion engines”. They ran the model and computed the indicated efficiency by varying design parameters such as compression ratio, heat transfer coefficient, cylinder volume, and combustion speed. They modelled both ideal scenarios and more practical ones. Among the practically achievable ones, their highest indicated efficiency values were in the range of 50%-55% for compression ratios in the range of 50. The results are indicated efficiencies and therefore do not include pumping nor friction losses.

Given the wealth of literature on the topic and given the complexity of the modelling required to capture the interaction among the various design parameters, it is decided to use the loss breakdown method to estimate the efficiency limits.

Efficiency Limit Estimation

The efficiency limit is estimated by combining literature estimates of the reduction potential of each loss mechanism (methodology B) scaled according to increases in the main efficiency parameter, the compression ratio.

Data on the loss breakdown of a high performance Diesel engine studied by the ORNL is used [373] as an engine representative of current best practice (peak η_{bte} = 43.3%).

The effect of increased compression ratio is simulated by assuming that real world efficiency is proportional to the Otto cycle efficiency, but scaled by a factor k such that,

$$\eta_{bte} = k\ \eta_{otto}\ (CR, \gamma) \tag{4.35}$$

The scaling parameter k, is obtained by comparing the theoretical efficiency for a given value of CR with real world engines. For light duty vehicle the ORNL reference engine parameters are used for the calibration, while for Marine applications, the best performing engines form the EPA database of large engines [375] are used. This exercise results in values of k in the 0.6-0.66 range for light duty vehicles and 0.67-0.73 for heavy duty engines.

The loss breakdown is then applied to different compression ratios by assuming that the loss breakdown shares remain equal at all compression ratios. The resulting loss break down is shown in figure 4.14. The expected loss reductions are subsequentially applied to these values using equation 4.5.

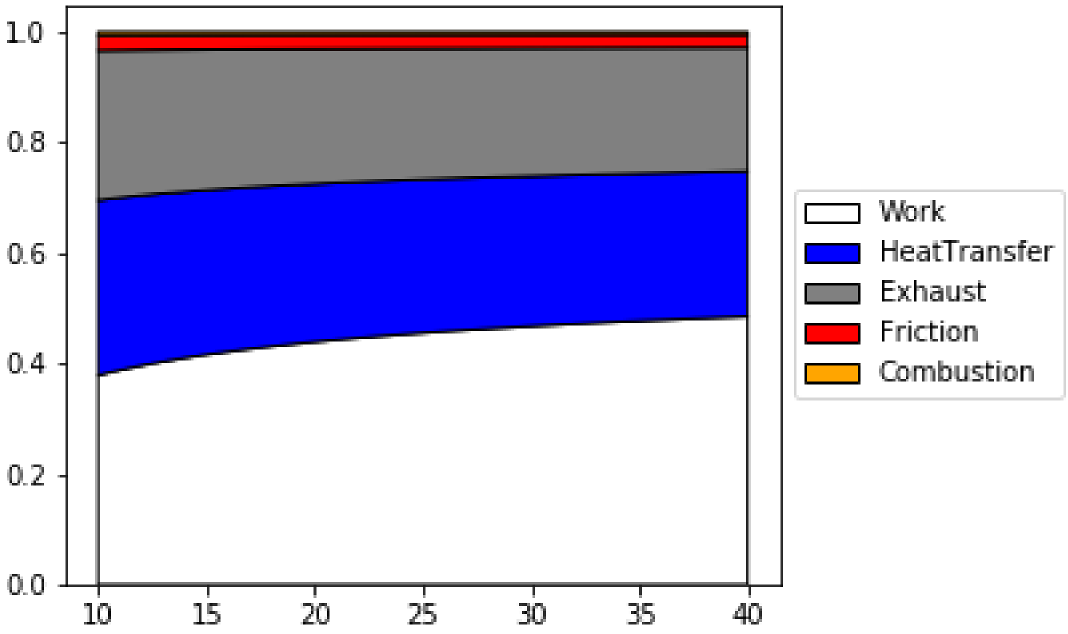


Fig. 4.14 Assumed loss breakdown in a reciprocating engine for different compression ratio

In the following sections, the logic behind each reduction potential is explained with reference to the literature whenever possible. The limits are summarised in Table 4.10

Compression Ratio Miller et al. [376] have shown empirically that efficiency is proportional to CR for values of CR up to 55. For higher CR efficiency decreases because heat transfer and friction losses become larger than the benefits from higher CR. Lui et. al [374] came to a similar conclusion with peak indicated efficiencies being observed for CR values of 60. Both studies show that the additional benefits of higher CR flatten out for values above 30. Given the complexity associated with further increasing CR, it is assumed that the practical limit of CR must lie between 30 and 35.

Heat Transfer Loss A well studied method to reduce heat transfer losses is to coat the cylinder walls with a layer of low conductivity ceramic. Experimental studies had shown heat loss reductions of 19% [377]. Increasing the allowable temperature of the engine walls, for example by using Nickel alloyed metals, would also decrease the heat transfer losses. Decreasing the equivalence ratio is also likely to reduce heat transfer because it would result in lower peak flame temperatures [378]. All these possible improvements are estimated to account for a cumulative loss reduction of 45%-55%. It is well known that reduction in heat transfer losses do not translate directly into gains in work extraction, but that most energy savings are transposed to higher exhaust losses. According to Liu et al. roughly 33% of heat transfer savings are translated in work extraction while Edwards estimates that only 10% is converted. The value of 30% is used in this analysis.

Friction Reduction Engine friction can be reduced by means of several mechanisms, improved lubricants, improved cylinder wall textures and the application of low friction coatings. Holmber et al. [379] estimated that current laboratory scale developments have shown 90% decrease in coefficient of friction for all engine friction mechanisms compared to typical cars from 2010. They expect further reductions for cars in production in the 2020s. Their value is used as the practical limit for engine reduction, thus friction losses are estimated to decrease by a maximum of 80%-90%.

Exhaust Heat Recovery Three main technologies have been put forward to recover energy from exhaust gases: turbo compounding, bottoming Rankine cycles and, thermoelectric generation. Turbocompounding extracts energy from the exhaust gases by installing a turbine at the exhaust used to generate either shaft work or electricity [380]. A bottoming Rankine cycle (either steam based or organic based) extracts work by using the exhaust gas to superheat a working fluid from which work can be extracted using a turbine [381]. Thermoelectric generation is based on the physical properties of semiconductor wafers that generate electricity when exposed to a temperature differential [382].

A review of options for exhaust heat recovery has indicated that Organic Rankine Cycles have the highest theoretical efficiency improving potential [383]. Edwards estimated the potential for exhaust gas recovery to be 20%, which is in line with results from studies on ORC exhaust heat recovery which mention efficiencies ranging between 15% and 20% [381]. These values will be used as the technical maximum recovery from waste heat.

Table 4.10 Summary of loss reduction potential and efficiency limit for reciprocating engines

Application	Current Efficiency Range	Parameter	Limit value	Efficiency Limit
Light and Medium Duty	25%-45%	CR	30-35	56-62%
		Friction Loss	80%-90%	
		Heat Loss	40%-50%	
		Exhaust Loss	15%-20%	
Shipping and Industrial	45%-55%	CR	30-35	60-66%
		Friction Loss	80%-90%	
		Heat Loss	40%-50%	
		Exhaust Loss	15%-20%	

Comparison to the literature

The results obtained are inline with most of the literature on the subject. In particular, the colloquium on the practical efficiency limits of concluded that the maximum efficiency for reciprocating engines would have been under 60%. Also Parametric studies by Caton show that by stretching all design parameters, efficiencies around 60% could be achievable [378]. The only disagreement is seen with the results of Liu et. al which show maximum indicated efficiency ranging around 55% for their realistic scenarios.

4.2.8 Electric Motor

Description

Electric motors convert electrical energy into work thanks to the electromotive force that is exerted on a current-carrying conductor placed in a magnetic field. These devices are used to deliver mechanical energy to industrial processes, such as conveyor belts or milling machines, and to residential processes such as ventilation or food blending. They are also used in rail transport. Their power density is very high and they have the benefit of being silent and emission free when compared to other work delivering devices. The main components of an electric motor are the stator and the rotor. The magnetic field circuit is called the core which is usually made of a Ferrous alloy, while the electrical circuit is made of copper.

Characterisation

Electric motors are firstly characterised by the type of power source: direct current or alternating current. AC motors are used in most applications since they can be powered directly from the grid. In particular the induction motor is the most widely used design due to it's simple design, high power density and low cost. The three-phase induction motor is mostly used for high loads in the industrial and commercial sector while the single phase motor is used mostly for residential appliances. Synchronous electric motors are used for high power density and high efficiency applications such as for vehicle propulsion. DC motors are mostly valued for their precision and ease of control, they are mostly used as actuators in vehicles and manufacturing. DC motors are also used in some high power applications where speed control is very important [384].

Induction motors account for the vast majority of electricity consumption from electric motors. Almeida et. al [385] estimated that induction motors with variable speed accounted for 64% of the EU's energy consumption from motors in the early 2000's, while in Japan three-phase induction motors accounted for 55% of national electricity consumption [386]. Similar trends are also observed in the USA [387].

Permanent magnet motors are used for the vast majority of electric vehicles due to their high power density and efficiency [388, 389]. Most electric motors used in railway are also based on permanent magnet motors for the same reasons.

Given the prevalence of the induction motor, the analysis will use this type of technology as the baseline for all stationary applications. On the other hand, the baseline for electric motors used for transport will be the permanent magnet motor.

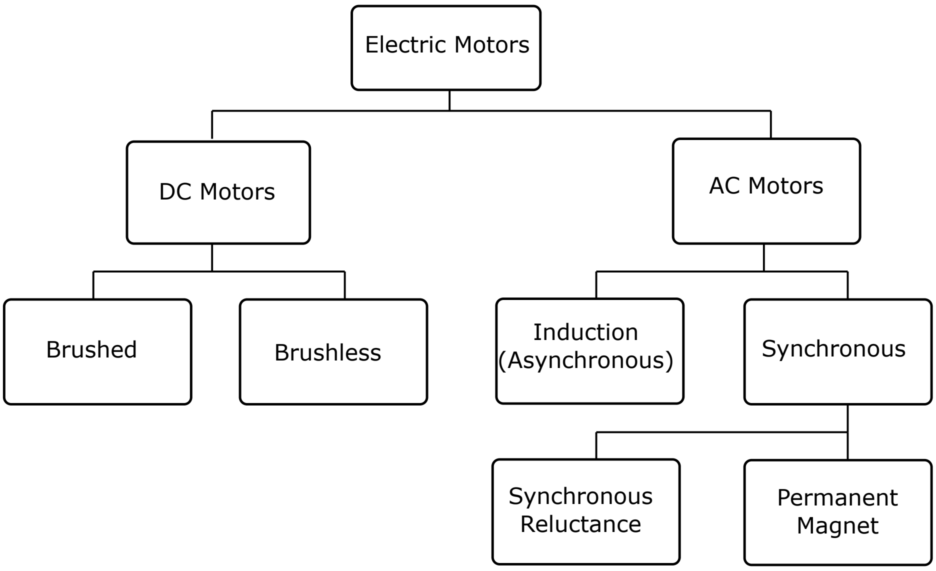


Fig. 4.15 Classification of electric motors types currently in use, taken from De Almeida et al. [384]

Efficiency Measure

Efficiency in electric motors is defined as work output over electrical energy input. There is no thermodynamic limit to the energy conversion efficiency, meaning that in theory the conversion could occur at 100% efficiency.

Efficiency Standards The efficiency of motors is regulated in all major markets. The efficiency of motors is classified by the International Electrotechnical Commission. There are currently four efficiency standards, IE1 to IE4. These standards establish the efficiency of each class as a function of rated power, number of poles and frequency (50Hz or 60Hz). The latest efficiency standards are the second edition of the IEC 6400-31 standard [390]. They cover motors with rated power between 0.75 kW and 800 kW. The minimum efficiency for each standard for a 4-pole 50Hz motor can be seen in Figure 4.16. While this standard defines efficiencies classes from IE1 to IE4, a higher future IE5 class is mentioned. This class is expected to be defined as a 20% reduction in losses compared to the IE4 class.

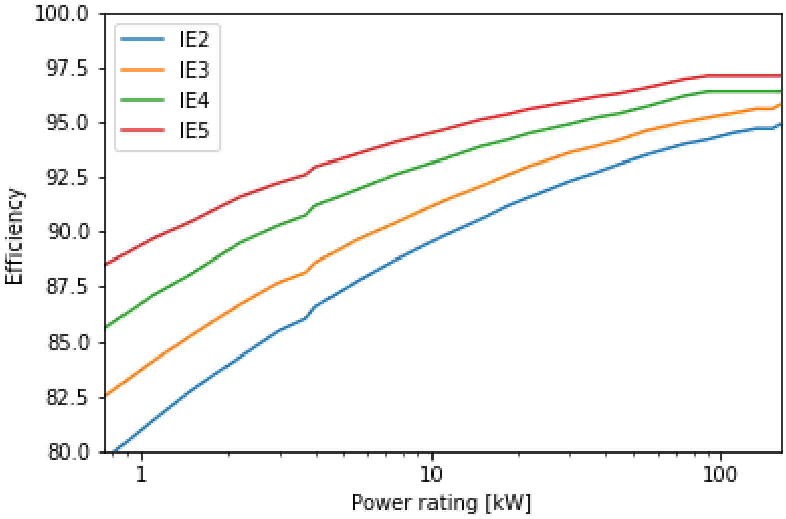


Fig. 4.16 International electric motor efficiency classes for four pole motors at 50Hz from 0.75kW to 375 kW [391]. The IE5 class has only been proposed and has not been officially established.

Minimum efficiency standards are now implemented in most of the major markets [386]. Currently in the USA, the EU, and China the minimum performance standard of electric motors is the IE3 class. Therefore, the IE3 efficiency level is regarded as the current baseline technology.

Key Parameters

The parameters linked to the efficiency of EMs are five commonly defined loss mechanisms: iron, stator copper, rotor copper, friction and windage losses.

Iron losses are losses in the magnetic circuit which occur in the core of the electric motor. There are two loss mechanisms in action: the hysteresis loss and the Eddy current loss. These two losses are usually grouped together and measured in Watts per kg of core material (W/kg). The magnitude of these losses depends on the material properties of the core material, the lamination thickness, the design magnetic flux density and the frequency at which the motor is operated [392].

The stator copper losses occur in the magnetising windings on the stator. They are due to the Joule effect in the winding conductors and are equivalent to IR^2, that is, they are proportional to the current and to the square of the conductor resistance. The resistance of the conductor depends on their cross-sectional area hence a motor with the same current but larger conductor volume will have lower losses [393].

The rotor copper losses occur in the rotor conductors and are proportional to IR^2. For induction motors, this loss is proportional to the motor slip (difference between motor rotational speed and synchronous speed), which is a design parameter. Also for these losses, a larger conductor volume leads to lower losses. Rotor losses are not experienced by synchronous motors [393].

Friction and windage losses are the sum of the friction losses occurring in the bearing and the energy required to cool the motor. Motors are often cooled by a fan on one end of the motor as well as by internal flanges. This loss mechanism is proportional to the rotational speed of the motor, to the quality of bearings and to the optimisation of the cooling system [392].

Stray Load losses are those losses that are not accounted by the aforementioned loss mechanisms. They occur due to unwanted currents and magnetic flux occurring at certain points in time in the motor as well as due to losses in the air gap between the stator and the rotor [394]. They are difficult to model but are mostly dependent on the manufacturing quality and the width of the air gap [395].

Power Rating is highly correlated to the efficiency of electric motors. The reason for this is that copper and iron losses are a function of respectively the current and flux density experienced in the motor, therefore motors with more active material are more efficient [396]. The relationship between power rating and active material is mostly constrained by standardised frame sizes [391, 397]. In these frame sizes, the motors with higher power rating have more active material per unit of power and are therefore more efficient.

The relative proportion of each loss term changes as a function of power rating, as shown in Figure 4.17.

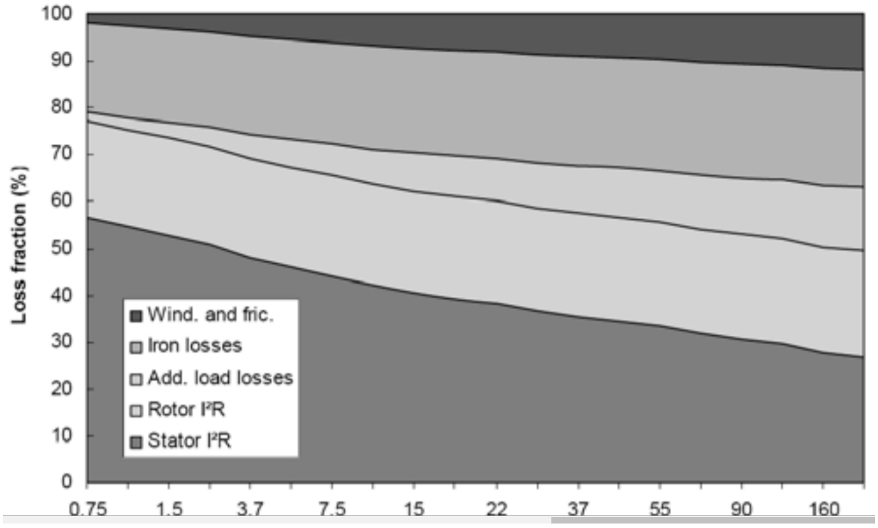


Fig. 4.17 Relative share of losses in IE3 Squirrel Cage Induction Motor for different power ratings. Adapted from De Almeida et al. [275, 398]

Efficiency Limits

Previous Work

Two publications by the same research group, estimated the technical efficiency limits of electric motors.

In their 2011 article, De Almeida et al. [399], estimates the efficiency limits of line-started permanent magnet synchronous motor (PMSM) technology. Using an IE3 efficiency level induction motor as the reference, the author makes three assumptions to obtain the efficiency limit: a) elimination of rotor copper losses, by moving towards synchronous machines b) 58% reduction of stator copper loss and c) 60% reduction of core losses. Assumption b) and c) are extrapolated from the fact that 60% less core steel and 58% less copper volume is required for the same power in PMSM. It is further assumed that by keeping the same current and magnetic density and the same volume, the losses would decreased proportionally to the decrease in mass requirements. However, these comparisons are made with an IE2 motor and then applied to an IE3 motor for the efficiency improvement, meaning that there are likely to be over estimations. In this estimate, the author ignored the efficiency improvement effects that could be obtained by the use of amorphous metals as core material.

In a 2014 article, Almeida et al. [398], present a review of the possible technologies to move to higher efficiency levels. Their main aim is to assess whether there are technical pathways to reach an higher efficiency class, the IE5 class, that was introduced indicatively in IEC

60034-30. The authors analyse the improvements to the induction motor as well as looking at two alternative synchronous technologies, the PMSM and the Synchronous Reluctance (SynRM) motor. They estimate the efficiency limit by taking into consideration the following reduction measures: general improvement in motor design, optimised fan design, copper rotor cage, use of amorphous metals in core, synchronous operation, and larger frame size for equal power output.

The resulting efficiency from the two studies are show in in Figure 4.18. Interestingly, the limit estimated in 2011 with only a few rough assumptions is higher than the limit determined if a more thorough step by step analysis.

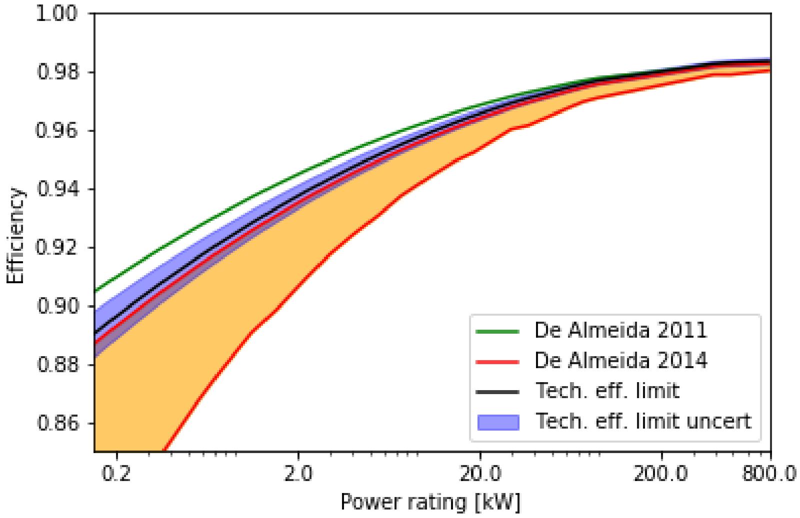


Fig. 4.18 Comparison of two efficiency limits estimates made by De Almeida and the efficiency limit established in this study. The blue shading represents the uncertainty associated with the estimate, the orange shading represents the range of possiblities considered by De Almeida in his 2014 article.

Efficiency Limit Estimation

The efficiency of electric motors is dependent on a large number of design parameters, some of which are complex to define, such as the shape of the core which required Finite Element Analysis for performance evaluation. While design simplified design equations (based on empirical correlations) could be used, most advanced designs are still under preliminary investigation, hence these correlations are not available [396]. Therefore, efficiency limit is estimated by the loss reduction method (Methodology B).

Iron losses Iron losses can be reduced by minimising the thickness of the laminar sheets and improving the interlaminar insulation between sheets. Currently, Silicon Steel is used as a core material due to its good magnetic properties. Given the magnetic properties of ,Silicon steel sheets can be as thin as 0.35 mm. A large reduction could be brought about by the use of amorphous alloys, which have superior magnetic properties having effective lamination thickness of 0.025 mm. These materials are already used in some very high efficiency transformers, and in laboratory scale electric motors [400]. De Almeida et al. [398] estimate that the use of amorphous metal can reduce iron losses by up to 70% while other design improvements could bring a further 19% reduction. On the other hand, Hayashi et al. have observed iron loss reduction of 50% by substituting silicon steel with amorphous metals [401]. In this study we will assume the practical level of iron loss reduction to be 60% to 75%.

Stray load losses These are reduced by minimising the air-gap between the rotor and the stator as well as by implementing copper squirrel cages. De Almeida et al. [398] estimate a loss reduction potential of 30%, in this study the loss reduction is estimated to range between 20% and 35%.

The stator copper losses Stator copper losses can be reduced by optimising the design of the motor and by maximising design parameters such as slot filling factor. Often these manufacturability limitations prevent optimal designs. The replacement of aluminium in the squirrel cage with copper also contributes to reduction in these losses. De Almeida et al. [398] estimate a potential reduction of 19% for these losses. In this study, a reduction potential ranging between 15% and 25%.

The rotor copper losses Rotor copper losses are generated by the induced current requred to produce a magnetic field in the Induction Motor. By switching to sychronous motors, either permanent magnet or Synchronous reluctance motors, this loss mechanism can be competely avoided. Therefore the loss reduction assumed is 100%.

Friction and winding losses Friction and windage losses can be reduced by optimising the fan design and heat transfer in the motor as well as by reducing friction from bearings. [398] estimate a potential reduction of 26% of these losses. However, reductions friction coefficients in bearings have been estimated to be able to decrease by up to 90% [379].

However, since friction doesn't account for the totality of this loss mechanism, a lower estimate is more reasonable. This study estimates a loss reduction between 25% and 30%.

These losses reductions are applied to the distribution of loss mechanisms shown in Figure 4.17. The loss distribution for motors with power output above 170 kW is assumed to keep the same distribution as the values for motors with a power rating of 170 kW. Table 4.11 summarises the assumed technical maximum loss reductions, where ranges are interpreted as uniform distributions. The efficiency that would be reached with these loss reduction levels for each power rating, is shown as the *Tech. eff limit* line in Figure 4.18.

Table 4.11 Summary of Assumed technical limit of loss reduction in electric motors and efficiency limits

Type	Current Efficiency	Loss Reduction		Efficiency Limits
Stationary Motors	80%-94%	Friction	25%-30%	91.6%-98.2%
		Iron	60%-75%	
		Stray Loss	25%-30%	
		Rotor Copper	100%	
		Stator Copper	15%-25%	
Transport Motors	95%-96%	–	–	95%-98%

Comparison with literature

The result of this estimate for the efficiency limit of electric motors is lower than the De Almeida's 2011 estimate. The 2011 efficiency limit was estimated in a quick way, only using the ratio of active material between a PMSM and an SCIM. In his 2014 estimate, the results are from an analysis of the improvement potential of each loss mechanism and covers several cases (hence the uncertainty band between his estimates). The technical limit established in this study is in line with the most extreme efficiency improving case in Almeida 2014.

4.3 Energy saving potentials

Summary of Technical Efficiency analysis

In this section Table 4.12 summarises and describes each of the technical parameters and loss mechanisms that have been used to estimate the efficiency limit of each conversion device. The maximum value obtainable by each technical parameter is shown as a range to indicate the uncertainty associated with the estimation. In the following section, the key technical challenges associated with the improvement of each parameter are touched upon.

Table 4.12 List and description of the technical parameters and loss mechanisms used to characterise the efficiency limit of each device. The optimal value of a parameter represents either the highest or lowest achievable value of the parameter depending on whether it is proportional or inversely proportional to efficiency.

Device	Parameters	Optimal value		Description
Chemical to Work				
Jet Engine	Pressure Ratio	80–100	–	Ratio of pressures at the entry of the turbine and the one at the exit of the compressor.
	Turbine Inlet Temperature	1900–2100	K	Temperature at the exit of the combustion chamber, highest temperature experienced in the cycle
	Polytropic efficiency	90–95	%	Indicator of the compressor and turbine quality
	Propulsive efficiency	85–90	%	Indicator of the efficiency with which the jet's momentum is converted in useful kinetic energy
RE Engine	Compression Ratio	35–40	–	Ratio of top dead center volume to bottom dead center volumes
	Heat Loss Reduction	40–50	%	Reduction of heat transfer through cylinder walls
	Exhaust Loss Reduction	15–20	%	Reduction of losses in exhaust gasses by means of work recuperation
	Friction Loss Reduction	80–90	%	Reduction of friction in piston–wall assembly, cam–valve assembly and crank assembly
Electrical to Work				
Electric Motor	Rotor copper loss reduction	100	%	Avoidance of rotor copper losses by use of synchronous machines
	Stator copper loss reduction	15–25	%	Reduction of current induced losses in the stator windings
	Stray loss reduction	25–30	%	Reduction of losses occurring at stator–rotor interface
	Iron loss reduction	60–75	%	Reduction of losses induced by the magnetic flux
	Friction loss reduction	25–30	%	Reduction of losses in bearings and ventilation system
Chemical to Thermal				

Boiler	Equivalence ratio	1.01–1.1	–	Ratio of the actual air flow compared to the airflow required for stoichiometric combustion
	Minimum temperature difference	6 – 9	K	Temperature difference between flue gas exit temperature and inlet water temperature
	Heat Loss	0.5 – 1	%	Share of output lost to the environment rather than transferred to water
Electrical to Thermal				
Cooler	Compressor isentropic efficiency	80–85	%	Measure of compressor quality and efficiency
	Evaporator delta temperature	3–6	K	Temperature difference between evaporator temperature and required internal temperature, mesure of internal heat exchanger effectivness
Electrical to Illumination				
LED	Driver efficiency	92–97	%	Efficiency of AC to DC conversion
	Optical efficiency	90–95	%	Ratio of photons exiting the lightbulb over photons being generated by the device
	Wall plug efficiency	90–100	%	Ratio of radiative flux (photon generated) over DC electricl power input
	Spectral efficacy	348–414	lm/W	Convolution of produced radiative flux spectrum and the human's luminous spectrum

For jet engines, the TEL is defined by the propulsive efficiency and by operating parameters of turbomachiery, the pressure ratio (PR), the turbine inlet temperature (TIT), and the the polytropic efficiency of compression and expansion. To achieve the maximum values of turbomachinery parameters, materials able to sustain higher temperatures such as ceramics or ceramic composites, are required. While improvements in polytropic efficiency and PR can be bought about by optimised design and ever smaller tolerances in blade manufacturing. Propulsive efficiency (including transfer efficiency) can be improved by switching from high bypass ratio engines to an open rotor architecture. All these solutions require further R&D since solutions are not yet available.

For reciprocating engines the technical advances associated with the TEL are: reduction of the in-cylinder heat losses by the use of thermal barriers and higher temperature materials for the engine block; recovery of exhaust gas losses by means of an Organic Rankine Cycle, reduction of whole engine friction losses by use of advanced lubricants. The compression ratio (CR) increases to around 30, therefore stronger materials are required in the engine block. In addition, increased CR is related to much higher pollutant formation during combustion, thus advanced exhaust gas treatment are needed. All these advances have important technical challenges and require R&D advances.

For electric motors, the most important design changes required to achieve the TEL (without modifying majorly the energy density of the motors) are: a shift to synchronous technology, thus removing rotor copper losses, and the use of amorphous metals in the core, thus halving the iron losses in the rotor. Synchronous motors built using permanent magnet or synchronous reluctance technology are already available for specialised applications while amorphous metals are commonly used in transformers. Other improvements which require further research include design optimisation to reduce stray losses and stator copper losses as well as the use of advanced lubricants to reduce friction losses.

For boilers, the equivalence ratio, the condenser pinch point temperature difference, and the ambient heat losses define the TEL. The optimal values can be reached by further increasing the effectiveness or the area of the heat exchangers and by developing burner designs that enable efficient combustion near stoichiometric conditions. Heat losses can be avoided by better heat exchanger design and larger insulation. The greatest technical challenge for boilers is the improved equivalence ratio, since flame stability and emission control become more difficult at near stoichiometric conditions. The other options require mostly design changes rather than technological improvements.

For coolers, the TEL represents a vapour compression cycle with a much lower temperature difference between the evaporation temperature and the desired room temperature and by improving compressor efficiency. Smaller temperature differences are achievable by designing larger heat exchangers and improved heat transfer coefficients. The compressor efficiency can be improved by a shift towards radial compressors and enhancements in their design. The lower temperature difference in the evaporator can be achieved mostly by design changes, while the improved compressor efficiency required further research. The same technical improvements are required for improved Heat pumps.

The TEL of light devices is estimated by focusing on LED technology because of its combination of high efficiency potential and high quality light output. The TEL is estimated taking in consideration marginal improvements in driver (AC/DC inverter) efficiency and in optical efficiency of light bulbs. The largest efficiency improvement contribution is made by important advances in the wall plug efficiency which is estimated to be able to reach values just under unity. This value is limited by the practical power density requirements of (1-5 W/cm^2) and manufacturing considerations since values above unity have been measured in laboratory scale devices. While R&D is required to improve wall plug efficiency and spectral efficiency, the other parameters could mostly be improved by design changes.

Table 4.13 Summary of current efficiency and efficiency limit of conversion devices used in various sectors.

Device	Sector/End-use	Power Rating		Current Efficiency	BAT	TEL
Chemical to Work						
Gas Turbine	Industry	5 - 50	MW	30-42%	43%	59-62%
	Aviation	10 - 30	MW	30-40%	41%	54-58%
SI Engine	Road Transport	50 - 200	kW	15-23%	36.5%	56-62%
	Other	<10	kW	15-30%	30%	56-62%
CI Engine	Road Transport	80 - 400	kW	21-35%	36.5%	56-62%
	Rail Transport	2 - 5	MW	30-45%	43%	60-66%
	Navigation	1 - 30	MW	40-46%	55%	60-66%
	Industry	0.5 - 5	MW	40-46%	55%	60-66%
Electrical to Work						
Electric Motor	Residential	<5	kW	79-88%	90.5%	91.6-92.8%
	Services	5 - 20	kW	93-95%	96.5%	94.7-95.4%
	Industry	10 - 200	kW	81-96%	96.8%	97.8-98.2%
	Road Transport	50 - 150	kW	86-96%	96.5%	97.8-98.2%
	Rail Transport	2 - 10	MW	93-95%	96.8%	97.8-98.2%
Chemical to Thermal						
Boiler	Buildings	8 - 50	kW	80-93%	93%	93-101%
	Industry	50 - 5000	kW	70%-90%	90%	82-101%
Electrical to thermal						
Cooler	Space Cooling	5 - 50	kW	550-850%	850%	900%-1100%
Cooler	Process Cooling	0.5 - 500	kW	100-300%	300%	320%-380%
Electrical to Illumination						
LED	Residential	-		50-80 lm/W	107lm/W	284-350 lm/W
	Services and Street lighting			80-100 lm/W	107lm/W	284-350 lm/W
	Industry			90-110 lm/W	107lm/W	284-350 lm/W

4.3.1 Technical efficiency limits

The TEL estimation results are summarised in Table 4.13 which shows the current efficiency, the current final energy conversion, the approximate power rating range and the efficiency limit for each device. Quantities provided as ranges represent the range between the 10^{th} and 90^{th}percentile of the values shown.

