CORA Cork Open Research Archive
Cartlann Taighde Oscailte Chorcaí

Title	Modelling sustainable energy and the implications for policy
Authors	Clancy, John Matthew
Publication date	2018
Original Citation	Clancy, J. M. 2018. Modelling sustainable energy and the implications for policy. PhD Thesis, University College Cork.
Type of publication	Doctoral thesis
Rights	© 2018, Matthew Clancy. - http://creativecommons.org/licenses/by-nc-nd/3.0/
Download date	2026-11-04 17:06:34
Item downloaded from	https://hdl.handle.net/10468/7331



UCC
University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

Modelling sustainable energy and the implications for policy

John Matthew Clancy



National University of Ireland

School of Engineering

Thesis submitted for the degree of Doctor of Philosophy

June 2018

Supervisors: Professor Brian P. Ó Gallachóir (UCC), Dr. John Curtis (ESRI)

Head of School: Prof. Liam Marnane

Contents

Declaration viii

Acknowledgements ix

Executive Summary x

Units and Abbreviations xi

List of Tables xiv

List of Figures xv

Chapter 1 17

Introduction

1.1. Background 17

1.2. Purpose of thesis 19

1.3. Methodology 21

1.3.1. Power system simulation 22

1.3.2. Mixed-methods simulation of bioenergy and renewable heat policy 23

1.3.3. Empirical analysis 24

1.4. Thesis in brief 24

1.4.1. Part I – power system modelling 24

1.4.2. Part II – Mixed-method simulation of bioenergy and renewable heat policy 25

1.4.3. Part III – Empirical analysis 25

1.5. Role of collaborations 26

1.6. Thesis outputs 27

1.6.1. Journal papers 27

1.6.2. Conference proceedings 28

1.6.3. Invited talks and presentations 28

Part I – Power Systems Modelling 29

Chapter 2 30

Reduction of CO_2 emissions due to wind energy – methods and issues in estimating operational emission reductions

Abstract 30

2.1. Introduction 31

2.2. Methodologies for estimating CO_2 reductions 31

2.2.1. Displacement estimation 32

2.2.2. Empirical statistical methods applied to historical data (econometric methods) 33

2.2.3. Detailed simulation: dispatch models 33

2.2.4. Detailed simulation: generation expansion models with dispatch models 35

2.3. Examples of methodology implementation 35

2.3.1. Displacement estimation 35

2.3.2. Empirical statistical methods for historical data (Econometric methods) 36

2.3.3. Detailed simulation: dispatch models 37

2.3.4. Detailed simulation: generation expansion models with dispatch models 39

2.4. Discussion and conclusions 39

Chapter 3 42

Fossil-fuel and CO_2 emissions savings on a high-renewable electricity system – a single-year case study for Ireland

Abstract 42

3.1. Introduction 43

3.2. Methods 46

3.2.1. The All-Island electricity system and market 46

3.3. Factors that influence fossil-fuel and CO_2 savings 48

3.3.1. Variability and uncertainty 48

3.3.2. Reserve 49

3.3.3. System flexibility 50

3.3.4. Generation mix, fossil-fuel/CO_2 prices and 'must run' units 51

3.3.5. Network constraints 51

3.3.6. Cross-border trade 52

3.4. Simulation methodology 52

3.4.1. Validated market model 53

3.4.2. Reserve, network constraints and non-synchronous limits 53

3.4.3. Interconnection 54

3.4.4. Renewable electricity generation 55

3.4.5. Electricity demand, generator outages and 'must run' units 55

3.4.6. Fuel prices 55

3.4.7. Dispatch decisions under uncertainty-simulation approach 56

3.4.8. PLEXOS software 56

3.5. Results and discussion 57

3.5.1. Model calibration 57

3.5.2. Overall fossil-fuel use and CO_2 savings 59

3.5.3. Impact of renewable generation on fossil-fuel generator operation and CO_2 production intensity 60

3.5.4. Network constraints 65

3.5.5. Seasonal CO_2 emissions 65

3.6. Conclusion and policy implications 66

Chapter 4 68

The short-run price and CO_2 impacts of using waste heat from CCGT generators for district heating on a high-renewable electricity system

Abstract 68

4.1. Introduction 69

4.2. Background 71

4.2.1. Energy cost of heat production in power generators – the Z-factor 71

4.2.2. Power and heat market interaction 72

4.2.3. Allocation of CHP fuel use to heat and power 74

4.3. Data and method 74

4.3.1. Dispatch model 75

4.3.2. Dublin heat demand 77

4.3.3. The Irish electricity system 78

4.3.4. Generation capacity and electricity demand 78

4.3.5. Heat demand and heat network 79

4.3.6. CCGT-CHP retrofits 79

4.3.7. Fuel and CO_2 prices 81

4.4. Results 82

4.4.1. Electricity and heat prices 82

4.4.2. Impact of prices changes 86

4.4.3. Impact of electricity trade 89

4.4.4. Industry perspective 90

4.5. Discussion 91

4.6. Conclusion 93

Part II – Mixed-method simulation of bioenergy and renewable heat policy 95

Chapter 5 96

BioHEAT: A policy decision support tool in Ireland's bioenergy and heat sectors

Abstract 96

5.1. Introduction 97

5.2. Method 101

5.2.1. Cost of bioenergy pathways 103

5.2.2. Least-cost way to meet demand in Transport and Power sectors 106

5.2.3. Consumer investment behaviour to calculate uptake of heating technologies 108

5.2.4. Interaction between heat, power and transport sectors 111

5.2.5. Allocation of bioenergy resource over time 112

5.3. Data 112

5.3.1. Cost of bioenergy pathways 112

5.3.2. Least-cost way to meet demand in Transport and Power sectors 113

5.3.3. Consumer investment behaviour to calculate uptake of heating technologies 114

5.3.4. Fuel costs and emissions 119

5.4. Illustrative scenarios and results 119

5.4.1. Definition of Baseline, High-Power Sector Demand and Carbon Tax scenarios 120

5.4.2. Bioenergy resources used in the Baseline scenario 120

5.4.3. Impact of high bioenergy demand in Power on the Heat sector 124

5.4.4. Uptake of renewable heat technologies in the Baseline and Carbon Tax scenarios 125

5.5. Discussion 127

5.6. Conclusions 128

Chapter 6 130

Modelling national policymaking to promote bioenergy in heat, transport and electricity to 2030 – interactions, impacts and conflicts

Abstract 130

6.1. Introduction 131

6.2. Background 133

6.2.1. EU policy context 133

6.3. Drivers of policy in Ireland 133

6.3.1. Electricity sector 133

6.3.2. Heat sector 134

6.3.3. Transport sector 135

6.4. Methodology 135

6.4.1. BioHEAT techno-economic decision support model 135

6.4.2. Scenarios examined 137

6.5. Data 138

6.5.1. Biomass supply 138

6.6. Bioenergy demand 140

6.6.1. Power sector demand 140

6.6.2. Transport sector 140

6.6.3. Heat demand 141

6.6.4. Pathway costs 141

6.6.5. Fossil-fuel and carbon prices 142

6.7. Results 142

6.7.1. Renewable energy production 143

6.7.2. CO_2 emissions 147

6.7.3. CO_2 emissions outside of the ETS 148

6.7.4. Biomass resource use 150

6.7.5. Sensitivity analysis – fossil-fuel price and biomass availability 151

6.8. Discussion 152

6.8.1. Heat and power – policy implications 152

6.8.2. Transport sector – policy implications 154

6.9. Conclusions 154

Part III – Empirical analysis 156

Chapter 7 157

What are the factors that discourage companies in the Irish commercial sector from investigating energy-saving options?

Abstract 157

7.1. Introduction 158

7.2. Literature background 159

7.3. Data and methods..... 161

7.3.1. Data 161

7.3.2. Model.....165

7.4. Results 170

7.4.1. Fabric upgrade logit model result.....170

7.4.2. Behaviour change logit model results 174

7.5. Discussion..... 176

7.6. Conclusion 179

Chapter 8 182

Conclusions

8.1. Policy 183

8.2. Recommendations..... 188

8.3. Modelling 189

8.3.1. Power system modelling 189

8.3.2. Mixed-method simulation of bioenergy and renewable heat policy.....190

8.3.3. Empirical analysis 191

8.4. Limitations and further work 191

Bibliography.....193

Declaration

"This is to certify that the work I, John Matthew Clancy, am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism."

_____

Matthew Clancy

Acknowledgements

To my supervisors Prof. Brian Ó Gallachóir and Dr. John Curtis, thank you for the guidance, support and mentorship throughout the last four years. A special thanks Brian, for the encouragement to embark on this course of study and for your help throughout. Also, John, a special thanks for your co-supervision – being Dublin based, the time you volunteered to my study was essential to maintaining momentum in my work. In particular, I would like to acknowledge the encouragement you both offered through the trying times after the birth of my daughter – it was indispensable in allowing me to reach this stage. Thank you.

This research would not have been possible without the help of the Sustainable Energy Authority of Ireland. I am very grateful for the funding and support provided.

To my colleagues in the Energy Policy and Modelling Group in UCC thank you for the welcoming and generous culture I have experienced during my studies. In particular, I would like to thank my EPMG colleagues Fiac Gaffney, Paul Deane, Emma Hanley and Séan Collins for the help and collaboration. Similarly, to my colleagues in the Sustainability Authority of Ireland, especially in the Low Carbon Technologies team, thank you for your interest, support and help. A very special thanks to John McCann, Jim Scheer, Kevin O'Rourke, Martin Howley, Denis Dineen and Emer Cotter for the advice and data. It is a privilege to work with you all at the EPMG and at SEAI. Thanks also to Emrah Durusut, Sam Foster and Foaad Tahir for the collaboration on developing the BioHEAT model and to Hannele Holttinen for co-ordinating a conference paper with IEA Wind research task 25.

To the employees at the Economic and Social Research Institute, thanks for the hospitality and interesting conversation during the many Fridays I spent studying at your offices. Also, to the staff of the libraries of Dún Laoghaire-Rathdown thank you for the superb public service provision I experienced on the many Saturday's I used the facilities.

Finally, to my wife Elaine and to my children James and Grace, thank you for everything.

Executive Summary

The Paris Agreement sets out the collective ambition of the world's nations to prevent dangerous climate change. However, at national level across the world, there is a gap between action and the required rate of effort. Long-term models show technology pathways but governments must act to realise them. Long-term pathways are often based on a single aim – achieving a level of CO_2 reduction at least cost. Yet governments have wider objectives beyond climate mitigation. Economic competitiveness, wellbeing of citizens and employment also feature. This thesis approaches the modelling of sustainable energy from a policymaker's perspective. The aim is to improve the evidence base and inform policy development.

Showing citizens the impact of current policy helps governments to bring forth further support. These assessments can be difficult to implement. The first part of this thesis examines the emissions impact of existing renewable electricity policy. Several methods have been used to explore this question. This thesis applies a comprehensive method: an *ex-post* power system optimisation model. The purpose is to address questions raised about the effectiveness of wind power in reducing CO_2 emissions in Ireland. Using 2012 data, the modelling shows that renewable electricity saved 0.43 – 0.46 tCO_2/MWh. Power system modelling is also employed to examine the impact of using waste heat from power generation in heat networks. Linking heat and electricity sectors in this way affects both. The findings show that using waste heat is competitive and results in CO_2 savings in both sectors.

The second part of the thesis focuses on the challenge of developing coherent supports for bioenergy. A decision support tool that uses mixed methods simulates policy options in Ireland. The model incorporates least-cost use of bioenergy resources and a detailed representation of consumer decision-making in the heat sector. The results show that using domestic biomass resources in the power sector slows the uptake of renewable heat and hence diminishes the benefits of renewable heat policy. This has negative implications for national climate targets.

Many decarbonisation pathways need consumers to make sustainable energy decisions. Part three applies empirical methods to representative data from Ireland's commercial sector. Logistic regressions identify key factors that can help to target policy on the barriers faced by consumers. Tenants in business units that do not make investment decisions locally are 16 times less likely to investigate energy options. Other factors such as the approach to budgeting and knowledge of the building floor area are also important.

The primary contribution of this thesis is to provide evidence-based insights for policymaking in Ireland and beyond. The thesis also makes contributions to advancing modelling methods.

