Multi-period whole system optimisation of an integrated carbon dioxide capture, transportation and storage supply chain

by

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Abstract

Carbon dioxide capture and storage (CCS) is an essential part of the portfolio of technologies to achieve climate mitigation targets. Cost efficient and large scale deployment of CCS necessitates that all three elements of the supply chain (capture, transportation and storage) are co-ordinated and planned in an optimum manner both spatially and across time. However, there is relatively little experience in combining CO_2 capture, transport and storage into a fully integrated CCS system and the existing research and system planning tools are limited. In particular, earlier research has focused on one component of the chain or they are deterministic steady-state supply chain optimisation models. The very few multi-period models are unable to simultaneously make design and operational decisions for the three components of the chain. The major contribution of this thesis is the development for the first time of a multi-period spatially explicit least cost optimization model of an integrated CO_2 capture, transportation and storage infrastructure under both a deterministic and a stochastic modelling framework. The model can be used to design an optimum CCS system and model its long term evolution subject to realistic constraints and uncertainties. The model and its different variations are validated through a number of case studies analysing the evolution of the CCS system in the UK. These case studies indicate that significant cost savings can be achieved through a multi-period and integrated system planning approach. Moreover, the stochastic formulation of the model allows analysing the impact of a number of uncertainties, such as carbon pricing or plant decommissioning schedule, on the evolution of the CSS system. In conclusion, the model and the results presented in this thesis can be used for system planning purposes as well as for policy analysis and commercial appraisal of individual elements of the CCS network.

Declaration

This is to certify that:

1. The material contained within this thesis is my own work and other work is appropriately referenced.

2. This thesis is less than 100,000 words in length.

Nasim Elahi

Contents

Multi-period whole system optimisation of an integrated carbon dioxide capture, transport and storage supply chain i

Acknowledgements iii

Abstract iv

Declaration v

List of Figures 9

List of Tables 11

List of Abbreviations 12

Nomanclature 13

List of Publications 14

Chapter 1 Introduction 15

1.1 Evidence on climate change 15

1.2 Mitigation options 18

1.3 CCS contribution to climate change mitigation and its limitations 21

1.3.1 CO_2 capture and storage background 21

1.3.2 CCS' potential for contribution to climate change mitigation 22

1.3.3 CCS deployment barriers 23

1.4 CCS demonstration projects to date 26

1.5 Research goals and objectives 28

1.5.1 Multi-period least cost optimisation model of an integrated CCS network 29

1.5.2 Effects of market and leasing alternatives on the performance of complex CCS value chains 30

1.5.3 Multi-stage stochastic optimisation of CCS supply chains under uncertainty 31

1.6 Thesis structure 32

Chapter 2 Literature review 35

2.1 Components of the CCS supply chain 36

2.1.1 Carbon dioxide capture 37

2.1.2 Carbon dioxide transport 39

2.1.3 Carbon dioxide geological storage 40

2.2 Deterministic whole system supply chain optimisation 40

2.2.1 Steady state whole system supply chain optimisation 41

2.2.2 Multi-period whole system supply chain optimisation 54
2.3 Lessons learnt and gap in knowledge 63
Chapter 3 Multi-period deterministic optimisation of an integrated CCS supply chain 65
3.1 Optimisation framework 65
3.2 CCS supply chain issue, a Mixed Integer Linear Programming problem 66
3.3 MILP solvers and modelling languages 66
3.4 Spatial mapping of the supply chain elements 67
3.5 Techno-economic modelling of supply chain components 67
3.5.1 CO_2 capture 68
3.5.2 CO_2 storage 70
3.5.3 CO_2 transport 70
3.6 Mathematical model 73
3.6.1 Sets and indices 73
3.6.2 Input parameters 74
3.6.3 Integer variables 75
3.6.4 Binary variables 75
3.6.5 Constraints 76
3.6.6 Objective function 78
3.7 Case study: Development of an integrated minimum cost CCS supply chain in the UK up to year 2050 81
3.7.1 Scope of the case study 82
3.7.2 Results and discussion 86
3.8 Conclusion 90
Chapter 4 The effect of market and leasing conditions on the techno-economic performance of CO_2 transport and storage value chains 91
4.1 Real options analysis of CO_2 transport and geological storage chains 92
4.1.1 CO_2 storage life cycle cost modelling framework 93
4.2 Life cycle cost modelling of a single CCS value chain-anchor case 94
4.2.1 Key parameters and assumptions 95
4.2.2 Application of the CO_2 storage life cycle cost model- anchor case 98
4.2.3 Application of the multi-period CCS network model- anchor case 99
4.2.4 Sensitivity analysis of the integrated life cycle cost model 100
4.3 Life cycle cost modelling of CCS value chain-CNS multi-store case 100
4.3.1 Key parameters and assumptions 101
4.3.2 Evolution of the optimal CO_2 transport and storage network 103
4.3.3 Storage sites' leasing options 105
4.4 Conclusion 107
Chapter 5 Multi-stage stochastic optimisation of an integrated CO_2 capture, transportation and storage supply chain109

5.1 Optimisation under uncertainty- review of current methods 110
5.1.1 Literature review 112
5.1.2 Approaches suitable to modelling uncertainty in CCS supply chains 121
5.2 Mathematical model 121
5.2.1 Problem description 122
5.2.2 Sets and indices 122
5.2.3 Parameters 123
5.2.4 Variables 123
5.2.5 Constraints 124
5.2.6 Total cost of a scenario 126
5.2.7 Objective function 128
5.3 Flexible CCS development planning in the UK under carbon price uncertainty 128
5.3.1 Future carbon price trajectories 129
5.3.2 Scenario tree development 134
5.3.3 Results and discussion 136
5.3.4 CCS development in the UK under carbon price uncertainty 142
Chapter 6 Conclusions and recommendations for future work 147
6.1 Thesis objectives 148
6.2 Achievements 148
6.3 Summary of novel contributions 150
6.4 Recommendations for future work 151
6.4.1 Stochastic analysis of TCE options for management of UK CO_2 transport and storage networks 151
6.4.2 Minimum regret strategies for storage site portfolio development in the UK 152
References 153
Appendix A: Supply chain nodes – UK CCS case study 160
Appendix B: Capture cost parameters 162
Appendix C: Storage cost parameters 165
Appendix D: Transport cost parameters 167
Appendix E: IHS CERA cost index 168
Appendix F: Future inflation rates 171
Appendix G: Multi-period deterministic CCS planning in the UK 172
Appendix H: Longannet – Goldeneye single CCS value chain 177
Appendix I: Dynamic multi-storage Central-North Sea CCS case 179
Appendix J: Flexible stochastic CCS supply chain optimization – UK case study 185

List of Figures

Figure 2.1 Schematic view of CCS supply chain 36

Figure 2.2 CO_2 capture concepts..38

Figure 2.3 The simCCS modelling process. (a) GIS cost surface; (b) potential pipeline routes and network-thinning interface; (c) post-thinning simplified network; (d) cost and capacity data; and (e) optimal CCS infrastructure results. 48

Figure 2.4 Pipeline costs ($/km/tonne of CO_2) for ten pipeline capacities 48

Figure 2.5 piecewise linearization of the onshore transport cost function 52

Figure 2.6 Superstructure of a multi-period hydrogen supply chain model 55

Figure 2.7 Pipeline investment cost vs. Pipeline diameter and geography...59

Figure 3.1 Total pipeline transport cots on per km basis vs. Annual mass flow rate. 72

Figure 3.2 Piecewise linearization of the onshore transport cost function. 73

Figure 3.3 Selected source‘ shares of total emission by asset class...83

Figure 3.4 Sources and sinks of the UK CCS scenario and the assumed gas lines 85

Figure 3.5 The UK's gas infrastructure (National grid) 85

Figure 3.6 UK CCS network under a capture target of 27MtCO_2 per year (2010-2020).......................86

Figure 3.7 UK CCS network under a capture target of 54MtCO_2 per year (2020-2030).......................87

Figure 3.8 UK CCS network under a capture target of 81MtCO_2 per year (2030-2040).......................87

Figure 3.9 UK CCS network under a capture target of 108MtCO_2 per year (2040-2050)....................88

Figure 4.1 The life cycle of a CO_2 storage project 93

Figure 4.2 Life cycle cost modelling framework implemented 94

Figure 4.3 the Longannet-Goldeneye CCS chain 95

Figure 4.4 CO_2 storage cost analysis - anchor case 96

Figure 4.5 The life cycle cash flow of CO_2 storage at Goldeneye -anchor case 98

Figure 4.6 Total capital and operational costs of transport at each time period – anchor case 99

Figure 4.7 Analysis of a single chain CCS system's levelised costs–anchor case........................100

Figure 4.8 CO_2 storage sites selected for the Central North Sea multi-storage scenario..................101

Figure 4.9 The evolution of the optimised CO_2 transportation and storage network- multi-store ...104

Figure 4.10 CO_2 transportation network cash flow with a 15% IRR CNS multi-store scenario.........107

Figure 5.1 EUA spot prices between 2005 and 2013 130

Figure 5.2 Carbon price scenario tree – Stochastic modelling of CCS supply chains in the UK 135

Figure 5.3 Simplified carbon price scenario tree – Stochastic modelling of CCS supply chains 136

Figure 5.4 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K7.......138

Figure 5.5 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K8.......139

Figure 5.6 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K9.......140

Figure 5.7 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K10.....142

Figure 5.8 Evolution of price of carbon ($/tonne) throug the four stages – Scenarios K7 to K11.....143

Figure 5.9 Total cost of carbon credits vs.CCS through the four stages – Scenarios K7 to K11 143

Figure 5.10 Role of CCS through the four stages– Scenarios K7 to K11 145

Figure E-1: IHS CERA upstream capital cost index. Onshore/offshore pipeline and LNG projects....168

Figure E-2: IHS CERA upstream operating cost index.Onshore/offshore pipeline and LNG projects 168

Figure E-3: IHS CERA European power capital cost index. Power generation points 169

Figure E-4: IHS CERA downstream capital cost index. Refinery and petrochemical construction 169

Figure E-5: IHS CERA upstream capital cost index. Oil and gas fields 170

Figure I-1: (a) Open season leasing cash flow per storage site during the planning horizon (2011 to 2050); (b) Auctioning with reserve price leasing cash flow per storage site during the planning horizon (2011 to 2050); (c) Dependence on market conditions leasing cash flow per storage site during the planning horizon (2011 to 2050)...184

List of Tables

Table 3-1 Average costs of the CCS components 89

Table 3-2 Cost per unit of mitigated CO_2 during time period T..89

Table 3-3 Summary of computational results 89

Table 4-1 Key parameters considered for the CO_2 storage anchor case [22] 95

Table 4-2 Assumptions used to calculate the annualised transport capital cost per km 97

Table 4-3 Capital cost of the segments of the CO_2 transport line 97

Table 4-4 Assumptions used to calculate the annual transport operational cost per km 97

Table 4-5 Breakdown of the transport operational cost 97

Table 4-6 Storage sites considered in the multi-store scenario 101

Table 4-7 CO_2 emission sources considered in the multi-store scenario 102

Table 4-8 Amount of CO_2 captured at each source at each time period – multi-store scenario 103

Table 4-9 Amount of CO_2 stored at each storage site at each time period – multi-store scenario....104

Table 4-10 Average cost of the components of CCS supply chain– CNS multi-store scenario 105

Table 4-11 Average cost of the CCS components at each time period– CNS multi-store scenario....105

Table 4-12 Storage sites' performance under alternative leasing conditions..................................106

Table 5-1 Reference scenarios to assess the main policy options with respect to targets.... 132

Table 5-2 Carbon prices for energy intensive industries under scenarios with reference settings ...134

Table 5-3 Average costs of the CCS components 145

Table 5-4 Cost per unit of mitigated CO_2 during stage s for each scenario.......................................146

Table 5-5 Summary of computational results 146

Table A-1: Sources, sinks and dummy nodes considered in the multi-period case study................160

Table B-1: Cost estimates for capture facilities on coal plants...162

Table B-2: Cost estimates for capture facilities on CCGT and CHP plants 162

Table B-3: Cost estimates for capture facilities on steel manufacturing plants 163

Table B-4: Cost estimates for capture facilities on cement manufacturing plants 163

Table B-5: Summary of CO2 capture plants' cost estimates 164

Table C-1: Injection infrastructure cost estimates 165

Table C-2: Summary of storage costs estimates 165

Table D-1: Slopes of the linearised segments of the transport cost curve......................................167

Table D-2: Intercepts of the linearised segments of the transport cost curve.................................167

Table D-3: Maximum flow rates corresponding to the linearised segments of transport curve 167

Table F-1: U.S. Treasuries..171

Table F-2: U.S. Inflation Indexed Treasuries...171

Table F-3: U.S. Inflation rates corresponding to the time periods of the UK case study chapter 3 ..171

Table G-1: CO_2 captured (Mt/year) from surcces of the multiperiod UK case study 172

Table G-2: CO_2 stored (Mt/year) at sinks of the multi-period UK case study 172

Table G-3: CO_2 transported (Mt/year) between nodes of the multi-period UK case study 173

Table H-1: Coordinates and elevation of the supply chain nodes – Goldeneye anchor case 177

Table H-2: Life cycle costs (kEur) of CO_2 storage– Goldeneye anchor case............................177

Table H-3: Average cost of the supply chain components– Goldeneye anchor case 178

Table H-4: Total annual transport cost– Goldeneye anchor case 178

Table I-1: Supply chain nodes – CNS multi-storage case 179

Table I-2: Fixed storage cost parameters used in the GAMS models 179

Table I-3: Variable storage cost parameters used in the GAMS models 179

Table I-4: Time of construction and NPV of accumulated capital cost of transport links 180

Table I-5: CO_2 flow rate and NPV of accumulated operational cost of transport............................180

Table I-6: CO_2 transportation network cash flow with a 15% IRR – CNS multi-storage case 182

Table J-1: CO_2 captured at each source for scenario k of stage s 185

Table J-2: CO_2 stored at each sink for scenario k of stage s 186

Table J-3: CO_2 transported from node i to node j for scenario k of stage s.....................................186

Table J-4: Contribution of CCS and carbon credits to the reduction target for each scenario 190

Table J-5: Evolution of carbon price and the role of CCS vs. Carbon credits for pathway K7 -K11...191

Table J-6: Evolution of cost of CCS vs. Cost of carbon credits for pathway K7 -K11................192

List of Abbreviations

CCS	Carbon dioxide capture and storage
GHG	Greenhouse gas
IPCC	Intergovernmental Panel on Climate Change
IEA	International Energy Agency
CCGT	Combined cycle gas turbine
CHP	Combined heat and power
PCC	Post combustion capture
WEO	World Energy Outlook
ZEP	Zero Energy Platform
2DS	An energy system scenario described by the International describes an energy which is consistent with an emissions trajectory that recent climate science research indicates would give an 80% chance of limiting average global temperature increase to 2°C
OECD	Organisation for Economic Co-operation and Development
EMR	Electricity Market Reform
CfD	Contract for Difference
EU ETS	The EU Emissions Trading System
EPS	Emissions Performance Standard
CAPPCCO	The Chinese Advanced Power Plant Carbon Capture Options project

UNFCCC	The United Nation's Framework Convention on Climate Change

Nomanclature

Scalars

R	Discount rate
cut-off	Maximum distance (km) above which nodes i and j cannot be directly connected

Parameters

x(i)	X coordinate of cell i
y(i)	Y coordinate of cell i
d(i,j)	Distance (km) between cells i and j
ΔCAPEX(p,l)	Annual capital cost (M$/km/year) relevant to segment l, phase p of pipeline cost curve
slope (p,l)	Annual operational cost (M$/km/Mt$CO_2$/year) of transporting a unit of CO_2 over a kilometre (Slope relevant to segment l, phase p of pipeline cost curve)
ftc(p,l,t)	Fixed cost (M$) of building pipeline of segment l at time period t to transport of CO_2 in phase p
vtc(p,l,t)	Operational cost of transporting a unit of CO_2 every year in phase p using pipeline of segment l for all years in time period t
Qmax(p,l)	Maximum flow rate (MtCO_2/year) relevant to phase p of CO_2 segment l of pipeline cost curve
a(i,t)	Annual CO_2 emission at node i at time t
ΔCAPEXcapture	Annual capital cost (M$/year) of retrofitting a source with capture facility
ΔOPEXcapture	Annual operational cost (M$/Mt/year) of capturing a unit of CO_2
fcc(i,t)	Fixed capital cost (M$) of retrofitting source i with capture facility at the beginning of time period t
vcc(i,t)	Operational cost (M$) of capturing a unit of CO_2 every year at source i for all years in time period t
b(i)	Maximum capacity at node i
ΔCAPEXstorage	Annual capital cost (M$/year) of building storage facility
ΔOPEXstorae	Annual operational cost (M$/Mt/year) of injecting a unit of CO_2
fsc(i,t)	Fixed capital cost (M$) of building storage facility at sink i at the beginning of time period t
vsc(i,t)	Operational cost (M$) of injecting a unit of CO_2 every year at sink i for all years in time period t
Ct(t)	CO_2 capture target at time period t
Leng(t)	Length of time period t
Capture_efficiency	Maximum fraction of emissions which can be captured

Continuous variables

C(i,t)	Annual amount of CO_2 captured at node i at time t
S(i,t)	Annual amount of CO_2 injected into node i at time t
Q(i,j,p,l,t)	Annual CO_2 flow rate through pipeline relevant to segment l of the linearised transport cost curve, in phase p, between cells i and j at time t
Z	Net present value of the total CCS over the planning horizon summed over all nodes
nx(i,j,p,l,t)	Total number of pipelines of segment l and phase p built between i and j up to and during time t
usedcap(i,t)	Total amount of CO_2 stored in node i prior to time t

Binary variables

xt(i,j,p,l,t)	1 if a pipeline relevant to segment l, phase p is built at time t between nodes i and j, 0 otherwise
xcap(i,t)	1 if a capture facility is built at node i, 0 otherwise
nxcap(i,t)	1 if a capture facility has been built at node i at or prior to time period t, 0 otherwise
xstor(i,t)	1 if a storage facility is built at node i at time t
nxstor(i,t)	1 if a storage facility has been built at node i at or prior to time period t, 0 otherwise

List of Publications

Elahi N., Shah N., Durucan S., Korre A., "Multi-period least-cost optimisation model of an integrated carbon dioxide capture, transportation and storage infrastrucutre in the UK", 12th Greenhouse Gas Control Technologies (GHG12), Austin, TX, United States, Oct2014, (to be published in Energy Procedia)

Korre A, **Elahi N**., Nie Z., Durucan S., Shah N., Ahmad S., Goldthorpe W., "The effects of market and leasing conditions on the techno-economic performance of complex CO_2 transport and storage value chains" 12th Greenhouse Gas Control Technologies (GHG12), Austin, TX, United States, Oct 2014, (to be published in Energy Procedia)

Elahi N., Shah N., Durucan S., Korre A., "Multi-period stochastic optimization model for integrated CCS supply chain under carbon price uncertainty" 11th Internation conference on Computational Management Science, Lisbon, Portugal, May 2014.

Relevant Industry Reports

"Preliminary analysis of the influence of leasing alternatives on the cash flow of a CCS value chain, Real options optimisation feasibility", Korre A, Elahi N., Nie Z., Shah N., Durucan S., Pan I., A report elaborated by Imerial College for the Crown Estate, Nov 2013.

"Multi-stage stochastic optimisation of CO_2 storage and transport networks under technical and market uncertainties – The Central North Sea multi-store case" Korre A, **Elahi N**., Nie Z., Shah N., Durucan S., A report elaborated by Imperial College for the Crown Estate, (to be published Jan 2015)

Chapter 1 Introduction

1.1 Evidence on climate change

It is certain that Global Mean Surface Temperature has increased since the late 19th century. Each of the past three decades has been warmer than all the previous decades in the instrumental record. The global combined land and ocean temperature data show an increase of about 0.89°C over the period 1901–2012 and about 0.72°C over the period 1951–2012 when described by a linear trend. It is also virtually certain that maximum and minimum temperatures over land have increased on a global scale since 1950 [1].

Global energy-related CO_2 emissions continue to rise. CO_2 emissions have grown between 1970 and 2004 by about 80% (28% between 1990 and 2004) representing 77% of total anthropogenic GHG emissions in 2004 [2]. The largest growth in global greenhouse gas, GHG emissions between 1970 and 2004 has come from the energy supply sector (an increase of 145%) [2]. In 2011 the emissions increased by 3.2% from 2010, reaching a high record of 31.2 Gt [3]. If this trend continues, it will put emissions on a trajectory corresponding to an average global temperature increase of around 6°C in the long term [3].

The greater the emissions of greenhouse gases such as CO_2, the greater the warming and severity of the associated consequences. These consequences include a rise in sea levels, causing dislocation of human settlements, as well as extreme weather events, including a higher incidence of heat waves, destructive storms, and changes to rainfall patterns, resulting in droughts and floods affecting food production, human disease and mortality [2]. Global-scale assessment of observed changes shows that it is likely that anthropogenic warming over the last three decades has had a discernible influence on many physical and biological systems [4].

Coal continues to be the largest incremental source of global primary energy consumption. Over the last decade, coal has been the fastest growing source of primary energy, with incremental consumption over 50% higher than the incremental demand for oil and gas combined. Coal demand grew by 4.3% from 7,080 Mt in 2010 to 7,384 Mt in 2011, with most of this growth arising in non-OECD countries, particularly China and India [3]. This continued expansion of coal and other fossil fuels, despite strong advances in clean energy technologies worldwide, has meant that overall energy-related emissions have grown [5].

The effect on global emissions of the decrease in global energy intensity (-33%) during 1970 to 2004 has been smaller than the combined effect of global per capita income growth (77%) and global population growth (69%); both drivers of increasing energy-related CO_2 emissions [2] . Differences in terms of per capita income, per capita emissions, and energy intensity among countries remain significant. In 2004, the The United Nation's Framework Convention on Climate Change (UNFCCC) Annex I countries held a 20% share in world population and accounted for 46% of global GHG emissions [2].

This global dependence on fossil fuels has led to the release of over 1100 Gt CO_2 into the atmosphere since the mid-19th century. Currently, energy-related GHG emissions, mainly from fossil fuel combustion for heat supply, electricity generation and transport, account for around 70% of total emissions including carbon dioxide, methane and some traces of nitrous oxide [2]. The International energy agency has reported that 40% of global electricity came from coal and resulted in 75% of the CO_2 emissions in 2009 [3]. Combustion of fossil fuels continues to dominate a global energy market that is striving to meet the ever-increasing demand for heat, electricity and transport fuels. GHG emissions from fossil fuels have increased each year since the Intergovernmental Panel on Climate Change' (IPCC) third assessment report in 2001 despite greater deployment of low- and zero-carbon technologies, the implementation of various policy support mechanisms by many states and countries, the advent of carbon trading in some regions, and a substantial increase in world energy commodity prices [6]. To continue to extract and combust the world's rich endowment of oil, coal and natural gas at current or increasing rates is no longer environmentally sustainable, unless mitigation technologies currently being developed can be widely deployed [6].

In the IPCC's 4th assessment report it is predicted that without the near-term introduction of supportive and effective policy actions by governments, energy-related GHG emissions are projected to rise by over 50% from 26.1 $GtCO_2$ (i.e. 7.1 GtC) in 2004 to 37–40 $GtCO_2$ (i.e. 10.1–10.9 GtC) by 2030. Mitigation has therefore become even more challenging [6].

In another report by the IPCC, the non-mitigation scenarios project an increase of baseline global GHG emissions by a range of 9.7 $GtCO_2$-eq to 36.7 $GtCO_2$-eq between 2000 and 2030 [7]. In these scenarios, fossil fuels are projected to maintain their dominant position in the global energy mix to 2030 and beyond. Hence CO_2 emissions between 2000 and 2030 from energy use are projected to grow 40 to 110% over that period [2].

In the UK in the 3rd quarter of 2013, the Department of Energy and Climate Change published that the total UK greenhouse gas emissions has been provisionally estimated at 576.2 Mt carbon dioxide [8]. The total CO_2 emissions from the energy supply sector amounted to approximately 40% of the total emissions as a moving annual total on a temperature adjusted basis [8].

A range of policies, including those on climate change, energy security and sustainable development, has been effective in reducing GHG emissions in different sectors and many countries. The scale of such measures, however, has not yet been large enough to counteract the global growth in emissions [2]. The International Energy Agency (IEA) reports investing in clean energy makes economic sense. Every additional dollar invested can generate three dollars in future fuel savings by 2050. Investments in clean energy need to double by 2020. The 2°C scenario, 2DS is the focus of the IEA's Energy technology perspective [3]. The 2DS describes an energy system consistent with an emissions trajectory that recent climate science research indicates would give an 80% chance of limiting average global temperature increase to 2°C. Achieving the 2DS would require USD 36 trillion (35%) more in investments from today to 2050 than under a scenario in which controlling carbon emissions is not a priority. However, by 2025, the fuel savings realised would outweigh the investments; by 2050, the fuel savings amount to more than USD 100 trillion. Even if these potential future savings are discounted at 10%, there would be a USD 5 trillion net saving between now and 2050 [3].

In 2012, the IEA stressed that there is a pressing need to accelerate the development of low-carbon energy technologies in order to address the global challenges of energy security, climate change and economic growth. This challenge was acknowledged by ministers from G8 countries at their meeting in June 2008 in Aomori, Japan where they declared the wish to have the IEA prepare a series of global roadmaps to advance innovative energy technology [3].

Despite technology's potential, progress in clean energy is too slow. Nine out of ten technologies that hold potential for energy and CO2 emissions savings are failing to meet the deployment objectives needed to achieve the necessary transition to a low-carbon future. Some of the technologies with the largest potential are showing the least progress. The IEA's analysis of current progress in clean energy shows that only a portfolio of more mature renewable energy technologies including hydro, biomass, onshore wind and solar photovoltaic are making sufficient progress. Other key technologies for energy and CO_2 emission savings are lagging behind. Particularly worrisome are the slow uptake of energy efficiency technologies and the lack of progress in commercial scale deployment of carbon dioxide capture and storage (CCS). The scale-up of projects using these technologies over the next decade is critical. CCS could account for up to 20% of cumulative CO_2 reductions in the 2DS by 2050. In 2012 the IEA reported that this requires rapid deployment of CCS which remains to be a significant challenge since there are no large-scale CCS demonstrations currently in operation in electricity generation [3]. The world's first power sector CCS project, the Boundary Dam CCS demonstration project in Canada with CO_2 capture capacity of only 1 Mtpa only became operational in October 2014 [9].

1.2 Mitigation options

Adaptation to climate change is already taking place, but on a limited basis. Societies have a long record of adapting to the impacts of weather and climate through a range of practices. However, climate change poses novel risks often outside the range of experience, such as impacts related to drought, heat waves, and accelerated glacier retreat and hurricane intensity. Adaptive capacity is uneven across and within societies. There are substantial limits and barriers to adaptation [4]. Bottom-up and top-down studies indicate that there is substantial economic potential for the mitigation of global GHG emissions over the coming decades, that could offset the projected growth of global emissions or reduce emissions below current levels [2].

Decision-making about the appropriate level of global mitigation over time involves an iterative risk management process that includes mitigation and adaptation, taking into account actual and avoided climate change damages, sustainability, equity, and attitudes to risk. Choices about the scale and timing of GHG mitigation involve balancing the economic costs of more rapid emission reductions now against the corresponding medium-term and long-term climate risks of delay. Changes in lifestyle and behaviour patterns can contribute to climate change mitigation across all sectors. Management practices can also have a positive role [2]. New energy infrastructure investments in developing countries, upgrades of energy infrastructure in industrialised countries, and policies that promote energy security can in many cases create opportunities to achieve GHG emission reductions.

In the short and medium term (until 2030), the IPCC emphasises on the mitigation technologies and practices currently commercially available in the Energy sector; Improved supply and distribution efficiency, fuel switching from coal to gas, nuclear power, renewable heat and power and combined heat and power. Biomass and coal-fired electricity generation facilities, advanced nuclear power and advanced renewable energy are listed as technologies to be commercialised before 2030 [2]. Amongst these technologies, they emphasise on the role of CCS on mitigation of climate change in the medium term. Innovative supply-side technologies, on becoming fully commercial, may enhance access to clean energy, improve energy security and promote environmental protection at local, regional and global levels. They include thermal power plant designs based on gasification, combined cycle and super-critical boilers using natural gas as a bridging fuel, second-generation renewable energy systems and advanced nuclear technologies. One of the main solutions considered involves further development and uptake of CCS [6]. The options for the mitigation of climate change are briefly discussed below.

Plant efficiency and fuel Switching

Reductions in CO_2 emissions can be gained by improving the efficiency of existing power generation plants through employing more advanced technologies using the same amount of fuel. For example, a 27% reduction in emissions (GCO_2/kWh) is possible by replacing a 35% efficient coal-fired steam turbine with a 48% efficient plant using advanced steam, pulverized-coal technology. Replacing a natural gas single-cycle turbine with a combined cycle gas turbine (CCGT) of similar output capacity would help reduce CO_2 emissions per unit of output by around 36% [6]. The IEA recommends increasing the average efficiency of global coal-fired power generation plants will be essential over the next 10 to 15 years through the deployment of supercritical and ultra-supercritical technologies. Minimising generation from older, less efficient coal plants and accelerating the development of advanced technology are also recommended [3].

Nuclear

Proposed and existing fossil fuel power plants could be partly replaced by nuclear power plants to provide electricity and heat. Since the nuclear plant and fuel system consumes only small quantities of fossil fuels in the fuel cycle, net CO_2 emissions could be lowered significantly. However, assessments of potential for nuclear power are uncertain and controversial. In 2006 the IEA anticipated a 50% increase in nuclear energy (to 4,106 TWh/yr) by 2030 in the World Energy Outlook (WEO) alternative scenario[10]. The IEA assumed a mitigation potential of 0.4–1.3 $GtCO_2$ by 2030 from the construction of Generation II, III, III+ and IV nuclear plants [11]. Following a review of the literature and the various scenario projections described above it is assumed that by 2030 18% of total global power-generation capacity could come from existing nuclear power plants as well as new plants displacing proposed new coal, gas and oil plants [6]. In 2007, the IPCC reported that given the costs relative to other supply options, nuclear power can have an 18% share of the total electricity supply in 2030 at carbon prices up to USD 50/tCO_2-eq, but safety and waste remain as constraints [2].

Renewable energy

Renewable energy generally has a positive effect on energy security, employment and on air quality. Fossil fuels can be partly replaced by renewable energy sources to provide heat (from biomass, geo-thermal or solar) or electricity (from wind, solar, hydro, geo-thermal and bio-energy generation) or by combined heat and power (CHP) plants. Ocean energy is immature and assumed unlikely to make a significant contribution to overall power needs by 2030. In 2007, the IPCC reported the total contribution of renewable energies (Hydro, wind, Solar, Bio-fuels excluding bio-fuels for transport and geo-thermal) to the World's energy mix will be 35% by 2030 [6].

Carbon dioxide capture and storage

Fossil fuels are an important part of the electricity mix and will remain so for some time to come because they let us balance the intermittency of wind and the inflexibility of nuclear. If developed at scale CCS could allow the safe removal and storage of carbon dioxide emissions from coal and gas power stations and permanently store emissions from large industrial sources such as steel or cement factories [12].

The wide range of energy sources and carriers that provide energy services need to offer long-term security of supply, be affordable and have minimal impact on the environment. However, these three government goals often compete. There are sufficient reserves of most types of energy resources to last at least several decades but how best to use these resources in an environmentally acceptable manner is a great challenge. The transition from surplus fossil fuel resources to constrained gas and oil carriers, and subsequently to new energy supply has begun. However, it faces regulatory and acceptance barriers and market competition alone may not lead to reduced GHG emissions. Coal remains abundant. It can be converted to liquids, gases, heat and power. More intense utilization will demand viable CCS technologies if GHG emissions from its use are to be limited [6]. CCS in underground geological formations is a new technology with the potential to make an important contribution to mitigation by 2030. However, technical, economic and regulatory developments will affect the actual contribution of CCS [2].

The IPCC's fourth assessment report introduces CCS as a 'transitional technology', with deployment anticipated from 2015 onwards; peaking after 2050 as existing heat and power plant stock is turned over. CCS is likely to decline thereafter as the de-carbonization of energy sources progresses [11]. Other studies show a more rapid deployment starting around the same time, but with continuous expansion even towards the end of the century [2, 7].

In 2012, the IEA in their Energy Technology perspective discuss that CCS is the only technology on the horizon today that would allow industrial sectors (such as iron and steel, cement and natural gas processing) to meet deep emissions reduction goals. Abandoning CCS as a mitigation option would significantly increase the cost of achieving the 2DS explained above. The additional investment that would be required to meet the 2DS would increase by a further 40% if CCS is not available, with a total extra cost of USD 2 trillion over 40 years. Without CCS, the pressure on other emissions reduction options would also be higher. In the 2DS scenarios, heavy industries like iron, steel and cement rely heavily on CCS to prevent substantial emissions. In the power sector, about 80% of coal-fired generating capacity will be equipped with CCS units by 2050. In addition, In the 2DS scenario as natural gas becomes high carbon after 2030 (relative to the carbon intensity required), the application of CCS to gas-fired power steps up appreciably [3]. Therefore they emphasise

CCS must be demonstrated and developed at commercial scale rapidly if it is to be deployed widely after 2020.

1.3 CCS contribution to climate change mitigation and its limitations

1.3.1 CO_2 capture and storage background

Carbon dioxide capture and storage is an essential part of the portfolio of technologies to achieve climate mitigation targets. CCS is a process consisting of the separation of CO_2 from industrial and energy-related sources and transporting it to a storage location for long-term isolation from the atmosphere. Capturing CO_2 can be applied to large point sources. The CO_2 would then be compressed and transported for storage in geological formations, in the ocean, in mineral carbonates or for use in industrial processes [7]. Available technology captures about 85–95% of the CO_2 processed in a capture plant. The net result is that a power plant with CCS could reduce CO_2 emissions to the atmosphere by approximately 80–90% compared to a plant without CCS [7].

Storage of CO_2 can be achieved in deep saline formations, oil and gas reservoirs and deep coal seams using injection and monitoring techniques similar to those utilized by the oil and gas industry. Between the different types of potential storage formations, storage in coal formations is the least developed. If injected into suitable saline formations or into oil and gas fields at depths below 800m, various physical and geochemical trapping mechanisms prevent the CO_2 from migrating to the surface. Projects in all kinds of reservoirs are planned. In 2005, the IPCC reported 675 to 900 $GtCO_2$ storage potential for the relatively well-characterised gas and oil fields, more than 1000 $GtCO_2$ (possibly up to an order of magnitude higher) for saline formations, and up to 200 $GtCO_2$ for coal beds [7].

CCS has the potential to reduce overall mitigation costs and increase flexibility in achieving greenhouse gas emission reductions. The widespread application of CCS would depend on technical maturity, costs, overall potential, diffusion and transfer of the technology to developing countries and their capacity to apply the technology, regulatory aspects, environmental issues and public perception (IPCC 2005).

IPCC's 2005 Special report on CO_2 capture and storage states that in least-cost portfolio of mitigation options, the economic potential of CCS amounts to between a 15% to 55% contribution to the cumulative mitigation effort worldwide until 2100, averaged over a range of baseline scenarios. It is likely that the technical potential for geological storage is sufficient to cover the high end of the economic potential range [7]. Economic potential is the amount of greenhouse gas emissions reductions from a specific option that could be achieved cost-effectively, given prevailing circumstances such as a market value of CO_2 reductions and costs of other options. However, uncertainties in these economic potential estimates are significant.

For CCS to achieve this economic potential, several hundreds to thousands of CO_2 capture systems would need to be installed over the coming century, each capturing some 1–5 $MtCO_2$ per year. The actual implementation of CCS, as for other mitigation options, is likely to be lower than the economic potential due to factors such as environmental impacts, risks of leakage and the lack of a clear legal framework or public acceptance. However one important aspect of the cost competitiveness of CCS systems is that CCS technologies are compatible with most current energy infrastructures [7].

1.3.2 CCS' potential for contribution to climate change mitigation

The European Commission has confirmed that Europe cannot be decarbonised cost-effectively and maintain security of energy supply without CO_2 Capture and Storage (CCS). Indeed, with fossil fuels currently meeting over 80% of global energy demand and as much as 85GW of additional capacity expected in Europe alone, CCS is "vital for meeting the European Union's greenhouse gas reduction targets" [13]. Yet the benefits of CCS go far beyond that of climate change mitigation; with annual investments worth billions of Euros, CCS will create and preserve jobs, boost industry and fuel economic growth, ensuring Europe remains competitive on the world stage as a leader in low-carbon energy technologies [13]. In a CCS technology roadmap [5], the IEA describes the rationale for CCS; CCS offers a solution for dealing with emissions from fossil fuel use preserving the value of existing infrastructure. CCS is also a low-cost emissions reduction option for the electricity sector. If CCS is removed from the list of emissions reduction options in the electricity sector, the capital investment needed to meet the same emissions constraint is increased by 40% [3]. In addition, emissions from industrial sectors such as cement, iron and steel, chemicals and refining represent one-fifth of total global CO_2 emissions, and the amount of CO_2 they produce is likely to grow over the coming decades. Retrofitting infrastructure currently in operation or under construction with CCS will help prevent the "lock-in" of emissions [5].

In a publication by the Zero Energy Platform (ZEP) in support of CCS deployment in Europe beyond 2020, it is discussed that the critical role of CCS in meeting the EU's energy, climate and societal goals is now indisputable: CCS must account for 19-32% of total emissions reductions in the power sector by 2050. This means that for all fossil fuels, carbon capture and storage will have to be applied from around 2030 onwards [14]. In another report co-authored by ZEPP and the European Bio fuels Technology Platform the need for carbon-negative solutions such as Bio-CCS is emphasised in order to keep global warming below 2°C. In Europe, Bio-CCS could remove 800Mt of CO_2 from the atmosphere every year by 2050 using available sustainable biomass – equivalent to over 50% of current emissions from the EU power sector [15]. Koorneef et al [16] investigated the bio-CCS technical potentials for six bio-CCC technology routes. The results show the global technical potential for bio-CCS technologies is large and, if deployed, can result in negative greenhouse gas emissions (GHG) up to 10.4Gt CO_2 on an annual basis in 2050. The economic potential reaches up to 3.5Gt of negative GHG emissions when assuming a CO_2 price of 50 Eur/tonne.

The IEA also argues CCS is not just a technology for coal; it is applied to multiple different fuels used in electric power generation, including biomass [3]. The IEA predicted that in 2050 63% of coal fired electricity generation (630GW) is CCS equipped, 18% of gas (280 GW) and 9% of biomass (50 GW) [3]. They argue that today 471GW of coal-fired plants are larger than 300MW and younger than ten years and in most general terms, larger, more efficient (i.e. younger) plants are suitable for retrofit. Besides, the same CO_2 capture technologies applied in power generation can be applied to industrial processes. Currently some routes to CO_2 capture are in pilot-testing or demonstration stages for power and industrial applications [3]. However, over time CCS will become cost-competitive with fossil-fuel power plants, due to cost reductions from technology learning and the increasing CO_2 price penalty for fossil-fuel generation without CCS. In addition, although in the near term, most power generation equipped with CCS will be built in OECD countries; by 2050, the majority is located in non-OECD countries. By 2050, over one-third of power generation capacity with CCS is in China with the next largest fraction in OECD North America [3].

In the UK in order to meet the national de-carbonisation targets, the government has proposed an Electricity Market Reform (EMR) programme. This will, in principle, put in place public policy support for all low-carbon power options including long-term feed-in tariff contracts for difference (CfD) which will be effective in driving CCS deployment [13]. Also, based on the outcome of a model developed by ZEP to present low carbon cost effective technologies that meet expected electricity needs, ZEP recommended CCS measures by country including for the United Kingdom. They discuss the UK's set of measures seems likely to be successful in implementing CCS demonstration projects in the UK and the modelling shows that FiTs, which provide support to CCS in a very similar way to CfDs, will incentivise investment in CCS up to 2030. In combination with CCS certificates and other grant schemes, the UK would therefore be an attractive place for the first projects to be built [13]. The current Energy Bill in the UK introduces an Emissions Performance Standard (EPS) which limits emissions to around half that produced by unabated coal. This policy reaffirms a political commitment to incremental decarbonisation, reassuring market actors of the long-term necessity of CCS for continued fossil fuel use. It also underpins measures in place that requires at least 300MW of CCS to be installed on new coal-fired power stations and for all new combustion power stations to be CO_2 capture-ready [13].

1.3.3 CCS deployment barriers

There are regulatory issues and other uncertainties as a result of limited practice especially regarding the deployment of CCS chain as a whole [7]. The IPCC describe the uncertainties in the deployment of CCS as uncertainties that relate to improving the technologies, anticipating environmental impacts and how governments should incentivise uptake [2]. In 2013, ZEP argued the EU Emissions Trading System (EU ETS) does not provide sufficient incentives to drive investment in low carbon energy generation and a re-structured EU ETS is the backbone of the incentive system to reduce CO_2 emissions towards meeting the 2050 objectives [17]. On the other hand, there are gaps in currently available knowledge regarding some aspects of CCS. Ongoing R&D for CCS is essential in order to facilitate decision-making with respect to the deployment of CCS, drive down costs, and deliver the EU climate targets [14]. Some CO_2 capture technologies are commercially available today and the majority can be applied across different sectors. While most remain capital-intensive and costly, they can be competitive with other low-carbon options [3]. However the CCS Challenges lie in integrating these technologies cost effectively into large-scale projects [3].

In the UK, the Department of Energy and Climate Change has stated that the technologies used in CCS (capture, transport and storage) are not particularly new or unique. They have been used for many years individually (notably in the oil and chemical sectors) but there are no projects that use all three components together at commercial scale to capture and store carbon dioxide from a power station. To bring down costs and allow CCS to be more widely used, the full chain of capture, transport and storage needs to be built and operated on a commercial scale at power stations that are already generating electricity [12].

In 2009, the IEA's CCS roadmap presented a vision for CO_2 transport and storage that started with analysis of CO_2 sources, sinks and storage resources, followed by the development of best-practice guidelines and safety regulations by 2020 and leading to a roll-out of pipeline networks to developed storage sites [5]. However in the IEA's 2013 technology roadmap for CCS it is discussed that considerable progress has been made in understanding the size and distribution of technically accessible storage resources, factors affecting the cost of storage, and in the development of best-practice recommendations and standards for geologic storage. However much more needs to be done to develop the elements of the CCS chain to support the scale of CCS deployment required in the near future [5].

In the 2DS scenarios, the IEA predicts that for between 2015 and 2030, 13 $GtCO_2$ are captured and stored globally; through 2050, this total grows to 123 $GtCO_2$. Capturing this amount of CO_2 and at these rates will require the development of transport and storage infrastructure globally [3]. The IEA emphasises that governments must implement appropriate and transparent incentives to drive CCS deployment. They must develop enabling legal and regulatory frameworks for demonstration and deployment of CCS. Also as part of the recommended actions for the near term they discuss that government and industry increase emphasis on CO_2 transport and storage infrastructure development so that integrated CCS projects can be successful [3].

A report published by ZEP in 2013 makes clear that it is vital to exploit the enabling power of properly planned CO2 infrastructure with CO_2 hubs, networks and emissions clusters providing the essential foundations for wide-scale CCS deployment. Due to long development lead times, 6 to 10 years to build facilities such as pipelines and storage sites – development must start now, ahead of wide-scale deployment of CCS in order to meet the EU's greenhouse gas emission reduction targets. Commenting on the report's findings, ZEP Chairman argues that without urgent investment in CO_2 infrastructure – at least €2.5 billion by 2020 – the EU will fail to meet its own climate change targets. The cost of delay will be massive. A 10 year delay in the deployment of CCS will increase the global costs of decarbonising the power sector alone by $1 trillion [18].

In terms of knowledge available to deploy a large-scale CCS chain, complete CCS systems can be assembled from existing technologies that are mature or economically feasible under specific conditions. However, the state of development of the overall system may be less than some of its separate components. Globally there are 13 CCS projects, which have become operational recently with a further nine under construction. Most of these systems are for enhanced hydrocarbon recovery [9]. The main challenge here is to develop these single chain CCS systems in a way, which supports the future expansion of the system into cost effective complex integrated networks of sources, transportation and storage points which can cope with future targets and constraints. Therefore, the main barrier is not only in combining CO_2 capture, transport and storage into a fully integrated CCS system but to build the foundations of wide-scale CCS deployment in the face of considerable uncertainties. Not only CCS deployment strategies must be able to deliver the targets for the near future, in order to minimise losses they must also be based on the anticipated changes in the longer term and preferably allow flexibility at every stage of expansion considering the future path of mitigation policies.

In terms of the risks associated with the deployment of CCS transport and storage infrastructure, there is the risk of seismic activity causing a rapid release of CO_2 and the impact of old and poorly sealed well bores on the storage integrity of depleted oil and gas fields [7]. Some regulations for operations in the subsurface do exist that may be relevant or, in some cases, directly applicable to geological storage, but few countries have specifically developed legal or regulatory frameworks for long-term CO_2 storage. CO_2 might be captured in one country and stored in another with different commitments. Issues associated with accounting for cross-border storage are not unique to CCS. Risks in CO_2 transportation include rupture or leaking of pipelines. If moisture is removed, dry CO_2 is not corrosive to pipelines even if it contains contaminants [7].

1.4 CCS demonstration projects to date

The IEA's 2013 roadmap for CCS technology describes the need for CCS to move to demonstration scale and therefore the necessity of integration of the CCS value chain to provide the market place with new information on the possible performance of a large commercial scale CCS chain [5]. In preparation for future deployment of a large-scale CCS chain, governments have funded several pilot projects in order to test the performance of components of the chain, capture in particular. The funding from government and industry has driven a compound annual growth rate of 46% in CCS-related patent applications between 2006 and 2011 [5]. The growth in cumulative spending between 2007 and 2012 on projects that demonstrate CCS or component technologies in the CCS chain at large scale is a sign of growing confidence in CCS technology [5].

Examples of large-scale pilot projects that began operation between 2009 (or thereabouts) and 2013 include: Schwarze Pumpe, (Germany), Mountaineer, (United States), Lacq, (France), Brindisi, (Italy), Plant Barry, (United States), Test Centre Mongstad, (Norway), Compostilla, (Spain), Callide-A, (Australia), Decatur, (United States) and Citronelle (United States) [5]. Pipeline transport of CO_2 operates as a mature market technology. Also, storage of CO_2 in deep, onshore or offshore geological formations uses many of the same technologies that have been developed by the oil and gas industry and has been proven economically feasible under specific conditions for oil and gas fields and saline formations. The Sleipner project in an offshore saline formation in Norway, the Weyburn EOR project in Canada, and the Salah project in a gas field in Algeria are examples of industrial-scale storage projects currently in operations [7]. The industry can also build on knowledge obtained through the geological storage of natural gas. The ferrybridge Carbon Capture Pilot in the UK, Renfrew Oxyfuel (Oxycoal 2) Project and China Advanced Power Plant Carbon Capture Options (CAPPCCO) are projects to test carbon capture technologies in real operating conditions of power plants [19]. Following completion of its construction phase, the Ferrybridge Carbon Capture Pilot was launched in 2011 to test amine based post combustion capture (PCC) technology and it ran during 2012 and 2013 to optimise the process. Ferrybridge is a significant step forward in the world of CCS as a critical bridge between research and commercialisation. The Oxyfuel pilot project at Doosan Power System's Clean Combustion Test Facility in Renfrew was another, which successfully completed and it was concluded that the technology could be used on commercial scale plants. The gap lies in cost effective integration of the components of the chain in order to achieve a commercial scale CCS power project in operation [15].

The following explores the large-scale (0.8Mt per year or above) projects and demonstration projects currently in operation as well as some large-scale projects in progress and the government actions taken to facilitate the future deployment of CCS.

Globally, there are 13 large-scale CCS projects in operation, with a further nine under construction. The 22 projects in operation or under construction represent an increase of 50% since the start of this decade. The total CO_2 capture capacity of these 22 projects is around 40 Mt per annum. There are another 14 large-scale CCS projects at the most advanced stage of development planning, the Concept Definition (or Define) stage, with a total CO_2 capture capacity of around 24 Mt per annum. Large-scale CCS projects in the power sector are now a reality. The world's first large-scale power sector CCS project – the Boundary Dam Integrated CCS project in Canada is the first large-scale operational demonstration project since October 2014 with a capture capacity of 1Mt per year. Commissioning activities on a new-build 582 MW power plant have begun at the Kemper County Energy Facility in Mississippi. This project has a capacity of 3 Mt per year and is expected to commence in the first half of 2016. The Petra Nova Carbon Capture Project at the W.A. Parish power plant near Houston, Texas entered construction in July 2014, with CO_2 capture anticipated by the end of 2016. Outside the power sector, the Abu Dhabi CCS Project with a capture capacity of 0.8 Mt per year is the world's first iron and steel project to apply CCS at large scale. This project moved into construction in the UAE in the latter part of 2013 [9].

The Department of Energy and Climate Change in the UK is working with industry to create a new cost-competitive CCS industry in the 2020s. The CCS Development Forum Chaired by DECC overcomes barriers by bringing government and CCS stakeholders together. A Cost Reduction Task Force has been created to identify technology cost reduction opportunities, develop the supply chain and share knowledge from the UK projects to help develop the CCS infrastructure. Their support for the development of CCS includes a £1 billion commercialisation competition to support practical experience in the design, construction and operation of commercial-scale CCS. Also included are a £125 million, 4-year co-ordinated research, development and innovation programme and the reform of the UK electricity market to enable CCS to compete with other low-carbon energy sources [12].

The White Rose CCS project in the UK is an oxyfuel power and carbon capture and storage (CCS) demonstration project of up to 450 MWe gross outputs announced by project partners Alstom, Drax and BOC. The proposal was awarded in 2013 a FEED contract by the UK government, which also includes the planned development of a CO_2 transportation and storage solution. In 2014, the European commission announced it will award the project with up to 300 million Euros in funding as part of its NER300 scheme [9]. The plant will also have the potential to co-fire biomass. The project is intended to prove CCS technology at commercial scale. It will also play an important role in establishing a CO_2 transportation and storage network in the Yorkshire and Humber area [20]. The standalone power plant will be located at the existing Drax Power Station capturing approximately 2Mt of CO_2 per year. The CO_2 will be transported through National Grid's proposed pipeline for permanent undersea storage in the North Sea [20].

The Peterhead CCS project is another CCS demonstration project in the UK which is in the Front-End-Engineering design phase following an agreement between Shell and the UK government in February 2014. Up to 10Mt of CO_2 emissions could be captured from the Peterhead Power station in Scotland and transported by pipeline offshore to Goldeneye in the North Sea. this project will be a significant step in decarbonising the UK's power sector [21].

These demonstration projects and the government's support for the development of CCS places the UK in the forefront of commercial scale CCS chain deployment. However although full CCS chain demonstration projects such as the White Rose project are essential first steps to enable full deployment of CCS and achieve the future reduction targets assigned to CCS technology, demonstration projects are single CCS chains. As mitigation targets increase, the large commercial scale expansion of the single CCS chain into a network of sources and sinks and pipelines requires cost optimised whole system optimisation of an integrated supply chain under technical and market constraints. As explained in section 1.3.3, it is essential that the current CCS projects demonstrate that the elements of the chain can be integrated into a fully functional system. However, the next step is not merely delivering near term targets. The CCS supply chain design must be carried out with a long-term perspective. Cost effective deployment requires that every stage of expansion, the potential future changes are considered. Strategies must aim to minimise the overall costs and offer flexibility considering the uncertain nature of the environment in which CCS develops. In chapter 2, we will discuss that the gap in knowledge lies in the analysis of the techno-economic performance of an integrated CCS chain and its evolution path. This is the main driver behind the goals and objectives of this thesis as discussed in section 1.5.

1.5 Research goals and objectives

As discussed in section 1.2 CCS is an essential part of the portfolio of technologies to achieve climate decarbonisation targets. As discussed in section 1.3, one of the barriers to accelerating the deployment of CCS is optimal integration of the CCS supply chain components taking into account that current strategies must also support potential future changes in the development of CCS networks. Large-scale and cost effective CCS deployment requires that all three components of the supply chain (capture, transport and storage) are co-ordinated both spatially and across time. On the other hand due to the dynamic nature of the parameters such as targets and policies which affect the evolution of the CCS network, it is essential that current and future investment and operational strategies are harmonised so to minimise the overall cost of the supply chain. For instance as the mitigation burden on CCS becomes larger the network of emitters and sinks connected by pipelines will have to expand. Therefore, it is only sensible to acquire an investment strategy that ensures optimum evolution of the network under anticipated targets and constraints. In other words, this becomes a dynamic or multi-stage whole system supply chain optimisation problem.

There is very little experience in combining CO_2 capture, transportation and storage into a fully integrated system and most of the existing research or planning tools are limited. As discussed in chapter 2, the earlier work were mostly focused on one component of the chain or the very few whole system models were deterministic and steady-state optimisation models which only demonstrate a snap-shot of an optimal CCS network. The very few multi-period optimisation models are unable to simultaneously make decisions for the three components of the chain for an overall optimum system.

The major objective of this thesis is the development for the first time of a multi-period spatially explicit least cost optimization model of an integrated CO_2 capture, transportation and storage infrastructure under both a deterministic and a stochastic modelling framework. The initial optimisation will be based on the assumption of deterministic parameters. The model is used to design an optimum CCS system and model its long-term evolution subject to realistic constraints. The model and its different variations will then be validated through a number of case studies analysing the evolution of the CCS system in the UK. Once complete, the issue of optimal supply chain planning under uncertainty will be addressed. The stochastic model will offer decision making flexibility in the face of future uncertainties. The generic formulation of the model will allow the analysis of the impact of a number of uncertainties, such as carbon pricing or plant decommissioning schedule, on the evolution of the CSS system. In conclusion, the model and the results presented on this thesis can be used for system planning purposes as well as for policy analysis and commercial appraisal of individual elements of the CCS network. The features of the deterministic and stochastic optimisation models to be developed as part of the research objectives of this thesis are discussed in detail in sections 1.5.1 to 1.5.3.

1.5.1 Multi-period least cost optimisation model of an integrated CCS network

The first objective of this thesis is a whole system cost minimisation associated with the future development and operation of a generic integrated CCS supply chain infrastructure. The infrastructure will be responsible for capturing CO_2 at selected sources (i.e. power plants, refineries, cement or steel manufacturing, etc), transporting the CO_2 using a shared transportation infrastructure of pipelines to selected sinks (depleted oil and gas fields, EOR fields, saline aquifers, etc). The problem practically becomes a multi-period supply chain optimisation issue where a product (i.e. CO_2) produced at stationary sources (i.e. power plants) is to be delivered to consumers (i.e. sinks). The elements of the supply chain must be spatially explicit. The network is subject to dynamic constraints that vary with the pre-specified periods or increasing mitigation targets. This will then become the driver behind the evolution of the system with time.

Given how the logical and design constraints and the capital and operational cost parameters evolve throughout the planning horizon, the model should provide a comprehensive pathway for the CCS network development i.e. investment and operational decisions for the three components of the supply chain at every time period which result in an overall minimum cost. The investment and operational decisions must be represented by binary and continuous variables, which respectively correspond to the building of infrastructure and the amounts of the product captured, transported and injected. Therefore, the optimisation problem can be solved using Mixed Integer Linear Programming methods.

The coding environment must be flexible to allow investigating any scenario in terms of geographical scope, time period specifications, availability of the sources and sinks, design or geographical constraints. The model and its variations are then validated through a number of case studies for the evolution of CCS systems with respect to the sources in the UK and the surrounding sinks.