For the jet engine and reciprocating engines used in road transport, the efficiency measures the work delivered to the aircraft and to the wheels respectively. Therefore, the Jet Engine efficiency includes both losses associated from work extraction in the engine's core (thermal efficiency $\approx$ 0.6) and with the transfer of momentum (propulsive efficiency $\approx$ 0.9). For road transport engines, the efficiency includes the losses in the engine as well as in the transmission system. For the technical limit, the maximum engine efficiency is compounded with the efficiency associated with a hybrid propulsion of 85%. Higher efficiency limits are found for large reciprocating engines (for industrial, rail, and marine applications) and for stationary gas turbines. Large reciprocating engines have a higher TEL than those used for road transport because they mostly work at constant load and because their larger size makes them inherently more efficient (lower RPM, higher volume to area ratio). Higher uncertainties are associated with RE engine estimates that jet engines because the latter are estimated with method A while the former with method B.

The BAT for jet engines equals the maximum efficiency and is representative of the GE9X engine [402]. The BAT of road transport engines is representative of a 1.9l General Motor Diesel (combined with a hybrid powertrain with 85% efficiency) studied by the DOE to determine the efficiency limits of engines [373] , while for large engines the efficiency is representative of the Wärtsilä 31 engine [403]– currently recognised as the most efficient engine in use.

The efficiency of electric motors only takes into consideration the losses associated with electrical to shaft work conversion and excludes the wider motor system (fans, pumps, etc.). The current efficiency and TEL are both highly proportional to the power rating of the motor. Therefore, motors in different sectors are given a different efficiency range which is a function of the power rating distribution in each sector. TELs range between the high values of 92% to 98%. The uncertainty in the TEL estimation for electric motors is comparatively small, despite being estimated with the loss reduction method, because high quality loss reduction estimates are present in the literature and because the loss mechanisms are mostly independent of each other. The BAT assumed for electric motors are devices with the IE4 efficiency classification [390]. This is the highest possible standard, which only a small minority of devices reach.

For boilers, the efficiency is a measure of the chemical energy transfered to the hot water flow exiting the boiler. Efficiency can be greater than unity because energy statistics are compiled using the lower heating value of fuels while condensing boilers are able to recover the latent heat of vaporisation. The boiler efficiency is strongly dependent on the temperature of the input water (return water temperature) because this determines the maximum amount of heat that can be extracted from the flue gasses. For boilers in buildings, the efficiency is computed as the average efficiency between return water temperatures of 60 C° and 30 C°, as prescribed by European standards [404]. The resulting large variation of values in TEL is due to the fact that boilers powered by different fuels have varying net efficiency values due to their different HHV to LHV ratios. The TEL of boilers reaches 101% for gas and 93% for coal, however within the same fuel the uncertainty range is small ($\leq$1%). There is high variability of operating conditions of industrial boilers due to varying steam temperature, pressure, condensate return temperature, make up water share, therefore it is not possible to estimate their average TEL with any precision. However, it is assumed that industrial boilers can improve their efficiency by as much as residential ones. For boilers BAT is equivalent to the highest efficiency found in the UK's product characteristics database [267].

For light devices, the efficiency is defined as the lumens at the outlet of the light bulb over the input electrical power (in alternating current). The TEL of LEDs is estimated to range between 284 and 350 lm/W. The large uncertainty is associated with the maximum achievable spectral efficiency, which is difficult to define. The BAT represents the 2015 benchmark technology identified by the US Department of Energy solid state lighting report [348]. In industry and services (which includes street lighting), the current efficiency is higher than the BAT because of widespread use of sodium-lamps which have efficacies around 200 lm/W but low colour quality (CRI $\approx$50).

For coolers used for space cooling, the efficiency is defined as the Seasonal Efficiency (defined by European standards) which reflects the average efficiency of a cooler to maintain a room at a constant 20 C° throughout the year in an average European climate. The BAT for coolers in space heating is taken as the air conditioning with the highest SEER in the Eurovent database [323]. Coolers used for process cooling have varied use cases meaning that it is difficult to characterise their average efficiency. Therefore a wide range of efficiencies is assumed, the gap between BAT and TEL for process cooling is assumed to be equivalent to the one for space cooling.

4.3.2 UK Energy Saving Potential

The above calculations of TELs for each device in each sector enables a more reliable estimate of the energy saving potential (ESP) and the carbon saving potential (CSP) associated with each conversion technology. The methodology is applied to end-use energy consumption data in the UK in 2013.

The average Final to Useful energy efficiency in the UK in 2013 is estimated to be 69% ± 3%, while if all devices operated at their TEL, the average efficiency would be 88% ± 2%. This corresponds to a total technical potential of 1460 PJ and of 110 $MtCO_2$, or 25% of total energy demand and emissions. If conversion devices operated at their BAT levels of efficiency, the average efficiency would be 79 % ± 2% and 920 PJ of Final energy could be avoided, equating to 16% of total demand. Table 4.14 shows the breakdown of the Final and Useful energy consumption in the UK as well as the Final energy demand that would result if all devices were operating at their TEL or at their BAT, and the associated percentage savings.

Table 4.14 Breakdown of the Final and Useful energy consumption of the UK by sector. The Final energy consumption that would be obtained if all devices were operating at their TEL or at BAT, and the associated savings are also displayed. Energy consumption values are in PJ, values in brackets represent the percentage savings.

Sector	2013 Final energy consumption	2013 Useful energy consumption	Final energy consumption if CD operate at TEL	Final energy consumption if CD operate at BAT
Transport	**2229**	**634**	**1189 [46%]**	**1591 [28%]**
Road	1550	375	752 [51%]	1023 [34%]
Aviation	495	173	309 [37%]	420 [15%]
Navigation	142	61	97 [32%]	111 [21%]
Rail	42	25	31 [27%]	38 [11%]
Buildings	**2461**	**2371**	**2127 [14%]**	**2227 [10%]**
Residential	1729	1662	1507 [13%]	1560 [10%]
Services	733	709	619 [16%]	666 [9%]
Industy	**1103**	**1004**	**1019 [8%]**	**1056 [4%]**
Industry	1015	933	943 [7%]	973 [4%]
Primary	89	71	76 [14%]	83 [6%]
Total	**5793**	**4010**	**4334 [25%]**	**4874 [15%]**

As shown in Figure 4.19 the largest ESP and CSP is associated with diesel engines and spark ignition engines which account for 683 and 333 PJ of savings respectively, followed closely by boilers and gas turbines. Devices powered by electricity show the lowest saving potentials with overall savings of 250 PJ with most of the saving coming from light devices which have the highest overall efficiency gap.

In Figure 4.20, the ESP and CSP are grouped and ordered by sector. The highest impact can be seen in the transport sector, with an ESP of 1186 PJ and a CSP of 85 t CO2; this is equivalent to 75% of the overall ESP. Road transport ESP alone accounts accounts for more savings that all other sectors, with 61% of total savings.

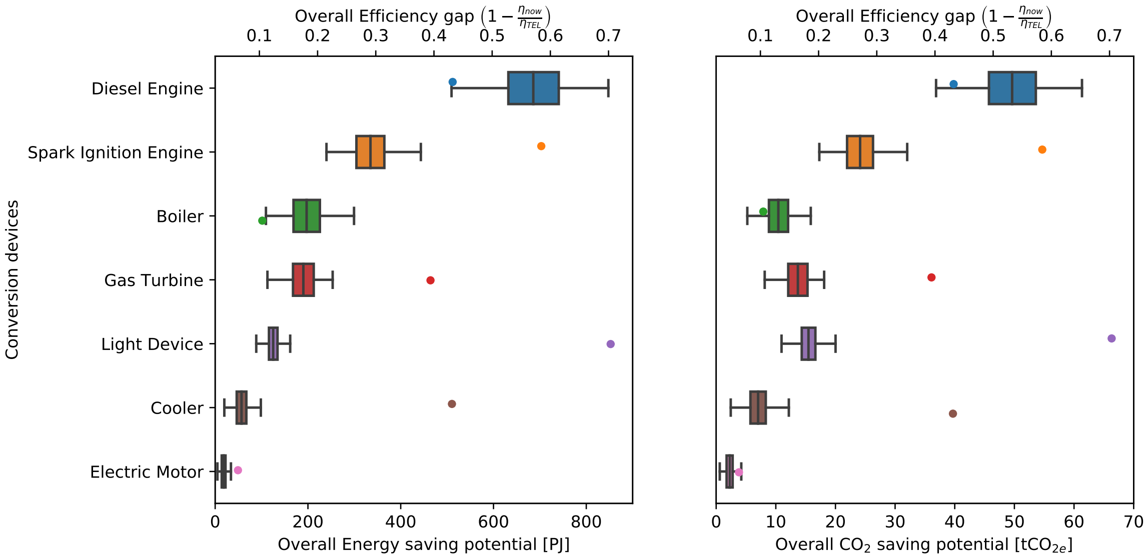


Fig. 4.19 Boxplot showing the ESP and CSP associated with each conversion device (bottom horizontal axis), the points refer to the efficiency gap of each device (top horizontal axis)

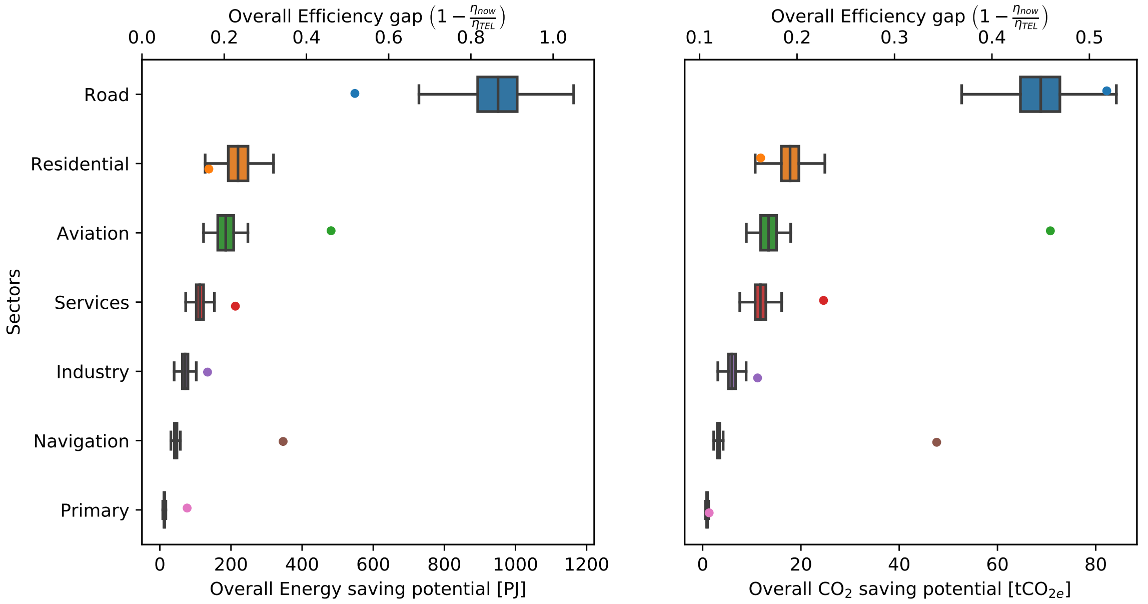


Fig. 4.20 Boxplot showing the ESP and CSP associated with each sector (bottom horizontal axis), the points refer to the efficiency gap of each device (top horizontal axis)

In Figure 4.21 each device-sector combination is plotted with the scale of energy conversion on the x-axis and the efficiency gap on the y-axis. The figure shows that similar saving potentials can be of different nature: for some devices there is a large efficiency gap and a low energy conversion, such as lights; while others have low efficiency gaps but a high energy throughput, such as residential boilers. Devices with the highest ESP (Diesel and Spark Ignition engines) have both a high technical efficiency gap and a high throughput.

Figure 4.22 shows another characteristic of each conversion device: the difference between the current efficiency gap and the technical efficiency gap. Devices with a high technical efficiency gap have a TEL that is is much larger than the current BAT levels. Devices with a large current efficiency gap have a current average efficiency that is much lower than the BAT. Only light devices and gas turbines have a technical efficiency gap that is higher than the current efficiency gap. For devices with the highest ESP, the current efficiency gap is around 2.5 times larger than the technical efficiency gap.

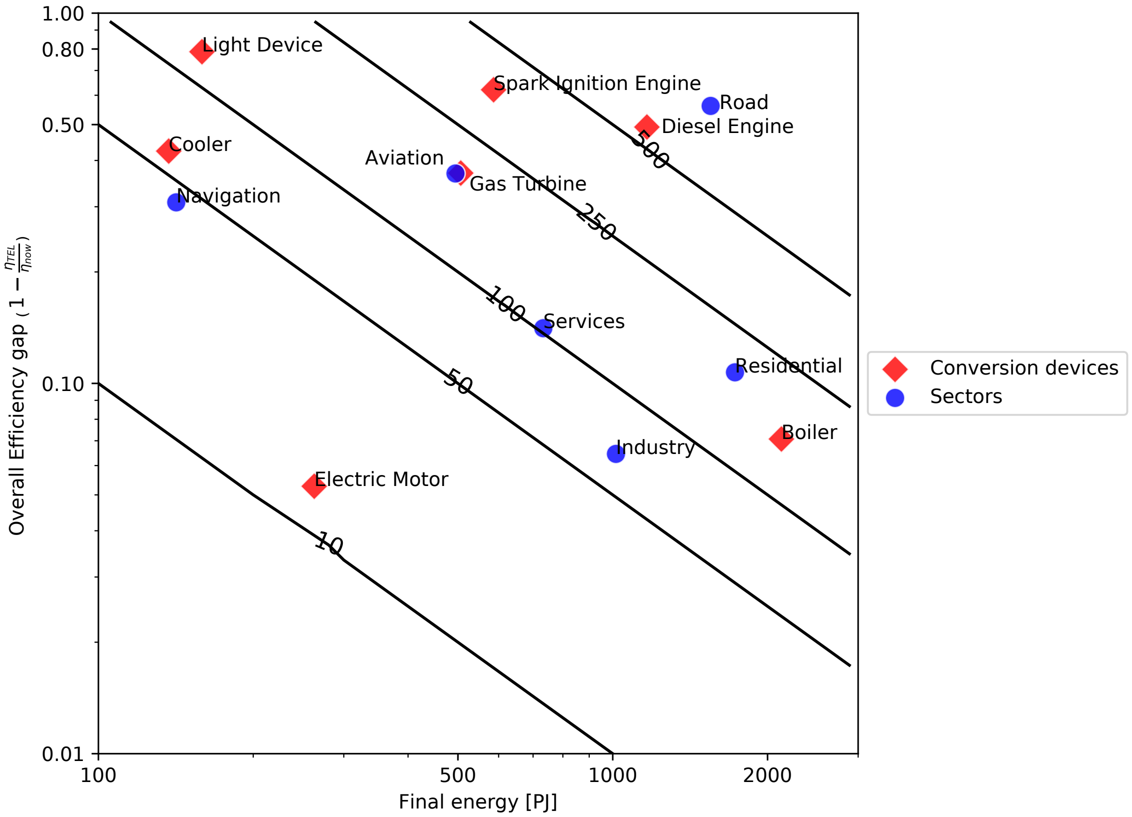


Fig. 4.21 Log-log plot showing combinations of sector and conversion device where the x-axis represents the final energy throughput of each sector-device combination, while the y axis represents the gap between the current efficiency and the TEL. The contours represent lines of constant energy saving potential and range from 1 PJ to 500 PJ. Device-sector combinations with final energy consumption lower than 100 PJ have been omitted.

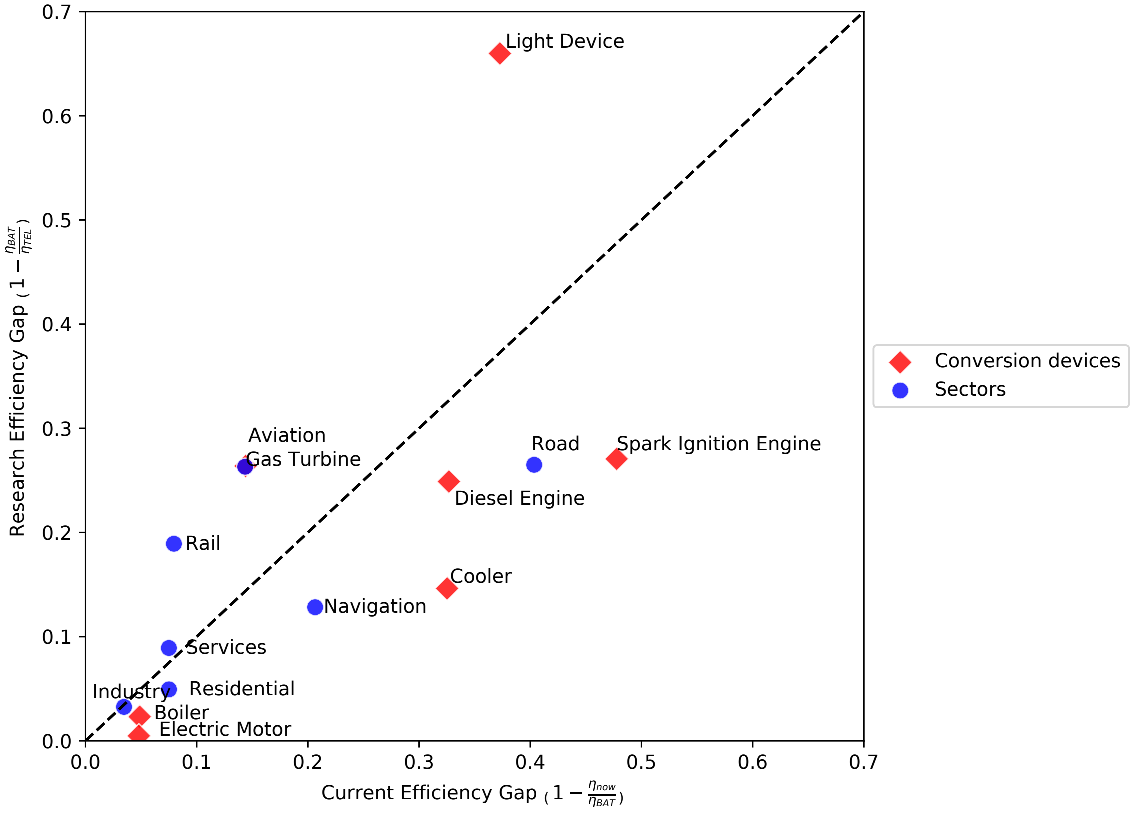
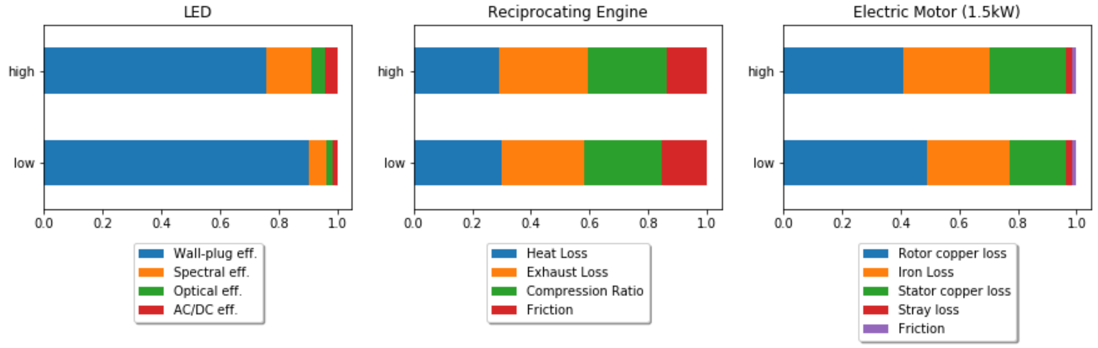


Fig. 4.22 Plot showing sectors and conversion devices where the x-axis represents the efficiency gap between current median efficiency and the best available technology, the y-axis represents the technical improvement gap between the best available technology and the technical efficiency limit. Sectors and devices above the dotted lines have a higher technical efficiency gap than a current efficiency gap.

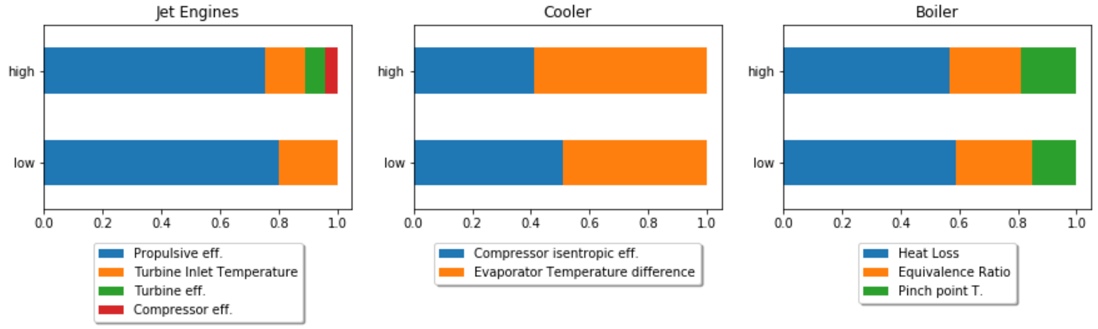
4.3.3 Technical parameter contribution

Figure 4.23 shows the relative importance of each parameter on the technical efficiency limit, including the share of efficiency improvement attributed to each parameter. Two bars are shown for each device which represent the lower and upper bounds of possible parameter improvement. A single parameter dominates the saving potential in three of the devices: wall-plug efficiency (0.7 -0.8) for LEDs; propulsive efficiency (0.7-0.8) for Jet engines; heat loss (0.5-0.6) for Boilers. In contrast, the loss mechanisms are distributed more widely for reciprocating engines, electric motors, and coolers.

Knowing the relative importance of each parameter to move from BAT efficiency to the TEL, it is possible to estimate a saving potential for each technical improvement. Figure



(a) TEL estimated using method B



(b) TEL estimated using method A

Fig. 4.23 Relative contribution of each parameter to the TEL. The lower and high column represent the lower and upper bound of the probability distribution for each parameter.

4.24 shows the energy saving potentials grouped into broad engineering research areas: "Turbomachinery" (which includes improvements in compressors and turbines across all devices), dominates the ESP at 260 PJ for the UK. This is closely followed by "Heat Transfer" (which includes savings from both heat transfer reduction and improvements across devices) and "Material Science" (which includes parameters that are mostly driven by improvements in material properties). "Semiconductor design" also plays an important role, as increases in LED wall plug efficiencies have a large ESP. Electrical engineering (related to electric motor improvements) and "Tribology" (related to reduction of friction losses across all devices) have lower ESPs. Viewing the ESP through the lens of engineering disciplines can help indicate priorities for energy efficiency research agenda setting and investment.

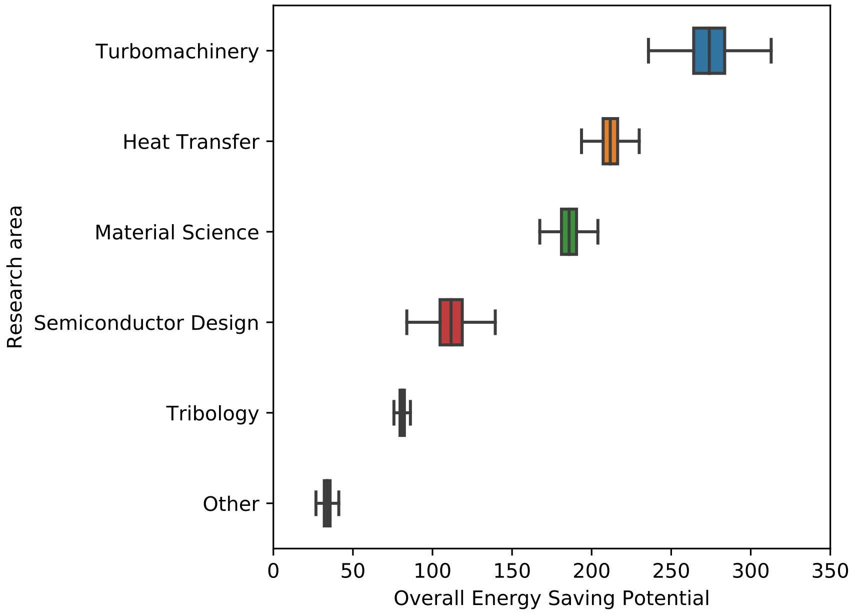


Fig. 4.24 Energy saving potential of each technical parameter grouped into major engineering research areas. The boxplot represents the uncertainty associated with the estimate of saving potential.

The main limitation of this approach is to consider the energy system to retain the current structure when estimating the saving potentials. Therefore there is likely to be an overestimation of saving potential for incumbent technologies such as boilers and internal combustion engines.

4.4 Discussion

In this chapter the technical efficiency limits (TELs) of six categories of end-use technologies were estimated and the impact on energy savings of each key design parameter was quantified. TELs are important for energy system modellers to ensure the physical realism of their models while the impact of each design parameter is relevant to R&D agenda setting. In this section, two main insights that can be gained from the results are discussed.

4.4.1 Insights from conversion efficiency limit study

The results from this chapter show that the largest potential improvements in conversion efficiency are found in devices that convert chemical energy to work, despite the optimisation of engines and turbines being an historically important area of research and investment. There are two reasons that might help explain this observation. First, the conversion of chemical energy to work is concentrated in the transport sector, where high power density is required. It is plausible that designers have historically favoured improvements in power density over efficiency gains. This idea is supported by studies investigating the improvement rates of vehicle performance in the USA [405]. Second, in chemical energy to work conversions, increased efficiency is related to parameters which depend on technological development and material science, such as maximum temperatures and pressure. Whereas for most other conversion routes improved efficiency can be achieved more easily by sacrificing power density. For example, over-sizing the heat exchange surface area in a boiler or the windings in an electric motor results in higher efficiency levels, yet these design changes can be implemented without moving outside of readily available technical options.

For all conversion devices there is a trade off between power density (volumetric and gravimetric) and efficiency, since most loss mechanisms are proportional to the intensity with which energy is converted. For example, copper and iron losses in electric motors are proportional to the current and flux density; the energy losses from boilers and coolers are proportional to the heat exchanger surface area per unit of power output. However, not all key performance parameters are subject to this trade off. For example, increasing the compression ratio in reciprocating engines, the turbine inlet temperature is gas turbines or the equivalence ratio in boilers, benefits both power density and efficiency. For these devices, it is easier to establish objective limits for a parameter, because only the physical limitations need to be considered. On the other hand, parameters that are subject to the efficiency/power density trade-off require further assumptions about the effect of a given parameter on power density meaning that is this harder to objectively define a TEL.

This novel definition of technical efficiency limits should be taken into account by scholars studying the links between energy efficiency and economic growth, since the technical limits are considerably lower than the theoretical limits, often used in studies using the exergy metric. In particular, authors claiming the important role of thermodynamic efficiency improvements in economic growth [94, 406] can now explore the impact of technical limits to efficiency growth on their economic models.

4.4.2 Prioritisation of actions

The total estimated ESP (energy saving potential) for conversion derives in the UK equates to for 25% of the country's final energy in 2013. This compares to the 89% reduction in global energy demand that was estimated by Cullen and Allwood [36] using theoretical efficiency limits to conversion devices, demonstrating that many identified energy losses cannot be resolved in practice. The 25% ESP for UK conversion devices is not sufficient to reach climate goals, and this does not take into account further limitations related to the economic viability of implementing these efficiency options. When calculating the ESP associated with bringing the average efficiency up to current BAT levels, the estimated saving potential is 16%. This means that overall, most efficiency savings can come from wider use of current technologies. Yet, further innovation in conversion devices can substantially increase the saving potential. It's important to note that there are sectoral variations to this conclusion. For example, in the transport sector conversion efficiency improvement still plays an important role, with up to 50% reductions in energy demand possible. This is particularly important for aviation, where the conversion of energy could be improved by 37% and where passive system improvements are more difficult to obtain. Conversely, in the residential and industrial sectors, reaching the TEL for conversion efficiency has a relatively limited impact on the saving potentials. For the residential sector, this is because boilers, which consume the majority of energy, have only a limited efficiency improvement gap. While in the industrial sector, a significant share of energy demand is used directly (i.e chemical reactions and direct heating), without being converted in a conversion device. On the other hand, large passive system improvements are readily available in these sectors, mostly in the form of better heat insulation. Passive systems have larger technical saving potentials since Cullen and Allwood [37] found that their technical ESP is equivalent to 73% of global energy demand.

The results can be use to differentiate between types of actions required to fully leverage the capabilities of each energy conversion technology. In boilers and electric motors, the difference between the current BAT and the TEL is small, while the gap between current average efficiency and BAT is much larger. These technologies have been under development for over a century, leading to efficiencies approaching their TEL. For these devices, efforts should concentrate on moving the average conversion efficiency towards the BAT, by stimulating the market uptake of more efficient devices. Options include driving policy towards more stringent minimum performance standards or employing scrappage schemes, such as those sporadically implemented for road vehicles. In contrast, technologies such as light bulbs and reciprocating engines display similar gaps between average efficiency, BAT, and TEL. For such devices, research and technology development should be pursued in addition to efforts to increase market penetration of efficient devices.

Having taken a probabilistic approach to the estimation of the ESP, it is possible to compare the uncertainty associated with each estimate. This makes the prioritisation and comparison of efficiency options more robust. For example, Figures 4.19, 4.20, and 4.24 show clear overlaps of ESP for devices, sectors and engineering research areas, meaning a more simplistic prioritisation based on averages could be misleading. Table 4.13 shows that there is considerable spread in the efficiency ranges, however, uncertainty associated with the estimates of current average efficiency is higher than than the one for the TELs.

The use of technical parameters in the assessment of ESPs for conversion devices has enabled the links to engineering research areas to be made. Turbomachinery, which enables improvements in both axial and radial turbines and compressors is shown to have the highest energy conversion saving potential. This is followed by material science and heat transfer improvements, with similar potentials, while tribology (the study of friction reduction) has a smaller impact. While these results are only a first order analysis, and only apply to energy conversion devices, this study provides example of how a granular and technically consistent models of the energy system can be used in the setting appropriate research agendas. Furthermore, these results should serve as a reminder that traditional mechanical engineering research fields can play an important role in climate mitigation.

4.4.3 Limitations

Two limitations to the approach taken to estimate the TELS are:

1. The reliance on previous literature and on individual assessments for the upper limits of design parameters and loss mechanism reduction. This implies that the estimates might

be conservative as they don't rely on up-to-date knowledge and might be imprecise especially for devices for which no physical model was developed

2. The focus of the analysis on devices operating at their rated power rather than at their realistic operating condition. This implies that all values calculated in this assessment are too high compared to real operating conditions

There are two important limitations on the data used for this study. Firstly, the data on current conversion efficiencies is only as good as what was possible to estimate in Chapter 3, which is not perfect due to the lack of direct efficiency surveys, most importantly, some of the efficiency values used do not refer directly to the UK, but have been used as proxies. Secondly, the definition of the BAT efficiency level for each conversion device had to be the result of informed expert judgement, again because there is no comprehensive data on all devices available on the market in the UK.

It is important to be aware that the identified technical saving potentials could not be realised in full even if all energy conversion were operating at their TELs for two reasons.

1. Efficiency improvements caused by technological innovation could lead to increased energy service demand. In developed countries, this would be detrimental for the achievement of climate goals, especially if the saved monetary resources are used to increase demand for highly carbon intensive activities such as air travel. It is therefore advisable that in addition to policies fostering efficiency improvement, governments put in place economic policies aimed at limiting the extent of energy demand rebound, both direct and indirect [407].

2. Second, the present analysis assumes a static energy system, that is, static energy conversion chains that deliver Useful energy. However, the energy system is undergoing a transition to a low carbon future. This transition implies profound changes in the way in which energy is transformed to deliver energy services. One key trend in this process is the increased share of electricity as an energy vector. Increased electrification across sectors would have a sizeable impact on the relative importance of the savings from each conversion device. This effect will be explored in Chapter 5.