Units and Abbreviations

°C	Degrees Celsius
3G	3rd generation district heat network
4G	4th generation district heat network
AIP	All-Island Project
ASHP	Air-source heat pump
BEAM	Bioenergy Assessment Model
BEIS	Department for Business, Energy Industry & Industrial Strategy (UK)
BER	Building Energy Rating
Capex	Capital expenditure
CCGT	Combined-cycle gas turbine
CCGT-CHP	Combined-cycle gas turbines with combined heat and power capabilities
CDM	Clean development mechanisms
CER	Commission for Energy Regulation
CHP	Combined heat and power
CO_2	Carbon dioxide
COP	Conference of Parties
CRU	Commission for Utility Regulation
CSO	Central Statistics Office
DCCAE	Department of Communications, Climate Action and Environment
DCENR	Department of Communications, Energy and Natural Resources
DEAP	Dwellings Energy Assessment Procedure
DECC	Department of Energy and Climate Change (UK)
EC	European Commission
ECN	Energy Research Centre of the Netherlands
EEA	European Environment Agency
EED	Energy Efficiency Directive
EPA	Environmental Protection Agency
ESB	Electricity Supply Board
ETS	Emissions Trading Scheme
ETSAP	Energy Technology Systems Analysis Program
EU	European Union
EWEA	The European Wind Energy Association
EWIC	East-West Interconnector
GB	Great Britain
GHG	Greenhouse gas
GJ	Giga joule
GLOBIOM	Global Biomass Optimisation Model
GSHP	Ground-source heat pump
GWh	Giga watt hour
HRES	High Renewable Electricity System
IEA	International Energy Agency
ILUC	Indirect Land Use Change
INDC	Intended Nationally Determined Contributions

IP	Intermediate pressure
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
LCOE	Levelised Cost of Energy
LFG	Landfill gas
LIEN	Large Industry Energy Network, a voluntary grouping facilitated by SEAI
Logit	Logistic model
LOLE	Loss of Load Expectation
LP	Low pressure
MAPE	Mean Average Percentage Error
MDT	Minimum Down Time
MIP	Mixed Integer Programming
MSL	Minimum Stable Level
MUT	Minimum Up Time
MW_e	Megawatt of electrical capacity
MWh	Megawatt hours
MW_{th}	Megawatt of thermal capacity
NCM	National Calculation Methodology
NCV	Net Calorific Value
ND-BER	Non-Domestic Building Energy Rating
NIAUR	Northern Ireland Authority for Utility Regulation
NMAE	Normalised Mean Absolute Error
non-ETS	Non-Emissions Trading Scheme
NORA	National Oil Reserves Agency
NREAP	National Renewable Energy Action Plan
NREL	National Renewable Energy Laboratory
OCGT	Open-cycle gas turbines
Opex	Annual operating expenditure
OR	Odds ratio
PEE	Primary Energy Equivalent
PES	Primary Energy Standard
pr	Marginal probability
RE	Renewable energy
RES	Renewable Share in Gross Final Consumption of Energy
RES-E	Renewable Share in Electricity
RES-H	Renewable Share in Heat
RES-T	Renewable Share in Transport
ROI	Republic of Ireland
RQ	Research question
SBEM	Simplified Building Energy Model
se	Standard error
SEAI	The Sustainable Energy Authority of Ireland
SEM	Single Electricity Market
SEMC	Single Electricity Market Committee
SEMO	Single Electricity Market Operator
SME	Small and medium enterprises

SNSP	Synchronous non-synchronous penetration
SONI	System Operator of Northern Ireland
SRMC	Short-Run Marginal Cost
SSRH	Support Scheme for Renewable Heat
TSO	Transmission System Operator
TIAM	Times Integrated Assessment Model
UCO	Used Cooking Oil
UK	United Kingdom of Great Britain and Northern Ireland
UNFCC	United Nations Framework Convention on Climate Change
US	United States of America
WSHP	Water-source heat pump
WtE	Waste to energy
WTP	Willingness to pay
Z-Factor	Ratio of electricity lost to heat produced for a generator in CHP mode

List of Tables

Table 3-1: EU member states' binding renewable targets (RES), and proportion of electricity demand planned to come from renewable electricity (RES-E) (ECN, 2011) 44

Table 3-2: Demand, wind generation output and net load variability at various time intervals in 2012 49

Table 3-3: Quarterly fuel and CO_2 prices for 2012 56

Table 4-1: Technical details and retrofit adjustments for CCGT units 81

Table 4-2: Fuel and CO_2 price assumptions 82

Table 4-3: Gas prices, excluding network costs, for residential and business customers 82

Table 4-4: Average short-run costs of CCGT & CCGT-CHP units and shadow prices for heat and electricity (all scenarios) 83

Table 4-5: Average short-run costs of CCGT and CCGT-CHP units and shadow price of heat and electricity with no interconnection (all scenarios) 89

Table 5-1: Resources included in the BioHEAT model 104

Table 5-2: Existing energy production from technology pathways 116

Table 5-3: Existing uptake of renewable heat technologies 116

Table 5-4: Fraction of laggards in BioHEAT 118

Table 6-1: Summary of scenarios examined 138

Table 6-2: Power generation key technical parameters (Baringa for CRU, 2016) 140

Table 6-3: Details of tariffs offered under the support scheme for renewable heat 141

Table 6-4: Renewable shares overall and in each end-use sector as compared to Baseline in 2030 144

Table 6-5: Cumulative non-ETS emissions in each scenario compared to the Baseline and the contribution to the estimated gap to target 149

Table 6-6: Conversion efficiency in each scenario (GWh/PJ) 151

Table 7-1: Number of buildings by commercial activity 162

Table 7-2: Summary of survey data by variable and by business activity 163

Table 7-3: Reasons given for not investigating energy efficiency upgrade, number of responses 165

Table 7-4: Information collected in commercial sector attitudes survey 169

Table 7-5: Logit regression with odds ratios of likelihood of having investigated a fabric upgrade 170

Table 7-6: Results of logit regression on likelihood of company to not provide a response to question on floor area 173

Table 7-7: Logit odds ratios for likelihood of a company investigating a behaviour change 174

List of Figures

Figure 1-1: Results from the Stanford Energy Modelling Study (EMF) - EMF27 450 Full Tech Scenario from TIAM World 2012 model (Kriegler et al., 2014) 18

Figure 2-1: Emission reductions of wind power in Ireland according to different methodologies (green), compared to estimates for North America (blue) 40

Figure 3-1: All-Island electricity system capacities in 2012, by fuel (MW) 47

Figure 3-2: Model details and input assumptions overview 53

Figure 3-3: Share of fossil-fuel generation by type, actual 2012 data and model simulation predictions 58

Figure 3-4: Fossil-fuel and CO_2 emissions savings by fuel source. 60

Figure 3-5: Online hours per start-up for fossil-fuel generators in the 2012 Base Model and scenarios 61

Figure 3-6: Average number of ramps per day and ramp intensity by fossil-fuel generation technology, 2012 Base Model and scenarios 62

Figure 3-7: Online capacity factor of fossil-fuel generators as % of available output, 2012 Base Model and scenarios 63

Figure 3-8: CO_2 production intensity by fossil-fuel generation type, 2012 Base Model and scenarios 64

Figure 3-9: All-Island system CO_2 production intensity, 2012 Base Model and scenarios 64

Figure 3-10: Total quarterly CO_2 emissions and CO_2 emissions intensity, 2012 Base Model and scenarios 66

Figure 4-1: Price dynamics for CHP feeding a DH network (illustrative) 73

Figure 4-2: Linear heat density of Dublin City – MWh/km (Sustainable Energy Authority of Ireland, 2016a) 77

Figure 4-3: Price duration curve for heat price (all scenarios) 84

Figure 4-4: Electricity market prices by component (€/MWh_e) 85

Figure 4-5: Price and heat output interactions for sample week for 3G Scenario in 2030 86

Figure 4-6: Load duration curves for coal generation and gas CCGT generation in Baseline and 3G scenarios 87

Figure 4-7: CO_2 emissions; scenarios relative to Baseline for electricity and heat ($ktCO_2$) 88

Figure 4-8: Emissions intensity of electricity production (tCO_2/GWh_e) 89

Figure 4-9: CO_2 emissions for scenarios relative to Baseline for electricity and heat production with no interconnection ($ktCO_2$) 90

Figure 4-10: Total revenues pre and post upgrade for CCGT units 91

Figure 5-1: BioHEAT model diagram 103

Figure 5-2: Bioenergy pathways in BioHEAT. 104

Figure 5-3: Illustration of the consumer decision-making process 109

Figure 5-4: Heating demand by sector and fuel type in BioHEAT for 2016 (final energy) 116

Figure 5-5: Willingness-to-pay curves used in BioHEAT.....118

Figure 5-6: Bioenergy resource used in all sectors (Baseline scenario).....120

Figure 5-7: Bioenergy resource used for Power (Baseline scenario) 121

Figure 5-8: Electricity demand met by bioenergy in Power in 2030.....121

Figure 5-9: Bioenergy resource used in Heat (Baseline scenario) 122

Figure 5-10: Utilisation of key bioenergy resources in Heat over time (Baseline scenario) 123

Figure 5-11: Proportion of counterfactual fuel replaced by each bioenergy resource type (Baseline scenario) 124

Figure 5-12: Bioenergy in Power in 2020 – comparison of Baseline and high co-firing sensitivity124

Figure 5-13: Bioenergy in Heat in 2020 – comparison of Baseline and high co-firing sensitivity..125

Figure 5-14: Number of installations 2018-2030 by sector and technology 126

Figure 5-15: Total investment to 2030 by sector and technology (undiscounted) 126

Figure 5-16: Cumulative CO_2 savings to 2030 by technology 127

Figure 6-1: Imported biomass availability 139

Figure 6-2: Biomass fuel use for each end-use sector in the Baseline (GWh primary) 143

Figure 6-3: Renewable output in each end-use sector compared to the Baseline (GWh) 144

Figure 6-4: Difference in renewable heat output by sector as compared to the Baseline – all scenarios (GWh) 145

Figure 6-5: Difference in renewable heat output by technology as compared to the Baseline – all scenarios (GWh) 146

Figure 6-6: Difference in fuel replaced by renewable technologies in the heat sector as compared to the Baseline (GWh primary) 147

Figure 6-7: Cumulative CO_2 emissions impacts in each scenario for each end-use sector ($MtCO_2$) 148

Figure 6-8: Cumulative CO_2 emissions impact in each policy scenario for ETS and non-ETS sectors ($ktCO_2$).....150

Figure 6-9: Resource use by sector in each scenario (GWh primary).....151

Figure 7-1: Primary and final energy in the Irish commercial sector by building activity (Element Energy and The Research Perspective for SEAI, 2015a) 162

Figure 7-2: Maximum time an energy efficiency measure must pay back in, by business activity164

Figure 7-3: Marginal probability of fabric investigation at each year of acceptable PAYBACK by tenure and by decision-making responsibility of the respondent.....171

Figure 7-4: Marginal probabilities by company ACTIVITY of investigating a fabric upgrade (95% interval).....172

Figure 7-5: Marginal probabilities by company ACTIVITY and BUDGET approach of investigating a behaviour change measure (95% interval) 175

Chapter 1

Introduction

1.1. Background

The Paris Agreement, negotiated by representatives of 196 parties and adopted on the 12th of December 2015, is an agreement setting out the global political response to dangerous climate change. It deals with adaptation, mitigation and finance. A headline aim of the agreement is to hold the global average temperature increase to "well below 2^0C", as compared to pre-industrial levels, and to pursue efforts to limit the temperature increase to less than 1.5^0C (UNFCCC, 2016). The production and use of energy has contributed substantially to the problem of climate change, accounting for an estimated two-thirds of global greenhouse-gas (GHG) emissions (IEA, 2017a). Solutions will involve the decarbonisation of the energy system. Figure 1-1 shows an optimistic pathway arising from analysis carried out with the World Times Integrated Assessment Model (TIAM). The scenario shown is optimistic about technological developments such as the ability of energy systems to integrate large amounts of wind and solar, the development of carbon capture and storage technologies, and the availability of biomass resources to produce bioenergy. Long-term modelling of decarbonisation ambitions, such as the TIAM analysis, show challenging pathways characterised by radical changes in how we produce and consume energy (IPCC, 2015; Kriegler et al., 2014). The decarbonisation pathways suggested by the different modelling analyses vary but tend to agree on fundamental points, including: the longer mitigation measures are delayed, the more onerous the task of meeting the ambition of the Paris Agreement; and the current nationally determined commitments fall significantly short of the required trajectories (Rogelj et al., 2016).

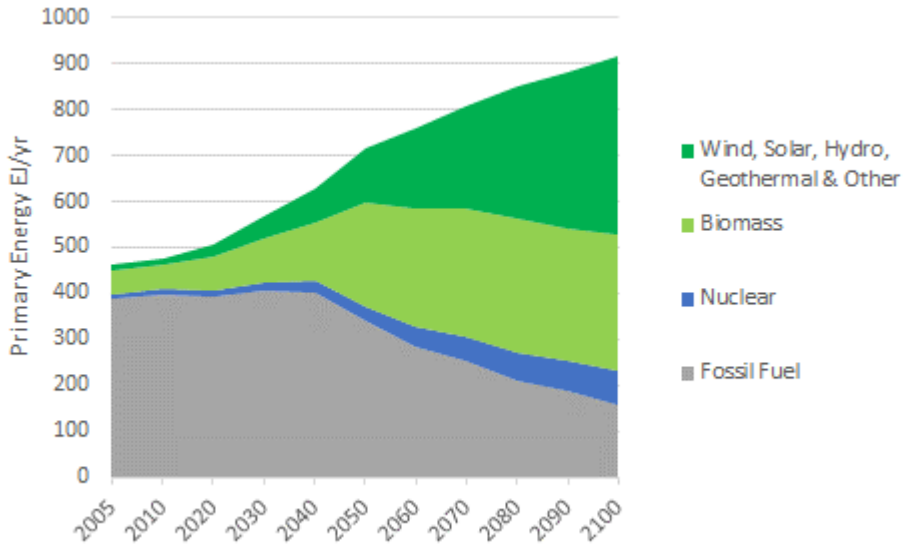


Figure 1-1Results from the Stanford Energy Modelling Study (EMF) - EMF27 450 Full Tech Scenario from TIAM World 2012 model (Kriegler et al., 2014)

Intended Nationally Determined Contributions (INDCs) are the pledges made by countries stating their plans to combat climate change (UNFCCC, 2015a). All countries that signed the United Nations Framework Convention on Climate Change (UNFCCC) were asked to publish INDCs ahead of the 2015 United Nations Convention on Climate Change Conference. Much of the GHG emissions reduction set out in the INDCs do not have specific national policies currently in place to deliver on the pledges. For example, the EU's pledge to reduce emissions by 40% by 2030 first requires negotiation of individual member-state targets to share the effort of achieving the cuts and then that each member state implement policies to deliver them (Fragkos et al., 2017).

In most cases, long-term modelling efforts focus on a single objective: to minimise the costs of achieving the required reductions in GHG emissions (IEA, 2017a; IPCC, 2015; Rogelj et al., 2015). But policy is made at national or regional levels and governments must consider several other factors, including: social acceptance, employment, economic competitiveness, other exchequer spending priorities, long-term lock-in of public funds, energy security, and energy costs. From a government's perspective, a sustainable energy system is one that delivers on a broad set of these priorities.