1.5.2 Assessment of the effects of market and leasing alternatives on the techno-economic performance of complex CCS value chains

An important objective behind building a dynamic CCS cost optimisation model is its adaptability to user-defined technical and market constraints. This transforms the model into a tool that enables policy makers to gain insight into factors that affect the economic performance of CCS value chains and hence encourage market development through strategies that ensure pre-determined rates of return and manage investor's risk. This objective might necessitate another important feature of the multi-period CCS supply chain optimisation model, which is its versatility for integration with existing detailed cost models of the components of the supply chain. Utilising accurate life cycle cost modelling of the components in the network model provides an opportunity to improve the supply chain model's solution. On the other hand, the optimal high-level solution as provided by the supply chain model can be utilised to carry out cash flow analysis of the supply chain component of interest and hence assess the feasibility of alternative operation strategies or project finances, which minimise risk or it can highlight the necessary market conditions to avoid loss.

Here, the multi-period CCS model is integrated with a CO_2 storage life cycle cost model also developed at Imperial college [22]. First as an anchor case, the combined model must b validated though life cycle cost analysis of a single CCS value chain in the Central North Sea followed by an investigation of the effects of modifications to the top injection cost contributors to the cash flow of the transport and storage network. In a multi-store scenario, the multi-period supply chain model's boundary conditions must be levelised with the life cycle cost model's outcome for multiple storage sites in the Central North Sea each under specific injection conditions and availability dates. The multi-period model's solution will then be utilised to carry out a storage sites' cash flow analysis in scenarios that mimic real leasing options. The aim is for the scenarios to illustrate the following; The combined model's ability to investigate individual storage site's performance under fixed market conditions, how investment can be encouraged through flexible royalty rates that ensure a target return for all sites or the market conditions required for each site to become favourable. In particular the outcome should validate that a portfolio of storage sites, as a whole stabilises the economic performance and lowers the economic entry barriers which results in better utilisation of the resources [22].

1.5.3 Multi-stage stochastic optimisation of CCS supply chains under uncertainty

Although multi-period and comprehensive, the CCS network optimisation model described in section 1.5.1 has some limitations. The solution provides a deterministic view of the evolution of the CCS system. In reality, there is a considerable degree of uncertainty associated with the parameters, which directly affect CCS planning such as the evolution of the energy system and carbon emitting industries, the price of emitting CO_2 or the future oil and gas prices. This lack of uncertainty or risk management affects the viability of the solution. Therefore, a natural path for improving the deterministic multi-period whole system optimisation model is to modify the model to a stochastic optimisation tool, which considers the uncertainties in arriving at the optimal solution.

There are several optimisation methods for multi-stage planning under uncertainty. The differences lie in the defined objective, the consideration of decision flexibility and modelling risk averseness. Approaches that deal with risk tend to be suited to problems where the risks are few and discrete in nature. Here the objective remains as minimising the net present cost of the CCS network over the entire planning horizon. The objective is not only to consider the entire scenario tree before making any investment decisions, the solution should also be in the form of a strategy as opposed to a series of discrete decisions. In other words, the objective is to allow flexibility of decision making at every stage depending on the changes at that state and preceding stages.

Flexible stochastic optimisation will address the problem of CCS planning under uncertainty using two stage mathematical programming; the here-and-now decisions for the current deterministic stage and the wait-and-see decisions for the future stochastic stages. The latter can then be represented by a scenario tree, which demonstrates the potential realisations of the uncertainty at every stochastic stage. The stochastic model will be validated through a case study, which investigates the optimal strategy for the development of CCS in the UK for potential pathways for the future price of carbon. Uncertainty is expressed in the form of a scenario tree describing the evolution of the future price of carbon. Through decision flexibility we show how the wait and see approach enables the implementation of an optimal strategy depending on how the uncertainty materialises at each stage.

1.6 Thesis structure

This thesis is organised in six chapters. Chapter 2 describes the available methods and technologies for the components of the supply chain, capture transportation and storage. In addition, chapter 2 contains a review of the existing CCS supply chain optimisation tools to confirm the gap in knowledge for multi-period whole-system CCS supply chain optimisation. This chapter then covers the methods for deterministic, comprehensive and multi-period optimisation of other supply chains, which can be applied to the CCS supply chain problem of this thesis.

Chapter 3 presents the deterministic multi-period integrated CCS supply chain optimisation model developed according to the first objective explained in section 1.5.1. First the optimisation framework and the relevant solvers and modelling languages are described. The methods used for techno-economic modelling of the supply chain components are discussed followed by the mathematical model's formulation. To validate and highlight the model's feature a case study is undertaken which investigates the evolution of a minimum cost CCS supply chain in the UK over four time periods up to year 2050.

In chapter 4 the multi-period model developed in chapter 3 is combined with a CO_2 storage life cycle cost model and validated though life cycle cost analysis of a single CCS value chain [22]. The outcome shows that the cost reduction potential of whole system optimisation makes it imperative to evaluate the economic performance of CCS components within a whole-system framework. Different injection scenarios are devised to investigate the effects of disturbances in the top storage cost contributors on the life cycle cost of the transport and storage network. The combined life cycle cost model is also used to carry out a cash flow analysis of the optimal evolution of a multi-storage CO_2 transport and storage network in the Central North Sea. Scenarios that mimic real leasing options are devised to illustrate that the combined model can be used to effectively capture the effects of leasing and market conditions on the techno–economic performance of the storage sites and the transport network. This demonstrates that for user-defined technical and market constraints the models can provide insight into factors that encourage market development through risk reduction.

Chapter 5 presents a multi-stage stochastic optimisation model of an integrated CCS supply chain. This chapter starts with a review of the current methods for optimisation under uncertainty followed by a description of the method selected for modelling a future CCS supply chain under uncertainty. The stochastic model's mathematical formulation is then presented. The model is showcased through a case study for flexible CCS development planning in the UK under carbon price uncertainties. A scenario tree for future carbon price trajectories is constructed based on an analysis of de-carbonisation policies and scenarios, which assess the main policy options with respect to targets and measures. The outcome verifies that through decision flexibility, the stochastic model provides a unique solution depending on the realisation of the uncertainties at each stage and the parent stages hence minimising the risk associated with deterministic planning.

Chapter 6 starts with an overview of CCS' potential as a mitigation option and the challenges in accelerating CCS deployment and the gap in knowledge, which help shape the objectives of this thesis. This is followed by a description of the achievements of the thesis and a summary of the novel contributions. Chapter 6 ends with some recommendations for future work.

Chapter 2 Literature review

The International Energy Agency's Blue Map scenario on stabilisation of CO_2 emissions by 2050 requires an energy technology revolution involving a portfolio of solutions. In this scenario, CCS contributes significantly to the total emission reductions required in 2050 [3]. To enable large scale deployment of CCS, a joint planning of CCS network infrastructure is required globally [23]. In the UK, the government recognises CCS as one of the most cost effective technologies for decarbonisation of the UK's power and industrial sectors. The CCS roadmap published by the UK's department of Energy and Climate Change sets out ways to achieve commercial deployment of CCS in the UK in the 2020s. It is discussed that CCS will contribute to diversity and security of electricity supply, and also has a unique role in providing a flexible fossil fuel capacity that is able to respond to demand in the way that other low carbon technologies are not able to [24].

Without a doubt CCS technology improvement, performance and cost modelling on component level are significantly important. Hence a large proportion of CCS related scientific literature has concentrated on components of the chain particularly CO_2 capture technologies and costs. However to build and operate a CCS network, understanding the minimum cost configuration of sources, sinks and transport links is crucial. Also since the network will have to gradually expand in order to contribute to the goal of a stabilised CO_2 emission level by 2050; it is only sensible if investment and operational decisions made at every stage aim for an overall minimum cost network. Here 'overall' implies both the entire system as well as over the entire planning horizon. In the field of CCS supply chain optimisation, very little research has been carried out to provide an optimal and comprehensive investment and operational solution for the components of a dynamic CCS network to optimise the overall performance of the CCS system. Therefore as discussed in detail in section 1.5 of this thesis the main objective of this thesis is to build a multi-period whole-system cost optimisation model of an integrated carbon dioxide capture, storage and transportation supply chain in both deterministic and stochastic frameworks respectively.

This chapter is a critical review of the scientific research carried out in the field of deterministic multi-stage whole system CCS supply chain optimisation in order to identify the gaps and limitations of different approaches. Multi-stage and comprehensive optimisation of similar supply chains other than CCS is also reviewed to explore any aspects, which can be adapted to resolving the problem introduced in this thesis. A separate literature review is carried out in chapter 5 for multi-stage optimisation methods under uncertainty.

Section 2.1 briefly describes each component of a CCS supply chain; Capture transportation and storage. Section 2.2, which is the main body of this chapter aims to identify the gap that exists in the literature in the field of multi-period whole system CCS supply chain optimisation and to learn from previous research in the general field of multi-period whole-system supply chain optimisation. Section 2.3 is a categorised summary of the literature review to highlight the areas where most scientific research has been carried out, hence indicating the lessons learnt and more importantly the limitations and the gap in knowledge.

2.1 Components of the CCS supply chain

CCS refers to a suite of technologies that allow for volumes of CO_2 to be captured at fixed points of generation such as power plants and cement manufacturing, compressing it to a supercritical fluid and transporting the fluid by pipeline or to the reservoirs such as depleted oil and gas fields or for enhanced oil recovery [25], [26], [27]. These three components are the dimensions of CCS technology. Figure 2.1 shows a schematic view of the CCS chain. The most common methods of capture are post-combustion, pre-combustion and oxy-fuel capture systems as described below.

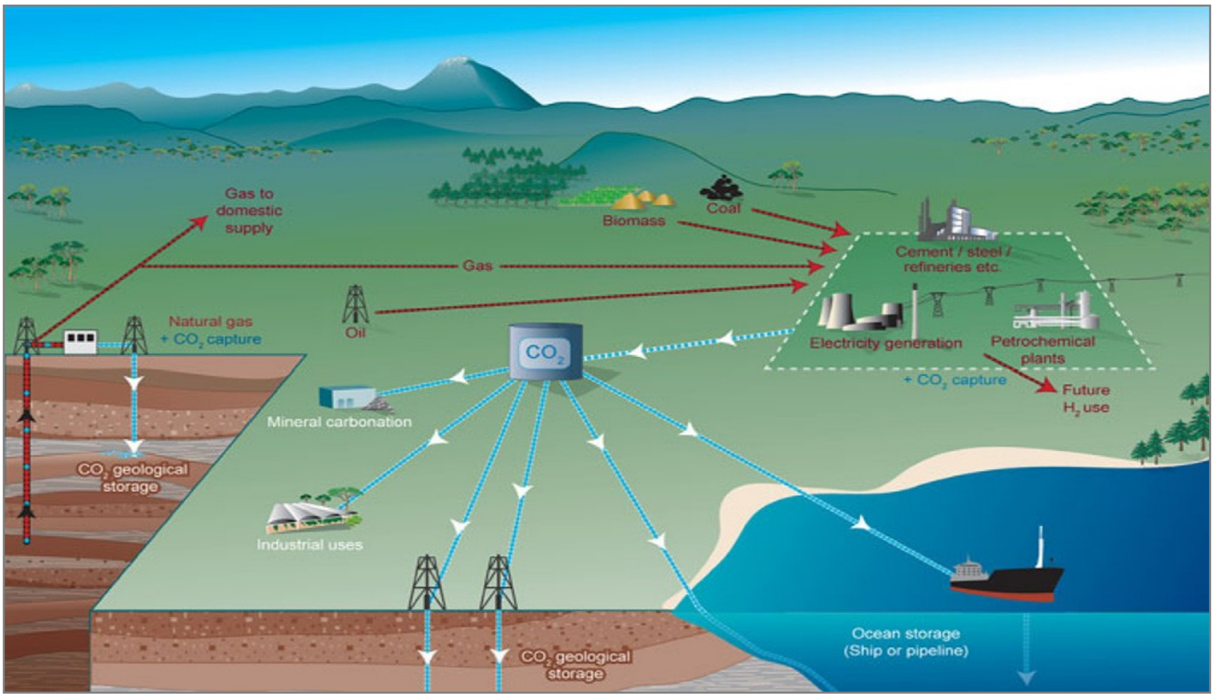


Figure 2.1 Schematic view of CCS supply chain [7]

The CO_2 storage options comprise geological storage, ocean storage and mineralization. The CO_2 capture part represents the major fraction of the total costs, with values ranging from 24 to 52 Euros/tonne of CO_2 [28]. The transportation cost varies with the pipeline dimensions (length and diameter), pressure of CO_2 and landscape characteristics, ranging from 1 to 6 Euros/tonne of CO_2 per 100 km of pipeline. The CCS total costs can vary from −3 to 106 Euros/tonne of CO_2. The negative values are expected for the injection of CO_2 in enhanced oil recovery (EOR) fields [29].

2.1.1 Carbon dioxide capture

The purpose of CO_2 capture is to produce a concentrated stream that can be readily transported to a CO_2 storage site. CO_2 capture is most applicable to large, centralized sources like power plants and large industries. The CO_2 capture can be performed following three different technological concepts: post-combustion, pre-combustion and oxy-fuel capture systems.

<u>Post-combustion Capture</u>

Capturing CO_2 from flue gases produced by combustion of fossil fuels and biomass in air is referred to as post-combustion capture. Instead of being discharged directly to the atmosphere, flue gas is passed through equipment, which separates most of the CO_2. The CO_2 is fed to a storage reservoir and the remaining flue gas is discharged to the atmosphere. A chemical sorbent process would normally be used for CO_2 separation [7]. The most used CO_2 separation process is absorption using an amine as the absorbent [30], [31], [32]. For post-combustion technology, the exhaust gas contains CO_2 with low concentrations (4–14% v/v) and pressures which represents an important limitation for CO_2 capture [33], [34]. The low CO_2 concentrations in flue gas require powerful chemical solvents and, when applied, high energy amounts have to be expended to regenerate the solvents by re-heating to temperatures around 120°C. Post-combustion capture is applied to produce high purity CO_2, which can be applied in enhanced oil recovery, urea production and in the food/beverage industry [35]. Post-combustion capture has the advantage of being able to be installed on both existing and future power plants. This is of vital importance given that the average power plant operates for 40 years, sometimes longer [36].

<u>Pre-combustion capture</u>

Pre-combustion capture involves reacting the fuel with oxygen or air and/or steam to give mainly a synthesis gas (syngas) or fuel gas composed of carbon monoxide and hydrogen. The carbon monoxide is reacted with steam in a catalytic reactor, called a shift converter, to give CO_2 and more hydrogen. CO_2 is then separated, usually by a physical or chemical absorption process, resulting in a hydrogen-rich fuel which can be used in many applications, such as boilers, furnaces, gas turbines, engines and fuel cells [7]. The aim of these systems is to convert the carbon fuel to carbonless fuel [34]. Biomass, coal and natural gas can be used for pre-combustion capture technology. An important advantage relative to post-combustion systems is the higher CO_2 concentration and pressure achieved in the output stream. Thus, the applied equipment to separate CO_2 from the referred stream can be smaller and different solvents can be used with lower energy penalties for regeneration [35]. The main disadvantage of pre-combustion capture is the high investment costs [34].

Oxy-fuel combustion capture

In oxy-fuel combustion, nearly pure oxygen is used for combustion instead of air, resulting in a flue gas that is mainly CO_2 and H_2O. If fuel is burnt in pure oxygen, the flame temperature is excessively high, but CO_2 and/or H_2O-rich flue gas can be recycled to the combustor to moderate this. Oxygen is usually produced by low temperature (cryogenic) air separation. Novel techniques to supply oxygen to the fuel, such as membranes and chemical looping cycles have also been developed [7]. The combustion products are essentially CO_2 and H_2O, which are separated by condensing water [33]. Another advantage to post-combustion systems is that NOx is not formed [37]. Also the concentration of CO_2 in the output stream is high, with values above 80% v/v [34]. The main costs of oxy-fuel technology are related to the separation of O_2 and N_2 with the air separation unit. The cryogenic distillation where gaseous components of a mixture are separated by condensation is a very expensive process and requires high energy consumption [38], [39], [40].

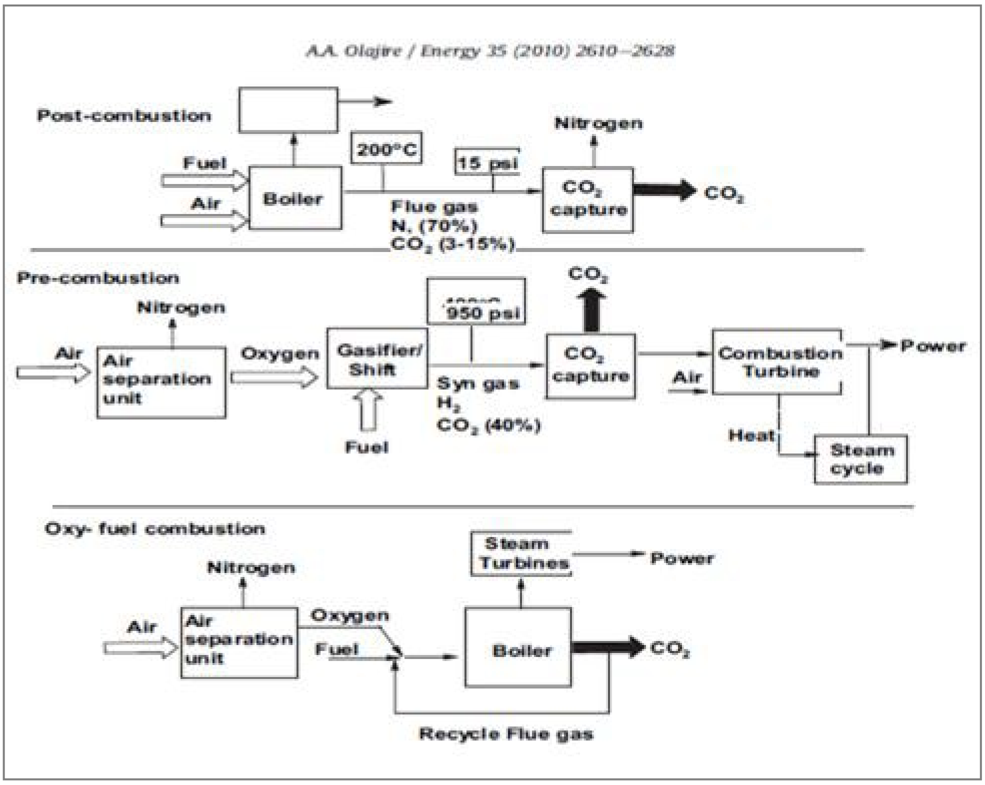


Figure 2.2 CO_2 capture concepts [34]

2.1.2 Carbon dioxide transport

CO_2 can be transported between the point of capture to the storage site in three states: gas, liquid or supercritical phase. Commercial-scale transport uses tanks, pipelines and ships. Gaseous CO_2 is compressed and transported by pipeline. CO_2 pipeline operators have established minimum specifications for composition. Volume can be further reduced by liquefaction. Liquefaction is an established technology for gas transport by ship as LPG (liquefied petroleum gas) and LNG (liquefied natural gas). This existing technology and experience can be transferred to liquid CO_2 transport. CO_2 is continuously captured at the plant on land, but the cycle of ship transport is discrete, and so a marine transportation system includes temporary storage on land and a loading facility. The capacity, number of ships and shipping schedule should be planned taking into account the capture rate, transport distance and social and technical restrictions [7].

To transport large volumes of CO_2, pipelines are considered to be the most cost-effective and reliable method [41], [27]. However, in some situations or locations, CO_2 transport by ship may be economically attractive, particularly when the CO_2 has to be moved over large distances or overseas. Vandeginste and Piessens published a review about the CO_2 pipeline transportation and revealed that the pipeline diameter is the crucial parameter for cost estimation of this transport method [42]. Several millions of tonnes of CO_2 are already transported by pipelines, most of it being transported to enhanced oil recovery (EOR) fields and quantitative risk assessment for CO_2 pipeline transportation was evaluated in several studies, some of them in the context of CCS projects [43], [44], [45].

Pipelines linking several industrial regions can be shared, allowing the greatest emission reductions for the lower cost. A computer tool for economic analysis was developed within the EU-funded GeoCapacity project to evaluate the CO_2 transportation systems based on low-cost pipeline networks to connect sources of CO_2 and storage reservoirs [46]. Additionally, an engineering economical model was proposed to evaluate the cost per ton of transporting CO_2 for a range of CO_2 flow rates, over a range of distances in the United States [27].

Captured CO_2 may contain impurities such as water vapour, H_2S, N_2, methane, O_2 and hydrocarbons [35]. Before the transport, the CO_2 stream is conditioned to remove impurities and compressed into supercritical form. The water should be reduced to a lower percentage, as it reacts with CO_2 and other acidic compounds to form acids, which are corrosive [45]. The CO_2 transport in supercritical form (at pressures ranging 80–150 bar, CO_2 behaves as a compressible liquid with a density of about 900 kgm^{-3}) is more efficient, because of the lower density of gaseous CO_2 and relatively high pressure drops per unit of length [27], [41]. The energy requirement for the conditioning processes will depend on the composition and pressure of the CO_2-rich stream and the selected transport process [35] and is typically between 90 and 120 kWh/tonne of

CO_2 [47]. In ship transport most of the volatiles must be removed in order to avoid very low temperatures and dry ice formation in the liquid CO_2. For pipeline transport, removal is not necessarily required, however it makes sense from an economic point of view [35].

2.1.3 Carbon dioxide geological storage

The storage options are grouped into geological storage, ocean storage or mineralization. Underground accumulation of carbon dioxide is a widespread geological phenomenon, with natural trapping of CO_2 in underground reservoirs. Geological storage of carbon dioxide involves injecting it into suitable deep rock formations. Information and experience gained from the injection and/or storage of CO_2 from a large number of existing enhanced oil recovery (EOR) and acid gas projects, as well as from the Sleipner, Weyburn and In Salah projects, indicate that it is feasible to store CO_2 in geological formations as a CO_2 mitigation option. Injection of CO_2 in deep geological formations uses technologies that have been developed for and applied by the oil and gas industry. Well-drilling technology, injection technology, computer simulation of storage reservoir dynamics and monitoring methods can potentially be adapted from existing applications to meet the needs of geological storage. The geological storage options are oil and gas reservoirs (depleted) or enhanced gas recovery (EOR), saline aquifers and unminable coal seams (in combination with enhanced coal bed methane recovery). The requirements for geological storage are adequate porosity and thickness (storage capacity), permeability (injectivity) and a satisfactory sealing cap rock [29], [48].

Another storage option is mineralisation. Mineralisation is the conversion of CO_2 to solid inorganic carbonates using chemical reactions. Challenges remain to make the process economically attractive and to reduce its energy use. Significant niche opportunities exist where waste materials are used as feedstock and/or the process produces value-added products, but markets would not be at the level required to meet the mitigation targets [49]. Ocean storage consists of the CO_2 injection at great depths where it dissolves or forms hydrates or heavier-than water plumes that sink at the bottom of the ocean [35]. Several techniques were tested to perform the CO_2 transfer to the ocean, vertical injection, inclined pipe, pipe towed by ship and dry ice [50]. However, the increase of CO_2 concentration in the ocean can have serious consequences for marine life. CO_2 leads to ocean acidification, affecting the growth rate of corals [48]. Therefore the CO_2 geological sequestration is considered the most viable option [51], [52], [53].

2.2 Deterministic whole system supply chain optimisation

This section is a critical review of deterministic whole system optimisation models developed so far for CCS supply chains or similar supply chains. The purpose of the former is to highlight the gap in previous scientific research in the field of deterministic CCS network optimisation and the latter is to gain knowledge of the fundamental aspects of deterministic whole system optimisation (steady state or multi-period).

Section 2.2.1 is a review of steady state whole system optimisation models of CCS or similar supply chains. Section 2.2.2 is a review of multi-period whole system optimisation models of supply chains similar to CCS. This is to learn about the fundamentals of multi-period modelling. Then this section attempts to identify any multi-period CCS optimisation models developed so far and highlights the limitations and hence justifies the first objective of this thesis as discussed in section 1.5.1.

2.2.1 Steady state whole system supply chain optimisation

Multi-period supply chain optimisation of an integrated CCS supply chain is naturally an extension of steady state optimisation. Therefore, in order to construct a multi-period optimisation tool, steady state supply chain planning and optimisation methods must be reviewed to help decide on the most appropriate basis for formulating the problem.

2.2.1.1 Steady state supply chain optimisation modelling applications

This section is a review of existing steady state planning tools or whole system supply chain optimisation models. In this section publications where the formulated problem is similar to the CCS supply chain problem have been analysed in detail. This is to gain knowledge of principles of whole system optimisation applied so far.

Pooly [54] presented the results of a Mixed Integer Linear Programming (MILP) formulation used by the Ault Foods company to restructure their supply chain. The model aims to minimise the total operating cost of a production and distribution network. The model is used to determine the location of plants, the production rate allocation and how the customers should be served. Hindi et al [55] present a solution procedure for large-scale, single-source, capacitated plant location problems (SSCPLP). They present an MILP formulation of the problem, with two types of decision variables relating to the selection of plants and to the allocation of customers to plants, respectively.

Tsiakis et al [56] used MILP to propose a strategic planning model which integrates components associated with production, facility location, multiproduct, multi-echelon supply chain networks operating under uncertainty. The network comprised a number of manufacturing sites, each using a set of flexible, shared resources for the production of a number of products. The manufacturing sites were assumed already to exist at given locations and so do the customer zones. The establishment of a number of potential warehouses and distribution centres at locations were to be selected from a set of possible candidates as part of the optimization. The problem was formulated as an MILP optimisation problem and solved using branch-and-bound techniques. The model took into account the complexity introduced by the multiproduct nature of the production facilities, the economies of scale in transportation and the uncertainty inherent in product demand. The authors introduced binary variables to decide whether warehouses and distribution centres are built at candidate positions and which warehouse is to supply which distribution centre and which customer zone. Continuous variables were introduced for the production rate, the flow rate and the warehouse and distribution centre capacities. They define the objective function as the sum of the capital cost associated with the establishment of the infrastructure and the operating costs incurred on a daily basis. Since this was a constrained optimisation problem, the authors apply network structure constraints whereby for instance for a link to exist between a warehouse and a distribution centre, the warehouse has to exist in the first place. Other constraints include transportation flow constraints, material balance, limits on production rates and capacity of warehouse and distribution centres.

Bruglieri [57] proposed a mathematical programming model to solve an optimisation problem arising from the deployment of a bio-mass based energy production system over a time horizon of one year in central Italy. The problem was broken down into three optimisation problems. The first is that of modelling the production process as a net gain maximisation where the type of plants and the demand are known. In the first linear programming model, they represent the process site by a set of vertices, the logistic connections by a set of arcs, and a set of commodities for each vertex. The supply cost, the transportation cost and the processing cost of a unit of commodity plus the maximum quantity, the transportation capacity and the yield for a commodity as well as the demand are parameters that define the problem instance. The variables are the quantity of the commodity in a vertex, on an arc connecting two nodes and the quantity processed into another commodity in a vertex. The objective function is to minimise the total operation cost which is the sum of the total supply, transportation and processing costs. In the second and the third models (planning models) some of the parameters were changed to decision variables for a simplified planning of the installation of the processing plants used in the production process. This changes the problem into a mixed integer non-linear (MINLP) one. The non-linear models are non-convex, exhibit multiple local minima, and therefore need to be either reformulated or solved using global optimisation techniques. However, they show that the spatial branch and bound algorithm converges exactly to the optimum and that the MINLP models can be reformulated to MILP models.

Zamboni and Shah [58] developed a spatially explicit static model for the strategic design of a future bioethanol production system based on cost optimisation. The design task was formulated as an MILP problem for the integrated management of the key issues affecting the supply chain. The model decides on the capacity of the plants taking into account the scaling factors which in turn affect the production costs. In part two of the publication, a multi objective optimisation model investigates the best trade-off between economic and environmental needs in other words the minimisation of GHG emissions. The mathematical formulae Zamboni and Shah [58] used in building a design framework are similar to the approaches applied in multi-echelon supply chains by Tsiakis et al [56] and Hugo et al [59] and the spatially explicit features of a hydrogen supply chain network as designed by Almansoori and Shah [60]

Hugo et al [59] presented their decision making process as a generic optimization-based model for the strategic long-range investment planning and design of future hydrogen supply chains by utilizing Mixed Integer Linear Programming (MILP) techniques. The model is capable of identifying optimal investment strategies and integrated supply chain configurations from the many alternatives. Kamarudin et al [61] also developed a model using an MILP method in GAMS which determines the optimum hydrogen delivery network in Peninsular Malaysia.

Zamboni et al [58] divided a biomass production network into two main substructures: an upstream fuel production and a downstream product distribution. They broke down the design problem into a set of inputs and a set of variables. The inputs are geographical distribution of demand centres, biomass fuel demand, biomass geographical availability, biomass production costs, biofuel production facility operating and capital costs and transport logistics (modes, capacities, distances, availability, and costs). The key objective is to find the optimal system configuration in terms of supply chain operating costs. Therefore, the key variables to be optimised are the geographical location of biomass production sites, biomass production for each site, supply strategy for biomass delivery to production facilities, biofuel production facilities location and scale, distribution process for biofuel to be sent to blending terminal and supply chain management costs. Zamboni et al [58] however developed their model under steady state conditions and the variant nature of demand was addressed by formulating different demand scenarios. The model distinguishes between different plant sizes to take into account the plant scale influence on the capital costs and the biofuel production cost. The aim of the model is to minimise the total daily cost, TDC (Euros/day) in establishing and operating a biofuel supply chain. The facilities capital costs FCC (Euros) is annualized through a capital charge factor CCF and divided by the network operating period α (days/year); the additional terms are the production costs PC (Euros/day) and the transport costs TC (Euros/day).

$$\mathrm{TDC} = \frac{\mathrm{FCC}}{\propto}\mathrm{CCF} + \mathrm{PC} + \mathrm{TC} \tag{2.1}$$

They then define all terms included in the objective function as explicit functions of the design variables. The facility capital cost is the sum of the capital cost of all single fuel conversion plants of all sizes in the territory. The planning is done over a grid of territorial elements g. The production cost is the cost per tonne of operating fuel conversion plants and biomass cultivation multiplied by the production rates summed over all grid elements. Zamboni et al [58] treat the transport system as already existing and therefore the transport cost only entails in simple terms the unit cost of transfer of a product multiplied by the flow rate of the product which is a product of the number of fully loaded transport units and the capacity of each unit. They have distinguished between the cost of transfer between grid squares and the local cost of transfer within a single grid square and assigned different modes of transport to the regional transport while the local one only entails a single delivery mode by truck. However, the technique used here may not apply to the CCS supply chain since pipelines are normally selected as the method of delivery for CCS.

Zamboni et al [58] explain that the cost terms in the objective function depend upon variables related to production, demand and the mass fluxes between grid points. The supply chain behaviour is then captured through the definition of mass balances as well as logical constraints that must be satisfied in each of the supply chain nodes. They identify demand as the driver of the design process of the supply network. Therefore, demand has to be defined in terms of the logical relation to the other main variables. They introduce a constraint whereby the total local demand has to equal the demand satisfied by local production and the demand satisfied by importing from other grid squares. The next constraint then confirms that the total local production has to at least equal and cannot be greater than the mass fluxes entering the region. Finally, global constraints are applied whereby the total production must at least equal the total demand and the total production and total demand are obtained by adding up the total local productions and demand. They applied a global mass balance to grid square g for each product whereby the total production of a product in a certain grid square is equal to the total demand of that product in that grid square plus the net flow of product. In addition, another constraint imposes that the total amount of fuel produced in each grid square is the sum of the production rates of plants of all scales. Also, the fuel and biomass production rates as well as the mass flux between grid squares must fall within the logical capacity limitations. Through another constraint on decision variables, which determine the direction of the flow of product relative to a grid, they ensure that flow can only take place in one direction.

These constraints on mass balances or the inequalities, which impose logical constraints, could be applicable to the CCS supply chain problem. The use of grid cells/squares for spatial modelling of the network as also introduced by Almansoori and Shah [60] and Prada [48] can be considered in formulating the CCS network problem.

Almansoori and Shah [60] designed a steady state snapshot model of a hydrogen supply chain that integrates the components of the supply chain ; production, storage and distribution within a single framework. The network is formulated as a mixed integer linear programming problem using Great Britain as a backdrop. Although in reality demand as the driver behind the establishment of new facilities and transportation links varies with time, the network is assumed to operate at steady state conditions. Almansoori and Shah, as covered later in this thesis, considered the migration pathway from the existing infrastructure in a later publication. The production plant decisions include the number, location and capacity of plants and the production rate within the grid square. The transportation decisions include whether to build a link between different grid squares and the flow rates. The storage decisions include the number, location and capacity of storage types as well as the total average inventory of hydrogen in each grid square. The hydrogen model decides on the location of the production plants based on the geographical distribution of demand, the failure of a grid square to fulfil its needs from neighbouring ones and the cost of transportation versus the cost of building a new facility. The decision on the location of the storage facilities is independent of the plant location but to serve demand and supply fluctuations. On the contrary, the CCS model, given the location of the sources and the sinks, will only decide which should be given capture or injection facilities to optimise the cost of the network also taking into account the transport costs. The objective of the hydrogen model by Almansoori and Shah [60] is to minimise the total daily cost of the network which is the sum of the capital and the operating cost terms.

The behaviour of the supply chain is driven by the logical constraints applied to each node As with Zamboni et al (2009), Almansoori and Shah apply constraints whereby the total local demand equals imports and local production and the demand satisfied by importing cannot be greater than the mass fluxes entering the grid square. In addition, the total production rate in a grid square must equal the total demand within that square plus the net mass flux to its neighbours. Another constraint ensures that the total production rate is not greater than the product of the number of facilities and their maximum production rates.

If the CCS supply chain is spatially defined by grids, similar constraints can be applied to the CCS supply chain. In addition, logically the total amount of CO_2 mitigated cannot be greater than the total amount captured from all capture sites or what is stored in a grid square cannot be greater than what is captured in that square and what is imported into the grid square. Also, the total rate of capture or storage in a grid is limited by the number of facilities and their relevant emission or injection rates. Almansoori and Shah [60] also applied a set of constraints whereby a particular grid can only import from other grids or export to them or neither but not both. For the case of the CCS supply chain if grid squares are used, a technique must also be applied to prevent simultaneous bi-directional flow for a particular grid square.

2.2.1.2 Steady state whole system CCS supply chain optimisation

This section is a review of the existing steady state integrated CCS supply chain optimisation models to detect the areas where improvement is essential.

Middleton et al [62] developed a static spatial optimization model that comprehensively models a carbon dioxide capture and storage (CCS) infrastructure, from source to sink. This model is formulated as a mixed integer linear programming (MILP) problem. Middleton et al [63] then went on to introduce a scalable infrastructure model for CCS (SimCCS) that generates a fully integrated, cost-minimizing CCS system. They explain that a comprehensive CCS infrastructure model should simultaneously consider and integrate seven key decisions (1) how much CO_2 to capture (2) at which sources (3) where to construct pipelines (4) of what size (5) which reservoirs should store CO_2 and (6) how much to inject and (7) how to distribute CO_2 from the dispersed sources through the network to the reservoirs in order to minimise the combined annualised costs of sequestering a given amount of CO_2.

Some of the pioneering work in the CCS literature focused on just a few of these seven decisions at a time, and made simplifying assumptions about the configuration of the pipeline network. Most earlier studies typically assumed that a single CO_2 pipeline directly connects a single source to a single injection site [64]; that these pipelines will be straight [65]; that there is a minimum and maximum distance for pipelines between sources and reservoirs [66] and that all CO_2 at a source must be captured regardless of system-wide economics [65], [66]. Kobos et al [67] moved an important step away from this direct-pipeline restriction. Their method begins with a source and constructs a pipeline of sufficient diameter to carry the entire source volume to the nearest reservoir. It then finds the next sink nearest to the first reservoir and constructs a pipeline sufficient to carry the remaining CO_2 to it, and so on, creating a "string of pearls". However, none of these CCS infrastructure models deploys a realistic network with capacitated pipelines or can generate high-capacity trunk lines.

Middleton et al [63] examined the sensitivity of the infrastructure to varying CO_2 targets. They demonstrated the tool SimCCS using a set of 37 CO_2 sources and 14 reservoirs for California.

Although comprehensive, SimCCS developed by Middleton et al. [62, 63] is only a steady state snapshot model and cannot demonstrate the progression of the optimal network. SimCCS is a static model, which re-optimises the system for each CO_2 target. This implies that if it were built, a source, pipeline or reservoir that was opened for a smaller CCS system might be closed or moved for a larger system. Also SimCCS is also only a deterministic model that assumes all cost and capacity coefficients are known with certainty.

SimCCS uses a candidate network generation sub-model used. They discuss although most models opt in for a predetermined set of candidate networks, here a sub-model generates the candidate network from which the optimisation model selects the optimal set of arcs. Kuby et al [68] divided the process into four steps required to solve a comprehensive CCS infrastructure system:

GIS cost surface grid : They take GIS layers representing the main geographical factors that influence the costs of constructing pipelines, converted into a 1km by 1km grid squares and multiplied by cost multiplier factors and combined together to create a pipeline construction cost surface. The final multiplier for each grid is multiplied by the base cost for building natural gas pipelines. The layers, base costs and multipliers are all editable by the users.

Potential pipeline routes : The location of CO_2 sources and sinks are added to the GIS and a grid based shortest path routine is applied to the cost surface from the first step to find the least cost path among all pairs of points. This results in a large number of duplicative routes, which must be simplified.

A simplified set of potential nodes and arcs: The grid is converted into a network of nodes and arcs. Nodes are inserted anywhere that pipeline routes among different pairs of points meet. The segment of the route between two adjacent nodes is then called arcs. Then overlapping arcs are removed.

Cost minimisation by SimCCS: The nodes and arcs along with cost and capacity data are fed into SimCCS to minimize cost while achieving a target. The network of candidate nodes and arcs is formulated as an MILP and solved using commercial software packages such as CPLEX or XPressMP. The model minimises the total cost of building and operating an integrated CCS and makes key decisions simultaneously. In their network-based approach, the amount of CO_2 to flow through any pipeline arc is decided by taking into account the nature of the sources and the reservoirs selected and which flows can be efficiently combined.

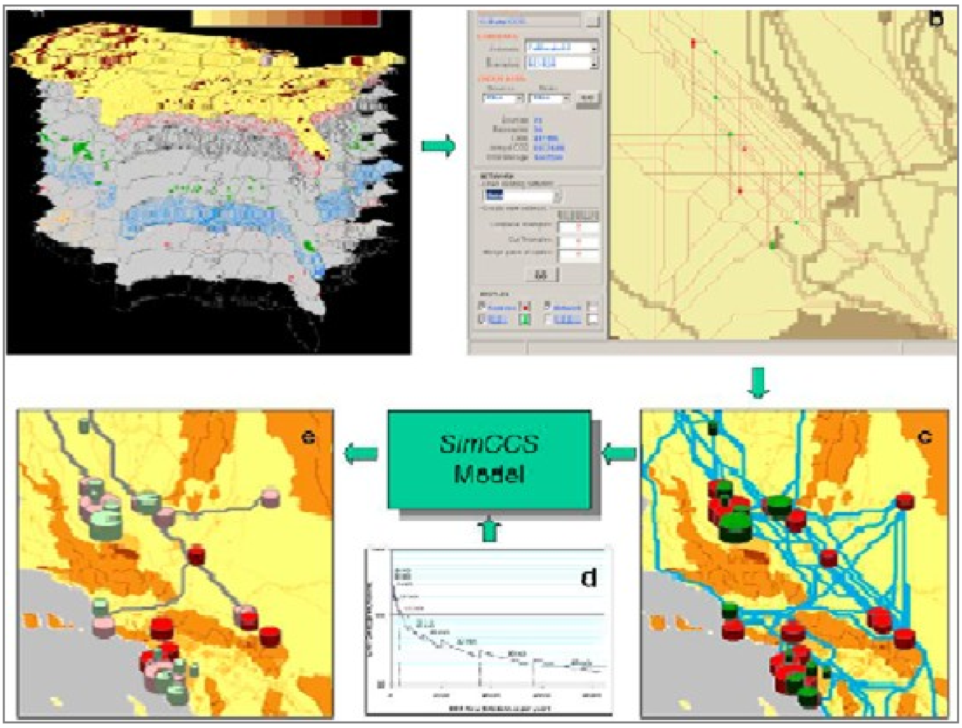


Figure 2.3 The simCCS modelling process. (a) GIS cost surface; (b) potential pipeline routes and network-thinning interface; (c) post-thinning simplified network; (d) cost and capacity data; and (e) optimal CCS infrastructure results. [68]

Middleton et al [63] define the pipeline diameter as a set and the parameter for the fixed transport cost is a function of the diameter. Hence in minimising the fixed cost the model decides on the optimal diameter. This is a key element of the model for incorporating economies of scale, in that it allows the model to build pipelines of the most cost efficient diameter for transporting any particular amount of CO_2. A similar approach will be adapted in the CCS supply chain model of this thesis. However Middleton et al [63] use a set of parameters for the variable transport cost each associated with a maximum flow rate which in turn is dependent on the diameter..

The pipeline cost curve input to the SimCCS model represents cost versus the CO_2 flow rate for pipelines of different diameters ranging from 4 to 42 inches. The curve displays economies of scale and economies of utilisation. The overall declining shape of the curve displays economies of scale with a 4inch pipeline having a maximum capacity of 190kt/year at an average cost of \$498/kt/km and a 42inch pipeline having a maximum capacity of 84Mt/year at an average cost of \$15.45/kt/km/year. Economies of utilisation is a different concept and is seen in the shape of the curve for each pipeline size, which drops as the fixed costs of the pipelines are spread across more tonnes.

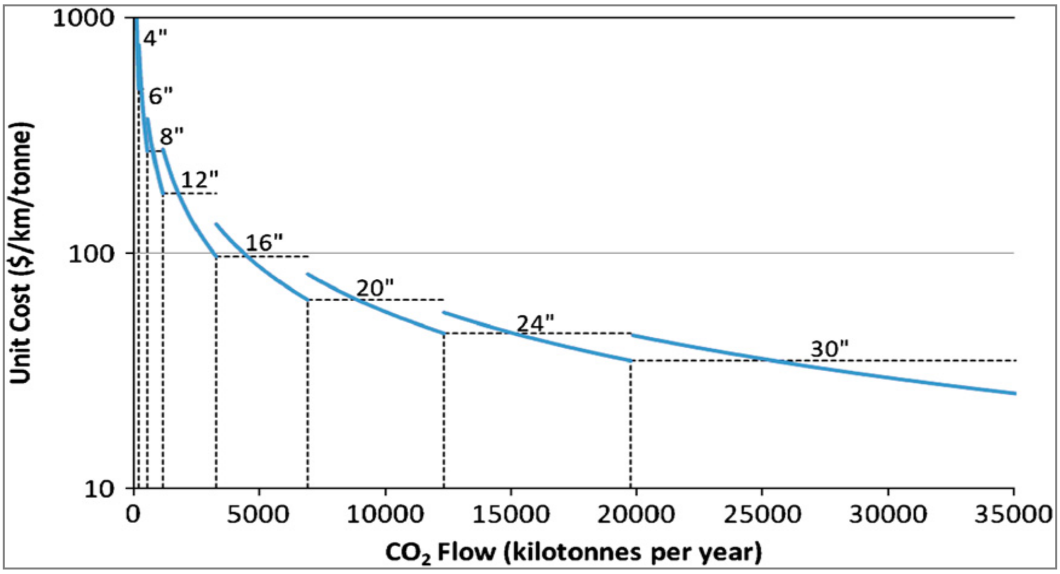


Figure 2.4 Pipeline costs (\$/km/tonne of CO_2) for ten pipeline capacities. [63]

Kuby et al [68] used a case study of Midwest USA consisting of eight coal-fired power plants and seven depleted oil fields as potential sources and sinks to demonstrate the cost savings of using a model like SimCCS. The results for building a networked pipeline system for 1Mt to 22Mt CO_2 per year in increments of 1Mt are then compared to results from constrained runs of SimCCS in which the pipeline branching capability is restricted to allow only direct pipelines between sources and sinks. Although the first four solutions from 1 to 4 $MtCO_2$ were identical. As the target increased, the networked model shows a greater efficiency. The networked model achieves a higher capacity utilisation and a lower total length therefore saving cost. Kuby et al [68] analysis showed that as soon as the scale of a CCS system becomes large enough to include more than one source and one sink, the benefits of networking the pipelines begin to appear. However, despite these transport cost economies, average CCS costs in the networked system begin trending upwards after 10 Mt CO_2/year because of the steady increase in capture costs as the model is forced to utilize more and more expensive CO_2 sources.

Fimbres Weihs et al [69] developed a cost optimisation model for CCS pipeline networks including multiple emission sources, capture plants and injection locations. The optimisation was based on minimising the cost of the network i.e. the costs of building, operating and abandoning the capture plants, pipelines and storage sites using a genetic algorithm. For a case study in the South Eastern Queensland region, they conclude the pipeline and compression costs for the optimal network are approximately US$15 per tonne of CO_2 avoided. Their model although comprehensive is a steady state optimisation tool only illustrating a snapshot of the optimal CCS network.

Pinto-Varela et al [70] addressed the problem of designing supply chain structures for annual profit maximization, while considering some environmental aspects. They used a bi-objective optimisation approach for economic versus environmental performance optimisation. The supply chain optimisation part of their work is modelled as a mixed integer linear programming (MILP) optimization problem using the Resource-Task-Network (RTN) methodology.

Han et al [71] used mixed integer linear programming to design an integrated energy infrastructure. A two-fold strategy was used for the energy infrastructure design; one is to use CCS facilities and the other to accelerate the introduction of renewable energy systems. The objective function was to minimise the total annual costs of CO_2 disposal and H_2 supply restricted by constraints such as CO_2 capture ad H_2 demand constraints. They developed a case study to illustrate an optimal infrastructure network of capture, storage and sequestration as well H_2 infrastructure for a specified annual reduction target. The method however is deterministic and does not illustrate the evolution of the system as energy demands and therefore carbon emissions increase.

Arasto et al [72] modelled carbon capture processes and process integration options using Aspen Plus process modelling software and the results were used to estimate CO_2 emission reduction possibilities and carbon abatement costs. They then used a whole chain approach, including CO_2 capture, processing, transport and storage. The results show significant reduction potential at an integrated steel manufacturing plant with carbon capture technologies. Ship transportation of CO_2 is considered due to the location of the installation. Cost breakeven points for carbon capture for the plant owner and costs for globally avoided emissions are calculated. The optimal CCS supply chain was also demonstrated. However, this is only a snapshot of the CCS system at a particular time.

Jakobsen et al [73] proposed a methodology which provides means for evaluation of several economic and environmental criteria to enable selection of appropriate CCS options. The process of the quantitative assessment of CCS with this tool contains the following. A scenario is developed where the chain environment is defined in terms of global assumptions on governing factors; market regulations and incentives. A case is developed for one particular chain design and an assessment of technical specifications follows. Once the CCS chain design is complete, modelling on the component level is carried out to include lower level of detail or parameterised cost functions, risk assessment or environmental and techno-economic assessments. Then a whole chain analysis is carried out which includes economic analysis (profit vs. cost), environmental analysis and a technical risk assessment. The simulation tool is coded in the programming language C# and it is designed as a bank of components that the user can apply freely to build the particular chain of interest. The tool allows for evaluation of key performance indicators on several levels including chain component and the overall chain.

Although the tool allows for simultaneous chain design and economical or environmental assessments of CCS deployment for the selected scenarios, the chain design solution does not provide whole system optimality given a group of potential emitters and storage site and the model is unable to provide the evolution of the network.

Prada [48] investigated the deployment of an integrated minimum cost CCS infrastructure for the UK and the North Sea. The scope of the work included 33 UK emitters and six southern North Sea sinks. Prada et al identified the problem of minimising the cost of an integrated CCS infrastructure given an annual reduction target as a supply chain optimisation issue where a product (i.e. carbon dioxide) produced at stationary sources (i.e. power and industrial emitters) need to be delivered to consumers (i.e. sinks) via a delivery infrastructure. They identified an MILP framework, a suitable natural approach allowing for optimisation of the network and selection of the optimal sources and sinks within a specific area and given certain constraints. However they formulated the problem as an MILP snapshot problem operating at steady state. They introduced square grid cells as spatial reference. A number of binary and continuous variables are defined to account for strategic and operational decisions respectively. As used in equations 2.3 and 2.4, $yc_{i,k}$, $ys_{i,k}$ are binary variables which indicate whether capture or storage facilities of type k are built at grid cell i. $xt_{i,j,l}$ indicates whether a transport link of specifications l is built between grid cells i and j. This variable is used in calculating the cost of transport as shown in equation 2.5. Prada et al set their objective function Z as to minimise the total costs associated with the deployment of an integrated CO_2 capture, transportation and storage infrastructure.

$$\mathrm{Z} = \text{Total capture cost} + \text{Total storage cost} + \text{Total transport cost} \tag{2.2}$$

Prada et al define the yearly costs associated with CO_2 capture as the sum of a fixed and a variable component. The fixed component is the product of the decision variable and $\mathrm{fcc_{i,k}}$,an annual pro-rata of the upfront cost of building capture facility k in grid cell i, obtained by multiplying overall capital expenses by the capital charge factor. The variable component is the annual operational expenses, which are the product of the unit operational cost of capture in plant type k, cell i, $\mathrm{vcc_{i,k}}$ and the CO_2 capture rate $\mathrm{C_{i,k}}$.

$$\mathrm{CC} = \sum_{\mathrm{i,k}} (\mathrm{fcc_{i,k}}\ \mathrm{yc_{i,k}} + \mathrm{vcc_{i,k}}\ \mathrm{C_{i,k}}) \tag{2.3}$$

Similarly, the storage cost is calculated as follows.

$$\mathrm{SC} = \sum_{\mathrm{i,k}} (\mathrm{fsc_{i,k}}\ \mathrm{ys_{i,k}} + \mathrm{vsc_{i,k}}\ \mathrm{S_{i,k}}) \tag{2.4}$$

Prada [48] expresses the transportation cost as a pure function of flow rate and pipeline length. They first obtain a graph of cost versus Diameter from the IEA GHG pipeline calculator [74]. They then use an iterative approach to relate pipeline diameter to flow rate based on the equation used by McCoy [27, 75] and Romeo et al [76]. They then combine the two to obtain a non-linear graph of cost (k$/km/year) versus flow rate ($MtCO_2$/year). Since the presence of a nonlinear function is not allowed in an MILP model, they carry out a piecewise linearization of the curve as shown in figure 1.5. Each segment's intercept and slope respectively represent annual fixed capital cost $\mathrm{ftc_l}$ and an annual variable cost $\mathrm{slope_l}$ per kilometer. Considering the associated costs and flow rates the model then decides on the optimal segment. Therefore, CO_2 flow rates are optimised whilst pipeline sizing is considered secondary and not performed. The overall cost per km is the sum of the capital cost plus the variable cost proportional to the specific mass flow rate and the slope of the segment.

$$\mathrm{TC} = \sum_{\mathrm{i,j,l}} (\mathrm{ftc_l}\ \mathrm{xt_{i,j,l}} + \mathrm{Q_{i,j,l}}\ \mathrm{slope_l})\ \mathrm{d_{i,j}} \tag{2.5}$$

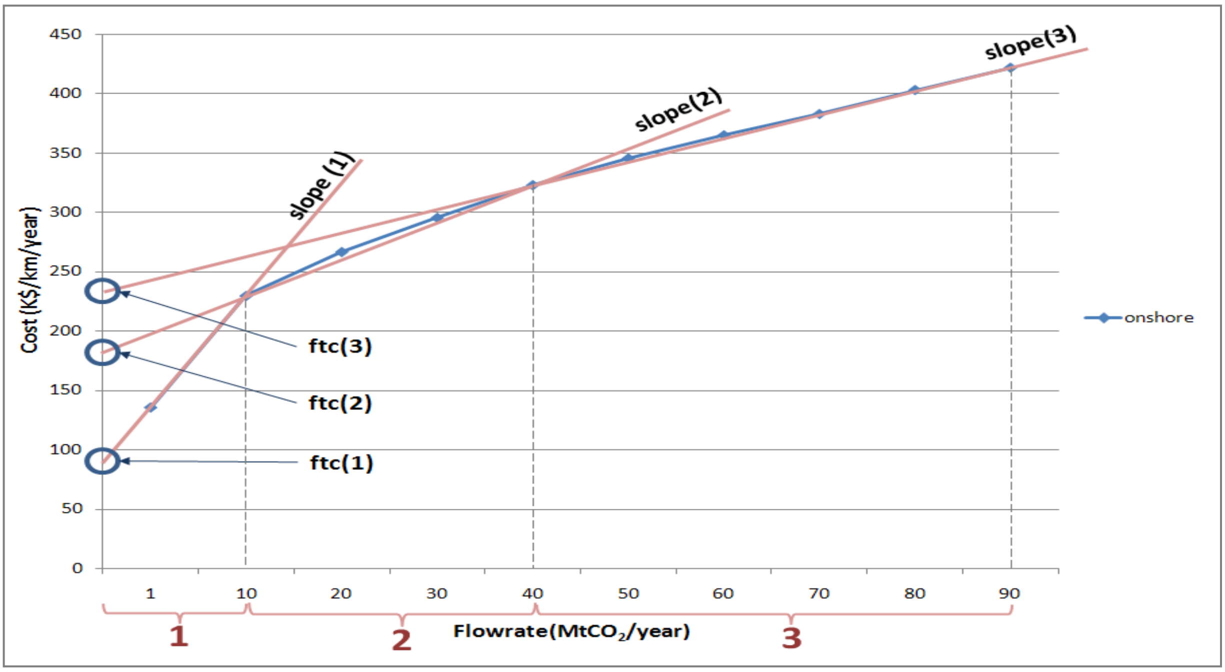


Figure 2.5 piecewise linearization of the onshore transport cost function. (Prada et al.2010)

Some of the logical and design constraints applied by Prada [48] which with necessary modifications can be adapted to multi-period CCS model of this thesis are listed below. At each cell, a mass balance is performed among yearly mass flow rates of CO_2 captured from local sources, stored in local sinks, imported from other cells and exported to other cells.

$$\sum_{jl} Q_{i,j,l} - \sum_{jl} Q_{jil} - \sum_{k} C_{ik} + \sum_{k} S_{ik} = 0 \tag{2.6}$$

Equation 2.7 shows that If a capture plant is deployed at emitter k within cell i, the yearly CO_2 captured $C_{i,k}$ should be below the maximum capture limit $a_{i,k}$, fixed as 90% of the average plant yearly emissions. The same concept applies to the CO_2 stored in cell i, storage site k, $S_{i,k}$ and the storage capacity $b_{i,k}$. A multi-period model however must take into account that the remaining capacity of the storage site declines with time if CO_2 is injected at the site. Equation 2.9 ensures that the total CO_2 captured at least satisfies a pre-determined capture target.

$$C_{i,k} \leq a_i \text{ x } yc_{ik} \tag{2.7}$$

$$S_{i,k} \leq b_{j,k} \text{ x } ys_{j,k} \tag{2.8}$$

$$\sum_{i,k} C_{i,k} \geq ct \tag{2.9}$$

They apply constraints, which restrict the yearly flow rate between cells to a minimum and a maximum depending on the segment of the transport cost curve selected for the pipeline between the two cells.

$$Q_l^{min}\ xt_{i,j,l} \leq Q_{i,j,l} \leq Q_l^{max}\ xt_{i,j,l} \qquad 2.10$$

Another constraint prevents building a second pipeline in the opposite direction in case a link is already present.

$$xt_{i,jl} + xt_{jil} \leq 1 \qquad 2.11$$

Using equation 2.12 they avoid the deployment of multiple pipelines with flow rates relevant to different segments within the linearised transport cost curves.

$$\sum_{l} xt_{i,j,l} \leq 1 \qquad 2.12$$

Prada et al devised several scenarios with varying capture targets from 5 to 105 $MtCO_2$ per year and found that each generated a different infrastructure layout. An initial seed infrastructure is implemented in South Yorkshire and Humber and CO_2 is transported to the Southern North Sea depleted gas fields via Theddlethorpe terminal. As the reduction target increases, the infrastructure evolves to incorporate Thames estuary emitters whose CO_2 is separately routed offshore via the Bacton terminal. At first the system mainly captures from coal plants primarily Drax, while CCGT contributions are more expensive and play a part above 75$MtCO_2$ per year. An optimal overall cost of \$81.5/tCO_2 is achieved at 30$MtCO_2$ per year after an initial decline primarily due to a shared use of transport and storage. However as the reduction target increases above 30$MtCO_2$ per year more expensive CO_2 sources are required, hence the overall cost increases to \$99.8/tCO_2 at 105$MtCO_2$ per year. Above 30$MtCO_2$ per year the transportation and storage costs stabilise around \$2.6/tCO_2 and \$9.0/tCO_2 respectively, however as the target increases, so does the capture cost. They then carry out a sensitivity analysis which indicates that overall cost and the timing of retrofit of gas-based power generation is affected by parameters such as scaling factors and gas price, while oil refineries, cement works and smaller capacity CCGTs are discarded at all stages.