Chapter 5

The future role of energy conversion efficiency

The aim of this thesis is to study in depth end-use conversion devices in order to provide policymakers with insights on the relative importance of the different technologies. In Chapter 3, it was shown that current data of end-use efficiency is sufficiently robust to provide meaningful advice on these technologies. In Chapter 4 the technical efficiency limits of each conversion devices were defined and the relative importance of technical parameter quantified by applying the results to the UK energy system. In that chapter, limits of using a static picture of the energy sytem became apparent, as the energy saving potentials of each technology are likely to vary substantially according to how the energy system will change. An analysis that takes into account the expected future pathways of energy conversion technologies is required to provide decisions makers with a set of recommendations. Changes in the structure of the energy system will affect the relative importance of the various technologies. Therefore, it would be desirable to provide advice that takes this into account to enable a ranking of the different conversion devices that is robust with respect to different possible futures and that is consistent with climate ambitions. While several energy models and scenarios exist in the literature, conversion devices are never analysed individually. Therefore it is not necessary to develop an additional model and scenario as it is sufficient to reverse engineer an existing technology-rich energy model to understand the expected role of conversion devices in decreasing GHG emissions. The model and scenarios developed by the international energy agency for their 2017 Energy Technology Perspective report is chosen as the tool to explore future of conversion technologies

There are two broad set of measures that can be enacted to improve end-use conversion efficiency: a) to bring the average efficiency towards BAT levels of efficiency; and b) to push the limit of BAT technologies towards the device's technical limit. This chapter focuses on the latter. Increasing the efficiency of the BAT requires R&D and innovation efforts since improved technical knowledge enables the design and manufacture of better performing machines without necessarily increasing their cost [408]. At present, there is no well established way to quantify innovation activity at a sufficiently granular level to analyse individual conversion devices. In this chapter, the use of patent counts is proposed as a method to compare innovation activity levels to energy saving potentials at a more granular level than has been done before. Such a metric would enable decisionmakers (especially in the field of R&D budget allocation) to become aware of current trends and assess effectiveness and R&D policies in this field.

By combining the expected savings due to energy conversion efficiency improvements, and an estimate of the current innovation activity, this study will be able to provide an explicit guide on the importance of different conversion technologies that can be compared to the current state of innovation activity. It will thus be possible unveil possible mismatches between the expected role of technologies and current innovation practices among efficiency measures.

This chapter begins by describing the scenarios developed by the international energy agency's ETP 2017 (section 5.1). The following section (5.2) describes the methods used to extract the information relevant to conversion efficiency from the ETP report and to count patents relating to conversion efficiency innovation. In section 5.3 the estimated future efficiencies and energy conversion flows are provided both in table form and as Sankey diagrams and the cumulative saving potential of each technology is provided while in section 5.3.4 the results from the patent counts are shown and compared to the aforementioned saving potentials. In section 5.4 the results are discussed and specific policy advice is provided.

5.1 IEA Energy Technology Perspective scenarios 2017

Since 2006, the IEA has been publishing an energy technology perspectives (ETP) publication with the aim of assessing the energy technologies that can steer the energy system towards climate targets and of providing advice to policy makers on what action to take. The IEA's ETP scenarios are developed using the ETP model which is formed of three energy demand models (buildings, transport, and industry) and an energy supply model. The supply model is a technology rich, least-cost optimisation model based on the TIMES modelling framework [227]. The residential and transport [409] models are regionally defined global stock simulations where demand is defined by technology choices, but without a cost optimisation logic. Conversely, the industry model uses a least-cost modelling approach for the five key energy intensive industries. The four sub-models are "soft-linked", meaning that they work independently but some key parameters, such as fuel prices, are coordinated across all sub-models. This results in a model that is rich in technological detail and where scenarios are explicitly dependent on technological choices. The deployment of each technology is mostly exogenously defined by analysts on the basis of realistic penetration rates, technology readiness levels, and strategic political choices made by governments across the world. While other energy models have higher technological resolution compared to the ETP model, its global and long term scope make it well suited for the analysis in this chapter. The model explores three scenarios with a modelling window that spans from 2014 (base year) to 2060.

Reference Technology Scenario

The Reference Technology Scenario (RTS) represents a scenario where government policies are in line with current climate pledges, including the Nationally Determined Contributions defined in the Paris Agreement. This means that the RTS scenario is not a Business as Usual scenario, but rather one where the energy system will transition at the speed dictated by current policy rather than by more ambitious policies. Green house gas emissions decrease in the scenario however they translate in a temperature rise of 2.7 °C by 2100 compared to pre-industrial climate. However, it is unlikely that the climate will have stabilised by then and temperatures would continue to rise into the next century.

2 Degrees Scenario

The Two Degrees Scenarios (2DS) is considered the central climate mitigation scenario which is consistent with a carbon budget that would give a 50% chance of limiting warming by 2 C° by the year 2100. In this scenario the the energy system becomes carbon neutral by 2100. This scenario represents an ambitious transformation of the energy system which would require more decisive climate action compared to today's goals.

Below 2 Degrees Scenarios

The Below Two Degrees scenario (B2DS) enables a drastic reduction in emissions that is consistent with a 50% chance of a 1.75 C° temperature rise by 2100. This falls within the targets of the Paris agreement which aims to limit global warming to 1.5 C°. The scenario focuses exclusively on technological options, allowing full projected economic growth to be retained. The targets are reached by making substantial use of negative emission technology in the second half of the century, such as Bio-energy with carbon capture and storage (BECCS).

The scenarios developed in the IEA ETP publication are used to define three possible future energy systems. While these scenarios are extensively discussed and analysed in the ETP publication as well as in other academic work [410, 17], the aim of this analysis is to focus on the changes that will occur in the conversion of end-use energy.

5.2 Methods

In this section, the methods to assess the future role of end-use conversion efficiency are described. First, the methodologies used to extract end-use conversion efficiency from the ETP publication and to calculate their cumulative saving potentials are outlined. Second, the methods used to obtain patent counts for each end-use conversion devices are presented.

5.2.1 ETP data and classification

The modelling results of the ETP scenarios are provided in excel tables from the IEA website [411]. While summary results are split by region and sectors, the full breakdown of results are provided for the global energy system with time intervals of five years, therefore the scope of this analysis is aggregated at the global level. The term "climate scenarios" is used to refer to both the 2DS and the B2DS since both scenarios respect climate targets.

Final energy consumption is broken down by end-use and fuel and grouped into Service, Residential, and Industry sectors. As described in Chapter 3, this is sufficient to allocate final energy consumption to most conversion devices with acceptable confidence. The two exceptions are: the allocation of mechanical energy in Industry to different types of engines (reciprocating engines, and gas turbines) and the allocation of space heating from electricity to resistance heaters and heat pumps. The first exception is handled by assuming that the energy consumption is distributed in line with the global sales of these devices as described in Chapter 3, while the second exception requires different treatment. The ETP report provides projected stocks for different heating equipment in the building sector. These values are used to estimate the share of final energy consumption for heat pumps and resistance heating, by taking into account the relative efficiency of both technologies.

For industry, an extra step is required since energy consumption is not broken down by end-use, but rather by type of industry: Aluminium, Cement, Iron and Steel, Petrochemical, Pulp and Paper, and non-intensive industry. Therefore, additional information on the end-use of energy in Industry is required. The 2014 US Manufacturing Energy Consumption Survey [74] (MECS) is used for this purpose. The MECS provides information on the end-uses of energy for 50 industrial sub-sectors defined with three digits in the North American Industry Classification System. The ETP industrial sub-sectors are linked to the NAICS codes used in the MECS according to Table 5.1 while non-intensive industries were associated to an average of all remaining NAICS codes. The energy consumption for each sub-sector and fuel was normalised such that it would represent an allocation vector (referred to as ϕ^{e}_{sf} in section 3.1) which is then applied to the ETP energy consumption values.

Table 5.1 Matching of ETP industrial sub-sectors to NAICS codes used in the MECS

ETP subsector	NAICS code
Aluminium	3313
Cement	327310
Iron and Steel	331110, 3312
Chemical and Petrochemicals	324, 325, 326
Pulp and Paper	322

Uncertainty

The methodology for uncertainty allocation developed in chapter 3 for the UK are transposed to global level energy data. Uncertainty in the allocation of final energy to end-use categories and devices is estimated using the Dirichlet distribution as described in Chapter 3. Defining an allocation uncertainty metric for the IEA's end-use allocation data is not possible from the extensive documentation provided [412] because uncertainty in the data quality is only described qualitatively. An analysis of the uncertainty of global energy data is deemed outside the scope of this chapter since it would not help answer the research question at hand. Instead, the assumed allocation uncertainty metric is assumed to be 25%, which is equivalent to the highest estimate for the UK end-use data.

No further uncertainty is associated to the energy consumption values for future years because those values are not estimates of a true value, but rather, they are representative of a scenario. There is no likelihood attached to the scenario, therefore it would be meaningless to attach a probability distribution to the projected final energy demand values. Instead, the uncertainty calculated for the base year is projected forwards.

5.2.2 Conversion Efficiency in 2060

Even though the ETP model is a bottom-up model, conversion efficiency is not always modelled explicitly–for example vehicle fuel consumption (in units of l/100km) is the modelled efficiency metric, not engine efficiency–while in other cases conversion efficiency is modelled explicitly (e.g. boiler efficiency in buildings) but the assumed values are not always described in the publication. To isolate the improvement in conversion device efficiency assumed in the model additional information is retrieved from the background literature used by the modellers and from personal communication with IEA staff. In this section, the general method to attribute energy intensity improvements to efficiency improvements is described, then the data sources and assumptions used for each conversion device are described in detail.

Where energy efficiency improvements are included within energy intensity metrics two steps are required to convert these estimates into conversion efficiency improvements. An energy intensity (i) defines the Final energy input (E^{in}) required to provide a unit of service (S).

$$i = \frac{E^{in}}{S}$$

However, this reduction includes all types of technical improvements which include improvements in passive systems, operation, and conversion device efficiency. The first step is to identify the share of this reduction attributable to conversion devices (s_η). Therefore the energy intensity reductions attributable to conversion devices are defined as

$$\left(\frac{\Delta i}{i}\right)_\eta = s_\eta \times \frac{\Delta i}{i}$$

The value for s_η is determined by inspecting the sources used by the modellers to quantify the energy intensity reduction. The sources include breakdowns of the effects of the different technical improvements that lead to the state energy intensity reduction. The second step is to convert this value in a change in conversion efficiency. Starting from the definition of an energy intensity change from t to t+1

$$\begin{aligned}\left(\frac{\Delta i}{i}\right)_\eta &= \frac{E^{in}_{t+1} - E^{in}_t}{E^{in}_t} \\ &= \frac{E^{in}_{t+1}}{E^{in}_t} - 1\end{aligned}$$

and from the definition of conversion efficiency

$$\eta = \frac{E^{out}}{E^{in}}$$

$$\left(\frac{\Delta i}{i}\right)_{\eta} = \frac{E_{t+1}^{out}\ \eta_t}{E_t^{out}\ \eta_{t+1}} - 1$$

Since the change in intensity is only referring to the changes occurring thanks to the conversion device improvements, the energy output per unit of service at time t and t+1 is equal ($E_{t+1}^{out} = E_t^{out}$). Therefore, the above equation can be written as

$$\left(\frac{\Delta i}{i}\right)_{\eta} = \frac{\eta_t}{\eta_{t+1}} - 1$$

and re-arranged as

$$\eta_{t+1} = \frac{\eta_t}{\left(\frac{\Delta i}{i}\right)_{\eta} + 1} \tag{5.1}$$

taking into account that the energy intensity term is always negative when it refers to a reduction in energy intensity due to efficiency improvements.

Transport

Road - light duty In the ETP publication, the fuel economy (l/100km) of cars is expected to improve by 36% respectively by 2060, with only small variations among scenarios. The estimate is based on a technical assessment developed by the EU's Joint Research Center [413], where the contribution engine improvements accounts for 44% f the total fuel economy improvements for gasoline and diesel engines respectively. As described in chapter 4, the difference between spark ignition and compression ignition is likely to fade in the coming decades, therefore these separate categories of conversion devices, are considered as a single one named "Reciprocating Engines" and its efficiency improvements are defined as the weighted average of spark ignition and diesel engines. The average efficiency of engine operation in road transport is also a function of the share of vehicles with hybrid powertrains. Hybrid cars are more efficient as the engine always operate at a single speed and peak efficiency therefore the share of hybrids must be taken into account to assess the expected engine efficiency. Hybrid engines are assumed to have 85% of the losses of conventional vehicles, as described in section 4.2.7. The share of hybrids in 2060 is 62%, 52%, and 31% in the B2DS, 2DS and RTS respectively. For electric vehicles, fuel economy improvements of 6% are assumed for all scenarios by the year 2060. Of these improvements, 44% is assumed to be attributable to motor improvement (same as for gasoline vehicles).

Road - heavy duty The fuel consumption (l/100km) of trucks is expected to decrease by 35% in the B2DS and 23% in the RTS, by 2060. The estimate is based on a study performed by the Global Fuel Economy Initiative [414], where a 10 percentage point increase in engine break thermal efficiency is assumed possible. This increase corresponds to a 18% energy intensity reduction. The share of hybrids in the heavy duty trucks sector influences the average engine efficiency in each scenario, with 78%, 71% and 11% in the B2DS, 2DS and RTS respectively.

Navigation The energy intensity of freight ships (MJ/vkm) is assumed to decrease by 37% and 65% in the RTS and B2DS scenario with respect to 2015 consumption. These values were obtained from a report commissioned by the International Marine Organisation on the potential for GHG emission reduction [415, 416]. The report lists a number of technical measures and provides an estimate for energy reduction potential of each. Energy efficiency improvements in engine account for 19% of overall energy reduction, with the remainder resulting from passive system and operational improvements.

Aviation : The energy intensity of air transport (MJ/pkm) is assumed to decrease by 57% and 68% in the RTS and B2DS respectively, compared to 2015. These values are in line with industry association climate targets, and are deemed technologically feasible, according to the IATA Technological Roadmap [417, 418]. The contribution of engine improvements in the IATA Roadmap can be isolated from the overall fuel reduction measures (i.e. including passive system improvement) and its contribution ranges from 39% to 49% of the overall fuel burn reduction.

Buildings

Heat Pumps In the ETP report it is stated that the efficiency of Heat pumps is expected to reach values that range from 4 to 4.5 but no mention is made with respect to how this value might vary in the different scenarios. Personal communication with the IEA staff suggests that global average COP values of around 4.0 are to be expected for the RTS scenario while 4.5 is in line with the values assumed for the two climate scenarios. Higher uncertainty is associated with heat pumps in the model due to the low quality of the available information.

Air conditioning The IEA's ETP publication provides no specific information on the efficiency of coolers in the different scenarios. However, a more recent publication focusing on future air conditioning [419] developed using the same model, provides explicit estimates about future seasonal efficiency ratings. This new publication uses two scenarios, a baseline and an efficient scenario. In terms of assumed SEERs the baseline scenario is similar to the RTS and the efficient scenario is in line with both the 2DS and B2DS according to personal communication with IEA staff. Therefore, the SEER for air conditioners is believed to range between 4.9 and 5.6 in RTS, and between 8.5 and 9.5 in the climate scenarios

For air conditioners it is also necessary to update the technical efficiency limit value obtained in section 4.2.4 because the TEL of air conditioners is a function of the average climatic conditions, and the TEL are scaled to reflect the seasonal efficiency of an air conditioner in western Europe, using the EU's SEER metric. Therefore, this value needs to be scaled to reflect the global average climate, where summer temperatures are higher on average compared to EU temperatures. The UNFCC has developed tools that provide a methodology to translate these values using standard conversion factors [420]. These conversion factors range from 89% to 90% to convert EU standard into those of other countries. Therefore, the TEL obtained in section 4.2.4 is scaled by multiplying it with a uniform distribution ranging from 0.89 to 1.

Boilers The IEA's ETP states that gas boilers have efficiencies that range from 80% to 90% but does not explicitly mention their efficiency developments in future years. Yet, the report mentions condensing boilers with an efficiency of 90%. This is in line with the ETSAP [227] data on new boilers. It therefore seems like no improvement beyond this value is assumed in any of the scenarios. Since the information on boilers is scarce, the uncertainly associated with the efficiency estimates is larger than for other devices.

Industry and other devices

The IEA's ETP report gives not data on efficiency improvements in cross-sector technologies in industry such as electric motors and steam generators. That is because the industry module is based on industrial processes rather than on individual technical devices. For this reason, it will be assumed that efficiency remains constant for these industrial devices, as efforts will likely be focused on process level changes that will substitute carbon intensive processes with carbon neutral ones. Lighting efficiency is assumed to be the same as the one calculated for the UK in absence of global efficiency estimates.

Energy balances and Sankey diagram

The assumptions outlined in the previous sections enable the estimation of Useful energy balances for the global energy system in each scenario and at each point in time through to 2060. This is done simply by multiplying the Final energy demand for each device with its estimated conversion efficiency at each time point and for each scenario. The resulting Useful energy consumption values are then aggregated and presented in the form of an energy balance and compared to the standard Final energy balance.

The resulting energy balances are displayed using a Sankey diagram which has been recognised as a useful tool to facilitate the communication of large energy consumption data set [421]. As seen in previous chapters, efficiency values for boilers and vapour compression devices (heat pumps and air coolers) can be above unity because the useful energy output is higher than the Final energy input. For boilers this is a result of convention on the reporting of energy statistics (net heating value instead of gross), while for vapour compression it is because thermal energy is effectively extracted from the environment. Therefore, to balance Final and Useful energy consumption it is necessary to take into account both conversion losses and conversion gains. The latter are referred to as “ambient gains” and are calculated as the difference between the thermal Useful energy output and the Final energy input in Vapour compression devices.

5.2.3 Conversion efficiency contribution to energy savings

Having isolated the efficiency value for each conversion device in each scenario, the next step is to estimate the evolution of efficiency between 2014 and 2060. A linear increase in efficiency is chosen (Figure 5.1) since a more rapid increase in efficiency, either in the early or later modelling period, is deemed unlikely. Moreover, previous accounts of conversion efficiencies have mostly shown linear increases in end-use conversion efficiency [146, 147].

The efficiency of each device, in each year, is modelled as a triangular probability distribution where all distribution parameters of the distribution increase linearly between the 2013 and 2060 values, selected for each scenario.

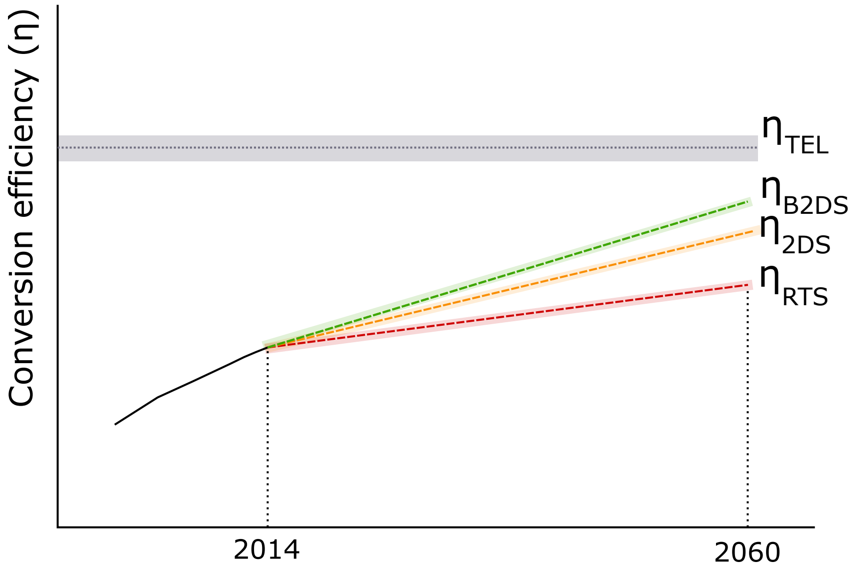


Fig. 5.1 Schematic showing the linear interpolation of conversion efficiency from current values to the values assumed in each IEA scenario. The band around each line signifies that uncertainty is applied to each estimate.

The ESP (Energy Savings Potential) metric, described in Chapter 4 is used to estimate the energy savings attributed to conversion efficiency improvements. Equation 4.7 can be rewritten for each year y using the following equation

$$ESP_y = E_i n_y \left(1 - \frac{\eta_{2014}}{\eta_y}\right) \tag{5.2}$$

The value ESP$_y$ is interpreted as the energy savings associated with an increase in conversion efficiency from η_{2014} to η_y. The ETP models display results with a time interval (Δt) of five years (except for the first model interval from 2014 to 2025), therefore, the cumulative savings between 2014 and 2060 (CS) are calculated using the equation:

$$CS = \sum_{y=2013}^{2060} \frac{ESP_y + ESP_{y+\Delta t}}{2} \Delta t \tag{5.3}$$

The yearly ESP for each device is scaled by the fuel CO_2 intensity to obtain the device carbon emission savings. In the case of heat and electricity, the grid carbon intensity from each scenario is used. Similarly, the ESP can be converted from Final Energy to Primary Energy by scaling by the Primary-to-Final conversion efficiency for each fuel. In the two climate scenarios, the CO_2 intensity of electricity becomes negative in the second half of the modelling window due to large additions of biomass with carbon capture and storage generation capacity. In this analysis, CO_2 intensity is not allowed to take negative values as that would result in nonsensical results (i.e. that increasing efficiency increases emissions).

Conversion efficiency effect on renewable installed capacity

The climate benefits of conversion efficiency are not fully captured by the direct inpacts of energy savings since lower energy demand facilitates the task of decarbonising primary energy supply. For the power sector, lower electricity demand is linked to lower generation capacity requirements since peak power demand would decrease. Considering that the majority of generation capacity additions (especially in the climate scenarios) will come from renewable sources, it is possible to convert the Energy saving potential into a renewable capacity avoided (RCA_y) metric. To do this, the ESP is converted to the yearly RCA_y as a function of the yearly average renewable capacity factor (Cf_s), where the Cf_s is defined as the installed capacity for a given source s (in units of GW) over the electricity generation from that source s (in units of PJ) obtained from the model results. Therefore, the yearly RCA is obtained as follows

$$RCA_y = ESP_y \, Cf_{ren} \tag{5.4}$$

$$RCA_y = ESP_y \, \frac{\sum P_s \, Cf_s}{\sum P_s} \tag{5.5}$$

The renewable generation sources considered are: solar PV, geothermal, wind (onshore and offshore), concentrating solar power, and ocean energy. Hydropower generation is excluded because the scalability of the technology depends on geography, and most available reserves are exploited in the early years of the modelling window.

5.2.4 Patent count for conversion devices

To test whether efficiency savings potential align with current innovation activity it is necessary to quantify innovation activity. In chapter 2 it was shown that patent counts offer an effective way to quantify the innovation taking place for different technologies at a high degree of granularity. This section describes how the patent counts are performed for each conversion device.

There are two databases that are used by the innovation science community to count patents.

- PATSTAT is maintained by the European Patent Office and contains all information on patent applications in Europe but also contains data on patents registered in most other countries. This database is also equipped with the Y02 classification [422] which was developed to track all patents that are related to technologies that have a potential to mitigate carbon emissions. This database is not easily accessible from third parties and requires a subscription
- The United States Patent and Trademark Office (USPTO) database contains patents registered in the USA classified according to the US patent codes and the International Patent Classificaiton. This database is often used by scholars because it is considered the most representative national database as 50% of all included patents are registered by non-US inventors [237] and thus has an international dimension to it. Moreover, it is easily accessible through an Application Programming Interface called "PatentsView" [423].

The USPTO database is chosen as it is deemed sufficiently representative of global innovation patterns as international comparisons are not needed for this study and because of its superior accessibility compared to PATSTAT. The "PatentsView" API enables to query the database with access though a Package in the R programming language.

The database was queried using International Patent Codes (IPC) which classify patents according to the type of technology in the patent. Table 5.2 is used to associate a patent to a conversion device. For light devices, heat pumps, coolers, and boilers, the association of codes to technologies follows the work of Noailly et al [240], which linked IPC codes to building efficiency technologies in conjunction with experts at the Netherlands Patent Office. For electric motors, the allocation follows Nabitz et al. [424], and in addition to the IPC codes, patents are selected only if they contain the terms "motor" or "machine". For the remaining devices (reciprocating engines, and gas turbines), the allocation was made following indications of the World Intellectual Property Organisation's "IPC Green Inventory" [236] which maps IPCs to the UNFCCC's Environmentally sound technologies. Diesel and spark ignition engines are categorised as a single conversion device category: "Reciprocating Engines".

Table 5.2 Contingency table linking International Patent Classification (IPC) codes to conversion devices. Different depths of IPCs are used for different devices. The official IPC descriptions of each code are shown on the rightmost column.

device	IPC	Description

Light device	F21K 9/00	Light Sources Using Semiconductor Devices As Light-Generating Elements, E.G. Using Light-Emitting Diodes [Led] Or Lasers [2016.01]
	H01L 33/00	Semiconductor Devices With At Least One Potential-Jump Barrier Or Surface Barrier Specially Adapted For Light Emission; Processes Or Apparatus specially Adapted For The Manufacture Or Treatment Thereof Or Of Parts Thereof
Gas turbine	F02K	Jet-Propulsion Plants
	F02C 7/00	Features, Component Parts, Details Or Accessories, Not Provided For In, Or Of Interest Apart From, Groups F02C 1/00-F02C 6/00; Air Intakes For Jet-Propulsion Plants
	F02C 9/00	Controlling Gas-Turbine Plants; Controlling Fuel Supply In Air-Breathing Jet-Propulsion Plants
Electric Motor	H02K/1	Details Of The Magnetic Circuit
	H02K/3	Details Of Windings
	H02K/9	Arrangements For Cooling Or Ventilating
	H02K/15	Methods Or Apparatus Specially Adapted For Manufacturing, Assembling, Maintaining Or Repairing Of Dynamo-Electric Machines
	H02K/17	Asynchronous Induction Motors; Asynchronous Induction Generators
	H02K/19	Synchronous Motors Or Generators
	H02K/21	Synchronous Motors Having Permanent Magnets; Synchronous Generators Having Permanent Magnets
	H02P	Control Or Regulation Of Electric Motors, Electric Generators Or Dynamo-Electric Converters; Controlling Transformers, Reactors Or Choke Coils
Reciprocating Engines	F01B	Machines Or Engines, In General Or Of Positive-Displacement Type
	F01L	Cyclically Operating Valves For Machines Or Engines
	F02B	Internal-Combustion Piston Engines; Combustion Engines In General
	F02D	Controlling Combustion Engines
Boiler	F22B	Methods Of Steam Generation; Steam Boilers
	F23D 14/00	Burners For Combustion Of A Gas, E.G. Of A Gas Stored Under Pressure As A Liquid
	F22G	Superheating Of Steam
	F24D 1/00	Steam Central Heating Systems
	F24D 3/00	Hot-Water Central Heating Systems
	F24D 17/00	Domestic Hot-Water Supply Systems
Cooler	F25B 1/00	Compression Machines, Plant Or Systems With Non-Reversible Cycle
	F25B 3/00	Self-Contained Rotary Compression Machines, I.E. With Compressor, Condenser, And Evaporator Rotating As A Single Unit

	F25B 5/00	Compression Machines, Plant, Or Systems, With Several Evaporator Circuits, E.G. For Varying Refrigerating Capacity
	F25B 6/00	Compression Machines, Plant, Or Systems, With Several Condenser Circuits
	F25B 7/00	Compression Machines, Plant, Or Systems, With Cascade Operation, I.E. With Two Or More Circuits, The Heat From The Condenser Of One Circuit Being Absorbed By The Evaporator Of The Next Circuit
	F25B 9/00	Compression Machines, Plant, Or Systems, In Which The Refrigerant Is Air Or Other Gas Of Low Boiling Point
	F25B 11/00	Compression Machines, Plant, Or Systems, Using Turbines, E.G. Gas Turbines
	F25B 13/00	Compression Machines, Plant, Or Systems, With Reversible Cycle
	F25B 15/00	Sorption Machines, Plant, Or Systems, Operating Continuously, E.G. Absorption Type
	F25B 17/00	Sorption Machines, Plant, Or Systems, Operating Intermittently, E.G. Absorption Or Adsorption Type
Heat Pump	F25B 30/00	Heat Pumps
	F24D 3/18	Hot-Water Central Heating Systems - Using Heat Pumps
	F24D 15/04	Other Domestic- Or Space-Heating Systems - Using Heat Pumps

The resulting patent counts provide and indication of the innovation effort for each device. The patent abstract text is used to filter only patents which target efficiency, providing a metric of efficiency innovation. The following character vectors are used to filter the patents: “ efficient”, “efficiency”, “fuel consumption”, “fuel economy”, “efficacy”, and “coefficient of performance”.

5.3 Results

This analysis models efficiencies for energy conversion devices, from 2014 to 2060, and uses this to calculate the energy and carbon emissions savings potentials for each device. Patents are used to contrast these savings potential with current innovation efforts, to test alignment.

5.3.1 Global conversion efficiency in 2060

Figure 5.2 shows the estimated efficiency attained by six major conversion devices in 2060 for each scenario. Efficiencies are shown as distributions for the baseline (2014), each scenario (RTS, 2DS, B2DS) and the Technical Limit. Significant increases are observed for most devices, with higher efficiencies reached in the climate scenarios (2DS and B2DS) than in the RTS. For the reciprocating engines there is no discernible distinction between the 2DS and B2DS scenarios. This occurs because modellers expect to reach their maximum attainable efficiency in the 2DS, with no additional headroom for improvement. The technical efficiency limit for reciprocating engines used in heavy duty applications aligns well with the maximum attainable efficiency in the 2DS scenario, but is considerably higher for light duty applications. This is because of the much lower starting efficiency of SI engines and the similar rates of improvements assumed for both technologies by the modellers. However, in the coming decades the difference between these two devices will continuously decrease, therefore these values can be more easily interpreted in terms of sector: engines used for heavy duty road and seafaring transport are expected to each their TEL than light duty road applications. Large efficiency improvements are observed for lighting and for coolers, both treble their efficiency in the climate scenarios.

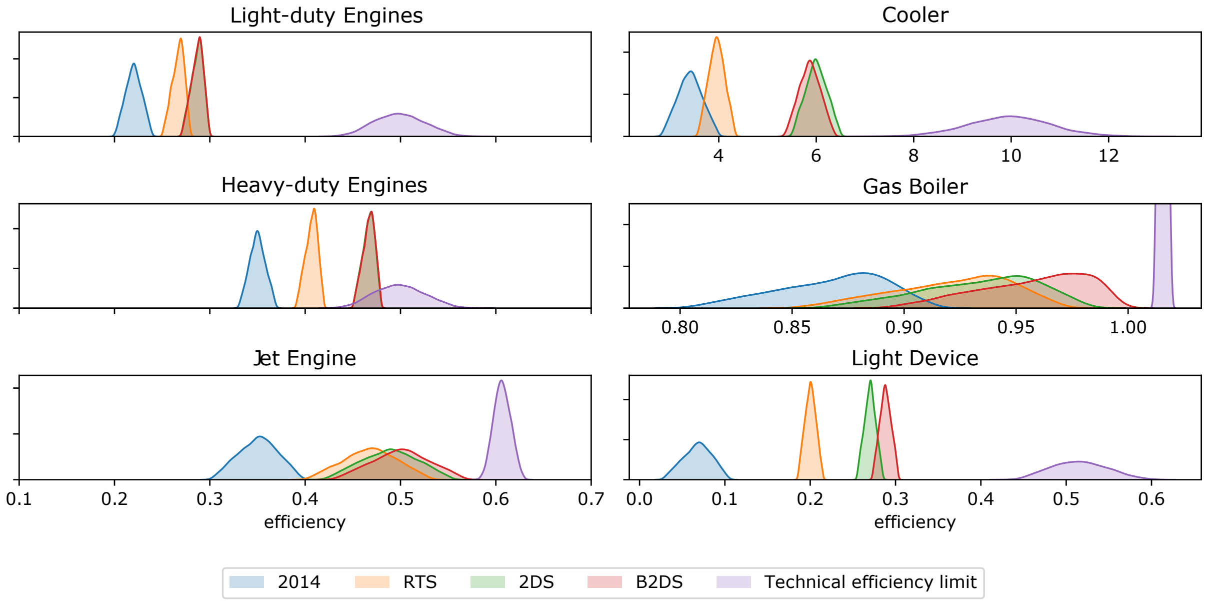


Fig. 5.2 Estimated conversion efficiency for six devices in the three scenarios compared to the current efficiency estimate and their technical efficiency limit. The distribution plots represent the uncertainty around the average value

For gas boilers and coolers, there is large uncertainty associated with the efficiency estimates. In the case of boilers, this is because more precise information is not available in the ETP report, nor in personal communication with modellers. For coolers, the broad variability in performance, particular for the TEL, results from the strong dependency on geographic distribution and climatic conditions.

The technical limit is only approached for the case of reciprocating engines, where there is a 24% probability that the expected efficiency in the B2DS and 2DS is higher than the TEL. This indicates that there is a 24% probability that the expected improvements in the IEA's ETP will not be achievable, purely on technical grounds.

5.3.2 Future Energy Balance

The estimated evolution path of conversion efficiency in each ETP scenario is used to build Useful energy balances. These results are compared to standard final energy balances and the ETP modelling results are analysed with a focus on the dynamics of energy conversion pathways in each scenario.