Like other advanced economies, Ireland faces challenges to decarbonise the energy system. Ireland's energy system continues to rely on fossil-fuel - 92% of the 604 PJ used in 2016 came from fossil fuels (Howley and Holland, 2016a). At present renewable energy sources supply 49 PJ (8%) of the energy used in Ireland and the increased deployment of renewable technologies and fuels in recent years has helped reduce the fossil-fuel share from 96% in 2005. Unlike other advanced economies, the largest single source of emissions is the agriculture sector (EPA, 2017a). Maintaining activity in the agriculture sector places an extra burden on the energy sector to decarbonise. Relative to other countries, Ireland's total GHGs are small but, on a per capita basis, they totalled 12.9 tCO_2 in 2016, the third

highest of the member countries of the European Union (EU) (EPA, 2017a). Emissions have been on an increasing trajectory; the most recent inventory numbers recorded a 2.1% increase in 2016 with annual emissions rising from 59.43 $MtCO_2$ in 2015 to 61.55 $MtCO_2$ in 2016 (EPA, 2017a). Projections that model the policy currently in place to halt this trend shows the demand for energy supplied by fossil-fuels continuing to increase, reaching 696 PJ in 2030 (SEAI, 2017a).

In spite of this, there have been some notable policy success. In recent years, Ireland has moved up the rankings world for wind-energy penetration and now is 2nd in the world for wind output as a proportion of electricity demand (IEA Wind, 2017). The deployment of high amounts of wind on a small island with a synchronous electricity system has brought about operational, market and other innovations that lead the way internationally and act as a blueprint for those electricity systems now reaching higher levels of electricity production from variable renewable sources. This has helped to move Ireland towards the mandatory renewable energy targets for 2020 and also to reduce Ireland's dependence on imported fossil fuels (SEAI, 2016). But the electricity sector is covered by the EU emissions trading scheme (ETS), so this progress does not contribute to Ireland's legally enforceable climate obligations under the European Union's effort-sharing agreement (EC, 2009). Emissions and energy projections show that Ireland is likely to fall short of national targets and EU obligations for 2020 (EPA, 2017b). Ireland is expected to reduce non-ETS emissions by 4%-6% by 2020, but the target is to reduce by 20%, as compared to the quantity of greenhouse gases emitted in 2005. This leaves the country's exchequer exposed to the costs of purchasing compliance, penalties and fines.

To meet the INDC commitment, the EU must reduce emissions by at least 40% by 2030. The burden of this will be shared among member countries. Under the effort-sharing proposal, Ireland must reduce non-ETS GHG emissions by 30% as compared to 2005 (European Parliament, 2017). Long-term modelling efforts at a global and national level show potential pathways to adequate GHG emissions reductions (Chiodi et al., 2013b; IPCC, 2015). There are many different technological and behavioural options available but, to make the decarbonisation pathways a reality, evidence-based analysis and analytical decision tools that consider consumer behaviour and the interactive effects of policy have key roles.

1.2. Purpose of thesis

The aim of this thesis is to provide insights and evidence, based on transparent methods, to inform policy decisions as well as the wider social debate on the options to decarbonise energy. The thesis also contributes innovative new approaches to energy modelling, with a specific focus on the perspective of the policymaker. A number of different methods are applied to deliver the analysis, and these are discussed in more detail in the next section.

Four research questions are addressed. First, the effectiveness of existing policy is a key factor in helping to inform future policymaking and, perhaps more

importantly, to establish the credibility of policy interventions to support the energy transition in general. While the transition to a low-carbon system creates opportunities for industry and communities, existing interests will be negatively affected. Voter perception of the value for money achieved in the past may well influence future policy direction. In this context, it is important that the evidence relating to policy impacts is established in a methodologically sound and transparent way. As opposition to infrastructure and the deployment of wind farms has increased, questions have been raised about the credibility of the estimated savings (Wheatley, 2013). Ireland has had early success in the deployment of wind generation but local opposition is a feature of the policy debate. The first research question is motivated by this Irish context and explores the impact of renewable electricity generation of fossil-fuel displacement and CO_2 reduction in two parts:

RQ1 (a): What are the methods available to assess the GHG emissions savings contribution of renewable electricity generation?

RQ1 (b): What fossil fuel and GHG emissions savings impacts have resulted from the renewable power generation currently deployed in Ireland?

Secondly, the infrastructure required to enable energy system decarbonisation is frequently assessed within the boundaries of the electricity, heat or transport system in which it is deployed. In many cases, the impacts of the infrastructure choices affect emissions across end-use sectors. The second research question looks at the impacts of using waste heat from existing power generators in district heating networks on energy prices and CO_2 emissions in the heat and power sectors. The impacts of high penetrations of renewable electricity generation on these factors are also explored. The research question is motivated by need to understand the broader implications of energy system infrastructure investments that couple end-use sectors – in this case the heat and electricity sectors.

RQ2: What are the short-run price and CO_2 impacts of using waste heat from CCGT generators for district heating on a high-renewable electricity system?

Thirdly, long-term pathways show an important role for bioenergy in decarbonising the energy system. Unlike energy efficiency and energy technologies that rely on ambient sources of power like the wind and sun, bioenergy generation has extensive supply chains, and individual biomass feedstock can often be refined into separate products suitable for use in heat, power or transport sectors. In addition, government policy related to bioenergy is also concerned with aspects such as rural economic development, sustainability, employment, air quality and security of supply. Biomass resources are limited and the ability of the end-use sectors to compete for them is directly related to government policy choices. This means that bioenergy policy choice may have negative interactive effects. To understand these effects, models must represent bioenergy demand in heat, power and transport sectors. While demand in the power and transport sectors is largely influenced by investments by commercial actors in the energy sector – power stations and fuel refineries – demand for

bioenergy use in the heat sector is a more complicated picture. Heat sector consumers come from industry, services and residential viewpoints and require different services from heat production, and are primarily concerned with non-energy activities. To examine the policy options in the Irish context two research questions are addressed, motivated by the need to understand the implications of policy choices on energy-related CO_2 reductions – including the impact on CO_2 emissions that count towards national climate targets:

RQ3 (a): How can demand for bioenergy in the heat, power and transport sectors be represented in a decision support tool to aid policymaking?

RQ3 (b): What are the interactive and cumulative impacts of bioenergy policy options for the heat, transport and power sectors in Ireland?

Lastly, the energy transition will require policy developments that incentivise homeowners and businesses to choose low-carbon and energy-efficient options related to behavioural and technological choice. The reasons why the 'rational economic actor' assumption does not hold in practice is well documented and the barriers have been detailed. In many cases, financial support alone will not incentivise a change from the status quo (Sorrell, 2004). Policy packages that can address the circumstances faced by various market segments may perform better than broad financial incentives or mandates. The question for policymakers is how to identify the factors that are having the largest impact on consumer engagement with the energy transition. A survey of commercial businesses in Ireland comprises detailed data on attributes and attitudes in the sector that allows these factors to be investigated. The last research question addressed in this thesis is motivated by the need for policy makers to identify factors that prevent energy users from engaging with the low-carbon options available so more targeted and effective policy can be implemented.

RQ4: What are the factors that discourage commercial businesses from considering energy-related decisions?

1.3. Methodology

Pfenninger et al., in their assessment of the challenges faced by energy modelling, define four modelling paradigms and explore some challenges faced by energy modellers based on a comprehensive review of the energy modelling literature (Pfenninger et al., 2014). The categories defined are: optimisation models, simulation models, power system models, and qualitative and mixed-methods scenarios. The authors explore the challenges related to the resolution of time and space, balancing uncertainty and transparency, complexity and the integration of human behaviour. The various modelling approaches typically do not have representations of human behaviour; Pfenninger et al. identify this as a key emerging approach. Similarly, Horschig and Thrän reviewed modelling approaches for policymaking. They suggest that hybrid models can minimise the drawbacks of using a single approach and recommend that policymakers use several modelling approaches to examine a policy question and to determine a course of

action. They also point to the usefulness of using linking approaches to combine models to answer a broader set of questions (Horschig and Thrän, 2017). Bazilian et al. make the point that, while there are several models available to examine energy and other water, food and land-use questions, these are often focused on long-term policy research-orientated work rather than short-term applied policy decision support tools (Bazilian et al., 2011a).

The analysis presented in this thesis applies:

- *Ex-post* simulation of power system operation that incorporates simulation and optimisation methods to evaluate the emission reduction impact of renewable energy electricity generation;
- *Ex-ante* simulation of heat and power market interaction, enabled by district heating infrastructure, to examine the emissions impact;
- A mixed-methods simulation of the emissions impact of future bioenergy policy options, using a policy decision support tool that incorporates a detailed representation of consumer decision-making,
- And econometric methods to examine how consumer attributes influence energy-related decision-making.

1.3.1. Power system simulation

Power system models draw from optimisation and simulation modelling approaches. The technical detail and high temporal resolution of the models are defining features, as is the requirement to match supply and demand exactly in each simulation period. This type of modelling is widely used by utilities, regulators, policymakers and in academic studies. The models can examine production costs, electricity network flows, market pricing (including locational marginal pricing), maintenance scheduling, storage optimisation, impact of powerful market actors, and capacity investment and expansion. These models can typically be solved for a range of objectives such as the minimisation of production costs, network losses and emissions or the maximisation of renewable energy use. The modelling carried out in this thesis uses a production cost minimisation objective. For production cost studies, the objective function minimises system costs by dispatching a chronologically consistent, least-cost arrangement of generation units to meet demand across the time horizon.

The model used for the analysis in this thesis are based on publicly available information, validated and published by the market regulators on the island of Ireland. The model represents generator capabilities through constraints on maximum and minimum outputs, start-up times, minimum online and offline periods, and how quickly generators can change output. Constraints also define the capacities and losses on interconnector power lines and the maximum allowable instantaneous penetrations of variable renewable sources. The model contains information on: generator heat rates, forced outage rates and mean repair times, and start-up fuel requirements.

Software called PLEXOS is used for the analysis described in this thesis to address *RQ 1 (b)* and *RQ 2.* The PLEXOS software, developed by Energy Exemplar, is used by several utilities, market operators and system operators to examine power system questions. It is available free of charge to academic institutions. The model has high temporal resolution and allows the impact of uncertainty and the stochastic nature of some variables to be incorporated into simulation outcomes.

For *RQ 1(b),* a detailed model that approximates actual system operation is implemented. It incorporates forecast uncertainty for wind output and demand by using a multiple-stage unit commitment and dispatch approach. The first stage uses forecast data to decide on unit commitment; the second stage takes the initial conditions from stage one and then dispatches units under actual conditions. The model was implemented using historical data for a number of variables including network constraints, electricity demand, hydro output, fuel prices and power station availability.

For *RQ 2* the production costs and emissions impact are determined using a single-stage optimisation. Scenario and sensitivity analysis is used to explore the impact of investment in district heating infrastructure.

1.3.2. Mixed-methods simulation of bioenergy and renewable heat policy

A techno-economic model that combines cost-effective allocation of limited raw bioenergy resources in Ireland is developed to address *RQ3 (a)* and used to simulate policy impacts to explore *RQ 3 (b).* The model is mixed-methods in that it combines techno-economic modelling with a detailed representation of consumer decision-making.

The model represents the technical characteristics of various bioenergy production pathways, including the costs of transporting feedstock, producing and transporting refined fuels, and converting the energy into a useful form. The initial demand for bioenergy in the power and transport sectors is an exogenous input from other models. Bioenergy demand in the heat sector is based on uptake of heat technologies across the various combinations of consumer and building types. The available feedstocks are deployed though pathways in order of least cost until demand is met or until the cost of the pathway is greater than the market value of the energy produced.

The inclusion of the consumer decision-making aspect enhances the representation of technology uptake in the heat sector as factors beyond payback and cost are accounted for in consumer decisions. It also provides a more authentic representation of the impact of policy support.

Scenario and sensitivity analysis is used to determine the impact of various policy options as compared to a business-as-usual baseline. Scenario analysis can provide some insights within the range of variable uncertainty without overly compromising transparency or increasing the complexity. As this modelling is

focused on informing policy development and design, this approach was chosen to enhance the accessibility of the results to policymakers.

1.3.3. Empirical analysis

The use of econometric techniques can provide useful insights for policy design. Many energy policies are focused on incentivising consumers to make a technological change. At the industry, services and household level, the characteristics of individual consumers are likely to influence how they respond to policy interventions. Knowledge of the significance and magnitude of individual factors as well as the interactive effects of multiple factors can improve how policies are tailored and targeted to achieve larger impacts.

In *RQ 4* a logistic model is fitted to a statistically representative sample of Irish businesses in the commercial sector to examine energy retrofit decisions. The data set analysed has information on both building and business unit characteristics. The statistical representativeness of the underlying data allows population-wide conclusions to be inferred from the analysis. The logistic model estimates the probability that a business unit would consider energy investment options given the characteristics of that business and the characteristics of the building they operate from.

1.4. Thesis in brief

1.4.1. Part I – power system modelling

- **Chapter 2** – Review of methods to assess emissions impacts of wind energy (*RQ1 (a))*

  This chapter presents approaches for quantifying CO_2 reductions from wind power using different methodologies. The strengths and pitfalls in various methodological approaches are discussed. The chapter proposes appropriate methods to perform the calculations. Results for CO_2 emission reductions are shown from several countries.

- **Chapter 3** – Detailed *ex-post* simulation model of Ireland's electricity systems system to determine fossil-fuel and CO_2 reductions (*RQ 1 (b))*

  A detailed dispatch model is applied to *ex-post* data of the All-Island system for a single year. The influential factors for reductions in fossil-fuel and CO_2 emissions are considered. The findings show that each MWh of renewable electricity saves 0.43 tCO_2. The impact of altered running profiles for fossil-fuel units were found to be minor (<2%). Policy can affect several influential factors to maximise the savings achieved from renewable electricity.