Although through running several scenarios they obtain a comprehensive optimal solution for each snapshot of the system, however the steady state nature of the solution is a major limitation of the model here. It does not make economic sense to plan the expansion of an infrastructure according to the results obtained from discrete snapshot scenarios. Minimum cost planning for a dynamic system requires that decisions at every stage are made considering the future changes. However, some lessons have also been learnt; for example we find MILP to be the most suitable approach in addressing the issue of multi-period whole system supply chain optimisation of an integrated CCS network. This is because the solution aims to identify the optimal values of a number of investment decisions, which can be defined using binary variables, and operational decisions represented through continuous variables. Some of the logical and operational constraints reviewed above can also be adapted to the multi-period CCS supply chain problem presented in this thesis. The spatial reference system of grid cells will also be considered amongst other methods for the CCS infrastructure planning problem presented here. Despite the lessons learnt, it also became apparent that so far no scientific research was found on the topic of optimisation of a CCS supply chain pathway under dynamic targets and constraints. However having investigated the above steady state supply chain optimisation methods, the model developed by Prada [48] in particular can be a platform to formulate the multi-period CCS supply chain problem of this thesis.

2.2.2 Multi-period whole system supply chain optimisation

Section 2.2.1 reviewed whole system supply chain optimisation methods. Although comprehensive, the models presented steady state supply chains and did not consider the evolution of the network under dynamic constraints. Hence, it became clear that the gap so far is in fact a comprehensive CCS supply chain solution, which also shows an optimal pathway for the progression of the CCS system. Section 2.2.2.1 is a review of the literature for methods to model dynamic supply chains fundamentally similar to CCS. Then section 2.2.2.2 explores any temporal spatially explicit CCS network optimisation models and if any, their limitations that will need to be addressed by the model developed in this thesis will be discussed.

2.2.2.1 Multi-period supply chain optimisation modelling applications

Publications included in this section explore the temporal and spatial aspects of supply chain optimisation for supply chains similar to CCS. They were reviewed to learn the dimensions, which can be adapted to or improved in the temporal modelling of an optimal CCS supply chain. If directly relevant, these dimesions are discussed further.

Ball et al [77] developed a model to assess the geographic and temporal set-up of an infrastructure for a hydrogen-based transport system in Germany up to 2030. They then analysed the effects on the national energy system and the price sensitivity of the energy mix ratios. Qadrdan et al [78] developed a generic optimization-based model for the long-range energy planning and design of future hydrogen supply systems. By applying Linear Dynamic Programming techniques, the model is capable of identifying optimal investment strategies and integrated supply chain configurations. They modelled a hydrogen supply system for Iran in the time span between 2008 and 2050. The model minimizes the total discounted costs of an energy supply system, which includes capital, operational and maintenance over a given period and represents the flow of energy from resources to the end users based on the technical, environmental and economic features of various technologies. Some of the principles of economic optimisation of a multi-period supply chain can be adapted to modelling a dynamic CCS supply chain.

Almansoori and Shah [79] designed a multi-period hydrogen supply chain (HSC) model using a simulation based approach as an extension of the earlier publication on designing a deterministic steady state network. The MILP model is designed to consider the variation of demand and the possibility of selecting different scales of production and storage facilities leading to phased infrastructure development. The model decides on the number, location, capacity and type of production and storage facilities, type and amount of feedstock, the production rate of plants and the average inventory as well as the hydrogen flow rate and the transportation links. The model also determines the utilisation rate of primary energy sources in each grid and their distribution throughout the network. In this work, Almansoori and Shah address the variation of demand with time and the geographical distribution of demand and supply. The UK CCS model should also be able to address similar issues such as the variation of the CO_2 reduction target over time, the geographical distribution of the sources and perhaps partial CO_2 capture. The hydrogen model is of interest here because it considers some essential elements in the design of supply chain networks; first the evolution of the network i.e. “the pathway” as well as the scale of production and storage facilities and deciding on the type and the quantity of the primary source.

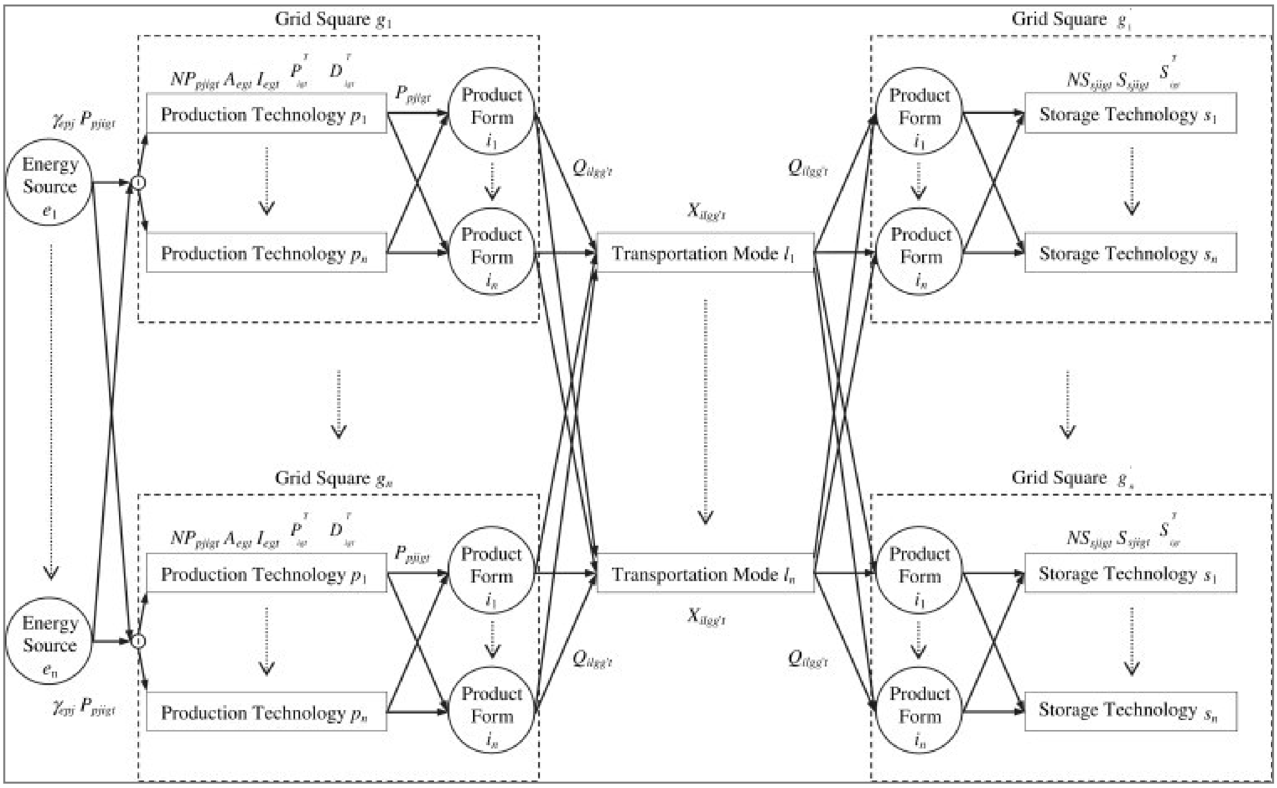


Figure 2.6 Superstructure of a multi-period hydrogen supply chain model. [79]

Almansoori and Shah [79] developed a superstructure for the multi-period model using the interconnectivity between the processes. From this superstructure the optimisation algorithm finds the best configuration or improves the behaviour of a pre-specified system. A grid system is used within the superstructure. The grid squares g enclose different types P and sizes J of the hydrogen production technologies. Also, there are grids g' enclosing different types S and sizes J of storage technologies. The production technologies will use various energy sources e, there are different transportation modes l to transport products i from production to storage. The hydrogen supply chain model determines the establishment of the plant types depending on the demand of the grid square, the failure of the grid square to fulfil its needs from neighbouring grid squares and the trade-offs between establishing plants or transportation links. The transportation decisions include whether to use a transportation link between grid squares or not, the mode and the flow rate. The storage decisions include number, location, capacity and the total average amount of product stored. Almansoori and Shah set the objective function to minimise the average total daily cost of the HSC network over a long-term planning horizon. They also show that the unit production and storage costs benefit from economies of scale.

Similar to the hydrogen supply chain problem addressed here, because of the nature of the questions that the model needs to answer, Mixed Integer Linear Programming will be used for modelling the CCS problem of this thesis. Depending on whether a grid system is considered to map out all possible configurations of the CCS supply chain, the logical mass balance constraints and the connections between the elements of the supply chain can be adapted to the CCS problem.

An interesting element of this work by Alamnsoori and shah [79] is the constraints which enforce the time dependant evolution of the system. They defined NP^0_{pjig} the existing number of plants or storage facilities at time t^0, as a parameter and the number of new production plants that need to be invested in early during the first time period t^1, IP_{pjigt1} as a variable. As the below equations show, they then stated that the number of production plants at time t^1 equals the existing plants plus the new investments at t^1. Then as the network evolves, the second constraint restrains the number of production plants at time t to the number of production plants at time t-1 plus the new investments at time t. In turn, the variable 'the number of facilities' appears in the objective function or in the constraints applied to restrain the inventory or the production rates. The evolution of the CCS system will also be expressed through the accumulation of the number of facilities through time.

$$\mathrm{NP_{pjigt1}} = \mathrm{NP^0_{pjig}} + \mathrm{IP_{pjigt1}} \qquad 2.13$$

$$NP_{pjigt} = NP_{pjig(t-1)} + IP_{pjigt} \quad 2.14$$

Konda et al [80] developed a multi-period optimization framework based on a comprehensive techno-economic analysis used to design spatially-explicit and time-evolutionary hydrogen supply networks. The detailed mathematical formulation is similar to that of the models presented by Almansoori and Shah [79]. The model inputs are; number and length of time intervals, demand, number and location of existing plants and techno-economic data of various components of the chain and finally financial data i.e. discount rate, inflation and taxes. The model will output optimal values of existing plants used, number of new plants, type, location and scale as well as quantities of hydrogen and transport modes. The objective function is to minimise the sum of the annualised costs of the entire supply chain. Future cash flows are discounted to compute the net present value or cost in order to account for the time value of money. The model formulation is based on Mixed Integer Linear Programming (MILP), and is solved in the General Algebraic Modelling System (GAMS) environment using the CPLEX solver. The main principles of the models reviewed here are applicable and will be considered in modelling the problem of this thesis, the first aim of which is to develop a supply chain optimisation framework maximising a spatio-temporal CCS network's economic performance.

2.2.2.2 Multi-period whole system CCS supply chain optimisation

Finally, this section focuses on temporal and spatial CCS optimisation models developed so far and their limitations hence the gap in knowledge and the main objective of this thesis will be justified.

Kemp and Kasim [81] carried out a study to determine the least-cost CO_2 transportation and storage network for eight power plants in the UK and twenty fields in the UK continental shelf over a 20 year time period (2018-2037). Although they only highlighted the transport cost issues and the study does not explicitly consider capture costs, their approach is based on fundamentals of supply and demand and methods, which demonstrate network development over time and hence relevant to the supply chain optimisation issue introduced in this report. They identify the central issues of concern in the economics of CO_2 transportation namely the when, the where and how much of CO_2 delivery, as a constrained optimisation problem to be solved as a transportation problem using a linear programming solver. Kemp and Kasim used the Linear Programming package in GAMS to determine the minimum cost of shipping CO_2 from i capture sources to j CO_2-EOR and k permanent storage sinks. The approach of the model is useful for matching sources, determining CO_2 flow rates, injection rates and pipeline routes. The study attempts to investigate how the timing and the size of CO_2 sources and facilities affect pipeline network configuration given the annual supply quantities from the sources, the timing of the availability of fields as sinks, the storage capacities of the sinks and the annual injection rates as well as the rational utilisation of the pipeline infrastructure. Four scenarios were developed to determine the sensitivity of cost to constraints on the volumes of CO_2 captured from the sources and the injection rates as well as the availability of field for EOR. Despite the fact that the study does not explicitly consider the capture costs, their approach is a direct source to sink pipeline connection similar to the study carried out by the Illinois Geological Survey [65] and BERR's analysis of a CO_2 network in the North Sea [82]. The solutions can be used in the MIT CO_2 pipeline transport and cost model [64] or Middleton and Bielicki's SimCCS models [63] both for pipeline routing solutions.

Kemp and Kasim [81] emphasize that one of the problems of designing an integrated CCS project is the need to preserve compatibility of supply with the injection capability at the sink. In reality, there are variations between the annual supply and the annual injection capability at the sink. They consider future supply capacities of eight plants in the UK from year 2020 to 2035 based on companies contemplating future investments in the capture facilities. The study considers a gradual capacity build up consistent with the general view of a learning by doing process and assumes the capture capacities are built up as 40%, 53%-56%, 70%-73% attaining 90% of emissions in the fourth cycle.

The authors produce a list of EOR and permanent sinks, where the original capacity of the reservoirs was calculated as indicated by BGS [83], then using DECC data available in the public domain the space freed up by the cumulative production of oil is deducted from the original capacity. They also list the close of production dates calculated by Kemp's economic model [84]. The storage capacities are then refined to calculate the eventual capacity considering not all capacity will be available due to water invasion. The maximum annual injection rate i.e. demands are then calculated by dividing the capacity over the 20 years planning horizon.

Kemp and Kasim [81] explain that the pipeline construction cost depends on the diameter, geography, distance, dry or wet CO_2 and regulations which determines the nature of the material used. Using the below graph by the IEA [85] which gives an idea of how pipeline diameter and geography affect the capital cost of pipeline networks, the study assumes a diameter of 0.762m with a corresponding CAPEX of between £1m/km to £3m/km. However, Kemp and Kasim do not mention factors such as pressure and phase of CO_2. They simply take £2m/km as the central value, which is higher than the estimate for offshore USA pipelines to reflect the increased cost from 2008. The chosen value is consistent with estimates in Poyry Enery Consulting [86] and Scottish Centre for Carbon Storage [87]. The estimated cost of onshore storage is no lower than offshore to take into account the problems of topography and planning as discussed in Shackly and Gough [88].

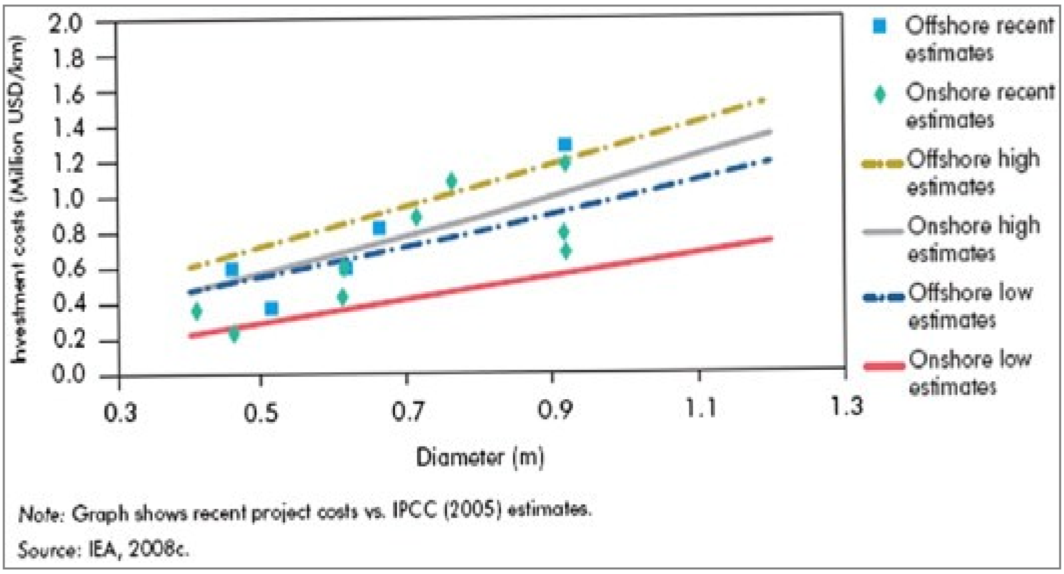


Figure 2.7 Pipeline investment cost vs. Pipeline diameter and geography. [85]

Kemp and Kasim calculated the shortest distances using data on location coordinates of sources and sinks using the Haversine formulae. Kemp and Kasim's objective function expresses the goal of determining the volumes of CO_2 to be shipped from capture source i to the two storage sink types i and k at time t at a minimised cost. The objective function is minimised subject to some constraints including the CO_2 material and demand balance constraints. For example, the gross supply of CO_2 at source i at time t must be shipped to sinks j and k and across the industry the total volume of CO_2 captured at the sources must equal the sum of the delivered and the surplus or the undelivered CO_2 to the sinks. Through the demand constraints, Kemp and Kasim define demand as the sums of the volumes transported and injected plus any shortfall. Here it is assumed that although it is desirable for the supply to equal demand, however at least during the supply capacity build up, demand can potentially exceed supply therefore they introduced the shortfall expressions. The central issues of concern in Kemp and Kasim's model are the economics of CO_2 transportation. While the approach of the model is useful for pipeline routes and determining CO_2 flow and injection rates, the objective function does not consider the cost of capture or storage. The authors approach in determining the source and storage capacities as well as the constraints discussed above provide useful insight in modelling the UK CCS issue.

Johnson and Ogden [89] combined a CO_2 pipeline optimization tool with techno-economic models for CCS components and regional spatial data to examine how CCS infrastructure might develop in the South Western United States under the American Power Act. A CCS deployment scenario specifies CO_2 reduction targets for six deployment periods from 2016 to 2050. For each target, a CCS infrastructure optimization tool identifies the lowest cost infrastructure for matching CO_2 sources and sinks within the region. Specifically, this tool identifies the location and number of required CO_2 sources, the location and number of CO_2 injection sites, and the diameter and location of pipelines. The optimisation tool is a mixed integer linear programming model, which is formulated in GAMS and solved in CPLEX. The selected sources, sinks and pipeline segments are exported for further analysis in a geographic information system (GIS) and a techno-economic model for the components of the chain. The model demonstrates the evolution of an optimal pipeline infrastructure and the number and location of necessary capture and storage sites needed to satisfy the mitigation target. The MILP model keeps the pipeline infrastructure costs at minimum at all times, however it has not been mentioned whether the sources and sinks are also selected in a way to minimise the cost of the chain as a whole. It seems the optimal criteria for the operation of sources and sinks are only determined in separate techno-economic models for capture and storage components of the chain. Therefore, although the pipeline network might represent the optimal configuration for connecting the sources to the sinks, the model does not make simultaneous decisions for all elements of the chain with an aim to minimise the cost of the combined system.

Kjärstad et al [90] explored the potential layout of CCS infrastructure in Europe, by combining techno-economic modelling of Europe's electricity sector with a detailed modelling and analysis of a CO_2 transport infrastructure. First, the electricity sector is described using an electricity Investment model, which yields the technology mix including CCS until the year 2050. The model gives the lowest system cost under a given CO_2 emission reduction target. Thus, the model gives the annual flows of CO_2 being captured. These flows are then used as input to InfraCCS, a cost optimisation tool for bulk CO_2 pipelines. Finally the InfraCCS results are applied along with Chalmers database on power plants and CO_2 storage sites [91] to design the development over time of a detailed CO_2 transport network across Europe considering the spatial restriction of power plants and storage locations. The work shows that the spatial distribution of capture plants over time along with individual reservoir storage capacity and injectivity are key factors in determining routing and timing of the pipeline network. It is found that the total investments for the pan-European pipeline system is 31 billion Euros if onshore aquifer storage is allowed and 72 billion Euros if aquifer storage is restricted to offshore with corresponding specific cost of 5.1 to 12.2 Euros per tonne of CO_2 transported. In this work, CCS development planning is done considering the evolution of the energy system; however, the optimisation of the transport system is carried out separately from the source and sinks selection process. The outcome is an integrated optimisation of the CCS infrastructure as a whole.

Boavida et al [92] explored the temporal and spatial aspects of the development of the energy sector and other industrial activities with relation to CCS and its participation in CO_2 reduction targets in the West Mediterranean area as part of the work conducted through the EU FP7 COMET project. This was the first large scale study of the costs and challenges to the large scale deployment of a CO_2 transport and storage infrastructure in the West Mediterranean area and co-funded by the EU 7th Framework Programme. Special attention is given to a balanced optimisation performed on transport modes, matching sources and sinks. The overall strategy of the model TIMES-COMET can be summarized into the following fundamental tasks; MarkalTimes, an optimisation model that represents the energy systems of Morocco, Portugal and Spain and their possible long term developments (2005-2050) is used to perform the least cost modelling of national and regional energy systems. A least cost optimisation based on the maximisation of the total energy system surplus provides the optimal energy-technology pathway, which also satisfies final services demands considering constraints such as emission limits. In addition, the fuel price and the associated emissions are provided at each period. Then a harmonized inventory and mapping of CO_2 sources and storage capacities in the region is carried out. The source/sink information is integrated in a geographical information system (GIS). Routing algorithms were used to find optimal routes. TIMES-COMET shows the most cost effective source-sink combination between the three countries (Portugal, Spain, and Morocco) considering the possible future energy system developments. Finally, an in-depth assessment of the selected transport network is carried out. Kanudia et al [93] prepared some scenarios with the TIMES-COMET model discussed above. This was done in the MARKAL-TIMES modelling framework given the assumptions on the development to 2050 of mitigation levels, economic growth and CO_2 capture, and transport and storage characteristics. The outcome showed the optimal levels of CCS contribution to mitigation compared to other energy system options. The results also indicate the layout of the main capture, transport and storage infrastructures.

Although the outcome of TIMES-COMET model indicates the development of CCS according to the future energy systems development, however the mapping of sources and sink capacities is carried out separately and the information is then fed into a GIS for network routes optimisation. In other words although the selected source-sink combinations or the selected routes might each be cost optimal however an integrated selection process with an aim to minimise the overall cost might indicate a different combination of the components of the chain.

Broek [94] carried out a study planning and designing a CO_2 transport infrastructure in the Netherlands, incorporating both temporal and spatial aspects. Broek developed a toolbox that allows assessments of the spatially explicit development of a CO_2 infrastructure over time. This toolbox takes into account location and the time-path of individual infrastructure elements. It integrates ArcGIS, a geographical information system with spatial and routing functions, and an energy bottom-up model based on linear optimisation (Markal). Application of this toolbox led to blueprints of a CO_2 infrastructure in the Netherlands. Besides the electricity and cogeneration sector, also the CO_2 intensive industry is included in the analysis. However it is not specified whether the solution simultaneously makes investment decisions for all components of the network and also whether operational questions such as how much CO_2 to capture, transport and inject and the where and when are also answered.

Lately Middleton et al. [95] expanded the tool SimCCS developed in 2009 [63] to design a dynamic integrated CCS infrastructure. The newly developed model is capable of spatially and temporally optimising the management of large quantities of CO_2 by capture, transport, and storage. They demonstrated the SimCCSTIME model using real data from the Texas panhandle.

(Middleton et al 2012) developed a similar model lately by expanding the static CCS model developed in 2009 [63] to design a dynamic integrated CCS infrastructure. They demonstrated the model using real data from the Texas Panhandle.

This model was published 2 years after the start of this phD by which time the multi-period model of this thesis was already developed. During the development of the deterministic multi-period model presented in this chapter 3 of this thesis, there was no other whole system and multi-period optimisation model for CCS supply chains. The multi-period model of this thesis has been used for analysis of CCS development in scenarios of different scope focusing on the evolution of CCS in the UK. The model has been utilised in an ongoing a real options project for the Crown Estate in the UK for optimum investment strategies and building a business model for the operation of storage sites. The UK is in the forefront of CCS commercialisation and the utilisation of our deterministic multi-period model by the policy makers in this process justifies the necessity of its development. Moreover the deterministic model developed as part of this PhD is the foundation of the multi-stage CCS models for planning under uncertainty which has been used for several scenarios for the Crown Estate as described below and is being developed even further:

- Analysis of transport and storage network performance under carbon price and storage site injection uncertainties
- Optimal interim investment strategies for CCS development under appraisal uncertainty and EOR optionality
- The model is currently being extended into a minimum regret optimisation tool to consider options which hedge against the worst case scenarios and hence initiate market development.

Also the flexibility of the multi-period developed here allows us to integrate the model with existing detailed cost models for the component of the supply chain. As discussed in chapter 4, combination can open a window for detailed assessment of the feasibility of alternative operation strategies or project finances to minimise risk.

The dynamic model developed by Middleton et al. (2012) does not take into account that with use, the available capacity of the storage sites decreases through the planning horizon. It seems the amount of CO_2 that can be injected into the storage site is only bound by the original capacity of the storage site. Also in terms of the transport network, the model developed by Middleton et al. 2012 employs a sub-model to calculate the shortest path between each pair of nodes. The main model then selects from the candidate paths. In our multi-period model, the optimisation of the transport routes is carried out within the main body of the model simultaneously with the selection of sources and sinks. The routes are selected so as to enable the network to collect CO_2 from several sources en-route the storage sites adjusting the capacity of the pipelines as necessary. The cost is proportional to the pipeline capacity and the pipelines also branch and merge to create trunk lines if necessary. The model allows the user to add constraints to divert the pipelines as necessary. For example a cost incentive encourages following the existing gas lines or shoreline terminals are added where the trunklines meet.

Section 2.3 will summarise the findings of this literature review to justify the necessity of developing a multi-period least cost optimisation model of an integrated carbon capture, transportation and storage supply chain.

2.3 Lessons learnt and gap in knowledge

This section is a summary of the literature review. In order to clearly identify the gap in the literature in the field of CCS supply chain optimisation, the most applicable publications discussed in sections 2.2.1 and 2.2.2 have been categorised for better understanding of the areas where research has been carried out. The four categories are as follow:

- In section 2.2.1.2, whole system CCS supply chain optimisation models were reviewed. Although comprehensive the following publications were only steady state snapshots models; [48, 62, 63, 68, 69, 71, 73].
- In section 2.2.2.1 we explored multi-period whole system optimisation models for supply chains, which are fundamentally similar to a CCS supply chain; [78-80].
- In section 1.2.2.2 a spatially explicit temporal CCS supply chain model by Kemp and Kasim [81] was discussed, however it only demonstrated the evolution of the transport infrastructure.
- Section 2.2.2.2 reviewed a few spatially explicit temporal CCS supply chain models; [89, 90, 92]. These models demonstrated the development of CCS according to possible future energy develop-

ments. However, they were unable to simultaneously make decisions for the three components of the chain with the goal to minimise the cost of the whole system. In other words, an optimal source-sink combination was selected followed by the selection of an optimal route.

So far, the gap in the literature is clear since none of the earlier work in the field of CCS supply chain optimisation has constructed an optimisation model for a fully integrated CCS supply chain across space and time. Only lately Middleton at al [95] developed a model which demonstrates the development of an optimal spatially explicit CCS infrastructure over time. This model was published after the multi-period model of this thesis was developed. Furthermore, the novelty of the multi-period model of this thesis has been discussed in section 2.2.2.2.

Chapter 3 Multi-period deterministic optimisation of an integrated CCS supply chain

Chapter 1 stressed the necessity of climate change mitigation through the reduction of greenhouse gas emissions. Several mitigation options were discussed including CCS. It was concluded that CCS is an essential medium-term carbon abatement technology and will play a significant role in decarbonising coal. It was discussed that to achieve the goal of large-scale commercial deployment of CCS, deployment of full chain CCS demonstration projects must be accelerated. Also despite sufficient knowledge in operating each component of the CCS chain separately, combining them to construct an efficiently functioning fully combined CCS chain remains to be a challenge. Chapter 2 established the gap in the literature in modelling an integrated optimum CCS network of capture points, transportation and storage sites under dynamic constraints or targets. This chapter will discuss the development of a generic, deterministic, multi-period least cost optimisation model of an integrated carbon dioxide capture, transport and storage network. The model is showcased through a case study, which demonstrates the evolution of an optimal CCS network in the UK over four time periods up to year 2050.

3.1 Optimisation framework

As discussed previously, the problem introduced here is a cost minimisation associated with the future development and operation of a CCS infrastructure. The problem practically becomes a multi-period supply chain optimisation issue where a product (i.e. CO_2) produced at stationary sources (i.e. CO_2 emitters such as power plants) is to be delivered to consumers (i.e. sinks). The following is a brief overview of the framework of the supply chain optimisation model. Unlike the supply chain models discussed in chapter 2, this model will not use a grid system for spatial mapping of the sources and the sinks. The sources and the sinks are introduced as nodes. The geographical coordinates of each node is provided. Each node is also assigned an emission and a storage capacity. For example for the case of the CO_2 sources, the storage capacity is set to zero. A mass balance is performed at each node at each time period among the yearly mass flow rates of the CO_2 captured at the node, stored at the node, imported from other nodes or exported to them via pipelines. The transportation routes allow for an overall mass balance. At each time period, the solution for the optimal mass flow rates, capture and injection rates is provided as annual values. The fixed capital costs are introduced as annual pro-rata by multiplying the upfront capital costs by a capital charge factor. The model makes all the investment and operational decisions for the three components of the chain, to minimise the overall net present value of the accumulated future cash flows of the entire supply chain.

3.2 CCS supply chain issue, a Mixed Integer Linear Programming problem

The multi-period CCS network model provides a solution which simultaneously answers the following questions at each time period; which sources/sinks will be facilitated with capture/injection facilities, which two points are connected via a transport link and the associated pipeline specifications, how much CO_2 is captured/injected at the sources/sinks and how much CO_2 is transported between two points given capture/storage facilities are built at the nodes or the nodes are connected by pipeline respectively. In other words, the solution contains answers to two types of variables; investment decisions as to whether or not to build a capture/storage facility or a transport link between two points are represented by binary variables, which can only take 0 or 1 values. Operational decisions indicate the amounts of CO_2 captured, stored or transported and are represented by continuous variables since they can take any value subject to certain constraints. The objective function to be minimised i.e. the sum of the present value of the all the future annual capital and operational costs over the planning horizon is a linear function. The design and operational constraints are also linear functions. Therefore, the problem is a mixed integer linear programming (MILP) problem.

3.3 MILP solvers and modelling languages

Although MILP problems are harder to solve in general than linear programming (LP) problems, there are a number of commercial and non-commercial packages designed to solve MILP problems. Generally, non-commercial MILP software tools cannot match the speed or robustness of the commercial tools. In this project the commercial modelling language; The General Algebraic Modelling System (GAMS) is selected to solve the MILP problem of multi-period CCS supply chain optimisation. The reasons for this selection are as follow; the methods used to solve mixed integer programming problems require dramatically more mathematical computation than those for similarly sized pure linear programs and GAMS is suitable for complex, large-scale modelling applications. GAMS is a high-level modelling system for mathematical optimisation including MILP. Although there are other modelling languages that support MILP solvers; for example the modelling language AMPL is suitable for solving large scale optimisation and scheduling problems and supports commercial solvers including CPLEX and Gurobi. AIMMS is also an integer programming software that supports the mixed integer solvers XA, CPLEX, GURABI and MOSEK. It offers extended analytics tools and the user can influence the solver through solver call backs. However GAMS is the most common programming language for solving MILP problems such as scheduling, planning, supply chain optimisation problems and generally management science and OR. GAMS is also a prominent modelling language for stochastic programming and general equilibrium applications and the work presented in this chapter will progress towards stochastic optimisation. Also GAMS allows the user to describe the problem in easily understandable algebraic statements. GAMS supports most of the MILP solvers such as MOSEK, XPRESS, CPLEX and Gurobi. The solver CPLEX is selected here. CPLEX is used to solve a variety of different optimisation problems in a variety of computing environments. For problems with integer variables, CPLEX uses branch and cut and branch and bound algorithms, which solve a series of LP sub problems. GAMS/CPLEX also supports semi-continuous and semi-integer variables. For GAMS/CPLEX the MIP algorithm is an implementation of a branch-and-bound search with modern algorithmic features such as cuts and heuristics. Features also include settable priorities on integer variables, choice of different branching and node selection strategies.

3.4 Spatial mapping of the supply chain elements

The CCS supply chain optimisation process requires defining the geographical locations of the sources and the sinks, coastal landfalls or any other geographical points or obstacles, which might play a role in the supply chain. Within the MILP model, every source, sink or dummy node has an associated longitude and latitude expressed in radians. In case of the CO_2 emitters and the sinks, this data represent the location of the actual plant or the location of the central well selected as the surface reference for the sink. The model then calculates the shortest on-earth distance $\mathrm{d(i,j)}$ between each two nodes using the Haversince formulae shown below. $\mathrm{Lat(i)}$ and $\mathrm{Lon(i)}$ represent the latitude or longitude of node i. R is the earth's mean radius.

$$\mathrm{d'(i,j)} = \sin\big(\mathrm{lat(i)}\big) * \sin\big(\mathrm{lat(i)}\big) + \cos\big(\mathrm{lat(i)}\big) * \cos\big(\mathrm{lat(j)}\big) * \cos\,(\mathrm{lon(j)} - \mathrm{lon(i)}) \tag{3.1}$$

$$\mathrm{d(i,j)} = \left(\frac{\Pi}{2} - \mathrm{atan}\left\{\frac{\mathrm{d'(i,j)}}{\mathrm{sqrt}(1-\mathrm{d'(i,j)^2})}\right\}\right) * \mathrm{R} \tag{3.2}$$

3.5 Techno-economic modelling of supply chain components

This section contains a brief overview of the methods used to derive the capital and operational costs of the three components of the CCS supply chain i.e. capture, transport and storage. These cost figures are incorporated into the MILP framework as parameters based on which the model makes minimum cost investment and operational decisions throughout the planning horizon. The cost estimates may differ depending on the scenarios. Therefore, a more thorough description of the parameters for this chapter's scenario is included in appendices B, C and D. Only the main principles behind the estimation of the cost figure have been included here in order to help draw a clear picture of the MILP framework developed to address the multi-period CCS network problem.

For the future time periods, the annual capital and operational cost parameters are adjusted according to the estimated inflation rates. However, it is assumed that the cost figures remain constant during a time period. The future inflation rates and the relevant estimation methods for the scenario discussed in this chapter are included in Appendix F. Since the model's outcome is based on the minimisation of the total cost of the CCS infrastructure over the planning horizon, which is an accumulation of the future annual investment, and operational costs, therefore a reliable solution necessitates taking into account the time value of money. Therefore, all future annual cash flows are discounted to their present values using equation 3.3 where PV and FV represent the present and future values respectively, r is the discount rate and $\mathrm{h(t)}$ is the number of years from the beginning of the planning horizon up to time period t.

$$\mathrm{PV} = \mathrm{FV} * (1 + \mathrm{r})^{-\mathrm{h(t)}} \tag{3.3}$$

Within the MILP model, the capital cost figures are expressed in terms of the annual pro-rata of the actual costs. This is achieved by multiplying the capital cost figures by a capital charge factor. The capital charge factor is calculated as per equation 3.4. For the purposes of this project, regardless of the asset type, an asset life of 25 years and a discount rate of 10% are assumed for all components of the CCS infrastructure in the scenario of this chapter. For scenarios where a specific operational period is considered for the emitters or the storage sites, the capital charge factor is re-calculated accordingly. Operational cost figures are also expressed on an annual basis.

$$\text{Capital charge Factor (CCF)} = \frac{\mathrm{r} * 1 + \mathrm{r}^{\mathrm{n}}}{(1 + \mathrm{r})^{\mathrm{n}} - 1} \tag{3.4}$$

3.5.1 CO_2 capture

The methods discussed in this section have been obtained from the snapshot CCS supply chain optimisation model developed by Prada [48] to investigate an optimal CCS network in South East England and the Southern North Sea. Their data is obtained from several sources mostly a study commissioned by the International Energy Agency GHG programme to Mott MacDonald engineering consultants [96] and another study commissioned by IEA-GHG to Jacobs consultancy [97]. Older cost figures are updated using IHS CERA cost indices.

The cost of capture is calculated separately for different types of emitters. Appendix B includes a breakdown of the capital and operational capture cost figures and the assumptions used to update some cost figures, for each type of emitter i.e. coal plants, CCGT and CHP plants, other plants, cement and steel manufacturers for the scenario of this chapter. This section however briefly explains the fundamentals of calculating the capital and operational costs of capture. The capture cost is assumed to be the additional expenses incurred due to the capture process retrofit on the existing plants. ΔCAPEX (USD per year), the fixed yearly cost and ΔOPEX (USD per year per tonne CO_2 captured), the variable yearly cost represent the additional expenses incurred due to the retrofit and running the capture plant respectively. They are parameters directly used within the MILP model.

Amine based post-combustion is the most viable option in terms of readiness for near future deployment. Therefore, it is selected as the preferred capture technology at 90% capture efficiency. It is also assumed that within the capture cost, the cost of compression is also included as well as additional processing such as dehydration of the captured CO_2 to prepare it for transportation by pipeline. Given the high level approach of the cost model considered here, the small differences in the calculation of such additional costs would not affect the outcome of this model. Equations 3.5 and 3.6 demonstrate the general principles behind calculating the differential capture costs ΔCAPEX and ΔOPEX. The annual capital cost of retrofitting an existing plant with capture facilities is calculated by multiplying the capital cost (USD per MW) by the electricity consumption of the retrofit plant (MW) multiplied by a capital charge factor.

$$\Delta\text{CAPEX} = \text{CAPEX}_{\text{Retrofit plant}}\left(\frac{\$}{\text{MW}}\right) \text{x Electricity consumption}_{\text{Retrofit plant}}(\text{MW})\ \text{CCF} \tag{3.5}$$

$$\begin{aligned}\Delta\text{OPEX} \\ = (\Delta\text{OPEX}_{\text{fuel}_{\text{retrofit plant}}}(\frac{\frac{\$}{\text{MWh}}}{\text{yr}}) \\ +\ \Delta\text{OPEX}_{\text{nonfuel}_{\text{Retrofit plant}}}(\frac{\frac{\$}{\text{MWh}}}{\text{yr}})\}\ \frac{\text{Capture Efficiency}}{\text{Reference plant's CO2 intensity }(\frac{\text{tonne}}{\text{MWh}})}\end{aligned} \tag{3.6}$$

The annual variable cost of capture as shown by equation 3.6 is the sum of the additional fuel costs and the non-fuel operational costs. The assumptions used in calculating the parameters $\Delta OPEX_{Fuel}$ and $\Delta OPEX_{non\_fuel}$ of equation 3.6 vary depending on the emitter's type and can be found in Appendix B. The reference plant's CO_2 intensity referred to in equation 3.6 is the emission of the power plant retrofitted with capture facilities.

3.5.2 CO_2 storage

In chapter 4, the CO_2 storage life cycle cost model developed by Korre et al [98] carries out a thorough techno-economic modelling for the selected storage sites. However, a simpler storage cost model is used for the UK's multi-period CCS network scenario of this chapter. A breakdown of the injection cost figures used in the case study of this chapter has been included in Appendix C. These parameters as well as the methods and the assumptions are obtained from the snapshot CCS supply chain model of Prada [48]. Using a series of assumptions, they leveraged the data obtained from a study commissioned by BERR to POYRY consulting [82].

Estimating the adaptation costs to re-utilise the existing gas infrastructure is not within the scope of this project. It is assumed that new storage infrastructures are developed for CCS purposes. It is assumed the infrastructure contains a fixed platform, injection wells and relevant equipments. It is assumed no platform compression is required and the CO_2 arrives at the injection facility at a pressure above the critical pressure and therefore ready for injection.

The capital cost is defined as the sum of survey and development costs, fixed cost per well, drilling cost per well and a platform cost. It is also assumed geological data is available from previous oil and gas exploration. The number of platforms and the number of wells are assigned proportional to the sink capacity and both bound by maximum values. Each well is associated with a good or reasonable injectivity rate of 1 or 0.75MtCO_2 per year respectively. OPEX is assumed to be 10% of CAPEX.

3.5.3 CO_2 transport

The multi-period CCS network model allows for multiple modes of transport such as transport by ship or pipeline. However, the scenario of this chapter only considers pipelines as a transport option. This is due to both technical and economical reasons; despite the larger initial investment required for pipeline installation, the operational costs are lower [48] and also this option accommodates a variable flow of CO_2 which is realistic because of the variable nature of electricity generation output. Also using pipelines, a shared network can be created to benefit from economies of scale as the supply chain expands. This section is a brief overview of the derivation of the fixed and variable transport cost parameters, which are fed into the MILP model. For the purposes of this project, it is assumed that the onshore and offshore transport costs are the same.

The transport cost within the optimisation framework will be expressed as a pure function of flow rate and is given on a per km basis. Therefore, the total transport cost is calculated as shown in equation 3.7.

$$\text{Transport Cost}\left(\frac{\text{USD}}{\text{yr}}\right) = \text{Transport Cost}\left(\frac{\frac{\text{USD}}{\text{yr}}}{\text{km}}\right)\text{x Pipleine length (km)} \qquad 3.7$$

The transport cost parameters are obtained from the CCS supply chain model developed by Prada [48]. They first obtained a curve to relate pipeline cost (USD per inch per km) to pipeline diameter(inch) for off-shore and onshore pipelines based on the information obtained from the IEA GHG CO_2 Pipeline Calculator [74] which includes extensive data sets regarding pipeline costs. They made the following assumptions to select the appropriate cost estimate set:

- Pipeline length: above 50 km
- Flat open countryside terrain (onshore)
- UK-specific cost factor: 1.2
- CAPEX Cost index: Chemical Engineer Index (2006 to 2010)
- OPEX: 2% CAPEX
- Material: high-pressure steel

Secondly, the relationship between mass flow rate and pipeline diameter had to be established. They defined the relationship between pipeline diameter (D), pipeline length (L), mass flow rate (Q) and pressure drop along the pipeline ($P^2_{in} - P^2_{out}$) per equation 3.8 obtained from McCoy [27, 75]. ρ represents the CO_2 density, $P_{ave}$the average pressure along the pipeline, f_F represents the Fanning friction factor which is in turn defined by equation 3.9 obtained from Romeo et al [76]. The Fanning friction is also a function of pipeline diameter, the Reynolds number and pipeline roughness ϵ.

$$D = \left(\frac{64 \text{ x } f_F \text{x } Q^2 \text{x } L}{\Pi^2 \text{x } \rho \text{ x } \frac{P_{in}^2 - P_{out}^2}{P_{ave}}}\right)^{\frac{1}{5}} \qquad 3.8$$

$$\frac{1}{\sqrt{f_F}} = -2\,log(\frac{\frac{\varepsilon}{D}}{3.7065} - \frac{5.0272}{Re}log\{\frac{\frac{\varepsilon}{D}}{3.827} - \frac{4.567}{Re}log(\left(\frac{\frac{\varepsilon}{D}}{7.7918}\right)^{0.9924} + \left(\frac{5.3326}{208.815 + Re}\right)^{0.9345})\}) \qquad 3.9$$

They calculated the Reynolds number using the assumptions below:

- Pipeline inlet pressure: 110 bar, pipeline outlet pressure: 80 bar

- CO_2 Temperature: 31 °C, CO_2 density: constant along pipeline, Pipe roughness: 0.0457 mm
- No intermediate compression stations
- CO_2 density (ρ) and viscosity (μ) were obtained (i.e. 784 kg/m^3 and 73.91 MPa*s, respectively) [99], [100].

With these parameters known, they then iteratively solved equations 3.8 and obtained a curve for the relationship between diameter (inch) and a discrete set of flow rates ($MtCO_2$ per year).

Finally, results from the previous two steps were merged to obtain curves relating cost to mass flow rate for the onshore and offshore cases as shown in figure 3.1. Cost figures were expressed in terms of an annual pro-rata (USD per km per year) including the capital and operational costs. They used linear interpolation to estimate the relevant costs, where the diameter values did not match the data obtained from IEA GHG [74].

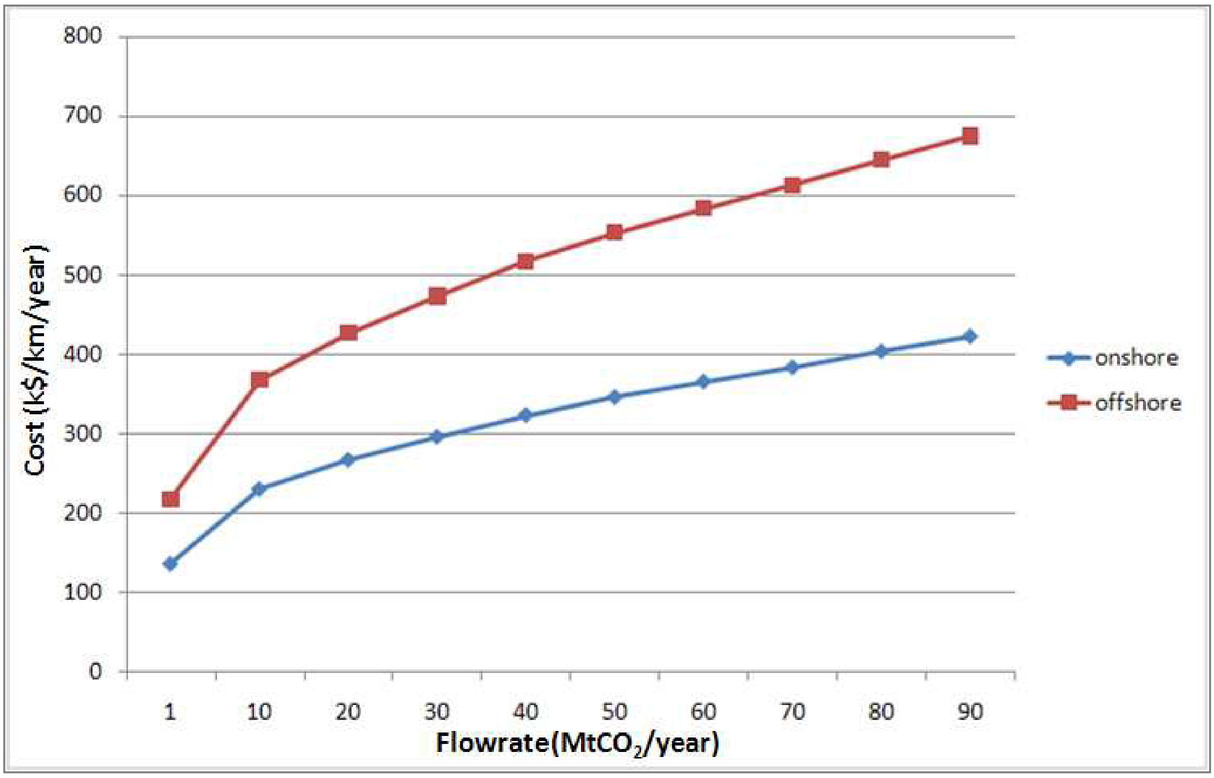


Figure 3.1 Total pipeline transport cots on per km basis vs. Annual mass flow rate. [48]

Piecewise linearization methods were used to divide the curve into three segments as shown in figure 3.2. The intercepts of the straight lines with the cost axis and the lines' gradients represent the annual capital cost $\Delta\text{CAPEX}\left(\frac{\frac{\text{USD}}{\text{km}}}{\text{Year}}\right)$ and the annual operational cost, $\text{slope}\left(\frac{\frac{\text{USD}}{\text{km}}}{\text{MtCO2/year}}\right)$ respectively. Each segment represents a pipeline of a certain maximum flow rate.

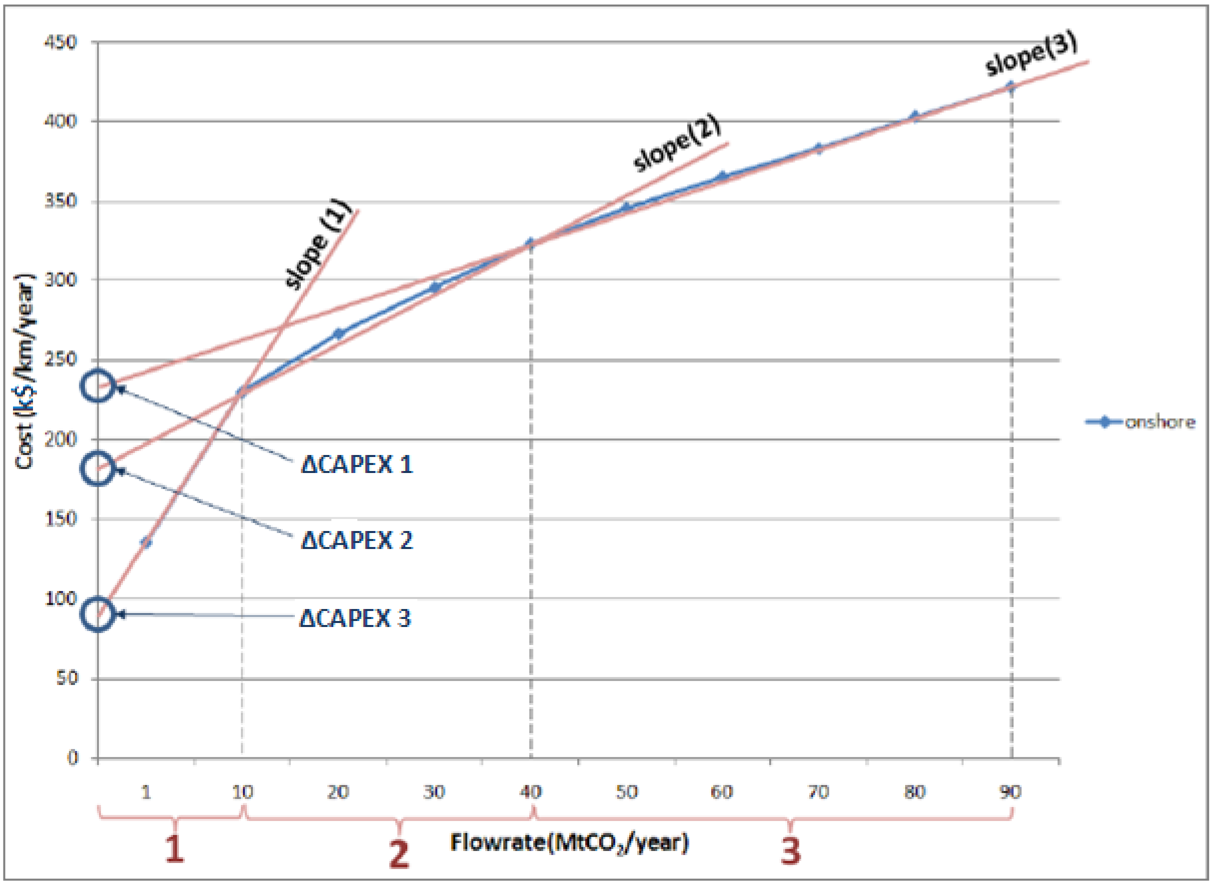


Figure 3.2 Piecewise linearization of the onshore transport cost function. [48]

3.6 Mathematical model

This section explains the mathematical model of an integrated multi-period CCS supply chain. The parameters or the inputs and the variables or the outputs of the model are defined. Then all design or operational constraints expressed as equations or inequalities are explained. The objective function to be minimised here is the sum of net present investment and operational costs of capture, storage and transportation of CO_2 summed over all nodes and time periods. The MILP solution values for the variables must result in a minimum value for the objective function and simultaneously satisfy all the constraints.

3.6.1 Sets and indices

The sets below correspond to the indices in the algebraic representation of the constraints and the objective function included later in this chapter.

Sets

i , j	Grid cells

p	CO_2 phases (gas, dense) for transport via pipeline

l	Linearised segments of the pipeline cost curve

t	Time periods

n(t)	The year number of the first year of each time period t

m(t)	The year number of the last year of each time period t

h	Set for the years in the planning horizon

3.6.2 Input parameters

The parameters are either scalar or defined as part of the sets.

Scalars

R	Discount rate
cut-off	Maximum distance (km) above which nodes i and j cannot be directly connected

Parameters

x(i)	X coordinate of cell i
y(i)	Y coordinate of cell i
d(i,j)	Distance (km) between cells i and j
ΔCAPEX(p,l)	Annual capital cost (M$/km/year) relevant to segment l, phase p of pipeline cost curve
slope (p,l)	Annual operational cost (M$/km/Mt$CO_2$/year) of transporting a unit of CO_2 over a kilometre (Slope relevant to segment l, phase p of pipeline cost curve)
ftc(p,l,t)	Fixed cost (M$) of building pipeline of segment l at time period t to transport of CO_2 in phase p
vtc(p,l,t)	Operational cost of transporting a unit of CO_2 every year in phase p using pipeline of segment l for all years in time period t
Qmax(p,l)	Maximum flow rate (MtCO_2/year) relevant to phase p of CO_2 segment l of pipeline cost curve
a(i,t)	Annual CO_2 emission at node i at time t
$\Delta CAPEX_{capture}$	Annual capital cost (M$/year) of retrofitting a source with capture facility
$\Delta OPEX_{capture}$	Annual operational cost (M$/Mt/year) of capturing a unit of CO_2
fcc(i,t)	Fixed capital cost (M$) of retrofitting source i with capture facility at the beginning of time period t
vcc(i,t)	Operational cost (M$) of capturing a unit of CO_2 every year at source i for all years in time period t
b(i)	Maximum capacity at node i
$\Delta CAPEX_{storage}$	Annual capital cost (M$/year) of building storage facility
$\Delta OPEX_{storae}$	Annual operational cost (M$/Mt/year) of injecting a unit of CO_2
fsc(i,t)	Fixed capital cost (M$) of building storage facility at sink i at the beginning of time period t
vsc(i,t)	Operational cost (M$) of injecting a unit of CO_2 every year at sink i for all years in time period t

Ct(t)	CO_2 capture target at time period t
Leng(t)	Length of time period t
Capture efficiency	Maximum fraction of emissions which can be captured

3.6.3 Integer variables

The variables are either continuous or binary. The continuous variables mostly relate to the operational decisions i.e. the amount of CO_2 captured or stored at a node or transported between two nodes at each time period. The continuous variables can only take positive integer values. The variable $\mathrm{nx}(\mathrm{i},\mathrm{j},\mathrm{p},\mathrm{l},\mathrm{t})$, the number of pipelines relevant to segment l and phase p built between i and j, can only take integer values as it is only the sum of the binary variable $\mathrm{xt}(\mathrm{i},\mathrm{j},\mathrm{p},\mathrm{l},\mathrm{t})$ of all the preceding time periods and the current time period.