Tables 5.3 and 5.4 show the estimate of the global energy balance in 2060 for the three different scenarios, where the Useful energy is computed based on the conversion efficiency estimates while the Final energy estimates are provided by the model results. Global Useful energy demand in 2060 is expected to range between 447 EJ in the B2DS and 543 EJ in the RTS, while Final energy demand ranges from 335 EJ to 545 EJ. Thermal energy dominates the Useful energy demand, accounting for 77% of Useful Energy demand in all scenarios, followed by Work at 20% and Information at 3%. Most Useful energy demand is found in the Buildings sector, in all scenarios, but notably the B2DS building's share of useful energy demand is higher than in the RTS.

Table 5.5 shows the global energy balance in 2014, to Tables 5.3 and 5.4. It is observed that the distribution of useful energy demand into energy services remains almost unchanged over the modelling period. There is just a small (3%) decrease in the share of thermal comfort demand and a small increase Information and Work dictated by better insulation in buildings and by the development of countries that currently have low transportation and information energy demand.

Useful demand is expected to be higher than Final demand in all scenarios because of the high share of energy that will be converted in vapour compression cycles (air conditioners and heat pumps) that can use ambient energy to deliver thermal comfort. Already in 2014, the average delivery of thermal comfort has a Final to Useful efficiency of 112%, and this is set to increase to 176% by 2060 in the B2DS. This effect, alongside efficiency increases for other Useful energy categories, mean that the overall Final to Useful energy efficiency moves from 81% in 2014 to 100% in 2060, in the RTS, and to 133% in the B2DS.

The RTS has the highest energy demand (both Useful and Final) because of higher activity and lower passive system efficiency compared to the other two scenarios since lower building insulation and less vehicle lightweighting are assumed.

However, while the Final energy demand in B2DS is 40% lower than in the RTS, the Useful energy demand is only 20% lower. The energy demand difference between scenarios is smaller for Useful energy than Final energy because the conversion efficiency differences are already accounted for in the Useful energy metric. That is, the 40% difference in Final energy demand between RTS and B2DS includes conversion device, passive system and fuel switching differences. While the 20% difference between in Useful energy only takes into account passive system and fuel switching differences.

Table 5.3 Summary of global 2060 Useful energy balance [EJ]

Useful Energy	Information			Thermal			Work		
Sector	B2DS	2DS	RTS	B2DS	2DS	RTS	B2DS	2DS	RTS
Industry	2	2	2	131	137	198	23	24	32
Buildings	11	12	14	216	216	218	8	8	9
Transport	0	0	0	0	0	0	57	59	71
Total	13	14	16	347	353	416	87	90	112

Table 5.4 Summary of global 2060 Final energy balance [EJ]

Final Energy	Information			Thermal			Work		
Sector	B2DS	2DS	RTS	B2DS	2DS	RTS	B2DS	2DS	RTS
Industry	5	5	6	107	113	170	27	30	41
Buildings	16	18	22	89	103	128	9	9	11
Transport	0	0	0	0	0	0	82	102	167
Total	20	22	28	196	216	298	119	142	219

Table 5.5 Summary of global 2014 Final and Useful energy balance [EJ]

	Information		Thermal		Work	
Sector	Final	Useful	Final	Useful	Final	Useful
Industry	3	1	109	120	26	18
Buildings	13	6	106	119	5	4
Transport	0	0	0	0	107	33
Total	15	7	214	239	138	54

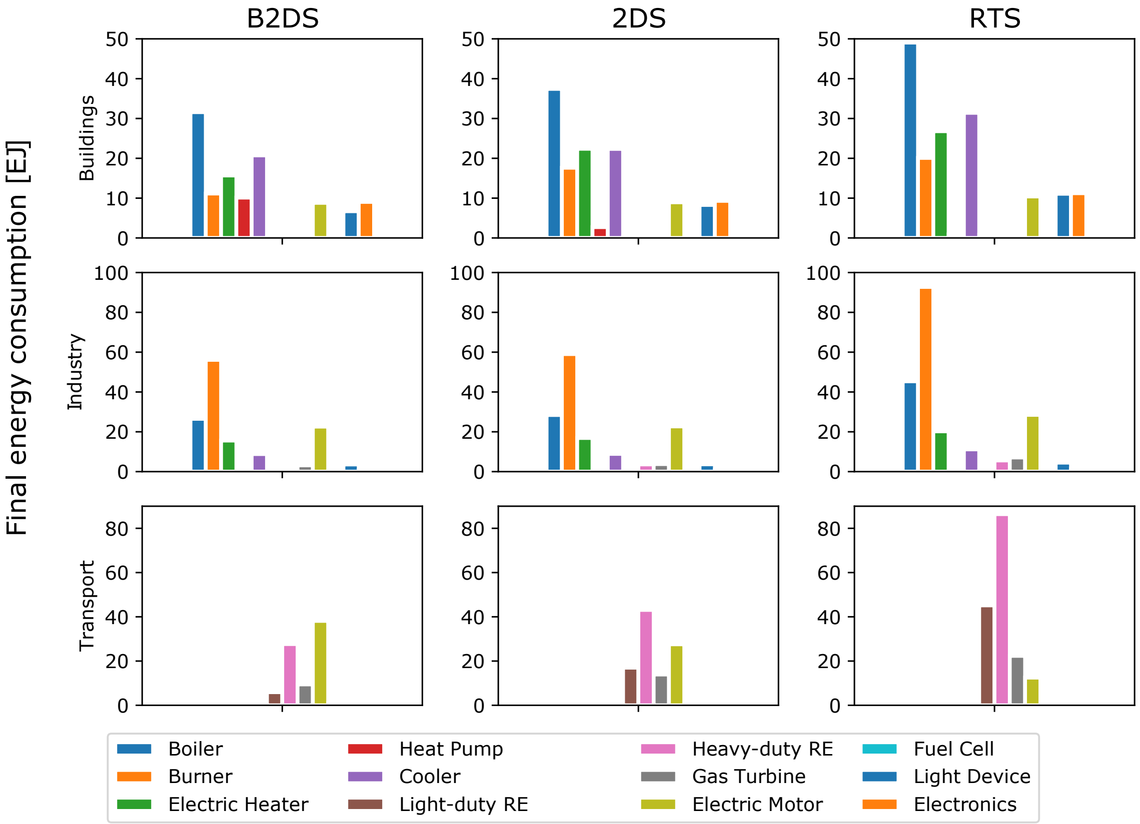


Fig. 5.3 Summary of the estimated final energy consumed by each device in each scenario and sector. For transport sector, reciprocating engine energy consumption is divided into Heavy-duty and Light-duty engine.

Figure 5.3 shows the Final energy conversion in each device, for each scenario, within each sector in 2060, thus expanding the granularity of Table 5.4. The purpose of the figure is to map the evolution of each device in each sector. In buildings, about half (51% to 56%) of the Useful energy is delivered by coolers in all scenarios. This is followed by boilers in the RTS and by Heat Pumps in the most extreme climate scenario (B2DS), where vapour compression cycles (Air conditioners and Heat Pumps) account for 69% of all Useful energy delivered in buildings. Boilers remain the main consumers of final energy in all scenarios. Light devices deliver around 2 EJ of useful energy in all scenarios, but their final energy requirement varies from 7 EJ in B2DS to 11 EJ in RTS, due to efficiency differences.

In transport, electric motors dominate useful energy delivery in both climate scenarios, while reciprocating engines delivers most useful energy in the RTS. Reciprocating engines still deliver a substantial share of useful energy (22%) even in the B2DS, this share is even higher in terms of Final energy (33%). The largest differences between the scenarios is seen in the use of reciprocating engines in light duty applications, which convert 27% of Final energy in the RTS and only 5% in the B2DS. This is due to the use of reciprocating engines in freight transport (both on road and on sea) even in the most ambitious climate scenario, whereas reciprocating engines used for light duty transport will mostly be displaced by electric motors in the climate scenarios.

In industry, there is a net reduction of energy demand by 2060 in both climate scenarios, while in the RTS demand increases. The main difference between the scenarios is seen in the Useful energy delivered by direct combustion, accounting for 76 EJ in the RTS but only 37 EJ in the B2DS, and by indirect combustion which is reduced from 36 EJ in the RTS to 17 EJ in the B2DS. On the other hand, energy transformation in electric motors and electric heaters remains mostly unchanged in the scenarios.

Figures 5.4 and 5.5 present Sankey diagrams, providing an holistic picture of the energy system and conversion trends for the reference year and the B2DS.

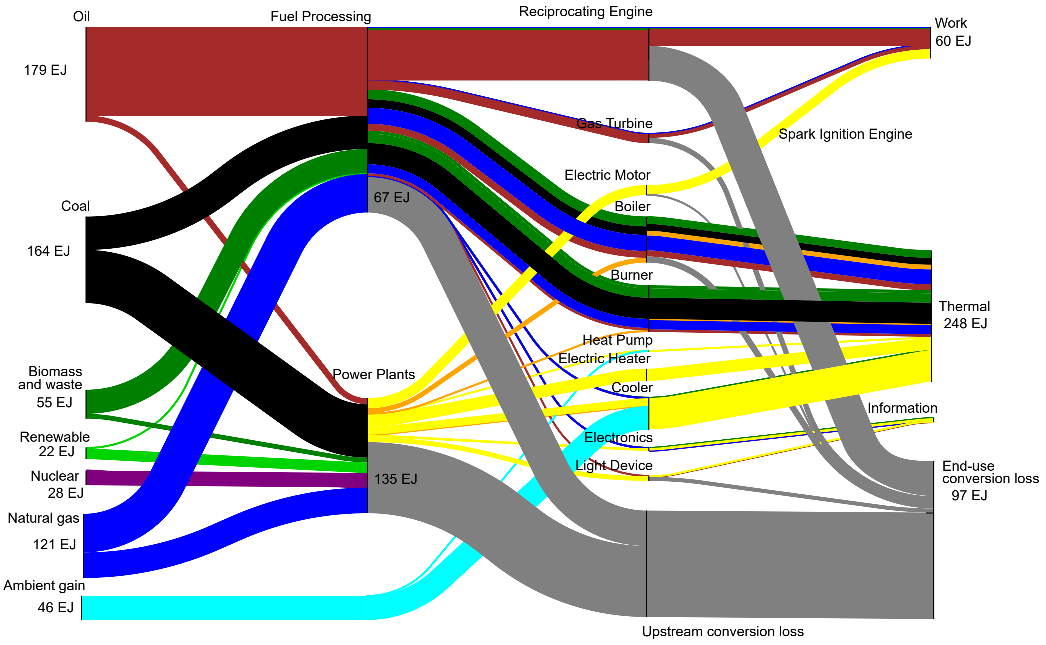


Fig. 5.4 Sankey diagram of global energy system in 2014

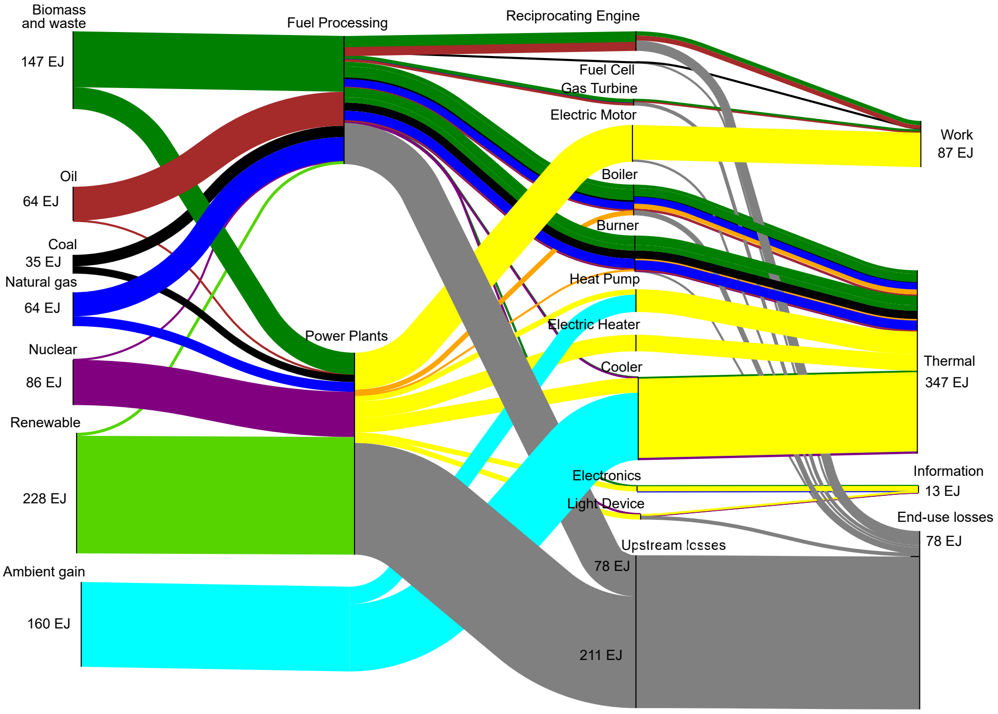


Fig. 5.5 Sankey diagram of global energy system in 2060 in the B2DS scenario

The Sankey diagram provide an instant visual representation of the present and future energy system described in detail in Tables 5.3 and 5.4. The trend of increased renewable energy and electrification of the economy (by switch from internal combustion engines to electric motors and from boilers to heat pumps) is clearly observable by comparing the two diagrams. In addition, the Sankey diagram shows the magnitude of the ambient gain and of the losses in both energy systems. The ambient gain refers to the energy that is transferred from the environment (ground or atmosphere) to Useful energy flows by means of the vapour compression cycle. This flow is expected to increase in the future due to the increased demand for cooling in Asia and due to the increased use of heat pumps for space heating. The magnitude and structure of the energy loss flows changes significantly: end-use losses decrease substantially, mostly due to decreased use of internal combustion engines; while upstream conversion efficiency remains mostly unchanged, because the lower efficiency of biofuel processing and of nuclear power counteract the improved refining efficiency and increased renewable share.

5.3.3 Impact of conversion efficiency improvement

Energy Saving Potential

Between 2014 and 2060, the final cumulative energy savings attributable to conversion efficiency amounts to 750 EJ, 830 EJ, and 710 EJ in the RTS, 2DS and B2DS scenarios respectively. (Figure 5.7). These savings are equivalent to 3.2% to 4.2% of the total final energy demand over this period. In terms of Primary energy demand, the savings account for 1030 EJ, 1300 EJ and 1170 EJ in the RTS, 2DS and B2DS respectively, which is equivalent to the 3.1% to 4.6% of total primary demand in the period. In terms of sector distribution, the savings in the transport sector is the largest component and accounts for 68% of savings in the RTS and 51% in the B2DS.

There are higher potential savings in the RTS than in the other climate scenarios because overall energy demand is higher (as shown in Tables 5.3 and 5.4). This is due to: higher activity in more energy intensive sectors such as aviation; higher direct use of fossil fuels in inefficient combustion engines; lower passive system efficiency gives increase demand. Similarly, the conversion efficiency savings in the 2DS are higher than in the B2DS because of an larger overall energy throughput, despite the slightly lower average conversion efficiency.

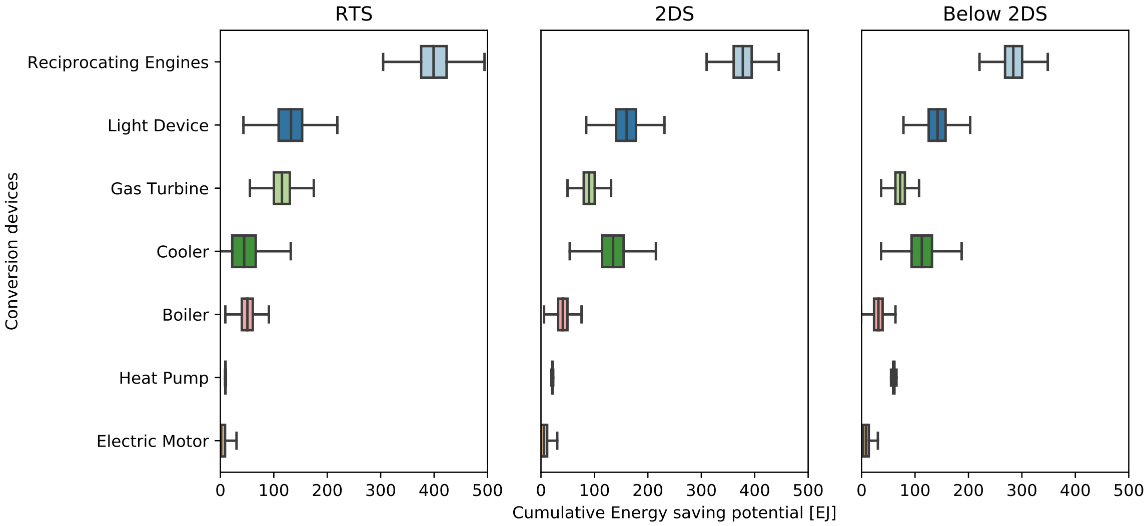


Fig. 5.6 Cumulative final energy savings attributable to increased energy conversion efficiency for the different devices in the period between 2014 and 2060 in each scenario. The boxplot represents the uncertainty associated with the estimate

In the RTS, most energy conversion savings come from improvements in reciprocating engines, both accounting for around 200 EJ of savings each (Figure 5.6). This is followed by improvements in light devices and gas turbines, with 140 EJ and 120 EJ respectively. In the climate scenarios, savings from reciprocating engines used in light duty applications contribute less; in the B2DS these engines are only the fourth highest contributor to savings, at just under 100 EJ. This is because of the rapid substitution of engines by electric motors in the climate scenarios, driven by a shift to electric vehicles. In contrast, engines used in heavy duty applications are the main contributors to conversion efficiency savings in all scenarios, because of the continued use of these engines in freight transport, with no obvious viable alternatives. Similarly, the gains from gas turbines and boilers are roughly equal across scenarios. Savings from efficiency improvements in heat pumps become sizeable only in the B2DS. In climate scenarios, savings from improvements in light devices and coolers are at the second and third place in terms of contribution, resulting from increased efficiency improvements.

Figure 5.8 shows the trends in yearly efficiency savings due to conversion efficiency improvements. In the RTS, savings for all devices increase year on year. In climate scenarios, the figure shows that for devices converting fossil fuels, the yearly savings peak and then decrease towards the end of the modelling period. This is because the assumed rate of efficiency improvement is outweighted by the decrease in energy throughput. Light devices and coolers increase their yearly savings in all scenarios.

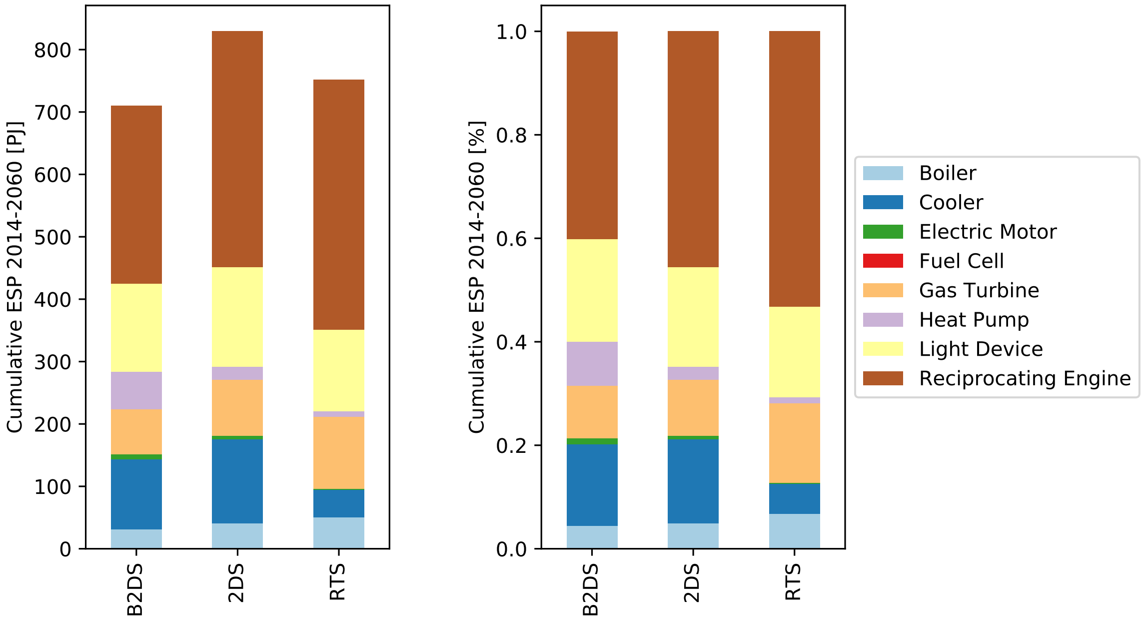


Fig. 5.7 Cumulative saving potential from each conversion device in the period between 2014 and 2060.

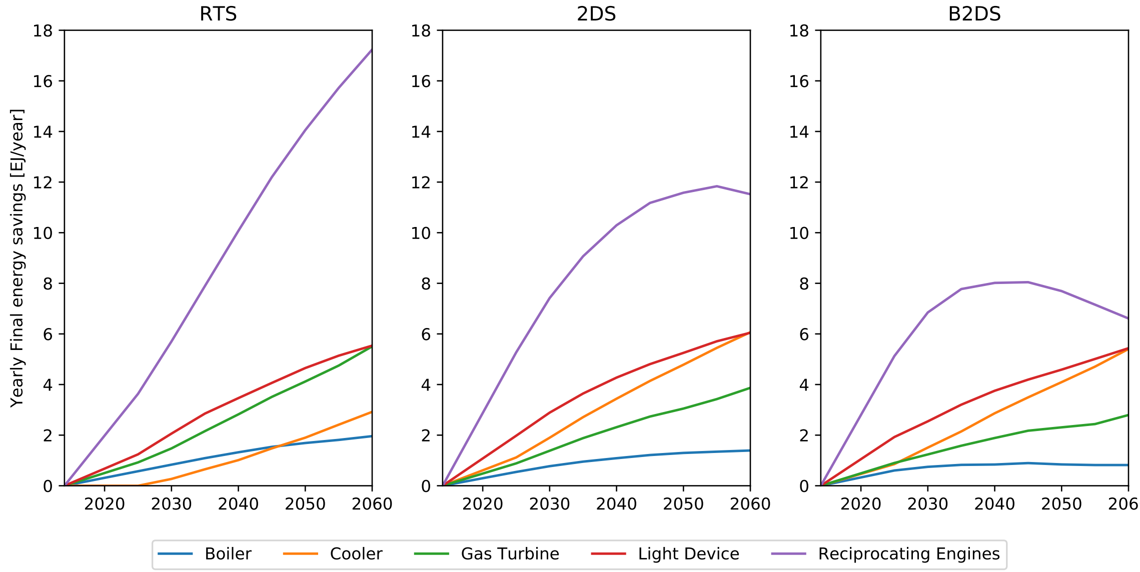


Fig. 5.8 Yearly final energy savings attributable to conversion efficiency improvement for three devices. Linear increases are associated to a constant energy consumption of a given device, faster than linear increases correspond to increases in the energy use, all other trends correspond to a decrease in energy use.

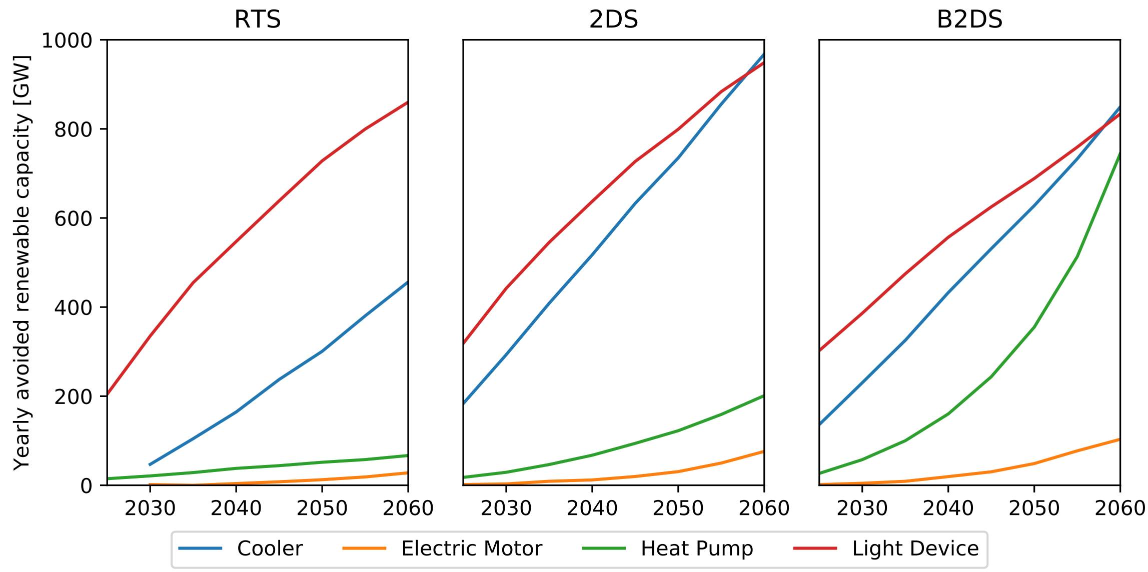


Fig. 5.9 Renewable energy capacity avoided tanks to conversion efficiency improvements for each electrical powered device. Linear increases are associated to a constant energy consumption of a given device, faster than linear increases correspond to increases in the energy use, all other trends correspond to a decrease in energy use.

Figure 5.9 shows the renewable generation capacity that is avoided as a result of improvements in energy conversion. Most savings come from light devices and coolers in the RTS and 2DS, while in the B2DS improvements in heat pumps also have an impact. The highest avoided generation capacity is observed in 2060, with 1 411 GW, 2 193 GW, and 2 530 GW in the RTS, 2DS and B2DS respectively. When comparing the avoided capacity to the projected renewable installed capacity in each scenario, the savings account for 18% to 23% of installed renewable capacity. Therefore, increase conversion efficiency facilitates the decarbonisation of the grid since lower generation capacity means lower costs and less land consumption.

CO_2 emission savings

The carbon dioxide savings attributable to conversion efficiency are 24 Mt, 35 Mt, 54 Mt in the B2DS, 2DS and RTS scenarios (Figure 5.10). These are equivalent to 2.8-3.3% of cumulative emissions in each scenario. The climate scenarios have lower emissions savings because of the increased rate of decarbonisation of the energy grid and road fuels. As an example of this trend, savings from lighting in the RTS account for 13 Mt, whereas in the B2DS savings are reduced to 3 Mt, despite the higher conversion efficiency of lighting. The trend of CO_2 savings from each device is shown in Figure 5.11. As the grid decarbonises the potential savings from conversion efficiency quickly reduce. By 2060 in the B2DS and 2DS respectively, net zero grid emissions mean that conversion efficiency improvements have no impact on CO_2 emissions.

This effect is accentuated by the fact that the share of final energy demand delivered through electricity in the climate scenarios increases from 33% in RTS to 54% in B2DS. For combustion engines, savings from conversion efficiency improvements remain important throughout the modelling period. However, in the climate scenarios the CO_2 savings decline more rapidly than Energy savings (Figure 5.8) because of increased use of biofuels, with lower CO_2 intensities, in these conversion devices.

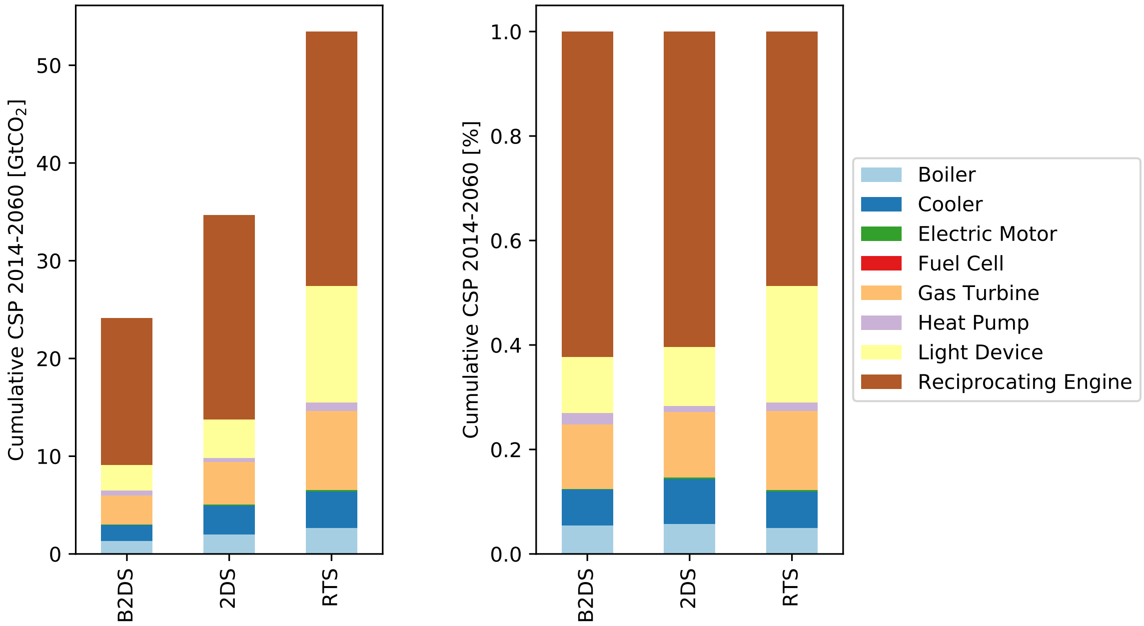


Fig. 5.10 Cumulative CO_2 emission savings attributable to increased energy conversion efficiency for the different devices in the period between 2014 and 2060 in each scenario. The boxplot represents the uncertainty associated with the estimate

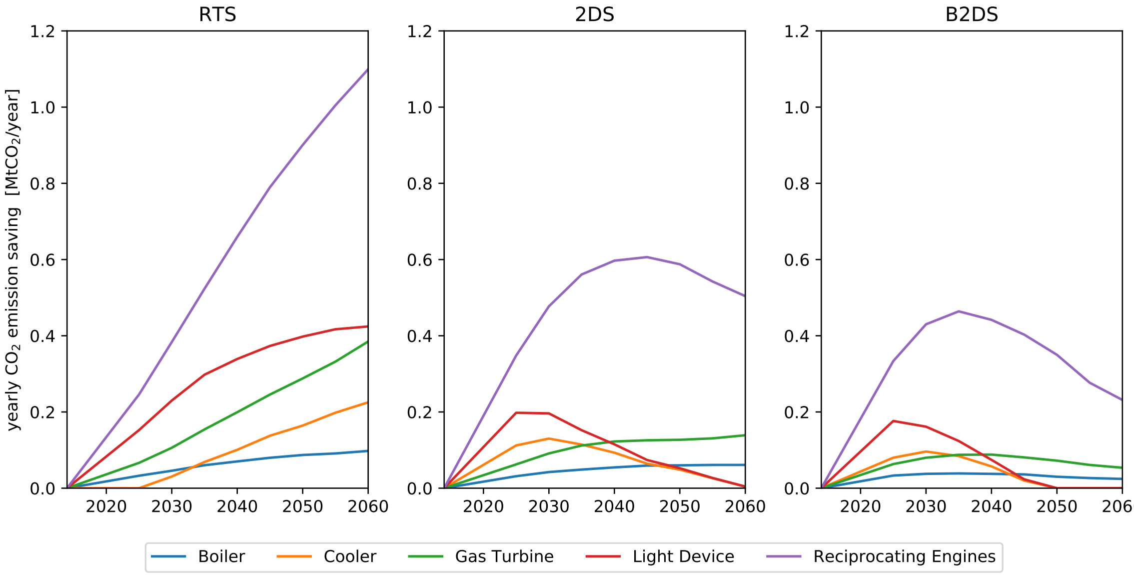


Fig. 5.11 Yearly CO_2 emission savings attributable to conversion efficiency improvement for three devices. Linear increases are associated to a constant energy consumption of a given device, faster than linear increases correspond to increases in the energy use, all other trends correspond to a decrease in energy use.

Pushing the boundaries of conversion efficiency

This section presents the results of a what if-analysis, exploring the potential savings from extreme-level conversion efficiency improvements. For this analysis, it is assumed that TEL (Technical Efficiency Limits) are reached for all conversion devices by the year 2060, while the resulting final energy consumption in each scenario is calculated assuming that the useful energy demand would remain constant. This scenario is named the TEL scenario (TELS).