- **Chapter 4** – Examination of the role of district heating in enabling emissions reductions and cost savings in the wider energy system (*RQ 2)*

High-resolution heat-demand profiles are estimated and included in a simulation model of electricity and heat systems. The heat demand can be met using heat from CCGTs retrofitted with CHP and storage capabilities. Heat revenue allows CCGT-CHPs to offset electricity production costs and increase capacity factors. Cumulative reductions of 3.5 $MtCO_2$ result – 44% in the heat sector and 56% in the electricity sector. While carbon prices are low, CCGT-CHP displaces some coal generation. The shadow price of electricity reduces by 4%, which increases power exports. Producing heat at CCGT-CHP units is competitive with gas boilers except at times of low electricity prices. More renewables lower the electricity price, reducing the competitiveness of heat production. Overall, the results are promising for the viability of CCGT-CHPs on high-renewable electricity systems.

1.4.2. Part II – Mixed-method simulation of bioenergy and renewable heat policy

- **Chapter 5** – Decision support tool to examine bioenergy policy trade-offs *(RQ 3 (a))*

A methodology for an integrated bioenergy and heat policy decision support tool is developed. The result is a techno-economic model with a novel representation of consumer decision-making in the heat sector. The method explores supply-chain competition from a policy perspective. Results for three high-level and indicative scenarios are examined to demonstrate the model functionality.

- **Chapter 6** – Implementation of the model to examine the interactive and cumulative impacts of a range of future scenarios for bioenergy policy in Ireland *(RQ 3 (b))*

Bioenergy policy options for the heat, power and transport sectors in Ireland are examined using the simulation model developed in Chapter 5. As national climate targets are helped most by renewable heat and transport, policy action in these areas is examined initially. The cumulative impact of further policy in the electricity sector is then explored. Policy supporting co-firing of biomass and peat is found to increase CO_2 emissions in the power and heat sectors. Increased demand for resources in the power sector slows the uptake of renewable heat. This is negative for national climate targets in EU countries. Increased use of advanced biofuels in Ireland is likely to depend on imports.

1.4.3. Part III – Empirical analysis

- **Chapter 7** – Identification of the factors that discourage business in the commercial sector from considering energy technology options (*RQ 4)*

Two Logit models are applied to representative data of the Irish commercial sector. The likelihood that a business unit would consider an energy-saving

option is investigated and the determining factors identified. Companies are more likely to investigate a fabric upgrade when: they own the building they operate from, make energy-related decisions locally, have more than 10 employees, have had a recent renovation, accept longer paybacks, and apply a case-by-case approach to budget decisions. Hotels and offices were found to be more likely to investigate energy efficiency retrofit options. Lack of knowledge of building floor area indicated that companies were less likely to investigate both fabric upgrade and behavioural options, while companies that have undertaken a renovation of some sort are more likely to implement a behavioural measure.

1.5. Role of collaborations

This thesis is the summation of my research work, but it would not have been possible without collaborative efforts that played a greater or lesser part in the formation of all chapters. This section details my specific contributions and the role of collaborators. Chapter 2 has been published in peer-reviewed conference proceedings. Chapter 3, Chapter 5 and Chapter 7 have been published in peer-reviewed scientific journals. Chapter 4 and Chapter 6 are currently under review in peer-reviewed journals.

Chapter 2 was published in collaboration with some members of the International Energy Agency's research task on the grid integration of wind power. The paper is based on my extensive literature review on the methods and findings of analysis that examined the fossil-fuel and CO_2 savings impact of renewable energy generation. The role of my colleague in SEAI, John McCann, was to bring the analysis to the IEA Task 25 group. Dr Hannele Holttinen co-ordinated the comments from the other co-authors. This resulted in some minor amendments. Dr. Holttinen also submitted the paper to the IEEE workshop on 'Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants'.

Chapter 3 was published in a peer-reviewed scientific journal of which I am lead author. I developed the research question, determined the method, ran scenarios and wrote the paper. Fiac Gaffney and I collaborated on the model development and Fiac Gaffney helped to quality-assure and present the results. Dr Paul Deane provided advice and guidance on the modelling approach and reviewed drafts. Prof. Brian Ó Gallachóir and Dr John Curtis provided guidance and reviewed drafts.

Clancy J.M., Gaffney F, Deane JP, Curtis J, Ó Gallachóir BP (2015), Fossil fuel and CO_2 emissions savings on a high renewable electricity system – A single year case study for Ireland. *Energy Policy*, 83, 151-164.

Chapter 4 has been submitted to a peer-reviewed scientific journal of which I am lead author. I developed the research idea, carried out the analysis and wrote the paper. Dr Paul Deane provided guidance on the modelling approach and reviewed drafts. Prof. Brian Ó Gallachóir and Dr John Curtis provided guidance and reviewed drafts.

Clancy, J.M., Gartland, D., Deane, J.P., Curtis, J., Ó Gallachóir B.P (2018), The short run price and CO2 impacts of utilising waste heat from CCGT generators for district heating on a high renewable electricity system. *Applied Energy* (in review).

Chapter 5 has been published in a peer-reviewed journal of which I am corresponding author. I developed the research question and the specification for the modelling tool, and contributed to method development and data-gathering. I drafted the introduction and literature review parts of the paper and provided overall editorial oversight. Emrah Durusut and Sam Foster contributed to the method development and data-gathering. Emrah Durusut also drafted the elements of the method section and the results section. Foaad Tahir built the model and, along with Dr Denis Dineen, tested the model performance. Foaad Tahir drafted much of the method section and Dr Dineen drafted the conclusions.

Durusut, E., Tahir, F., Foster, S., Dineen, D. and **Clancy, M.** (2018), BioHEAT: A policy decision support tool in Ireland's bioenergy and heat sectors. *Applied Energy,* 213, pp.306-321.

Chapter 6 has been submitted to a peer-reviewed scientific journal of which I am lead author. I developed the research question, conducted the modelling and wrote the manuscript. Prof. Brian Ó Gallachóir and Dr John Curtis provided guidance and reviewed drafts.

Clancy, J.M., Curtis, J. and Ó Gallachóir, B.P. (2018). Modelling national policy making to promote bioenergy in heat transport and electricity to 2030 – interactions, impacts and conflicts. *Energy Policy* (in review).

Chapter 7 has been published as a paper in a peer-reviewed journal of which I am lead author. I developed the research question, developed the method and model, performed the analysis and wrote the paper. Dr John Curtis advised and contributed to method development, provided guidance and reviewed drafts. Prof. Brian Ó Gallachóir provided guidance and reviewed drafts.

Clancy, J.M., Curtis, J. and Ó Gallachóir, B.P. (2017), What are the factors that discourage companies in the Irish commercial sector from investigating energy-saving options? *Energy and Buildings,* 146, pp.243-256.

1.6. Thesis outputs

1.6.1. Journal papers

Clancy, J.M., Gaffney, F., Deane, J.P., Curtis, J. and Ó Gallachóir, B.P. (2015), Fossil fuel and CO_2 emissions savings on a high renewable electricity system – A single year case study for Ireland. *Energy Policy*, 83, pp.151-164.

Durusut, E., Tahir, F., Foster, S., Dineen, D. and **Clancy, M.** (2018), BioHEAT: A policy decision support tool in Ireland's bioenergy and heat sectors. *Applied Energy*, 213, pp.306-321.

Clancy, J.M., Curtis, J. and Ó Gallachóir, B.P. (2018), Modelling national policy making to promote bioenergy in heat transport and electricity to 2030 – interactions, impacts and conflicts. *Energy Policy* (in review).

Clancy, J.M., Curtis, J. and Ó Gallachóir, B.P. (2017), The impact of a large-scale district heating system on energy, environmental and economic factors in the heat and electricity sectors. *Applied Energy* (in review).

Clancy, J.M., Curtis, J. and Ó Gallachóir, B.P. (2017), What are the factors that discourage companies in the Irish commercial sector from investigating energy saving options? *Energy and Buildings*, 146, pp.243-256.

1.6.2. Conference proceedings

Holttinen, H., Kiviluoma, J., **Clancy, M.**, McCann, J., Pineda, I., Milligan, M. (2014), Estimating the Reduction of Generating System CO_2 Emissions Resulting from Significant Wind Energy Penetration. Presented at the 13th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants, Berlin

1.6.3. Invited talks and presentations

Clancy. M, "Renewable heat in Ireland". International Energy Research Centre 7th annual conference, Fota Island Hotel, Cork, 14th March 2018.

Clancy. M, "Reducing carbon emissions: The environmental impact of CHP", Combined Heat & Power Conference, Radisson Blu Hotel, Cork, 7th Feb 2018.

Clancy. M, "The outlook and challenges for renewable heat". Irish Renewable Energy Summit. Croke Park, Dublin, 31st January 2018.

Clancy. M, "The Biomethane Opportunity". Department of Communications Climate Action and Environment. Biomethane Stakeholder Engagement Workshop. Camden Court Hotel, Dublin, 17th January 2018.

Clancy. M, "District Heating – summary of research". Department of Communications Climate Action and Environment – District Heating Working Group. 29-31 Adelaide Rd, Dublin, 9th of November 2018.

Clancy. M, "Bioenergy in Ireland – challenges and opportunities". Irish Bioenergy Association's National Bioenergy Conference, Castleknock Hotel, Dublin, 9th February 2017.

Clancy. M, "What does Bord na Móna's announcement mean for energy costs, competitiveness, security of supply and jobs?". The Sustainable Energy Authority of Ireland, Wilton Place, Dublin, 20th October 2015.

Part I – Power Systems Modelling

Chapter 2

Reduction of CO_2 emissions due to wind energy – methods and issues in estimating operational emission reductions

Abstract

This chapter presents ways of estimating CO_2 reductions of gird connected wind power using different methodologies. Estimates based on historical data have more pitfalls in methodology than estimates based on dispatch simulations. Taking into account exchange of electricity with neighbouring regions is challenging for all methods. Results for CO_2 emission reductions are shown from several countries. Wind power will reduce emissions for about 0.3-0.4 $MtCO_2$/MWh when replacing mainly gas and up to 0.7 $MtCO_2$/MWh when replacing mainly coal-powered generation. The chapter focuses on CO_2 emissions from power system operation phase, while long-term impacts are briefly discussed.[1]

[1] Chapter based on contribution to conference paper of Task 25 on wind integration under IEA wind technology collaboration platform: Holttinen, H., Kiviluoma, J., Clancy, M., McCann, J., Pineda, I., Milligan, M. (2014), Estimating the Reduction of Generating System CO2 Emissions Resulting from Significant Wind Energy Penetration. Presented at the 13th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants, Berlin.

2.1. Introduction

One primary policy driver for wind power uptake in recent years has been CO_2 emission reduction in support of environmental policy objectives. Wind power is a renewable electricity generation source that does not itself emit CO_2 in operation, and has very low lifecycle CO_2 emissions when compared with the lifecycle emissions of fossil-fuelled generation. The vast majority of wind deployment has been gird connected wind farms, built for the purpose of exporting electricity to the grid (IEA Wind, 2017). Micro generation is costlier and has seen less deployment but may offer some additional advantages. For example, when incorporated into smart grids micro-generation may improve system resilience (Wang et al., 2016). There is also some evidence that small scale generation is more socially acceptable (Burton and Hubacek, 2007).

This chapter will examine methods for estimating avoided CO_2 emissions in the power system, since those constitute by far the biggest share of the total lifecycle emissions of the whole power generation chain. Research elsewhere has examined the other elements of lifecycle CO_2 emissions for both wind power and fossil-fired plant (Kubiszewski et al., 2010). In principle, the methods to estimate the emission reductions should be the same for any power source or change in demand. However, in this analysis we concentrate on the particular application of these methods to the calculation of the CO_2 abatement due to wind power.

When wind power replaces electricity from legacy (older) coal power plants, the CO_2 emission savings in power generation can be more than 1,000 gCO_2/kWh. If generating plant other than coal power plant is displaced, the emission savings will be less. Due to a scarcity of examples of complete power systems with high wind-power penetrations, most of the early studies examining the CO_2 emissions reductions levels from wind power in electricity systems have been for hypothetical future scenarios, with controlled assumptions on system operation. More recently, with high penetrations of wind power being achieved in several power systems internationally, it has been possible to quantify the actual CO_2 emissions levels within these systems. Attributing decreased CO_2 emissions from electricity generation to wind power in real historical power system operational contexts presents several challenges, and a number of approaches have been used.

2.2. Methodologies for estimating CO_2 reductions

In order to estimate CO_2 reductions caused by wind power, one should isolate the impact of wind power from all other changes in the system and compare the system with wind power to the situation that would have prevailed in its absence. However, the complexity of the electricity system makes estimation of fossil-fuel and CO_2 emissions an intricate task. The primary parameters affecting emissions intensity can vary significantly across short timescales and no 'natural experiment' exists to facilitate analysis.

Regarding operational impacts of wind power, an ideal natural experiment would involve two identical systems having the same generation portfolio, demand profile, forecast accuracy, dynamic fuel price changes, generator and interconnector availability, interconnector trade flows and network constraints in each time period across a year. In other words, one should change only those things that would change with vs. without wind power. The CO_2 emissions on the system with renewable energy generation could be compared to the system without any renewable energy in order to determine the impact.

However, there is no fully objective way to establish the comparative cases and therefore, at least, the assumptions need to be clearly laid out. The difficulty in establishing the base case or the counterfactual scenario is one reason for divergent methodologies and results concerning CO_2 reductions due to any power source.