Integer variables

C(i,t)	Annual amount of CO_2 captured at node i at time t
S(i,t)	Annual amount of CO_2 injected into node i at time t
Q(i,j,p,l,t)	Annual CO_2 flow rate through pipeline relevant to segment l of the linearised transport cost curve, in phase p, between cells i and j at time t
Z	Net present value of the total CCS over the planning horizon summed over all nodes
nx(i,j,p,l,t)	Total number of pipelines of segment l and phase p built between i and j up to and during time t
usedcap(i,t)	Total amount of CO_2 stored in node i prior to time t

3.6.4 Binary variables

The investment decisions are made through binary variables, which indicate whether a capture or storage facility is built at a node or a pipeline is built to connect two nodes.

Binary variables

xt(i,j,p,l,t)	1 if a pipeline relevant to segment l, phase p is built at time t between nodes i and j, 0 otherwise
xcap(i,t)	1 if a capture facility is built at node i, 0 otherwise
nxcap(i,t)	1 if a capture facility has been built at node i at or prior to time period t, 0 otherwise
xstor(i,t)	1 if a storage facility is built at node i at time t
nxstor(i,t)	1 if a storage facility has been built at node i at or prior to time period t, 0 otherwise

3.6.5 Constraints

The output of the model must result in a minimum cost infrastructure and simultaneously all operational or design constraints discussed in this section must be satisfied. It should be noted that all continuous variables represent annual values.

Mass balance constraint

A mass balance is performed at each node i at each time period t. This is essential to ensure that at each node the total yearly quantity of CO_2 captured minus the total yearly quantity injected equals the difference between flow out of and into the node.

$$\sum_{j,p,l}\{Q(i,j,p,l,t) - Q(j,i,p,l,t)\} - C(i,t) + S(i,t) = 0 \;\; \forall\, i,t \tag{3.10}$$

Transportation constraint

In case a pipeline is built from i to j or from j to i, the annual CO_2 flow rate from i to j cannot be greater than the maximum capacity of the pipeline.

$$Q(i,j,p,l,t) \leq QMax(p,l)\; nx(i,j,p,l,t) + QMax(p,l)\; nx(j,i,p,l,t) \;\; \forall\, i,j,p,l,t \tag{3.11}$$

Capture facility constraint

The annual amount of CO_2 captured from node i at time t cannot be greater than the maximum annual emissions of node i at time t a(i,t) multiplied by the capture efficiency, given a capture facility has been built at node i.

$$C(i,t) \leq \text{capture efficiency} * nxcap(i,t)\; a(i,t) \;\; \forall\, i,t \tag{3.12}$$

Storage facility constraint

Equation 3.13 calculates the total amount of CO_2 stored at each node prior to time t. This is equal to usedcap(i,t-1) which is the total amount of CO_2 stored at node i up to time period t-1 plus the total amount of CO_2 stored at node i during time period t-1. The latter is calculated as the product of the annual amount stored at node i at time period t-1, S(i,t-1) and the length the length of time period t-1.

$$usedcap(i,t) = usedcap(i,t-1) + S(i,t-1) * Leng(t-1) \;\; \forall\, i,t \tag{3.13}$$

Through equation 3.14 the model in fact takes into account the decreasing capacity of sink i once it is used to store CO_2. This equation states that if an injection facility is built at node i, the annual amount of CO_2 injected in node i cannot be greater than the remaining capacity of node i (i.e. the initial capacity of node i minus the used capacity) divided by the length of time period t in years.

$$\mathrm{S(i,t)} \leq \frac{1}{\mathrm{Leng(t)}} * \{\mathrm{nxstor(i,t)\ b(i)} - \mathrm{usedcap(i,t)}\}\ \ \forall\, \mathrm{i,t} \tag{3.14}$$

<u>Time evolution constraints</u>

The model decides which nodes should be equipped with capture and injection facilities. The number of future emitters and their locations are pre-determined data sets that are fed into the model. In the scenario of this chapter, it is assumed that at the start of the time horizon there are no sources or sinks already retrofitted with capture or injection facilities.

Binary variables are used for both, the total number of capture or storage facilities that have already been built at node i by time t and the number of capture or storage facilities built at node i at time t. Therefore, equations 3.15 and 3.16 indicate that whether a facility exists at node i at time t depends on if a facility has already been built by time t or if a facility is built at time t.

$$\mathrm{nxcap(i,t)} = \mathrm{nxcap(i,t-1)} + \mathrm{xcap(i,t)}\ \ \forall\, \mathrm{i,t} \tag{3.15}$$

$$\mathrm{nxstor(i,t)} = \mathrm{nxstor(i,t-1)} + \mathrm{xstor(i,t)}\ \ \forall\, \mathrm{i,t} \tag{3.16}$$

$$\mathrm{nx(i,j,p,l,t)} = \mathrm{nx(i,j,p,l,t-1)} + \mathrm{xt(i,j,p,l,t)}\ \ \forall\, \mathrm{i,t} \tag{3.17}$$

Equation 3.17 indicates that at time t the total number of pipelines of segment l, phase p between nodes i and j is determined by the total number at the previous time period which is expressed by the integer variable nx(i,j,p,l,t-1) plus the binary variable xt(i,j,p,l,t) which determines whether another pipeline of segment l, phase p is built between i and j at time period t.

<u>Capture target constraint</u>

A constraint is imposed on the total quantity of CO_2 captured per time period in terms of a minimum capture target at that time period.

$$\sum_{\mathrm{i}} \mathrm{C(i,t)} \geq \mathrm{Target(t)}\ \ \forall\, \mathrm{t} \tag{3.18}$$

<u>Reverse flow</u>

Equation 3.19 is added to imply that if a reverse flow is to take place in the future, there will be no need to build a second pipeline. Simultaneous reverse flow is automatically avoided since it results in higher costs.

$$\mathrm{xt}(\mathrm{i},\mathrm{j},\mathrm{p},\mathrm{l},\mathrm{t}) = \mathrm{xt}(\mathrm{j},\mathrm{i},\mathrm{p},\mathrm{l},\mathrm{t}) \ \ \forall\ \mathrm{i},\mathrm{j},\mathrm{p},\mathrm{l},\mathrm{t} \tag{3.19}$$

Maximum distance constraint

This constraint is applied to reduce the number of discrete variables and hence speed up the model. Through equation 3.20, the model does not consider building a direct route between nodes i and j if the distance between them is greater than a certain threshold. However, the value of this parameter should be large enough so that the model is still able to find a feasible route and that feasible route is also the minimum cost option. The value is selected following an analysis of a balance between speeding up the model and a possible increase in the cost of transport. The cut-off parameter for the following case study is set to 100km.

$$\mathrm{xt}(\mathrm{i},\mathrm{j},\mathrm{p},\mathrm{l},\mathrm{t}) = 0 \quad \text{if} \quad \mathrm{d}(\mathrm{i},\mathrm{j}) > cutoff \ \ \forall\ i,j,p,l,t \tag{3.20}$$

Non-negativity constraints

Finally, non-negativity constraints are set for all continuous variables.

$$\mathrm{C}(\mathrm{i},\mathrm{t}) \geq 0 \ \ \forall\ \mathrm{i},\mathrm{t} \tag{3.21}$$

$$\mathrm{S}(\mathrm{i},\mathrm{t}) \geq 0 \ \ \forall\ \mathrm{i},\mathrm{t} \tag{3.22}$$

$$\mathrm{Q}(\mathrm{i},\mathrm{j},\mathrm{p},\mathrm{l},\mathrm{t}) \geq 0 \ \ \forall\ \mathrm{i},\mathrm{j},\mathrm{p},\mathrm{l},\mathrm{t} \ \ \mathrm{i} \neq \mathrm{j} \tag{3.23}$$

$$\mathrm{usedcap}(\mathrm{i},\mathrm{t}) \geq 0 \ \ \forall\ \mathrm{i},\mathrm{t} \tag{3.24}$$

3.6.6 Objective function

The aim of the model is to reach a CO_2 reduction target at each time period minimising Z the total cost over the planning period. The cost of the network is divided into three parts; capture, transportation and storage each including a fixed capital cost and a variable operating cost.

$$\mathrm{Z} = \ \mathrm{tot.cap.cost} + \mathrm{tot.tran.cost} + \mathrm{tot.stor.cos} \tag{3.25}$$

The methods to calculate the total cost of each component of the chain are as follows.

Total capture cost

The total capture cost is the sum of capital and operational costs of capture at all nodes over the planning horizon. We first define the fixed and variable capture cost parameters as fed into the objective function in GAMS.

Parameter $\mathrm{fcc(i,t)}$ is the total capital cost of retrofitting source i with capture facility at time t. As shown below $\mathrm{fcc(i,t)}$ is the sum of annuatised capital costs of retrofitting a source with capture facility, $\Delta\mathrm{CAPEX_{capture}}(\frac{\mathrm{M\$}}{\mathrm{Year}})$ from the first year of the time period of investment $\mathrm{n(t)}$ until the last year of the horizon $\mathrm{m(tfinal)}-1$, each discounted to present value and summed over for all nodes. The method to calculate $\Delta\mathrm{CAPEX_{capture}}$ in included in section 3.5.1.

$\mathrm{fcc(i,t)}$ is the parameter that is fed to GAMS.

$$\mathrm{fcc(i,t)} = \sum_{\mathrm{n(t)\epsilon h}}^{\mathrm{m(t\,final)\epsilon h}\ -1} \frac{\Delta\mathrm{CAPEX_{capture}}}{(1+\mathrm{r})^{\mathrm{h}}} \qquad 3.26$$

Parameter $\mathrm{vcc(i,t)}$ is the operational cost of capturing a unit of CO_2 at capture facility i during the length of time period t. As shown below $\mathrm{vcc(i,t)}$ is the sum of annual operational costs $\Delta\mathrm{OPEX_{capture}}(\frac{\frac{\mathrm{M\$}}{\mathrm{Mt}}}{\mathrm{Year}})$ of capturing a unit of CO_2, over all the years in time period t, each discounted to present value. The method to calculate $\Delta\mathrm{OPEX_{capture}}$ is included in section 3.5.1.

$\mathrm{vcc(i,t)}$ is the parameter that is fed to GAMS.

$$\mathrm{vcc(i,t)} = \sum_{\mathrm{n(t)\epsilon h}}^{\mathrm{m(t)\epsilon h}\ -1} \frac{\Delta\mathrm{OPEX_{capture}}}{(1+\mathrm{r})^{\mathrm{h}}} \qquad 3.27$$

The capital cost of retrofitting source i at time t is determined by the product of the value of the decision variable $\mathrm{xcap(i,t)}$, whether to retrofit source i with a capture facility at time t and the fixed capture cost parameter $\mathrm{fcc(i,t)}$ explained above. The operational cost of source i during time period t is the product of $\mathrm{C(i,t)}$, the annual amount of CO_2 captured at source i during time period t and $\mathrm{vcc(i,t)}$ the operational cost of capturing a unit of CO_2 every year for all the years in time period t as explained above. The total capture cost is then the sum of capital and operational costs of capture summed over all nodes and time periods.

$$\mathrm{Tot.\,cap.\,cost} = \sum\nolimits_{\mathrm{i,t}} \{\ \mathrm{vcc(i,t)}\,.\,\mathrm{C(i,t)} +\ \mathrm{fcc(i,t)}\,.\,\mathrm{xcap(i,t)}\ \} \qquad 3.28$$

<u>Total storage cost</u>

Similarly the total storage cost is the sum capital and operational costs of storage at all nodes over the planning horizon.

$\Delta \mathrm{CAPEX_{storage}}(\frac{\mathrm{M\$}}{\mathrm{Year}})$ and $\Delta \mathrm{OPEX_{storage}}(\frac{\frac{\mathrm{M\$}}{\mathrm{Mt}}}{\mathrm{Year}})$ are the annuatised capital cost of building an injection facility and annual operational cost of injecting a unit of CO_2 respectively. The methods to calculate $\Delta \mathrm{CAPEX_{storage}}$ and $\Delta \mathrm{OPEX_{storage}}$ can be found in appendix C.

Similar to the fixed and variable capture cost parameters, the fixed and variable storage cost parameters as fed into the objective function in GAMS are defined as follows.

$$\mathrm{fsc(i,t)} = \sum_{\mathrm{n(t)\epsilon h}}^{\mathrm{m(t\,final)\epsilon h}\ -1} \frac{\Delta \mathrm{CAPEX_{storage}}}{(1+\mathrm{r})^{\mathrm{h}}} \tag{3.29}$$

$$\mathrm{vsc(i,t)} = \sum_{\mathrm{n(t)\epsilon h}}^{\mathrm{m(t)\epsilon h}\ -1} \frac{\Delta \mathrm{OPEX_{storage}}}{(1+\mathrm{r})^{\mathrm{h}}} \tag{3.30}$$

The capital cost of building an injection facility at sink i at time t is the product of the value of the decision variable $\mathrm{xstor(i,t)}$, whether to build an injection facility at sink i at time t and the fixed storage cost parameter $\mathrm{fsc(i,t)}$. The operational cost of sink i during time period t is the product of $\mathrm{S(i,t)}$, the annual amount of CO_2 injected into sink i during time period t and $\mathrm{vsc(i,t)}$, the operational cost of injecting a unit of CO_2 every year for all the years in time period t. The total storage cost is then the sum of capital and operational costs of storage summed over all nodes and time periods.

$$\mathrm{Tot.stor.cost} = \sum\nolimits_{\mathrm{i,t}} \{\ \mathrm{vsc(i,t)\,.\,S(i,t)} + \ \mathrm{fsc(i,t)\,.\,xstor(i,t)}\ \} \tag{3.31}$$

<u>Total transport cost</u>

The total transport cost is also the sum capital and operational costs of transport between all nodes over the planning horizon.

$\Delta \mathrm{CAPEX(p,l)}\ \frac{\mathrm{M\$/km}}{\mathrm{Year}}$ is the annuatised capital cost of building a kilometre of pipeline relevant to segment l of the transport cost curve and CO_2 in phase p. $\mathrm{slope(p,l)}\ \frac{\mathrm{M\$/km}}{\mathrm{Year/MtCO2}}$ is the annual operational cost of transporting a unit of CO_2 over a kilometre. As explained in section 3.5.3 the annual capital and operational costs are obtained by piecewise linearization of the transport cost curve. Adjustments are then made to take into account the CO_2 phase p.

Similar to the capture or storage cost parameters, the fixed and variable transport cost parameters as fed into the objective function in GAMS are defined as follows.

$$\mathrm{ftc(p,l,t)} = \sum_{\mathrm{n(t)\epsilon h}}^{\mathrm{m(t\,final)\epsilon h}\ -1} \frac{\Delta \mathrm{CAPEX(p,l)}}{(1+\mathrm{r})^{\mathrm{h}}} \tag{3.32}$$

$$\mathrm{vtc}(p,l,t) = \sum_{n(t)\epsilon h}^{m(t)\epsilon h\ -1} \frac{\mathrm{slope}(p,l)}{(1+r)^{h}} \qquad 3.33$$

The capital cost of building a kilometre of pipeline at time t with a capacity relevant to segment l and CO_2 in phase p is the product of the value of the decision variable $xt(i,j,p,l,t)$, whether to build a pipeline between i and j at time t and the fixed transport cost parameter $ftc(p,l,t)$. The operational cost of a pipeline of 1 kilometre between nodes i and j during time period t is the product of $Q(i,j,p,l,t)$, the annual amount of CO_2 transported between nodes i and j during time period t and $vtc(p,l,t)$, the operational cost of transporting a unit of CO_2 for a kilometer every year for all the years in time period t. The total transport cost is then the sum of capital and operational costs multiplied by $d(i,j)$, the distance between nodes i and j and summed over all nodes and time periods.

$$\mathrm{Tot.\,tran.\,cost} = \sum_{i,j,t} \{\ vtc(p,l,t)\,.\,Q(i,j,p,l,t) +\ ftc(p,l,t)\,.\,xt(i,j,p,l,t)\ \}\,.\,d(i,j) \qquad 3.34$$

3.7 Case study: Development of an integrated minimum cost CCS supply chain in the UK up to year 2050

In the UK, 2012 saw publication of the Government's CCS Roadmap and in December 2013 it was announced that, with funding from the Commercialisation Programme set out in the Roadmap [8], a Front End Engineering Design (FEED) study would go ahead on the White Rose CCS project in Yorkshire. In addition, the Peterhead CCS demonstration project in Aberdeenshire as a full-scale gas CCS project will be a significant step forward in helping to decarbonise the UK's power sector and placing the UK on the forefront of CCS technology development and commercialisation. An updated CCS Roadmap by the UK Department of Energy and Climate Change has emphasised the Government's desire for a strong CCS industry with projects beyond the current Commercialisation Projects.

In a report published in January 2014, the UK's Advanced Power Generation Technology Forum, APGTF, announced that in the UK successful deployment could cut the cost of meeting carbon reduction targets by up to 1% of Gross Domestic Product (GDP) by 2050 [101]. Despite decarbonising the UK's energy system, achieving major cuts in industrial carbon emissions and boosting energy security; generating billions of pounds in income and tens of thousands of jobs for 'UK plc' are all within reach benefits if large-scale deployment of CCS becomes a reality in this country.

The APGTF recommends a strategy which considering the recommendations of the UK's CCS Cost Reduction Task force (CRTF), sets out a clear vision, a component of which is adoption of a target of around 10% of UK electricity to be generated from fossil fuel plants fitted with CCS by 2025. This enables CCS to make a major contribution to meeting the UK's target of an 80% cut in greenhouse gas emissions by 2050. This strategy aims to capitalise on progress to date while focusing on remaining barriers. In consultation with APGTF members, the Carbon Capture and Storage Association (CCSA) and the UK CCS Research Centre (UKCCSRC), the APGTF has therefore developed a list of recommendations that focus on fields of activity that include; whole systems issues, CO_2 transport and storage as well as supply chain development [101].

Therefore having identified the necessity of techno-economic modelling of the evolution of an integrated optimal CCS network in the UK, to validate the multi-stage CCS network, a case study is devised in this chapter to show the development of an optimum CCS network with respect to the UK emitters and the sinks in the surrounding seas over four 10 year time periods until year 2050.

3.7.1 Scope of the case study

The case study includes the 18 biggest CO_2 emission sources in the UK and 10 largest sinks in the Southern North Sea and the East Irish Sea. The aim of this scenario is to illustrate the development of a CCS network from 2010 (i.e. the beginning of this PhD programme) until 2050 over four 10 year time periods. The conditions or parameters under which the network functions i.e. costs, inflation rates, capture targets etc are assumed to remain constant throughout each phase. The driver behind the expansion of the network is a capture target that begins with 15% for the first time period and linearly increases to 60% mitigation of the total emission during the last time period.

3.7.1.1 CO_2 emitters

A full list of the selected CO_2 emission sources can be found in Appendix A. The eighteen sources include thirteen coal power plants, three CHP and CCGT plants and two Iron and steel manufacturers. The sources' annual CO_2 emissions range from 22.4Mt CO_2 per year from the Drax coal power plant down to annual emissions of around 3MtCO_2 per year. A total emission of 112 Mt per year is considered for capture and storage.

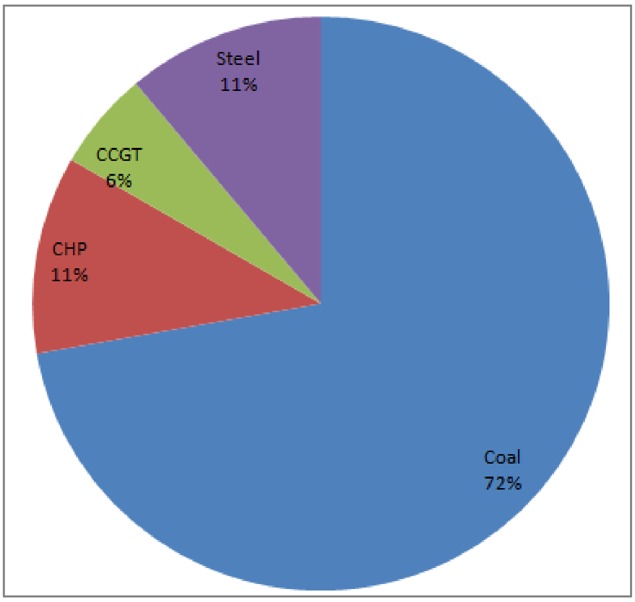


Figure 3.3 Selected source' shares of total emission by asset class

The sources have been selected from a list of UK emitters obtained from the data published by the EU ETS [102]. The selection process was based on the most CO_2 intensive sources in the UK regardless of their geographical locations. The case study aims to produce a picture of a UK wide CCS network through the geographical diversity of the selected sources and sinks. If required, the generic nature of the model easily allows for developing scenarios, which include a larger number of the UK emitters or potential storage sites.

3.7.1.2 CO_2 storage sites

The UK's potential storage capacity in hydrocarbon fields and saline aquifers is significant. The British Geological Survey estimates a capacity of 14,880 $MtCO_2$ in the saline aquifers of the Southern North Sea and the East Irish Sea, however the estimated saline aquifer capacity is associated with more uncertainty than the hydrocarbon reservoirs. The BGS also reported an EOR capacity of 1,175Mt CO_2 in the Central and Northern sea basin and in the Southern North sea, the gas fields' capacity is estimated to store 5,140$MtCO_2$ [83, 103]. On the other hand, the East Irish Sea oil and gas fields have considerable potential to store CO_2. The East Irish Sea is well placed to receive CO_2 from power plants and other industrial sources in North Wales and North West England. The best storage potential is likely to be in the larger gas fields such as Morecambe South and Morecambe North. The calculated CO_2 storage capacity in the oil and gas fields of the East Irish Sea basin is approximately 1,047 Mt [104].

Southern North Sea Rotliegend gas fields are selected as the potential candidates for the storage sites of the UK CCS scenario. This is because these sinks are placed close to many of the UK's emission intensive sources. Also the availability of seismic data for hydrocarbon fields and their cap-rock integrity makes them attractive candidate for storing CO_2. The Triassic East Irish sea basin sinks, Morecambe North and South are also selected to explore if an optimal CCS network in fact chooses to transport and store CO_2 in this location and how that affects the layout of the network.

Eight of the largest depleted gas fields in the Southern North Sea were selected. A total capacity of 3.43Gt is assumed for the selected Southern North Sea and the East Irish Sea sinks. A complete list of the selected fields and their storage capacities has been included in Appendix C. Appendix C also contains the assumptions regarding the number of platforms, the number of wells, the maximum injection rates and the capital and operational cost figures for both the Southern North Sea and the East Irish Sea sinks.

3.7.1.3 A CCS transport infrastructure that follows the existing gas lines

For the UK scenario, a cost incentive is introduced in the model to encourage the new CO_2 pipelines to follow the routes of the existing gas infrastructure. Concerns regarding adverse environmental impacts such as crossing and interrupting certain ecosystems, route surveys, issues with the landowners in the path of the pipeline, obtaining rights of way etc will have already been resolved, if the existing gas lines are followed.

In the CC supply chain model, these potential benefits are introduced through a constraint, which applies a cost reduction factor if a route is built between the nodes, which represent the UK's current gas infrastructure. Either the nodes are at the locations of gas terminals or they are dummy nodes. If connected they represent a layout very similar to parts of the existing gas lines. The dotted lines of figure 3.4 indicate the routes of the gas lines as fed to the GAMS model. This can be compared with parts of the actual UK gas infrastructure shown in figure 3.5.

The scenario of this chapter was tested for several cost incentives and it was concluded that cost incentives less than 50% do not result in a notable portion of the CCS pipeline infrastructure following the existing gas lines. Tests indicated that as expected increasing the cost incentive encourages the CCS network to follow the existing lines extensively. However considering some of the potential benefits listed above for following the existing infrastructure, costs savings above 50% may not be realistic. Therefore, in the scenario presented here, a cost reduction factor of 50% was applied if the model selects to connect two nodes between which a gas pipe has already been built.

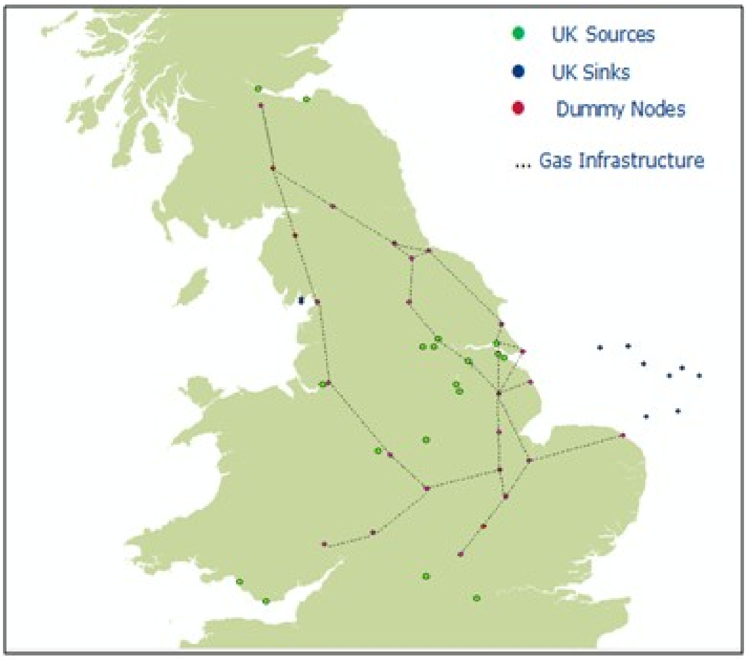


Figure 3.4 Sources and sinks of the UK CCS scenario and the assumed gas lines

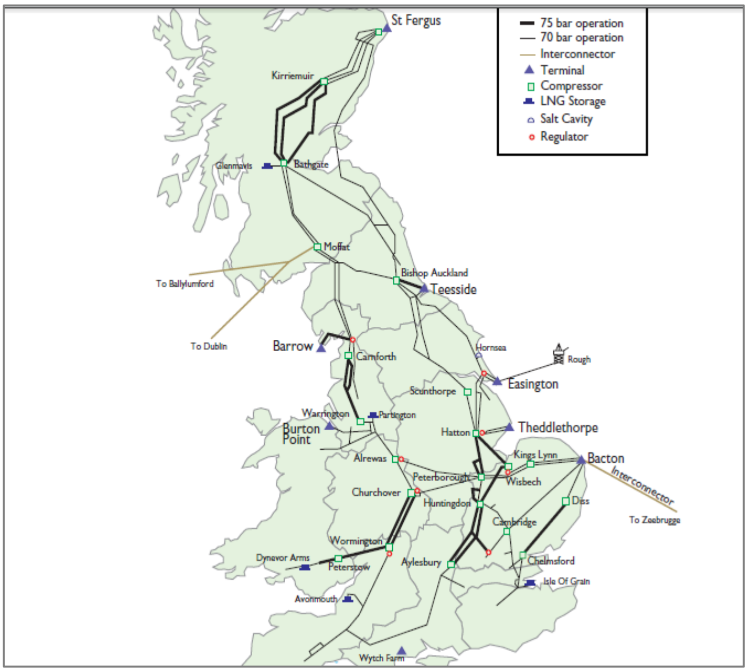


Figure 3.5 The UK's gas infrastructure (National grid)

3.7.1.4 Elevation or depth of the supply chain nodes

An elevation or depth parameter is introduced for every node. The model considers extra costs associated with taking into account the actual distances. The elevations of the sources range between 0-69m with majority only as high as 10m. The water depth values at the location of the sinks are taken as depth values ranging from -25m to -40m. The depth and elevation data can be found in appendix A.

3.7.2 Results and discussion

Figures 3.6 to 3.9 demonstrate the development of the CCS supply chain during the planning horizon 2010 to 2050. A complete list of the employed sources and the sinks as well as the amounts of CO_2 captured or stored at each source or sink at every time period can be found in Appendix G. The appendix also includes a list of the connected nodes and the segments of the pipeline cost curve, which correspond to the pipelines, and the amounts of CO_2 transported via each route during each time period. In the following diagrams, the blue lines indicate a CO_2 transport pipeline, which follows the existing gas infrastructure. The red lines indicate CO_2 flows through the pipeline in a reverse direction compared with the previous time periods.

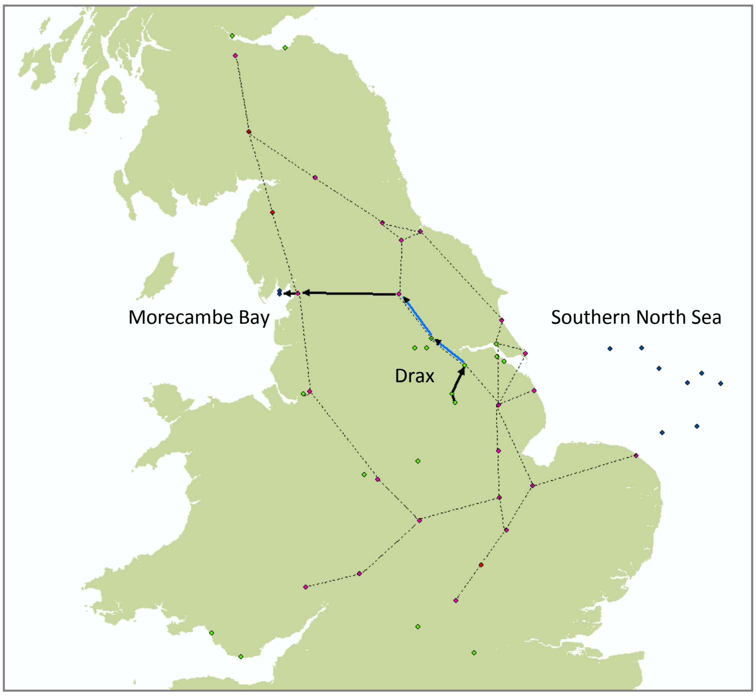


Figure 3.6 UK CCS network under a capture target of 27MtCO_2 per year (2010-2020)

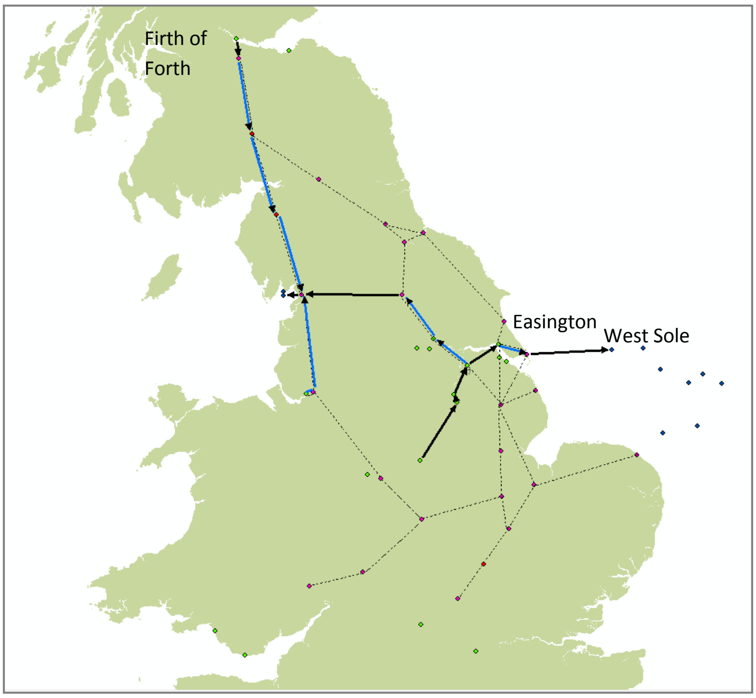


Figure 3.7 UK CCS network under a capture target of 54MtCO_2 per year (2020-2030)

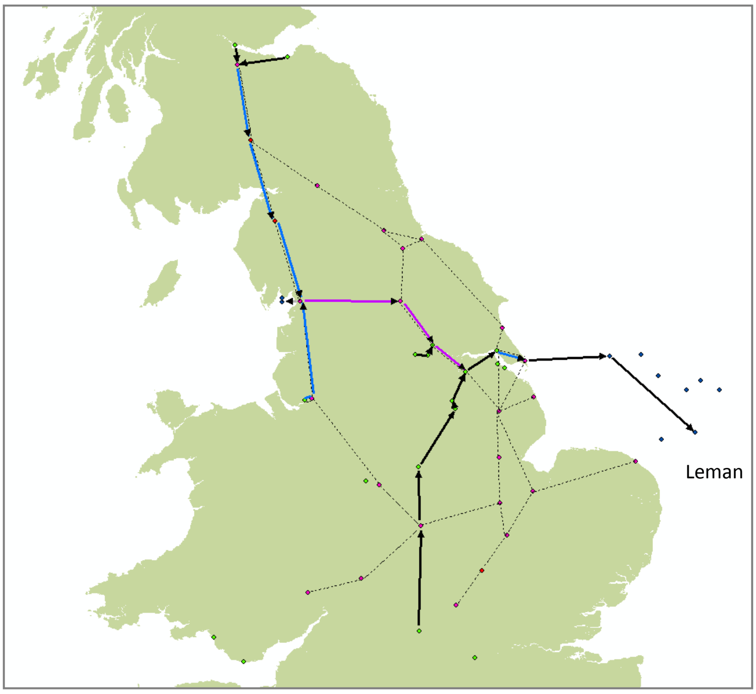


Figure 3.8 UK CCS network under a capture target of 81MtCO_2 per year (2030-2040)

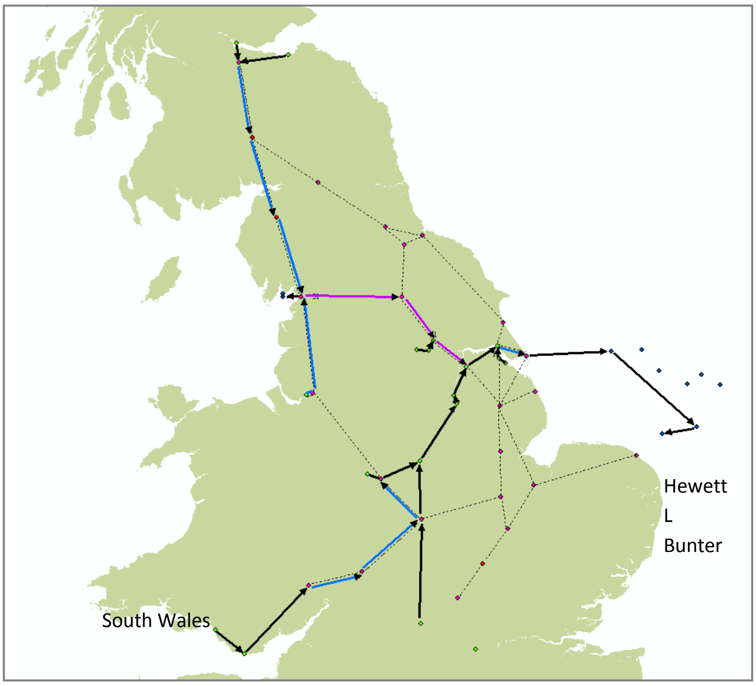


Figure 3.9 UK CCS network under a capture target of $108MtCO_2$ per year (2040-2050)

In the first time period under an annual capture target of 27Mt, the model connects Cottam and West Burton in North Yorkshire to Drax via Scunthorpe Steel. The CO_2 captured from Cottam and Drax is transported to Morecambe South in the East Irish Sea via Carnforth at the north east of Morecambe Bay. During the second time period, Ratcliffe-on-Soar in Nottinghamshire is also connected to the network at Cottam. A pipeline connects Scunthorpe to West Sole in the Southern North Sea via the Easington terminal. Only a small percentage of the capture target is stored in West Sole. In the North West Fiddlers Ferry is now also connected to the Morecambe Bay sinks. CO_2 is also captured at Longannet on the Firth of Forth in Scotland and transported south to the East Irish Sea via Bathgate.

In the third decade, Didcot power station in the South East is linked to the existing network via Ratcliffe-on-Soar in Nottinghamshire. In the Southern North Sea CO_2 is now transported via West Sole to be injected in Leman. In Scotland, a pipeline connects Cockenzie on the Firth of Forth to Bathgate. Morecambe South in the East Irish Sea has no more capacity at this period, the entire amount of CO_2 captured during this period from The 11 emitters in the North West, Scotland, North Yorkshire, and the South East is injected into Leman in the Southern North Sea. In the final time period, CO_2 is stored in Leman, Hewett L Bunter and West Sole in the Southern North Sea and Morecambe North in the East Irish Sea. In this period, the network expands to connect Port Talbot steel and Aberthaw on the Coast of South Wales to the network via the dummy nodes in the South East. Around the Humber, the South Humber bank power station is also linked to the Easington Terminal. CO_2 is captured from all eighteen sources considered in the scope of the case study.

Throughout the planning horizon, Drax remains to be a major provider of CO_2 with almost 20Mt captured per year. Leman is a major storage site in the Southern North Sea. As high as almost 50% of the entire mitigated CO_2 is captured from the emitters close to the Humber and is transported to the nearby Leman, which benefits from low injection costs per unit of CO_2. The results also show that the East Irish Sea sinks stored almost 35% of the total CO_2 captured from various parts of the network throughout the planning horizon. The results confirm that since the model considers the future changes, to ensure an overall optimal solution, the model's recommended strategy at a point in time might be non-intuitive. For example, some of the CO_2 captured from the North East is transported to the Morecambe Bay rather than the obvious Southern North Sea or as shown in figure 3.9, some of the previously built pipelines are now used to transport CO_2 in an opposite direction across England towards the Southern North Sea. Tables 3.1 and 3.2 contain a breakdown of the costs of the components of the supply chain as per the GAMS calculations.

Table 3-1 Average costs of the CCS components (Total cost over the planning horizon divided by the total mitigated CO_2)

Cost over the planning horizon (\$/tonneCO_2 mitigated)	
Capture	13.15
Transport	0.95
Storage	2.75

Table 3-2 Cost per unit of mitigated CO_2 during time period T

Cost at time T (\$/tonneCO_2 mitigated)	**T1(2010-2020)**	**T2(2020-2030)**	**T3(2030-2040)**	**T4(2040-2050)**
Capture	35.555	18.76	11.263	6.152
Transport	3.473	1.43	0.671	0.294
Storage	9.755	3.45	2.227	1.035

Table 3-3 Summary of computational results

Model statistics	
Single equations	224,549
Sinlge variables	203,737
Discrete variables	68,264
Resource usage (s)	664 – 852
Average resource usage(s)	762

3.8 Conclusion

So far, in this thesis, we discussed that large-scale commercial deployment of CCS requires whole system cost optimisation of a dynamic CCS supply chain. Also, as the CCS system is bound to expand with the increasing popularity of CCS, multi-stage optimisation is necessary to ensure an optimum investment and operational plan at each phase. I t was then confirmed that there is a gap in scientific research for whole system CCS supply chain optimisation across both time and space. In this chapter, a quantitative multi-period whole system optimisation tool was developed that makes cost optimised design and operational decisions i.e. provides a pathway for a dynamic CCS network. Considering the UK's geographical suitability for CCS, the current CCS demonstration projects and the government's Roadmap's emphasis on placing CCS on the forefront of its strategies, in this work we studied the evolution of a UK CCS system over four time periods up to year 2050 under increasing capture targets. The case study validated the multi-period model's unique ability in capturing the optimal evolution of CCS development and operational strategies as the supply chain environment changes with time. The non-intuitive results of the multi-period model indicated the necessity of such a tool as part of CCS commercialising planning. The results show that although the model considers that building infrastructure as late as possible saves costs, however it also considers the necessary future changes and hence the current investments are made in the most cost effective way, overall. This case study together with the scenarios of chapter 4, will demonstrate the flexibility of the developed tool to accommodate various scenarios in terms of scope, geography, operational constraints, specifications of each time period, availability of sources or sinks, market parameters etc. Next chapter will also access the full capability of the model in real options analysis of complex CCS value chains.

Chapter 4 The effect of market and leasing conditions on the techno-economic performance of CO_2 transport and storage value chains

The multi-period CCS supply chain optimisation model of chapter 3 was used together with a CO_2 storage life cycle cost model developed at the department of Earth Sciences, Imperial College to build a life cycle cost modelling tool for CO_2 transport and geological storage. This was done as part of a project carried out by Imperial College for the Crown Estate on real options analysis of complex CO_2 transport and storage networks. The integrated model can capture the geological characteristics, engineering aspects and the economics of complex CCS chains and investigate the optimal pathway for the configuration and operation of CO_2 transport and storage networks considering the market conditions in which they develop. Through cash flow analysis of alternative leasing conditions under user defined market and technical constraints, the outcome can be used to highlight an individual storage site's performance and provide insights into factors that encourage investment and hence market development.

A preliminary study is carried out to demonstrate to the Crown Estate the background methodology. The first scenario demonstrates a single chain CCS system connecting Longannet power station in Scotland to the Goldeneye platform per the 2011 Scottish Power FEED study [105]. A multi-storage scenario is also devised where a number of Scottish emitters are connected to seven storage sites in the Central North Sea for a planning horizon of 35 years. The progression of the network is due to availability of storage sites at different times and the variations in the maximum injection rates.

The aim is to illustrate to the Crown Estate that through dynamic whole system optimisation, the solution provided for each component of the CCS chain at every phase satisfies the financial viability of the whole CCS project throughout the planning horizon. The solution also ensures cost reduction through transport and storage network sharing and optimisation. On the other hand, the two models can be integrated seamlessly to form a generic tool that can be adapted to any user defined CCS supply chain technical or financial boundaries and benefit from the detailed cost modelling as performed by the storage life cycle cost model. This work aims to illustrate to the Crown Estate that the real options analysis work will address the site owner's and operator's technical and market risks through whole system optimisation. In addition, the combination of the tools can enable quantitative assessment of the storage sites considering their technical differences and market evolution to maximise value for the Crown Estate. In effect the assessment of storage sites' leasing conditions in the multi-storage scenario not only serves as a preliminary evaluation of the model's potential to assess the influence of real options on the cash flow of a CCS value chain and hence provide insight into decision making regarding the future operation and management of storage and transport network. It also shows the potential benefits of further developing the model towards a flexible planning tool, which considers market, operational or technical uncertainties.

The material in this chapter was prepared for a report presented to the Crown Estate [98] and it is due to be published in proceedings of the 12th Greenhouse Gas Control Technologies (GHGT12) conference [22]

4.1 Real options analysis of CO_2 transport and geological storage chains

Recently, following the CCS Cost Reduction Task Force final report [106], the UK government has reaffirmed their wish to see CCS develop into a strong industry. ZEP has also published reports on the costs of the CCS components provided by the member organisations on existing pilot and future demonstration projects. However, the ZEP report demonstrated few cases of simple CO_2 transportation and storage facilities, which did not consider optimisation. On the other hand, the CO_2 storage processes involve considerable uncertainty due to the natural variability of geological, hydrogeological and geometrical properties of CO_2 storage formations [22]. Kemp and Kasim [81] developed an optimisation model of CO_2 transportation and storage in the UK. However the storage costs were not considered and the storage system was simplified [22]. As discussed above, this chapter presents a CO_2 transport and storage network life cycle cost model which is a combination of the multi-period CCS supply chain optimisation model developed in chapter 3 used together with a CO_2 storage life cycle cost model [22]. The CO_2 storage life cycle cost model framework is briefly discussed in section 4.1.1. The main project deliverable at this stage is a real options CCS optimisation tool for the assessment of the influence of storage site leasing alternatives on the performance of the CCS chain. Two scenarios, a single chain CCS system and a multi-storage CCS system, were devised to present the following to the Crown Estate.

The Multi-period CCS network model is a whole system cost optimisation tool, the outcome of which is the optimal investment and operational decisions for the potential pathway for an emergent CCS network in the UK. The integration of the CCS supply chain optimisation model and the CO_2 storage life cycle cost model shows that it is imperative to evaluate the technical and economic performance of the CCS value chain as a whole, rather than as individual components in order to ensure the financial viability of CCS projects. The combination allows for evaluation of the impact of the storage site's technical and operational alternatives on the overall system performance.

Through a multi-storage scenario, the generic nature of the CCS supply chain model is shown through a user-defined geographical scope, storage sites' availability dates, capacity and injection constraints and the enforcement of user-defined transport constraints. Also, it is shown that it is not wise to estimate costs for a single CO_2 storage value chain linking source to sink, as this may significantly overestimate the costs. This scenario shows that for alternative user-defined leasing scenarios, the supply chain model's optimal decisions around the injection of CO_2 can be used as guidelines within the CO_2 storage life cycle cost model for evaluating the internal rate of return of each storage site or to determine each site's required leasing conditions or benchmark rates for target costs of investment.

4.1.1 CO_2 storage life cycle cost modelling framework

The CO_2 storage life cycle model [22] developed at the department of Earth Sciences, Imperial College, accounts for the key performance characteristics of storage sites such as CO_2 injectivity and dynamic storage capacity with alternative injection options and strategy. Figure 4.1 shows the life cycle of a CO_2 storage project. Figure 4.2 shows the life cycle cost modelling framework, which also aims at addressing the uncertainties in the storage site properties. The cost model is modularised so that it contains the storage processes and site-specific operations.

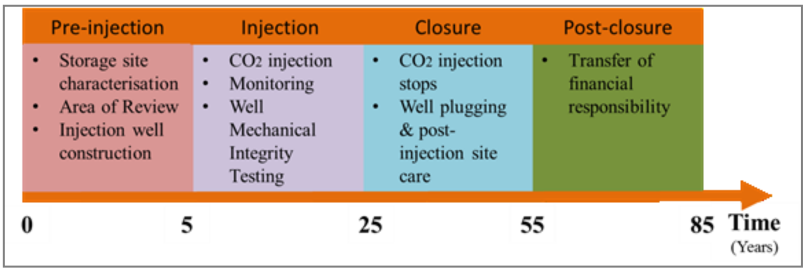


Figure 4.1 The life cycle of a CO_2 storage project [98]

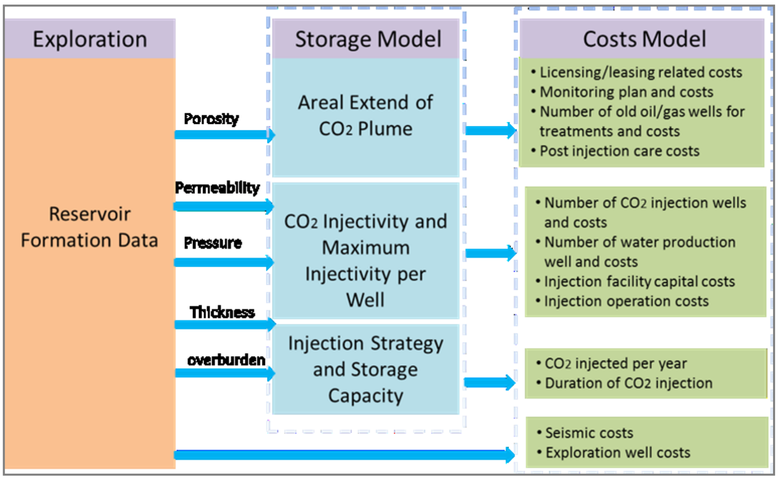


Figure 4.2 Life cycle cost modelling framework implemented [22]

The components of the CO_2 storage cost model as shown in figure 4.2 include site characterisation, assessment of the area of review and corrective actions, injection well construction, monitoring, well operations, water extraction and treatment. The Scottish Power FEED report [105] platform operation costs are used in this study. These costs include energy, maintenance, consumables, waste disposal staff, lease costs etc related to the operation of the injection platform

4.2 Life cycle cost modelling of a single CCS value chain-anchor case

An anchor case is devised using a single chain CCS system that connects Longannet power station in Scotland to the Goldeneye platform in the North Sea. The information used is based on the data provided in the Scottish Power FEED report [105]. According to the FEED study the CO_2 capture plant at Longannet captures a maximum of 2Mt CO_2 per year. The static CO_2 storage capacity at Goldeneye is estimated at 47Mt. The CO_2 supply chain must be designed so that by the end of an 11 year period, 20Mt CO_2 is stored at Goldeneye. As shown in figure 4.3, an onshore pipeline connects Longannet to the St Fergus compressor station via dummy nodes in Valleyfield and Kirriemuir. An offshore pipeline then connects the St Fergus compressor station to Goldeneye. Constraints were added to the GAMS model to enforce the FEED study transport route. The elevation and the coordinates of the nodes as inputs to the GAMS model are provided in appendix H.

Figure 4.3 the Longannet-Goldeneye CCS chain [105]

4.2.1 Key parameters and assumptions

Storage

Table 4.1 contains the key parameters considered for the CO_2 storage anchor case in the storage life cycle cost model. The levelised CO_2 storage cost for the base case is calculated as £20.32 per tonne CO_2 stored. Figure 4.4 demonstrates a breakdown of this cost between different activities.

Table 4-1 Key parameters considered for the CO_2 storage anchor case [22]

	Units	Value
Injection rate per year	Million tonnes per year	2.0*
Storage facility injection life	Years	11
Total CO_2 injected	Million tonnes	20
Area of review (Monitoring area during injection)	Km^2	160
CO2 storage financial responsibility	£/tonne CO_2	0.417
Number of injection wells	-	4
Modified injection platform	-	1
Water production well	-	0
Water production rate	Mt per Mt CO_2 injected	0

*** During 10th and 11th year of injection, the injection rates are 1.5 and 0.5 respectively**

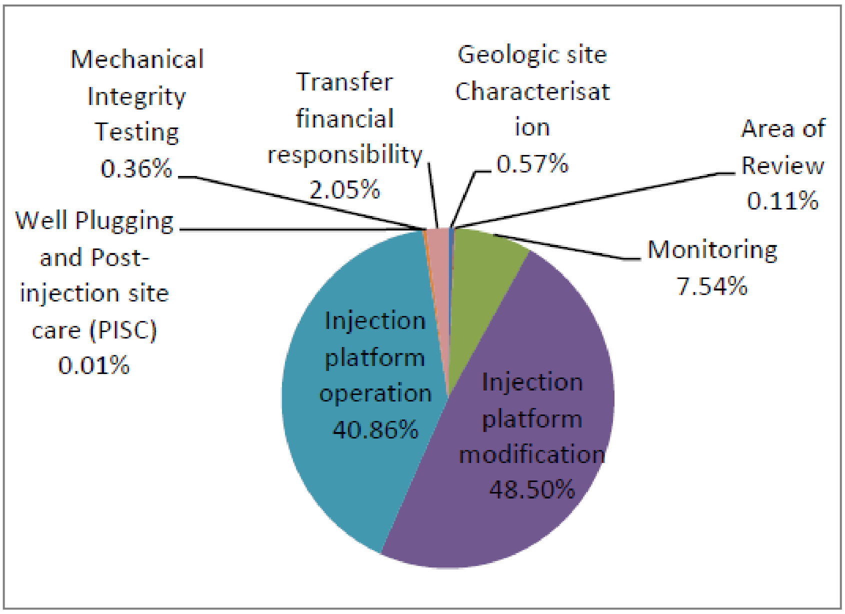


Figure 4.4 CO_2 storage cost analysis - anchor case [22]

Transport

The Scottish Power FEED report is used to calculate the costs of existing pipeline modification as well as new constructions and operation. The obtained parameters are then used as inputs to the GAMS model. It is assumed that a new pipeline is built from Longannet power station to Valleyfield and to the close by Dunipace. An existing pipeline (National Grid's No.10 Feeder) connects Dunipace to St Fergus. Then the CO_2 is compressed at Blackhill compression facilities near St.Fergus terminal. An offshore pipeline then transports the CO_2 to the Goldeneye platform to be injected underground.

The FEED study confirms that operation of the onshore pipeline in the gaseous phase at 34barg could provide the design flow requirement of 2Mt CO_2 per year. It is also confirmed that the transportation of CO_2 will take place in dense phase through the offshore pipeline. The maximum CO_2 inlet temperature to the offshore pipeline will reduce from 30°C to 29°C which requires the installation of a propane chiller at Blackhill compressor station for high ambient temperature conditions [105].The FEED study assumes all prices are in 2010 terms and real costs with no inflation are applied. The cost figures fed to the GAMS model have been inflated according to the inflation rates provided in appendix F. It is assumed that the rate of inflation varies linearly between the values provided in appendix F.

The capital cost figures have been consolidated using the following categories: Mobilisation and enabling, land, equipment, civil works, mechanical, electrical, building, testing and commissioning, insurance, legal and license fees, interconnections and other costs. Tables 4.2 to 4.5 contain the assumptions and a breakdown of the capital and operational costs of transport as per the FEED study [105].

Table 4-2 Assumptions used to calculate the annualised transport capital cost per km

Capital Charge Factor(calculated)	Exchange rate $/GBP	Length of pipelines (km)
0.09	0.636	301

Table 4-3 Capital cost of the segments of the CO_2 transport line

Chain segment	Total CAPEX (£M)	Cost Estimate range %	
Link between Longannet and Dunipace	81.3	-10	15
No. 10 Feeder (Existing pipe)	78.9	-10	15
Compression and facilities at St Fergus (Blackhill)	121	-10	15
Total cost (Post-FEED)	281.2		
Total cost (M$/km/year)	0.13		

Table 4-4 Assumptions used to calculate the annual transport operational cost per km

Gas price ($/MWh)	CO_2 flow rate (Mt/year)	Length of pipelines (km)	Exchange rate ($/GBP)
23.3	2	301	0.636

Table 4-5 Breakdown of the transport operational cost

Item	Item/Cost
Fuel/Power/Energy (MWh/tCO_2)	0.0453
Maintenance (£/per Month)	58,000
Staff(£/per Month)	350,000

Rates(£/per month)	4,000
insurance (£/per month)	33,000
overheads(£/per month)	602,000
Total operational cost (M$/Mt/km)	0.00231

Capture costs

The annualised capital and operational capture cost parameters calculated for coal-fired power plants as described in appendix B have been used in the GAMS model. The figures are then inflated according to the inflation rates provided in appendix F.

4.2.2 Application of the CO_2 storage life cycle cost model- anchor case

Table H.2 of the appendix contains the breakdown of the annual cash flows for the periods of construction and operation of the storage site as calculated by the CO_2 storage life cycle cost model. This is also shown in figure 4.5. During the first two years (pre-injection phase) a large amount of investment is required to cover platform modification. During the 11 years of injection, a majority of the expenditure is due to platform operation and monitoring.