Figure 5.12 shows the cumulative final energy demand and CO_2 emissions for each scenario, in the period 2014 to 2060. The CO_2 emissions refer only to energy sector emissions and are therefore lower than those reported in ETP publications as they do not include industrial process emissions and non-energy consumption emissions. In the TELS cumulative energy consumption is reduced by 11%, 8%, and 7%, and cumulative CO_2 emissions by 10%,7%, and 6%, in the RTS, 2DS and B2DS respectively. The largest gains from extreme conversion efficiency improvements are seen in the RTS scenario, due to the higher overall energy throughput, particularly in the transport sector. Yet, this scenario only delivers 25% of the required emission reduction needed to reach 2DS. This means that conversion efficiency under RTS conditions, can only account for a minority share of CO_2 emission reductions, even when pushed to its technical limits.

In a 2DS world, extreme efficiency contributes 38% of the emission reduction needed to reach B2DS. This is a not an insignificant amount, being roughly equal to the cumulative negative emissions removed from the atmosphere through Bio-energy with CCS (BECSS). Since large scale BECSS is still an unproven technology, it interesting to see that similar emission reductions could be achieved by extreme technical improvement in end-use conversion efficiency.

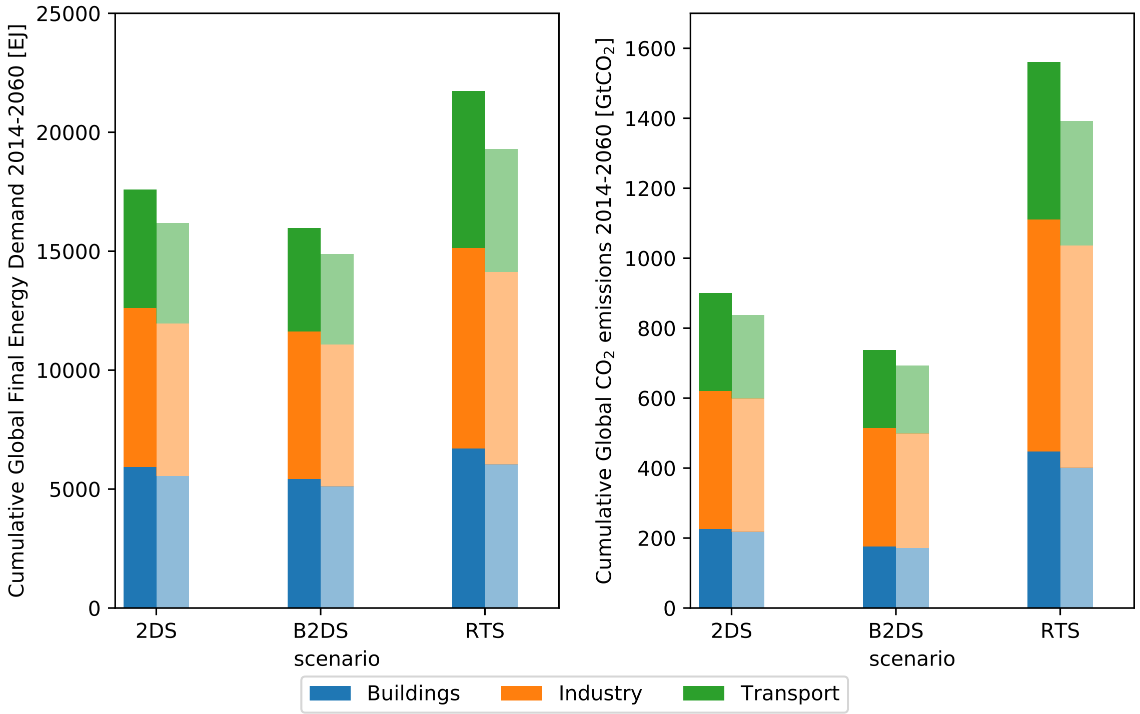


Fig. 5.12 Global cumulative CO_2 emission and Final energy demand for the period 2014-2060 for each scenario and each sector. The shaded column represent the results of the what-if analysis where the efficiency of all conversion devices reaches the TEL by 2060.

5.3.4 Patent counts

The patent search by IPC codes (defined in Table 5.2) returned a total of 99 207 patents for the period between 2000 and 2018. After applying the filters designed to identify only patents that are linked to efficiency improvement, only 4 819 patents remain. Figure 5.13 shows the trend in efficiency patenting for each device over the past eighteen years. For all devices, an increase in efficiency patenting is observed over the time period, with a noticeable acceleration after 2010. The largest increase in patenting activity is observed for Light devices (+600%), which can be explained by the surge in innovation for LED technology, over the past decade. Efficiency measures in engines also experience a large increase (+163%). A more in depth study of the reciprocating engine patents suggests that most refer to the development of turbocharging and supercharging technologies, which is in line with the increase of turbocharged vehicles being sold globally [276]. Surprisingly, patents specifically referring to efficiency in heat pumps only begin to appear after 2014.

The reason for the large number of efficiency patents related to turbocharging and supercharging is that these technologies have often been developed with the aim of increasing the duty cycle efficiency of engines. As explained in section 4.2.7, the peak efficiency is not affected by supercharging. Turbocharging on the other hand, can be considered a form of waste heat recovery.

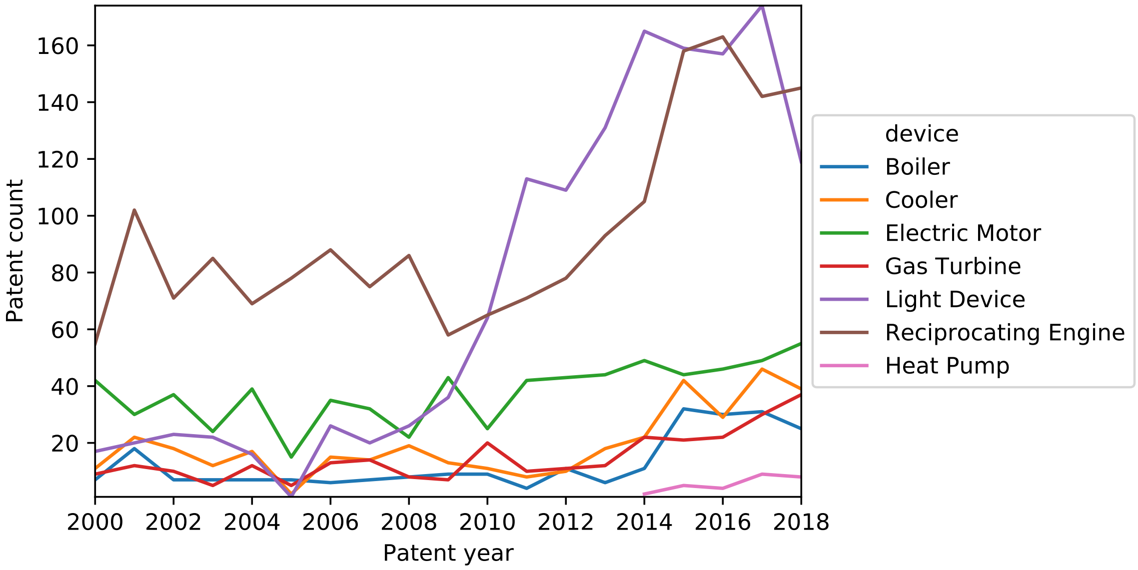


Fig. 5.13 Patent count for each conversion device where energy efficiency is mentioned in the Patent abstract for the period 2000-2018.

Current innovation activity is represented by the number of patents referring to efficiency improvements in conversion devices of the past three years (2016-2018). Figure 5.14 shows the distribution conversion efficiency patent among six conversion devices as well as the share of the expected cumulative savings attributed to conversion efficiency, for each device and each scenario. Most efficiency patents are observed in reciprocating engines, light devices and electric motors, which together account for 76% of all efficiency patents over the past three years. The share of patenting activity is moderately correlated with the share of potential energy savings, with Pearsons' correlation coefficients ranging from 0.69 to 0.73. Patent activity is much higher than the expected energy savings for electric motors and light devices, while it is lower for gas turbines.

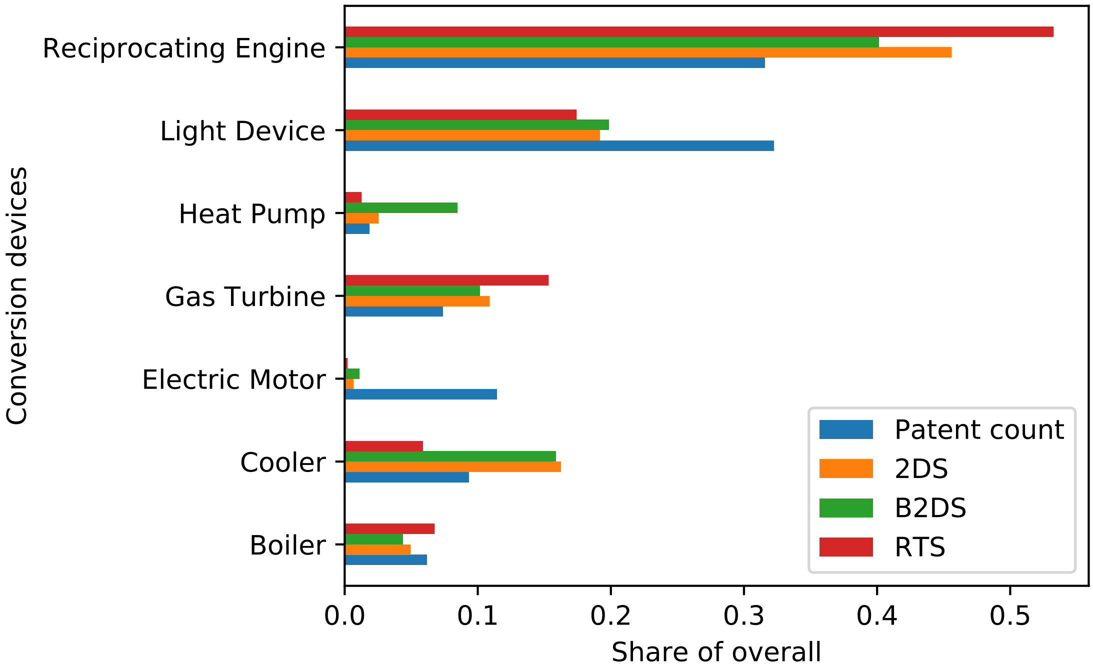


Fig. 5.14 Share of patent counts compared to the share of cumulative conversion efficiency energy savings for each device, in each scenario.

5.4 Discussion

5.4.1 Conversion efficiency in ETP 2017

The aims of this research were twofold: to explore the role of end-use conversion efficiency in different possible future global energy systems taking into account the novel knowledge of the technical efficiency limits of conversion devices; and to quantify the innovation activity in each conversion device.

The conversion efficiency of final energy to useful energy is set to increase from 81% in 2014 to at least 101% in 2060 (RTS). There are two components in this efficiency increase: efficiency improvements in devices and structural shifts between devices. The efficiency component is explained by the expected increase in device conversion efficiency, through a combination of market driven technical innovation and policy incentives. The structural component is driven by shifts in the geographical changes in energy consumption and in energy conversion routes. As countries in Asia and in the global south develop, demand for cooling will exceed demand for heating. Since cooling is provided with a much higher final-to-useful efficiency, this contributes significantly to expected improvements in conversion efficiency. As electricity becomes a more common final energy vector, the Final to Useful efficiency increases.

In the climate scenarios (2DS and B2DS), the overall efficiency is higher than in the RTS because policy plays a much stronger role in bringing efficiency levels to "socially optimum levels". Efficiency improvement rates in these scenarios are significantly higher than in the RTS. However, as seen in Figure 5.2, the difference in conversion efficiency between the 2DS and B2DS is small. One reason for this is that many analysts, including those who contributed to the IEA's ETP report, expect that efficiency potentials will already be fulfilled in the 2DS, giving no headroom for further improvements in the B2DS. However, for most technologies the expected efficiency in 2060 in the B2DS is lower than the TEL, meaning that analysts could be more ambitious in their efficiency projections. The results also show that freight and aviation–two modes that are difficult to decarbonise–are modelled with different ambition. While reciprocating engines are expected to nearly reach their TEL of 55% ± 2%, jet engines are only expected to attain 50%, which is 5% below their expected TEL. Analysts at the IEA base their assumption on available studies of future potential efficiency gains. Interestingly, the efficiency estimates for trucks are based mostly on reports made or commissioned by governments or third party organisations, while aviation estimates come almost exclusively from reports commissioned within the aviation industry.

Therefore, it is possible that the lower ambition might result from the nature of the studies available to analysts. Energy efficiency in the aviation industry is currently not regulated by governments, meaning few independent studies are available. In contrast, regulation initiatives for the road freight industry are already in place in the USA [375] and the EU [425]. Yet, there are also reasons to believe that jet engines might not reach their TEL as they are designed to optimise not just efficiency parameters, but also more stringent safety considerations than freight transport.

For both Jet and reciprocating engines, the assumed efficiency in the climate scenarios is worryingly close to their estimated TEL. There are several reasons why devices might not be able to reach the TEL in practice, ranging from the high cost of the materials needed to reach these efficiency levels to the need to sacrifice efficiency in exchange of lower pollutant emissions. Therefore, an important result of this assessment is that energy modellers should be pay more attention to the technical limitations of some of the underlying assumptions of energy models.

For LEDs, there is a large gap between the expected efficiency in 2060 and TEL efficiencies, whereas gas boilers have only a small gap. One could draw the conclusion that there are more technical challenges in achieving additional savings for boilers than it is for LEDs due to the law of diminishing returns: as efficiency gets closer to its technical limit additional gains become more costly to achieve. However, as discussed in chapter 4, devices providing thermal energy can reach their technical limit with less innovation than those providing work because their efficiency depends on extensive properties; making them larger increases efficiency. Therefore, the difference between the expected efficiency in 2060 and the TEL is not an indicator for the difficulty of technical challenge of reaching the 2060 efficiency. Going back to the above example, reaching the TEL for LEDs requires major advances in semiconductor physics and nanometer-scale manufacturing techniques, while reaching the TEL for gas boilers requires mostly larger heat exchangers and better fuel combustion. In this respect, it is surprising to see that the gap between the efficiency of coolers in the B2DS and their TEL is so large. However, making devices larger increases their costs, and since most coolers will be installed in developing countries, it is unlikely that high cost premiums will be tolerated by consumers, even in an extreme climate scenario.

The magnitude of the savings attributable to end-use conversion efficiency improvements is a significant contribution to energy and carbon savings. For comparison, the end-use conversion efficiency savings (30.6 EJ/year in 2060) in the 2DS are higher than the energy use from the iron and steel sector (27 EJ in 2060). Therefore, the lack of analysis focusing on end-use conversion efficiency as a tool for climate mitigation is not justified in light of the results present in this study.

Furthermore, the relative importance of conversion efficiency across the scenarios was not expected and deserves further attention. Higher overall end-use efficiency in the B2DS does not result in higher energy savings from efficiency, but instead is the lowest absolute savings among the three scenarios. This is because the structural changes in the energy system required to achieve a B2DS emission level undermine the role of efficiency. Most importantly, the shift to electrification of the transport sector decreases the savings in conversion efficiency, because the percentage efficiency gains in electric motors are small compared to those in reciprocating engines.

The impact of conversion efficiency on CO_2 emissions, is significant in the RTS, but much smaller in the climate scenarios. This is because Primary energy in these scenarios as a lower carbon content. The question of whether efficiency improvements will still be necessary in a net-zero carbon world are still needed is answered in this thesis: Reductions in final energy consumption make reaching the required decarbonisation targets more feasible in two ways. Firstly, Figure 5.9 which shows that up to 2.5 TW of new renewable capacity is avoided thanks to end-use efficiency improvements. Secondly, efficiency improvements are necessary to keep the demand for biofuels in hard-to-abate sectors within sustainable boundaries.

The picture that results from this analysis is that improvements in end-use conversion efficiency are a no-regret option for climate action. If governments follow through on the decarbonisation targets committed to in the Paris Agreement, then end-use efficiency will make the transition easier and lower-cost. If, on the other hand, governments fail to step up their ambition, resulting in the world following a trajectory that is in line with the RTS scenario, then conversion efficiency improvements will deliver a much larger impact, helping to counteract the serious impacts of inaction.

There are two methodological and data quality issues that deserve to be discussed.

1. Not all sectors are treated in the same fashion, particularly, conversion efficiency improvements in industry are not accounted for by conversion device, because of the way in which industrial energy is disaggregated in the ETP model. Improvements in industrial steam generators and electric motors are likely to be significant, but are not quantified in this analysis. Furthermore, the end-use allocation vector in the industrial sector is assumed to remain constant between 2014 and 2060, which may lead to increased uncertainty.

2. The quality of conversion efficiency values for coolers and heat pumps is highly dependent on the chosen environmental temperature, which results in higher uncertainty when assuming deployment of these devices across different climatic regions.

5.4.2 Prioritising action

This analysis provides a robust assessment of the relative importance of efficiency improvements in conversion devices. The patent count analysis can be used as a proxy for current innovation activity for each conversion device. Figure 5.14 shows that the relative innovation in light devices and electric motors is much higher than the corresponding potential savings from these devices. Interestingly, the IEA's Tracking Clean Energy Progress [426] publication highlights that only lighting and electric vehicles (which use electric motors) are on track (in terms of market penetration and efficiency improvements) towards a climate friendly environment.

This result reinforces the important link between technical innovation and achieving progress towards climate targets. Conversely, the relative patent count for coolers and heat pumps are currently in line with the efficiency savings in the RTS scenario, pointing to the need for further innovation in these technologies to maximise the climate mitigation potential. The issue of quickly rising demand for cooling in Asia and Africa has been discussed in the literature and by policymakers [419]. This analysis suggests the possibility of a principal-agent problem slowing down innovation in air conditioning. The problem is that most global OEMs are in developed and mild climate countries (Korea, Japan, USA, EU) where the incentives to innovate and improve efficiency are lower, potentially resulting in missed opportunities to realised efficiency savings in warmer developing countries.

This study also shows the importance of combustion engine efficiency improvements throughout all scenarios, confirming the results of Chapter 4. In particular, reciprocating engines used for road and sea freight are expected to continue delivering large shares of Useful energy, even in the B2DS. Even though a large and increasing share of patent counts relate to reciprocating engines, their number is decreasing. It is paramount to resist the temptation to halt efficiency innovation, with the idea that electrification will solve all the issues. All fuel economy standards are currently technology neutral, this means that OEMs can abide by the standards by investing in electrification while disregarding improvements in conventional and hybrid power-trains. Such a mechanism might result in lower than expected efficiency savings in a technology that is expected to remain important in all scenarios.

Two policy recommendations can be drawn from this study. Firstly, policy instruments to improve energy conversion efficiency, such as minimum energy performance standards and publicly funded research and development, should be pursued for coolers and heat pumps in all countries, because current innovation activity is currently well below the corresponding potential savings from these devices. Secondly, improvements in engine efficiency will deliver large savings irrespective of the future energy pathway chosen. Efficiency improvements should be fostered through power-train specific fuel economy incentives and by extending fuel economy standards to freight.

Chapter 6

Discussion and future work

This thesis aims to further our understanding of the class of technologies involved in the conversion of Final energy into Useful energy and to understand the role that these technologies can have to reduce energy demand and CO_2 emissions. Building upon a energy system framework that separates conversion devices and passive systems to study efficiency improvements, this thesis made use of novel methodologies developed to tackle its research questions which focused on: (a) a critical assessment of end-use energy statistics, (b) a robust estimation of technical limits to efficiency, and (c) an analysis of the expected role of these technologies in influential future energy scenarios. This thesis has shown the benefits that are associated with taking a cross-sectoral assessment of energy technologies compared to the more common approach on focusing on a single technology or a single sector. This final chapter is structured in two parts. First, the specific contributions to knowledge generated in each of the analytical chapters are addressed in turn. Second, the avenues for further investigation identified in the thesis are outlined; these include both suggestions to overcome the limitations encountered and suggestions to fulfil the potential of the analytical framework used.

6.1 Contributions to knowledge

Q1: What is the uncertainty of Useful energy consumption statistics in the United Kingdom?

This thesis provides in chapter 3 the first attempt to rigorously quantify the uncertainty that is associated with Final and Useful energy balances– which are extensively used in national level energy system modelling. This study provides three main contributions to the wider energy studies literature.

1. A novel methodology is developed to enable the quantification and assessment of the uncertainty associated with Final and Useful energy statistics using a Bayesian framework
2. New data on the efficiency of ten end-use conversion devices is compiled and it is used to estimate their average efficiency
3. The Useful energy balance of the United Kingdom is estimated with updated data

The uncertainty analysis shows that the largest source of uncertainty is the allocation to energy end-uses where the uncertainty of the energy flows goes from a median value of 5% to one of 34%. The transport sector results are the most certain while the provision of Useful Heating is the most certain Useful category. Conversely, the Industrial sector is subject to most uncertainty. Overall, 85% of Useful energy consumption has uncertainties below an uncertainty of ±25% which is deemed acceptable compared to other survey-based statistics. The advent of cheaper and widespread sensing equipment and data processing technology will bring about more information about the end-uses of energy. Statistical offices making use of this new information to improve data collection protocols will be able to improve the reliability of end-use energy statistics further.

The research question was answered by showing that most end-use energy statistics are sufficiently reliable for use in policy design, even though they are indeed more uncertain than Final energy statistics. In addition, the most promising areas of improvement for these statistics were identified.

Q2: What are the technical efficiency limits of end-use energy conversion devices?

This thesis has presented a engineering based analysis of the technical efficiency limits of conversion devices in the energy system across the energy system and used them to calculate the saving potentials – both in terms of energy and CO_2. While the literature has many examples of economic energy saving potential studies of technology options, this is the first attempt in the literature to consistently quantify the technical efficiency limits of energy conversion devices. These limits are estimated based on a combination of physical modelling and literature review. A stochastic approach has been used throughout the analysis to be open about the considerable uncertainties associated with this research area.

Knowledge about the technical limits of the six most used energy conversion devices, in conjunction with knowledge about the current efficiency, has enabled the classification of devices depending on their relative magnitude of the technical efficiency improvement potential and of the difference between median and highest available efficiencies. Only light devices and jet engines have a larger technical efficiency improvement potential compared to the potential associated with increasing average efficiency up to best practice. For all other devices most savings are achievable through current technologies. This observation implies that to increase end-use conversion efficiencies, it is best to focus on convergence towards BAT levels rather than on R&D projects aimed at increasing the performance conversion devices.

Data on current efficiency, technical limits, and current energy consumption, has been used to obtain a probabilistic estimate of the ESP from conversion efficiency improvements in the UK. The results of this analysis convey two key messages. Firstly, conversion efficiency alone is not sufficient to meet the United Kingdom's climate and energy reduction targets, since even at the technical limit, 25% of energy demand could be reduced. Secondly, conversion efficiency improvements can have the most impact in the transport sector, particularly for the road transport sector, accounting for half the total ESP. Comparing the results with previous literature suggest that passive systems hold a greater potential for technical efficiency improvements than conversion devices. The ESP was also used to provide a first order estimate of the ESP associated with each of the broad engineering research areas, thus showing the potential use of this metric in R&D agenda setting.

The ESP metric, provides an estimate of the potential savings from efficiency improvements for a given technology or sector, with all else being equal. However, it does not account for future changes in energy flows, technology choices, and energy transition pathways. Given the energy system is in a constant state of flux, the technical efficiency limits should be applied in context of possible long-term energy transitions. This limitation is addressed in chapter 5.

Notwithstanding these limitations, the results of the analysis answer the research question. Compiling a robust physical quantification of gains that have until now either been unquantified or only been available in technical literature and not compared to other devices, enriches the literature on this class of technologies.

Q3: how does the saving potential of end-use conversion devices vary in different climate scenarios and how does it compare with current innovation activity?

Chapter 4 addresses this question by estimating the energy savings associated with end-use conversion devices in three different global scenarios developed by the International Energy Agency in their 2017 Energy Technology Perspective report and by using patent counts as a metric for innovation.

The results have shown that 3.2-4.2% of cumulative Final energy demand and 2.8-3.3% of cumulative emissions are likely to be saved as a result of efficiency improvements in these technologies. In comparative terms, this means that by 2060 efficiency improvements will save more energy than that which is consumed by the entire iron and steel industry. In the B2DS scenario, savings from electricity consuming devices alone will prevent the deployment of 2.5 TW of new renewable capacity, which equates to nearly 5 times the new renewable capacity installed globally in 2013. Therefore, this analysis supports the claim that efficiency improvements are an indispensable tool in the transition to a net-zero carbon future. At the same time, overlaying these results with the TELs defined in chapter 4 shows that for some devices, namely lighting and air conditioning, the expected improvements in the IEA's scenarios imply conversion efficiencies in 2060 that are substantially lower than the TEL of these devices. This means that more ambitious improvement targets could be set for these technologies since for all other devices target efficiencies in 2060 approach the TEL.

Delving deeper into the results, shows that internal combustion engines retain the majority of efficiency related savings among all devices and in all sectors even though their importance is lower in the more ambitious scenarios. In particular, efficiency improvements in reciprocating engines are key to reducing energy demand and emissions as their use will persist in freight transport even with optimistic views on penetration of electric powertrains. This confirms that even in a low-carbon scenario, engine efficiency improvements have a large impact.

The use of patent counts to provide a granular metric of innovation activity for the different devices was explored. The results show two important trends. First, there is a moderate correlation between current innovation efforts and the saving potential of each device. Yet, for some important devices such as heat pumps and air conditioners, estimated innovation activity is worryingly low compared to their expected gains. This can be attributed to the mature-technology status of these devices meaning that they do not benefit from substantial public R&D funding and due to a principal-agent problem deriving from OEMs being based in mild-climate countries and most of the future growth coming from the global south. Second, there seems to be a positive correlation between having high innovation activity and rapid deployment as shown by the case of lighting technology and electric motors. However, this correlation should be more thoroughly studied both in terms of statistics and in terms of theory.

6.2 Research implications

This thesis has answered the four research questions that were posited at its inception, thus helping further the understating of the role of end-use conversion devices in climate mitigation plans. In addition to answering the three specific questions, there are further implications of this research that are of interest to three stakeholders in the decisionmaking processes relevant to climate mitigation: modellers and analysts, energy statistical offices, and policymakers in the fields of energy and science policy.

6.2.1 Implications for energy modellers and analysts

This thesis has shown the usefulness of applying the framework developed by Cullen [24] to analyse technical efficiency improvements. The distinction between passive systems and conversion devices allows to isolate two very different classes of technologies while retaining a holistic view of the energy system. This is an in-depth study of technologies that are often hidden within broader technology categories (such as passenger vehicles, or industrial processes) which showed how these individual devices can affect the entire energy system. Three implications of this work for energy modellers and analysts are identified.

1. It is common practice for modellers interested in long time horizons to define “floor performances” for the technologies involved. This practice is often performed making use of modeller discretion, at best, based on a set of technology specific studies employing different definition of performance limit, and a worst, based on cursory overarching theoretical limits. The results of Chapter 4 provide developers of technology focused models with a consistent set of technical limits for some key technologies in the energy sector.
2. Another common characteristic of energy models is their blindness towards the epistemic uncertainty of the underlying data. While much effort has been devoted to exploring ways to assess and communicate uncertainty of future results, the core data informing the models has always been taken as fully deterministic. Chapter 3 shows that most energy statistics, especially those related to energy end-uses, are far from being deterministic values. Methods for assessing the uncertainty of underlying data exist and have been successfully been applied throughout this thesis. By taking an approach that is explicit about uncertainty this thesis increases the trustworthiness of the conclusions derived from energy assessments.

3. The societal exergy analysis academic community has been one of the main user and proponents of conversion efficiency as an important metric for energy system assessment. For this field of research, this thesis has two major implications. First, the extensive research conducted on the current status of end-use energy conversion efficiency can be used to update the values used in their studies, with the added value of providing information on the uncertainty of each data point. Second, the field has been involved in exploring the relationships between improvements in thermodynamic efficiency and economic growth. In this endeavour, knowledge about the technical limitations of energy conversion can allow these scholars to explore the future of this relationship in the long term, when efficiency gains will no longer be possible.

It is hoped that the results and methodologies developed in this thesis will be used in the construction of robust and technically explicit models that will serve the academic community to provide much-needed policy advice.

6.2.2 Implications for statistical offices

In this thesis much emphasis was placed in the assessment of the quality of available energy statistics. In particular the UK statistics were scrutinised in detail because the quality and transparency of statistics is among the best publicly available globally. As a result of the study, two recommendations specific to the UK data can be made.

1. The analysis of uncertainty of the different allocations to energy end uses showed that the industrial end-use allocations are the least reliable. That is because the allocation is based on a single survey conducted in 2000 and for which very little documentation is publicly available. Therefore, improving statistics on this sector is of paramount importance. The availability of technical expertise within the industrial sector means that there are opportunities to obtain granular and reliable statistics with more ease compared to the building's sector. An example of best practice in industrial energy data collection can be found in the Manufacturing Energy Consumption Survey [74] conducted in the USA.

2. The UK is the subject of a wealth of studies on energy consumption, however, only a limited number of sources are used for the development of the official statistics. In the case of the residential sector, one important study on electricity consumption conducted in 2012 [55] is not being used for the end-use statistics. The reason is possibly that this study was commissioned to assess the hourly profile of electricity consumption in order

to understand the potential for demand side management. However, the data generated is perfectly suitable to use for end-use statistics and, most importantly, is of higher quality than the one currently used which comes from a bottom-up engineering model calibrated before 2009 [64]. Therefore, end-use statistics in the UK could quickly improve by making use of all available knowledge in the field.

Further improvements in statistics could be obtained by taking an innovative approach with regards to the data generated by regulation, sensor availability and artificial intelligence.

- Increased sensor availability means that ever cheaper and less intrusive sensing technology will become available. This means that the cost of conducting large-sample assessment will decrease and much more data will become available for collection.
- Artificial intelligence advances are continuously improving the performance of non-intrusive sensing methods that are especially well suited to assessment of energy consumption in buildings where current methodologies are either costly measurements or unreliable since users are often unaware of their own patterns of energy use.
- Data generated by regulation can also be leveraged for improved statistics. For instance, Article 8 of the Energy Efficiency Directive [427] mandates all large industrial energy users to undergo energy audits or to make use of an energy management system. The application of this regulation generates vast quantities of energy use information that can be leveraged by statistical offices to provide a level of accuracy and resolution in their consumption data otherwise impossible to achieve. The Italian energy agency has already been making use of this new data for some benchmarking studies [428], but more consistent use of this data for energy statistics has not been made yet. In the UK, this data is managed by the Environmental Agency and if standardised and anonymised appropriately, could serve as an excellent source of end-use data for industry. For the transport sector, a recent commission draft regulation proposes the introduction of mandatory installation of devices automatically measuring fuel consumption in new vehicles [429]. This measure is being introduced as a response to the unreliability of laboratory tested fuel economy values. However, the data generated by these devices could be used for very precise bottom-up energy consumption and efficiency statistics collection.

A general conclusion of this study is that statistical offices should be more explicit about the uncertainty of their estimates, even if that implies resorting to expert judgement. Any estimate is better than assuming 100% certainty. This is important for traditional energy statistics, but even more for end-use statistics as these have been shown to be subject to higher uncertainty. Being explicit about uncertainty does not undermine the authority of the publish statistics, on the contrary it increases their applicability as users can be more confident about the true meaning of the information provided. A more transparent treatment of uncertainty is believed to help improve the reliability of end-use energy assessments.

6.2.3 Implications science and energy policy

The changes in the energy system required to deliver climate ambitions are unlikely to be brought about solely by market forces. Radical changes away from business as usual will be required in all branches of the energy sector– including end-use conversion devices. Governments possess the tools to both stimulate the adoption of best available technologies through product regulations and incentives; and to speed up innovation in key technologies by steering public R&D budgets. As described in Chapter 2, the availability of indicators to measure policy additionality and progress are required to develop successful legislation. In this context, this thesis has implications for those seeking to increase energy efficiency.

In Chapter 3 it was shown that end-use statistics can be sufficiently reliable to serve as indicators in energy policy. With only small additional improvements, the entire energy sector and all conversion devices can be covered by reliable end-use statistics. This means that government departments involved in drafting legislation aimed at increasing efficiency should make use of these indicators to set targets. For example, the efficiency of thermal comfort (heating and cooling) efficiency should be closely monitored to ensure that this hard-to-decarbonise sector makes the required advances in terms of efficiency. Having successfully collected data on conversion efficiency for the UK, this thesis shows that data is indeed available for policymakers to track this important metric. Moves such as the EU's ruling mandating all the creation of an open-access database containing performace data for all energy-using products [430] are what is needed to stop thinking of conversion efficiency as "analytically intractable". The analysis in Chapter 5 using patent counts also has implications in this direction. It is suggested that patent counts could become indicators for the assessment of innovation policies targeting specific end-use energy technologies.