Extra complexity is introduced when estimating emission impacts for a region that is part of a larger market area – in all cases where exchange of electricity is significant. Emission reductions also occur in the neighbouring region to which electricity is exported. Also, in a more comprehensive, long-term approach, the changes caused by wind power to power plant fleet and to other power system components during the lifetime of wind power plants would be taken into account.

Four main categories of methods have been used to show the impacts of renewable energy on fossil-fuel displacement and CO_2 emissions reduction. These vary in complexity and approach, and are outlined below.

2.2.1. Displacement estimation

The simplest approach to estimate CO_2 reduction is to assume that wind power replaces the average annual emissions of the power system, which are often readily available as statistics. The Clean Development Mechanisms (CDMs), the system used to issue Certified Emissions Reductions (CERs) for electricity production renewables in developing countries, uses the average carbon intensity of the existing electrical generation capacity as a benchmark to estimate the avoided CO_2 emissions from wind and other renewables (UNFCCC, 2006). Basing the calculations on the carbon intensity of a generation mix will generally give a lower figure for avoided CO_2 than is realistic. Part of the generation mix is such that wind will not replace it (like 0 emission technologies hydro or nuclear power in most cases). It is also an oversimplification as wind power does not generate electricity in tandem with electricity demand. It would be more correct to weight the CO_2 emissions of each scheduling period with wind-power output, but even this suffers from the assumption that wind power replaces all forms of generation.

A more accurate way is to make assumptions on the type of fossil fuel that renewable energy is likely to replace and the conversion efficiencies of this electricity generation. The Primary Energy Equivalent (PEE) method equates the energy produced from renewable sources with the amount of primary fossil-fuel energy required to generate the same amount of electricity.

The PEE approach requires an assumption of the efficiency of the fossil-fuel plant being displaced by renewable electricity sources and the type of fuel used. A weighted average approach can be used by assuming that fossil-fuel generation is displaced in proportion to the individual shares in the fossil-fuel mix (Howley et al., 2014). This method may over- or underestimate the fossil-fuel and CO_2 displacement as the impact of renewable energy tends to be focused on a subset of the generation portfolio, typically the more expensive or marginal generators. As fuel costs are the main contributor to the cost of generation, the marginal units tend to be of the same fossil-fuel type. Using the proportional approach spreads the displacement effect over more fuel types and does not account for the marginal displacement effect.

The assumption can also be based on time series about marginal units, if that data is available. However, depending on the amount of wind energy during operating hour and the amount of energy from marginal unit at that time, there may be other units displaced also that are likely to have a different emission rate.

A further complication is that wind power may displace thermal power production in neighbouring countries. The marginal CO_2-emission reduction benefit on a system-wide basis and a national basis might differ considerably, because of international power markets.

The data of the PEE method is usually easily available and computational requirements are light. PEE provides a relatively straightforward and understandable way to estimate fuel and emissions displacement. However, the simplifying assumptions can introduce some inaccuracy, even if care is taken to use the fuels that wind is replacing only. The PEE method cannot account for any additional dynamic changes that renewable electricity may introduce into the system. Fossil-fuel units may operate in less efficient modes and may be subject to additional start-ups.

2.2.2. Empirical statistical methods applied to historical data (econometric methods)

Empirical econometric methods have applied statistical tools to (hourly) data on emissions production, changes in electricity demand, renewable electricity generation, and weather conditions. By establishing the marginal reduction in emissions as the share of renewable electricity rises, inferences are made on the displacement effectiveness of renewable electricity. These methods seek to isolate the impact of renewable electricity generation by accounting for variables that are statistically related to emissions. The problem is that CO_2 emissions can have sensitive and non-linear relationships to individual independent variables.

2.2.3. Detailed simulation: dispatch models

The dispatch model method uses detailed information on components of the electricity system to establish a representation of how the electricity system

operates. Data and information on the full range of influencing factors prevailing over a particular historic or future period may be included. Scenario analysis compares identical systems with and without renewable electricity generation. Kartha et al. (2004) describe this approach as "the most sophisticated and accurate operating margin approach" for establishing CO_2 displacement impacts (Kartha et al., 2004). Dispatch models, unlike the PEE and empirical methods, are generally used to investigate possible future effects of changing electricity system conditions.

The system characteristics and prevailing external conditions are identical across scenarios, apart from the level of renewable energy generation. By comparing the fuel use and resultant CO_2 emissions over the scenarios, the effectiveness of renewable electricity generation in displacing fossil fuel can be estimated. The models typically arrange the generators into a merit order, from the lowest-cost generator to the highest-cost, and dispatch the least-cost arrangement of generators required to meet demand, subject to a range of constraints (system operation requirements, network constraints, generator capabilities). These models can optimise dispatch for a given period by looking at how system conditions are likely to change over the coming periods.

The challenge in the dispatch method is how well reality is simulated. There are complications when simulating the power system operation with and without wind power. Variability and uncertainty of wind power causes need to procure more reserves and increases the use of those reserves and balancing markets. Also, cycling of conventional power plants[2] is likely to increase, and this will influence the emissions from the power system. A detailed model can incorporate the impact of any forecasting uncertainty and variability, and capture additional efficiency losses due to ramping and start-ups. The detailed nature of a dispatch model means it can be labour-intensive to build, and the resulting models can suffer from a lack of transparency. The results are highly sensitive to assumptions such as fossil-fuel prices or generator performance. Without an extensive validated database on generator performance and cost data, and information on system operational rules, these models are difficult to develop and review.

Another challenge is studying future high shares of wind power. If large amounts of wind are added, the generation mix should also be reoptimised to manage the increased variability and uncertainty from wind energy. However, this case is unlikely to have the ability to function effectively without wind energy (this issue may also apply to some systems in the near future that are adapting, or have adapted, the generation mix for wind energy).

[2] Cycling refers to the operation of electric generating units at varying load levels, including on/off, load following, and minimum load operation, in response to changes in system load requirements.

2.2.4. Detailed simulation: generation expansion models with dispatch models

The knowledge that wind power will be built is likely to change what other generation will be built – and once built, it will continue influencing future investment decisions. New investments affecting the marginal emissions can change the emissions considerably. When comparing future scenarios containing a large share of wind power, the generation mix should be optimised to both cases separately in order to get a more realistic estimate on what kind of emission reductions wind power actually allows.

Some studies have used this approach, but have tended to focus on cost data. To compare the CO_2 emission reductions in operation of the systems is, again, more challenging as other things other than wind power (including electricity price, power generation investment, demand) will change in the cases compared.

It is also natural that in future high-renewable systems, when most fossil-fuel-based sources are replaced, further CO_2 reductions can only be very limited.

2.3. Examples of methodology implementation

2.3.1. Displacement estimation

Kartha et al. suggest three possible options to estimate marginal fossil-fuel displacement: the operating margin, the build margin, or the combined margin approach (Kartha et al., 2004). Low-cost and must-run generators are assumed to be unaffected by the addition of renewable capacity. The system average of the remainder of the generation portfolio determines the operating margin. The build margin is based on the historical data for the generation: the weighted average of the most recent 20% of plant additions to the portfolio or, if the data is inadequate, using a proxy plant method. Implementation of the proxy plant method in Ireland has tended to assume gas-fired CCGT as the proxy plant (Howley et al., 2014; Ó Gallachóir et al., 2006). The combined margin approach combines the previous two methods. SEAI previously estimated the fuel displacement from renewable electricity generation using the operating margin approach. The associated emissions displacement was estimated as 2.42 million tonnes of CO_2. This represents a displacement rate equalling 0.489 tCO_2/MWh of wind-generated electricity in Ireland (Howley et al., 2014). Using a similar approach based on the average CO_2 intensity of the system, EWEA estimated that wind energy avoided 126 million tonnes of CO_2 in 2010 or 0.696 tCO_2/MWh (EWEA, 2011). This figure was increased to 175 million tonnes in 2013 or 0.674 tCO_2/MWh. The average CO_2 intensity of the EU system stems from modelling of the European Commission (Capros et al., 2013) which used a detailed simulation method similar to the method described in Section 2.2.4 above.

2.3.2. Empirical statistical methods for historical data (Econometric methods)

Kaffine et al. specified a model that took into account hourly wind-energy output, hourly load, average hourly temperature, the expansion of wind capacity and the day-of the-week changes in electricity demand (Kaffine et al., 2013). They found that marginal emissions reduction due to wind energy in the Texas region was 0.523 tCO_2/MWh of wind generation. The paper highlights the sensitivity of the results to the makeup of the generation portfolio in operation over a given period. In a large system, such as the Texas system, plant and interconnector outages are averaged over a large generation portfolio. In a small system like the All-Island system, comprised of the synchronous grids of the Republic of Ireland and Northern Ireland, an outage of a single plant can significantly alter the generation portfolio and affect system flexibility and the fossil-fuel and emissions displacement estimates for a given period.

A similar method has been used for the Republic of Ireland by Wheatley (Wheatley, 2013). This model accounts for wind generation and system demand only and how these relate to changes in plant-specific emissions. This excludes possible influencing factors such as the impact of network constraints, and unexpected generator outages. The analysis was for Republic of Ireland electricity generation only and was therefore not a whole-system analysis that considered the effects of interconnector flows. Thus changes in plant emissions have been interpreted as being caused by changes in wind output when other dynamic factors might also have been influencing emissions at the same time. The 2011 period examined in the analysis was exceptional due to the reduction in system flexibility. The pumped storage capacity was offline for maintenance and the interconnection capacity was also offline. The paper suggests that the marginal displacement due to wind energy in 2011 was 0.28 tCO_2/MWh.

Amor et al. looked at several years of data in Ontario to establish the impacts of wind generation on electricity price and GHG emissions (Amor et al., 2014). The model specification accounts for variations in demand, wind output, baseload generation from hydro and nuclear, and output from marginal generators. The impact of network constraints is also included. The study finds that wind displacement effects are strongly influenced by the level of network constraints. The paper estimates GHG displacement in the range 0.283 to 0.394 tCO_2/MWh.

Cullen examined the impact of wind in the Texas system between 2005 and 2007 (Cullen, 2013). Wind output, electricity demand, network congestion and changing efficiencies of fossil-fuel generators are included. As the generation output of fossil-fuel generators influences future output, due to the additional costs and inefficacies involved in starting up a generator that has been offline for a longer period of time, Cullen includes lagged data for these variables to help explain the generator output. Generator outages and fossil-fuel spot prices are also included as well as controls for generator pricing strategies. The relationship between these variables is expressed as linear and non-linear relationships that can capture some

of the more nuanced effects of wind generation of fossil-fuel generator output. The results show that wind tends to displace natural-gas CCGTs but also displaces less efficient natural-gas generation from OCGTs. Overall, the CO_2 reduction is estimated as 0.43 tCO_2/MWh.

Analysis by di Cosmo and Malaguzzi Valeri examines the displacement impact of wind between 2008 and 2012 in the All-Island system. The estimation relates changes in power-plant emissions to variations in the output of wind generators, fluctuations in demand, and changes in other influencing factors. Findings show a displacement effect that varied across individual years due to changing system conditions affecting the generation mix and system flexibility (Di Cosmo and Valeri, 2014).

An empirical method that includes a full specification of the explanatory factors that contribute to emissions of the electricity grid could provide some insight into the impact of renewable electricity generation on emissions reduction. Historical data is required for several influencing variables over short-time horizons of several years to better understand the historical period examined. The nature of the relationship between the explanatory variables and emissions can be difficult to identify, with the possibility that the influence of some factors is non-linear and lagged in time.

The empirical models tend to focus on what the past displacement impact of renewable electricity was, with models specified to fit the available data as closely as possible. Models capable of predicting and explaining the impact of the various factors require different specifications that include the influence of network constraints, forecasting uncertainty, demand in preceding periods, must-run generators and the availability and flexibility of plant in the generation portfolio. Amor et al. point out that, due to the complexity of electricity systems, empirical methods are unable to fully explain the reasons for observations and that the strength of empirical models lies in their ability to observe an emissions reduction impact in historical data (Amor et al., 2014).

2.3.3. Detailed simulation: dispatch models

EirGrid, the Irish electricity system operator, conducted a study in 2007 (EirGrid, 2007) that updated earlier analysis (ESB National Grid, 2004), using the dispatch model methodology applied to future renewable electricity deployment scenarios. Four electricity system scenarios were examined: a no-wind reference case and three scenarios with increasing levels of wind-power generation. The impact of additional cycling was examined as part of the analysis. It showed that wind energy displaces between 906 and 974 tCO_2/MW of capacity installed. This is equivalent to between 0.260 and 0.502 tCO_2/MWh. Denny and O'Malley confirmed the effect of fossil-fuel and CO_2 displacement, including the impact of any additional cycling, estimating a CO_2 displacement impact of 0.33–0.438 tCO_2/MWh (Denny and O'Malley, 2007).

The National Renewable Energy Laboratory (NREL) outlined in a detailed report a method to analyse the effect of renewables (wind and solar) on increased thermal plant cycling (Lew et al., 2013). Using PLEXOS power market simulation software, a dispatch model was created to simulate scenarios with various levels of renewable penetration in the Western Interconnection of the United States. To carry out the analysis, detailed emission curves for nearly all thermal power plants in the West were obtained from the US Environmental Protection Agency, which tracks and collects these data. These emission curves were directly incorporated into the production simulation model. Emission penalties for start-up and part-load operation were modelled also, with CO_2 penalties for part-load operation ranging from 6%-18%, based on type of unit. Ramping emissions were also penalised; however, it was found that CO_2 ramping impacts are equivalent to less than three minutes of full-load operation. The generation mix was not-reoptimised for the wind energy that was added to the system. The generation assumptions were adopted from the Western Electricity Coordinating Council (WECC) transmission planning process, which has representatives from all regions in the West and produces a collaborative model of the generation fleet and transmission network.