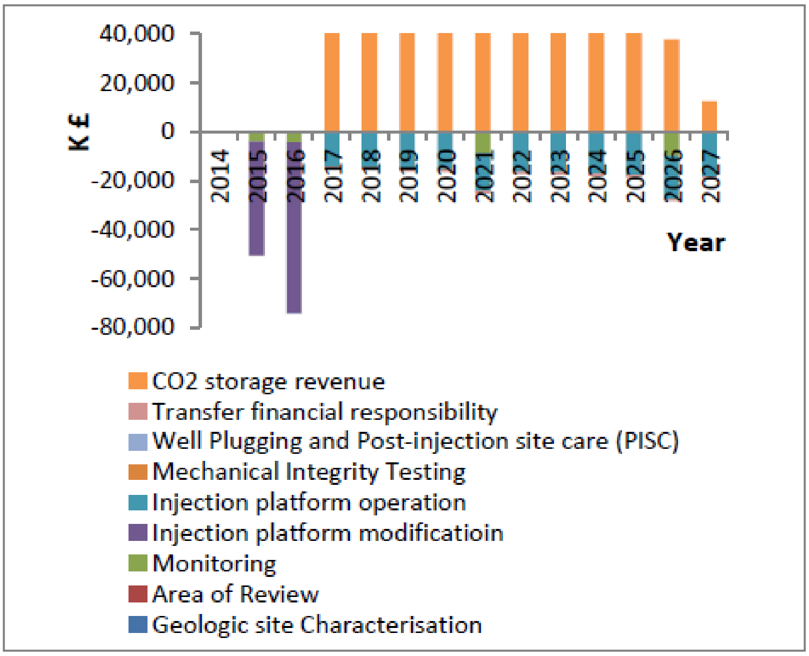


Figure 4.5 The life cycle cash flow of CO_2 storage at Goldeneye -anchor case [22]

Figure 4.4 shows that almost 80% of the levelised storage costs are linked to injection platform modification and operation. A sensitivity analysis was carried out by Korre at al [22] to determine the sensitivity of the overall storage cost to the changes in the top cost contributors. The analysis suggests that sharing or optimising infrastructure capacity has the potential to significantly reduce the storage costs through the reduction of platform modification or operation costs. Storage cost also shows moderate sensitivity to the required water production rate and exploration drilling. They used the life cycle cost model to analyse the internal rate of return (IRR) for the project storage costs. Their analysis suggests that at a CO_2 price of £21.25 per tonne and a royalty at £0.833 per tonne, the project breaks-even [98]

4.2.3 Application of the multi-period CCS network model- anchor case

The annual storage costs provided by the CO_2 storage life cycle cost model for the Goldeneye anchor case presented in figure 4.5 were set as input to the multi-period CCS network model developed in chapter 3 of this thesis. The planning horizon is divided to fourteen years; three construction years followed by eleven years of injection. The annual capital and operational transport cost parameters are obtained per section 4.2.1. Since this is a single CCS value chain, all of the CO_2 captured at Longannet is transported and injected in Goldeneye. The purpose of this case study is to validate the integration of the two models and determine the combined life cycle cash flow of the transport and storage system.

Figure 4.6 demonstrates the annual cost of transport (capital and operational) for all connected nodes. The initial higher expenditure is due to the costs of construction or modification of pipelines. This represents a discounted accumulation of all the annual payments until the end of the horizon. For the remaining years, transportation costs are the operational costs and proportional to the amounts transported.

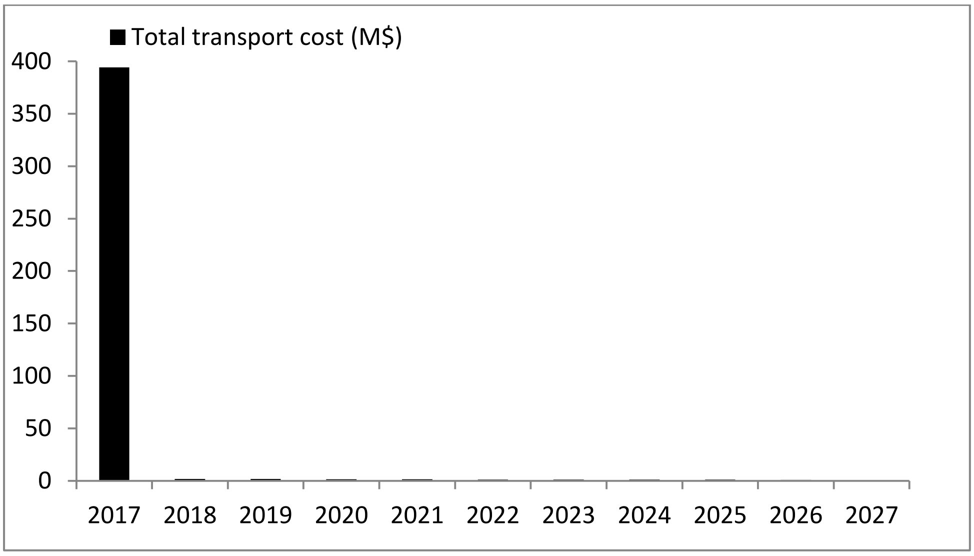


Figure 4.6 Total capital and operational costs of transport (onshore and offshore) at each time period – anchor case

4.2.4 Sensitivity analysis of the integrated life cycle cost model

A sensitivity analysis of the effects of disturbances in the top storage cost contributors was carried out. The boundary conditions of the multi-period supply chain model were reset using the storage model's sensitivity analysis results for the anchor case. Four scenarios were compared with the base scenario, each representing a different length of operation and injection rate. Figure 4.7 illustrates the levelised costs of storage and transport i.e. per tonne of CO_2 for each case. Keeping the same injection rate but increasing the injection period or storage capacity should reduce the levelised CO_2 storage and transport costs. The levelised transport or storage costs are much lower for the cases which assume larger storage capacity or injection rate. This implies that sharing or optimising infrastructure, for example the optimised use of adjacent storage sites could considerably reduce the overall costs [22]. Figure 4.7 also shows that the transportation costs in single chain CCS systems are significant and only slightly lower than the storage costs. This implies the potential of a shared transport network in reducing the overall CCS network costs.

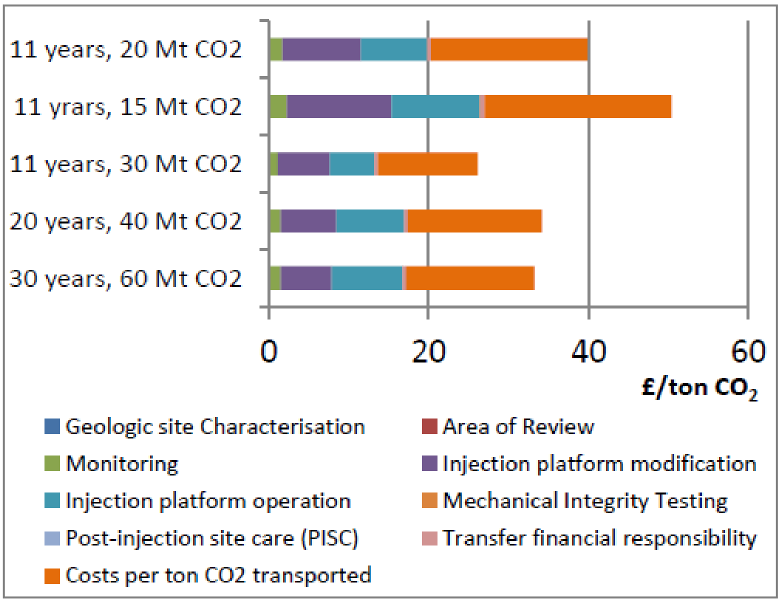


Figure 4.7 Analysis of a single chain CCS system's levelised costs for different injection scenarios– anchor case [22]

4.3 Life cycle cost modelling of CCS value chain-CNS multi-store case

The anchor case demonstrated to the Crown Estate the functionality and accuracy of the combined model and the importance of cost assessment through whole system optimisation. The multi-storage scenario will illustrate the tool's flexibility in computing any user-defined scenario and demonstrate that the solution is an optimal pathway for an expanding CCS network and that the proposed real options CO_2 network optimisation tool enables a cash flow analysis in the context of optimal network design. Finally based on the optimisation model's solution for the storage sites' operation, the CO_2 storage life cycle cost model can determine the profitability of each site under financial or market constraints or each site's necessary leasing specifics can be calculated for the Crown estate as guidelines for target rates of return.

4.3.1 Key parameters and assumptions

Seven Central North Sea storage sites are selected for this scenario comprising the three saline aquifers and four depleted oil and gas reservoirs shown in figure 4.7. Two of the aquifers are distinct blocks that are part of the Captain aquifer, while the third comprises part of the larger Britannia aquifer system. The depleted oil and gas systems considered are Goldeneye, Blake, Scapa and Britannia. These fields are considered available at different times in the future. The CO_2 storage capacity per site and assumed availability are detailed in Table 4.6. The CO_2 emission sources considered for the scenario are all in Scotland as shown in table 4.7 providing a total annual CO_2 emission of approximately 19.5 Mt. Table I-1 of the appendix contains a list of the supply chain nodes and their coordinates.

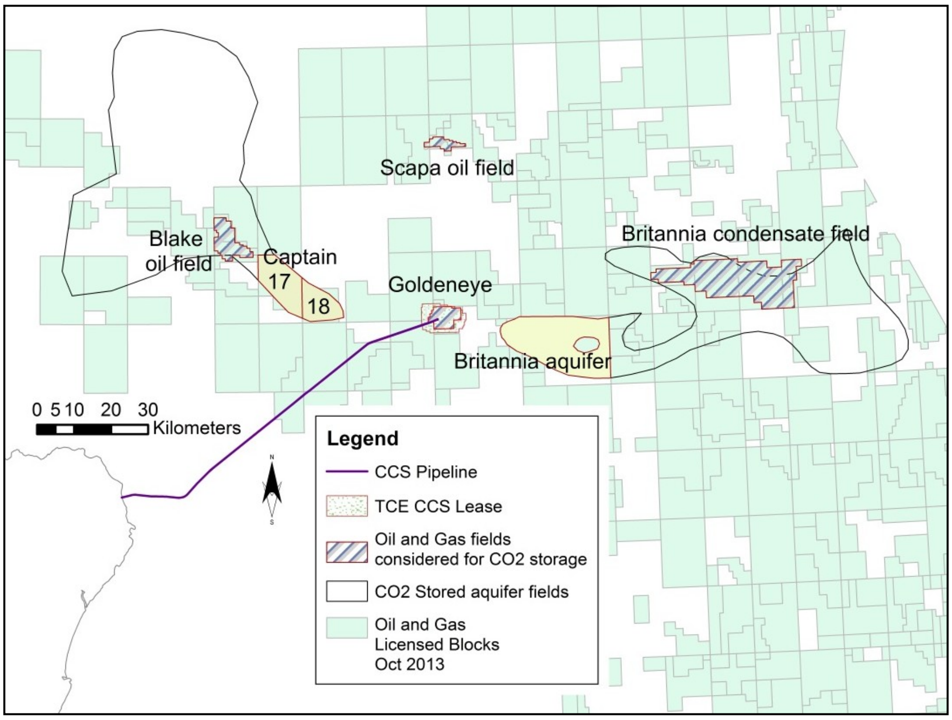


Figure 4.8 CO_2 storage sites selected for the Central North Sea multi-storage scenario [22]

Table 4-6 Storage sites considered in the multi-store scenario [22]

Description	Site availability(Year)	Leasing area storage capacity(Mt)
Britannia aquifer block	Available now	22.98
Captain aquifer block 17	Available now	16.98
Captain aquifer block 18	Available now	11.24
Goldeneye gas condensate field	Available since 2011	20

Blake Oil field	Available since 2015	28
Scapa Oil field	Available since 2020	48.32
Britannia condensate field	Available since 2025	130.2

Table 4-7 CO_2 emission sources considered in the multi-store scenario

Installation	Source type	2011 verified CO_2 emission (Mt/year)
Peterhead power station	CCGT plant	2.48
Longannet power station	Coal	9.12
Grangemouth refinery	Refinery	1.49
Cockenzie power station	Coal	3.95
Lynemouth power station	Coal &biomass	2.55

The multi-period CCS supply chain model connects the sources and sinks in the cheapest way considering the added constraints. Since the capture target remains the same throughout, the progression of the network is due to availability of storage sites at different times and the variations in the maximum injection rate. The following assumptions/constraints are applied.

Mitigation target: the model aims to achieve a mitigation target of 90% of the Scottish CO_2 emissions (90% of 19.5 Mt) by purchasing carbon credits or through CCS. The model is driven to use CCS as far as it is feasible (i.e. as far as capacity or injection rate allow) using a very high carbon price.

Time horizon and periods: The time horizon is from 2014 to 2050. Four time periods are introduced with each time period correlated with the availability of a new storage site: 2014-2018, 2018-2023, 2023-2028, 2028-2039 and 2039-2050.

Storage capacity: The available storage capacity is set as 277.73 $MtCO_2$ in total. The model considers the availability dates and injection rates of storage sites.

Existing pipelines: Constraints are applied to enforce a route through St Fergus and to create the kinks in the pipeline routes as shown in figure 4.7. Through an incentive of 50% cost reduction, the model enforces building a trunk line with a capacity of 8Mt per year, which follows the existing route between St Fergus and Goldeneye.

CO_2 capture and transportation costs: The capital costs and operational costs are annualised using a capital charge factor per the methods discussed in chapter 3.

Storage costs: Every storage site has a lifetime, a capital, and an operational cost value, which are provided on an annual basis throughout the life of the storage site generated by the CO_2 storage life cycle cost model. The costs are then adjusted to match the GAMS model's environment which eventually converts the cost parameters to the accumulated present value of the future annual cash flows depending on the time of investment or the period of operation. Tables I-2 and I-3 contain the fixed and variable storage cost parameters adapted from the results provided by the storage life cycle cost model for each storage site and fed to the GAMS model.

CO_2 injection rate: A parameter is introduced to limit the annual amount of CO_2 injected into each individual sink.

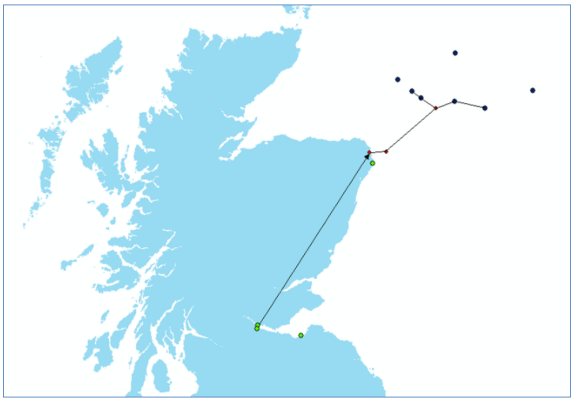
The CO_2 storage life cycle cost model accounts for geological conditions, technological alternatives and operation options, however certain assumptions were made: injection rates were decided based on current industrial scale CO_2 storage projects. Storage capacity of the aquifer blocks is calculated proportional to the considered area. For simplicity, it is assumed that water extraction is only necessary for reservoir pressure control for aquifer sites. The monitoring area is also assumed fixed and equal to the lease area [98].

4.3.2 Evolution of the optimal CO_2 transport and storage network

The evolution of the optimised network is demonstrated in Figure 4.9, under constraints of storage site availability and injection rate. Tables 4.8 and 4.9 contain the amount of CO_2 captured or stored in each node during each time period respectively.

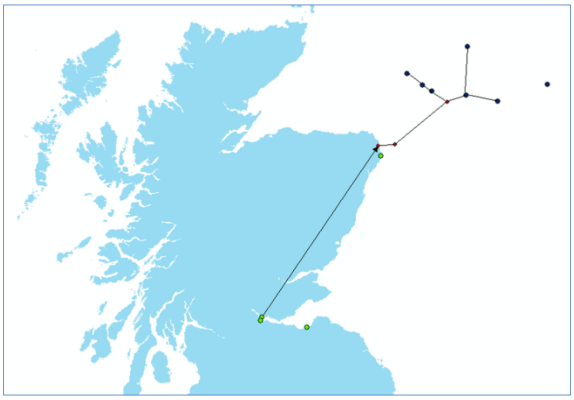
Table 4-8 Amount of CO_2 captured at each source at each time period – CNS multi-store scenario

CO_2 captured at time T (Mt/year)	**T1(2014-2018)**	**T2(2018-2023)**	**T3(2023-2028)**	**T4(2028-2039)**	**T5(2039-2050)**
Length of time period (years)	**4**	**5**	**5**	**11**	**12**
Source Longannet power station	8.00	7.63	8.21	8.21	5.35
Source Peterhead Power Station	0	0	0	1.09	0
Annual sum (Mt)	8.00	7.63	8.21	9.30	5.35
Total CO_2 captured during the time period (Mt)	32.00	38.15	41.06	102.31	64.20
Total CO_2 captured between 2014-2050 (Mt)			277.3		

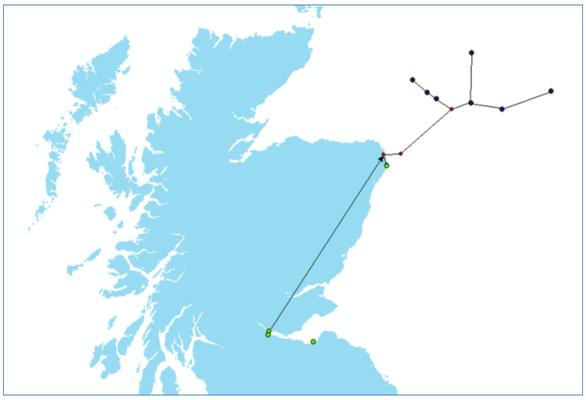


(a) Time period 1 (2014-2018) Storage sites : Britannia saline aquifer, Captian 17, Captian 18, Goldeneye

(b) Time period 2 (2018-2023) Storage sites : Britannia saline aquifer, Captian 17, Captian 18, Goldeneye, Blake oil field



(c) Time period 3 (2023-2028) Storage sites : Britannia saline aquifer, Scapa, Goldeneye, Blake oil field



(d) Time period 4 (2028-2039) Storage sites : Britannia condensate, Scapa, Blake oil field

(d) Time period 5 (2039-2050) Storage sites : Britannia condensate

Figure 4.9 The evolution of the optimised CO_2 transportation and storage network- CNS multi-store scenario

Table 4-9 Amount of CO_2 stored at each storage site at each time period – CNS multi-store scenario

CO_2 stored at time T (Mt/year)	**T1(2014-2018)**	**T2(2018-2023)**	**T3(2023-2028)**	**T4(2028-2039)**	**T5(2039-2050)**
Length of time period (yrs)	4	5	5	11	12

Britannia Saline aquifer block	2	2	1.00		
Goldeneye Gas Condensate Field	2	1.19	1.22		
Britannia Condensate Field				6	5.35
Scapa Oil Field			4	2.58	
Captain Saline Aquifer 1	2	1.80			
Captain Saline Aquifer 2	2	0.65			
Blake oil fields		2	2	0.73	
Annual sum (Mt)	8	7.63	8.21	9.30	5.35
Total CO_2 injected during the time period (Mt)	32	38.15	41.06	102.32	64.20
Total CO_2 stored between 2014-2050 (Mt)			277.3		

In the multi-period CCS model, the cost of capital is calculated as the accumulation of the present value of all the annual capital payments from the time of investment until the end of the horizon. Therefore, the results also confirm that in order to save cost, building infrastructure is delayed until required. Table 4.11 and 4.12 provide the corresponding average costs of each component.

Table 4-10 Average cost of the components of CCS supply chain– CNS multi-store scenario

Leveslised cost ($/tonne)- Total cost summed over nodes and time periods divided by the total mitigated CO2		
Capture	**Storage**	**Transport**
12.16	2.64	10.75

Table 4-11 Average cost of the components of CCS supply chain at each time period– CNS multi-store scenario

Average costs at each time period ($/tonne)	**T1(2014-2018)**	**T2(2018-2023)**	**T3(2023-2028)**	**T4(2028-2039)**	**T5(2039-2050)**
Capture	62.40	11.28	7.00	5.77	1.14
Storage	15.65	1.99	1.81	0.68	0.19
Transport	44.58	12.81	7.80	6.41	1.45

4.3.3 Storage sites' leasing options

The supply chain optimisation model's solution for the storage sites in the Central North Sea scenario and the Storage life cycle cost model were used to carry out an analysis of the storage cash flows in various scenarios which mimic the financial constraints of real leasing options discussed with the Crown Estate [22]. Three scenarios were devised each emulating a leasing option; Open season leasing was considered through a scenario allowing the full utilisation of the optimal CNS multi-storage capacity for a fixed CO_2 price (£25) and royalty rate (15% of the CO_2 price) to determine each site's rate of return. Auctioning with a reserve price was considered through a scenario where a target IRR (10%) is set for all sites and the royalty fee that can be afforded per site is calculated as a guide, considering a fixed CO_2 price (£30). Finally, the effect of market conditions on project finances is investigated for a scenario of fixed royalty rate (15% of the CO_2 price) and IRR (15%). As shown in table 4.12 both saline aquifers and depleted oil and gas fields may differ significantly in terms of economic performance. It is also shown that a multi-store portfolio as a whole stabilises the economic performance. For example it is shown that in the last scenario, as soon as the expected CO_2 storage price reaches £26.33 per tonne, all of the seven storage sites can be leased as a package to meet the target IRR (15%) and royalty rate (15% of the CO_2 price) [22].

Table 4-12 Storage sites' performance under alternative leasing conditions [22]

Storage site	Open season IRR (%)	Auctioning with reserve price Royalty rate (% of CO2 price)	Dependence on market conditions CO2 price (£/tonne)
Britannia aquifer	17.91	43.18	23.03
Captain aquifer block 17	30.77	57.67	17.01
Captain aquifer block 18	25.87	47.94	20.26
Goldeneye gas condensate field	6.85	22.87	31.08
Britannia condensate field	3.89	17.88	33.19
Scapa oil field	34.25	62.91	15.18
Blake oil field	12.18	33.34	26.99
Multi-storage portfolio	17.08	39.65	26.33

Figure I-1 of the appendix demonstrates the cash flows and leasing royalty incomes of the storage sites during the planning horizon (2014-2050) for alternative leasing scenarios. This analysis can be used for project finance budgeting and for the identification of expenditure outliers [22].

We also carried out a cash flow analysis of the whole transportation network for the multi-store scenario. A target IRR of 15% and a royalty rate of 15% of the transport price were assumed for the transportation network. Table I-5 of the appendix contains the amounts of CO_2 transported through each route at each time period. It also contains the net present value of the accumulated operational cost of transport. Table I-

4 contains the time of construction and the net present value of the accumulated annual transport capital costs. In order to obtain the transport network cash flows we transformed these values back to the equivalent nominal cash flows. On the other hand, the annual revenues are defined as the product of the transported mass and the price. The royalty is set at 15% of the annual revenue. A price is then calculated for every unit of CO_2 transported at which the internal rate of return is 15%. This price was calculated to be £8.51 or $13.61 per tonne. Figure 4.10 shows the cash flow of the transportation network for the Central North Sea multi-storage scenario based on the assumptions above. The relevant figures can be found in table I-6.

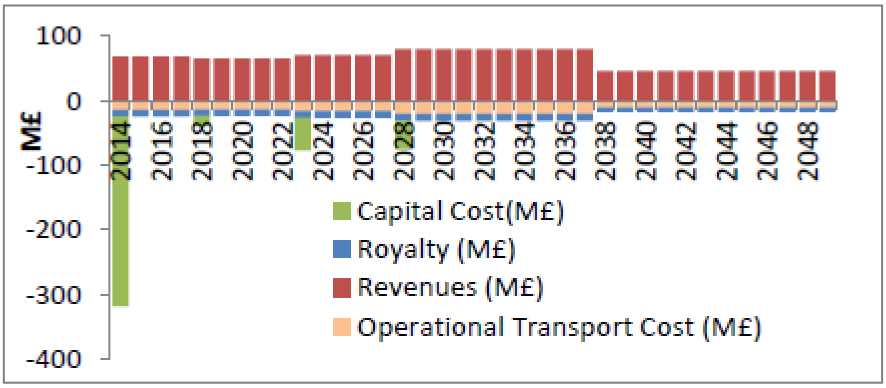


Figure 4.10 CO_2 transportation network cash flow with a 15% IRR (2011-2050)- CNS multi-store scenario [22]

4.4 Conclusion

This preliminary study demonstrates to TCE the background methodology that will be used to implement the real option analysis of complex CCS supply chains. The results illustrate that our network optimisation tool provides cost optimal solutions for all components of an evolving CCS chain. Through the scenarios, it is also demonstrated that the model is a generic tool that can be adapted to any user defined CCS supply chain boundaries or analyse the sensitivity of the system's techno-economic performance to any of the operational, design or market dependent parameters.

On the other hand, the combined CO_2 transport and storage cost modelling of the anchor case reinforced that to ensure financial viability of CCS projects, whole system evaluation of their technical and economic performance of the supply chain has to be carried d out. A multi–period, multi-storage scenario connecting the Scottish emitters to several Central North Sea storage sites showed that it is not wise to estimate costs for a single CO_2 storage value chain as this neglects the opportunity to reduce costs through transport and storage network sharing and optimisation. In addition, the scenario analysis and the results illustrate that our network optimisation and life cycle cost model for CCS value chains can sensibly capture the effects of technical and market constraints on individual storage site costs, as well as complex multi-storage scenarios

[22]. It is shown the models can be used to make cost optimal decisions in managing storage sites' leasing alternatives under user-defined financial constraints or targets.

This work successfully illustrated to TCE that the risks that may be imposed on site owners and operators can be reduced by optimisation during pre-project planning [98]. However considering the technical and market uncertainties, rigid strategies could undermine the solution's viability. As per the objectives of this thesis to address the issue of deterministic optimisation, the multi-period supply chain optimisation model of chapter 3 is improved to become a stochastic optimisation tool in chapter 5. The stochastic model of chapter 5 is used (discussed in chapter 6) in quantitative assessment of the choice between the storage sites for different realisations of uncertainties around injection strategies and also considering the uncertainties in the evolution of market conditions, so as to maximise value for TCE and the operators. In the next stage of the real options project, Imperial College's models will also be used to assess the value of additional data collection for individual storage sites in the decision making context.

Chapter 5 Multi-stage stochastic optimisation of an integrated CO_2 capture, transportation and storage supply chain

A deterministic method was adapted earlier in this thesis to optimise the future evolution of a CCS network. This method could also be viewed as "most probable scenario optimisation". The optimal expansion plan is determined based on the best available data for the uncertainties of the future system. Although widely used due to computational simplicity, it does not include uncertainty or any risk analysis and the lack of consideration of other plausible scenarios could result in substantial unexpected system costs. Different techniques and approaches have been deployed to solve problems arising in supply chain management under uncertainty. A Non-flexible probabilistic optimisation approach can be used to incorporate uncertainty into the multi-period CCS model. This method is not selected because although all alternative scenarios are represented, the investment strategy is only on average an optimal strategy given any of the possible scenarios [107]. It is risk-neutral and does not allow for flexibility or future optionality either. In that sense it is similar to deterministic optimisation, although the entire scenario tree is considered as opposed to the condensed deterministic equivalent. Section 5.1 reviews the optimisation methods in the literature that deal with uncertainty and identifies which approaches are most suitable to the objectives of this chapter (also discussed in detail in chapter 2 as part of the main thesis objectives).

This chapter extends the multi-period CCS model to consider uncertainty and allow for flexibility in decision making. A mathematical programming approach is used for stochastic optimisation of a multi-stage CCS network. In section 5.2, the mathematical formulation of the stochastic model is developed. In section 5.3 a case study is developed to examine the optimal strategy for CCS investment and operation in the UK under carbon price uncertainties. The case study entails four stages, eighteen biggest emitters in the UK and ten largest sinks in the surrounding seas. In a report published in January 2014, The Climate Economics Chair [108] analysed the simulations from the ZEPHYR model [109] to determine the combined effect of 2030 GHG targets [110], amendments to the EU ETS directive such as back-loading and Market Stability Reserve mechanisms on future price trajectories. This analysis together with the European Commission's latest assessment of the economic impacts of 2030 decarbonisation scenarios [110] have been used to develop a scenario tree for the potential carbon price evolution paths from 2014 to 2040. The simplified scenario tree contains six potential paths for the evolution of the price of carbon throughout the planning horizon. The stochastic model then outputs the optimal strategy in terms of CCS investment and operation according to the system stage changes i.e. the price of carbon at every stage.

The results are discussed in detail in section 5.3. In summary, the results show that at a current price of 12Eur per tonne, CCS is not part of the portfolio for all scenarios. Investment in CCS begins at stage 2 at a carbon price of 40Eur per tonne. At stage 3, for the scenarios where the price of carbon drops to 27Eur per tonne, the role of CCS drops from 78% to 53% of the target whereas in the scenarios which exhibit a price increase to 53Eur per tonne, the model invests further in a vast CCS infrastructure which is responsible for mitigating 96% of the target. At stage 4, neither of the two carbon prices; 100Eur per tonne and 152Eur per tonne offers a cheaper solution than carbon capture. Hence the CCS infrastructure is developed enough to handle 100% of the mitigation target which is 52% of the annual emissions considered or 59Mt per year.

5.1 Optimisation under uncertainty- review of current methods

Lainez and Puigjaner [111] divide the approaches that deal with uncertainty into two categories; reactive and preventive procedures. Reactive approaches attempt to modify a nominal plan obtained by a deterministic formulation so as to adjust it to the changes. Rule based methodologies, heuristics and intelligent agents are commonly used to perform the required changes. Model Predictive Control (MPC)and parametric programming have been applied to supply chain design as reactive approaches [112]. Lainez and Puigjaner [111] explain that preventive approaches that deal with uncertainty take into account uncertainty in formulating the problem. The most common preventive approach is stochastic programming with recourse as explained by Birge [113]. Scenarios are included in the model and the selected solution has the optimum expected performance. Chance constraint programming and fuzzy programming where parameters are defined with elements of uncertainty i.e. a realistic interval for the parameters are other preventive approaches. The main issue here is to effectively describe the uncertain parameters. Simulation-based optimisation as discussed by Sahinidis [114] is also another preventive approach for optimisation under uncertainty.

Before reviewing the literature, in order to provide some background, the optimisation methods for multi-stage planning under uncertainty are briefly reviewed below.

<u>Most probable scenario optimisation</u>

This method determines the optimal expansion plan based on the best available data for the uncertainties of the future system. Cost optimisation is performed based on one possible scenario known as the most probable scenario and the optimal investment plan is determined. The downside is the lack of consideration of other plausible scenarios. This is essentially the same as the deterministic method.

Non-flexible probabilistic optimisation

In this method, the aim is to determine an investment strategy which is on average an optimal strategy given any of the possible scenarios. This method is risk-neutral and does not allow for flexibility or future optionality. This is similar to deterministic optimisation, except that the entire scenario tree is considered in this case as opposed to the condensed deterministic equivalent. The formulation is changed slightly so that the solution reflects a representation of all alternative scenarios [107]. This method can be a natural next step in improving deterministic models.

Stochastic optimisation (with flexibility)

Stochastic optimisation offers a solution in the form of a strategy as opposed to deterministic investment decisions. Decisions are made based on the realisation of the uncertainties at every stage and the events at the parent stages. An increased number of variables as a result of the possibilities for flexible decisions cause computational complexities. However reduction methods such as decomposition techniques are usually utilised to reduce the size of the problem [107].

This method might be appropriate in enabling the CCS tool to allow for flexibility depending on the system stage changes. The decision criterion is still the expected system cost and a solution in the form of strategy would be more valuable, considering that the expansion of the CCS system very much depends on how the system state unfolds at every stage for example the changes in the energy system, other mitigation options, price of carbon, government incentives or technical and operational uncertainties around the CO_2 injection strategies etc.

Mini-max stochastic optimisation

The decision criterion here, unlike the above methods, is the maximum regret. It is the potential loss which would have been avoided given prior knowledge that a particular scenario would materialise [107]. The solution is an investment strategy which minimises the maximum loss as defined here, over all scenarios. This is more useful for cases where the uncertainties occur less frequently, hence in case an adverse scenario occurs; it is not so easy to offset that. The probability of occurrence is not considered; risk is minimised under all scenarios regardless of probability of occurrence. One of the advantages of this method is that it does not require the probability distribution for the uncertain parameters and an accurate prediction of the probability distribution considering its effects on the optimal solution is very important yet a challenge. Also if the uncertainties of interest in CCS planning are of low frequency, then a min-max regret scenario might be suitable as minimising investor's maximum loss could also encourage market development. However this method is not selected here because it results in extra costs to secure acceptable performance in case very unlikely scenarios materialise, and therefore reflects a very risk-averse perspective. Decision flexibility can also be added to the method, but it causes even more computational complexity.

Risk constrained stochastic optimisation

Risk constrained stochastic optimisation minimises whole system costs while ensuring that risks are constrained to lie within set bounds. Risk minimisation is managed through introducing a measure in the objective function in which case it becomes the primary objective to minimise risk. Risk can also be managed through placing a constraint on the variance from the expected cost. This method is more suitable for scenarios where certain safety measures have to be taken.

Therefore the two methods which are most applicable at this stage to multi-stage modelling of a future CCS network under uncertainty are non-flexible probabilistic optimisation followed by flexible stochastic optimisation. Non-flexible optimisation offers limited benefits for the reasons discussed above.

In general, decision making under uncertainty is also divided into two categories from the perspective of the objective; methods which optimise the expected NPV and risk minimising methods. In the presence of uncertainty, most strategic decisions have been based on maximising the expected return or NPV. However optimising the expected NPV is incomparable with lowering risk measures [111]. The expected NPV measures are more suited to problems where uncertainties are many and distributed in nature. Where the risks tend to be few, significant and discrete in nature, the modelling approaches extend the expected NPV to deal with risk [115]. Sections 5.1.1 will review the advances in both categories. Section 5.1.2 will conclude with the approach most suitable to modelling uncertainty in CCS planning.

5.1.1 Literature review

This section reviews the advances in both categories of decision making under uncertainty; methods which optimise the expected NPV and risk minimising methods.

5.1.1.1 Maximizing expected NPV

This section explores the application of first simulation and then mathematical programming methods found in the literature for modelling uncertainty in supply chain planning and optimisation with an aim to maximise the expected NPV.

Shah [115] describes supply chain simulation as a popular tool to formulate policy. Simulation is useful in identifying the potential dynamic performance of the supply chain as a function of different operating policies, ahead of actual implementation of the policy. Simulations in most cases are stochastic in that they repetitively sample from distributions of uncertain parameters to build distributions of performance measures.

Blau et al [116] used a repetitive, rolling horizon approach to draw conclusions regarding the benefits and drawbacks of the dynamic behaviour of consumer goods supply chains under different degrees of co-ordination between the supply and demand entities. Perea-Lopez et al [117] present the balance of inventories and orders in a polymer manufacturing and distribution supply chain using ordinary differential equations and using a de-centralised decision making framework they identify the policies that cause the least amount of perturbations. Later Pera-Lopez et al [118] developed an MILP- based scheduling model in a model predictive control framework which illustrates the benefits of central decisions making as opposed to de-centralised autonomous approach for each component of the supply chain.

A stochastic simulation approach that samples from the uncertain parameters is a useful way of determining expected future performance. Hung et al [119] developed a very efficient (Quasi Monte Carlo) sampling procedure and Shah [120] describes two pharmaceutical studies based on this, an area where stochastic simulation is shown to be very useful is in refining the design and structural decisions made by optimisation models. Here simulation evaluates the distribution of performance measures under changes in uncertain parameters. A simulation approach is also reported by Karabakal at al [121] who examined the VW distribution network in the USA and Gnoni et al [122] who studied the planning procedure for a multi-site automotive components facility.

Blau et al [116] modelled the pharmaceutical development activities as a probabilistic activity network where each activity has a probability of success. The risk of a set of decisions must be balanced against the potential rewards. This is used to compare different candidates. A heuristic approach using simulation with local rules is used. The rules are in response to trigger events (success or failure). Optimisation-simulation frameworks were later developed to overcome the barriers of simulation methods in making choices. A simulator, based on discrete-event dynamic systems (DEDS) techniques, which copes well with stochastic elements, uses optimisation to resolve conflicts as opposed to local rules. This is reported by Subramanian et al [123].

Wan et al [124] proposed a simulation-based optimisation framework for supply chain planning and analysis under customer demand uncertainty. Originally the framework determines safety stock levels for meeting a customer satisfaction level. The introduced strategy uses deterministic supply chain planning and scheduling in a rolling horizon mode. The simulation results are systematically accumulated to capture the relation between the key variables and the supply chain performance. The key variables are adjusted as an outer loop optimisation and a simulator implements the plans obtained via the optimisation model.

Mele et al [125] developed a discrete event-driven model where each supply chain entity is an agent and its activity is characterised by a set of parameters whose values can be optimised to achieve a better system performance. Genetic algorithms are incorporated to solve complex problems. They also addressed the problem of sequential decision-making under uncertainty using a multi-agent simulation approach at both strategic and tactical levels [126].

Simulation methods are mostly used to examine the detailed dynamic operation of a fixed configuration under operational uncertainty. On the other hand analytical methods optimise high level decisions such as network design [115]. Most recent work applied to process supply chains is based on stochastic programming formulations. The most popular of these involves two-stage mathematical models comprising two types of decision variables: here-and-now(design) variables of the first stage and wait-and-see (control) variables of the second stage; these decisions are determined before and after realisation of uncertain parameters, respectively. In terms of modelling uncertainty, the latter can be represented either by a discrete number of scenarios or by probability distributions [127]. Below is a literature review for mathematical approaches that deal with uncertainty.

Sahinidis and Grossmann [128] improved the efficiency of a process planning MILP model using tighter linear programming relaxation. Later they included multi-product demand scenarios. The resulting stochastic programming problems were formulated as large deterministic equivalent models and solved by decomposition and iteration. Iyer &Grossman [129] developed a number of scenarios for each time period thus resulting in a multi-period multi-scenario optimisation models. This method was computationally enhanced using bi-level decomposition.

Gupta and Maranas [130] consider the problem of mid-term supply chain planning under demand uncertainty. They used a two-stage stochastic approach where production decisions are here-and-now and distribution decisions are wait-and-see decisions. Maravelias and Grossmann [131] consider the problem of planning of pharmaceutical testing tasks and capacity with an aim to optimise the expected NPV. The testing network is probabilistic and production only takes place if the tests are passed. The stochastic problem with discrete uncertainties is represented by a scenario tree. The large MILP is solved by Lagrangian decomposition.

Tsiakis et al [56] developed an MILP model for the design of multi-product, multi-echelon supply chain network under demand uncertainty. They adopt a scenario planning approach for handling the uncertainty in product demands where each scenario represents a discrete future outcome. They explain that the overall aim should be to construct a set of scenarios representative of both optimistic and pessimistic situations within a risk analysis strategy. The binary variables relating to investment decisions remain the same, the operating variables relating to production and transportation flows will be dependent on the demand scenario which materialises. The relevant constraints must be enforced separately for each scenario too. The objective function is to minimise the expected value of the costs of the network over all scenarios. Tsiakis et al [56] utilise a multi-purpose production model with flexible production capacity between different products. This however was based on a given rigid fundamental structure and the design procedure focuses on the number of components in each fixed echelon and the connectivity. Later they extended this work by constructing a general framework which combines all parts of the supply chain however there is no prior assumption as to the network structure [132].

An interesting area for planning under discrete uncertainty is the problem of testing and capacity planning related to product tests and clinical trials which has been reviewed by Shah [120]; The problem of capacity planning under clinical trials uncertainty was captured by Rotstein et al [133]. They use a scenario tree to capture the outcomes of the trial and used a two-stage stochastic programming with recourse formulation to model the problem. The here-and-now and wait-and-see decisions related to immediate capacity expansion and expansions dependent on trial outcomes respectively. Gatica et al [134] presented an optimization based stochastic MILP model that captured the uncertainty of capacity planning for the pharmaceutical industry so as to select the optimal investment strategy for producing new drugs. Later Gatica et al [135] extend this work to include products at different stages in their life-cycle which leads to a multi-stage stochastic problem with more than two outcomes (success or failure) for the completion of the trial. This optimization-based approach selects the final product portfolio and the production planning and investment strategy simultaneously subject to the uncertainty of the outcomes of the clinical trials for each potential drug. As the trial's outcomes have different probabilities of occurrence and the information from the trials will become available at different times, the investment problem becomes a large-scale, multistage, multi-period stochastic optimization problem, which is then reformulated as a multi-scenario, mixed integer linear programming (MILP) model. The objective function is the sum of the weighted profits of all scenarios.

Ryu et al [136] aim to deal with the problems of uncertainty in data in supply chain planning using a parametric programming approach. Neiro and Pinto [137] account for the uncertainty in product prices in a refinery planning model through scenarios. They choose the decision variables to be here-and-now decisions to ensure a robust solution. A multi-period supply chain planning model under demand uncertainty is described by Gupta and Maranas [138] by adapting a real options framework. Levis and Papageorgiou [139] extend previous work of Papageorgiou et al [140] (2001) and propose a two-stage multi-scenario, multi-period model to account for uncertainty of the outcome of the clinical trials in determining the product portfolio and capacity planning.

Guillen et al [141] developed a multi-objective stochastic MILP model for the design and retrofit of supply chains. They utilised a multi-scenario approach to represent the supply chain. Tsang et al [142, 143] developed a stochastic multi-period, multi-stage and multi-scenario mixed integer optimisation model to support investment strategy subject to uncertainty of demands for multiple vaccines. A probabilistic analysis finds an approximate expression for the expected NPV for vaccine production with different scenarios. The outcome of the model exhibits the expected NPV distribution for the multi-scenario case against the probability of occurrence of the scenarios.

You and Grossman [144, 145] integrated stochastic inventory and supply chain design. This resulted in a large scale non-convex MILP which was solved using Lagrangian decomposition. Colvin and Maravelias [146] developed a multi-stage stochastic program for clinical trial planning in new drug development. The contribution of this model is the reduction of the non-anticipativity constraints essential for modelling indistinguishable scenarios. Al-Qahtani et al [147] also developed mathematical programming for modelling petrochemical networks under uncertainty in process yield, raw material costs and product prices. They also modelled risk in terms of variations in benefits. Puigjaner and Laı´nez [148] and Puigjaner et al [149] incorporated a stochastic supply chain decision-making model into a model predictive control (MPC) framework to integrate scheduling decisions into the design of the supply chain and react to supply chain dynamics and disturbances.

Kim et al [150] used a global sensitivity analysis to determine the uncertain factors affecting a biomass supply chain's NPV. The results were then used to construct a two stage stochastic supply chain design model. Gebreslassie et al [151] used a multi-objective stochastic programming approach to design hydrocarbon bio-refinery supply chains under uncertainty. They also studied risk measures such as CVar and downside risk and applied benders decomposition to handle the complexity of the problem.

Liu et al [152] developed an optimisation framework for a multi-echelon multi-period process supply chain under demand uncertainty considering price fluctuations. They developed an MILP considering the classic formulation of the travelling salesman problem (TSP). The objective function considers the profit and inventory deviations from the desired trajectories and price changes simultaneously. They used a model predictive control approach (MPC) to tackle the uncertain issues, as well as the inventory and price maintenance. In this case the initial demand is identified as the disturbance. In each time period, the initial demands in the current time period are realised, while all the future demands in the control horizon are unknown. Therefore initial demand forecasts are used in the future time periods. The relationship between product price at time t and its final demand i.e. forecast demand at time t, is then defined by the price elasticity of demand. Here the main idea of MPC also referred to as receding horizon control or moving horizon optimal control is to choose the control action by repeatedly solving online an optimal control problem, aiming to minimise a performance criterion, which consists of the deviation of the future controlled process from a reference trajectory over a future horizon.

Almansoori and Shah [153] developed a multi-period MILP model of a future hydrogen supply chain which incorporated uncertainty in hydrogen demand using a scenario based approach. They also evaluated the performance of the model using sensitivity and risk analysis. In the presence of the stochastic behaviour, they divide the decisions into here-and-now and wait-and-see categories. The former are associated with predicting the structure of the network. The latter incorporate operational or expansion decisions. They constructed a scenario tree where each scenario has a definite demand value and a probability of occurrence. Using this information the network for each of these scenarios is determined by the optimisation procedure. The formulation of the tree structure was accomplished through using a condition known as non-anticipativity introduced initially by Wets [154] which states that if a set of scenarios have the same available information up to time period t then the values of the variables corresponding to these scenarios are identical up to time period t. Therefore in the last time period, there is a different realization of variables for each scenario due to the unique set of information available to each scenario.

5.1.1.2 Minimising risk

In a paper on key strategies of pharmaceutical supply chains, Shah [120] describes that most strategic/infrastructural decisions in optimisation have historically been based on NPV or some for expected NPV which in turn utilise weighted average costs of capital or some required return on investment. NPV is better suited to situations where uncertainties are many, small and continuously distributed. Risk measurement approaches are better suited to situations where uncertainties are discrete i.e. bimodal, i.e. one leads to failure, one to success. For example in the pharmaceutical industry, future capacity planning has to be balanced with anticipated demands in the face of uncertainties in the outcome of clinical trials.

In CCS network planning, depending on the nature of the uncertainty of interest, extending the objective function i.e. the expected NPV to take into account relevant risk measurements such as limiting the variability of the expected NPV could be beneficial in transforming the CCS planning tool into a more robust decision making framework. For example in the face of uncertain price fluctuations, the variability of costs i.e. CCS costs vs. the cost of emissions could be the focus.

This section lists the approaches that extend the expected NPV metric to deal with risk.

Mean-Variance

Shah [120] introduces the mean-variance objective function (Equation 5.1) as used by Mulvey et al [155] as the most classical of approaches that consider risk. 'r' is the reward from the project and 'α' is the parameter to trade off the relative importance of the expected return and its variability.

$$\text{Max Z} = \alpha \text{ mean } (\text{r}) - (1-\alpha)\text{var}(\text{r}) \quad 5.1$$

Objective function penalty

Penalising parts of the objective function is an approach used by Ahmed and Sahinidis [156] where the objective is extended beyond the expected return and the downside-risk described as costs above the expected costs is penalised.

Downside risk

Shah [120] introduces three formulations that focus on downside risk;

Constraints can be used to allow a maximum probability for the reward being less than a particular figure. This is utilised by Kall and Wallace [157]. As shown in equation 5.2, 'r^0' is a minimum threshold return and 'β' is the maximum allowed probability that the actual reward 'r' is below 'r^0'. Shah [120] explains that discrete uncertainties can be imposed through the worst case scenario probability.

$$\text{Prob}\,\{(\text{r}) \leq \text{r}^0\}\beta \quad 5.2$$

A "risk factor" is developed by Eppen et al [158]. As shown by equation 5.3, the weighted risk factor is the probability of scenario 'k', 'Pr_k' multiplied by the loss (i.e. from a threshold return) summed over all scenarios 'k' where the return would be less than a threshold return. Shah [120] introduced this method as suitable for problems where there are many solutions, the higher the probability of occurrence which is associated with a return lower than threshold the higher the risk factor 'RF'. An upper bound can be imposed on 'RF' by tightening the constraint on downside risk. For example this method can be used in CCS planning to eliminate some solutions where 'r' is less than the threshold. If 'RF' is close to zero, then the risk associated with the investment decisions is almost zero.

$$\text{RF} = \sum_{k:r_k \leq r_0} \Pr_k (r_0 - r_k) \quad 5.3$$

A risk premium approach is introduced by Applequist et al [159]. An investment decision is approved if the expected return is higher than the return from a financial market's instrument with a similar variance. They tackle the problem of capital investment and production plans for uncertain product demands, continuously distributed. The problem here is determining the expected return of an investment 'μ' (Equation 5.4) and variance of the expected return 'σ^2' (Equation 5.5) which they solve using polytope volume integration. 'f(x)' is the probability density function.

$$\mu = \int x\, f(x).\, dx \tag{5.4}$$

$$\sigma 2 = \int (x - \mu^2)\, f(x) dx \tag{5.5}$$

Shah [120] discussed another measure, capital asset pricing (CAPM, Equation 5.6) utilised by Bhagwat and Griggs [160] who believed as well as a market measure such as risk premium, systematic risks should be considered. If 'R' is the riskless rate of return and '$E(r_m)$' is the expected market rate of return, '$E(r_m) - R$' is the risk premium. 'β_i' can be thought of as the systematic risk associated with the i^{th} asset. It is argued that the uncertainty in the CAPM lies in the fact that the expected rate of return is normally higher for higher risk.

$$k_i = R + \beta_i(E(r_m) - R) \tag{5.6}$$

Risk-constrained stochastic optimisation

In order to manage the financial risk associated with different capacity expansion options, Tsang et al [142] adapted some classical risk measures such as expected downside risk 'EDR' as discussed below. In this approach also known as risk constrained stochastic optimisation, the objective function still minimises the expected cost. However a risk measure is still applied simultaneously. This risk measure is either integrated within the objective function or applied through a constraint. Here the risk is defined as higher than expected costs. This two criterion approach is used by Gatica et al [135] for capacity planning under uncertainty as introduced by Eppen et al [158]. This approach gives a measure of the failure to meet a certain target profit. As shown by equation 5.7, this is the sum of the expected downside risk of all scenarios Δ_k weighted by the scenario probability Pb_k. A constraint is then added to tighten the risk factor. Guillen et al [141] apply these measures to design or retrofit of supply chains. Tsang et al [142] also balance risk and expected NPV to make optimal investment decisions for vaccine development planning under demand uncertainty.

$$RF = \sum Pb_k \ \Delta_k \quad 5.7$$

$$\Delta_k \geq z - \ eNPV_k \quad 5.8$$

$$\Delta_k \geq 0 \quad 5.9$$

$$RF \ \leq \ \Omega \, RF^* \quad 5.10$$

$0 \leq \Omega \leq 1$, RF* is obtained from an optimisation of the eNPV without any risk constraints.

Opportunity Value and Value-at-risk

Tsang et al [142] used Opportunity value (OV), value-at-risk (Var) and conditional value-at-risk (CVaR) to be used in their earlier scenario-based model to develop new models that manage financial risks. VaR or Value-at-risk is described as the difference between the mean value of NPV (i.e. the eNPV at a cumulative probability of 50%) and NPV corresponding to the p-quartile of the cumulative distribution. Normally VaR measures the deviation of the NPV from the expected NPV at 5% risk. Opportunity value or OV was proposed by Aseeri and Bagajewicz [161]. OV is at the other end of the cumulative property curve and is described as the value the portfolio might gain over the expected value if the uncertainties are better than expected. Tsang at al [142] describe VaR and EDR as selecting safe alternatives, whereas expected NPV and OV give bigger potential gains at higher risk levels.

Mini-max stochastic optimisation

In this technique the decision criterion is no longer the expected system cost. The decision criterion is in terms of the potential losses or the regret experienced. In other words it is the difference between the outcome of a solution and the outcome of a solution which would have been selected given prior knowledge that a particular scenario would materialise. The objective is to minimise the maximum loss over all scenarios. This method takes into account the risk-averseness of the decision maker. One potential downside is that the optimal solution which is the solution with the minimum maximum loss, results in extra costs to secure acceptable performance in case very unlikely adverse scenarios materialise. This method does not consider the probabilities associated with the scenarios. It ensures risk under all scenarios is minimised ignoring the likelihood of occurrence. This could be beneficial since in most stochastic cases it is difficult to determine a reliable probability distribution. This method can be extended to include the flexibility aspects of stochastic optimisation, however that causes computational complexities.

5.1.2 Approaches suitable to modelling uncertainty in CCS supply chains

As discussed above, simulation methods are more suitable for detailed analysis of operational uncertainty in a fixed configuration. Analytical methods are mostly used for problems of high level network optimisation under uncertainty. Most recent work applied to process supply chains is also based on stochastic programming formulations with flexibility. Decision making flexibility depending on system state changes at each stage and the preceding parent stages is a key feature required in stochastic CCS planning. Although non-flexible methods consider the entire scenario tree and the associated probabilities, the solution is still a sequential series of non-flexible decisions which are only on average optimal.

The problem of CCS optimisation under uncertainty can be modelled using two stage mathematical programming; the here-and-now decisions for the current deterministic stage and wait-and-see decisions for the future stochastic stages. The latter can then be represented by a scenario tree, which demonstrates the potential realisations of the uncertainty at every stochastic stage. Therefore the rest of this chapter will focus on constructing a stochastic MILP CCS model. The objective function aims to minimise the expected weighted NPV of all scenarios. As discussed risk measurement approaches are more suited to industries where development and capacity planning decisions are subject to almost bimodal risks such as product failures i.e. the risks are few and discrete in nature [120]. In the case of CCS infrastructure planning, risks such as fluctuations in the future price of carbon are closer to the "continuously distributed" category of uncertainties which is more suited to the approaches which maximise the expected NPV.

However, in case the uncertainty of interest in the planning of a future CCS network is less frequent, taking an average performance may not ensure solution credibility. In case an unfavourable scenario takes place, the consequences may not be offset so easily. Another criterion might need to be used to point out the potential losses by a selected solution. Therefore as part of future work, a risk measure can be added to the stochastic optimisation model. In that case based on the reviewed methods, given a known probability distribution for the future scenarios, risk constrained stochastic optimisation could be a suitable extension to the model. As discussed, this method will balance risk and expected NPV to make the optimal decisions. A multi-scenario minimum regret approach is also suitable if the aim is to determine the option value of discrete CCS investment decisions considering potential future market and energy pathways and hence encourage CCS market development.

5.2 Mathematical model

This section describes a stochastic mixed integer linear programming model of a multi-stage, multi-period CCS supply chain under parameter uncertainty.

5.2.1 Problem description

The multi-period model demonstrated the development of a cost optimal future CCS supply chain over a long-term planning horizon, assuming deterministic future parameters. This model assumed a pre-determined capture target for every time period. In reality, the amount of CO_2 mitigated via CCS will depend on the potential pathways for the evolution of price of carbon (amongst other policy measures). This stochastic behaviour could significantly affect the design and operation of the future CCS supply chain. Therefore the rest of this chapter explains a generic stochastic CCS planning model where certain parameters could be subject to uncertainty. The overall planning period involves multiple stages. This multi-stage model is built with the first stage relating to the near future with deterministic parameters and the subsequent stages relate to the uncertain future. The model is generic in terms of the scope and the geography of the supply chain, the properties of the sources, sinks and the transportation links, time periods, other scenario specific constraints, the uncertainties of interest and hence the shape of the scenario tree which describes the potential realisations of the uncertain parameters.

As explained in section 5.3, a scenario based approach using mathematical programming is used for capturing uncertainty in CCS supply chain design. Every scenario is a set of distinct realisations of the uncertain parameter throughout the planning horizon. Each scenario is also associated with a certain probability of occurrence. The mathematical model described in the following sections is solved using the commercial software GAMS.

5.2.2 Sets and indices

The following sections contain the sets, parameters and the variables defined in formulating the problem of multi-period CCS supply chain optimisation under uncertainty.

<u>Sets</u>

i , j	Grid cells
p	CO_2 phases (gas, dense) for transport via pipeline
l	Linearised segments of the pipeline cost curve
s	Decision stages , s=[1,...,S]
k	Scenario ,k=[1,...,K]

<u>Subsets</u>

KS_s	Set of scenarios of stage s
PK_{sk}	Parent scenario of scenario k of stage s
h	Set for the years in the planning horizon

5.2.3 Parameters

Parameters

n(s)	The year number of the first year of each stage s
m(s)	The year number of the last year of each stage s
x(i)	X coordinate of cell i
y(i)	Y coordinate of cell i
d(i,j)	Distance (km) between cells i and j
ftc(p,l,k,s)	Fixed cost (M$) of building pipeline of segment l at scenario k stage s to transport of CO_2 in phase p
vtc(p,l,k,s)	Operational cost (M$) of transporting a unit of CO_2 every year in phase p using pipeline of segment l for all years in stage s
a(i,k,s)	Annual CO_2 emission at node i at stage s, scenario k
fcc(i,k,s)	Fixed capital cost (M$) of retrofitting source i at scenario k with capture facility at the beginning of stage s
vcc(i,k,s)	Operational cost (M$) of capturing a unit of CO_2 every year at source i at scenario k for all years in stage s
b(i)	Maximum storage capacity at node i
fsc(i,k,s)	Fixed capital cost (M$) of building storage facility at sink i at scenario k at the beginning of stage s
vsc(i,k,s)	Operational cost (M$) of injecting a unit of CO_2 every year at sink i at scenario k for all years in stage s
usedcap(i,k,s)	Total amount of CO_2 stored at node i for scenario k, prior to stage s
Pr(k)	Probability of occurrence of scenario k of last stage
Pc(k,s)	Price of carbon relevant to scenario k of stage s
mp(s)	Mitigation target at stage s as a percentage of the total emission at stage s
length(s)	Number of years in stage s

5.2.4 Variables

Decisions regarding investments in capture or storage facilities or building pipelines are represented through binary variables. Decisions regarding the operation of the supply chain i.e. the optimal amounts of CO_2 captured, injected or transported are made through continuous variables. TCC(i,k,s), TSC(i,k,s), TTC(i,k,s), $\lambda_{k,s}$ and Λ_K have been listed below to show a breakdown of the components of variable Z, the objective function, later in this section.