As electricity generation decarbonises, transport is quickly overtaking the power sector becoming the first source of emissions in most countries (in both the USA and UK, this happened in 2016). Despite advances in electromobility over the past two years, the fuel economy of conventional vehicles must increase drastically, especially in hard-to-electrify freight and air travel. As long as consumer preferences continue to favour larger vehicles, more drastic passive system improvements due to lightweighting are unlikely. On the other hand, this thesis has shown that engine efficiency still has large potential margins of improvement and that saving potentials from these devices are the largest in all assessed climate scenarios. To achieve such improvements, fuel economy standards in developed countries should be ambitious and strictly implemented, while coverage of standards should widen to cover (a) developing countries where vehicle sales are rapidly increasing, and (b) heavy duty vehicles. Good signs in this direction are coming from the implementation of the WLTP test cycle in the EU which should improve OEM compliance and from the extension of fuel economy targets to trucks both in the USA and the EU [375, 425]. However, current policies are based on technology neutrality meaning that sales of electric vehicles can substitute improvements in engine efficiency. While this approach has the benefit of allowing each OEM to optimise its compliance strategy, it might prove to be insufficient to meet climate goals.

This thesis has shown that the average efficiency of ICEs must reach 41% in 2060 up from 33% in 2013 in the 2DS and B2Ds scenarios. For this to happen substantial improvements in engine design and high temperature materials are necessary, as was shown in the section 4.2.7. Such important technological advances require both a technology push from R&D, but also a demand pull stemming from regulation if market drivers are not sufficiently strong. To this end, it is suggested that fuel economy regulation should not be technology neutral and should instead stimulate efficiency improvements for specific powertrains in addition to incentivising the adoption of electromobility. Investments in engine efficiency are no-regret options as they will likely be used well into the second half of the century for several applications. In addition, if consumer preference eventually favour smaller vehicles (due to environmental concern or shared mobility) then improved engine technology will still be beneficial. In the in-depth analysis of engine efficiency, it was shown that 23% of improvements can come from increased compression ratios. To enable these improvements, government should also be mindful of fuel standards to ensure that fuels of sufficiently high octane number are available for the next generation of advanced engines. For now, low octane fuel is mostly an issue in developing countries, however, in the future more advanced engines might require a revision of fuel standards in all countries.

The results of this thesis show that most conversion efficiency improvements can be obtained by increasing the penetration of current best available technologies. Therefore, policies such as minimum energy performance standards, scrappage schemes, building codes, and energy labelling should take precedence over R&D efforts. This message is already commonly repeated among efficiency policy analysis circles based on the fact most end-use devices have several decades of development history behind them and thus improvements were not expected to be large. However, this in-depth assessment has quantified the improvement potential of each of the major conversion devices and uncovered exceptions to this often cited rule of thumb. The two exceptions being LED lighting, and vapour compression devices, and jet engines.

Comparing current innovation outcomes with the assumed saving potential for each technology has shown that vapour-compression cycle devices are dangerously underrepresented in the innovation mix. On the one hand, air conditioners and heat pumps are mature technologies and that can be designed with higher efficiency by simply increasing their heat exchanger area. On the other hand, technical advances and cost reductions in small size radial compressors are needed to substitute current scroll and reciprocating compressor designs, and improved low global warming potential refrigerants must be found. Therefore, it is advised that research funding agencies and innovation ministries become aware of this gap and find ways to convey public and private investment towards R&D in vapour compression. It is of paramount importance for this technology push to happen as soon as possible since over the next decades most households in southeast Asia and Africa are expected to purchase air conditioners, bringing total cooling capacity from 6.2 TW in 2016 to 23 TW in 2050 [431]. If these newly installed units are not as efficient as possible it will place an unnecessary burden on the decarbonisation of electricity in these regions. Instead of seeing this rise of cooling demand as a challenge, one could see it as an opportunity to develop new technologies that can have their cost amortised over an increased number of sold units. In addition, the improvements needed by air conditioners can have an equally beneficial effect on heat pumps which must be installed in great numbers in colder regions to decarbonise space heating and hot water provision.

6.3 Future work

As is always the case, the knowledge generated in this thesis by answering its research questions spurs further research questions and avenues for further investigation. In this section, three main question arising from shortcomings of the present study and from its results are outlined.

6.3.1 Improving technical efficiency assessment

This thesis has provided the first overarching assessment of end-use conversion devices, building upon Cullen's analytical framework. Three elements for further research are needed to fully exploit the the benefits of this distinctions.

The methodology used to assess technical limits can be refined. The use of physical models and loss mechanism breakdowns has been successful for developing a first estimate. However, key shortcomings of this method have been (a) the reliance on literature estimates and individual expert judgement to define the limits of individual parameters, and (b) the use of the loss mechanism assessment when physical modelling proved too complex.

- To improve the robustness of the assessments, the technique of expert elicitation could be used. This technique consists in conducting structured interviews with a series of experts for each device where the interviewer elicits the experts to provide a probabilistic assessment of a performance parameter. This method has been extensively used in the field of energy technology research mostly on cost-related metrics [246, 288]. There are well defined interview protocols that take all the necessary steps to limit the impact of known cognitive biases and thus to obtain robust opinions from experts. For the assessment of technical limits, the best expert categories include design engineers involved in the development of new products and R&D engineers involved with research of radically new designs.
- To expand the physical modelling (Methodology A) to all devices it is required to draw on more specialised knowledge and to make use of commercial engineering models for each device. Such an expanded modelling effort would require a team of researchers as each modelling task could be a substantial research endeavour by itself.

This thesis has highlighted that most of energy conversion improvements and saving potentials are linked to the internal combustion engine, however its TEL in this thesis has been estimated using the loss reduction method. Therefore, the most urgent future work should focus on developing a physical representation of the combustion engine enables a robust assessment of its maximum efficiency potential as well as the implication of the required design changes on other key performance parameters. The use of a state-of-the art engine simulation software is necessary for this assessment, but it is not a sufficient one. The simulation tool would have to be paired with knowledge on the limits of each design parameter and with a reasoned estimation of the power density loss that is tolerable by consumers. The modelling framework to reflect the variety of uses of internal combustion engines (from two-wheelers to container vessels) and the variety of mission profiles. The trade-offs between pollutant emission and efficiency should also be explored in greater detail, since efficiency can only go hand in hand with cleaner exhausts.

While this thesis has been able to quantify the saving potentials for each technology and thus provide guidance on how to prioritise action, the results fall short of providing precise guidance on “effort” allocation because of the lack of an optimisation analysis. The reason for this is that optimisation analyses require some information or estimate on costs of different technologies. Since the scope of this thesis was purely technical, this aspect has been left out. Further research should include the cost estimates for the improvement of the various technical parameters. While data on the subject is not easily available, a combination of engineering based estimates (based on engineering manuals and material costs) and targeted interviews with private sector engineers could inform the model. Once the data is collected, there are numerous tools to conduct the cost optimisation assessment with TIMES [432] being a widely used option.

6.3.2 Improving end-use energy statistics

In chapter 3 a Bayesian approach for the assessment of uncertainty of end-use energy statistics was developed. While characterising the UK’s Useful energy uncertainty has been an important first step, yet, future research should focus on how this novel approach could be improved and, most importantly, on how it could be used to improve the energy data available to policymakers and modellers. This section contains three ideas that head in that direction.

1. There are at least two ways to improve the robustness of the data used to assess the uncertainty of available end-use energy statistics. Firstly, one could employ expert elicitation techniques to canvas a number of practitioners from which to extract probability density functions that can be associated to the allocation matrix. Secondly, the uncertainty analysis could be performed directly on the models that are used by statistical offices to estimate the end-use energy consumption in each sector. For this to happen, it would be necessary to engage directly with the statistical offices and gain access to the staff involved in energy statistic collection to conduct the expert elicitation. To better understand the uncertainty within the models used, it would be required to have access to said models and run them through Montecarlo’s simulations.
2. Large variability among the methodologies used for end-use statistic compilation was identified. This implies that there is variability in the uncertainty of the statistics

available. It's therefore important to compare the uncertainty associated with each method and its associated costs to understand the additional investments in surveying that would be required to increase the reliability of results. However, the literature is lacking such a comparative study of the techniques used to estimate energy end-uses. Such an assessment could help identify international best practices that could then be followed by other countries, thus increasing the overall reliability of energy statistics, and thus indirectly improve the way in which we track our progress towards emission reduction.

3. The detailed assessment of energy data quality has focused on the United Kingdom – a country with a well-established statistical information and collection for several years. However, most uncertainty sources in global energy statistics and most expected growth in energy consumption are associated to developing countries that in many cases have limited end-use statistics. The methodologies developed in this research can be modified to help tackle the lack of information available for these countries in two ways:

    (a) Conducting a similar analysis on a developing country would show which sectors have the least-reliable data and enable the ranking of data collection needs as a function of their impact on the improvement of the overall energy system picture. This would enable national statistical offices (or non-governmental organisations) to focus their limited resources on the collection of statistics with the largest impact.

    (b) For countries lacking official end-use energy data-sets, energy system modelling and its beneficial insights for policymakers are not fully exploited. However, small-sample data collected for ad hoc academic studies (for example [433]) can at times be available and may be used to scale energy uses, although with higher uncertainty. Other organisations such as CLASP [434] and the Clean Cooking Alliance [435] are collecting information on end-use devices in hopes of both improving the efficiency of the devices on the market and generating knowledge about what is used. The information collected through the previously described ways could be used in the allocation of aggregate energy consumption to different end-uses and devices rigorously if the methodology described in Chapter 3 is applied. Doing so, would enable the development of bottom-up energy models for these countries that can be updated with better data as it becomes available.

6.3.3 Tracking innovation in all energy efficiency technologies

The energy innovation literature has long been highlighting an important mismatch between technological needs for decarbonisation and public budgets in R&D, however, only minor improvements in this direction have been observed this far. To help governments assess the effectiveness of their R&D budgets and innovation policy, it is desirable to have technologically granular statistics on innovation activities that can be readily be compared with technological needs for decarbonisation. This thesis has explored the use of patent counts with this aim, however two key limitations remain. First, only patent counts from the USA have been used and secondly, only seven conversion devices have been analysed. To address the first shortcoming, further work should make use of PATSTAT [436], a database maintained by the European Patent Office that collects patent information from most national patent offices and has a very robust classification system to identify patents related to technologies with the potential of mitigating climate change. The scope of the analysis should be expanded to include all conversion devices and passive systems, as well as technologies that enable improvements in operational efficiency (eg. smart thermostats or variable speed drives). If these steps were taken, it would be possible to reliably track the progress of all the technologies that are needed to decrease the economy's energy intensity at the rates required by our climate ambition. Such a tracking system can incentive the allocation of research budgets towards necessary, but underfunded technologies, by making this information available to the relevant decision maker bodies. An ideal starting point for this research is the "Innovation Gaps" material collected by the IEA where all key clean energy technologies are rated based on their current Technology Readiness Level. Such material could be complemented by up-to-date patent counts for each technology to help inform policymakers on innovation activity for each technology.

References

[1] Jeff Tsao, Nate Lewis, and George Crabtree. Solar faqs. *US department of Energy*, pages 1–24, 2006.

[2] International Energy Agency. *Key world energy statistics*. International Energy Agency, 2018.

[3] D. J. Arent R. Bertani A. Faaij M. Hand W. Krewitt E. D. Larson J. Lund M. Mehos T. Merrigan C. Mitchell J. R. Moreira W. Sinke V. Sonntag-O'Brien B. Thresher W. van Sark E. Usher Turkenburg, W. C. Chapter 11 - renewable energy. In *Global energy assessment: toward a sustainable future*. Cambridge University Press, 2012.

[4] Paul Warde. Energy consumption in England and Wales, 1560-2004. 2007.

[5] E Anthony Wrigley. The classical economists, the stationary state, and the industrial revolution. In *Was the Industrial Revolution Necessary?*, pages 39–54. Routledge, 2012.

[6] Vaclav Smil. *Energy and civilization: a history*. MIT Press, 2017.

[7] Edward Anthony Wrigley. Energy and the english industrial revolution. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 371(1986):20110568, 2013.

[8] Roger Fouquet. Long-run demand for energy services: Income and price elasticities over two hundred years. *Review of Environmental Economics and Policy*, 8(2):186–207, 2014.

[9] International Energy Agency. *Key world energy statistics*. International Energy Agency Paris, 2018.

[10] Myles R Allen, Vicente R Barros, John Broome, Wolfgang Cramer, Renate Christ, John A Church, Leon Clarke, Qin Dahe, Purnamita Dasgupta, Navroz K Dubash, et al. IPCC fifth assessment synthesis report-climate change 2014 synthesis report. 2014.

[11] R Fouquet and PJG Pearson. Seven centuries of energy services: The price and use of light in the United Kingdom (1300-2000). *The Energy Journal*, 2006.

[12] Rajendra K Pachauri, Myles R Allen, Vicente R Barros, John Broome, Wolfgang Cramer, Renate Christ, John A Church, Leon Clarke, Qin Dahe, Purnamita Dasgupta, et al. *Climate change 2014: synthesis report. Contribution of Working Groups I, II and*

III to the fifth assessment report of the Intergovernmental Panel on Climate Change. International Panel on Climate Change, 2014.

[13] World Bank Data. CO_2 emissions (kg per PPP $ of GDP), 2018.

[14] International Energy Agency. *CO_2 emissions from fuel combustion*. International Energy Agency, 2018.

[15] UNFCC. Policymakers summary of th e response strategies working group of the intergovernmental panel on climate change (working group III), 1990.

[16] Kevin Anderson, Corinne Le Quéré, and Carly Mclachlan. Radical emission reductions: the role of demand reductions in accelerating full decarbonization, 2014.

[17] Joeri Rogelj, Drew Shindell, Kejun Jiang, Solomone Fifita, P Forster, Veronika Ginzburg, Collins Handa, Haroon Kheshgi, Shigeki Kobayashi, Elmar Kriegler, et al. Mitigation pathways compatible with 1.5 c in the context of sustainable development. 2018.

[18] United Nations / Framework Convention on Climate Change. Adoption of the paris agreement. *21st Conference of the Parties*, 2015.

[19] International Energy Agency. Tracking clean energy progress - carbon capture and utilisation in power, 2018.

[20] Corinne Le Quéré, Robbie M Andrew, Pierre Friedlingstein, Stephen Sitch, Judith Hauck, Julia Pongratz, Penelope A Pickers, Jan Ivar Korsbakken, Glen P Peters, Josep G Canadell, et al. Global carbon budget 2018. *Earth System Science Data (Online)*, 10(4), 2018.

[21] World Bank Data. Energy intensity level of primary energy (mj/$2011 ppp gdp), 2018.

[22] UNFCC. Ar5 climate change 2014: Mitigation of climate change, 2014.

[23] Y Kaya. Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. *IPCC energy and industry subgroup, response ...*, 1990.

[24] Jonathan M Cullen. *Engineering fundamentals of energy efficiency*. PhD thesis, University of Cambridge, 2010.

[25] Chunbo Ma and David I Stern. China's changing energy intensity trend: a decomposition analysis. *Energy economics*, 30(3):1037–1053, 2008.

[26] Ian Sue Wing. Explaining the declining energy intensity of the US economy. *Resource and Energy Economics*, 30(1):21–49, 2008.

[27] Peter Mulder and Henri LF De Groot. Structural change and convergence of energy intensity across oecd countries, 1970–2005. *Energy Economics*, 34(6):1910–1921, 2012.

[28] Lukas Hardt, Anne Owen, Paul Brockway, Matthew K Heun, John Barrett, Peter G Taylor, and Timothy J Foxon. Untangling the drivers of energy reduction in the UK productive sectors: Efficiency or offshoring? *Applied energy*, 223:124–133, 2018.

[29] Thomas B Johansson, Anand Prabhakar Patwardhan, Nebojša Nakićenović, and Luis Gomez-Echeverri. *Global energy assessment: toward a sustainable future*. Cambridge University Press, 2012.

[30] Felix Creutzig, Blanca Fernandez, Helmut Haberl, Radhika Khosla, Yacob Mulugetta, and Karen C Seto. Beyond technology: demand-side solutions for climate change mitigation. *Annual Review of Environment and Resources*, 41:173–198, 2016.

[31] Arnulf Grubler and Keywan Riahi. Do governments have the right mix in their energy R&D portfolios? *Carbon Management*, 1(1):79–87, 2010.

[32] Naoko Maruyama and Matthew J Eckelman. Long-term trends of electric efficiencies in electricity generation in developing countries. *Energy Policy*, 37(5):1678–1686, 2009.

[33] Matteo Muratori, Catherine Ledna, Haewon McJeon, Page Kyle, Pralit Patel, Son H Kim, Marshall Wise, Haroon S Kheshgi, Leon E Clarke, and Jae Edmonds. Cost of power or power of cost: a US modeling perspective. *Renewable and Sustainable Energy Reviews*, 77:861–874, 2017.

[34] Charlie Wilson, Arnulf Grubler, Kelly S. Gallagher, and Gregory F. Nemet. Marginalization of end-use technologies in energy innovation for climate protection. *Nature Climate Change*, 2(11):780–788, oct 2012.

[35] JM Cullen and JM Allwood. The efficient use of energy: Tracing the global flow of energy from fuel to service. *Energy Policy*, 2010.

[36] JM Cullen and JM Allwood. Theoretical efficiency limits for energy conversion devices. *Energy*, 2010.

[37] Jonathan M Cullen, Julian M Allwood, and Edward H Borgstein. Reducing energy demand: what are the practical limits? *Environmental science & technology*, 45(4):1711–1718, 2011.

[38] André Cabrera Serrenho, Jonathan B Norman, and Julian M Allwood. The impact of reducing car weight on global emissions: the future fleet in Great Britain. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 375(2095):20160364, 2017.

[39] John Heywood, Don MacKenzie, IB Akerlind, Parisa Bastani, Irene Berry, Kandarp Bhatt, Alice Chao, Eric Chow, Valerie Karplus, David Keith, et al. On the road toward 2050: Potential for substantial reductions in light-duty vehicle energy use and greenhouse gas emissions. *Massachusetts Institute of Technology*, 2015.

[40] Thomas S Blight and David A Coley. Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings. *Energy and Buildings*, 66:183–192, 2013.

[41] Linwei Ma, Julian M Allwood, Jonathan M Cullen, and Zheng Li. The use of energy in China: Tracing the flow of energy from primary source to demand drivers. *Energy*, 40(1):174–188, 2012.

[42] Chinhao Chong, Weidou Ni, Linwei Ma, Pei Liu, and Zheng Li. The use of energy in Malaysia: Tracing energy flows from primary source to end use. *Energies*, 8(4):2828–2866, 2015.

[43] Bojana Bajzel, Julian M Allwood, and Jonathan M Cullen. Designing climate change mitigation plans that add up. *Environmental science & technology*, 47(14):8062–8069, 2013.

[44] Gerardina Josephina Maria Phylipsen. Energy efficiency indicators: Best practice and potential use in developing country policy making, 2010.

[45] Energy Department for Business and Industrial Strategy. Energy consumption in the uk - data tables, 2017.

[46] Committee on Climate Change. Next steps for UK heat policy. Technical report, 2016.

[47] U.S. Energy Information Administration. Annual Energy Outlook 2015. *Office of Integrated and International Energy Analysis*, 1:1–244, 2015.

[48] AG Energiebilanzen. Anwendungsbilanzen für die endenergiesektoren in deutschland im jahr 2010, 2016.

[49] Energy Efficiency and Conservation Authority. Energy end use database, 2019.

[50] National Resource Canada. Energy use data handbook tables, 2019.

[51] Odysee Project. Definition of data and energy efficiency indicators in odyssee data base, 2017.

[52] International Energy Agency. Fundamentals on statistics - indicators, energy efficiency, 2014.

[53] International Energy Agency. Energy efficiency indicators, 2018.

[54] Jean Paul Zimmermann. End-use metering campaign in 400 households in Sweden assessment of the potential electricity savings. *Contract*, 17:05–2743, 2009.

[55] Intertek. Report r66141: Household electricity survey a study of domestic electrical product usage, 2012.

[56] Mario Berges, Ethan Goldman, H Scott Matthews, and Lucio Soibelman. Training load monitoring algorithms on highly sub-metered home electricity consumption data. *Tsinghua Science and Technology*, 13(S1):406–411, 2008.

[57] Anibal De Almeida, Paula Fonseca, Barbara Schlomann, and Nicolai Feilberg. Characterization of the household electricity consumption in the EU, potential energy savings and specific policy recommendations. *Energy and Buildings*, 43(8):1884–1894, 2011.

[58] Nigel Isaacs, Kay Saville-Smith, Michael Camilleri, and Lisa Burrough. Energy in new zealand houses: comfort, physics and consumption. *Building Research & Information*, 38(5):470–480, 2010.

[59] Zhengen Ren, Greg Foliente, Wan-Yee Chan, Dong Chen, Michael Ambrose, and Phillip Paevere. A model for predicting household end-use energy consumption and greenhouse gas emissions in australia. *International Journal of Sustainable Building Technology and Urban Development*, 4(3):210–228, 2013.

[60] Shuqin Chen, Nianping Li, Jun Guan, Yanqun Xie, Fengmei Sun, and Ji Ni. A statistical method to investigate national energy consumption in the residential building sector of China. *Energy and Buildings*, 40(4):654–665, 2008.

[61] International Energy Agency. Energy efficiency indicators:fundamentals on statistics, 2014.

[62] Robert K. Adler. Evaluating manufacturing energy consumption survey methodology, 1995.

[63] Ma Kavgic, A Mavrogianni, D Mumovic, A Summerfield, Z Stevanovic, and M Djurovic-Petrovic. A review of bottom-up building stock models for energy consumption in the residential sector. *Building and environment*, 45(7):1683–1697, 2010.

[64] Cambridge Architectural Research. Cambridge housing model - user guide, 2013.

[65] Department for Communities and Local Government. English housing survey - headline report 2013-14, 2017.

[66] Energy Department for Business and Industrial Strategy. Building energy efficiency survey - overarching report, 2013.

[67] Energy Department for Business and Industrial Strategy. Building energy efficiency survey - technical annex, 2013.

[68] Y Chan, R Kantamaneni, and M Allington. Study on energy efficiency and energy saving potential in industry from possible policy mechanisms. *ICF Consulting Limited, London*, 2015.

[69] Tobias Fleiter, Ernst Worrell, and Wolfgang Eichhammer. Barriers to energy efficiency in industrial bottom-up energy demand models—a review. *Renewable and sustainable energy reviews*, 15(6):3099–3111, 2011.

[70] Lukas G Swan and V Ismet Ugursal. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and sustainable energy reviews*, 13(8):1819–1835, 2009.

[71] Residential energy consumption survey (recs)- 2015 consumption and expenditures technical documentation summary. Technical report, Energy Information Administration, May 2018.

[72] Xinye Zheng, Chu Wei, Ping Qin, Jin Guo, Yihua Yu, Feng Song, and Zhanming Chen. Characteristics of residential energy consumption in China: Findings from a household survey. *Energy Policy*, 75:126–135, 2014.

[73] Dr.-Ing. Clemens Rohde. Erstellung von anwendungsbilanzen für die jahre 2013 bis 2015 mit aktualisierungen der anwendungsbilanzen der jahre 2009 bis 2012, 2016.

[74] Energy Information Agency. Manufacturing energy consumption survey - methodology and forms, 2014.

[75] Jacques Percebois. Is the concept of energy intensity meaningful? *Energy Economics*, 1(3):148–155, 1979.

[76] International Energy Agency. World energy model documentation, 2015.

[77] Birgit Fais, Nagore Sabio, and Neil Strachan. The critical role of the industrial sector in reaching long-term emission reduction, energy efficiency and renewable targets. *Applied energy*, 162:699–712, 2016.

[78] Luis Perez-Lombard, Jose Ortiz, and Ismael R Maestre. The map of energy flow in hvac systems. *Applied energy*, 88(12):5020–5031, 2011.

[79] N Pardo, K Vatopoulos, A Krook-Riekkola, JA Moya, and A Perez. Heat and cooling demand and market perspective. *European Commission Joint Research Centre: Luxembourg*, 2012.

[80] Jonathan M Cullen. *Engineering fundamentals of energy efficiency*. PhD thesis, University of Cambridge, 2010.

[81] Eurostat. Principles and methods of the energy balance sheet, 1978.

[82] Eurostat. Principles and methods of the energy balance sheet, 1988.

[83] Nicolas Pardo, Kostantinos Vatopoulos, Anna Krook Riekkola, and Alicia Perez. Methodology to estimate the energy flows of the european union heating and cooling market. *Energy*, 52:339–352, 2013.

[84] T Fleiter, M Ahrens, A Aydemir, R Elsland, C Frassine, A Herbst, S Hirzel, R Ragwitz, M Rehfeldt, M Reuter, et al. Mapping and analyses of the current and future (2020-2030) heating/cooling fuel deployment (fossil/renewables). *Work package*, 1, 2016.

[85] Ministério de Minas e Energia. de energia útil, balanço. Secretaria de Planejamento e Desenvolvimento Energético, Brasília, DF, 2005.

[86] Simon De Stercke. Dynamics of energy systems: A useful perspective. International Institute for Applied System Analysis, 2014.

[87] Nebojsa Nakićenović, Paul Viktor Gilli, and Rainer Kurz. Regional and global exergy and energy efficiencies. *Energy*, 21(3):223–237, 1996.

[88] David John Harris, H Nabb, and David Nuttall. *Coal, Gas and Electricity: Reviews of United Kingdom Statistical Sources*, volume 11. Pergamon Press, 1979. p. 9.

[89] Tânia Sousa, Paul E Brockway, Jonathan M Cullen, Sofia Teives Henriques, Jack Miller, André Cabrera Serrenho, and Tiago Domingos. The need for robust, consistent methods in societal exergy accounting. *Ecological Economics*, 141:11–21, 2017.

[90] GP Hammond and AJ Stapleton. Exergy analysis of the United Kingdom energy system. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*, 215(2):141–162, 2001.

[91] Ivar S Ertesvag. Society exergy analysis: a comparison of different societies. *Energy*, 26(3):253–270, 2001.

[92] Robert Ayres and Vlasios Voudouris. The economic growth enigma: Capital, labour and useful energy? *Energy Policy*, 64:16–28, 2014.

[93] Paul Edward Brockway. *National-level energy use, rebound and economic growth: Insights from useful work and exergy analysis*. PhD thesis, University of Leeds, 2016.

[94] Marco Sakai, Paul Brockway, John Barrett, and Peter Taylor. Thermodynamic efficiency gains and their role as a key 'engine of economic growth'. *Energies*, 12(1):110, 2019.

[95] André Cabrera Serrenho, Tânia Sousa, Benjamin Warr, Robert U Ayres, and Tiago Domingos. Decomposition of useful work intensity: The EU (European Union)-15 countries from 1960 to 2009. *Energy*, 76:704–715, 2014.

[96] Jonathan M Cullen and Julian M Allwood. The efficient use of energy: Tracing the global flow of energy from fuel to service. *Energy Policy*, 38(1):75–81, 2010.

[97] Jonathan M Cullen and Julian M Allwood. Theoretical efficiency limits for energy conversion devices. *Energy*, 35(5):2059–2069, 2010.

[98] Updated buildings sector appliance and equipment costs and efficiencies, 2018.

[99] Strachan N. Pye S. Anandarajah G. Balta-Ozkan N. Kannan, R. UK MARKAL Model Documentation, 2007.

[100] William Usher Fabian Kesicki Gabrial Anandarajah, Steve Pye and Christophe Mcglade. Tiam-ucl global model documentation -working paper, 2011.

[101] John Thomas. Drive cycle powertrain efficiencies and trends derived from EPA vehicle dynamometer results. *SAE International Journal of Passenger Cars-Mechanical Systems*, 7(2014-01-2562):1374–1384, 2014.

[102] John Thomas. Vehicle efficiency and tractive work: Rate of change for the past decade and accelerated progress required for US fuel economy and CO_2 regulations. *SAE International Journal of Fuels and Lubricants*, 9(1):290–305, 2016.

[103] Antje Kann and John P Weyant. Approaches for performing uncertainty analysis in large-scale energy/economic policy models. *Environmental Modeling & Assessment*, 5(1):29–46, 2000.

[104] Jeroen P Van der Sluijs, Jose Potting, James Risbey, Detlef van Vuuren, Bert de Vries, Arthur Beusen, Peter Heuberger, S Corral Quintana, Silvio Funtowicz, Penny Kloprogge, et al. Uncertainty assessment of the image/timer b1 CO_2 emissions scenario, using the NUSAP method. *Report commissioned by the Netherlands National Research Program on global Air Pollution and Climate Change, RIVM, Bilthoven, The Netherlands*, 225, 2002.

[105] Jeroen van der Sluijs, Penny Kloprogge, James Risbey, and Jerry Ravetz. Towards a synthesis of qualitative and quantitative uncertainty assessment: applications of the numeral, unit, spread, assessment, pedigree (NUSAP) system. In *Proceedings, International Workshop on Uncertainty, Sensitivity and Parameter Estimation*, 2003.

[106] Warren E Walker, Poul Harremoës, Jan Rotmans, Jeroen P Van Der Sluijs, Marjolein BA Van Asselt, Peter Janssen, and Martin P Krayer von Krauss. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated assessment*, 4(1):5–17, 2003.

[107] Kenneth Gillingham, William D Nordhaus, David Anthoff, Geoffrey Blanford, Valentina Bosetti, Peter Christensen, Haewon McJeon, John Reilly, and Paul Sztorc. Modeling uncertainty in climate change: A multi-model comparison. Technical report, National Bureau of Economic Research, 2015.

[108] Derek Lemoine and Haewon C McJeon. Trapped between two tails: trading off scientific uncertainties via climate targets. *Environmental Research Letters*, 8(3):034019, 2013.

[109] Xiufeng Yue, Steve Pye, Joseph DeCarolis, Francis GN Li, Fionn Rogan, and Brian Ó Gallachóir. A review of approaches to uncertainty assessment in energy system optimization models. *Energy strategy reviews*, 21:204–217, 2018.

[110] AT Booth, R Choudhary, and DJ Spiegelhalter. Handling uncertainty in housing stock models. *Building and Environment*, 48:35–47, 2012.

[111] Bas van Ruijven, Bert de Vries, Detlef P van Vuuren, and Jeroen P van der Sluijs. A global model for residential energy use: uncertainty in calibration to regional data. *Energy*, 35(1):269–282, 2010.

[112] Stefano Moret, Víctor Codina Gironès, Michel Bierlaire, and François Maréchal. Characterization of input uncertainties in strategic energy planning models. *Applied energy*, 202:597–617, 2017.

[113] Parisa Bastani, John B Heywood, and Chris Hope. The effect of uncertainty on US transport-related GHG emissions and fuel consumption out to 2050. *Transportation Research Part A: Policy and Practice*, 46(3):517–548, 2012.

[114] Niall PD Martin, Justin DK Bishop, Ruchi Choudhary, and Adam M Boies. Can uk passenger vehicles be designed to meet 2020 emissions targets? a novel methodology to forecast fuel consumption with uncertainty analysis. *Applied energy*, 157:929–939, 2015.

[115] Monika Culka. Uncertainty analysis using bayesian model averaging: a case study of input variables to energy models and inference to associated uncertainties of energy scenarios. *Energy, Sustainability and Society*, 6(1):7, 2016.

[116] Jordan Macknick. Energy and carbon dioxide emission data uncertainties. *IIASA Interim Report*, 2009.

[117] J MacCarthy, T Murrells, Y Pang, N Passant, J Ramirez Garcia, G Thistlethwaite, N Webb, S Choudrie, S Forden, S Gilhespy, et al. UK Greenhouse Gas Inventory, 1990 to 2014, 2016.

[118] Anwar Annut MacLeay Iain, Harris Kevin. *Digest of United Kingdom energy statistics*. The Stationery Office, 2014.

[119] Jonathan M Cullen, Julian M Allwood, and Margarita D Bambach. Mapping the global flow of steel: from steelmaking to end-use goods. *Environmental science & technology*, 46(24):13048–13055, 2012.

[120] Cristina Sendra, Xavier Gabarrell, and Teresa Vicent. Material flow analysis adapted to an industrial area. *Journal of Cleaner Production*, 15(17):1706–1715, 2007.

[121] Dominique Guyonnet, Mariane Planchon, Alain Rollat, Victoire Escalon, Johann Tuduri, Nicolas Charles, Stéphane Vaxelaire, Didier Dubois, and Hélène Fargier. Material flow analysis applied to rare earth elements in europe. *Journal of Cleaner Production*, 107:215–228, 2015.

[122] David Laner, Helmut Rechberger, and Thomas Astrup. Systematic evaluation of uncertainty in material flow analysis. *Journal of Industrial Ecology*, 18(6):859–870, 2014.