The study found that a 24-26%[3] wind and solar energy penetration avoids 29%-34% of the carbon dioxide compared to the base case, depending on the relative mix of wind and solar. This is approximately 0.489 to 0.523 tCO_2/MWh of wind/solar generation. The emission reduction rate exceeds the penetration rate because much of the displaced generation is natural gas, which has relatively low carbon emissions rates. In the high wind energy case, more coal was displaced, thus even less CO_2 emissions were produced (34% reduction from base case). Thus the study concluded that, even when start-up, additional cycling, and other efficiency penalties are incurred, overall CO_2 emissions are reduced significantly with the inclusion of high levels of wind and solar energy.

Valentino et al. examine the emissions impact of incorporating wind energy into the electric power system in Illinois (Valentino et al., 2012). Their findings showed a reduction in CO_2 for all levels of wind penetration of between 0.672 tCO_2/MWh and 0.847 tCO_2/MWh.

For Nordic countries, the electricity system is dominated by hydro power, in addition to coal and gas. Wind power was estimated to reduce CO_2 emissions by 0.3-0.7 tCO_2/MWh, depending on whether coal or gas-powered plants were substituted (Lund, 2005). The market model used in simulations optimises also the hydro power generation in the Nordic countries. Reservoir hydro can hold the water on windy periods, and even if it is replaced by wind during a single hour, it will be generated at a later stage. This is why wind will replace mostly coal and

[3] The percentage of renewable energy was 33% of the US demand, but when non-US parts of the interconnection were included in the modelling, the penetration rate declined with the increase in demand.

gas also in the Nordic system. However, adding larger amounts of wind power will result in CO_2 savings also outside the Nordic countries, for example in Germany.

2.3.4. Detailed simulation: generation expansion models with dispatch models

The All-Island Grid Study examined the impact of five future renewable electricity development scenarios for the 2020 power system on the island of Ireland. The analysis showed CO_2 savings due to renewable energy (DCENR (IE) / DETI (UK), 2008). The emissions reduced from 20 $MtCO_2$/year (16% share of renewables) to 15 $MtCO_2$/year (42% share of renewables), but different portfolios had different CO_2 emissions even for the three portfolios for a 27% share of renewables (18-22 $MtCO_2$/year). It also showed equal emissions reductions in the UK system to those in Ireland associated with wind additions solely in Ireland.

Analysing results from generation planning model simulations where wind power is one investment option shows a very high difference in CO_2 reductions (Kiviluoma and Meibom, 2010). Changing the level of wind-power investment cost resulted in a change in the amount of invested wind power. All scenarios analysed by Kiviluoma and Meibom had low levels of CO_2 emissions, since the system was based heavily on wind power and nuclear power. In a scenario where new nuclear power was not allowed, increasing amount of wind power reduced CO_2 by 1.20-1.22 tCO_2/MWh. This is more than emission from a coal plant and is explained by the dynamic factors in the system: coal power plants were increasingly replaced by natural gas power plants when there was more wind power. Gas power plants had lower capital costs and higher operational costs than coal power plants. They were not as influenced by the lower utilisation rate. The generation planning model did not include other cycling costs. In cases with a very low initial level of CO_2 emissions (a scenario where nuclear was allowed), the emissions actually increased when wind power increased (0.01-0.02 tCO_2/MWh increase). In these cases, more flexibility was needed and it was economic to source it partially from fossil-fuel sources. The availability of flexibility measures (smart-charging electric vehicles and flexibility in district heating) had also a sizeable impact on the emission reductions. The main conclusion from Kiviluoma and Meibom, 2010 is that the emission reductions of future systems are highly dynamic and dependent on the assumed system conditions and cost assumptions

2.4. Discussion and conclusions

Figure 2-1 shows the range of results from the various studies (PEE, empirical and dispatch) referenced above for displacement of fossil-fuel generation and associated CO_2 emissions for the All-Island electricity system (shown in green) and for systems in other countries (shown in blue). For the studies pertaining to the All-Island system, the overall range of emission displacement intensities, for different periods and under different scenarios, extends from 0.260 tCO_2/MWh to 0.502 tCO_2/MWh.

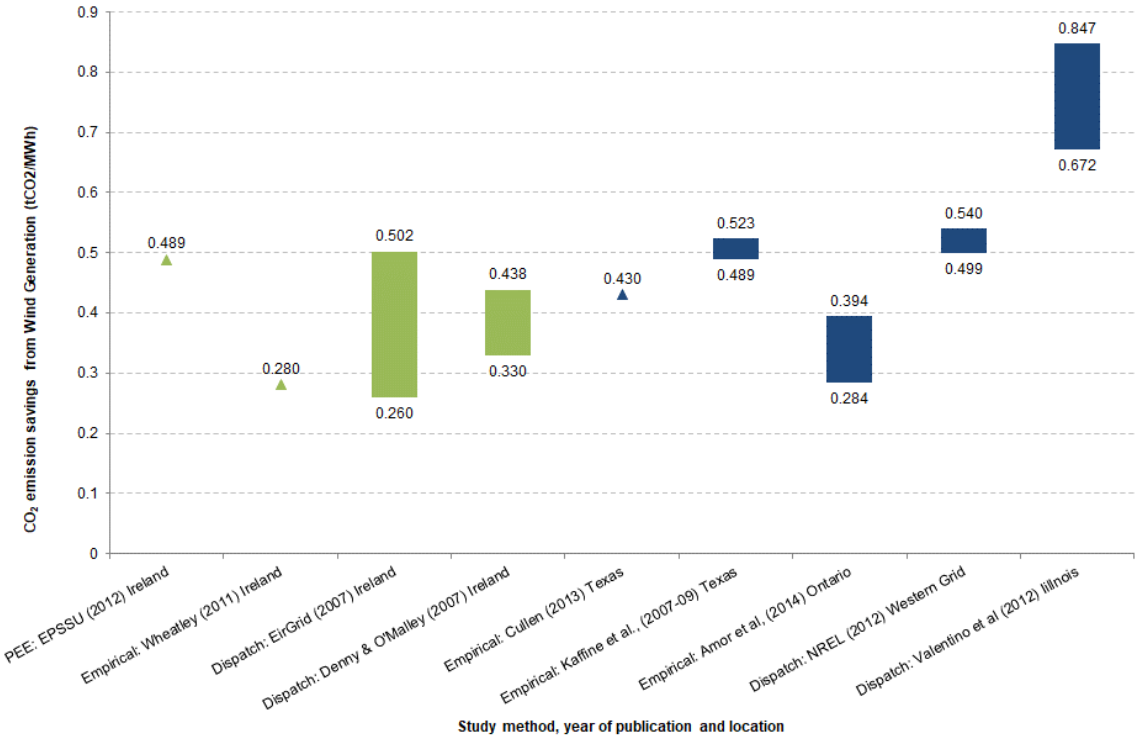


Figure 2-1: Emission reductions of wind power in Ireland according to different methodologies (green), compared to estimates for North America (blue)

The All-Island System and US Western Grid have high proportions of less carbon-intensive gas generation. In contrast, the Illinois system is dominated by more carbon-intensive coal combustion. Renewable energy displacing less carbon intensive gas results in a lower displacement impact than when renewable energy displaces coal – for coal-dominated systems 0.489 to 0.847 tCO_2/MWh has been estimated. Cycling impacts are shown to have a minor overall impact when compared to the absolute 'bottom line' reduction in CO_2 emissions.

Detailed dispatch simulations that capture additional cycling impacts are the most correct approach to estimate the impacts of wind power on CO_2 emissions in power system operation. Increased cycling due to wind capacity addition has to be clearly distinguished from the existing level of cycling in the system. Cycling impact has been estimated to be small and will not offset the benefits of wind energy in reducing emissions (Lew et al., 2013).

Using emission rate data and assumptions on fuels displaced is effective as a first estimate but, especially at higher penetrations, will not be accurate. Using historical data can give insight into CO_2 reductions, but separating the impacts due to wind power from other power system factors is challenging. For example, transmission system congestion may have a fundamental influence upon emissions but this is rarely quantified.

Exchange to neighbouring countries will complicate the analyses. The distinction between political and system boundaries is critical to proper analysis as

interconnector flows may effectively export or import CO_2 emissions. Governments are responsible for abatement only within their particular jurisdictions and external effects may go unreported if analysis and reporting is focused solely on national effects.

Systems that have appreciable penetrations of wind to date may not be using existing flexible resources and demand-side management to their full potential. This implies that greater CO_2 displacement may be possible. Incorporating wind into legacy generating systems may result in a non-optimal flexibility resource in the balance of generating plant. This will be resolved as the generating system evolves but *ex-post* analysis of a power system with steadily growing wind penetration (undergoing a wind-energy transition) may underrepresent the long-term potential for CO_2 displacement by wind power.

Most of the work so far has concentrated on capturing the impacts operationally in the short term. The impacts can be very different in the long term. Newly built wind power, together with other low marginal cost units, will push out the highest marginal cost units during each scheduling period. However, the same wind power will also influence what new generation or electricity demand is worthwhile to develop at a later time. Wind power will suppress prices during many hours of the year and decrease the incentive especially for baseload power plants. The CO_2 emissions of a system with high amounts of wind power are highly sensitive to the resource mix that results from past investments in generation and demand response (Kiviluoma and Meibom, 2010). Thus, the lifecycle emissions of a wind-power plant should consider the impact over the whole operational period of the plant (Soimakallio et al., 2011).

Chapter 3

Fossil-fuel and CO_2 emissions savings on a high-renewable electricity system – a single-year case study for Ireland

Abstract

Several electricity systems supply significant proportions of electricity from weather-dependent renewable sources. Different quantification methods have estimated the associated historical savings of fuel and CO_2 emissions. Primary energy equivalent and econometric methods do not readily quantify factors such as operational changes to fossil-fuel generation arising from the integration of renewable energy. Dispatch models can overcome these limitations, but are generally applied to future scenarios. A dispatch model is applied to *ex-post* data for the 2012 All-Island system in Ireland. Renewable electricity accounted for 20.4% of total generation, 15.8% from wind. The results show renewable generation averted a 26% increase in fossil fuels (valued at €297 million) and avoided an 18% increase in CO_2 emissions (2.85 $MtCO_2$), as compared to the simulated 2012 system without renewable generation. Wind averted a 20% increase in fossil-fuel generation and a 14% increase in CO_2 emissions (2.33 $MtCO_2$). Each MWh of renewable electricity avoided on average 0.43 t CO_2, with wind avoiding 0.46 tCO_2/MWh. Additional renewable-related balancing requirements had minor impacts on fossil-fuel generation efficiency; CO_2 production rates increased by <2%. Policy measures to alleviate network congestion, increase system flexibility and raise financial penalties on emissions can increase savings from renewable generation.[4]

[4] This chapter is based on the published journal article, Clancy, J.M., Gaffney, F., Deane, J.P., Curtis, J. and Gallachóir, B.Ó. (2015), Fossil fuel and CO_2 emissions savings on a high renewable electricity system – A single year case study for Ireland. *Energy Policy*, 83, pp.151-164.

3.1. Introduction

Renewable electricity generation is playing an expanding role in international efforts to reduce fossil-fuel dependency and greenhouse-gas (GHG) emissions (IEA, 2013a, 2013b; IRENA, 2014; Klessmann et al., 2011; Lind et al., 2013; Nelson et al., 2013). Some governments are implementing a range of policies to encourage the deployment of renewable technologies based on the understanding that these will improve energy security and reduce GHG emissions by displacing fossil fuels. A notable example is the EU Renewable Energy Directive (2009/28/EC, 2009a, p.28), which sets renewable targets for individual member states to be achieved by 2020. Table 3-1 shows that many member states are planning to achieve significant proportions of their binding renewable targets by deploying renewable electricity technologies – much of this from variable sources such as wind, ocean and solar PV (NREAPs 2011).

In 2005, 85% of the 2,785 TWh of EU electricity demand was supplied from fossil generation; achievement of the targets would see this reduce to 66% of an expected 2020 electricity demand of 3,530 TWh (ECN, 2011). Wind, solar and wave generation have a free source of fuel, and article 16 (2) of EU Renewable Energy Directive 2009/28/EC gives legal precedence to output from renewable sources. This implies significant operational changes for fossil-fuel generators as low marginal cost and must-run renewable generation moves fossil-fuel generation up the dispatch curve, resulting in reduced capacity factors and more variable running duties.

In addition, the output from variable renewable electricity generating sources changes with the prevailing weather conditions. These sources also tend to be non-synchronous[5] (EirGrid, 2010). At high penetrations, balancing the fluctuating output of variable renewable energy with output from fossil-fuel units can lead to additional start-ups and shutdowns (cycling), more frequent and intense output changes (ramping) and less efficient operation of these fossil-fuel units. The non-synchronous nature of variable renewable generation limits the proportion of electricity demand that can be met from wind and solar PV on smaller systems. At times of high non-synchronous availability and low demand, the output from these sources is turned down (curtailed) to maintain system security operational standards. These operational actions can negate some of the fuel and CO_2 savings from renewable electricity generation and this is cited by critics of renewable electricity policy as a critical flaw in the ability of variable renewable electricity sources to reduce fossil-fuel use and to save CO_2 emissions (Chris Heaton-Harris et al., 2012; Wheatley, 2013).

[5] Non-synchronous in electrical terms refers to electricity generators that do not operate at the standard system frequency and are connected asynchronously. The All-Island system has a system frequency of 50 Hz.