Integer variables

C(i,k,s)	Annual amount of CO_2 captured at node i at scenario k, stage s
S(i,k,s)	Annual amount of CO_2 injected into node i at scenario k, stage s
Q(i,j,p,l,k,s)	Annual flow rate via pipeline l, in phase p, between i and j at scenario k, stage s

Carbon_units(k,s)	Annual number of carbon units purchased at stage s, scenario k
Z	Total CCS cost averaged over the planning horizon
nx(i,j,p,l,k,s)	Total number of pipelines of segment l built between i and j up to and during scenario k , stage s
TCC(k,s)	Total cost of capture at scenario k, stage s
TSC(k,s)	Total cost of storage at scenario k at stage s
TTC(k,s)	Total cost of transport at scenario k at stage s
Credit(k,s)	Total cost of carbon credits purchased at scenario k, stage s
λ(k,s)	Total cost of carbon credits and CCS in scenario k, stage s
Λ_k	Total cost accumulated over all stages for scenario K of the last stage S
usedcap(i,k,s)	Used capacity of storage site i at stage s, scenario k
Binary variables	
xcap(i,k,s)	1 if a capture facility is built at node i, stage s, scenario k, 0 otherwise
nxcap(i,k,s)	1 if a capture facility is built at node i, at or prior to stage s, scenario k, 0 otherwise
xstor(i,k,s)	1 if a storage facility is built at node i at stage s, scenario k, 0 otherwise
nxsotr(i,k,s)	1 if a storage facility is built at node i at or prior to stage s, scenario, 0 otherwise
xt(i,j,l,p,k,s)	1 if a pipeline of segment l, phase p is built between i and j at stage s, scenario k, 0 otherwise

5.2.5 Constraints

In this case study the stochastic stages correlate with the time periods, therefore the parameters and the variables are only denoted with index ‘s’. However if for instance one stochastic stage contains more than one time period, different indices can distinguish between the two. The objective function i.e. the minimization of the total weighted cost of the supply chain for all scenario paths over the planning horizon is subject to some design and operational constraints as listed below.

Mitigation target constraint

A certain percentage of the total emission must be eliminated at each stage for each scenario. The sum of carbon credit units purchased and the amount of carbon captured must be greater or equal to the reduction target.

$$\sum_{\mathrm{i}} \mathrm{C(i,k,s)} + \mathrm{carbon_{units(k,s)}} \geq \mathrm{mp(s)} * \sum_{\mathrm{i}} \mathrm{a(i,k,s)} \ \forall \, \mathrm{k,s} \qquad 5.11$$

Mass balance constraints

At each stage s, scenario k and node i, the CO_2 captured minus the amount injected equals the net CO_2 flow out of the node.

$$\sum_{j,p,l}\{Q(i,j,p,l,k,s)-Q(j,i,p,l,k,s)\}-C(i,k,s)+S(i,k,s)=0\ \ \forall\, i,k,s \qquad 5.12$$

Transport constraint

The annual flow rate from i to j must not exceed the maximum pipeline capacity given a pipeline is built in either direction.

$$Q(i,j,p,l,s,k)\le QMax(p,l)\ nx(i,j,p,l,k,s)+QMax(p,l)\ nx(i,j,p,l,k,s)\ \ \forall\, i,j,p,l,k,s \qquad 5.13$$

Capture facilities' constraint

The amount captured at node i is limited by the emission of node i and the capture efficiency, given a capture facility is built at node i.

$$C(i,k,s)\le \text{capture efficiency} * nxcap(i,k,s)\ a(i,k,s)\ \ \forall\, i,k,s,t \qquad 5.14$$

Storage facilities' constraints

Equation 5.15 calculates the total CO_2 stored at node i prior to stage s as the sum of the used capacity of node i at the beginning of the parent scenario (i.e. k' the parent scenario in stage s-1) and the amount stored at node i during stage s-1. Equation 5.16 states that the amount injected at node i yearly during stage s cannot be greater than (1/length of stage s) multiplied by the remaining capacity of stage s.

$$usedcap(i,k,s)=usedcap(i,k',s-1)+s(i,k',s-1)*length(s-1)\ \ \forall\, i,k\epsilon ks_s,k'\epsilon PK_{sk} \qquad 5.15$$

$$S(i,k,s)\le (1/length(s)*\{nxstor(i,k,s)\ b(i)-usedcap(i,k,s)\}\ \ \ \forall\, i,k\epsilon ks_s,k'\epsilon PK_{sk} \qquad 5.16$$

Time evolution constraints

Equations 5.17 and 5.18 refer to the number of capture and storage facilities built at node i and equation 5.19 refers to the pipelines built between nodes i and j in scenario k at stage s, respectively. These equations indicate that whether a facility exists at node i in scenario k at stage s depends on if a facility existed at the parent scenario k' in stage s-1 or is built during scenario k at stage s.

$$nxcap(i,k,s)=xcap(i,k,s)+\ nxcap(i,k',s-1)\ \ \ \forall\, i,k\epsilon KS_s,k'\epsilon PK_{ks} \qquad 5.17$$

$$nxstor(i,k,s)=xstor(i,k,s)+\ nxstor(i,k',s-1)\ \ \forall\, i,k\epsilon KS_s,k'\epsilon PK_{ks} \qquad 5.18$$

$$nx(i,j,k,s) = xt(i,j,k,s) + nx(i,j,k',s-1) \quad \forall\, i, k \epsilon KS_s, k' \epsilon PK_{ks} \qquad 5.19$$

Reverse flow constraint

Equation 5.20 states that the same pipelines can be used in the future for flow in the opposite direction.

$$xt(i,j,p,l,k,s) = xt(j,i,p,l,k,s) \;\; \forall\, i,j,p,l,s \qquad 5.20$$

Non-negativity constraints

Finally non-negativity constraints are set for all continuous variables.

$$C(i,k,s) \geq 0 \;\; \forall\, i,k,s \qquad 5.21$$

$$S(i,k,s) \geq 0 \;\; \forall\; i,k,s \qquad 5.22$$

$$Carbon_{unit(k,s)} \geq 0 \;\; \forall\; k,s \qquad 5.23$$

$$Q(i,j,p,l,k,s) \geq 0 \;\; \forall\; i,j,p,l,k,s \qquad 5.24$$

$$used\_cap(i,k,s) \geq 0 \;\; \forall\; i,k,s \qquad 5.25$$

5.2.6 Total cost of a scenario

At each stage s, the total cost of a scenario k, $\lambda_{k,s}$ is the sum of total capture, transport and storage costs and the cost of carbon credits relevant to scenario k, at stage s.

$$\lambda_{k,s} = TCC_{k,s} + TSC_{k,s} + TTC_{k,s} + credits_{k,s} \; \forall\, k,s \qquad 5.26$$

Carbon credit cost

As expressed by equation 5.27 or equation 5.28, the cost of carbon credits is calculated as the product of the unit price of carbon $cp_{k,s}$ in scenario k at stage s multiplied by the number of carbon units purchased which is equal to the remainder of the mitigation target or the part which has not been captured and stored. The capture target is the product of $mp_{k,s}$, the mitigation percentage of scenario k, stage s, and the sum of $a_{i,k,s}$ the total emission of all nodes in scenario k, stage s.

$$credits_{k,s} = cp_{k,s} * \{\left(mp_s * \sum_i a_{i,k,s} \right) - \sum_i C_{i,k,s} \;\; \forall k,s \qquad 5.27$$

$$credits_{k,s} = cp_{k,s} * carbon_{units_{k,s}} \;\; \forall\; k,s \qquad 5.28$$

Total capture cost

The fixed capital cost arameter $\mathrm{fcc(i,k,s)}$ is the total capital cost of retrofitting source i with capture facility at scenario k, stage s. As shown below $\mathrm{fcc(i,t)}$ is the sum of annuatised capital costs of retrofitting a source with capture facility, $\Delta\mathrm{CAPEX_{capture}}(\frac{\mathrm{M\$}}{\mathrm{Year}})$ from the first year of the time period of investment $\mathrm{n(s)}$ until the last year of the horizon $\mathrm{m(s\ final)}-1$, each discounted to present value and summed over for all nodes.

$$\mathrm{fcc(i,k,s)} = \sum_{\mathrm{n(s)\epsilon h}}^{\mathrm{m(s\ final)\epsilon h}\ -1} \frac{\Delta\mathrm{CAPEX_{capture}}}{(1+\mathrm{r})^{\mathrm{h}}} \tag{5.29}$$

The variable cost parameter $\mathrm{vcc(i,k,s)}$ is the operational cost of capturing a unit of CO_2 at capture facility i during the length of stage s. As shown below $\mathrm{vcc(i,k,s)}$ is the sum of annual operational costs $\Delta\mathrm{OPEX_{capture}}(\frac{\frac{\mathrm{M\$}}{\mathrm{Mt}}}{\mathrm{Year}})$ of capturing a unit of CO_2, over all the years in stage s scenario k, each discounted to present value.

$$\mathrm{vcc(i,k,s)} = \sum_{\mathrm{n(s)\epsilon h}}^{\mathrm{m(s)\epsilon h}\ -1} \frac{\Delta\mathrm{OPEX_{capture}}}{(1+\mathrm{r})^{\mathrm{h}}} \tag{5.30}$$

The capital cost of retrofitting source i at stage s of scenario k is determined by the product of the value of the decision variable $\mathrm{xcap(i,k,s)}$, whether to retrofit source i with a capture facility at scenario k, stage s and the fixed capture cost parameter $\mathrm{fcc(i,k,s)}$ explained above. The operational cost of source i during stage s scenario k is the product of $\mathrm{C(i,k,s)}$, the annual amount of CO_2 captured at source i during stage s, scenario k and $\mathrm{vcc(i,k,s)}$ the operational cost of capturing a unit of CO_2 every year for all the years in stage s as explained above. The total capture cost at scenario k, stage s is then the capital and operational costs of capture summed over all nodes.

$$\mathrm{TCC_{k,s}} = \sum\nolimits_{\mathrm{i}} \{\ \mathrm{vcc(i,k,s)\,.\,C(i,k,s)} + \ \mathrm{fcc(i,k,s)\,.\,xcap(i,k,s)}\ \}\ \forall \mathrm{k,s} \tag{5.31}$$

<u>Total storage cost</u>

The fixed and variable storage cost parameter $\mathrm{fsc(i,k,s)}$ and $\mathrm{vcc(i,k,s)}$ are defined similar to the capture cost parameters. The total storage cost in scenario k of stage s is defined similar to the total capture cost as expressed by equation 5.29.

$$\mathrm{TSC_{k,s}} = \sum\nolimits_{\mathrm{i}} \{\ \mathrm{vsc(i,k,s)\,.\,S(i,k,s)} + \ \mathrm{fsc(i,k,s)\,.\,xstor(i,k,s)}\ \}\ \forall \mathrm{k,s} \tag{5.32}$$

<u>Total transport cost</u>

Similar to section 3.6.5, the fixed and variable transport cost parameters $\mathrm{ftc}(p,l,k,s)$ and $\mathrm{vtc}(p,l,k,s)$ relevant to scenario k and stage s are defined as follows.

$$\mathrm{ftc}(p,l,k,s) = \sum_{n(t)\epsilon h}^{m(t\,\mathrm{final})\epsilon h\ -1} \frac{\Delta \mathrm{CAPEX}(p,l)}{(1+r)^h} \tag{5.33}$$

$$\mathrm{vtc}(p,l,t) = \sum_{n(t)\epsilon h}^{m(t)\epsilon h\ -1} \frac{\mathrm{slope}(p,l)}{(1+r)^h} \tag{5.34}$$

Similar to equation 5.29, the total transport cost is then defined per equation 5.31.

$$\mathrm{TTC}_{k,s} = \sum\nolimits_{i,j} \{\ \mathrm{vtc}(p,l,k,s)\,.\,Q(i,j,p,l,k,s) +\ \mathrm{ftc}(p,l,k,s)\,.\,xt(i,j,p,l,k,s)\ \}\,.\,d(i,j) \tag{5.35}$$

5.2.7 Objective function

The total cost Λ_k accumulated over all stages for scenario k of the last stage S is defined as the sum of the cost $\lambda_{k,S}$ of all the parent scenarios plus $\lambda_{K,S}$, the total cost of scenario k of the last stage S.

$$\Lambda_K = \lambda_{k,S} + \lambda_{k',S-1} + \lambda_{k'',S-2} + \lambda_{k''',S-3} + \cdots \qquad k\epsilon KS_S\,,\, k'\epsilon PK_{k,S}\,,\, k''\epsilon PK_{k',S-1}, k'''\epsilon PK_{k'',S-2} \tag{5.36}$$

Finally the objective function is simply expressed as the weighted sum of the total costs of all last stage scenarios K. This function gives an expectation of the overall costs for all scenarios. A certain weight is given to each scenario by multiplying its cost factor by the scenario probability.

$$Z = \sum_{k\epsilon KS_S} \Lambda_k * \Pr_k \tag{5.37}$$

5.3 Flexible CCS development planning in the UK under carbon price uncertainty

A case study is devised where the uncertainty of interest is the future carbon price trajectories. Optimal investment decisions regarding the future development of CCS must be in the form of a strategy which allows for flexibility as potential changes occur in the price of carbon emissions. Based on an analysis of decarbonisation policies in section 5.3.1, section 5.3.2 forecasts future carbon price trajectories which help form a scenario tree. This scenario tree is utilised in testing the stochastic model developed in section 5.2

for CCS development in the UK. The results are discussed in section 5.3.3 and a conclusion is drawn in section 5.3.4.

5.3.1 Future carbon price trajectories

This section reviews decarbonisation policy reforms in Europe and decarbonisation scenarios which assess the main policy options with respect to targets and measures.

5.3.1.1 Decarbonisation policy in Europe

The EU Emission Trading Scheme (EU ETS) was meant to be the forefront of de-carbonisation schemes in Europe, whose aim was to establish an efficient price for carbon emissions (Eur per tonne of CO_2). The EU ETS is a cap-and-trade scheme. Carbon emitters are to submit one emission allowance (EUA) for every CO_2 tonne they emit. A limited number of EUAs are allocated or auctioned each year, matching the emissions targets, and their price is intended to reflect the marginal cost of reducing European carbon emissions by one tonne until emissions targets are reached. The EU ETS was launched in 2005 and was divided into three Phases: Phase I from 2005 to 2007, Phase II between 2008 and 2012 and Phase III between 2013 throughout 2020. During Phase I and II, the cap on allowances were set through National Allocation Plans which cover more than 11,000 power stations and plants in the European Union which represent more than 45% of the total emissions. Therefore the EU ETS has a strong impact on the economical conditions in which it evolves. Phase III, which began on 1st January 2013, introduced two major reforms to the EU ETS scheme [110]:

- Reform of the allocation process: the former allocation process is removed in particular for the power generators, in favour of auctions.
- Reform of the cap mechanism: during Phase I and II, the total cap on emissions was distributed among countries. Since the beginning of Phase III, the cap is set at the EU-wide level (2.05 billion tonnes for year 2013; all sectors included) and reduced by 1.74% per year.

5.3.1.2 Carbon price collapse and recommended solutions

The recent economic crisis led to a reduction in economic activity, the proliferation of renewable energy solutions (RES), the usage of international carbon credits and partially to energy efficiency measures which led to a reduction in GHG emissions in the EU. An excessive amount of EUAs were distributed compared to real emissions, which led to a collapse in market prices and failed to deliver a robust signal. As a consequence, a political intervention became necessary to ensure that EU ETS incentivises decarbonising technologies.

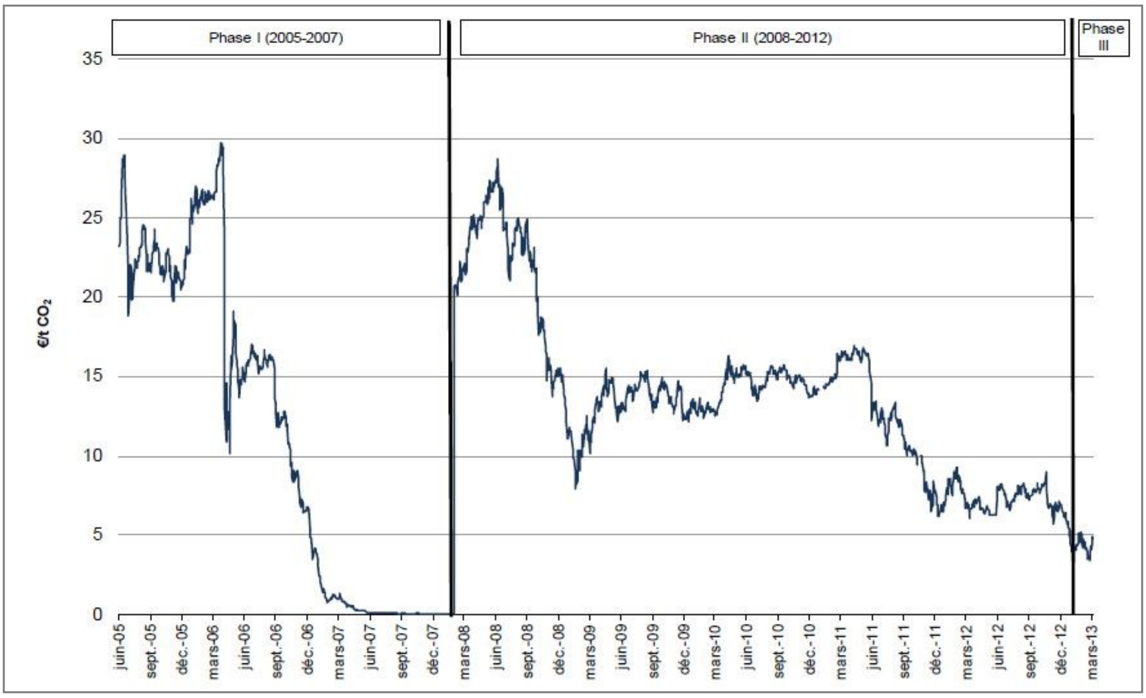


Figure 5.1 EUA spot prices between 2005 and 2013

On the other hand, in January 2014, the European Commission proposed a 40% GHG reduction target (compared to 1990) for 2030 with the ETS as the main tool to achieve this reduction. In order to bring about the required reduction in the ETS sector the following actions are taken [110]: The Commission forecasted that the structural surplus of EUAs will persist throughout the fourth phase of the ETS (2021 to 2027). To correct this situation the EU parliament voted on ‘Back-loading’ in December 2013. This is an amendment to the EU ETS Directive that would allow the EUC to perform a back-loading operation, which is a modification on the timing for auctioning EUAs in order to postpone (or “backload”) a portion of the 2013-2015 auction volumes towards the end of Phase III. However, the EU Parliament has restricted such action to a single back loading during Phase III for a maximum volume of 900 million EUAs.

The Proposed mechanisms for EU ETS reform post 2020 are listed below [110]:

The annual factor by which the cap on the maximum permitted emissions within the ETS decreases will have to be increased from 1.74% currently to 2.2% after 2020.

Also the Commission proposes to create a Market Stability Reserve (MSR) mechanism for the ETS starting form 2021. This would automatically adjust the availability of EUAs in the carbon market on an annual basis, thus controlling over and undersupply in the market and providing a higher but stable price as well as influencing the merit order for existing power sources.

5.3.1.3 Effect of policies on the price of carbon

This section reviews the Zephyr scenarios [109] produced by Climate Economic Chair and the European Commission scenarios [110] which consider the proposed mechanisms in section 5.3.1.2 to arrive at reasonable carbon price projections for periods up to 2050.

5.3.1.3.1 Zephyr scenarios – EU ETS reforms in the Climate Energy Package 2030

In a report published in January 2014, Climate Economic Chair [108, 109] analyzed the simulations from the Zephyr model to determine the combined effect of the actions discussed in section 5.3.1.2 i.e. back-loading, 2030 GHG targets and MSR on future price trajectories. The Zephyr model simulates the supply and demand for allowances on the market every year [109]. The Zephyr scenarios have exactly the same underlying assumptions in terms of GDP growth, RES and energy efficiency which affect the EUA demand. The scenarios however differ in the assumptions of how market participants are banking EUAs. Under the Zephyr 'High MSR' scenario participants' expectations lead them to reduce their emissions early and to keep a large quantity of allowances for a future use (high banking). Under the 'Low' scenario, participants do not consider it necessary to immediately reduce emissions or hold many allowances. So they quickly use the allowances they hold (low banking).Given the way that the MSR works the changes in allowance surplus trigger different reserve mechanism responses, which in turn result to different prices across the decade. In the high scenario price levels reach 50Eur/tCO_2 in 2021 and remain relatively high until 2030; in the low scenario prices rise to around 20Eur/tCO_2 by 2021 where they remain for the rest of the decade.

In summary, the recent measures will most likely result in a recovery of carbon prices. However, because there is significant surplus of EUAs, carbon prices will largely depend on the market expectations beyond 2020 as well as the banking behaviour of market participants. This creates significant uncertainty around the carbon price trajectory. However the analysis suggests that there are two likely base case scenarios. In the first scenario carbon prices range from 10 to 20Eur/tCO_2 during 2020s whereas in the second, they range from 35 to 45Eur/tCO_2. This conclusion together with the scenarios considered in the next section will help develop our scenario tree in section 5.3.2.

5.3.1.3.2 2030 decarbonisation scenarios – The European Commission's analysis

This section reviews the de-carbonisation scenarios analysed in a report by the European Commission [110]. They assess the impacts of each of the main scenarios representing the basis for policy options for decarbonisation targets and measures. The report focuses on the broad impacts of these options including economic impacts in the energy system which includes the ETS price projections. The scenarios considered and the reasons for selecting them are discussed below.

All potential scenarios without an explicit GHG reduction target for 2030 were discarded as there is a broad census between stakeholders that such a target is necessary. Apart from the reference scenario, all scenarios based on GHG reduction in the EU below 35% and above 45% were discarded. This is because many of the differential affects can be assessed by comparing different 40% reduction scenarios. Several scenarios with RES shares above 35% were discarded as they would result in GHG reductions of more than 45% in a 2030 perspective or would need significant nuclear energy incompatible with member state plans. No scenarios with pre-defined RES levels in specific sectors or pre-defined absolute energy savings objectives for 2030 were analysed as the target would have to be analysed once the approach for 2020 targets are clear. Scenarios considered combine GHG targets, RES targets and ambitious EE policies as this is a better reflection on potential future policies and their interaction. Table 5.1 is a summary of the selected scenarios for impact assessment.

Table 5-1 Reference scenarios to assess the main policy options with respect to targets and measures [110]

Scenarios selected for impact assessment	GHG reduction in 2030 wrt(1990)	RES 2030 (%final En.Cons.)	Energy savings in 2030 Evaluated against 2007 baseline projection for 2030
Reference Scenario	-32.4%	24.4%	-21%
GHG35/EE®	35%	No pre-set target (25.5%)	No pre-set target (-24.4%)
GHG37®	37%	No pre-set target (24.7%)	No pre-set target (-22.9%)
GHG40®	40%	No pre-set target (25.5%)	No pre-set target (-24.4%)

The ‘Roadmap’ referred to in the scenarios below, is an 80% reduction target below 1990 levels by 2050 which the EU should prepare for to be in line with the objective of limiting the global temperature increase to 2 degrees centigrade. A cost-effective pathway for that requires a 40% reduction by 2030. ‘®’ indicates that the scenario is set in Reference conditions i.e. it does not include ‘enabling conditions’ to achieve the Roadmap targets. ‘EE’ indicates the presence of explicit energy efficiency policies (at various levels of ambition) in the scenario, whereas the absence of ‘EE’ means that the scenario does not include such energy efficiency policies but are based on ‘carbon values’ providing a price signal driving GHG reductions which may also achieve higher levels of energy efficiency improvements or RES deployment than the Reference Scenario.

The EU Reference Scenario

The EU Reference scenario 2013 explores the consequences of current trends, including full implementation of policies adopted by late spring 2012. Key policies include the EU ETS Directive with the annual linear reduction factor of 1.74% continuing also post 2020. Also it is assumed The Renewable Energy Directive (Directive 2009/28/EC) [110] is implemented which achieves the legally binding national 2020 targets and the transport sub-targets, taking account of National Renewable Action Plans [110]. Also implementation of an energy saving directive is assumed leading overall to energy savings of -17% in 2020 compared to the relevant baseline.

GHG35/EE®

This scenario is set in reference conditions and it does not achieve GHG emission reductions in line with the Roadmaps in a 2050 perspective. This scenario presents a modest 35% in terms of GHG emission reduction. The ETS cap for stationary sources would stay as in the current legislation with the linear reduction factor of 1.74% of the average annual allocation during phase II. This is equivalent to an annual reduction of around 38 millions of allowances. Moderate explicit EE policies are the main driver. They are the same as the reference scenario until 2020 and continue at higher intensity after 2020. There is no pre-set RES target. An increased RES share of 25.5% as shown in table 5.1 is achieved through the ETS.

GHG37®

This scenario is set in reference conditions and does not achieve GHG emissions reductions in line with the Roadmap in a 2050 perspective. ETS prices are the same as in the Reference scenario. Carbon values in the non-ETS are raised to match ETS carbon prices in the Reference scenario. The projected result is a GHG reduction of 37% relative to 1990. There are no additional EE policies. There is no pre-set RES target. Increased RES share of 24.7% as shown in table 5.1 is due to the introduction of carbon values in the non-ETS sector.

GHG40®

This scenario is also set in reference conditions. This scenario is based on the assumption of equalisation of marginal abatement costs of GHG emissions across the economy. This is driven by increasing the price of carbon in the ETS and simulated carbon values as described by scenario GHG37. The increasing carbon price achieves 40% and 80% reduction targets in respectively 2030 and 2050 through fuel switching including RES penetration and improving energy efficiency. There are no additional EE policies compared to Reference and no pre-set RES targets.

Table 5.2 contains the price projection for 2030 and 2050 for the considered reference scenarios. Under the EU Reference Scenario 2013, the ETS price is expected to reach 35Eur/tCO_2 in 2030 and 100Eur/tCO_2 in 2050. Compared to the Reference scenario, explicit energy efficiency measures are introduced in scenario GHG35/EE®. In scenarios GHG37® and GHG40® simulated carbon values in the non-ETS and increasing carbon prices are introduced respectively. Scenarios with added energy efficiency measures such as scenario GHG35/EE® result in lower ETS prices compared to the policy scenarios driven by a GHG target. This shows the positive contribution of energy efficiency to emission reductions in the ETS sectors especially the power sector. However at the same time it reduces incentives of fuel switching or CCS in such industries. Introducing carbon values and increasing carbon prices in scenarios GHG37® and GHG40® are both reflected in the prices of table 5.2.

Table 5-2 Carbon prices for energy intensive industries under scenarios with reference settings [110]

Indicator		**Reference settings, concrete measures or carbon values 2030/2050**		
Scenario	Reference	GHG35®	GHG37®	GHG40®
ETS carbon price(Eur/tCO_2	35/100	27/99	35/100	53/152

5.3.2 Scenario tree development

Having discussed the Zephyr scenarios in section 5.3.1.3.1 and the European Commission scenarios in section 5.3.1.3.2, a scenario tree is developed in this section for stochastic multi-period modelling of the UK CCS supply chain under carbon price uncertainty. The price trajectories will be displayed over a current deterministic stage i.e. year 2014, and three stochastic stages 2020-2030, 2030-2040 and 2040-2050. At every stage, the model considers the potential realisations of the carbon price and outputs an optimal CCS network for each realisation. As shown in figure 5.2, the current carbon price is set to 12Eur/tCO_2. The analysis of section 5.3.1.3.1 of the effects of MSR, back loading and GHG targets on the price of carbon suggested two likely base case scenarios as discussed; in the first scenario carbon prices range from 10 to 20Eur/tCO_2 during 2020s whereas in the second, they range from 35 to 45Eur/tCO_2. Therefore, also assuming that the price projections for 2020 should probably be between the current price and the 2030 projections, the prices of 20 and 40Eur/tCO_2 have been assumed for the second phase which begins in year 2020. The 2030-2040 period considers the prices 27Eur/tCO_2 and 53Eur/tCO_2 of scenarios GHG35® and GHG40® of table 5.2 as lower and upper bounds. For the last phase the 2050 price projections of scenarios of table 5.2; 100Eur/tCO_2 and 152Eur/tCO_2 have been selected. The 2050 price of scenario GHG35® has been discarded since it is very close to those of scenarios GHG37® and the Reference.

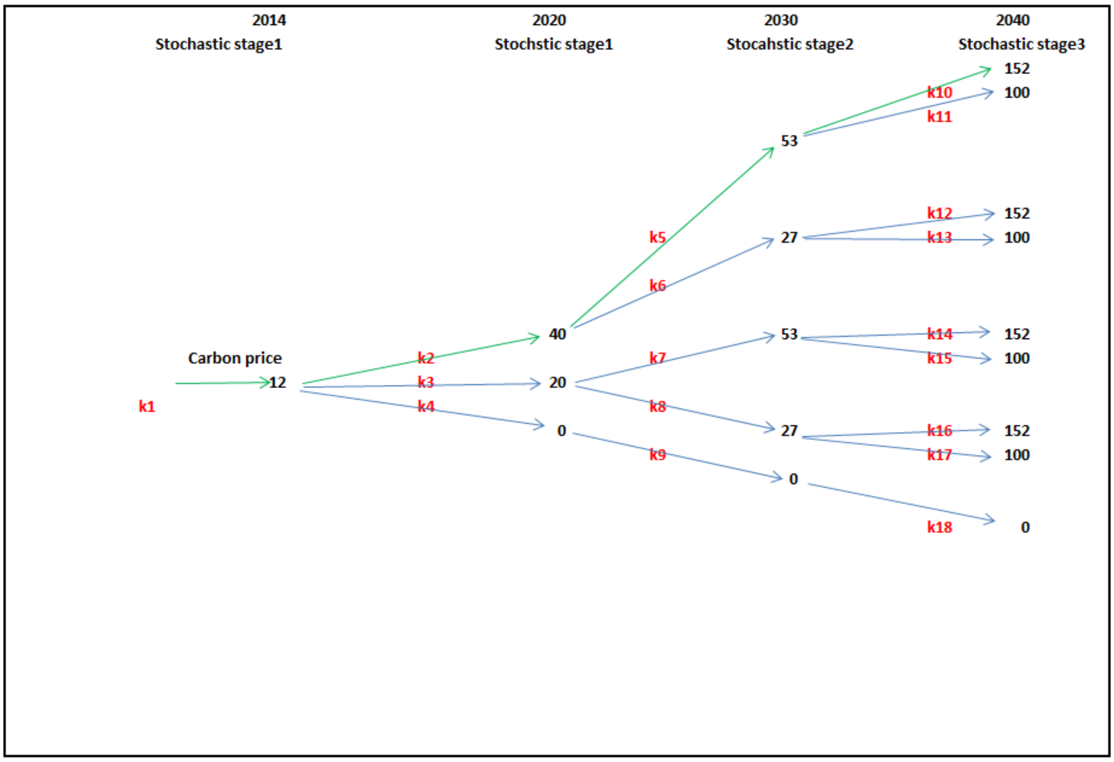


Figure 5.2 Carbon price scenario tree (2014 2050)– Stochastic modelling of CCS supply chains in the UK under carbon price uncertainty

The scenario tree of figure 5.2 encompasses nine distinct scenarios over the planning horizon. Although much attention has been given to creating a realistic scenario, the main purpose of scenario development here is to verify that the generic stochastic CCS optimisation developed earlier in this chapter performs correctly. Therefore the complexity of the scenario tree can be reduced without compromising on our aim to represent a wide range of price fluctuations. The tree of figure 5.2 has been simplified to that in figure 5.3.

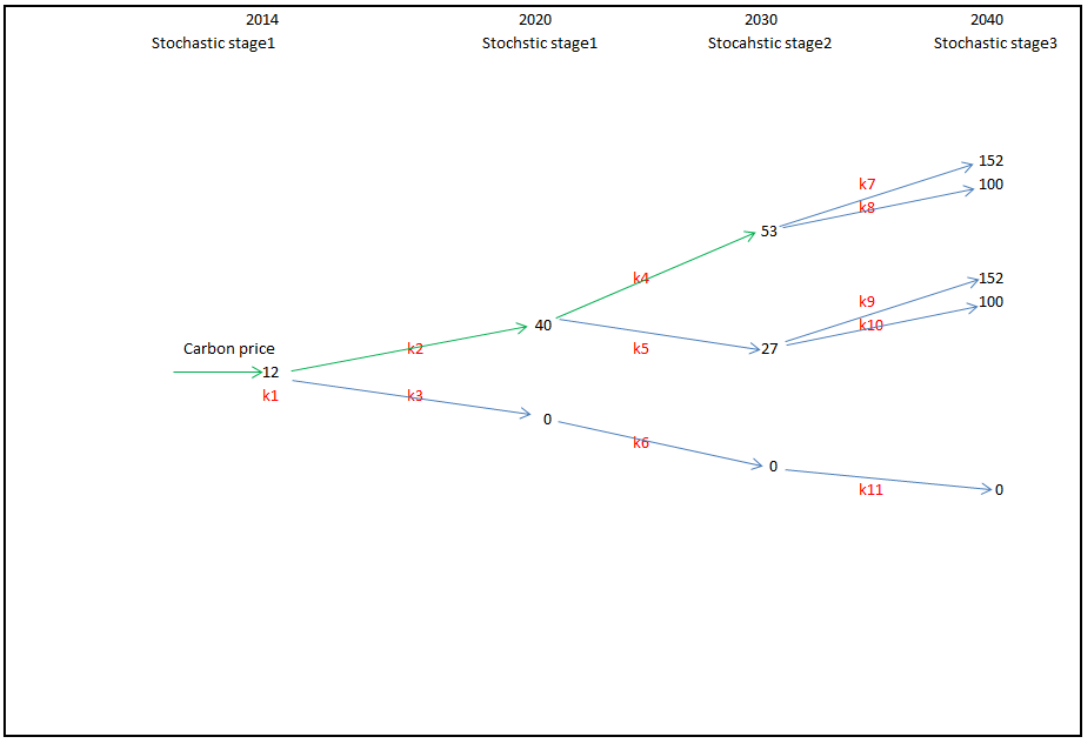


Figure 5.3 Simplified carbon price scenario tree (2014-2050) – Stochastic modelling of CCS supply chains in the UK under carbon price uncertainty

The multi-stage stochastic optimisation problem considers all potential variations of the price of carbon presented in figure 5.3 and is solved using a mixed integer linear programming approach using the commercial software GAMS. The geographical scope of the scenario, the sources, sinks and transport options and the relevant parameters remain the same as the multi-period scenario of chapter 3. The multi-stage stochastic model decides how much of the mitigation target is achieved through purchasing carbon credits and via carbon capture and storage at each stage for each scenario. If CCS is an option, the investment and operational decisions remain the same as the multi-period deterministic model of chapter 3; the investment decisions at each time period include building capture and storage facilities and transportation links. The operational decisions are the amount of CO_2 captured, stored at each facility and transported via each link.

5.3.3 Results and discussion

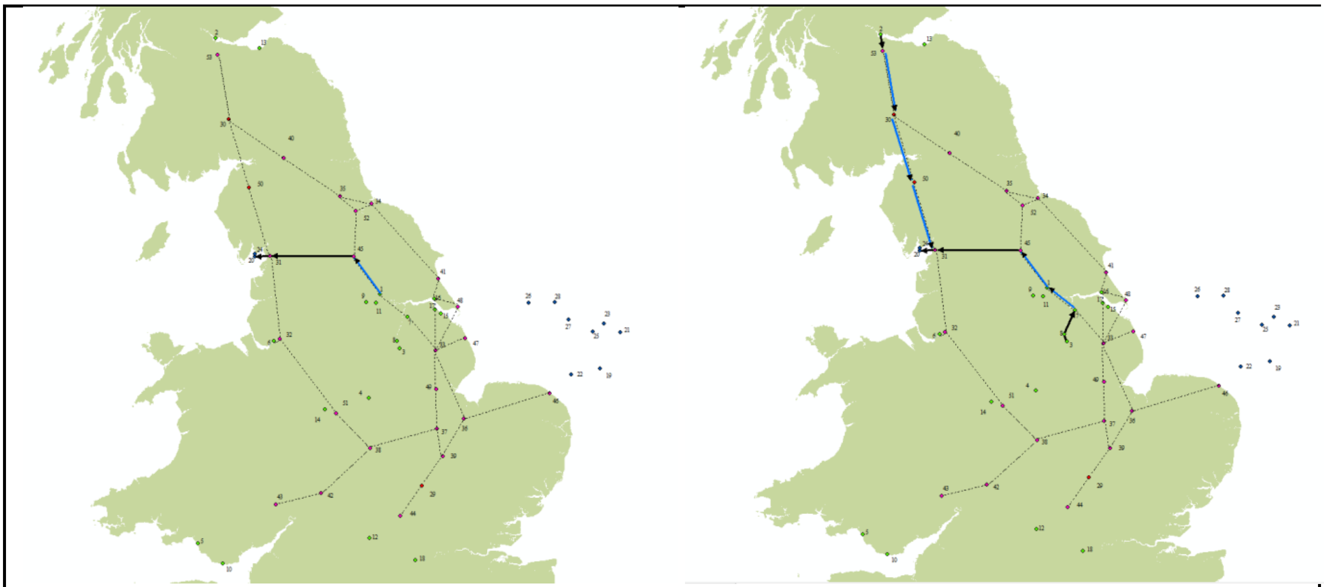
The results are discussed for each potential carbon price path shown in figure 5.3. For example, scenarios K1, K2, K4 and K7 of figure 5.3 demonstrate one potential path for the evolution of carbon price and the CCS network development. Therefore according to figure 5.3, this case study investigates five potential future pathways for CCS development in the UK. These pathways are referred to as scenarios K7 to K11 in sections 5.3.3.1 to 5.3.3.5 respectively.

Tables J-1 to J-3 of appendix J respectively contain the amounts of CO_2 captured, stored and transported between nodes for each scenario. Table J-4 contains the annual reduction target for each stage of the case study. It also contains the amount of CO_2 captured and the amount of carbon credits purchased for each scenario at each stage. Table J-5 demonstrates the evolution of the price of carbon for each scenario and the associated CCS contribution in achieving the mitigation target. Table J6 contains the cost of CCS vs. the cost of carbon credits for each scenario throughout the planning horizon.

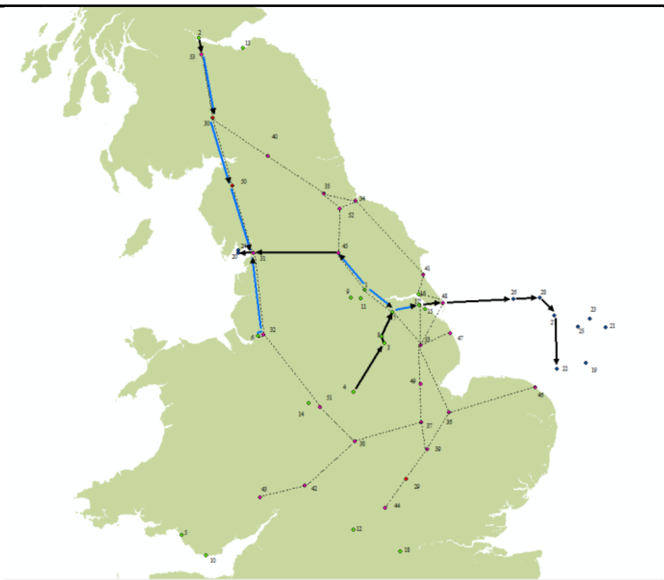
During the deterministic stage, stage s1 scenario k1, due to the low carbon price of 12Eur/tCO_2, carbon credits are purchased for the entire reduction target of 23.5Mt per year. As described in the following sections, CCS first enters the mitigation portfolio at stage s2. The results for all potential paths K7 to K11 as shown in the scenario tree of figure 5.3 are described below.

5.3.3.1 Scenario K7

Figure 5.4 demonstrates the development of CCS for scenario path K7, from stage s2 to stage s4.



(a) Stage s2, scenario k2, carbon price 40Eur/tCO_2 (b) Stage s3, scenario k4, carbon price 53Eur/tCO_2



(c) Stage s4, scenario k7, carbon price 152Eur/tCO_2

Figure 5.4 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K7

Figure 5.4(a) shows that at stage s2, as the price of carbon increases to 40Eur/tCO_2, the entire CO_2 emissions from Drax which make up 78% of the reduction target at this stage is captured and transported across to the East Irish Sea and stored in Morecambe South. Figure 5.4(b) shows the CCS network layout at stage s3, if scenario K4 materialises. At 53Eur/tCO_2, Cottam and West Burton power stations in Nottinghamshire are now connected to Scunthorpe Iron and Steel. The CO_2 captured from these power stations is then taken to Drax where 22Mt CO_2 is also captured and transported to Morecambe South for storage. Almost 9Mt CO_2 per year is now captured from Longannet power station on the Firth of Forth and transported to Morecambe South. This pipeline follows the existing gas lines.

During the last stage, if the price of carbon increases to 150Eur/tCO_2, the network will expand to include Ratcliffe power station in Nottinghamshire and all of the CO_2 captured from the Nottinghamshire and North Lincolnshire power stations will be transported to Hewett L Bunter via Easington Terminal and via the Southern North Sea sinks, West Sole, Barque and Galleon. Almost half of the CO_2 captured from Drax is also transported to Easington via Immingham CHP on the South bank of the Humber and stored in Hewett L Bunter. In this scenario almost 34Mt of CO_2 is stored in Hewett L Bunter every year. In the North West, CO_2 is now captured from Fiddlers Ferry and taken to Morecambe South as well as Morecambe North where more than 14Mt CO_2 is stored annually.

5.3.3.2 Scenario K8

Figure 5.5 demonstrates the development of an optimal CCS network for scenario path K8.

(a) Stage s2, scenario k2, carbon price 40Eur/tCO_2

(b) Stage s3, scenario k4, carbon price 53Eur/tCO_2

(c) Stage s4, scenario k8, carbon price 100Eur/tCO_2

Figure 5.5 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K8

The CCS network shown in scenarios K2 and K4 of figure 5.5(a) and 5.5(b) is discussed in section 5.3.3.1. Figure 5.5(c) shows the CCS network if scenario k8 i.e. carbon price of 100Eur/tCO_2 materialises at stage s4. Here although the price of carbon is lower than that of scenario k7, 100% of the target is still achieved through CCS. However the optimal pipeline routes in scenario k8 are slightly different from scenario k7 shown in figure 5.4(c). These differences result in a difference of 0.8% in the total cost of CCS between scenarios k7 and k8. The difference in the optimal paths for the two scenarios is because in order to speed up the model's computational time, the optimality gap has been increased from 1% to 2%. In scenario k8, the CO_2 captured from Nottinghamshire and a portion of Drax's emissions are transported to Hewett L Bunter via the dummy nodes in South East England.

5.3.3.3 Scenario K9

Figure 5.6 demonstrates the development of the optimal CCS network for scenario K9.

(a) Stage s2, scenario k2, carbon price 40Eur/tCO_2

(b) Stage s3, scenario k5, carbon price 27Eur/tCO_2

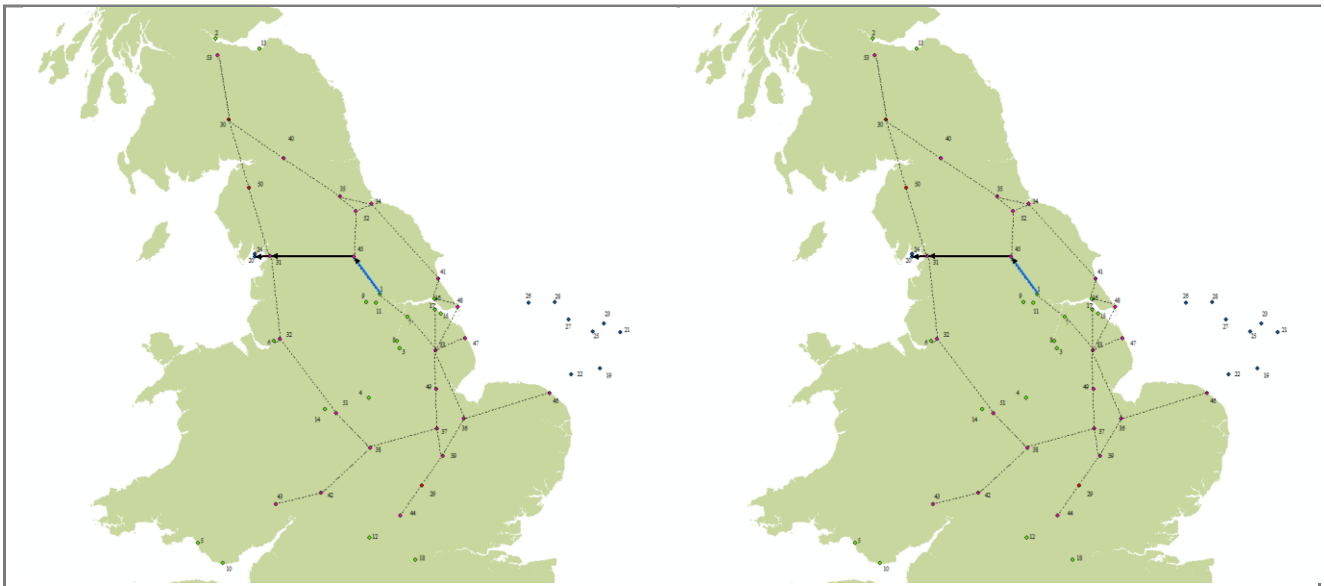
(c) Stage s4, scenario k9, carbon price 152Eur/tCO_2

Figure 5.6 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K9

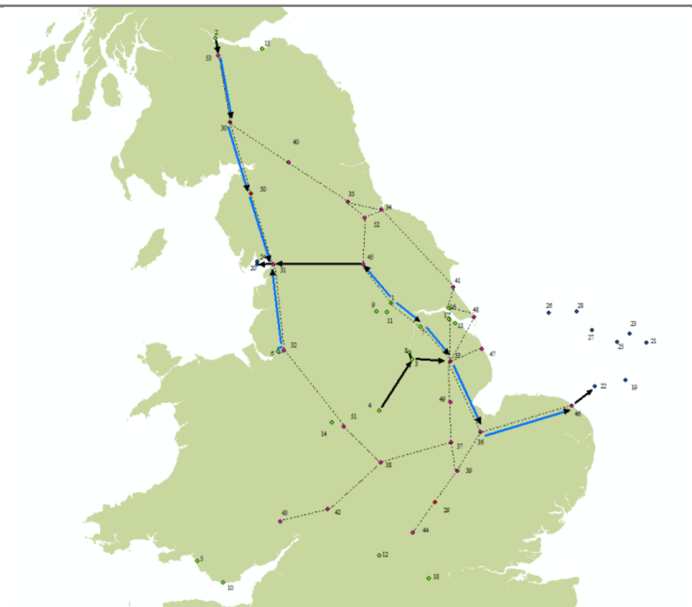
Scenario k2 of stage s2 is discussed in section 5.3.3.1. Figure 5.5(b) shows the CCS network for scenario k5 of stage 3. In scenario 5, the carbon price drops to 27Eur/tCO_2. No further CCS investments are made in this stage. The role of CCS drops from 78% in stage s2 to 53% of the reduction target in stage s3. The cost of CCS drops and the expenditure on carbon credits increases to 58% of the total annual costs of this scenario. However with the price of carbon increasing to 152Eur/tCO_2 in scenario k9, at stage s4, the system exhibits a very similar behaviour to scenarios k7 and k8. The CCS infrastructure development reaches the levels of scenarios k7 and k8 to cope with achieving 100% of the reduction target via CCS.

5.3.3.4 Scenario K10

Figures 5.7 demonstrates the development of CCS for Scenario path K10.



(a) Stage s2, scenario k2, carbon price 40Eur/tCO_2 (b) Stage s3, scenario k5, carbon price 27Eur/tCO_2



(c) Stage s4, scenario k10, carbon price 100Eur/tCO_2

Figure 5.7 Evolution of CCS network in the UK, stage (2020-2050) under carbon price path K10

The CCS characteristics for scenarios k2 and k5 were discussed in section 5.3.3.3. Figure 5.7(c) shows the optimal CCS network for scenario k10, stage s4. Scenario k10 has the same characteristics as scenario k9 discussed in section 5.3.3.3. Despite the lower carbon price of 100Eur/tCO_2, the model still recognises CCS as a cheaper option for achieving 100% of the reduction targets.

5.3.3.5 Scenario K11

In this scenario, the price of carbon falls to zero at stage s2, scenario k3. The price then remains at zero for the rest of the planning horizon. Therefore CCS never enters the mitigation portfolio.

5.3.4 CCS development in the UK under carbon price uncertainty

In this section too “scenario paths K7 to K11” refer to the potential price paths that end with scenario k7 to k11 of the last stage, respectively.

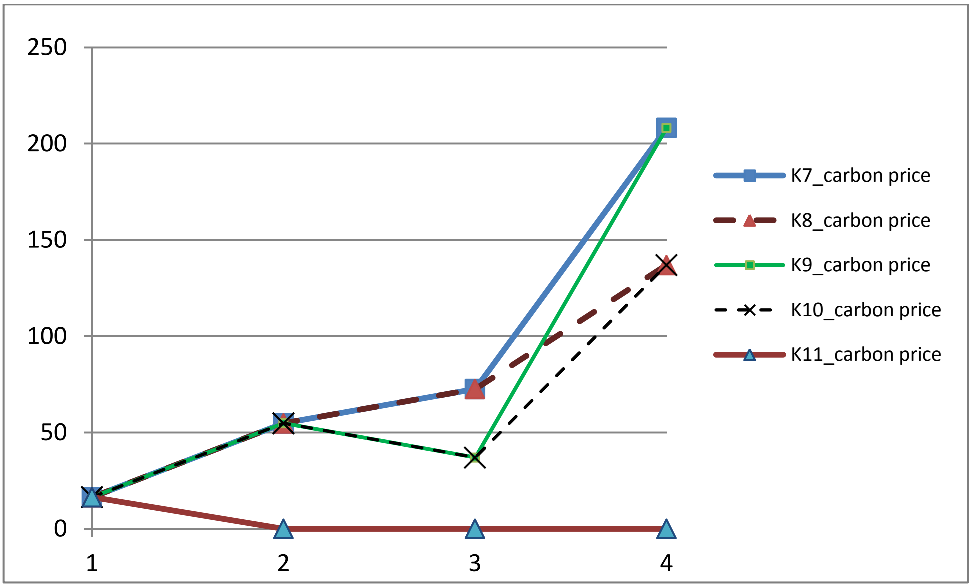


Figure 5.8 Evolution of price of carbon ($/tonne) throughout the four stages – Scenarios K7 to K11

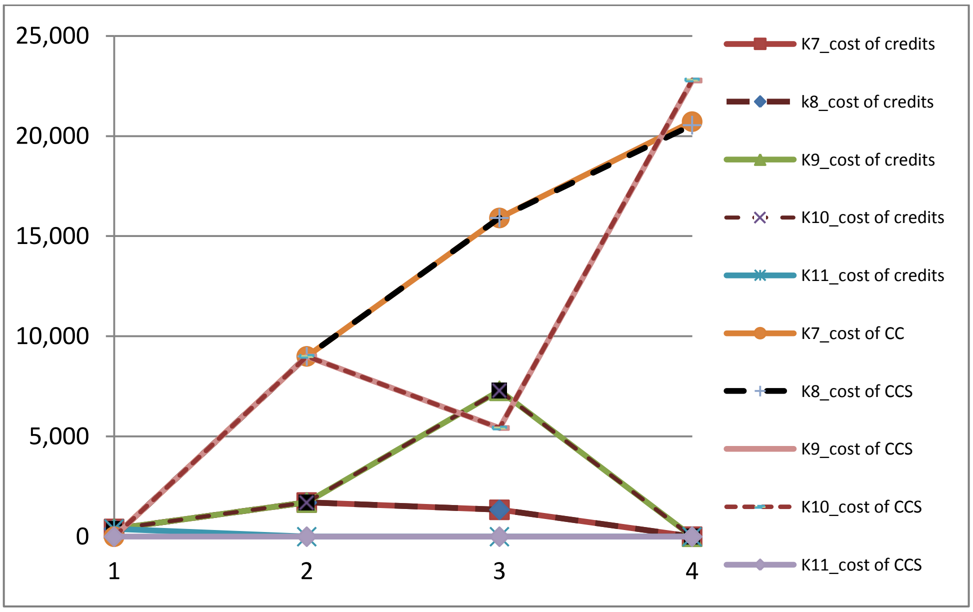


Figure 5.9 Total cost of carbon credits vs. Cost of CCs throughout the four stages – Scenarios K7 to K11

Figure 5.9 shows the cost of credits vs. the cost of CCS at each stage throughout the planning horizon for all possible scenario paths. In all scenarios at stage s1, at 12 Eur/tCO_2, the reduction target is achieved by purchasing carbon credits only. The graphs show for paths K7 and K8, the costs of credit and the CCS costs follow similar paths. In fact scenarios k7 and k8 only differ in the price of carbon at stage s4, however both prices prove to be too high compared to the cost of CCS. There is less than 1% difference in the cost of CCS for scenarios k7 and k8 at stage s4 and that is due to increasing the optimality gap to 2% in the GAMS model in order to speed up the model. Tables J-5 and J-6 in appendix J contain the figures for the evolution of carbon price and the role of CCS vs. Carbon credits and the corresponding costs.

For both scenarios, as the price of carbon increases to 42Eur/tCO_2 at stage s2, 78% of the reduction target is achieved via CCS. Later the price of carbon gradually increases to 53Eur/tCO_2 at stage s3 and 100Eur/tCO_2 and 150Eur/tCO_2 at stage s4 for scenarios k7 and k8 respectively. The model in both stages chooses to invest in an expanding CCS infrastructure and uses CCS to reduce the emissions by 96% at stage s3 and 100% at stage s4. In fact as shown in figure 5.9 ,the actual amount spent on purchasing carbon credits remains at the bottom of the chart; always below 1,700M$ throughout the stages reaching 0 at stage s4 for both scenarios.

Figure 5.8 shows that for the pair of scenario paths K9 and K10 the price of carbon drops at stage s3. This causes no further investment in CCS infrastructure at stage s3 in paths K9 and 10, compared to scenario paths K7 and K8 where the price continually increases. The cost of purchasing carbon credits increases to above 7,000 M$ and the CCS cost for this stage drops by almost 3,500 M$. However, again at stage s4, the price of carbon reaches the levels of scenarios k7 and k8. Although due to the lower price of carbon, the CCS infrastructure development had stopped at stage s3, at stage s4 the CCS infrastructure is as vast as that of scenarios k7 and k8 and 100% of the target is achieved by carbon capture and storage. Although CCS development stops in stage 3 in scenarios 9 and 10, the CCS infrastructure catches up by building all the additional facilities and pipelines in stage s4. This results in a slightly higher cost of capture for scenarios k9 and k10 at stage s4. However, the annual payments are only made for the remaining 10 years of the planning horizon.

In scenario paths K7 and K8, extra storage capacity is required due to a higher amount of injection at stage s3. Therefore storage site Morecambe North is also given injection facilities which results in extra storage costs in scenarios K7 and K8 compared to K9 and K10. On the other hand the pipeline infrastructure connecting Scunthorpe Iron to Drax and also the lines connecting West Burton and Cottam power stations as well as the pipelines connecting Longannet in Scotland to the network at Bathgate were constructed at stage s3 in paths K7 and K8. In paths K9 and K10 these investments are made later in the planning horizon. Scenario 11 exhibits the case where the price of carbon drops to 0 at stage s2 and remains there at s3 and 4. Hence all of the emission is offset against carbon credits.