[123] RB Abernethy, RP Benedict, and RB Dowdell. ASME measurement uncertainty. *Journal of Fluids Engineering*, 107(2):161–164, 1985.

[124] Robert J Moffat. Describing the uncertainties in experimental results. *Experimental thermal and fluid science*, 1(1):3–17, 1988.

[125] Robin Willink and Rod White. Disentangling classical and bayesian approaches to uncertainty analysis. Technical report, BIPM, Technical Report No. CCT/12-08, 2012.

[126] David Laner, Helmut Rechberger, and Thomas Astrup. Applying fuzzy and probabilistic uncertainty concepts to the material flow analysis of palladium in Austria. *Journal of Industrial Ecology*, 19(6):1055–1069, 2015.

[127] David Laner, Julia Feketitsch, Helmut Rechberger, and Johann Fellner. A novel approach to characterize data uncertainty in material flow analysis and its application to plastics flows in austria. *Journal of Industrial Ecology*, 20(5):1050–1063, 2016.

[128] Fadri Gottschalk, Roland W Scholz, and Bernd Nowack. Probabilistic material flow modeling for assessing the environmental exposure to compounds: methodology and an application to engineered nano-tio 2 particles. *Environmental Modelling & Software*, 25(3):320–332, 2010.

[129] Oliver Cencic and Rudolf Frühwirth. A general framework for data reconciliation—part i: Linear constraints. *Computers & Chemical Engineering*, 75:196–208, 2015.

[130] Richard C Lupton and Julian M Allwood. Incremental material flow analysis with bayesian inference. *Journal of Industrial Ecology*, 2017.

[131] K Paustian, NH Ravindranath, and AR van Amstel. 2006 IPCC guidelines for national greenhouse gas inventories, 2006.

[132] J Goldemberg. World Energy Assessment: Energy and the challenge of sustainability, 2000.

[133] Adam B. Jaffe and Robert N. Stavins. The energy-efficiency gap What does it mean? *Energy Policy*, 22(10):804–810, oct 1994.

[134] Shogren J. *Encyclopedia of Energy, Natural Resource, and Environmental Economics*. Newnes, 2013.

[135] Hunt Allcott and Michael Greenstone. Is there an energy efficiency gap? *Journal of Economic Perspectives*, 26(1):3–28, 2012.

[136] P Rohdin and P Thollander. Barriers to and driving forces for energy efficiency in the non-energy intensive manufacturing industry in Sweden. *Energy*, 31(12):1836–1844, sep 2006.

[137] S Sorrell, J Schleich, S Scott, and E O'malley. Reducing barriers to energy efficiency in public and private organizations. *Retrieved . . .* , 2000.

[138] Mark R Gaterell and Mike E McEvoy. The impact of energy externalities on the cost effectiveness of energy efficiency measures applied to dwellings. *Energy and Buildings*, 37(10):1017–1027, 2005.

[139] Erik T Verhoef. Externalities. In Jeroen C.J.M. Van den Bergh, editor, *Handbook of environmental and resource economics*, chapter 13, pages 197–2014. Edward Elgar Publishing, 2002.

[140] Will Rivers Foaad Tahir, Ian Walker. Review of potential for carbon savings from residential energy efficiency. *Final report for The Committee on Climate Change. Cambridge*, 2013.

[141] DECC. Capturing the full electricity efficiency potential in the UK, 2012.

[142] ICF Consulting Limited. Study on energy efficiency and energy saving potential in industry and on possible policy mechanisms, December 2015.

[143] HC Granade, J Creyts, A Derkach, and P Farese. Unlocking energy efficiency in the US Economy. Technical report, Mkkinsey & Co., 2009.

[144] Sabine Brueske Aaron Fisher Keith Jamison, Caroline Kramer. Bandwidth Study on Energy Use and Potential Energy Saving Opportunities in U.S. Iron and Steel Manufacturing. Technical report, Department of Energy, 2015.

[145] Rene Kemna. Methodology for ecodesign of energy-related products, 2013.

[146] Robert U. Ayres, Leslie W. Ayres, and Vladimir Pokrovsky. On the efficiency of US electricity usage since 1900. *Energy*, 30(7):1092–1145, jun 2005.

[147] Paul E Brockway, John R Barrett, Timothy J Foxon, and Julia K Steinberger. Divergence of trends in US and UK aggregate exergy efficiencies 1960–2010. *Environmental science & technology*, 48(16):9874–9881, 2014.

[148] Stefanie Lena Heinzle and Rolf Wüstenhagen. Dynamic adjustment of eco-labeling schemes and consumer choice–the revision of the EU energy label as a missed opportunity? *Business Strategy and the Environment*, 21(1):60–70, 2012.

[149] KH Bergey. The lanchester-betz limit (energy conversion efficiency factor for windmills). *Journal of Energy*, 3(6):382–384, 1979.

[150] William Shockley and Hans J Queisser. Detailed balance limit of efficiency of p-n junction solar cells. *Journal of applied physics*, 32(3):510–519, 1961.

[151] Michael J Moran, Howard N Shapiro, Daisie D Boettner, and Margaret B Bailey. *Fundamentals of engineering thermodynamics*. John Wiley & Sons, 2010.

[152] Bjarne Andresen, Peter Salamon, and R Stephen Berry. Thermodynamics in finite fille. *Physics today*, page 63, 1984.

[153] Yanlin Ge, Lingen Chen, and Fengrui Sun. Finite-time thermodynamic modelling and analysis of an irreversible otto-cycle. *Applied Energy*, 85(7):618–624, 2008.

[154] Chih Wu. Specific heating load of an endoreversible Carnot heat pump. *International Journal of Ambient Energy*, 14(1):25–28, 1993.

[155] Lal Chen, C Wu, and F Sun. Finite-time thermodynamic performance of an isentropic closed regenerated brayton refrigeration cycle. *International Journal of Energy-Environment-Economics*, 4(4), 1997.

[156] Massimiliano Esposito, Katja Lindenberg, and Christian Van den Broeck. Universality of efficiency at maximum power. *Physical review letters*, 102(13):130602, 2009.

[157] Curzon, FL and Ahlborn, B. Efficiency of a Carnot engine at maximum power output. *American Journal of Physics*, 43(1):22–24, 1975.

[158] Elias P. Gyftopoulos. On the Curzon–Ahlborn efficiency and its lack of connection to power producing processes. *Energy Conversion and Management*, 43(5):609–615, 2002.

[159] Jincan Chen, Zijun Yan, Guoxing Lin, and Bjarne Andresen. On the Curzon–Ahlborn efficiency and its connection with the efficiencies of real heat engines. *Energy Conversion and Management*, 42(2):173–181, 2001.

[160] Willem Van Gool. Energy policy: fairy tales and factualities. In *Innovation and technology—strategies and policies*, pages 93–105. Springer, 1997.

[161] GP Hammond and AJ Stapleton. Exergy analysis of the United Kingdom energy system. ... *Engineers, Part A: Journal of Power* ..., 2001.

[162] GP Hammond and AB Winnett. Interdisciplinary perspectives on environmental appraisal and valuation techniques. *Proceedings of the ICE-Waste and* ..., 2006.

[163] Aimee McKane and Ali Hasanbeigi. Motor systems energy efficiency supply curves: A methodology for assessing the energy efficiency potential of industrial motor systems. *Energy policy*, 39(10):6595–6607, 2011.

[164] Érika Mata, Angela Sasic Kalagasidis, and Filip Johnsson. Energy usage and technical potential for energy saving measures in the swedish residential building stock. *Energy Policy*, 55:404–414, 2013.

[165] Kenneth Hansen, David Connolly, Henrik Lund, David Drysdale, and Jakob Zinck Thellufsen. Heat roadmap europe: Identifying the balance between saving heat and supplying heat. *Energy*, 115:1663–1671, 2016.

[166] J Ke M McNeil V Letschert, L Desroches. Energy efficiency - how far can we raise the bar? revealing the potential of best available technology. *Energy*, 59:72–82, 2013.

[167] Bernard C Beaudreau and H Douglas Lightfoot. The physical limits to economic growth by r&d funded innovation. *Energy*, 84:45–52, 2015.

[168] Stefanie Hellweg and Llorenç Milà i Canals. Emerging approaches, challenges and opportunities in life cycle assessment. *Science*, 344(6188):1109–1113, 2014.

[169] Hanna-Leena Pesonen, Tomas Ekvall, Günter Fleischer, Gjalt Huppes, Christina Jahn, Zbigniew S Klos, Gerald Rebitzer, Guido W Sonnemann, Alberto Tintinelli, Bo P Weidema, et al. Framework for scenario development in LCA. *The International Journal of Life Cycle Assessment*, 5(1):21, 2000.

[170] Rickard Arvidsson, Anne-Marie Tillman, Björn A Sandén, Matty Janssen, Anders Nordelöf, Duncan Kushnir, and Sverker Molander. Environmental assessment of emerging technologies: Recommendations for prospective LCA. *Journal of Industrial Ecology*, 22(6):1286–1294, 2018.

[171] Thomas Dandres, Caroline Gaudreault, Pablo Tirado Seco, and Réjean Samson. Uncertainty management in a macro life cycle assessment of a 2005–2025 european bioenergy policy. *Renewable and Sustainable Energy Reviews*, 36:52–61, 2014.

[172] Beltran A Mendoza, Brian Cox, M Chris, Detlef P van Vuuren, Vivanco D Font, Sebastiaan Deetman, Oreane Y Edelenbosch, Jeroen Guinée, Arnold Tukker, et al. When the background matters: Using scenarios from integrated assessment models in prospective life cycle assessment. *Journal of Industrial Ecology*, 2019.

[173] Ester Van der Voet, Lauran Van Oers, Miranda Verboon, and Koen Kuipers. Environmental implications of future demand scenarios for metals: methodology and application to the case of seven major metals. *Journal of Industrial Ecology*, 23(1):141–155, 2019.

[174] Richard H Moss, Jae A Edmonds, Kathy A Hibbard, Martin R Manning, Steven K Rose, Detlef P Van Vuuren, Timothy R Carter, Seita Emori, Mikiko Kainuma, Tom Kram, et al. The next generation of scenarios for climate change research and assessment. *Nature*, 463(7282):747, 2010.

[175] Bastien Girod, Arnim Wiek, Harald Mieg, and Mike Hulme. The evolution of the IPCC's emissions scenarios. *Environmental science & policy*, 12(2):103–118, 2009.

[176] IPCC (Intergovernmental Panel on Climate Change). Climate change: the IPCC scientific assessment, 1990.

[177] Jeremy Leggett, William J Pepper, Rob J Swart, J Edmonds, LG Meira Filho, Irving Mintzer, and MX Wang. Emissions scenarios for the ipcc: an update. *Climate change*, pages 69–95, 1992.

[178] Nebojsa Nakicenovic, Joseph Alcamo, A Grubler, K Riahi, RA Roehrl, H-H Rogner, and N Victor. *Special report on emissions scenarios (SRES), a special report of Working Group III of the intergovernmental panel on climate change*. Cambridge University Press, 2000.

[179] Detlef P Van Vuuren, Jae Edmonds, Mikiko Kainuma, Keywan Riahi, Allison Thomson, Kathy Hibbard, George C Hurtt, Tom Kram, Volker Krey, Jean-Francois Lamarque, et al. The representative concentration pathways: an overview. *Climatic change*, 109(1-2):5, 2011.

[180] Keywan Riahi, Detlef P Van Vuuren, Elmar Kriegler, Jae Edmonds, Brian C O'neill, Shinichiro Fujimori, Nico Bauer, Katherine Calvin, Rob Dellink, Oliver Fricko, et al. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Global Environmental Change*, 42:153–168, 2017.

[181] Brian C O'Neill, Elmar Kriegler, Keywan Riahi, Kristie L Ebi, Stephane Hallegatte, Timothy R Carter, Ritu Mathur, and Detlef P van Vuuren. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic change*, 122(3):387–400, 2014.

[182] Timothy J Foxon. Transition pathways for a UK low carbon electricity future. *Energy Policy*, 52:10–24, 2013.

[183] Jason Chilvers, Timothy J Foxon, Stuart Galloway, Geoffrey P Hammond, David Infield, Matthew Leach, Peter JG Pearson, Neil Strachan, Goran Strbac, and Murray Thomson. Realising transition pathways for a more electric, low-carbon energy system in the united kingdom: Challenges, insights and opportunities. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*, 231(6):440–477, 2017.

[184] Geoffrey P Hammond, Hayley R Howard, and Craig I Jones. The energy and environmental implications of UK more electric transition pathways: a whole systems perspective. *Energy Policy*, 52:103–116, 2013.

[185] Robert Lempert, Nebojsa Nakicenovic, Daniel Sarewitz, and Michael Schlesinger. Characterizing climate-change uncertainties for decision-makers. an editorial essay. *Climatic Change*, 65(1):1–9, 2004.

[186] Mort Webster, Chris Forest, John Reilly, Mustafa Babiker, David Kicklighter, Monika Mayer, Ronald Prinn, Marcus Sarofim, Andrei Sokolov, Peter Stone, et al. Uncertainty analysis of climate change and policy response. *Climatic change*, 61(3):295–320, 2003.

[187] Hadi Dowlatabadi. Integrated assessment models of climate change: An incomplete overview. *Energy Policy*, 23(4-5):289–296, 1995.

[188] Christoph Böhringer and Thomas F Rutherford. Combining bottom-up and top-down. *Energy Economics*, 30(2):574–596, 2008.

[189] JC Hourcade, M Jaccard, C Bataille, and F Ghersi. Hybrid Modeling: New Answers to Old Challenges Introduction to the Special Issue of" The Energy Journal". *The Energy Journal*, 2006.

[190] Stefan Pauliuk, Anders Arvesen, Konstantin Stadler, and Edgar G Hertwich. Industrial ecology in integrated assessment models. *Nature Climate Change*, 7(1):13, 2017.

[191] Morna Isaac and Detlef P Van Vuuren. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy policy*, 37(2):507–521, 2009.

[192] Detlef P Van Vuuren. *Energy systems and climate policy-long-term scenarios for an uncertain future*. Utrecht University, 2007.

[193] Bastien Girod, Detlef P van Vuuren, and Sebastiaan Deetman. Global travel within the 2 c climate target. *Energy Policy*, 45:152–166, 2012.

[194] Sabine Messner and Manfred Strubegger. User's guide for message iii. 1995.

[195] Daniel Huppmann, Matthew Gidden, Oliver Fricko, Peter Kolp, Clara Orthofer, Michael Pimmer, Nikolay Kushin, Adriano Vinca, Alessio Mastrucci, Keywan Riahi, et al. The messageix integrated assessment model and the ix modeling platform (ixmp): An open framework for integrated and cross-cutting analysis of energy, climate, the environment, and sustainable development. *Environmental Modelling & Software*, 112:143–156, 2019.

[196] Leon Clarke, Jiyong Eom, Elke Hodson Marten, Russell Horowitz, Page Kyle, Robert Link, Bryan K Mignone, Anupriya Mundra, and Yuyu Zhou. Effects of long-term climate change on global building energy expenditures. *Energy Economics*, 72:667–677, 2018.

[197] PAGE KYLE MARSHALL WISE KATE CALVIN, LEON CLARKE. Introduction to the global change assessment model (gcam). Technical report, Pacific Northwest National Laboratory, 2014.

[198] Gouri Shankar Mishra, Page Kyle, Jacob Teter, Geoffrey M Morrison, Sanling Kim, and Sonia Yeh. Transportation module of global change assessment model (gcam): model documentation. Technical report, 2013.

[199] Shinichiro Fujimori, Mikiko Kainuma, and Toshihiko Masui. *Post-2020 Climate Action: Global and Asian Perspectives*. Springer, 2017.

[200] Shinichiro Fujimori, Toshihiko Masui, and Yuzuru Matsuoka. Development of a global computable general equilibrium model coupled with detailed energy end-use technology. *Applied Energy*, 128:296–306, 2014.

[201] Nico Bauer Elmar Kriegler Lavinia Baumstark Christoph Bertram Anastasis Giannousakis Jérôme Hilaire David Klein Antoine Levesque Ioanna Mouratiadou Michaja Pehl Robert Pietzcker Franziska Piontek Niklas Roming Anselm Schultes-Valeria Jana Schwanitz Jessica Strefler Gunnar Luderer, Marian Leimbach. Description of the remind model (version 1.6). Technical report, Potsdam Institut für Klimafolgenforschung, 2015.

[202] Neil Strachan, Birgit Fais, and Hannah Daly. Reinventing the energy modelling–policy interface. *Nature Energy*, 1(3):16012, 2016.

[203] Subhes C Bhattacharyya and Govinda R Timilsina. A review of energy system models. *International Journal of Energy Sector Management*, 4(4):494–518, 2010.

[204] Lisa MH Hall and Alastair R Buckley. A review of energy systems models in the UK: Prevalent usage and categorisation. *Applied Energy*, 169:607–628, 2016.

[205] Steven A Gabriel, Andy S Kydes, and Peter Whitman. The national energy modeling system: a large-scale energy-economic equilibrium model. *Operations Research*, 49(1):14–25, 2001.

[206] ICCS E3MLab. Primes model - detailed model description. Technical report, National Technical University of Athens, 2014.

[207] UK MARKAL Model Documentation. Technical report, 2007.

[208] World Energy Council. World energy insights brief- global energy scenarios comparison review. Technical report, 2019.

[209] Evangelos Panos, Martin Densing, and Kathrin Volkart. Access to electricity in the world energy council's global energy scenarios: An outlook for developing regions until 2030. *Energy Strategy Reviews*, 9:28–49, 2016.

[210] WEC. The grand transition. Technical report, World Energy Council, 2016.

[211] Energy information administration. Annual energy outlook. *Department of Energy*, 2017.

[212] Energy information administration. World energy projection system plus: Overview. *Department of Energy*, 2017.

[213] WEO. World Energy Outlook - documentation. *International Energy Agency*, 2018.

[214] WEO. World Energy Outlook. *International Energy Agency*, 2018.

[215] International Energy Agency. *Energy technology perspectives*. International Energy Agency, 2017.

[216] Ryoichi Komiyama, C Marnay, M Stadler, J Lai, S Borgeson, B Coffey, and IL Azevedo. Japan's long term energy outlook to 2050: Estimation for the potential of massive CO_2 mitigation. *The Institute of Energy Economics, Japan*, 2009.

[217] Japan The Institute of Energy Economics. Ieej outlook - energy transition and a thorny path for 3e challenges. 2009.

[218] International Renewable Energy Agency. Perspectives for the energy transition, 2017.

[219] BP. Energy outlook to 2040, 2018.

[220] Exxon. Outlook for energy : a view to 2040, 2018.

[221] Patrick Criqui, Silvana Mima, Philippe Menanteau, and Alban Kitous. Mitigation strategies and energy technology learning: An assessment with the poles model. *Technological Forecasting and Social Change*, 90:119–136, 2015.

[222] Enerdata. Enerfuture world energy scenarios to 2040, 2018.

[223] GL DNV. Energy transition outlook 2018: A global and regional forecast of the energy transition to 2050. 2018.

[224] Anna Chroni. Presentation on shell's new lens scenarios and the world energy model. 2019.

[225] Shell. New lens scenario - a shift in perspective for a world in transition. 2019.

[226] Equinor. Energy perspectives 2018. 2018.

[227] Richard Loulou and Maryse Labriet. Etsap-tiam: the times integrated assessment model part i: Model structure. *Computational Management Science*, 5(1-2):7–40, 2008.

[228] International Energy Agency. Energy technology perspectives 2017 - catalysing energy technology transformations. 2017.

[229] Jean Château, Bertrand Magné, and Laura Cozzi. Economic implications of the IEA efficient world scenario. 2014.

[230] Kelly Sims Gallagher, Laura Diaz Anadon, Ruud Kempener, and Charlie Wilson. Trends in investments in global energy research, development, and demonstration. *Wiley Interdisciplinary Reviews: Climate Change*, 2(3):373–396, 2011.

[231] Howard Geller, Philip Harrington, Arthur H Rosenfeld, Satoshi Tanishima, and Fridtjof Unander. Polices for increasing energy efficiency: Thirty years of experience in oecd countries. *Energy policy*, 34(5):556–573, 2006.

[232] R Fedrizzi S Pezzutto, W Sparbar. Assessment of energy saving potential and eu funding for heating and cooling, 2013.

[233] M Rosen. Using exergy to correlate energy research investments and efficiencies: Concept and case studies. *Entropy*, 15:262–286, 2013.

[234] OECD-EUROSTAT. OECD patent statistics manual, 2009.

[235] Keith Pavitt. Patent statistics as indicators of innovative activities: possibilities and problems. *Scientometrics*, 7(1-2):77–99, 1985.

[236] World Intellectual Property Organisation. IPC green technology, 2019.

[237] Vito Albino, Lorenzo Ardito, Rosa Maria Dangelico, and Antonio Messeni Petruzzelli. Understanding the development trends of low-carbon energy technologies: A patent analysis. *Applied Energy*, 135:836–854, 2014.

[238] Valeria Costantini, Francesco Crespi, and Alessandro Palma. Characterizing the policy mix and its impact on eco-innovation: A patent analysis of energy-efficient technologies. *Research Policy*, 46(4):799–819, 2017.

[239] Joëlle Noailly and Svetlana Batrakova. Stimulating energy-efficient innovations in the dutch building sector: Empirical evidence from patent counts and policy lessons. *Energy Policy*, 38(12):7803–7817, 2010.

[240] Joëlle Noailly. Improving the energy efficiency of buildings: The impact of environmental policy on technological innovation. *Energy Economics*, 34(3):795–806, 2012.

[241] International Energy Agency. Extended world energy balances (edition 2015/1).

[242] F. Seefeldt N. Anders C. Rohde T. Fleiter A. Aydemir H. Kleeberger L. Hardi B. Geiger A. Kemmler, S. Straburg. Datenbasis zur bewertung von energieeffizienz-maßnahmen in der zeitreihe 2005 – 2014. Technical report, Umweltbundesamt, 2017.

[243] Harish Agarwal, John E Renaud, Evan L Preston, and Dhanesh Padmanabhan. Uncertainty quantification using evidence theory in multidisciplinary design optimization. *Reliability Engineering & System Safety*, 85(1):281–294, 2004.

[244] Christopher J Roy and William L Oberkampf. A comprehensive framework for verification, validation, and uncertainty quantification in scientific computing. *Computer methods in applied mechanics and engineering*, 200(25):2131–2144, 2011.

[245] G Aprostolakis. The concept of probability in safety assessments of technological systems. *Science(Washington)*, 250(4986):1359–1364, 1990.

[246] M Granger Morgan. Use (and abuse) of expert elicitation in support of decision making for public policy. *Proceedings of the National Academy of Sciences*, 111(20):7176–7184, 2014.

[247] Bo Pedersen Weidema and Marianne Suhr Wesnaes. Data quality management for life cycle inventories—an example of using data quality indicators. *Journal of cleaner production*, 4(3-4):167–174, 1996.

[248] Salway AG. Treatment of uncertainties for national estimates of greenhouse gas emissions, 1998.

[249] Henri P. Gavin Philip Scott Harvey and Jeffrey T. Scruggs. Probability distributions, 2019.

[250] European Commission. Measuring instruments Directive 2014/32/EU. *Official Journal of the European Union*, March 2014.

[251] Michel Vermersch, Fatima Carteado, Alex Rizzo, Edgar Johnson, Francisco Arregui, and Allan Lambert. Guidance Notes on Apparent Losses and Water Loss Reduction Planning, 2016.

[252] Eurostat. Energy balances in ms excel file format, 2016.

[253] P Brown, M Broomfield, G Buys, L Cardenas, E Kilroy, J MacCarthy, T Murrells, Y Pang, N Passant, J Ramirez Garcia, et al. *UK greenhouse gas inventory, 1990 to 2014: annual report for submission under the Framework Convention on Climate Change*. Ricardo Energy & Environment, 2016.

[254] Department for Energy and Climate Change. Renewable energy statistics data sources and methodologies. www.gov.uk/government/publications/renewable-energy-statistics-data-sources-and-methodologies, 2017.

[255] Martin Hughes, Jason Palmer, Vicky Cheng, and David Shipworth. Sensitivity and uncertainty analysis of England's housing energy model. *Building Research & Information*, 41(2):156–167, 2013.

[256] Martin Hughes, Jason Palmer, Vicky Cheng, and David Shipworth. Global sensitivity analysis of England's housing energy model. *Journal of Building Performance Simulation*, 8(5):283–294, 2015.

[257] Energy Department for Business and Industrial Strategy. Energy consumption in the uk - table 3.02, 2016.

[258] Department for Business Energy and Industrial Strategy. Peer review of the building energy efficiency survey energy use model, 2013.

[259] Christina J Hopfe and Jan LM Hensen. Uncertainty analysis in building performance simulation for design support. *Energy and Buildings*, 43(10):2798–2805, 2011.

[260] Wei Tian and R Choudhary. A probabilistic energy model for non-domestic building sectors applied to analysis of school buildings in greater London. *Energy and Buildings*, 54:1–11, 2012.

[261] Ruchi Choudhary. Energy analysis of the non-domestic building stock of Greater London. *Building and environment*, 51:243–254, 2012.

[262] EH Borgstein, R Lamberts, and JLM Hensen. Evaluating energy performance in non-domestic buildings: A review. *Energy and Buildings*, 128:734–755, 2016.

[263] Christine H Pout. N-deem: the national non-domestic buildings energy and emissions model. *Environment and Planning B: Planning and Design*, 27(5):721–732, 2000.

[264] Matthias Rehfeldt, Tobias Fleiter, and Felipe Toro. A bottom-up estimation of the heating and cooling demand in European industry, 2017.

[265] HRI University of Warwick. Ac0401: Direct energy use in agriculture: opportunities for reducing fossil fuel inputs, 2007.

[266] Diesel and Gas Turbine Worldwide. Market surveys, 2017.

[267] Product charachteristics database. http://www.ncm-pcdb.org.uk/sap/searchpod.jsp?id=17. [Online; accessed July-2017].

[268] Nijs VanWortswinkel. Technology brief: Industrial combustion boilers. http://www.iea-etsap.org/Energy_Technologies/Energy_Demand.asp, 2010.

[269] Silvia D'Ovidio Eleonora Lusardi Clemens Rohde Ali Aydemir Simon Hirzel Berit Ostrander Sotirios Karellas Konstantinos Braimakis Paolo Gentili, Chiara Landini. Ecodesign preparatory study on steam boilers [lot 7], 2014.

[270] Jonathan M Cullen Matteo Craglia, Leonardo Paoli. Fuel for thought: Powertrain efficiencies of British vehicles. *Energy Proceedia*, 2017.

[271] Environmental Protection Agency. Engine testing regulations, 2017.

[272] Hyun D Kim, Jeffrey J Berton, and Scott M Jones. Low noise cruise efficient short take-off and landing transport vehicle study. In *6th AIAA aviation technology, integration and operations conference (ATIO)*, page 7738, 2006.

[273] Federal Aviation Administration. Aircraft registry releasable aircraft database, 2016.

[274] John L Lumley. *Engines: an introduction*. Cambridge University Press, 1999.

[275] Anibal T. De Almeida, Fernando J T E Ferreira, Joao a C Fong, and Conrad U. Brunner. Electric motor standards, ecodesign and global market transformation. *Conference Record - Industrial and Commercial Power Systems Technical Conference*, pages 1–9, 2008.

[276] International Energy Agency. Fuel economy in major car markets- technology and policy drivers 2015-2017, 2019.

[277] Environmental Protection Agency. Midterm evaluation of light-duty vehicle greenhouse gas emissions standards for model years 2022-2025, 2017.

[278] Derek Bird. Methodology for the 2004 annual survey of hours and earnings. *Labour Market Trends*, 112:457–464, 2004.

[279] eurostat. Handbook on precision requirements and variance estimation for ess households surveys, 2013.

[280] Environmental System Research Institute. The american community survey - an esri white paper, 2014.

[281] Michael Zeifman and Kurt Roth. Nonintrusive appliance load monitoring: Review and outlook. *IEEE transactions on Consumer Electronics*, 57(1), 2011.

[282] Sayed Saeed Hosseini, Kodjo Agbossou, Sousso Kelouwani, and Alben Cardenas. Non-intrusive load monitoring through home energy management systems: A comprehensive review. *Renewable and Sustainable Energy Reviews*, 79:1266–1274, 2017.

[283] Gabe Cohn, Sidhant Gupta, Jon Froehlich, Eric Larson, and Shwetak N Patel. Gassense: Appliance-level, single-point sensing of gas activity in the home. In *International Conference on Pervasive Computing*, pages 265–282. Springer, 2010.

[284] Fadi Shrouf, Joaquin Ordieres, and Giovanni Miragliotta. Smart factories in industry 4.0: A review of the concept and of energy management approached in production based on the internet of things paradigm. In *Industrial Engineering and Engineering Management (IEEM), 2014 IEEE International Conference on*, pages 697–701. IEEE, 2014.

[285] Chris A Mack. Fifty years of moore's law. *IEEE Transactions on semiconductor manufacturing*, 24(2):202–207, 2011.

[286] Bradley T Richards and Haydn NG Wadley. Plasma spray deposition of tri-layer environmental barrier coatings. *Journal of the European Ceramic Society*, 34(12):3069–3083, 2014.

[287] Xiaoyu Yan and Adam M Boies. Quantifying the uncertainties in life cycle greenhouse gas emissions for uk wheat ethanol. *Environmental Research Letters*, 8(1):015024, 2013.

[288] Erin Baker, Valentina Bosetti, Laura Diaz Anadon, Max Henrion, and Lara Aleluia Reis. Future costs of key low-carbon energy technologies: Harmonization and aggregation of energy technology expert elicitation data. *Energy Policy*, 80:219–232, 2015.

[289] Kevin Newman, John Kargul, and Daniel Barba. Benchmarking and modeling of a conventional mid-size car using alpha. Technical report, SAE Technical Paper, 2015.

[290] Energy Department for Business and Industrial Strategy. Greenhouse gas reporting - conversion factors 2013, 2013.

[291] Travis E Oliphant. *A guide to NumPy*, volume 1. Trelgol Publishing USA, 2006.

[292] David Gordon Wilson and Theodosios Korakianitis. *The design of high-efficiency turbomachinery and gas turbines*. MIT press, 2014.

[293] Saravanamutto HIH, Henry Cohen, Gordon Frederick Crichton Rogers, and Herbert Ian Howard Saravanamuttoo. *Gas turbine theory*. Pearson Prentice Hall, 6th edition, 2009.

[294] Gas turbine world handbook 2014-2015.

[295] RK Matta, GD Mercer, and RS Tuthill. *Power Systems for the 21st Century-" H" Gas Turbine Combined-Cycles*. GE Power Systems, 2000.

[296] RC Wilcock, JB Young, and JH Horlock. The effect of turbine blade cooling on the cycle efficiency of gas turbine power cycles. *Journal of Engineering for Gas Turbines and Power*, 127(1):109–120, 2005.

[297] Leroy H. Smith Jr. Axial Compressor Aerodesign Evolution at General Electric. *ASME J. Turbomachinery*, 124(3):321–330, 2002.

[298] H. Canière, A. Willockx, E. Dick, and M. De Paepe. Raising cycle efficiency by intercooling in air-cooled gas turbines. *Applied Thermal Engineering*, 26(16):1780–1787, 2006.

[299] CHEN Guang. Design characteristics of trent 1000. *Aeroengine*, 4:003, 2009.

[300] Paolo Chiesa, Stefano Consonni, Giovanni Lozza, and Ennio Macchi. Predicting the ultimate performance of advanced power cycles based on very high temperature gas turbine engines. In *ASME 1993 International Gas Turbine and Aeroengine Congress and Exposition*, pages V03AT15A074–V03AT15A074. American Society of Mechanical Engineers, 1993.

[301] David G. Goodwin, Harry K. Moffat, and Raymond L. Speth. Cantera: An object-oriented software toolkit for chemical kinetics, thermodynamics, and transport processes. http://www.cantera.org, 2017. Version 2.3.0.

[302] Paolo Chiesa and Ennio Macchi. A thermodynamic analysis of different options to break 60% electric efficiency in combined cycle power plants. In *ASME Turbo Expo 2002: Power for Land, Sea, and Air*, pages 987–1002. American Society of Mechanical Engineers, 2002.

[303] D. K. Hall, E. M. Greitzer, and C. S. Tan. Performance Limits of Axial Compressor Stages. *Volume 8: Turbomachinery, Parts A, B, and C*, page 479, 2012.

[304] D K Hall. *Performance Limits of Axial Turbomachine Stages*. PhD thesis, Massachusetts institute of technology, 2011.