Table 3-1: EU member states' binding renewable targets (RES), and proportion of electricity demand planned to come from renewable electricity (RES-E) (ECN, 2011)

Member state (*listed in order of planned contribution of renewable electricity to overall target*)	**Binding 2020 Renewable Energy Targets** *(%)*	**Planned % point contribution from renewable electricity towards RES target** (of which is from variable renewable sources)	**Proportion of electricity demand planned to come from renewable electricity in 2020** (of which from variable sources)
Malta	10%	7% (5%)	14% (9%)
Netherlands	14%	9% (6%)	37% (25%)
Spain	20%	13% (10%)	40% (29%)
Ireland	16%	8% (7%)	43% (37%)
Portugal	31%	16% (8%)	55% (27%)
United Kingdom	15%	7% (5%)	31% (22%)
Austria	34%	17% (2%)	71% (7%)
Germany	18%	9% (6%)	39% (26%)
Greece	18%	10% (7%)	40% (30%)
Sweden	49%	21% (3%)	63% (8%)
Slovakia	14%	6% (1%)	24% (3%)
Italy	17%	6% (2%)	26% (8%)
Slovenia	25%	10% (1%)	39% (2%)
Cyprus	13%	5% (4%)	16% (14%)
Belgium	13%	5% (2%)	21% (10%)
Romania	24%	9% (2%)	43% (12%)
France	23%	8% (4%)	27% (12%)
Denmark	30%	10% (6%)	52% (31%)
Bulgaria	16%	6% (2%)	21% (8%)
Finland	38%	10% (2%)	33% (6%)
Poland	15%	4% (2%)	19% (9%)
Czech Republic	13%	3% (1%)	14% (4%)
Latvia	40%	9% (2%)	60% (11%)
Estonia	25%	5% (4%)	5% (14%)
Lithuania	23%	4% (2%)	21% (9%)
Luxembourg	11%	2% (1%)	12% (5%)
Hungary	13%	2% (1%)	11% (3%)
EU-27	20%	9% (4%)	14% (9%)

Integration of variable renewables is more challenging in some power systems than others. Ireland is an interesting case study in this regard, being a relatively small AC power system (6,878 MW peak load, 35 TWh annual demand) with limited interconnection and a high share of variable non-synchronous renewable generation (Foley et al., 2013; O Gallachóir et al., 2007). Detailed data on the electricity system and market are also publicly available (SEMO, 2014). These factors point to the selection of Ireland as a suitable case study for the analysis described in this chapter.

As discussed in Chapter 2, the complexity of the electricity system makes estimation of fossil-fuel and CO_2 emissions savings an intricate task. Key parameters can vary significantly across short timescales and no 'natural experiment' exists to facilitate analysis. Three main methods have been employed to estimate fuel savings and CO_2 emissions reductions. Chapter 2 discusses these in detail but they are summarised again here for convenience.

The primary energy equivalent (PEE) method equates the energy produced from renewable sources with the amount of primary fossil-fuel energy that would have been required to generate that same quantity of electricity, by making assumptions on the type and efficiency of fossil-fuel generation displaced. The impact of renewable energy tends to be focused on a subset of the generators, typically the more expensive to run or marginal generators. Kartha et al. (2004) suggest three variants of the marginal method to estimate savings: the operating margin, the build margin or the combined margin approach. The operating margin approach has previously been implemented in Ireland, with gas-fired CCGT assumed as the marginal generation (Howley et al., 2014; Ó Gallachóir et al., 2006). The data and computational requirements of the PEE method provide a relatively straightforward way to estimate fuel and emissions savings. However, the simplifying assumptions can introduce some inaccuracy. The PEE method does not account for the impact of operational changes to fossil-fuel generators because of renewable generation and assumes that all savings occur within system borders.

Empirical methods fit econometric models to available data to estimate the marginal reduction in emissions due to renewable generation. Empirical models of varying complexity have been specified to assess CO_2 displacement (Amor et al., 2014; Cullen, 2013; Di Cosmo and Valeri, 2014; Kaffine et al., 2013; Wheatley, 2013). Model specification is dependent on data availability, with different specifications used across analyses. The influence of the dynamic temporal constraints of electricity generators and other system variables can be difficult to capture within econometric models. Limited model specification can lead to biased estimates of CO_2 impacts. As Amor et al. (2014) point out, due to the complexity of electricity systems empirical methods are limited in their explanatory power and their strength lies in their potential to confirm if renewable generation has a statistically significant impact on an emissions reduction in historical data.

The dispatch model method uses detailed information of electricity systems to simulate system operation. Dispatch models arrange generators into a merit order, from the lowest-cost generator to the highest-cost, and dispatch the least-cost generator arrangement required to meet demand, subject to a range of constraints, including system operation requirements, network constraints and generator capabilities. Scenario analysis compares a base system to alternative systems to quantify the operational impacts and system design implications of changes to the generation portfolio, transmission network and other influential variables. Kartha et al. (2004) describe this approach as "the most sophisticated and accurate operating margin approach" for establishing CO_2 displacement impacts. Several studies have used this method to examine the impacts of

renewable electricity generation on power system operation, engineering design requirements, electricity markets, and GHG emissions within the All-Island system and other electricity systems (Calnan et al., 2013; DCENR (IE) / DETI (UK), 2008; Denny and O'Malley, 2007, 2006; Diffney et al., 2009; EirGrid, 2007; ESB National Grid, 2004; Tuohy and O'Malley, 2011; Valentino et al., 2012). The detailed nature of dispatch models means they can be labour-intensive to build, and, in some cases, the resulting models can lack transparency. The availability of a validated model data set, published by the market regulatory authorities, and publicly available market data overcome these difficulties for models of the All-Island system. Dispatch models have typically been employed *ex-ante* to examine electricity systems under scenarios that vary system conditions and generation portfolios.

This chapter takes a novel approach by building a detailed dispatch model using *ex-post* data for a case-study system: the All-Island electricity system on the island of Ireland under the conditions that prevailed in 2012. The aim of the analysis is to quantify the amount of fossil fuel and CO_2 emissions saved by renewable electricity generation, to identify, explain and quantify where possible the important factors that influence savings and to quantify how the operational characteristics of renewable generation affect the CO_2 emissions intensity of the fossil-fuel generators. The dispatch model of the All-Island system is used to compare the outcome under the conditions that prevailed in 2012 with two hypothetical scenarios that reduce and remove the renewable electricity capacity from the 2012 system. The dispatch method applied to *ex-post* data overcomes some of the limitations of other methods and provides savings estimates for a historical period.

Section 3.2 describes why the All-Island system is a useful test case and outlines the factors that influence the displacement impact of renewable generation. The details of the simulation method are also described. Section 3.3 presents the results and the final section concludes.

3.2. Methods

3.2.1. The All-Island electricity system and market

The All-Island system is useful for this analysis for several reasons. The system already has a high proportion of renewable electricity. The share of electricity demand supplied from renewable sources was 19.6% in 2012 (Howley et al., 2014). In 2012, Ireland was fourth in the world for the proportion of wind generation in its electricity system (IEA Wind, 2013), contributing a total of 15.3% of electricity demand (normalised) in 2012. Instantaneous wind penetration regularly exceeded 40% of demand in 2012, peaking at a year-high penetration of over 50% in December 2012 (EirGrid Group, 2013).

The All-Island system has low levels of interconnection with neighbouring systems, which means that the potential for renewable electricity generation to displace fossil fuel and CO_2 outside of the system is reduced and savings tend to remain

within the system boundary. Therefore, savings estimates for the All-Island system are not strongly biased by leakage of displacement impacts to or from neighbouring systems.

In addition, market transparency rules mean that data on the generator characteristics, electricity demand and other operational variables are publicly available. The generator dataset underpinning this analysis is validated and published by the regulatory authorities (AIP 2012).

The All-Island market is a compulsory pool market that all generators bid into and from which all suppliers purchase electricity. Generators' bids include their short-run marginal costs, start costs and generator technical capabilities for each trading period over a full day. The most expensive generator required to meet demand in any trading period sets the market price. Additional demand-related market payments for capacity availability act to incentivise long-run investment in generation. Constraint and balancing payments ensure that generators are not over- or under-rewarded due to measures taken by the system operator to maintain system stability. Government support schemes for renewable electricity and peat generation are funded through consumer levies. Payment through these schemes is net of market revenue, with generators receiving support if their market revenue is less than support tariff levels for these generators.

Figure 3-1 shows the generation capacity on the All-Island system in 2012.

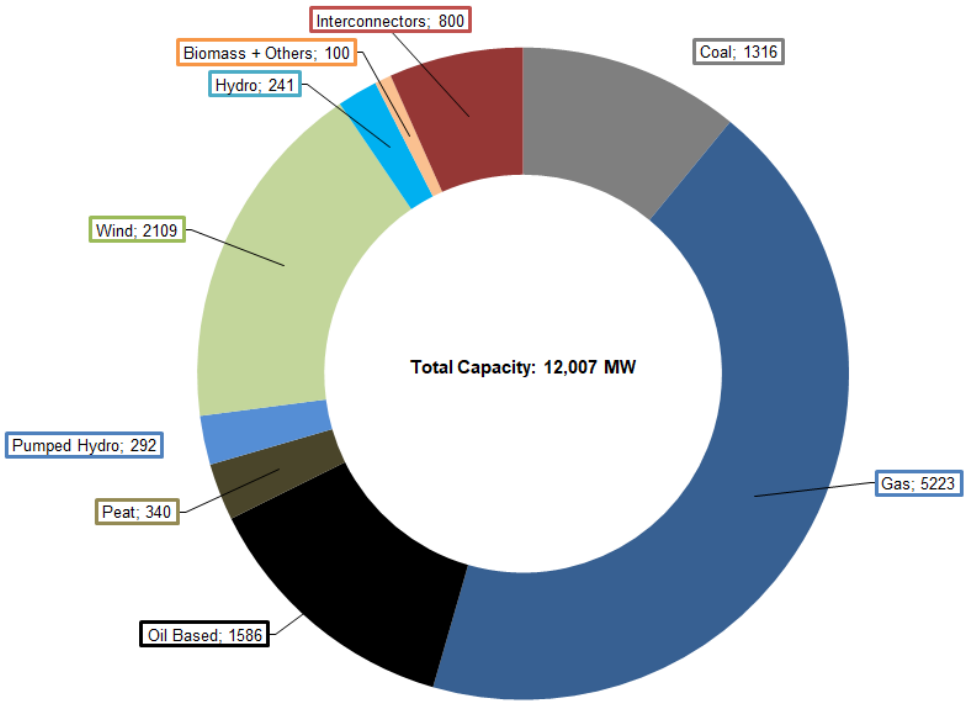


Figure 3-1: All-Island electricity system capacities in 2012, by fuel (MW)

3.3. Factors that influence fossil-fuel and CO_2 savings

3.3.1. Variability and uncertainty

The nature of renewable sources such as wind can add to system variability and uncertainty (Soder et al., 2012). Savings are reduced if fossil-fuel generators must use additional fuel to change output more frequently (ramping) and start up more often (cycling) to balance the output of renewable generation.

Thermal generators must have notice periods of several hours before they can start generating electricity. Supercritical pulverised coal units can start up within 24 hours from a hot state,[6] in 25–119h from a warm state and in over 120h from a cold state (Kumar et al., 2012). Gas CCGTs can typically start up in less than 5h from a warm state and in less than 12h from cold (Balling, 2011). Therefore, system operators must decide in advance which generators are required to satisfy anticipated demand. Forecasting accuracy plays a key role in optimising generator dispatch to minimise production costs (Fay and Ringwood, 2010; Foley et al., 2013; Hodge et al., 2012; Lew et al., 2013; McGarrigle and Leahy, 2013) Forecasting accuracy is measured using the inverse of the Normalised Mean Absolute Error (NMAE). NMAE expresses the deviation of the forecasted output from the actual as a proportion of installed capacity. The forecast predictability for wind is typically 80% for a day-ahead forecast, improving up to 95% for one-to-two-hour-ahead forecasts (Lang and McKeogh, 2010; Milligan et al., 2009). On the All-Island system in 2014, the 24h wind forecast showed an average accuracy of 93% and a minimum accuracy of 80% (EirGrid/SONI, 2014).

Wider spatial dispersion of wind-farms results in an aggregation benefit for forecast accuracy as forecast errors in one location balance errors elsewhere (Hodge et al., 2012). Similarly, wider dispersion reduces aggregate variation, as total generation from a distributed group of wind-farms fluctuates less and more slowly than the output from a single site (Holttinen, 2005). Wind output also varies less over shorter periods. Data from Ireland shows the maximum recorded change over a 15-minute period was 17% of installed wind capacity. In Germany the maximum variation was 5%. Over a one-hour period, the maximum output change was 29% and 13% respectively in the two countries (Holttinen et al., 2013).

The aggregation characteristics mean that negative impacts are likely to be more pronounced on spatially compact systems like the All-Island system. A statistical comparison of the temporal variation in demand and wind output shows that wind output varied less than demand on the All-Island system in 2012.[7] However, it is important to consider the combined effect on the system load that fossil-fuel generators must meet; i.e. the net load after the output of variable renewable generation is subtracted from electricity demand. Table 3-2 shows the average

[6] Hot, warm and cold are terms used to define the start-up readiness of a thermal generator as a function of the time required to raise the plant temperatures to operational requirements.

[7] F-test for equality of variance at 95% confidence interval for 15 min, 1h, 4h and 12h.

and maximum variation in wind output, demand and net load at various time resolutions in 2012. As wind output is not correlated to demand changes, the existing variability of the system absorbs much of the wind variability. Net load variation is less than the sum of the variations in demand and wind output, and similar in magnitude to the variations in electricity demand.