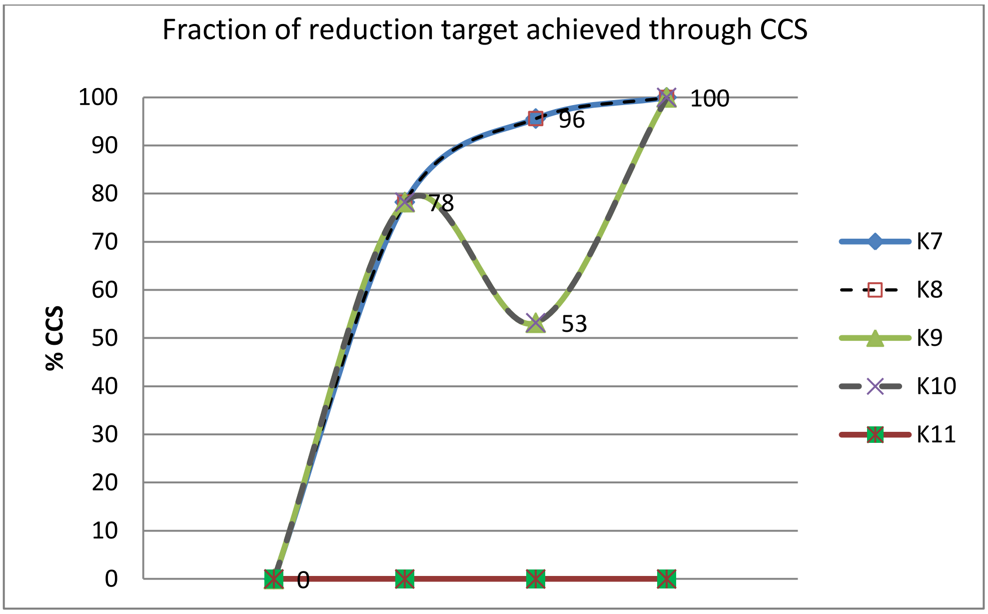


Figure 5.10 Role of CCS in reaching the mitigation target throughout the four stages– Scenarios K7 to K11

Finally figure 5.10 is in fact a summary of the optimal strategies faced with the carbon price changes considered in the scenario tree of figure 5.3. Figure 5.10 shows that at a price of 12Eur/tCO_2, CCS is not part of the portfolio for all scenarios. At stage s2, at 40 Eur/tCO_2, all paths K7 to K10 make the same CCS investment decisions. At stage 3, scenarios K9 and K10 reduce the use of CCS to 53% due to a drop on the price of carbon to 27 Eur/tCO_2 whereas scenarios K7 and K8 at a price of 53Eur/tCO_2 decide on further investments in a vast CCS infrastructure which is responsible for mitigating 96% of the target. At stage 4, neither of the two carbon prices; 100 Eur/tCO_2 and 152 Eur/tCO_2 offer a cheaper solution than carbon capture. Hence for all scenarios the CCS infrastructure is developed enough to handle 100% of the mitigation target which is 52% of the annual emissions of 59Mt per year for the given scenarios. As expected, in Scenario 11 which shows the price of carbon falling to zero after stage 1, no CCS facilities are developed at any time.

Table J-4 in appendix J includes the reduction targets (Mt/year) as well as the fraction of the target achieved via CCS or credits for each of the scenarios corresponding to the scenario tree of figure5.3.

Table J6 of the appendix contains the total CCS cost versus the total cost of purchasing carbon credits at every stage for each scenario. Table 5.3 shows the average cost of CCS components over the planning horizon, per unit of mitigated CO_2 for each scenario. Table 5.4 contains the CCS costs per unit of CO_2 at each stage for each scenario.

Table 5-3 Average costs of the CCS components (Total cost over the planning horizon divided by the total mitigated CO_2)

Scenario	**CCS cost over the planning horizon (stages 2-4) ($/tonneCO2)**			
	Total	Capture	Storage	Transport

K7	37.55	28.55	6.79	2.26
K8	37.40	28.55	6.79	2.17
K9	35.88	27.45	6.53	2.25
K10	35.90	27.45	6.53	2.19

Table 5-4 Cost per unit of mitigated CO_2 during stage s for each scenario

Cost at stage S (\$/tonneCO$_2$)				
Scenario		Stage 2 (2020-2030)	Stage 3 (2030-2040)	Stage 4 (2040-2050)
K7	Capture	50.01	33.25	26.69
	Storage	24.08	4.07	6.65
	Transport	6.32	2.27	1.90
K8	Capture	50.01	33.25	26.69
	Storage	24.08	4.07	6.65
	Transport	6.32	2.27	1.73
K9	Capture	50.01	19.80	31.28
	Storage	24.08	4.07	5.38
	Transport	6.32	0.362	2.63
K10	Capture	50.01	19.80	31.28
	Storage	24.08	4.07	5.38
	Transport	6.32	0.362	2.52

Table 5-5 Summary of computational results

Model statistics	
Single equations	1,528,000
Single variables	1,131,329
Discrete variables	380,116
Resource usage (s)	1,253 –1,922
Average resource usage(s)	1,495

Chapter 6 Conclusions and recommendations for future work

As discussed in Chapter 1, CCS as a 'transitional technology' has the potential to make an important contribution to mitigation. With fossil fuels currently meeting over 80% of global energy demand and as much as 85GW of additional capacity expected in Europe alone, CCS is vital for meeting the European Union's greenhouse gas reduction targets. Concrete steps have been taken across a number of jurisdictions for the commercialization of CCS technology. However, there are significant uncertainties regarding the deployment of CCS chain as a whole. These uncertainties relate to improving the technologies and government incentives, environmental impacts as well as gaps in currently available knowledge regarding some aspects of CCS [17]. Ongoing R&D is essential for addressing such gaps to facilitate decision making and drive down costs [14]. Although CO_2 technologies remain capital intensive, they are commercially available and the majority are applicable across sectors and can be competitive with other low-carbon options. However, the state of development of the overall CCS system may be less than some of its separate components. The main barrier to accelerating the deployment of CCS is in optimal integration of CO_2 capture, transport and storage into a fully integrated CCS system. Such systems must serve as the foundations of wide-scale CCS deployment in the face of considerable uncertainties. CCS planning must be done considering the anticipated changes in the longer term and preferably allow flexibility at every stage of expansion according to the future path of mitigation policies. In other words, large-scale and cost effective CCS deployment requires that all three components of the supply chain (capture, transport and storage) are co-ordinated both spatially and across time. In other words, this becomes a dynamic or multi-stage whole system supply chain optimisation problem.

large-scale deployment of CCS necessitates dynamic optimisation of the integrated system across both time and space. The earlier models were only steady state snapshot model or only demonstrated the evolution of the transport infrastructure. The few spatially explicit temporal CCS supply chain model were unable to simultaneousely make decisions for the three components of the chain.

6.1 Thesis objectives

The overall aim of this thesis was to develop a CCS decision making tool for policy making stake holders in the context of real options analysis of evolving CCS networks. The aim is to facilitate quantitative assessment of investment strategies under dynamic conditions, identify CCS development pathways considering opportunities and risks and the environment that CCS develops. Hence the first objective of this thesis was developing a multi-period whole system optimisation model of carbon dioxide capture, storage and transportation. The model must provide investment and operational strategies for all three components of the chain at every stage of the development of the system and simultaneously satisfy design, financial and operational constraint and pre-defined mitigation targets. A key attribute of the model must be the ability to integrate with component level models. Finaly the aim was to construct a stochastic optimisation tool that allows for flexibility depending on how the future uncertainties materialise at different stages. The aim was to be able to evaluate the relative effect of uncertain parameters on CCS development and to analyse the utilisation of assets accordingly.

6.2 Achievements

This section describes the achievements of this thesis, followed by a description of its contributions.

- **Multi-period whole system optimisation model of an integrated CCS supply chain**

Chapter 3 of this thesis presented a whole system cost minimisation associated with the future development and operation of a generic integrated CCS supply chain infrastructure. The MILP tool developed in GAMS overcomes many limitations of previous research in this field by incorporating both whole system and multi-period optimisation to arrive at an overall minimum cost supply chain. The model's unique ability to optimise an integrated CCS supply chain under increasing mitigation targets or dynamic constraints is invaluable for the assessment of the large scale commercial deployment of CO_2 supply chains which are also bound to expand with the increasing implementation of CCS and the expected changes in the policies around CCS. A fundamental attribute of the multi-period whole system CCS supply chain optimisation model is its adaptability to user defined technical and market constraints and its flexibility in accommodating any CCS supply chain scenario. The case study presented investigated the evolution of a UK CCS system over four time periods up to the year 2050 under increasing capture targets providing the means to test and validate the multi-period model. The results confirmed in order to minimise costs the model delays all investments until required, while current decisions are made anticipating the necessary future expansions. This non-intuitive outcome shows the advantages of such a tool as part of CCS commercialisation planning.

- **Real options analysis of complex CCS networks for the Crown Estate**

In chapter 4 it was shown that the multi-period model is a tool to assess the feasibility of alternative operation strategies or project finances, which minimise risk or highlight necessary market conditions to avoid loss. The model is used for a project on real options analysis of complex CO_2 transport and storage networks for the Crown Estate. The model's versatility allows integration with existing detailed cost models for the components of the supply chain to improve the supply chain model's solution. In addition, the optimal high-level solution is utilised to carry out cash flow analysis of the supply chain components. The CCS model was used together with a CO_2 storage life cycle cost model developed at Imperial College to form a life cycle cost modelling tool for CO_2 transport and geological storage. The integrated model can capture the geological characteristics, engineering aspects and the economics of complex CCS chains and investigate the optimal pathway for the configuration and operation of CO_2 transport and storage networks considering the market conditions in which they develop. Through cash flow analysis of alternative leasing conditions under potential user-defined real option conditions, the outcome can be used to manage the storage sites' leasing options, highlight individual storage site's performance and provide insights into factors that encourage investment and market development.

Through a single chain and a complex multi-storage scenario, it is shown that the model is a tool that enables the assessment of real alternative strategies that ensure target rates of return or manage investor's risk under specific market conditions. From the point of view of TCE, the real options project aims to increase TCE's revenue while de-risking the sector if storage sites were offered in a competitive way. The analysis of storage site's leasing alternatives, together with the stochastic model of chapter 5 build the foundations of the current real options project for TCE, the main purpose of which is to identify opportunities and risks involved in the management of the transport and storage network which maximise value for TCE and incorporate flexibility in expansion or downsizing of projects considering irreversible capital investments.

- **Multi-stage stochastic optimisation of an integrated CCS supply chain**

Beyond these strengths over earlier methods, the deterministic model's lack of consideration of uncertainty in parameters that directly affect the CCS development undermines the viability of the solution. Therefore, in chapter 5 the model was improved to become a stochastic multi-stage whole system optimisation mode of CCS supply chains under uncertainty. A tool is built for the first time that contrary to discrete sequential investment decisions for a solution, provides CCS strategies according to the realisations of the uncertain parameters. A scenario based approach using Mixed Integer Linear Programming is used for capturing uncertainty in CCS supply chain design and operation. The scenario tree describes the potential evolution paths for the future uncertainties as defined by the user. Every scenario associated with a certain probability is a set of distinct realisations of the uncertain parameters throughout the planning horizon. Through decision flexibility it is shown how the wait and see approach enables the implementation of an optimal strategy depending on system state changes at each stage and the preceding stages, hence reducing the risk of potential losses.

A scenario tree was developed for the future carbon price trajectories considering the combined effect of 2030 GHG targets and the amendments to the EU ETS directive such as back loading and market stability reserve mechanisms. The stochastic model was verified through a case study that examines the potential pathways for CCS development in the UK under such uncertainties. The results showed that anticipating the 2040 prices of 100EUR or 152Eur, CCS becomes favourable throughout and the actual amount spent on purchasing carbon credits remains low. In scenarios where the price drops in 2030, investment is still accelerated by building the additional facilities in 2040 and neither of the two 2040 carbon prices; 100 Eur/tCO_2 and 152 Eur/tCO_2 offer a cheaper solution than CCS.

Although the case studies of chapters 3 and 5 consider 10 year time periods, the progression of the UK CCS network can be demonstrated for shorter time periods. For example in the case studies of chapter 4, the lengths of the time periods are arranged to match the availability of additional storage sites. In chapter 3, the time periods can be made shorter e.g. 5 year periods with the mitigation target increasing in a manner that the total mitigated CO_2 by the end of the horizon remains the same. In that case, the increase in mitigation target happens more often but at a lower rate each time. Although the mitigated amounts at points equivalent to the ends of previous time periods remain the same, the need to support higher targets can be delayed until the second halves of the previous time periods. Considering the way the annual costs of investments are accumulated in the bjective function this could decrease the total capital cost of the CCS network. The effect of shorter time periods on the results of the case study presented in chapter 5, would also depend on the carbon price forecast for each segment of time.

6.3 Summary of novel contributions

In summary the major contribution of this thesis is the development for the first time of a generic spatially explicit multi-period whole system optimisation model of CO_2 capture, transport and storage supply chains within both deterministic and stochastic frameworks. The model can be used to design an overall optimum CCS system and model its long term evolution subject to realistic constraints and uncertainties. The model and its different variations are validated through a number of case studies analysing the evolution of the CCS system in the UK. These case studies confirm that significant cost savings can be achieved through whole system optimisation and multi-period planning approach. In addition, the stochastic formulation of the model allows the analysis of the impact of a number of uncertainties on the evolution of the CSS system and incorporates flexibility at every stage of development. The model presented in this thesis can be used for system planning purposes as well as for policy analysis and commercial appraisal of individual elements of the CCS network. The model is currently used for a real options analysis project for the Crown Estate. This project focuses on quantitative assessment of the value of assets under uncertainties. The aim is to identify opportunities or risks (i.e. storage site leasing or rental frameworks), approaches to reduce risk, rank options based on selected criteria that may change over time and determine the value of options to maximise value for TCE, reduce investor's risk and encourage market development.

6.4 Recommendations for future work

This section contains further work which is currently in progress and some recommenations for future work.

6.4.1 Stochastic analysis of TCE options for management of CO_2 transport and storage networks in the UK

The stochastic model is currently used as part of the real options analysis work for the Crown Estate. Once the risks and opportunities in CCS network development is recognised, by setting out representative scenarios possibilities for optimisation are explored through flexibility considering the path dependency of potential events that materialise in the future. The market uncertainties of interest within this stochastic analysis of potential CCS development paths in the UK will include price of CO_2, impacts and benefits derived from support mechanisms such as fiscal incentives and loans or carbon emission allowances, access to finance for CCS-EOR. Hence the outcome can be used to evaluate the relative importance of such market uncertainties, early investments or technical differences between sites and their effect on the value of investment. This enables TCE to incorporate real options analysis in decision making. For example, considering options such as expansions, downsizing or abandoning projects the real options analysis framework will allow operators to flexibly manage irreversible investment capital.

The key questions that the stochastic model of this thesis is expected to answer from the point of view of TCE include; to identify risk reduction approaches, if leasing and rental frameworks pose a significant risk to CCS infrastructure, to provide quantitative methods to decide on the value of TCE assets considering technical and market uncertainties, to identify opportunities that may be exploited and address the risks in order to maximise the value of TCE assets. Sections 6.4.1.1 and 6.4.1.2 describe two pieces of work which are currently in progress for TCE.

6.4.1.1 Storage site portfolio management strategies under injection and market unertainties

To showcase the capabilities of the stochastic model and verify its functionality to TCE, a test scenario is constructed and presented to TCE where the stochastic model is used for quantitative assessment of the choice between the storage sites for two types of uncertainties; storage site's injection strategies and the evolution of market conditions. This work investigates CCS development strategies for a network that connects Scottish emitters to a portfolio of EOR and storage sites in the Central North Sea over the next forty years. At every stage, each potential realisation is associated with a distinct price of carbon, constraints around injection rate and capacity and the corresponding capital and operational cost or EOR revenues based on the CO_2 price and the price of oil. The sites also become available at different times. For each potential pathway, the model provides an optimum portfolio of storage sites, injection strategies, pipeline routes, the EOR revenue and the strategy around purchasing carbon credits.

6.4.1.2 Robust interim investment strategies under appraisal uncertainties and EOR optionality

Under uncertainties around the appraisal of storage sites and EOR availability, for a portfolio of 7 storage sites in the Central North Sea, the multi-stage stochastic model is being used to identify optimal here-and-now strategies or future strategies which are common between the optimum solution for different paths. This is to identify actions which if taken result in no lossess regardless of the outcome of storage site appraisals or the availability of EOR for particular sites and hence accelerate CCS deployment.

Work is currently in progress to add some features to the model so that as part of the optimisation process the model decides the optimal way for the appraisal of storage site in order to minimise the overall costs. Constraints must also be satisfied so that appraisal starts and finishes before the construction of storage facilities can begin at a potential site. As for EOR sites, EOR activity must start before the injection only option can become available, however EOR capacity does not have to be exhausted.

6.4.2 Minimum regret strategies for storage site portfolio development in the UK

As part of the future work for the Crown Estate, mini-max stochastic optimisation or a minimum regret framework will be adapted. In this framework the solution will be an investment strategy which minimises the potential losses or regret. In other words the gap between a strategy and the strategy given prior knowledge that a scenario would occur. Despite the higher costs, this method does not require the probabilities of occurrence of the scenarios and the minimum maximum loss solution could be used to encourage CCS development by ensuring investors of acceptable performance even in case the worst case scenarios materialise. Once the interim min-max regret strategy is determined, the post resolution date strategies are re-optimised to move them closer to the perfect strategy.

References

1. IPCC. *5th Assessment report Working Group l, Climate Change 2013: The Physical Sciences Basis*. 2013; Available from: http://www.ipcc.ch/report/ar5/wg1/.
2. IPCC. *4th Assessment report Working Group III, Climate Change 2007, Mitigation of Climate Change, Summary for Plicymakers,2007b. http://www.ipcc.ch/publications_and_data/ar4/wg3/en/contents.html*.
3. IEA. *International Energy Agency, Energy Technology Perspectives 2012*. 2012; Available from: http://www.iea.org/etp/.
4. IPCC. *4th Assessment report, Working Group II, Climate Change 2007, Impact, Adaptations and vulnerability, Chapter 1: Assessment of observed changes and responses in natural managed systems, Executive summary*. 2007a; Available from: http://www.ipcc.ch/publications_and_data/ar4/wg2/en/ch1s1-es.html.
5. IEA. *International Energy agency Technology Roadmap, Carbon capture and Storage: 2013 Edition. http://www.iea.org/publications/freepublications/publication/technologyroadmapcarboncaptureandstorage.pdf*.
6. IPCC. *4th Assessment report, Working Group III, Climate Change 2007, Mitigation of Climate Change, Chapter 4: Energy Supply*. 2007c; Available from: http://www.ipcc.ch/publications_and_data/ar4/wg3/en/ch4.html.
7. IPCC. *A Special Report of Working Group III of the Intergovernmental Panel on Climate Chang, Carbon Dioxide Capture and Storage, Summary for Policymakers*. 2005; Available from: http://www.ipcc-wg3.de/special-reports/special-report-on-carbon-dioxide-capture-and-storage.
8. DECC. *UK Greenhouse Gas Emissions – 3rd Quarter 2013 Provisional Figures , Department of Energy and Climate Change*. 2013a; Available from: https://www.gov.uk/government/publications/quarterly-uk-emissions-estimates.
9. Global-CCS-Institute. *Global CCS Institure, Large Scale CCS Projects*. 2014; Available from: http://www.globalccsinstitute.com/projects/large-scale-ccs-projects.
10. IEA, *World energy outlook 2006. International Energy Agency, OECD Publication Service, OECD, Paris.* <*www.iea.org*> *accessed 02/07/07.* 2006b.
11. IEA, *Global energy technology perspectives, International Energy Agency, OECD, Paris.* <*www.iea.org*> *accessed 02/07/07.* 2006a.
12. DECC. *Gov.UK. Department of energy and Climate Change, Policies, Increasing the use of low carbon technologies*. 2012a; Available from: https://www.gov.uk/government/policies/increasing-the-use-of-low-carbon-technologies/supporting-pages/carbon-capture-and-storage-ccs.
13. ZEP. *Zero Emission Platform, CO2 Capture and Storage: Recommendations for transitional measures to drive deployment in Europe*. 2013a; Available from: http://www.zeroemissionsplatform.eu/library.html.
14. ZEP. *Zero Emission Platform, Recommendations for research to support CCS deployment in Europe beyond 2020, Update on CO2 Capture. 2013b. Available from: http://www.zeroemissionsplatform.eu/library/publication/236-zepcapturereport.html*.
15. ZEP. *Zero Energy Platform, Biomass with CO2 Capture and Storage (Bio-CCS) – The way forward for Europe*. 2013d; Available from: http://www.zeroemissionsplatform.eu/extranet-library/publication/206-biomass-with-co2-capture-and-storage-bio-ccs-the-way-forward-for-europe.html.
16. Koornneef, J., van Breevoort, Pieter., Hamelinck, Carlo., Hendriks, Chris., Hoogwijk, Monique., Koop, Klaas., Koper, Michèle., Dixon, Tim., Camps, Ameena., *Global potential for biomass and carbon dioxide capture, transport and storage up to 2050.* International Journal of Greenhouse Gas Control, 2012. **11**(0): p. 117-132.
17. ZEP. *Zero Emission Platform, ZEP Taskforce Policy & Regulation provides advice on policies and the regulative framework for incentivising deployment of CCS. 2013e. Available from: http://www.zeroemissionsplatform.eu/library.html*
18. ZEP. *Zero Emissions Platform, Resetting the ways to a decarbonised Europe*. 2013c; Available from: http://www.zeroemissionsplatform.eu/library/publication/229-decarbonisedeu.htm.
19. DECC. *Gov.UK. Department of energy and Climate Change, Case Studies developed relevant to CCS as part of the policy: reduction of carbon emissions by 80% by 2050*. 2012b; Available from: https://www.gov.uk/government/case-studies/carbon-capture-project-case-studies.
20. WhiteRoseCCS. *White Rose carbon capture and storage project*. 2014; Available from: http://www.whiteroseccs.co.uk/.

21. SHELL. *Peterhead CCS Project , SHELL UK* 2014; Available from: http://www.shell.co.uk/gbr/environment-society/environment-tpkg/peterhead-ccs-project.html.
22. Korre, A., Elahi, Nasim., Nie, Zhenggang., Durucan, Sevket., Shah, Nilay., Ahmad , Shabana., Goldthorpe, Ward. *The effects of market and leasing conditions on the techno-economic performance of complex CO2 transport and storage value chains*. in *12th Greenhouse Gas Control Technologies (GHGT12)*. 2014. Austin, TX, United States.
23. Lipponen, J., Burnard, Keith., Beck, Brendan., Gale, John., Pegler, Bob., *The IEA CCS Technology Roadmap: One Year On.* Energy Procedia, 2011. **4**(0): p. 5752-5761.
24. DECC. *Department of Energy and Climate Change, CCS Roadmap, Supporting deployment of Carbon Capture and Storage in the UK*. 2013b; Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48317/4899-the-ccs-roadmap.pdf.
25. Svensson, R., Odenberger, M., Johnsson, F., Strömberg, L., *Transportation systems for CO2– application to carbon capture and storage.* Energy conversion and management 2004; 42:2343-53, 2004.
26. Zhang, Z.X., Wang, G. X., Massarotto, P., Rudolph, V., *Optimization of pipeline transport for CO2 sequestration.* Energy Conversion and Management, 2006. **47**(6): p. 702-715.
27. McCoy, S.T., Rubin, Edward S., *An engineering-economic model of pipeline transport of CO2 with application to carbon capture and storage.* International Journal of Greenhouse Gas Control, 2008. **2**(2): p. 219-229.
28. Bode, S., Jung, M., *Carbon dioxide capture and storage-liability for non-permanence under the UNFCCC.* Int. Environ. Agreem. Politics Law Econ. 6, 173–186., 2006.
29. Solomon, S., Carpenter, Michael., Flach, Todd Allyn., *Intermediate storage of carbon dioxide in geological formations: A technical perspective.* International Journal of Greenhouse Gas Control, 2008. **2**(4): p. 502-510.
30. Kaggerud, K.H., Bolland, Olav., Gundersen, Truls., *Chemical and process integration: Synergies in co-production of power and chemicals from natural gas with CO2 capture.* Applied Thermal Engineering, 2006. **26**(13): p. 1345-1352.
31. Damen, K., Faaij, André., Turkenburg, Wim, *Health, Safety and Environmental Risks of Underground Co2 Storage – Overview of Mechanisms and Current Knowledge.* Climatic Change, 2006. **74**(1-3): p. 289-318.
32. Gibbins, J., Chalmers, Hannah., *Carbon capture and storage.* Energy Policy, 2008. **36**(12): p. 4317-4322.
33. Zanganeh, K.E., Shafeen, Ahmed., Salvador, Carlos., *CO2 Capture and Development of an Advanced Pilot-Scale Cryogenic Separation and Compression Unit.* Energy Procedia, 2009. **1**(1): p. 247-252.
34. Olajire, A.A., *CO2 capture and separation technologies for end-of-pipe applications – A review.* Energy, 2010. **35**(6): p. 2610-2628.
35. Pires, J.C.M., Martins, F. G., Alvim-Ferraz, M. C. M., Simões, M., *Recent developments on carbon capture and storage: An overview.* Chemical Engineering Research and Design, 2011. **89**(9): p. 1446-1460.
36. ZEP. *The costs of CO2 capture, post-demonstration CCS in the EU*. 2013f; Available from: www.zeroemissionsplatform.eu/library/publication/166-zep-costreportcapture.html.
37. Kather, A., Scheffknecht, G., *The oxycoal process with cryogenic oxygen supply.* Naturwissenschaften 96, 993–1010., 2009.
38. Blomen, E., Hendriks, Chris., Neele, Filip., *Capture technologies: Improvements and promising developments.* Energy Procedia, 2009. **1**(1): p. 1505-1512.
39. Burdyny, T., Struchtrup, Henning., *Hybrid membrane/cryogenic separation of oxygen from air for use in the oxy-fuel process.* Energy, 2010. **35**(5): p. 1884-1897.
40. Zhu, Y., Legg, Sean., Laird, Carl D., *Optimal design of cryogenic air separation columns under uncertainty.* Computers & Chemical Engineering, 2010. **34**(9): p. 1377-1384.
41. Haugen, H.A., Eldrup, Nils., Bernstone, Christian., Liljemark, Stefan., Pettersson, Helena., Noer, Marius., Holland, John., Nilsson, Per Arne., Hegerland, Georg., Pande, John O., *Options for transporting CO2 from coal fired power plants Case Denmark.* Energy Procedia, 2009. **1**(1): p. 1665-1672.
42. Vandeginste, V., Piessens, K., *Pipeline design for a least-cost router application for CO2 transport in the CO2 sequestration cycle.* International Journal of Greenhouse Gas Control, 2008. **2**(4): p. 571-581.
43. Chrysostomidis, I., Zakkour, Paul., Bohm, Mark., Beynon, Eric., de Filippo, Renato., Lee, Arthur., *Assessing issues of financing a CO2 transportation pipeline infrastructure.* Energy Procedia, 2009. **1**(1): p. 1625-1632.
44. Koornneef, J., Spruijt, M., Molag, M., Ramirez, A., Faaij, A., Turkenburg, W., *Uncertainties in risk assessment of CO2 pipelines.* Energy Procedia, 2009. **1**(1): p. 1587-1594.
45. Koornneef, J., Spruijt, Mark., Molag, Menso., Ramírez, Andrea., Turkenburg, Wim., Faaij, André., *Quantitative risk assessment of CO2 transport by pipelines—A review of uncertainties and their impacts.* Journal of Hazardous Materials, 2010. **177**(1–3): p. 12-27.

46. Kazmierczak, T., Brandsma, Ruut., Neele, Filip., Hendriks, Chris., *Algorithm to create a CCS low-cost pipeline network.* Energy Procedia, 2009. **1**(1): p. 1617-1623.
47. Aspelund, A., Jordal, Kristin., *Gas conditioning—The interface between CO2 capture and transport.* International Journal of Greenhouse Gas Control, 2007. **1**(3): p. 343-354.
48. Prada, P., Shah, Nilay., Konda, Murthy, N, V, S, N., *Development of an integrated CO2 capture, transportation and storage infrastructure for the UK and North Sea using an optimisation framework*, in *Energy Futures Lab*2010, Imperial College London: London.
49. ETI. *Carbon capture and storage. CCS mineralization* 2014; Available from: http://www.eti.co.uk/project/ccs-mineralisation/.
50. Khoo, H.H., Tan, Reginald B. H., *Life Cycle Investigation of CO2 Recovery and Sequestration.* Environmental Science & Technology, 2006. **40**(12): p. 4016-4024.
51. Celia, M.A., Nordbotten, J.M., *Practical modeling approaches for geological storage of carbon dioxide.* Ground Water 47, 627–638., 2009.
52. van der Zwaan, B., Smekens, Koen., *CO2 Capture and Storage with Leakage in an Energy-Climate Model.* Environmental Modeling & Assessment, 2009. **14**(2): p. 135-148.
53. Yang, F., Bai, Baojun., Tang, Dazhen., Shari, Dunn-Norman., David, Wronkiewicz., *Characteristics of CO2 sequestration in saline aquifers.* Petroleum Science, 2010. **7**(1): p. 83-92.
54. Pooly, J., *Integrated Production and Distribution Facility Planning at Ault Foods.* Interfaces, vol. 24, no. 4, 1994, pp. 113-121, 1994.
55. Hindi, K.S., kosz, K., *Efficient solution of large scale, single-source, capacitated plant location problems.* Journal of the Operational Research Society, 1999. **50**(3): p. 268-274.
56. Tsiakis, P., Shah, N., Pantelides, C. C., *Design of multi-echelon supply chain networks under demand uncertainty.* Industrial & Engineering Chemistry Research, 40, 3585-3604, 2001a.
57. Bruglieri, M., Liberti, Leo., *Optimal running and planning of a biomass-based energy production process.* Energy Policy, 2008. **36**(7): p. 2430-2438.
58. Zamboni, A., Shah, Nilay., Bezzo, Fabrizio., *Spatially Explicit Static Model for the Strategic Design of Future Bioethanol Production Systems. 1. Cost Minimization.* Energy & Fuels, 2009. **23**(10): p. 5121-5133.
59. Hugo, A., Rutter, Paul., Pistikopoulos, Stratos., Amorelli, Angelo., Zoia, Giorgio., *Hydrogen infrastructure strategic planning using multi-objective optimization.* International Journal of Hydrogen Energy, 2005. **30**(15): p. 1523-1534.
60. Almansoori, A., Shah, N., *Design and Operation of a Future Hydrogen Supply Chain: Snapshot Model.* Chemical Engineering Research and Design, 2006. **84**(6): p. 423-438.
61. Kamarudin, S.K., Daud, W. R. W., Yaakub, Zahira., Misron, Z., Anuar, W., Yusuf, N. N. A. N., *Synthesis and optimization of future hydrogen energy infrastructure planning in Peninsular Malaysia.* International Journal of Hydrogen Energy, 2009. **34**(5): p. 2077-2088.
62. Middleton, R.S., Bielicki, Jeffrey M., *A comprehensive carbon capture and storage infrastructure model.* Energy Procedia, 2009a. **1**(1): p. 1611-1616.
63. Middleton, R.S., Bielicki, Jeffrey M., *A scalable infrastructure model for carbon capture and storage: SimCCS.* Energy Policy, 2009b. **37**(3): p. 1052-1060.
64. MIT, *MIT CO2 Pipeline Transport and Cost Model (Version 1), Carbon Capture and Sequestration Technologies Program.*, 2007.
65. ISGS, *Illinois State Geological Survey . Assess carbon dioxide capture options for Illinois Basin carbon dioxide sources. Topical Report, Illinois State Geological Survey*, 2005.
66. Dooley, J.J., Dahowksi, R.T., Davidson, C.L., Wise, M.A., Gupta, M.A., Kim, S.H., Malone, E.L., *Carbon Dioxide Capture and Geologic Storage. Technology Report from the Second Phase of the Global Energy Technology Strategy Program.BattelleJointGlobalChangeResearchInstitute.*, 2006.
67. Kobos, P., Malcynski, L., Borns, D., McPherson, B., *'The String of Pearls': the integrated assessment of cost in a source-sink model. In Proceedings of the Sixth Annual Conference on Carbon Capture and Sequestration*, 2007.
68. Kuby, M.J., Middleton, Richard S., Bielicki, Jeffrey M., *Analysis of cost savings from networking pipelines in CCS infrastructure systems.* Energy Procedia, 2011. **4**(0): p. 2808-2815.
69. Fimbres Weihs, G.A., Wiley, D. E., Ho, M., *Steady-state optimisation of CCS pipeline networks for cases with multiple emission sources and injection sites: South-east Queensland case study.* Energy Procedia, 2011. **4**(0): p. 2748-2755.
70. Pinto-Varela, T., Barbosa-Póvoa, Ana Paula F. D., Novais, Augusto Q., *Bi-objective optimization approach to the design and planning of supply chains: Economic versus environmental performances.* Computers & Chemical Engineering, 2011. **35**(8): p. 1454-1468.

71. Han, J.-H., Ryu, Jun-Hyung., Lee, In-Beum., *A preliminary infrastructure design to use fossil fuels with carbon capture and storage and renewable energy systems.* International Journal of Hydrogen Energy, 2012. **37**(22): p. 17321-17335.
72. Arasto, A., Tsupari, Eemeli., Kärki, Janne., Sihvonen, Miika., Lilja, Jarmo., *Costs and Potential of Carbon Capture and Storage at an Integrated Steel Mill.* Energy Procedia, 2013. **37**(0): p. 7117-7124.
73. Jakobsen, J.P., Roussanaly, Simon., Mølnvik, Mona J., Tangen, Grethe., *A standardized Approach to Multi-criteria Assessment of CCS Chains.* Energy Procedia, 2013. **37**(0): p. 2765-2774.
74. IEA-GHG, *International Energy Agency GHG Programme (IEA GHG). Upgraded Calculator for CO2 Pipeline Systems*, 2009.
75. McCoy S. T., *The Economics of CO2 Transport by Pipeline and Storage in Saline Aquifers and Oil Reservoirs. PhD Thesis.* , 2008, Carnegie Mellon University.
76. Romeo, E., Royo, Carlos., Monzón, Antonio., *Improved explicit equations for estimation of the friction factor in rough and smooth pipes.* Chemical Engineering Journal, 2002. **86**(3): p. 369-374.
77. Ball, M., Wietschel, Martin., Rentz, Otto., *Integration of a hydrogen economy into the German energy system: an optimising modelling approach.* International Journal of Hydrogen Energy, 2007. **32**(10–11): p. 1355-1368.
78. Qadrdan, M., Saboohi, Yadollah., Shayegan, Jalal., *A model for investigation of optimal hydrogen pathway, and evaluation of environmental impacts of hydrogen supply system.* International Journal of Hydrogen Energy, 2008. **33**(24): p. 7314-7325.
79. Almansoori, A., Shah, N., *Design and operation of a future hydrogen supply chain: Multi-period model.* International Journal of Hydrogen Energy, 2009. **34**(19): p. 7883-7897.
80. Murthy Konda, N.V.S.N., Shah, Nilay., Brandon, Nigel P., *Optimal transition towards a large-scale hydrogen infrastructure for the transport sector: The case for the Netherlands.* International Journal of Hydrogen Energy, 2011. **36**(8): p. 4619-4635.
81. Kemp, A.G., Sola Kasim, A., *A futuristic least-cost optimisation model of CO2 transportation and storage in the UK/UK Continental Shelf.* Energy Policy, 2010. **38**(7): p. 3652-3667.
82. BERR, *Department for Business, Enterprise and Regulatory Reform (BERR). Development of a CO2 transport and storage network in the North Sea, November 2007*, 2007.
83. BGS, *British Geological Survey (BGS). Industrial Carbon Dioxide Emissions and Carbon Dioxide Storage Potential in the UK*, 2006.
84. Kemp, A.G., Stephen, L., *The Prospects for Activity in the UKCS to 2040: the 2009 Perspective. North Sea Occasional Paper No. 114. Department of Economics, University of Aberdeen, Aberdeen pp. 48.*, 2009.
85. IEA, *Energy Technology Perspectives 2008. Scenarios and Strategies to 2050, Paris. 2008*, 2008.
86. Poyry, *Poyry Energy Consulting. Analysis of Carbon Capture and Storage Cost–Supply Curves for the UK, Economic Analysis of Carbon Capture and Storage in the UK, London*, 2007.
87. SCCS, *Scottish Centre for Carbon Storage. Opportunities for CO2 Storage around Scotland-An Integrated Strategic Research Study, Edinburgh.*, 2009.
88. Shackley, S., Gough, C., *Carbon Capture and its Storage-An Integrated Assessment. Ashgate Publishing Company, Hampshire, United Kingdom*2006.
89. Johnson, N., Ogden, Joan., *Detailed spatial modeling of carbon capture and storage (CCS) infrastructure deployment in the southwestern United States.* Energy Procedia, 2011. **4**(0): p. 2693-2699.
90. Kjärstad, J., Morbee, Joris., Odenberger, Mikael., Johnsson, Filip., Tzimas, Evangelos., *Modelling Large-scale CCS Development in Europe Linking Techno- economic Modelling to Transport Infrastructure.* Energy Procedia, 2013. **37**(0): p. 2941-2948.
91. Kjärstad, J., *The European power plant infrastructure - presentation of the Chalmers energy infrastructure database with applications*2007.
92. Boavida, D., Carneiro, Júlio., Martinez, Roberto., Van den Broek, Machteld., Ramirez, Andrea., Rimi, Abdelkrim., Tosato, Giancarlo., Gastine, Marie., *Planning CCS Development in the West Mediterranean.* Energy Procedia, 2013. **37**(0): p. 3212-3220.
93. Kanudia, A., Berghout, N., Boavida, D., van den Broek, M., Cabal, H., Carneiro, J., Fortes, P., Gargiulo, M., Gouveia, J., Labriet, M., Lechón, Y., Martinez, R., Mesquita, P., Rimi, A., Seixas, J., Tosato, G., *CCS Infrastructure Development Scenarios for the Integrated Iberian Peninsula and Morocco Energy System.* Energy Procedia, 2013. **37**(0): p. 2645-2656.
94. Broek, M.v.d., *Modelling approaches to assess and design the deployment of CO2 capture, transport, and storage*, 2010, Utrecht Universitym the Netherlands.

95. Middleton, R.S., Kuby, Michael J., Wei, Ran., Keating, Gordon N., Pawar, Rajesh J., *A dynamic model for optimally phasing in CO2 capture and storage infrastructure.* Environmental Modelling & Software, 2012. **37**(0): p. 193-205.
96. IEA-GHG, *International Energy Agency GHG Programme (IEA GHG). CO2 Capture in the Cement Industry. Report number 2008/3, July 2008.*, 2008.
97. IEA-GHG, *International Energy Agency GHG Programme (IEA GHG). Retrofit of CO2 Capture to Natural Gas Combined Cycle Power Plants. Report no. 2005/1, January 2005.*, 2005.
98. Korre, A., Elahi, Nasim., Nie, Zhenggang., Durucan, Sevket., Shah, Nilay., Pan, Indranil., *Preliminary analysis of the influence of leasing alternatives on the cash flow of a CCS value chain, Real options optimisation feasibility*, 2013.
99. CO2-Properties. *Carbon Dioxide (CO2) Properties 2010. Available from: http://www.carbon-dioxide-properties.com/CO2TablesWeb.aspx*.
100. Fenghour, A., Wakeham, W. A., Vesovic, V., *The Viscosity of Carbon Dioxide. .* Journal of Phys. Chem. Ref. Data, Vol. 27, No. 1., 1997.
101. UK-APGTF, *UK Advanced Power Generation Technology Forum. Cleaner Fossil Power Generation in the 21st Century - Moving Forward. A technology strategy for carbon capture and storage* 2014.
102. EU-ETS. *EU ETS - Carbon Market Data*. 2011; Available from: https://www.carbonmarketdata.com/en/products/eu-ets-companies-database/presentation.
103. BGS. *British Geological Survey (BGS), (2010).*

. 2010; Available from: http://www.bgs.ac.uk/science/co2/ukco2.html.
104. Bentham, M. *An assessment of carbon sequestration potential in the UK – Southern North Sea case study. Tyndall Centre for Climate Research, Working Paper 85*. 2006; Available from: http://www.tyndall.ac.uk/sites/default/files/wp85.pdf.
105. SCOTTISH-POWER, *UK Carbon Capture and Storage Demonstration Competition SP-SP 6.0 - RT015 FEED Close Out Report. ScottishPower CCS Consortium*, 2011.
106. CRTF. *CCS Cost Reduction Task Force Final Report*. 2013; Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/201021/CCS_Cost_Reduction_Taskforce_-_Final_Report_-_May_2013.pdf.
107. Konstantelos, I., *A stochastic optimisation framework for anticipatory transmission investment.*, in *Department of electrical and electronic engineering* 2012, Imperial College London.
108. CEC. *Climate Economics Chair*. 2014a; Available from: http://www.chaireeconomieduclimat.org/?lang=en.
109. CEC, *Climate Economics Chair, EU ETS reform in the Climate-Enrgy Package 2030: First lessons from the ZEPHYR model.* 2014b.
110. EuropeanCommission. *Impact Assessment, Accompanying the Communication A policy framework for climate and energy in the period from 2020 up to 2030, 2014, the European Commission*. 2014; Available from: http://ec.europa.eu/clima/policies/2030/docs/swd_2014_xxx_en.pdf
111. Laínez, J.M., Puigjaner, Luis., *Prospective and perspective review in integrated supply chain modelling for the chemical process industry.* Current Opinion in Chemical Engineering, 2012. **1**(4): p. 430-445.
112. Camacho E, B.C., *Model Predictive Control in the process industry.* Springer; 1995, 1995.
113. Birge, Z., Louveaux, S., *Principals on Stochastic Programmin.* Springer Verlag;1997, 1997.
114. Sahinidis, N.V., *Optimization under uncertainty: state-of-the-art and opportunities.* Computers & Chemical Engineering, 2004. **28**(6–7): p. 971-983.
115. Shah, N., *Process industry supply chains: Advances and challenges.* Computers & Chemical Engineering, 2005. **29**(6): p. 1225-1236.
116. Blau, G., Mehta, Bharat., Bose, Shantanu., Pekny, Joe., Sinclair, Gavin., Keunker, Kay., Bunch, Paul., *Risk management in the development of new products in highly regulated industries.* Computers & Chemical Engineering, 2000. **24**(2–7): p. 659-664.
117. Perea-López, E., Grossmann, Ignacio E., Ydstie, Erik., Tahmassebi, Turaj., *Dynamic Modeling and Decentralized Control of Supply Chains.* Industrial & Engineering Chemistry Research, 2001. **40**(15): p. 3369-3383.
118. Perea-López, E., Ydstie, Erik., Grossmann, Ignacio E., *A model predictive control strategy for supply chain optimization.* Computers & Chemical Engineering, 2003. **27**(8–9): p. 1201-1218.
119. Hung, W.Y., Kucherenko, S., Samsatli, N. J., Shah, N.,, *A Flexible and Generic Approach to Dynamic Modelling of Supply Chains.* The Journal of the Operational Research Society, 2004. **55**(8): p. 801-813.
120. Shah, N., *Pharmaceutical supply chains: key issues and strategies for optimisation.* Computers & Chemical Engineering, 2004. **28**(6–7): p. 929-941.

121. Karabakal, N., Gunal, A., Ritchie, W., *Supply-Chain Analysis at Volkswagen of America.* Interfaces, 30(4), 46–55, 2000.
122. Gnoni, M.G., Iavagnilio, R., Mossa, G., Mummolo, G., Di Leva, A., *Production planning of a multi-site manufacturing system by hybrid modelling: A case study from the automotive industry.* International Journal of Production Economics, 2003. **85**(2): p. 251-262.
123. Subramanian, D., Pekny, J. F., Reklaitis, G. V., Blau, G. E., *Simulation-optimization framework for stochastic optimization of R&D pipeline management.* AIChE Journal, 49, 96–112, 2003.
124. Wan, X., Pekny, Joseph F., Reklaitis, Gintaras V., *Simulation-based optimization with surrogate models—Application to supply chain management.* Computers & Chemical Engineering, 2005. **29**(6): p. 1317-1328.
125. Mele, F.D., Guillén, Gonzalo., Espuña, Antonio., Puigjaner, Luis., *A Simulation-Based Optimization Framework for Parameter Optimization of Supply-Chain Networks.* Industrial & Engineering Chemistry Research, 2006. **45**(9): p. 3133-3148.
126. Mele, F., Espun˜a, A., Puigjaner, L. , *Supply chain management through dynamic model parameters optimization.* Industrial Engineering & Chemical Research 2006, 45:1708-1721, 2006.
127. Papageorgiou, L.G., *Supply chain optimisation for the process industries: Advances and opportunities.* Computers & Chemical Engineering, 2009. **33**(12): p. 1931-1938.
128. Sahinidis, N.V., Grossmann, I. E., *Reformulation of the Multiperiod MILP Model for Capacity Expansion of Chemical Processes.* Operations Research, 1992. **40**(ArticleType: research-article / Issue Title: Supplement 1: Optimization / Full publication date: Jan. - Feb., 1992 / Copyright © 1992 INFORMS): p. S127-S144.
129. Iyer, R.R., Grossmann, Ignacio E., *A Bilevel Decomposition Algorithm for Long-Range Planning of Process Networks.* Industrial & Engineering Chemistry Research, 1998. **37**(2): p. 474-481.
130. Gupta, A., Maranas, C. D., *A two-stage modeling arid solution framework for multisite midterm planning under demand uncertainty.* Industrial & Engineering Chemistry Research, 39, 3799–3813, 2000.
131. Maravelias, C.T., Grossmann, Ignacio E., *Simultaneous Planning for New Product Development and Batch Manufacturing Facilities.* Industrial & Engineering Chemistry Research, 2001. **40**(26): p. 6147-6164.
132. Tsiakis, P., Shah, N., Pantelides, C. C. *Optimal structures for supply chain network*. in *Alche Annual Meeting*. 2001b.
133. Rotstein, G.E., Papageorgiou, L. G., Shah, N., Murphy, D. C., Mustafa, R., *A product portfolio approach in the pharmaceutical industry.* Computers & Chemical Engineering, 1999. **23, Supplement**(0): p. S883-S886.
134. Gatica, G., Shah, N., Papageorgiou, LG., *Capacity planning under clinical trials uncertainty for the pharmaceutical industry.* Computer Aided Chemical Engineering, Vol:9, ISSN:1570-7946, Pages:865-870, 2001.
135. Gatica, G., Papageorgiou, L. G., Shah, N., *Capacity Planning Under Uncertainty for the Pharmaceutical Industry.* Chemical Engineering Research and Design, 2003. **81**(6): p. 665-678.
136. Ryu, J.-H., Pistikopoulos, Efstratios N., Dua, Vivek., *A bilevel programming framework for enterprise-wide process networks under uncertainty.* Computers and Chemical Engineering 28 (2004) 1121-1129, 2004.
137. Neiro, S.M.S., Pinto, J. M., *Supply chain optimisation of petroleum refinery complexes.* , in *In Proceedings of the fourth international conference on foundations of computer-aided process operations (pp. 59–72).*2003.
138. Gupta, A., Maranas, Costas D., *Managing demand uncertainty in supply chain planning.* Computers & Chemical Engineering, 2003. **27**(8–9): p. 1219-1227.
139. Levis, A.A., Papageorgiou, Lazaros G., *A hierarchical solution approach for multi-site capacity planning under uncertainty in the pharmaceutical industry.* Computers & Chemical Engineering, 2004. **28**(5): p. 707-725.
140. Papageorgiou, L.G., Rotstein, G. E., Shah, N., *Strategic supply chain optimization for the pharmaceutical industries.* Industrial & Engineering Chemistry Research, 40, 275–286, 2001.
141. Guillén, G., Mele, F. D., Bagajewicz, M. J., Espuña, A., Puigjaner, L., *Multiobjective supply chain design under uncertainty.* Chemical Engineering Science, 2005. **60**(6): p. 1535-1553.
142. Tsang, K.H., Shah, N., Samsatli, N. J., *Capacity Investment Planning for Multiple Vaccines Under Uncertainty: 2: Financial Risk Analysis.* Food and Bioproducts Processing, 2007b. **85**(2): p. 129-140.
143. Tsang, K.H., Shah, N., Samsatli, N. J., *Capacity Investment Planning for Multiple Vaccines Under Uncertainty: 1: Capacity Planning.* Food and Bioproducts Processing, 2007a. **85**(2): p. 120-128.
144. You, F., Grossmann, Ignacio E., *Integrated multi-echelon supply chain design with inventories under uncertainty: MINLP models, computational strategies.* AIChE Journal, 2010. **56**(2): p. 419-440.
145. You, F., Grossmann, Ignacio E., *Design of responsive supply chains under demand uncertainty.* Computers & Chemical Engineering, 2008. **32**(12): p. 3090-3111.
146. Colvin, M., Maravelias, Christos T., *A stochastic programming approach for clinical trial planning in new drug development.* Computers & Chemical Engineering, 2008. **32**(11): p. 2626-2642.

147. Al-Qahtani, K., Elkamel, A., Ponnambalam, K., *Robust Optimization for Petrochemical Network Design under Uncertainty.* Industrial & Engineering Chemistry Research, 2008. **47**(11): p. 3912-3919.
148. Puigjaner, L., Laínez, José Miguel., *Capturing dynamics in integrated supply chain management.* Computers & Chemical Engineering, 2008. **32**(11): p. 2582-2605.
149. Puigjaner, L., Laínez, José Miguel., Álvarez, Carlos Rodrigo., *Tracking the Dynamics of the Supply Chain for Enhanced Production Sustainability.* Industrial & Engineering Chemistry Research, 2009. **48**(21): p. 9556-9570.
150. Kim, J., Realff, Matthew J., Lee, Jay H., *Optimal design and global sensitivity analysis of biomass supply chain networks for biofuels under uncertainty.* Computers & Chemical Engineering, 2011. **35**(9): p. 1738-1751.
151. Gebreslassie, B.H., Yao, Yuan., You, Fengqi., *Design under uncertainty of hydrocarbon biorefinery supply chains: Multiobjective stochastic programming models, decomposition algorithm, and a Comparison between CVaR and downside risk.* AIChE Journal, 2012. **58**(7): p. 2155-2179.
152. Liu, S., Shah, Nilay., Papageorgiou, Lazaros G., *Multiechelon supply chain planning with sequence-dependent changeovers and price elasticity of demand under uncertainty.* AIChE Journal, 2012. **58**(11): p. 3390-3403.
153. Almansoori, A.S., N., *Design and operation of a stochastic hydrogen supply chain network under demand uncertainty.* International Journal of Hydrogen Energy, 2012. **37**(5): p. 3965-3977.
154. Wets, R.J.B., *The aggregation principle in scenario analysis and stochastic optimization.* In: Wallace SW, editor. Algorithms and model formulations in mathematical programming. Berlin: Springer-Verlag; 1989. p. 92-113, 1989.
155. Mulvey, J.M., Rosenbaum, Daniel P., Shetty, Bala, *Strategic financial risk management and operations research.* European Journal of Operational Research, 1997. **97**(1): p. 1-16.
156. Ahmed, S., Sahinidis, Nikolaos V., *Robust Process Planning under Uncertainty.* Industrial & Engineering Chemistry Research, 1998. **37**(5): p. 1883-1892.
157. Kall, P., Wallace, S. W., *Stochastic programming.* New York: Wiley, 1994.
158. Eppen, G.D., Martin, R. K., Schrage, L., *A scenario approach to capacity planning.* Operational Research, 37, 517–527, 1989.
159. Applequist, G.E., Pekny, J. F., Reklaitis, G. V., *Risk and uncertainty in managing chemical manufacturing supply chains.* Computers & Chemical Engineering, 2000. **24**(9–10): p. 2211-2222.
160. Bhagwat, Y., Griggs, F. T., *Analysis of riskiness of pharmaceutical industry firms.* Journal of Research in Pharmaceutical Economics,6, 65–76, 1995.
161. Aseeri, A., Bagajewicz, Miguel J., *New measures and procedures to manage financial risk with applications to the planning of gas commercialization in Asia.* Computers & Chemical Engineering, 2004. **28**(12): p. 2791-2821.
162. NRC, D., *Joint Statement from the Department of Natural Resources of Canada and the Department of Energy and Climate Change of the United Kingdom concerning Carbon Capture and Storage*, 2014.
163. DECC, *Department of Energy and Climate Change. Coal-Fired Advanced Supercritical Retrofit with CO2 Capture*, 2009a.
164. Ho, M.T., Allinson, Guy W., Wiley, Dianne E., *Comparison of MEA capture cost for low CO2 emissions sources in Australia.* International Journal of Greenhouse Gas Control, 2011. **5**(1): p. 49-60.
165. Simmonds, M., Hurst, P., Wilkinson, M. B., Watt, C., Roberts, C. A., *A study of a very large scale post combustion CO2 capture at a refining & petrochemical complex.* 2003.

Appendix A. Supply chain nodes – UK CCS case study

Table A-1: Sources, sinks and dummy nodes considered in the case study: Multi-period integrated CO_2 capture, storage and transportation supply chain in the UK

i	Node(Source/Sink/Dummy)	Type	x (Radians)	y (Radians)	Elevation/Depth (m)
1	Drax Power Station	Source	0.939	-0.019	6
2	Longannet Power Station	Source	0.978	-0.064	8
3	Cottam Power Station	Source	0.930	-0.014	5
4	Ratcliffe on Soar power station	Source	0.923	-0.022	34
5	Port Talbot Steelworks	Source	0.900	-0.066	11
6	Fiddlers Ferry Power Station	Source	0.932	-0.047	23
7	Scunthorpe Integrated Iron & Steel Works	Source	0.935	-0.011	45
8	West Burton Power Station	Source	0.931	-0.014	22
9	Ferrybridge 'C' Power Station	Source	0.938	-0.022	17
10	Aberthaw Power Station	Source	0.897	-0.059	40
11	Eggborough Power Station	Source	0.937	-0.020	14
12	Didcot B Power Station	Source	0.901	-0.022	64
13	Cockenzie Power Station	Source	0.977	-0.052	0
14	Rugeley Power Station	Source	0.921	-0.033	69
15	South Humber Bank Power Station	Source	0.936	-0.003	11
16	Saltend Cogeneration Company Limited	Source	0.938	-0.004	2
17	Immingham CHP	Source	0.936	-0.004	5
18	Kingsnorth power station	Source	0.897	-0.011	2
19	Leman	Sink	0.926	0.039	-40
20	Morecambe South	Sink	0.945	-0.052	-31
21	Indefatigable	Sink	0.931	0.045	-30
22	Hewett L Bunter	Sink	0.925	0.031	-37
23	Viking	Sink	0.933	0.041	-23
24	Morecambe North	Sink	0.945	-0.052	-27
25	V Fields (Vulcan, Valiant, Victor, Vampire, Viscount , Valkyrie)	Sink	0.932	0.038	-38
26	West sole	Sink	0.937	0.021	-28
27	Galleon	Sink	0.934	0.031	-25
28	Barque	Sink	0.937	0.028	-36.5
29	Between Huntigdon and Aylesbury	Dummy	0.909	-0.009	32
30	Moffat	Dummy	0.966	-0.060	117
31	Carnforth	Dummy	0.945	-0.048	26
32	Warrington	Dummy	0.932	-0.045	19
33	Hatton	Dummy	0.930	-0.004	40
34	Teesside	Dummy	0.953	-0.021	7
35	Bishop Auckland	Dummy	0.954	-0.029	105

36	Wisbech	Dummy	0.919	0.003	2
37	Peterborough	Dummy	0.918	-0.004	6
38	Churchover	Dummy	0.915	-0.022	121
39	Huntingdon	Dummy	0.913	-0.003	13
40	Between Moffat and Bishop Auckland	Dummy	0.960	-0.045	125
41	Hornsea	Dummy	0.941	-0.003	5
42	Wormington	Dummy	0.908	-0.035	53
43	Peterstow	Dummy	0.906	-0.046	80
44	Aylesbury	Dummy	0.904	-0.014	78
45	Between Carnfoth and Hornsea	Dummy	0.945	-0.026	44
46	Bacton	Dummy	0.923	0.025	18
47	Theddlethorpe	Dummy	0.932	0.004	1
48	Easington	Dummy	0.936	0.002	119
49	Between Peterborough and Hatton	Dummy	0.924	-0.004	3
50	Between moffat and carnforth	Dummy	0.955	-0.054	273
51	Alrewas	Dummy	0.920	-0.031	59
52	Between Teeside and Bishop Auckland	Dummy	0.95	-0.0250	11
53	Bathgate	Dummy	0.976	-0.0636	143

Appendix B. Capture cost parameters

Appendix B contains a detailed breakdown of the capital and operational costs of capture for different types of plants considered in the case study of chapter 3. The data included in this section is obtained from a study of a static CCS supply chain in the UK carried out by Prada [48] . The fixed and variable costs of CO_2 capture plant is categorised depending on the type of the CO_2 source i.e. coal Plants, CCGT and CHP plants and other plants. To obtain the reference cost figures Prada et al. 2010 used a UK-specific study commissioned by DECC to Doosan Babcock [163].