[305] J Do Denton. Loss mechanisms in turbomachines. In *ASME 1993 International Gas Turbine and Aeroengine Congress and Exposition*, pages V002T14A001–V002T14A001. American Society of Mechanical Engineers, 1993.

[306] NA Cumpsty. Jet propulsion (a simple guide to the aerodynamic and thermodynamic performance of jet engines), 1997.

[307] USS ATMOSPHERE. *US standard atmosphere*. Washington DC: National Oceanic and Atmospheric Administration, 1976.

[308] Richard Avellán. *On the design of energy efficient aero engines: Some recent innovations*. Chalmers University of Technology, 2011.

[309] J Whurr. Future civil aeroengine architectures and technologies, 2013.

[310] Ric Parker. From blue skies to green skies: engine technology to reduce the climate-change impacts of aviation. *Technology Analysis & Strategic Management*, 21(1):61–78, 2009.

[311] Mark D Guynn, Jeffrey J Berton, Eric S Hendricks, Michael T Tong, William J Haller, and Douglas R Thurman. Initial assessment of open rotor propulsion applied to an advanced single-aisle aircraft. In *Proceedings of the 11th AIAA Aviation Technology, Integration, and Operations Conference, Virginia Beach, VA, September*, pages 20–22, 2011.

[312] John Whurr and Jonathan Hart. A rolls-royce perspective on concepts and technologies for future green propulsion systems. *Encyclopedia of Aerospace Engineering*, 2010.

[313] Linda Larsson, Tomas Gronstedt, and Konstantinos G Kyprianidis. Conceptual design and mission analysis for a geared turbofan and an open rotor configuration. In *ASME 2011 Turbo Expo: Turbine Technical Conference and Exposition*, pages 359–370. American Society of Mechanical Engineers, 2011.

[314] S Arif Khalid, John P Wojno, Andy Breeze-Stringfellow, David P Lurie, Trevor H Wood, Kishore Ramakrishnan, and Umesh Paliath. Open rotor designs for low noise and high efficiency. In *ASME turbo expo 2013: turbine technical conference and exposition*, pages V06CT39A003–V06CT39A003. American Society of Mechanical Engineers, 2013.

[315] Dexin Wang, Rick Knight, Dennis Chojnacki, Peter Molvie, Boris Tynkov, and Dan Willems. Saving energy with the high efficiency super boiler. *Energy Engineering*, 105(3):38–48, 2008.

[316] Rinaldi Marchesi. Efficiency improvement of small boilers for domestic use: Energetic and exergetic analysis, 2007.

[317] V Ganapathy. *Industrial boilers and heat recovery steam generators: design, applications, and calculations*. CRC Press, 2002.

[318] S. Morrin. Field sampling of boilers - flue gas analysis - morrin ucd.

[319] VHK. Preparatory study on eco-design of ch-boilers, September 2007.

[320] J Kuck. Efficiency of vapour-pump-equipped condensing boilers. *Applied Thermal Engineering*, 16(3):233–244, 1996.

[321] Arden L Buck. New equations for computing vapor pressure and enhancement factor. *Journal of applied meteorology*, 20(12):1527–1532, 1981.

[322] P Rasmussen. „calculation of scop for heat pumps according to en 14825,". *Danish Technological Institute, Copenhagen*, 2011.

[323] Eurovent certified performance, 2018.

[324] James M Calm. The next generation of refrigerants–historical review, considerations, and outlook. *international Journal of Refrigeration*, 31(7):1123–1133, 2008.

[325] Björn Palm. Hydrocarbons as refrigerants in small heat pump and refrigeration systems–a review. *International journal of refrigeration*, 31(4):552–563, 2008.

[326] J Steven Brown, Samuel F Yana-Motta, and Piotr A Domanski. Comparitive analysis of an automotive air conditioning systems operating with CO_2 and r134a. *International Journal of refrigeration*, 25(1):19–32, 2002.

[327] HJ Van Gerner, G van Donk, A Pauw, and J van Es. A heat pump for space applications. *National Aerospace Laboratory*, 2015.

[328] J Steven Brown and Piotr A Domanski. Review of alternative cooling technologies. *Applied Thermal Engineering*, 64(1-2):252–262, 2014.

[329] Andrej Kitanovski, Uroš Plaznik, Urban Tomc, and Alojz Poredoš. Present and future caloric refrigeration and heat-pump technologies. *International Journal of Refrigeration*, 57:288–298, 2015.

[330] M Ožbolt, A Kitanovski, J Tušek, and A Poredoš. Electrocaloric refrigeration: thermodynamics, state of the art and future perspectives. *International journal of refrigeration*, 40:174–188, 2014.

[331] Ian Bell. Air conditioning and heat pump software.

[332] Ian H Bell, Sylvain Quoilin, Jorrit Wronski, and Vincent Lemort. Coolprop: An open-source reference-quality thermophysical property library. In *ASME ORC 2nd International Seminar on ORC Power Systems*, 2013.

[333] M Mi Shah. A general correlation for heat transfer during film condensation inside pipes. *International Journal of heat and mass transfer*, 22(4):547–556, 1979.

[334] Theodore L Bergman, Frank P Incropera, Adrienne S Lavine, and David P Dewitt. *Introduction to heat transfer*. John Wiley & Sons, 2011.

[335] Duncan Chisholm. A theoretical basis for the lockhart-martinelli correlation for two-phase flow. *International Journal of Heat and Mass Transfer*, 10(12):1767–1778, 1967.

[336] Pekka Röyttä, Teemu Turunen-Saaresti, and Juha Honkatukia. Optimising the refrigeration cycle with a two-stage centrifugal compressor and a flash intercooler. *international journal of refrigeration*, 32(6):1366–1375, 2009.

[337] Jurg Schiffmann and Daniel Favrat. Design, experimental investigation and multi-objective optimization of a small-scale radial compressor for heat pump applications. *Energy*, 35(1):436–450, 2010.

[338] Jonna Tiainen, Ahti Jaatinen-Värri, Aki Grönman, Tore Fischer, and Jari Backman. Loss development analysis of a micro-scale centrifugal compressor. *Energy Conversion and Management*, 166:297–307, 2018.

[339] C Rodgers. The efficiencies of single-stage centrifugal compressors for aircraft applications. In *ASME 1991 International Gas Turbine and Aeroengine Congress and Exposition*, pages V001T01A025–V001T01A025. American Society of Mechanical Engineers, 1991.

[340] Giovanni Ferrara, Lorenzo Ferrari, Daniele Fiaschi, Giovanni Galoppi, Sotirios Karellas, Riccardo Secchi, and Duccio Tempesti. A small power recovery expander for heat pump cop improvement. *Energy Procedia*, 81:1151–1159, 2015.

[341] LG Hays and JJ Brasz. Two-phase turbines for compressor energy recovery. *International Compressor Engineering Conference*, 1996.

[342] Ian K Smith, Nikola Stosic, and Ahmed Kovacevic. Power recovery from low cost two-phase expanders. *Transactions-Geothermal Resources Council*, pages 601–606, 2001.

[343] European Standards. Set din en 14511- standards for air conditioners.

[344] Siddha Pimputkar, James S Speck, Steven P Denbaars, and Shuji Nakamura. Prospects for LED lighting. *nature photonics www.nature.com/naturephotonics*, 3, 2009.

[345] Thomas W. Murphy. Maximum spectral luminous efficacy of white light. *Journal of Applied Physics*, 111(10), 2012.

[346] Thomas M. Katona, P. Morgan Pattison, and Steve Paolini. Status of Solid State Lighting Product Development and Future Trends for General Illumination. *Annual Review of Chemical and Biomolecular Engineering*, 7(1):263–281, 2016.

[347] Roland Haitz and Jeffrey Y Tsao. Solid-state lighting:'the case'10 years after and future prospects. *physica status solidi (a)*, 208(1):17–29, 2011.

[348] Kelsey Stober. Solid-state lighting 2017 suggested research topics supplement: Technology and market context. Technical report, 2017.

[349] Eric Bretschneider. Efficacy limits for solid-state white light sources. *Photonics Spectra*, 41(3):72–74, 2007.

[350] DIAL. Efficiency of LEDs: The highest luminous efficacy of a white LED.

[351] Po-Chieh Hung and Jeffrey Y. Tsao. Maximum White Luminous Efficacy of Radiation Versus Color Rendering Index and Color Temperature: Exact Results and a Useful Analytic Expression. *Journal of Display Technology*, 9(6):405–412, jun 2013.

[352] Jin Xue, Zheng Li, and Rajeev J Ram. Irreversible Thermodynamic Bound for the Efficiency of Light-Emitting Diodes. *Physical review applied*, 2017.

[353] Aurelien David, Christophe A Hurni, Nathan G Young, and Michael D Craven. Electrical properties of III-Nitride LEDs: Recombination-based injection model and theoretical limits to electrical efficiency and electroluminescent cooling. *Citation: Appl. Phys. Lett*, 109(083501), 2016.

[354] Parthiban Santhanam, Dodd Joseph Gray Jr, and Rajeev J Ram. Thermoelectrically pumped light-emitting diodes operating above unity efficiency. *Physical Review Letters*, 108(9):097403, 2012.

[355] Jin Xue. *Towards the efficiency limit of visible light-emitting diodes*. PhD thesis, Massachusetts Institute of Technology, 2017.

[356] Pierre Leduc, Benjamin Dubar, Alain Ranini, and Gaëtan Monnier. Downsizing of gasoline engine: an efficient way to reduce CO_2 emissions. *Oil & gas science and technology*, 58(1):115–127, 2003.

[357] Masahisa Yamakawa, Takashi Youso, Tatsuya Fujikawa, Toshiaki Nishimoto, Yoshitaka Wada, Kiyotaka Sato, and Hideaki Yokohata. Combustion technology development for a high compression ratio si engine. *SAE International Journal of Fuels and Lubricants*, 5(2011-01-1871):98–105, 2011.

[358] US DOE Vehicle Technology Office. Diverging Trends of Engine Compression Ratio and Gasoline Octane Rating, 2016.

[359] Oscar Delgado and Nic Lutsey. The us supertruck program: Expediting the development of advanced heavy-duty vehicle efficiency technologies. *International Council on Clean Transportation, San Francisco, CA*, 2014.

[360] Daniel Mohr, Timothy Shipp, and Xueting Lu. The thermodynamic design, analysis and test of cummins' supertruck 2 50% brake thermal efficiency engine system. Technical report, SAE Technical Paper, 2019.

[361] MA Ceviz and I Kaymaz. Temperature and air–fuel ratio dependent specific heat ratio functions for lean burned and unburned mixture. *Energy Conversion and Management*, 46(15):2387–2404, 2005.

[362] Noam Lior and George J Rudy. Second-law analysis of an ideal otto cycle. *Energy conversion and management*, 28(4):327–334, 1988.

[363] S Einecke, C Schulz, and V Sick. Measurement of temperature, fuel concentration and equivalence ratio fields using tracer lif in ic engine combustion. *Applied Physics B*, 71(5):717–723, 2000.

[364] Victor W Wong and Simon C Tung. Overview of automotive engine friction and reduction trends–effects of surface, material, and lubricant-additive technologies. *Friction*, 4(1):1–28, 2016.

[365] Pedro Luis Curto-Risso, A Medina, and A Calvo Hernández. Theoretical and simulated models for an irreversible otto cycle. *Journal of Applied Physics*, 104(9):094911, 2008.

[366] Fernando Angulo-Brown, J Fernandez-Betanzos, and CA Diaz-Pico. Compression ratio of an optimized air standard otto-cycle model. *European journal of physics*, 15(1):38, 1994.

[367] SA Klein. An explanation for observed compression ratios in internal combustion engines. *Journal of engineering for gas turbines and power*, 113(4):511–513, 1991.

[368] Vladimir N Orlov and R Stephen Berry. Power and efficiency limits for internal combustion engines via methods of finite-time thermodynamics. *Journal of applied physics*, 74(7):4317–4322, 1993.

[369] Xiaoyong Qin, Lingen Chen, Fengrui Sun, and Chih Wu. The universal power and efficiency characteristics for irreversible reciprocating heat engine cycles. *European journal of physics*, 24(4):359, 2003.

[370] Rahim Ebrahimi. Effects of mean piston speed, equivalence ratio and cylinder wall temperature on performance of an atkinson engine. *Mathematical and Computer Modelling*, 53(5):1289–1297, 2011.

[371] Yanlin Ge, Lingen Chen, and Fengrui Sun. Finite time thermodynamic modeling and analysis for an irreversible atkinson cycle. *Thermal Science*, 14(4):887, 2010.

[372] R.M. Wagner J.A. Caton C.S. Daw, R.L. Graves. Report on the transportation combustion engine efficiency colloquium held at USCAR. *Oak Ridge National Laboratories*, October 2010.

[373] K Dean Edwards, Robert M Wagner, TE Briggs, and Tim J Theiss. Defining engine efficiency limits. In *17th DEER Conference, Detroit, MI, October*, pages 3–6, 2011.

[374] Haifeng Liu, Junsheng Ma, Laihui Tong, Guixiang Ma, Zunqing Zheng, and Mingfa Yao. Investigation on the potential of high efficiency for internal combustion engines. *Energies*, 11(3):513, 2018.

[375] Environmental Protection Agency. Final rule for greenhouse gas emissions and fuel efficiency standards for medium- and heavy-duty engines and vehicles, 2016.

[376] SL Miller, MN Svrcek, KY Teh, and CF Edwards. Assessing the feasibility of increasing engine efficiency through extreme compression. *International Journal of Engine Research*, 12(3):293–307, 2011.

[377] Imdat Taymaz. An experimental study of energy balance in low heat rejection diesel engine. *Energy*, 31(2-3):364–371, 2006.

[378] Jerald A Caton. The thermodynamic characteristics of high efficiency, internal-combustion engines. *Energy Conversion and Management*, 58:84–93, 2012.

[379] Kenneth Holmberg, Peter Andersson, and Ali Erdemir. Global energy consumption due to friction in passenger cars. *Tribology International*, 47:221–234, 2012.

[380] Habib Aghaali and Hans-Erik Ångström. A review of turbocompounding as a waste heat recovery system for internal combustion engines. *Renewable and sustainable energy reviews*, 49:813–824, 2015.

[381] Charles Sprouse III and Christopher Depcik. Review of organic rankine cycles for internal combustion engine exhaust waste heat recovery. *Applied thermal engineering*, 51(1-2):711–722, 2013.

[382] John R Armstead and Scott A Miers. Review of waste heat recovery mechanisms for internal combustion engines. *Journal of Thermal Science and Engineering Applications*, 6(1):014001, 2014.

[383] Dimitrios Hountalas and Georgios Mavropoulos. Potential for improving hd diesel truck engine fuel consumption using exhaust heat recovery techniques. In *New trends in technologies: devices, computer, communication and industrial systems*. InTech, 2010.

[384] J. Fong P. Fonseca A. T. de Almeida, F. J. T. E. Ferreira. Energy using products lot 11 motors - final preparatory study, 2008.

[385] Aníbal T de Almeida, Paula Fonseca, and Paolo Bertoldi. Energy-efficient motor systems in the industrial and in the services sectors in the European Union: characterisation, potentials, barriers and policies. *Energy*, 28(7):673–690, June 2003.

[386] Chun Chun Ni. Potential energy savings and reduction of CO_2 emissions through higher efficiency standards for polyphase electric motors in japan. *Energy policy*, 52:737–747, 2013.

[387] Mitchell Rosenberg. The united states motor systems baseline: Inventory and trends. In *Energy Efficiency Improvements in Electric Motors and Drives*, pages 37–60. Springer, 1997.

[388] Jordi-Roger Riba, Carlos López-Torres, Luís Romeral, and Antoni Garcia. Rare-earth-free propulsion motors for electric vehicles: A technology review. *Renewable and Sustainable Energy Reviews*, 57:367–379, 2016.

[389] Juan De Santiago, Hans Bernhoff, Boel Ekergård, Sandra Eriksson, Senad Ferhatovic, Rafael Waters, and Mats Leijon. Electrical motor drivelines in commercial all-electric vehicles: A review. *IEEE Transactions on Vehicular Technology*, 61(2):475–484, 2012.

[390] IEC. Iec 60034-30-1: standard on efficiency classes for low voltage ac motors, 2014.

[391] Standard format for iec standards - learning from motor standards for other electric equipment.

[392] Austin Hughes and Bill Drury. *Electric motors and drives: fundamentals, types and applications*. Newnes, 2013.

[393] Marcel Jufer. *Motors: Characterization*, chapter 5, pages 87–100. Wiley, 1st edition, 2005.

[394] AI De Almeida, Fernando JTE Ferreira, John F Busch, and Pierre Angers. Comparative analysis of ieee 112-b and iec 34-2 efficiency testing standards using stray load losses in low-voltage three-phase, cage induction motors. *IEEE Transactions on industry applications*, 38(2):608–614, 2002.

[395] Aldo Boglietti, Andrea Cavagnino, Luca Ferraris, and Mario Lazzari. Induction motor equivalent circuit including the stray load losses in the machine power balance. *IEEE Transactions on Energy Conversion*, 23(3):796–803, 2008.

[396] Juha Pyrhonen, Tapani Jokinen, and Valéria Hrabovcová. *Design of rotating electrical machines*. John Wiley & Sons, 2009.

[397] EN 50347. General purpose three-phase induction motors having standard dimensionsand outputs—frame numbers 56 to 315 and flange numbers 65 to 740, 2001.

[398] Aníbal T de Almeida, Fernando JTE Ferreira, and Ge Baoming. Beyond induction motors—technology trends to move up efficiency. *IEEE Transactions on Industry Applications*, 50(3):2103–2114, 2014.

[399] Anibal T De Almeida, Fernando J T E Ferreira, and Joao a C Fong. Standards for Efficiency of Electric Motors. *IEEE Industry Applications Magazine*, 17(1):12–19, 2011.

[400] Renyuan Tang, Wenming Tong, and Xueyan Han. Overview on amorphous alloy electrical machines and their key technologies. *Chinese Journal of Electrical Engineering*, 2(1):1–12, 2016.

[401] Hiroaki Hayashi, Kensaku Nakamura, Akira Chiba, Tadashi Fukao, Kanokvate Tungpimolrut, and David G Dorrell. Efficiency improvements of switched reluctance motors with high-quality iron steel and enhanced conductor slot fill. *IEEE Transactions on Energy Conversion*, 24(4):819–825, 2009.

[402] J. Ostrower. Ge plans 10% fuel burn improvement for ge9x engine. *Flight Global*, 2012.

[403] Aalto University. Engine design, March 2017.

[404] Commission regulation 2016/2281 implementing directive 2009/125/ec of the european parliament and of the council establishing a framework for the setting of ecodesign requirements for energy-related products, with regard to ecodesign requirements for air heating products, cooling products, high temperature process chillers and fan coil units, November 2016.

[405] Don MacKenzie and John B Heywood. Quantifying efficiency technology improvements in US cars from 1975–2009. *Applied Energy*, 157:918–928, 2015.

[406] Reiner Kümmel and Dietmar Lindenberger. How energy conversion drives economic growth far from the equilibrium of neoclassical economics. *New Journal of Physics*, 16(12):125008, 2014.

[407] Blake Alcott. Impact caps: why population, affluence and technology strategies should be abandoned. *Journal of Cleaner Production*, 18(6):552–560, 2010.

[408] Kelly Sims Gallagher, Arnulf Grübler, Laura Kuhl, Gregory Nemet, and Charlie Wilson. The energy technology innovation system. *Annual Review of Environment and Resources*, 37:137–162, 2012.

[409] Lew Fulton, Pierpaolo Cazzola, and François Cuenot. IEA mobility model (momo) and its use in the etp 2008. *Energy Policy*, 37(10):3758–3768, 2009.

[410] Niall Mac Dowell, Paul S Fennell, Nilay Shah, and Geoffrey C Maitland. The role of co 2 capture and utilization in mitigating climate change. *Nature Climate Change*, 7(4):243, 2017.

[411] IEA. Energy technology perspectives2017, restricted access area, 2017.

[412] International Energy Agency. Energy efficiency indicators 2018 edition - database documentation, 2018.

[413] R Edwards, JF Larivé, D Rickeard, H Hass, L Lonza, and H Maas. Well-to-wheels report version 4a. jec well-to-wheels analysis. well-to-wheels analysis of future automotive fuels and powertrains in the european context. *JRC technical reports*, pages 1–98, 2014.

[414] Oscar Delgado, Josh Miller, Ben Sharpe, and Rachel Muncrief. Estimating the fuel efficiency technology potential of heavy-duty trucks in major markets around the world. *Working Paper*, (14), 2016.

[415] Tristan Smith, C Raucci, S Haji Hosseinloo, I Rojon, J Calleya, S De La Fuente, P Wu, and K Palmer. CO_2 emissions from international shipping. possible reduction targets and their associated pathways. *UMAS: London, UK*, 2016.

[416] Tristan Smith, C Raucci, S Haji Hosseinloo, I Rojon, J Calleya, S De La Fuente, P Wu, and K Palmer. CO_2 emissions from international shipping. possible reduction targets and their associated pathways. appendix b – technology and operational intervention assumptions. *UMAS: London, UK*, 2016.

[417] International Air Transport Association et al. The IATA technology roadmap report, 2009.

[418] DLR IATA and Georgia Tech. IATA Technology Roadmap. Technical report, Technical report, IATA, 2013.

[419] International Energy Agency. The future of cooling - opportunities for energyefficient air conditioning. *IEA*, 2018.

[420] UNFCC. Determination of standardized baselines for energy-efficient refrigerators and air-conditioners. *CLEAN DEVELOPMENT MECHANISM*, 2017.

[421] Kamal Soundararajan, Hiang Kwee Ho, and Bin Su. Sankey diagram framework for energy and exergy flows. *Applied energy*, 136:1035–1042, 2014.

[422] Victor Veefkind, J Hurtado-Albir, S Angelucci, K Karachalios, and N Thumm. A new epo classification scheme for climate change mitigation technologies. *World Patent Information*, 34(2):106–111, 2012.

[423] US Patents and Trademark Office. Patents view, 2019.

[424] Lisa Nabitz, Patrick Plötz, Sibylle Braungardt, and Matthias Reuter. Measuring policy-driven innovation in energy efficiency. Technical report, Fraunhofer ISI Discussion Papers Innovation Systems and Policy Analysis, 2016.

[425] European Commission. Proposal for a regulation setting CO_2 emission performance standards for new heavy-duty vehicles, 2018.

[426] International Energy Agency. Tracking clean energy progress - informing energy sector transformations, 2018.

[427] Energy Efficiency Directive. Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on energy efficiency. *Official Journal*, 315:1–56, 2012.

[428] Unità Tecnica Efficienza Energetica. Valutazione di indici di prestazioni energetiche per i settori: fonderie, ceramica e produzione della carta. Technical report, ENEA, 2017.

[429] European Commission. Amending Regulation (EU) 2017/1151 for the purpose of introducing devices for measuring the consumption of fuel and energy as a requirement for type approval, 2017.

[430] EU. Regulation 2017/1369 of the european parliament and of the council of 4 july 2017 setting a framework for energy labelling and repealing directive 2010/30/eu. 2017.

[431] Technology Directorate of Sustainability and Outlooks. The future of cooling: opportunities for energy-efficient air conditioning. *International Energy Agency*, 2018.

[432] Richard Loulou, Amit Kanudia, Antti Lehtila, and Gary Goldstein. Documentation for the times model part ii. 2005.

[433] Ricardo Piedrahita, Katherine L Dickinson, Ernest Kanyomse, Evan Coffey, Rex Alirigia, Yolanda Hagar, Isaac Rivera, Abraham Oduro, Vanja Dukic, Christine Wiedinmyer, et al. Assessment of cookstove stacking in northern ghana using surveys and stove use monitors. *Energy for Sustainable Development*, 34:67–76, 2016.

[434] Center for Law and Social Policy. Policy.

[435] Clean cooking alliance. The clean cooking catalogue.

[436] Monica Coffano and Gianluca Tarasconi. Crios-patstat database: sources, contents and access rules. *Center for Research on Innovation, Organization and Strategy, CRIOS working paper*, (1), 2014.

[437] BRE. Product carachteristics database.

[438] Ali Aydemir, Konstantinos Braimakis, Clemens Rohde, Sotirios Karellas, and Berit Ostrander. Energy saving potentials for industrial steam boilers-findings from the ecodesign process. *Fraunhofer Institute for Systems and Innovation Research ISI in support of the European Commission DG-ENTR Preparatory Study on Steam Boilers*, 2015.

[439] Luc Vanwortswinkel and Wouter Nijs. Industrial combustion boilers. In *Energy Technology System Analysis Programme*. 2010.

[440] Environmental Protection Agency. Annual certification data for engines and equipment, 2017.

[441] Görkem Kökkülünk, Adnan Parlak, and Hasan Hüseyin Erdem. Determination of performance degradation of a marine diesel engine by using curve based approach. *Applied Thermal Engineering*, 108(Supplement C):1136 – 1146, 2016.

[442] Personal communication with engineer at rotax, 2017.

[443] C Brunner, P Waide, and M Jakob. Harmonized standards for motors and systems. global progress report and outlook. *Proc. 7th EEMODS*, pages 444–456, 2011.

[444] Anibal T De Almeida and Paula Fonseca. Characterization of EU motor use. In *Energy Efficiency Improvements in Electronic Motors and Drives*, pages 143–167. Springer, 2000.

[445] Armines. Entr lot 6: Air-conditioning and ventilation systems, 2012.

[446] BO Bolaji. Experimental study of r152a and r32 to replace r134a in a domestic refrigerator. *Energy*, 35(9):3793–3798, 2010.

[447] Xiao Wang, Jianlin Yu, Mengliu Zhou, and Xiaolong Lv. Comparative studies of ejector-expansion vapor compression refrigeration cycles for applications in domestic refrigerator-freezers. *Energy*, 70:635–642, 2014.

[448] Tobias Fleiter, Rainer Elsland, Matthias Rehfeldt, Jan Steinbach, Ulrich Reiter, Giacomo Catenazzi, Martin Jakob, C Rutten, R Harmsen, F Dittmann, et al. Profile of heating and cooling demand in 2015. *Heat Roadmap Europe Deliverable*, 3(1), 2017.

[449] Paul Waide and Satoshi Tanishima. Light's labour's lost. *International Energy Agency*, 9, 2006.

[450] Liz Waters. Energy consumption in the uk 2016 user guide, November 2016.

[451] Isabelle Albert and Jean-Baptiste Denis. Dirichlet and multinomial distributions: properties and uses in Jags. 2012.

Appendix A

Conversion device efficiency in the UK

Table A.1 Summary of conversion device efficiency for the UK. Median efficiency, efficiency range and assumed probability distribution are included.

Device	Sectors	Fuel	Efficiency	Range	Reference
Boiler	Residential	Gas	87%	85% - 88%	[437, 45]
	Services	Gas	91%	87% - 94%	[269]
		Oil	84%	80% - 87%	
		Coal	75%	71% - 78%	
	Industry	Gas	89%	83.6% - 93.6%	[438, 439]
		Oil	89%	83.6% - 93.6%	
		Coal	85%	80% - 90%	
		Biomass	70%	65% - 75%	
Diesel Engine	Industry	Oil	39%	36.5% - 41.5%	[440, 266]
	Road	Oil	27%	25% - 29%	[270]
	Navigation	Oil	39%	36.5% - 41.5%	[440, 441]
SI Engine	Aviation	Oil	27%	24.5% - 29.5%	[442]
	Light Duty	Oil	21%	19% - 23%	[270]
Gas Turbine	Industry	Oil	35%	33.5% - 36.5%	[294]
	Aviation	Oil	38%	36% - 39%	[272, 273]
Electric Motors	Residential	Electricity	74%	70% - 77%	[443, 45, 444]
	Services	Electricity	87%	85.4% - 89.4%	
	Industry	Electricity	87%	85% - 89%	
	Rail	Electricity	96%	95% - 97%	
Space Coolers	Residential	Electricity	228%	208% - 248%	[445, 323]
	Services	Electricity	368%	343% - 393%	
Process Coolers	Residential	Electricity	250%	200% - 300%	[446, 447]
	Services	Electricity	250%	200% - 300%	
	Industry	Electricity	310%	260% - 360%	[448]
Light Device	Residential	Electricity	6%	5% - 7%	[449, 45, 450]
	Services	Electricity	8%	6.9% - 8.9%	
	Industry	Electricity	13%	12% - 14%	

Appendix B

Dirichlet Distribution

Given a certain allocation vector α_e, with an uncertainty Y, the The Dirichlet distribution is parametrised follows [451];

$$p_e \sim \mathbf{Dir}(\alpha_e, m) \tag{B.1}$$

where p$_e$ are the outputs of the model for each end-use, α_e are the allocation proportions for each end-use, and m is the "concentration parameter". The expected value of the output parameters is equal to the shares of the input parameters such that

$$\mathrm{Exp}\left[p_e\right] = \alpha_e \tag{B.2}$$

$$\sum_e p_e = 1 \tag{B.3}$$

while the variance of the output parameters is defined in equation [451].

$$\mathrm{Var}\left[p_e\right] = \frac{\alpha_e(1-\alpha_e)}{m+1} \tag{B.4}$$

$$\tag{B.5}$$

The reference parameter α^* is the parameter such that the variance of its output is equal to the specified variance. If Y is the specified uncertainty for the allocation vector, then the variance of the reference parameter is defined as B.6

$$\mathrm{Var}\left[p^*\right] = \sqrt{\frac{Y\alpha^*}{2}} \tag{B.6}$$

Equation B.4 and equation B.6 can be combined to provide and expression for m such that the reference parameter will have the desired variance.

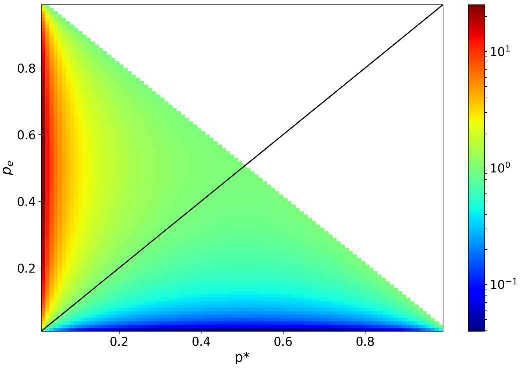


Fig. B.1 Ratio of the variance of output parameters p_e to the variance of the reference parameter $p*$. Only values such that pe+p*≤1 exist.

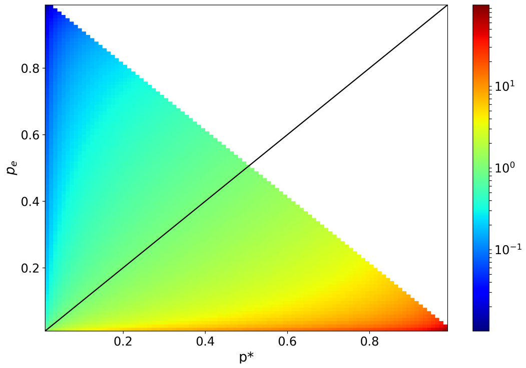


Fig. B.2 Ratio of the uncertainty of output parameters p_e to the uncertainty of the reference parameter $p*$. Only values such that pe+p*≤1 exist.

The variance of the other proportions p_e follow the equation

$$\mathrm{Var}\left[p_e\right] = \frac{\mathrm{Var}\left[p*\right]\alpha_e(1-\alpha_e)}{\alpha*(1-\alpha*)} \tag{B.7}$$

Therefore, the ratio (R$_v$) of the variance of each output e over the reference value * is given by equation B.8 and plotted in Figure B.1.

$$R_v = \frac{\alpha*(1-\alpha_e)}{\alpha_e(1-\alpha^*)} \tag{B.8}$$

Since uncertainty is defined as

$$Y = \frac{2\sigma}{\mu} \tag{B.9}$$

the ratio of uncertainties of each output e over the reference value * is given by equation B.10 and plotted in Figure B.2.

$$R_Y = \sqrt{\frac{\alpha_e(1-\alpha_e)}{\alpha^*(1-\alpha^*)}} \tag{B.10}$$

The contour plot in Figure B.1 shows that, when p* is larger than other p$_e$, the variance of other outputs p$_e$ is smaller than the reference value and vice versa. On the other hand, the uncertainty of p$_e$ is higher when p* > p$_e$ and vice versa, as can be seen in Figure B.1. Therefore, when the uncertainty U associated with an allocation vector is interpreted as the maximum uncertainty, $p^* = \min(p_e)$, while when U is the minimum uncertainty, $p^* = \max(p_e)$.

Therefore, to respect the rules defined in the Method's section, the specified allocation uncertainty (Y) is applied to the largest input share hence

$$\alpha^* = \max(\alpha_e) \tag{B.11}$$