Coal Plants

Table B-1: Cost estimates for capture facilities on coal plants

Sub type	Retro-fit Plant (MW)	ref. Plant CO_2 Inten-sity (kgCO2/MWh)	Ref.Add.CAPEX ($/kW)	Ref.Add.CAPEX (M$)	Ref.Add.CAPEX (M$/yr)	ΔOPEXnon-fuel ($/MWh/yr)	ΔOPEXfuel @spec. LF($/MWh/yr)	ΔOPEXTotal ($/t$CO_2$ cap-tured/yr)
Drax-Like	493	825	2491.1	1228.1	135.3	11.58	3.14	19.82
Ratcliffe-Like	459	868	2669	1225.1	135	11.8	2.7	18.56

The following assumptions were used to derive the figures in table B1.

- Exchange Rate: 1GBP=1.78USD
- Plant Load Factor:93%
- ΔOPEXnon-fuel: 30% of the full power plant operational expenses as referenced by Doosan
- ΔOPEXnon:Estimated based on coal price and efficiency loss
- CAPEX Cost Index: IHS CERA EU Power (2005-2006 to 2010)
- Opex Cost Index: none

CCGT and CHP Plants

Table B-2: Cost estimates for capture facilities on CCGT and CHP plants

Sub type	Retro-fit Plant (MW)	ref. Plant CO_2 Intensity (kgCO2/MWh)	Ref.Add.CAPEX ($/kW)	Ref.Add.CAPEX (M$)	Ref.Add.CAPEX (M$/yr)	ΔOPEXnon-fuel ($/MWh/yr)	ΔOPEXfuel @spec. LF($/MWh/yr)	ΔOPEXTotal ($/t$CO_2$ cap-tured/yr)
CCGT	626	373	1003.68	628.3	69.2	6.79	10.65	51.94
CCGT-	626	373	1003.68	628.3	69.2	6.79	8.94	46.86

CHP

The CCGT and CHP costs estimates of table B2 are based on a study commissioned by IEAGHG to Jacob consultancy and the following assumptions [97]:

- Plant Load Factor: 90%
- ΔOPEXfuel:Estimated based on coal price and efficiency loss
- CAPEX Cost Index: IHS CERA EU Power (2004 to 2010)
- Opex Cost Index: none

Steel manufacturing plants

Table B-3: Cost estimates for capture facilities on steel manufacturing plants

Sub-type	Capacity (Mt/yr)	Plant CO_2 intensity ($MtCO_2$/Mt)	Ref.Add.CAPEX (M$/Mt/yr)	Ref.Add.CAPEX (M$)	Ref.Add.CAPEX(M$/yr)	ΔOPEXTotal(M$/Mt/yr)	ΔOPEXTotal($/t$CO_2$captured/yr)
STEEL	2	1.5556	17.699	315	34.7	78.03	55.74

The costs included in table B3 are obtained from Ho et al [164] and Simmonds et al [165] and are based on the following assumptions:

- Plant load factor: 100%
- OPEX and CAPEX Cost Index: None (reference is recent i.e. 2010)

Cement manufacturing plants

Table B-4: Cost estimates for capture facilities on cement manufacturing plants

Type	Capacity (Mt/yr)	Ex. Plant CO2 intensity (MtCO2/Mt)	Ref.Add.CAPEX (M$/Mt/yr)	Ref.Add.CAPEX (M$)	Ref.Add.CAPEX(M$/yr)	ΔOPEXTotal(M$/Mt/yr)	ΔOPEXTotal($/tCO2captured/yr)
CEMENT	1	0.728	46.47	421.81	46.47	41.67	63.6

The figures included in table B4 are based on a study commissioned by IEA GHG to Mott MacDonald Data and following the assumptions below [96]:

- Exchange Rate(Source: Mott MacDonald): 1EUR=1.39USD
- Plant load factor:90%
- CAPEX Cost Index: IHS CERA downstream (2008-2010)
- Opex Cost Index: none

Table B-5: Summary of CO_2 capture plants' cost estimates

Type	Subtype	Reference ΔCAPEX(M$/yr)	ΔOPEX (M$/MtCO2captured/yr)
COAL	DRAX-Like	135.3	0.0198
COAL	RATCLIFFE-Like	135.3	0.0186
CCGT	General	69.2	0.0519
CHP	General	69.2	0.0469
REFINARY	General	94.6	0.097
STEEL	General	34.7	0.0557
CEMENT	General	46.5	0.0636

Appendix C. Storage cost parameters

Appendix C contains a breakdown of the cost of CO_2 injection considered in the case study of chapter 3. The cost of building an injection facility is divided as shown in table C1. These values have been obtained from Prada et al [48]. They leveraged the data included in a study commissioned by BERR to POYRY consulting [82] to arrive at value sin table C1.

Table C-1: Injection infrastructure cost estimates

Category	Cost (M$)
Survey and development Cost	3.89
Fixed Cost per well	17.71
Drilling Cost per well	16.44
Platform Cost	126.47

The fixed storage cost (M$/year) is then calculated per equation C1.

$$\mathrm{CAPEX}\left(\frac{\mathrm{M\$}}{\mathrm{year}}\right) = \left\{\begin{matrix} \mathrm{Survey}\ development\ cost + \\ (\mathrm{fixed}\ \&\ Drilling\ costs) \\ * \mathrm{No\ of\ wells} + \\ \mathrm{platform\ cost} \end{matrix}\right\} * \mathrm{Capital\ Charge\ factor} \qquad \text{Equation C-1}$$

The capital charge factor is calculated for a life time n of 25 years and a discount rate r of 10% per equation C2.

$$\mathrm{Capital\ Charge\ Factor} = \frac{\mathrm{r}\,(1+\mathrm{r})^{\mathrm{n}}}{(1+\mathrm{r})^{\mathrm{n}-1}} \qquad \text{Equation C-2}$$

The variable cost (M$/Mt/year) is calculated per equation C3.

$$\mathrm{OPEX}\left(\frac{\frac{\mathrm{M\$}}{\mathrm{Mt}}}{\mathrm{Year}}\right) = \frac{10\%\ \mathrm{CAPEX}}{\mathrm{Injection\ rate}} \qquad \text{Equation C-3}$$

The Following assumptions were then made to arrive at the fixed storage costs and the variable storage costs in table C2.

- Operational cost (M$/year)=10% CAPEX
- Injection rate= Injection rate per well * No of wells
- Injection rates of 100% and 75% for wells with good or reasonable injectivity respectively

Table C-2: Summary of storage costs estimates

Field Name	Area	CO2 stor-	No. Plat-	No. Well	Injection	Total Injection	CAPEX(M$)	Fixed Stor-	OPEX(M$/yr)	Variable Storage

		age capacity (Mt)	forms	s		Rate(Mt/yr)		age Cost (M$/yr)		Cost (M$/yr/Mt)
Leman A & B	SNS	1203	2	40	Good	40	1496.36	164.85	149.64	3.74
Morecambe South	EISB	736.08	1	24	Good	24	966.17	106.44	96.62	3.95
Indefatigable	SNS	357	1	12	Reasonable	9	535.73	59.02	53.57	6.02
Hewett L Bunter	SNS	237	1	8	Good	8	399.47	44.01	39.95	5.07
Viking	SNS	221	1	7	Reasonable	6	381.30	42.01	38.13	6.92
Frigg (UK)	C/NNS	170.76	1	6	Good	6	324.26	35.72	32.43	5.71
Morecambe North	EISB	143.51	1	5	Good	5	293.31	32.31	29.33	6.15
V Fields	SNS	143	1	5	Reasonable	4	292.74	32.25	29.27	8.21

Appendix D. Transport cost parameters

Appendix D contains the fixed and variable transport cost parameters used in the case study of chapter 3. Table D1 contains the slope of the three linearised segments of the transport cost curve derived by Prada et al [48]. Each slope is the variable cost of transport by pipeline with the corresponding maximum capacity given in table D3. Table D2 contains the intercepts of the linearised segments of the transport cost curve with the x axis which indicate the corresponding fixed annual cost of building a pipeline of the corresponding capacity.

Table D-1: Slopes of the linearised segments of the transport cost curve

Slope 1(K$/Km/MtCO2) L1	Slope2(K$/Km/MtCO2) L2	Slope3(K$/Km/MtCO2) L3
9.33	3.17	1.82

Table D-2: Intercepts of the linearised segments of the transport cost curve

Intercept 1 (k$/km/year) L1	Intercept 2(k$/km/year) L2	Intercept 3(k$/km/year) L3
90	186	236

Table D-3: Maximum flow rates corresponding to the linearised segments of the transport cost curve

Segment of linearised cost curve	Qmax (Mt/yr)
1	15
2	45
3	100

Appendix E. IHS CERA cost index

The IHS CERA cost indices of figures E1 and E2 have been used for updating CO_2 transportation costs. Figures E3/E4 and E5 have been used to update the capital and operating costs of CO2 capture plants and CO_2 injection facilities respectively.

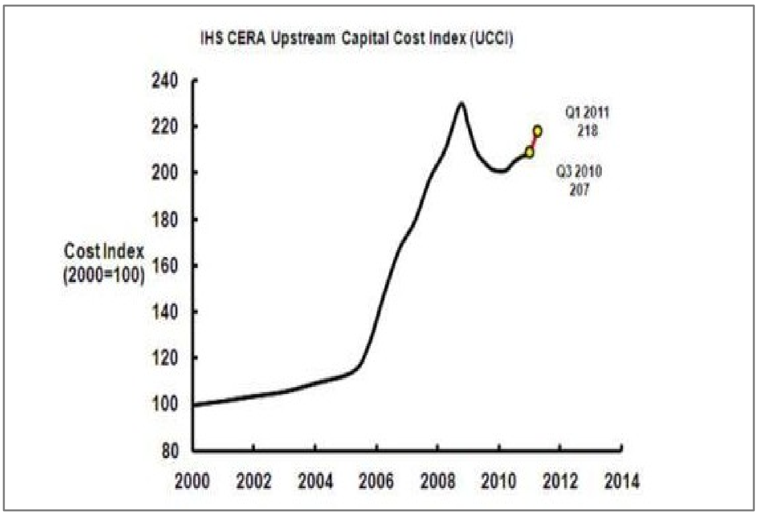


Figure E-1: IHS CERA upstream capital cost index. Onshore/offshore pipeline and LNG projects

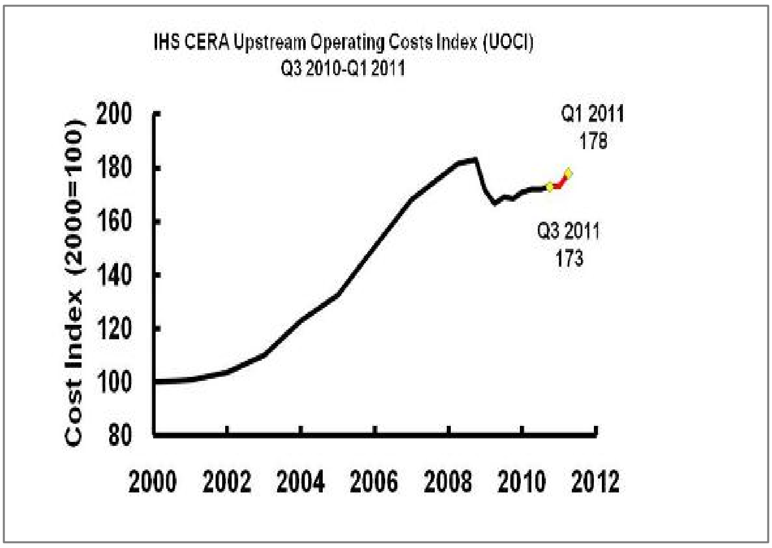


Figure E-2: IHS CERA upstream operating cost index. Onshore/offshore pipeline and LNG projects

.

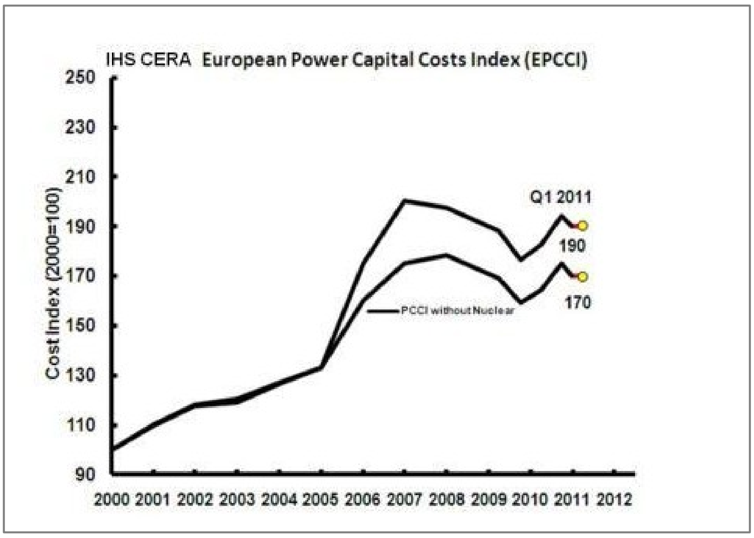


Figure E-3: IHS CERA European power capital cost index. Power generation points

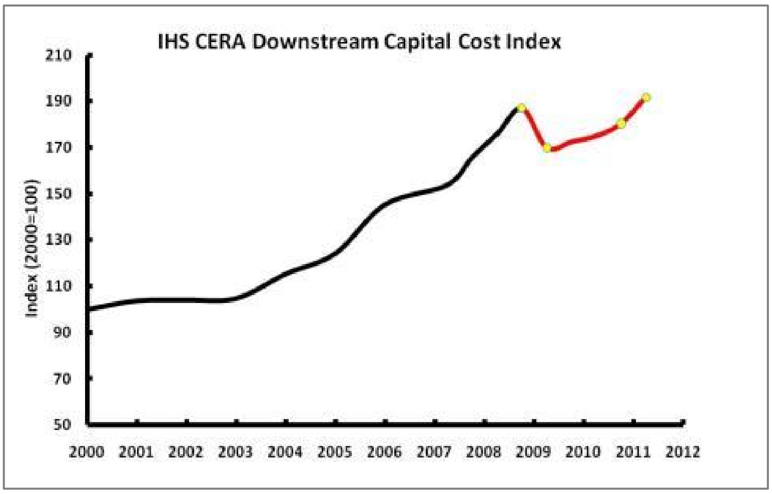


Figure E-4: IHS CERA downstream capital cost index. Refinery and petrochemical construction

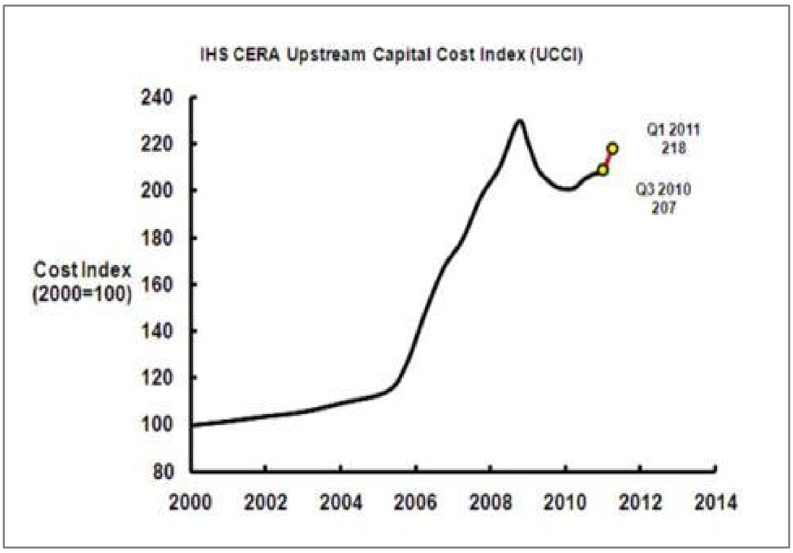


Figure E-5: IHS CERA upstream capital cost index. Oil and gas fields

Appendix F. Future inflation rates

Tables F1 and F2 contain the U.S. Treasuries and the U.S. Inflation Indexed Treasuries (Bloomberg Nov.2011).

Table F-1: U.S. Treasuries. (Bloomberg 2011)

U.S. Treasuries	Yield
5 year	1.41
10 year	2.01
20 year (Extrapolated value)	2.50
30 year	3.06
40 year (Extrapolated value)	3.50

Table F-2: U.S. Inflation Indexed Treasuries. (Bloomberg 2011)

U.S. Inflation Indexed Treasuries	Yield
5 year	-1.08
10 year	-0.08
20 year	0.42
30 year	0.73
40 year (Extrapolated value)	1.10

Table F3 is the difference between the U.S. Treasuries and the corresponding TIPS values as provided in tables F1 and F2. These values are assumed to be a good indication of the rate of inflation of the corresponding future time periods.

Table F-3: U.S. Inflation rates corresponding to the time periods of the UK CCS case study of chapter 3

Time Periods considered in the UK case study 2010-2050	Inflation Rate Forecast
2020-2030 (T2)	2.09
2030-2040 (T3)	2.08
2040-2050 (T4)	2.33

Appendix G. Multi-period deterministic CCS in the UK

Tables G1 and G2 contain the amounts of CO_2 captured and stored and the relevant nodes. Table G3 contains the amounts of CO_2 transported via the transport links for each time period considered in the multi-period UK CCS supply chain case study of chapter 3.

Table G-1: CO_2 captured (Mt/year) from each source during each time period – Multi-period UK CCS supply chain case study

C(i,t) Mt/year	CO2 emitters	T1	T2	T3	T4
1	Drax Power Station	20.153	20.153	20.153	20.153
2	Longannet Power Station		8.212	8.212	8.212
3	Cottam Power Station	4.847	7.844	7.844	7.844
4	Ratcliffe on Soar power station		7.527	7.527	7.527
5	Port Talbot Steelworks				5.584
6	Fiddlers Ferry Power Station		5.783	5.783	5.783
7	Scunthorpe Integrated Iron & Steel Works		0.482	5.225	5.321
8	West Burton Power Station			4.586	4.586
9	Ferrybridge 'C' Power Station			4.347	4.347
10	Aberthaw Power Station				4.265
11	Eggborough Power Station			4.123	4.123
12	Didcot B Power Station			3.65	3.65
13	Cockenzie Power Station			3.551	3.551
14	Rugeley Power Station				3.306
15	South Humber Bank Power Station				3.099
16	Saltend Cogeneration Company Limited				3.08
17	Immingham CHP				2.823
18	Kingsnorth power station				2.746

Table G-2: CO_2 stored (Mt/year) at each sink during each time period – Multi-period UK CCS supply chain case study

S(i,t) (Mt/year)	Sink	T1	T2	T3	T4
19	Leman			75	45.3
20	Morecambe South	25	48.608		
22	Hewett L Bunter				35.9
24	Morecambe North				14.351
26	West sole		1.392		4.449

Table G-3: CO_2 transported (Mt/year) from node i to node j at each time period – Multi-period UK CCS supply chain case study

Node i	Node i	Node j	Node j	l (Linearised segment of the transport cost curve)	Time period	Q(i,j,p,l,t) Flow rate between nodes i and j	Distance (km)
3	Cottam Power Station	8	West Burton Power Station	2	1	4.85	7.24
8	West Burton Power Station	7	Scunthorpe Integrated Iron & Steel Works	3	1	4.85	26.49
7	Scunthorpe Integrated Iron & Steel Works	1	Drax Power Station	3	1	4.85	45.77
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	1	25.00	35.65
45	Between Carnfoth and Hornsea	31	carnforth	3	1	25.00	84.66
31	carnforth	20	Morecambe South	3	1	25.00	15.27
4	Ratcliffe on Soar power station	3	Cottam Power Station	1	2	7.53	58.14
3	Cottam Power Station	8	West Burton Power Station	2	2	15.37	7.24
8	West Burton Power Station	7	Scunthorpe Integrated Iron & Steel Works	3	2	15.37	26.49
7	Scunthorpe Integrated Iron & Steel Works	16	Saltend Cogeneration Company Limited	1	2	1.39	31.86
16	Saltend Cogeneration Company Limited	48	Easington	3	2	1.39	25.54
48	Easington	26	West sole	3	2	1.39	71.19
7	Scunthorpe Integrated Iron & Steel Works	1	Drax Power Station	3	2	14.46	45.77
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	2	34.61	35.65
45	Between Carnfoth and Hornsea	31	carnforth	3	2	34.61	84.66

6	Fiddlers Ferry Power Station	32	Warrington	1	2	5.78	5.86
32	Warrington	31	carnforth	1	2	5.78	82.50
2	Longannet Power Station	53	Bathgate	1	2	8.21	16.48
53	Bathgate	30	Moffat	1	2	8.21	64.67
30	Moffat	50	between moffat and carnforth	1	2	8.21	70.59
50	between moffat and carnforth	31	carnforth	2	2	8.21	70.68
31	carnforth	20	Morecambe South	3	2	48.61	15.27
12	Didcot B Power Station	38	Churchover	1	3	3.65	88.53
38	Churchover	4	Ratcliffe on Soar power station	1	3	3.65	49.55
4	Ratcliffe on Soar power station	3	Cottam Power Station	1	3	11.18	58.14
3	Cottam Power Station	8	West Burton Power Station	2	3	19.02	7.24
8	West Burton Power Station	7	Scunthorpe Inte-grated Iron & Steel Works	3	3	23.61	26.49
9	Ferrybridge 'C' Power Station	11	Eggborough Power Station	1	3	4.35	10.13
11	Eggborough Power Station	1	Drax Power Sta-tion	3	3	8.47	9.04
2	Longannet Power Station	53	Bathgate	1	3	8.21	16.48
13	Cockenzie Power Station	53	Bathgate	1	3	3.55	42.46
53	Bathgate	30	Moffat	1	3	11.76	64.67
30	Moffat	50	between moffat and carnforth	1	3	11.76	70.59
50	between moffat and carnforth	31	carnforth	2	3	11.76	70.68
6	Fiddlers Ferry Power Station	32	Warrington	1	3	5.78	5.86
32	Warrington	31	carnforth	1	3	5.78	82.50
31	carnforth	45	Between Carnfoth and Hornsea	3	3	17.55	84.66
45	Between Carnfoth	1	Drax Power Sta-	3	3	17.55	45.77

	and Hornsea		tion				
1	Drax Power Station	7	Scunthorpe Integrated Iron & Steel Works	3	3	46.19	35.65
7	Scunthorpe Integrated Iron & Steel Works	16	Saltend Cogeneration Company Limited	3	3	75.00	31.86
16	Saltend Cogeneration Company Limited	48	Easington	3	3	75.00	25.54
48	Easington	26	West sole	3	3	75.00	71.19
26	West sole	19	Leman	3	3	75.00	96.55
18	Kingsnorth power station	12	Didcot B Power Station	1	4	2.75	51.32
12	Didcot B Power Station	38	Churchover	1	4	6.40	88.53
5	Port Talbot Steelworks	10	Aberthaw Power Station	1	4	5.58	32.08
10	Aberthaw Power Station	43	Peterstow	1	4	9.85	79.40
43	Peterstow	42	Wormington	2	4	9.85	46.49
42	Wormington	38	Churchover	2	4	9.85	66.78
38	Churchover	51	Alrewas	2	4	16.25	48.76
14	Rugeley Power Station	51	Alrewas	2	4	3.31	11.81
51	Alrewas	4	Ratcliffe on Soar power station	2	4	19.55	36.38
4	Ratcliffe on Soar power station	3	Cottam Power Station	2	4	27.08	58.14
3	Cottam Power Station	8	West Burton Power Station	2	4	34.92	7.24
8	West Burton Power Station	7	Scunthorpe Integrated Iron & Steel Works	3	4	39.51	26.49
2	Longannet Power Station	53	Bathgate	1	4	8.21	16.48
13	Cockenzie Power Station	53	Bathgate	1	4	3.55	42.46
53	Bathgate	30	Moffat	1	4	11.76	64.67
30	Moffat	50	between moffat and carnforth	1	4	11.76	70.59

50	Between moffat and carnforth	31	carnforth	2	4	11.76	70.68
6	Fiddlers Ferry Power Station	32	Warrington	1	4	5.78	5.86
32	Warrington	31	carnforth	1	4	5.78	82.50
31	carnforth	20	Morecambe South	3	4	14.35	15.27
20	Morecambe South	24	Morecambe North	2	4	14.35	3.10
31	carnforth	45	Between Carnfoth and Hornsea	3	4	3.19	84.66
45	Between Carnfoth and Hornsea	1	Drax Power Station	3	4	3.19	45.77
9	Ferrybridge 'C' Power Station	11	Eggborough Power Station	1	4	4.35	10.13
11	Eggborough Power Station	1	Drax Power Station	3	4	8.47	9.04
1	Drax Power Station	7	Scunthorpe Integrated Iron & Steel Works	3	4	31.82	35.65
7	Scunthorpe Integrated Iron & Steel Works	16	Saltend Cogeneration Company Limited	3	4	76.65	31.86
15	South Humber Bank Power Station	17	Immingham CHP	1	4	3.10	6.97
17	Immingham CHP	16	Saltend Cogeneration Company Limited	1	4	5.92	10.84
16	Saltend Cogeneration Company Limited	48	Easington	3	4	85.65	25.54
48	Easington	26	West sole	3	4	85.65	71.19
26	West sole	19	Leman	3	4	81.20	96.55
19	Leman	22	Hewett L Bunter	3	4	35.90	29.50

Appendix H. Longannet-Goldeneye single CCS value chain

Table H-1: Coordinates and elevation of the supply chain nodes – Goldeneye anchor case

Nodes	Longitude (Decimal degrees)	Latitude (Decimal degrees)	Elevation (m)
Longannet	56.05	-3.682337	8
Valleyfield	56.06	-3.60	29
Kirriemuir	56.67	-3.01	140
St Furgus (Blackhill compressor)	57.56	-1.84	12
Goldeneye	58.00	-0.38	0

Table H-2: Life cycle costs (kEur) of CO_2 storage provided by Storage life cycle cost model developed at the department of Earth Sciences – Goldeneye anchor case –Exchange rate $1.34/Eur [22]

Phase	Year	Geologic site Characterisation	Area of Review	Monitoring	Injection platform modification	Injection platform operation	Mechanical Integrity Testing	Well Plugging and Post-injection site care (PISC)	Permitting Authority Administration	Transfer financial responsibility	SUM (K€/ per year)	Amount of CO_2 injected (Million Tonnes)
Pre-injection (CAPEX)	2014	447									447	0
	2015	447	114	4,289	55,776						60,626	0
	2016	596	171	4,289	83,664	0		12			88,732	0
Injection (OPEX)	2017			232		15,379	136	2.0		1000	16,750	2.00
	2018			232		15,379	136	2.0		1000	16,750	2.00
	2019			345		15,379	136	2.0		1000	16,862	2.00
	2020			232		15,379	136	2.0		1000	16,750	2.00
	20			8,571		15,37	136	2.0		1000	25,0	2.00

21		9				88	
2022	385	15,379	136	2.0	1000	16,903	2.00
2023	273	15,379	136	2.0	1000	16,790	2.00
2024	273	15,379	136	2.0	1000	16,790	2.00
2025	385	15,379	136	2.0	1000	16,903	2.00
2026	8,611	15,379	136	2.0	750	25,129	1.50
2027	273	15,379	136	2.0	250	16,790	0.50

Table H-3: Average cost of the supply chain components– Goldeneye anchor case

Total costs $/tonne averaged over 11 years	
Total capture cost	63.109
Total storage cost	20.252
Total trasnport cost	19.189

Table H-4: Total annual transport cost– Goldeneye anchor case

Year	**Total transport cost(M$)**
2017	394.32
2018	1.82
2019	1.655
2020	1.505
2021	1.244
2022	1.1875
2023	1.131
2024	1.028
2025	0.934
2026	0.638
2027	0.194

Appendix I. Dynamic multi-storage Central North Sea CCS case

Table I-1: Supply chain nodes – CNS multi-storage case

Installation	Type	Latitude(Decimal degrees)	Longitude(Decimal degrees)
Peterhead Power Station	Source	57.477	-1.789
Longannet Power Station	Source	56.049	-3.682
Grangemouth Refining	Source	56.019	-3.698
Cockenzie Power Station	Source	55.968	-2.972
Lynemouth Power Station	Source	55.204	-1.519
Britannia Saline aquifer block	sink	57.941	0.157
Goldeneye Gas Condensate Field	sink	58.004	-0.365
Britannia Condensate Field	sink	58.076	0.997
Scapa Oil Field	sink	58.429	-0.330
Captain Saline Aquifer 1	sink	58.101	-1.097
Captain Saline Aquifer 2	sink	58.044	-0.943
Blake oil fields	sink	58.204	-1.344
St Fergus terminal	Dummy	57.571	-1.838
kink 1 in the pipeline from st fergus to Goldeneye	Dummy	57.578	-1.555
kink 2 in the pipeline from st fergus to Goldeneye	Dummy	57.950	-0.688

Table I-2: Fixed storage cost parameter for each storage site at each time period adapted from the results provided by the Storage life cycle cost model and used in the GAMS models

year(Start of T)	Time periods	Britan-nia/Saline (2014)	Cap-tain1/Saline	Captain2 2/Saline	Gold-eneye/Gas(2014)	Britan-nia/Gas (2028)	Blake/oil (2018)	scapa/oil (2023)
2014	1	27.86	36.87			18.14	19.80	
2018	2	27.86	36.87			18.14	19.80	29.71
2023	3	27.86	36.87		34.61	18.14	19.80	29.71
2028	4	27.86	36.87	122.55	34.61	18.14	19.80	29.71
2038	5	27.86	36.87	122.55	34.61	18.14	19.80	29.71

Table I-3: Variable storage cost parameter for each storage site at each time period adapted from the results provided by the Storage life cycle cost model and used in the GAMS models

year (Start of T)	time periods	Britan-nia/Saline	Captain 1/Saline	Capita 2/Saline	Gold-eneye/Gas	Britan-nia/Gas(2028)	Blake/oil (2018)	scapa/oil (2023)
2014	1	12.15	20.00			7.71	7.51	

2018	2	12.15	20.00			7.71	7.51	14.94
2019	3	12.15	20.00		7.44	7.71	7.51	14.94
2020	4	12.15	20.00	25.16	7.44	7.71	7.51	14.94
2021	5	12.15	20.00	25.16	7.44	7.71	7.51	14.94

Table I-4: Time of construction and NPV of accumulated capital cost of transport links

i(number)	j(number)	i	j	Phase (1:Gas 2:Liquid)	l(Segment of cost curve)	Time period of construction	capital cost(M$)
2	1	Longannet Power Station	Peterhead Power Station	1	1	1	261.98
13	1	St Fergus terminal	Peterhead Power Station	1	1	1	14.41
14	13	kink 1 in the pipeline from st fergus to Goldeneye	St Fergus terminal	1	1	1	11.26
15	14	kink 2 in the pipeline from st fergus to Goldeneye	kink 1 in the pipeline from st fergus to Goldeneye	1	1	1	44.05
15	7	kink 2 in the pipeline from st fergus to Goldeneye	Goldeneye Gas Condensate Field	1	1	1	13.33
7	6	Goldeneye Gas Condensate Field	Britannia Saline aquifer block	1	1	1	42.12
15	11	kink 2 in the pipeline from st fergus to Goldeneye	Captain Saline Aquifer 2	1	1	1	24.41
11	10	Captain Saline Aquifer 2	Captain Saline Aquifer 1	1	1	1	14.75
12	10	Blake oil fields	Captain Saline Aquifer 1	1	1	2	16.60
10	9	Captain Saline Aquifer 1	Scapa Oil Field	1	1	3	31.37
8	6	Britannia Condensate Field	Britannia Saline aquifer block	1	1	4	16.63

Table I-5: CO_2 flow rate and NPV of accumulated operational cost of transport

i (number)	j(number)	i	j	Time period	Q(CO_2 flow Mt/year)	Operational cost (M$) for the length of T
2	1	Longannet Power Station	Peterhead Power Station	1	8	45.63
1	13	Peterhead Power Station	St Fergus terminal	1	8	2.51

13	14	St Fergus terminal	kink 1 in the pipeline from st fergus to Goldeneye	1	8	3.92
14	15	kink 1 in the pipeline from st fergus to Goldeneye	kink 2 in the pipeline from st fergus to Goldeneye	1	8	15.34
15	7	kink 2 in the pipeline from st fergus to Goldeneye	Goldeneye Gas Condensate Field	1	4	2.32
7	6	Goldeneye Gas Condensate Field	Britannia Saline aquifer block	1	2	1.83
15	11	kink 2 in the pipeline from st fergus to Goldeneye	Captain Saline Aquifer 2	1	4	2.13
11	10	Captain Saline Aquifer 2	Captain Saline Aquifer 1	1	2	0.64
2	1	Longannet Power Station	Peterhead Power Station	2	7.63	35.54
1	13	Peterhead Power Station	St Fergus terminal	2	7.63	1.95
13	14	St Fergus terminal	kink 1 in the pipeline from st fergus to Goldeneye	2	7.63	3.06
14	15	kink 1 in the pipeline from st fergus to Goldeneye	kink 2 in the pipeline from st fergus to Goldeneye	2	7.63	11.95
15	7	kink 2 in the pipeline from st fergus to Goldeneye	Goldeneye Gas Condensate Field	2	3.19	1.51
7	6	Goldeneye Gas Condensate Field	Britannia Saline aquifer block	2	2	1.50
15	11	kink 2 in the pipeline from st fergus to Goldeneye	Captain Saline Aquifer 2	2	4.44	1.93
11	10	Captain Saline Aquifer 2	Captain Saline Aquifer 1	2	3.80	1.00
10	12	Captain Saline Aquifer 1	Blake oil fields	2	2	0.88
2	1	Longannet Power Station	Peterhead Power Station	3	8.21	23.76
1	13	Peterhead Power Station	St Fergus terminal	3	8.21	1.31
13	14	St Fergus terminal	kink 1 in the pipeline from st fergus to Goldeneye	3	8.21	2.04
14	15	kink 1 in the pipeline from st fergus to Goldeneye	kink 2 in the pipeline from st fergus to Goldeneye	3	8.21	7.99
15	7	kink 2 in the pipeline from st fergus to Goldeneye	Goldeneye Gas Condensate Field	3	2.21	0.65
7	6	Goldeneye Gas Condensate Field	Britannia Saline aquifer block	3	1.00	0.46
15	11	kink 2 in the pipeline from st fergus to Goldeneye	Captain Saline Aquifer 2	3	6	1.62
11	10	Captain Saline Aquifer 2	Captain Saline Aquifer 1	3	6	0.98
10	9	Captain Saline Aquifer 1	Scapa Oil Field	3	4	3.41
10	12	Captain Saline Aquifer 1	Blake oil fields	3	2	0.54
2	1	Longannet Power Station	Peterhead Power Station	4	8.21	25.27

1	13	Peterhead Power Station	St Fergus terminal	4	9.30	1.57
13	14	St Fergus terminal	kink 1 in the pipeline from st fergus to Goldeneye	4	9.30	2.46
14	15	kink 1 in the pipeline from st fergus to Goldeneye	kink 2 in the pipeline from st fergus to Goldeneye	4	9.30	9.63
15	7	kink 2 in the pipeline from st fergus to Goldeneye	Goldeneye Gas Condensate Field	4	6	1.88
7	6	Goldeneye Gas Condensate Field	Britannia Saline aquifer block	4	6	2.97
6	8	Britannia Saline aquifer block	Britannia Condensate Field	4	6	4.86
15	11	kink 2 in the pipeline from st fergus to Goldeneye	Captain Saline Aquifer 2	4	3.30	0.95
11	10	Captain Saline Aquifer 2	Captain Saline Aquifer 1	4	3.30	0.57
10	9	Captain Saline Aquifer 1	Scapa Oil Field	4	2.58	2.33
10	12	Captain Saline Aquifer 1	Blake oil fields	4	0.73	0.21
2	1	Longannet Power Station	Peterhead Power Station	5	5.35	6.05
1	13	Peterhead Power Station	St Fergus terminal	5	5.35	0.33
13	14	St Fergus terminal	kink 1 in the pipeline from st fergus to Goldeneye	5	5.35	0.52
14	15	kink 1 in the pipeline from st fergus to Goldeneye	kink 2 in the pipeline from st fergus to Goldeneye	5	5.35	2.04
15	7	kink 2 in the pipeline from st fergus to Goldeneye	Goldeneye Gas Condensate Field	5	5.35	0.62
7	6	Goldeneye Gas Condensate Field	Britannia Saline aquifer block	5	5.35	0.97
6	8	Britannia Saline aquifer block	Britannia Condensate Field	5	5.35	1.60

The annual figures in table I-6 are equivalent nominal cash flows the accumulated net present value of which results in the same costs as calculated by the multi-period CCS model in GAMS.

Table I-6: CO_2 transportation network cash flow with a 15% IRR (2011-2050) – CNS multi-storage case [22]

Year	Annual operational transport cost (M£)	Annual capital cost(M£)	Royalty (M£)	Revenues (M£)	Net value
2014	-14.66	-293.08	-10.21	68.05	-249.89
2015	-14.66	0.00	-10.21	68.05	43.19
2016	-14.66	0.00	-10.21	68.05	43.19
2017	-14.66	0.00	-10.21	68.05	43.19
2018	-14.32	-16.71	-9.74	64.90	24.14
2019	-14.32	0.00	-9.74	64.90	40.85

2020	-14.32	0.00	-9.74	64.90	40.85
2021	-14.32	0.00	-9.74	64.90	40.85
2022	-14.32	0.00	-9.74	64.90	40.85
2023	-16.25	-50.85	-10.48	69.85	-7.72
2024	-16.25	0.00	-10.48	69.85	43.13
2025	-16.25	0.00	-10.48	69.85	43.13
2026	-16.25	0.00	-10.48	69.85	43.13
2027	-16.25	0.00	-10.48	69.85	43.13
2028	-20.36	-43.43	-11.87	79.13	3.47
2029	-20.36	0.00	-11.87	79.13	46.90
2030	-20.36	0.00	-11.87	79.13	46.90
2031	-20.36	0.00	-11.87	79.13	46.90
2032	-20.36	0.00	-11.87	79.13	46.90
2033	-20.36	0.00	-11.87	79.13	46.90
2034	-20.36	0.00	-11.87	79.13	46.90
2035	-20.36	0.00	-11.87	79.13	46.90
2036	-20.36	0.00	-11.87	79.13	46.90
2037	-20.36	0.00	-11.87	79.13	46.90
2038	-10.95	0.00	-6.83	45.51	27.73
2039	-10.95	0.00	-6.83	45.51	27.73
2040	-10.95	0.00	-6.83	45.51	27.73
2041	-10.95	0.00	-6.83	45.51	27.73
2042	-10.95	0.00	-6.83	45.51	27.73
2043	-10.95	0.00	-6.83	45.51	27.73
2044	-10.95	0.00	-6.83	45.51	27.73
2045	-10.95	0.00	-6.83	45.51	27.73
2046	-10.95	0.00	-6.83	45.51	27.73
2047	-10.95	0.00	-6.83	45.51	27.73
2048	-10.95	0.00	-6.83	45.51	27.73
2049	-10.95	0.00	-6.83	45.51	27.73
				IRR	0.15

0

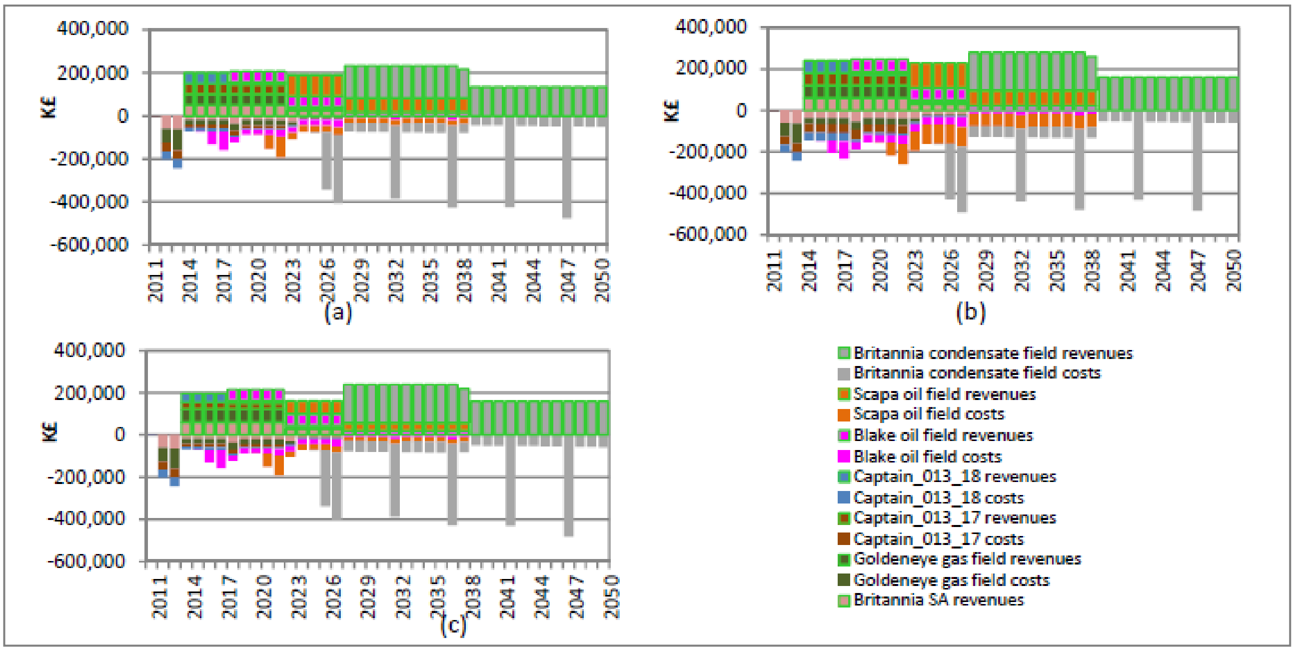


Figure I-1: (a) Open season leasing cash flow per storage site during the planning horizon (2011 to 2050); (b) Auctioning with reserve price leasing cash flow per storage site during the planning horizon (2011 to 2050); (c) Dependence on market conditions leasing cash flow per storage site during the planning horizon (2011 to 2050) [22]

Appendix J. Flexible stochastic CCS supply chain optimisation – UK case study

The supply chain nodes for the case study; UK CCS supply chain optimisation under carbon price uncertainty remains the same as that included in Appendix A. Specifications of each scenario k of stage s can be found in section 5.3.2 of this thesis. For specification of the pipeline segments referred to in table J-3, refer to appendix D.

Table J-1: CO_2 captured at each source for scenario k of stage s

i(number)	Source	K	s	CO_2 captured(Mt/year)
1	Drax Power Station	2	2	22.39
1	Drax Power Station	4	3	22.39
2	Longannet Power Station	4	3	9.13
3	Cottam Power Station	4	3	8.72
1	Drax Power Station	5	3	22.39
1	Drax Power Station	7	4	22.39
2	Longannet Power Station	7	4	9.13
3	Cottam Power Station	7	4	8.72
4	Ratcliffe on Soar power station	7	4	8.36
6	Fiddlers Ferry Power Station	7	4	5.22
8	West Burton Power Station	7	4	5.10
1	Drax Power Station	8	4	22.39
2	Longannet Power Station	8	4	9.13
3	Cottam Power Station	8	4	8.72
4	Ratcliffe on Soar power station	8	4	7.16
6	Fiddlers Ferry Power Station	8	4	6.43
8	West Burton Power Station	8	4	5.10
1	Drax Power Station	9	4	22.39
2	Longannet Power Station	9	4	7.92
3	Cottam Power Station	9	4	8.72
4	Ratcliffe on Soar power station	9	4	8.36
6	Fiddlers Ferry Power Station	9	4	6.43
8	West Burton Power Station	9	4	5.10
1	Drax Power Station	10	4	22.39
2	Longannet Power Station	10	4	7.92
3	Cottam Power Station	10	4	8.72
4	Ratcliffe on Soar power station	10	4	8.36
6	Fiddlers Ferry Power Station	10	4	6.43
8	West Burton Power Station	10	4	5.10

Table J-2: CO_2 stored at each sink for scenario k of stage s

i(number)	Sink	k	s	CO_2 stored(Mt/year)
20	Morecambe South	2	2	22.39
20	Morecambe South	4	3	40.23
20	Morecambe South	5	3	22.39
20	Morecambe South	7	4	10.98
22	Hewett L Bunter	7	4	33.58
24	Morecambe North	7	4	14.35
20	Morecambe South	8	4	10.98
22	Hewett L Bunter	8	4	33.58
24	Morecambe North	8	4	14.35
20	Morecambe South	9	4	28.82
22	Hewett L Bunter	9	4	30.09
20	Morecambe South	10	4	28.82
22	Hewett L Bunter	10	4	30.09

Table J-3: CO_2 transported from node i to node j for scenario k of stage s

i	Node Name (i)	j	Node Name (j)	l (pipeline segment)	Scenario k	Stage s	CO_2 flow Mt/year
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	2	2	22.392
45	Between Carnfoth and Hornsea	31	Carnforth	2	2	2	22.392
31	carnforth	20	Morecambe South	2	2	2	22.392
3	Cottam Power Station	8	West Burton Power Station	1	4	3	8.715
8	West Burton Power Station	7	Scunthorpe Iron & Steel	3	4	3	8.715
7	Scunthorpe Iron & Steel	1	Drax Power Station	2	4	3	8.715
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	4	3	31.108
45	Between Carnfoth and Hornsea	31	Carnforth	2	4	3	31.108
2	Longannet Power Station	53	Bathgate	1	4	3	9.125
53	Bathgate	30	Moffat	2	4	3	9.125
30	Moffat	50	between moffat and carnforth	2	4	3	9.125
5	between moffat and carn-	3	Carnforth	2	4	3	9.125

0	forth	1					
31	carnforth	20	Morecambe South	2	4	3	40.232
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	5	3	22.392
45	Between Carnfoth and Hornsea	31	Carnforth	2	5	3	22.392
31	carnforth	20	Morecambe South	2	5	3	22.392
4	Ratcliffe on Soar power station	3	Cottam Power Station	2	7	4	8.363
3	Cottam Power Station	8	West Burton Power Station	1	7	4	17.078
8	West Burton Power Station	7	Scunthorpe Iron & Steel	3	7	4	22.174
1	Drax Power Station	7	Scunthorpe Iron & Steel	2	7	4	11.404
7	Scunthorpe Iron & Steel	17	Immingham CHP	2	7	4	33.577
17	Immingham CHP	48	Easington	2	7	4	33.577
48	Easington	26	West sole	3	7	4	33.577
26	West sole	28	Barque	2	7	4	33.577
28	Barque	27	Galleon	2	7	4	33.577
27	Galleon	22	Hewett L Bunter	2	7	4	33.577
2	Longannet Power Station	53	Bathgate	1	7	4	9.125
53	Bathgate	30	Moffat	2	7	4	9.125
30	Moffat	50	between moffat and carnforth	2	7	4	9.125
50	between moffat and carnforth	31	carnforth	2	7	4	9.125
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	7	4	10.989
45	Between Carnfoth and Hornsea	31	carnforth	2	7	4	10.989
6	Fiddlers Ferry Power Station	32	Warrington	1	7	4	5.221
3	Warrington	3	carnforth	1	7	4	5.221

2		1					
31	carnforth	20	Morecambe South	2	7	4	25.334
20	Morecambe South	24	Morecambe North	1	7	4	14.351
3	Cottam Power Station	8	West Burton Power Station	1	8	4	8.715
4	Ratcliffe on Soar power station	8	West Burton Power Station	1	8	4	7.159
1	Drax Power Station	7	Scunthorpe Iron & Steel	2	8	4	12.608
8	West Burton Power Station	7	Scunthorpe Iron & Steel	3	8	4	20.97
7	Scunthorpe Iron & Steel	33	hatton	2	8	4	33.557
33	hatton	49	Between Peterborough and Hatton	2	8	4	33.577
49	Between Peterborough and Hatton	36	Wisbech	2	8	4	33.577
36	Wisbech	46	Bacton	3	8	4	33.577
46	Bacton	22	Hewett L Bunter	2	8	4	33.577
2	Longannet Power Station	53	Bathgate	1	8	4	9.125
53	Bathgate	30	Moffat	2	8	4	9.125
30	Moffat	50	between moffat and carnforth	2	8	4	9.125
6	Fiddlers Ferry Power Station	32	Warrington	1	8	4	6.425
32	Warrington	31	carnforth	2	8	4	6.425
50	between moffat and carnforth	31	carnforth	2	8	4	9.125
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	8	4	9.785
45	Between Carnfoth and Hornsea	31	carnforth	2	8	4	9.785
31	carnforth	20	Morecambe South	2	8	4	25.334
20	Morecambe South	24	Morecambe North	1	8	4	14.351
8	West Burton Power Station	3	Cottam Power Station	1	9	4	5.095

4	Ratcliffe on Soar power station	3	Cottam Power Station	1	9	4	8.363
3	Cottam Power Station	33	hatton	2	9	4	22.174
1	Drax Power Station	7	Scunthorpe Iron & Steel	2	9	4	7.915
7	Scunthorpe Iron & Steel	33	hatton	2	9	4	7.915
33	hatton	36	Wisbech	3	9	4	30.089
36	Wisbech	46	Bacton	3	9	4	30.089
46	Bacton	22	Hewett L Bunter	2	9	4	30.089
1	Drax Power Station	45	Between Carnfoth and Hornsea	3	9	4	14.477
45	Between Carnfoth and Hornsea	31	carnforth	2	9	4	14.477
2	Longannet Power Station	53	Bathgate	1	9	4	7.921
53	Bathgate	30	Moffat	2	9	4	7.921
30	Moffat	50	between moffat and carnforth	2	9	4	7.921
50	between moffat and carnforth	31	carnforth	2	9	4	7.921
6	Fiddlers Ferry Power Station	32	Warrington	1	9	4	6.425
32	Warrington	31	carnforth	3	9	4	6.425
31	carnforth	20	Morecambe South	2	9	4	28.823
8	West Burton Power Station	3	Cottam Power Station	2	10	4	5.095
4	Ratcliffe on Soar power station	3	Cottam Power Station	1	10	4	8.363
3	Cottam Power Station	7	Scunthorpe Iron & Steel	3	10	4	22.174
1	Drax Power Station	7	Scunthorpe Iron & Steel	3	10	4	7.915
7	Scunthorpe Iron & Steel	33	hatton	2	10	4	30.089
33	hatton	36	Wisbech	3	10	4	30.089
3	Wisbech	4	Bacton	2	10	4	30.089

6		6					
46	Bacton	22	Hewett L Bunter	2	10	4	30.089
1	Drax Power Station	45	Between Carnfoth and Horn-sea	3	10	4	14.477
45	Between Carnfoth and Horn-sea	31	carnforth	2	10	4	14.477
6	Fiddlers Ferry Power Station	32	Warrington	1	10	4	6.425
32	Warrington	31	carnforth	1	10	4	6.425
2	Longannet Power Station	53	Bathgate	1	10	4	7.921
53	Bathgate	30	Moffat	2	10	4	7.921
30	Moffat	50	between moffat and carn-forth	1	10	4	7.921
50	between moffat and carn-forth	31	carnforth	1	10	4	7.921
31	carnforth	20	Morecambe South	2	10	4	28.823

Table J-4: Contribution of CCS and carbon credits in achieving the reduction target for each scenario

Reduction target (Mt/year)	Stage (s)	Scenario (k)	Amount captured (Mt)	% CCS	Carbon credits (Mt)	% Carbon credits
23.56	1	1	0	0	23.56	100
28.61	2	2	22.39	78	6.22	22
28.61	2	3	0	0	28.61	100
42.08	3	4	40.23	96	1.85	4
42.08	3	5	22.39	53	19.69	47
42.08	3	6	0	0	42.08	100
58.91	4	7	58.91	100	0	0
58.91	4	8	58.91	100	0	0
58.91	4	9	58.91	100	0	0
58.91	4	10	58.91	100	0	0
58.91	4	11	0	0	58.91	100

Table J-5: Evolution of carbon price and the role of CCS vs. Carbon credits throughout the four stages for each potential pathway K7 to K11

Scenario K	Carbon price(Eur/tonne)	% CCS	% credits
1	16.44	0	100
2	54.8	78	22
4	72.61	96	4
K7	208.24	100	0

K	Carbon price(Eur/tonne)	% CCS	% credits
1	16	0	100
2	55	78	22
4	73	96	4
K8	137	100	0

k	carbon price(Eur/tonne)	% CCS	% credits
1	16.44	0	100
2	54.8	78	22
5	36.99	53	47
K9	208.24	100	0

k	Carbon price(EUR/tonne)	% CCS	% credits
1	16.44	0	100
2	54.8	78	22
5	36.99	53	47
K10	137	100	0

k	Carbon price (EUR/tonne)	% CCS	% credits
1	16.44	0	100
3	0	0	100
6	0	0	100
K11	0	0	100

Table J-6: Evolution of cost of CCS vs. Cost of carbon credits throughout the four stages for each potential pathway K7 to K11 respectively

Scenario k	Cost of credits (M$)	Cost of CCS (M$)
1	387.40	0
2	1704.76	9002.17
4	1341.61	15913.09
K7	0	20721.501

Scenario k	Cost of credits (M$)	Cost of CCS (M$)
1	387.403	0
2	1704.764	9002.167
4	1341.611	15913.088
K8	0	20546.249

Scenario k	Cost of credits (M$)	Cost of CCS (M$)
1	387.403	0
2	1704.764	9002.167
5	7282.331	5425.474
K9	0	22774.567

Scenario k	Cost of credits (M$)	Cost of CCS (M$)
1	387.403	0
2	1704.764	9002.167
5	7282.331	5425.474
K10	0	22799.854

Scenario k	Cost of credits (M$)	Cost of CCS (M$)
1	387.403	0
3	0	0
6	0	0
K11	0	0