Table 3-2: Demand, wind generation output and net load variability at various time intervals in 2012

	Time Resolution							
	15 minutes		***1 hour***		***4 hours***		***12 hours***	
	Standard Deviation (MW)	Maximum Change (MW)	Standard Deviation (MW)	Maximum Change (MW)	Standard Deviation (MW)	Maximum Change (MW)	Standard Deviation (MW)	Maximum Change (MW)
Demand	36	277	130	778	370	1,458	470	2,241
Wind Output	26	238	69	444	69	825	308	1,263
Net Load	**38**	**293**	**131**	**902**	**368**	**1,798**	**496**	**2,877**

3.3.2. Reserve[8]

Operating reserve is deployed to cover 'event' and 'non-event' risks. Event risk is managed with contingency reserves which are included in operational strategies to deal with a sequence of severe unexpected and unforeseeable events such as generator breakdowns and transmission line faults (Ela et al., 2011). By holding some of the available output from other generators as a backup that can be quickly called into action, the severe negative impacts of these occurrences on grid frequency stability are avoided. On the All-Island system, like on most systems, renewable electricity generation does not increase requirements for contingency reserve. Contingency reserve requirements are related to the maximum capacity of the largest individual generator or interconnector online (typically 300–500 MW) and are not increased by renewable generation at current levels of installed capacity as forecast errors and output variation from wind over the operational time periods covered by contingency reserve are much less than the variation caused by an unexpected generator breakdown.

Non-event risks refer to continuous events that are indistinguishable from one another (Ela et al., 2011). Balancing, regulating, dispatch and following reserve are terms commonly used to describe the deployment of generation to correct active power imbalances to the target frequency due to non-event risks. In isolated systems, like the All-Island system, the fast-acting reserve is provided by the automatic governor response of designated generation assets (Ela et al., 2011). On lower time-scales, generators are dispatched to correct forecast errors from earlier time periods or to overcome short-term generator ramping constraints due to a sharp increase or decrease in system load. Wind and other variable sources of power tend to increase these balancing requirements.

[8] Several naming conventions are defined for reserve depending on the region or electricity system. This paper uses the European Network of Transmission System Operators (ENTSO) naming conventions as defined by All-Island TSO.

Higher reserve requirements result in more online fossil-fuel capacity being kept in reserve. This tends to lower their operating efficiency and increases fuel use and CO_2 emissions. Additional deployment of reserve can lead to more cycling and ramping of fossil-fuel generators. Milligan et al. (2009) state, "the experience of countries and regions that already have quite a high wind penetration has been that the existing reserves are deployed more often after wind power is added to the system, but no additional reserve capacity is required". Soder et al. (2012) examined historical data for the All-Island system and found that no additional reserve was required during periods of high wind variability.

3.3.3. System flexibility

System flexibility is defined as "the ability of [an electricity] system to deploy its resources to respond to changes in net load" (Lannoye et al., 2012). Yasuda et al. (2013) identify interconnection levels, pumped storage hydro and conventional hydro capacity along with combined-cycle gas turbine (CCGT) capacity as being the main sources of flexibility in electricity systems with high penetrations of renewable generation. Hydro capacity and storage can start generating and change output quickly. Interconnection increases flexibility within the system boundary by exporting some of the impacts of variability to connected systems. CCGTs and open-cycle gas turbines (OCGTs) deliver flexibility through cycling and ramping.

A reduction in the availability of flexible assets constrains dispatch choices and can lead to the curtailment of variable renewable generators. Curtailment happens when grid security issues can only be resolved by reducing the output of renewable generators; at all other times renewable generation has priority over fossil-fuel generation.

As an electrically remote system, with light interconnection to other systems, flexibility on the All-Island system is not a new or entirely wind-focused concern (Yasuda et al., 2013). The system has developed a flexible generation portfolio, based on appropriately sized units, capable of changing load and starting up quickly to deal with unexpected variability over short time horizons (Holttinen et al., 2013). EirGrid reported that wind power in the All-Island system had been dispatched down by 110 GWh (2.1% of total available output) in 2012 (EirGrid, 2013), and 119 GWh (2.2% of total available output) in 2011 (EirGrid, 2012). These years were higher-than-average for curtailment due to a reduction in interconnector capacity that coincided with a long-term outage of pumped storage capacity. Outages of these flexible assets will tend to increase cycling, as CCGT and OCGT generators provide system flexibility.

Much of the new renewable electricity capacity has been integrated into electricity systems with older, less flexible fossil-fuel generators. Flexible operational strategies – rewarding flexibility in fossil-fuel and renewable generation units, increasing interconnection and storage, and encouraging demand-side participation – can mitigate the negative effects of variable renewable generation as modern electricity systems evolve (Holttinen et al., 2013).

3.3.4. Generation mix, fossil-fuel/CO_2 prices and 'must run' units

The dominant fossil fuel within the generation mix is a key determinant of how much CO_2 is saved. Electricity systems with high proportions of gas generation, like the All-Island system, have lower average emissions than a system dominated by coal. The average emissions intensity of electricity supply in 2012 for Ireland was 0.53 tCO_2/MWh (Martin Howley and Mary Holland, 2013) compared with 0.75 tCO_2/MWh for Australia (AEMO 2014). Therefore, renewable electricity generation added to a gas system will tend to displace less CO_2 than if added to a coal-dominated system.

In addition, fossil-fuel and CO_2 prices determine the marginal costs of coal and gas-fired generation, with the more expensive or marginal fuel tending to be displaced most often by renewable generation. Should prices dictate that less efficient, more carbon-intensive coal generation is the marginal generation, then renewable output will tend to displace more CO_2 than when gas generation is more expensive. Some of this additional emissions reduction is offset, however, by additional, emission-intensive start-ups of the marginal coal units (Denny and O'Malley, 2007).

For the All-Island system, when gas is the marginal plant, emissions savings tend to be below the system average; when coal is the marginal plant, displaced emissions will tend to be above the system average.

Some fossil-fuel units (notably peat-fired plants[9] (Tuohy et al., 2009)) receive fixed price support for their output through government policies and tend to run for long periods at high output. Renewable energy will only displace these units in periods where the system is highly constrained and/or periods where wind generation contributes a high proportion of total generation (SEMC, 2011).

3.3.5. Network constraints

Network congestion adds further constraints to the system operator's dispatch and reserve provision choices. Some generators (including renewable generators) may have to increase or decrease output to relieve network constraints on congested transmission lines.

Generation output on the All-Island system is currently constrained in several locations due to network congestion. This restricts the maximum output of generators in some regions and necessitates generators to remain online in others outside of merit order.

[9] Peat is indigenous to Ireland and peat-fired generation receives a fixed price payment for output as a security of supply measure paid for by the electricity consumer.

A congested transmission system can reduce the potential energy savings due to renewable electricity as constraints act to reduce system flexibility. Amor et al. (2014) show how constraints can reduce the CO_2 savings from wind energy.

3.3.6. Cross-border trade

GHG emissions are accounted for within national political boundaries, but most electricity systems cross numerous jurisdictions. Renewable electricity generation in one jurisdiction can reduce emissions in another. The higher the levels of interconnection, the more likely this is to occur and the more likely that assessments of fossil-fuel and CO_2 savings within a political boundary will not account for the full savings impact of renewable electricity.

The All-Island system has low levels of interconnection with other systems but it combines the national jurisdictions of Northern Ireland and the Republic of Ireland. Savings estimates for the All-Island system as a whole are more reflective of the full impact of renewable electricity generation than for either jurisdiction alone.

3.4. Simulation methodology

This chapter builds a dispatch model method and applies it to *ex-post* data of the actual 2012 conditions on the All-Island system. The validated electricity market model (AIP, 2012) is taken as a starting point and is adapted to capture the impact of network constraints, system security considerations and the impact of uncertainty on generator dispatch. The purpose of the resultant *2012 Base Model* is to provide a representation of the 2012 electricity system as benchmark, against which the scenario simulations can be compared. Two scenarios are analysed to assess the impact of renewable electricity in general, and wind in particular, in displacing fossil-fuel usage and CO_2 emissions. The three simulations may be summarised as:

- ***2012 Base model*:** Actual system conditions and portfolio in 2012
- ***No Wind*:** All wind capacity removed from the system
- ***No Renewables (No RE)*:** All renewable generation (wind, hydro and biomass) capacity removed from the system

The removal of electricity supply capacity reduces the system security standard as measured by loss of load expectation (LOLE) (EirGrid/SONI, 2013a). To maintain parity of generation adequacy across scenarios, it was necessary to provide the following additional thermal generation capacity (all gas-fired) into the system to replace the absent renewable capacity,[10] as follows:

- *No Wind* scenario: 238 MW OCGT added
- *No RE* scenario: 415 MW CCGT along with 168 MW OCGT

[10] The capacity credit for wind is based on EirGrid's evaluations in the Generation Capacity Statement. Other renewable energy is replaced by the same capacity of thermal plant.

Figure 3-2: Model summarises the model details and input assumptions expanded in the following sections.

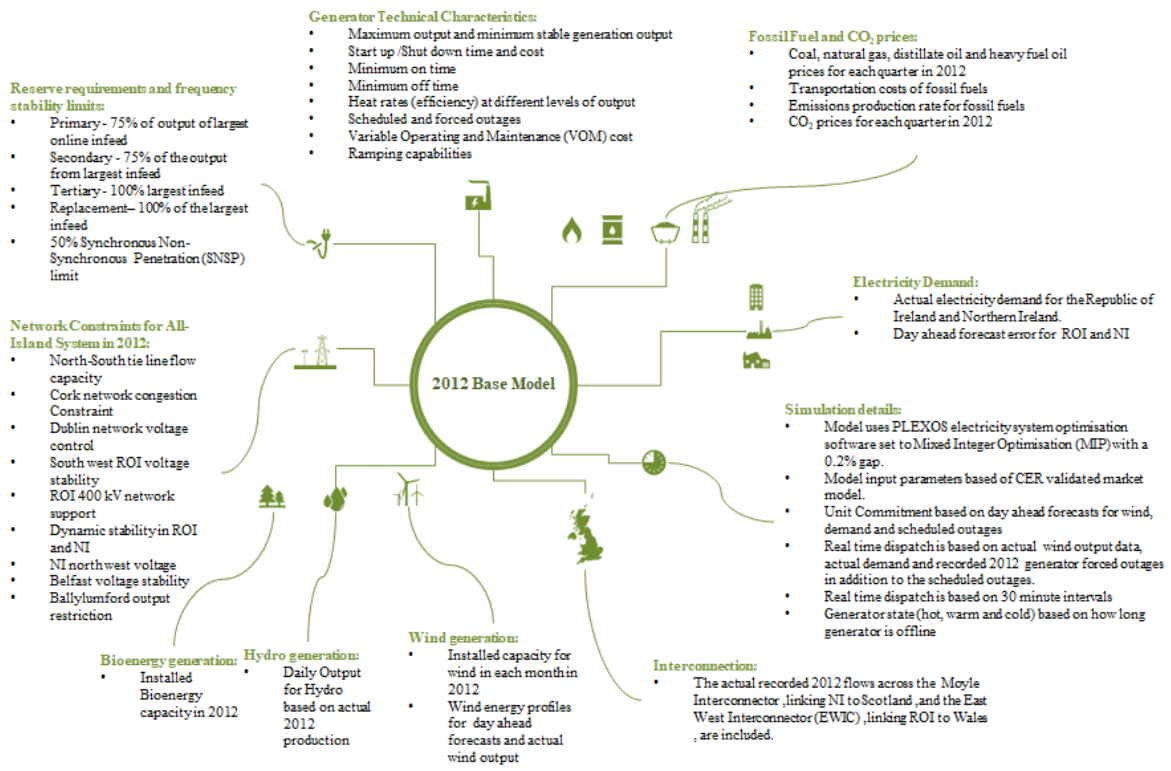


Figure 3-2: Model details and input assumptions overview

3.4.1. Validated market model

The energy market regulators publish a validated electricity market model that contains a dataset of generator technical parameters and their temporal constraints. Generation dispatch based on these factors is calibrated against historic market outcomes (AIP, 2012). Generator parameters in the validated model include: maximum and minimum outputs, generation efficiency at various output points, start-up times, minimum online periods for generator units once started, minimum off periods for generators once stopped, and how quickly generators can change output. As explained in Section 3.3, several other factors come into play during the real-time operation of the electricity system that must be accounted for in order to simulate operational fossil-fuel use and CO_2 emissions production.

3.4.2. Reserve, network constraints and non-synchronous limits

The Transmission System Operator (TSO) publishes the reverse requirements, network constraints and system stability limits for the All-Island system (EirGrid/SONI, 2013b). Contingency reserve on the All-Island system is classified as primary, secondary, tertiary and replacement reserve. As both primary and secondary reserves are called upon over short time periods (5–90s), they are

provided by units already online that can quickly change output to deal with unexpected load changes. Tertiary and replacement reserve act to ensure that sufficient capacity is available to replace primary and secondary reserve to ensure the system is prepared for further unexpected events and is provided by offline generators. Primary and secondary reserve requirements relate to 75% of the output of the largest online infeed; tertiary and replacement reserve is based on 100% of the output of the largest online infeed. Generation dispatch to meet electricity demand is co-optimised with the provision of contingency reserve.

A system-wide synchronous non-synchronous penetration (SNSP) constraint is implemented to ensure system frequency stability at times of high levels of wind penetration (EirGrid and SONI, 2010). The SNSP constraint means that no more than 50% of instantaneous system demand can be served from non-synchronous services, specifically imports across the interconnection from Great Britain and wind generation output.

The impact of network congestion is captured though constraints on generator commitment and output. The flow limits of the transmission line linking the Northern Ireland system and the Republic of Ireland system is explicitly included in the optimisation.

3.4.3. Interconnection

The All-Island system is connected to Great Britain through two direct current interconnectors: the Moyle line from Northern Ireland to Scotland and the East–West Interconnector (EWIC) from the Republic of Ireland to Wales. The Moyle interconnector can theoretically export 300 MW but is limited in operation to 80 MW due to network constraints in Scotland (Mutual Energy, 2011). The 500 MW of capacity of EWIC was commissioned in quarter 4 2012. Interconnectors imported electricity throughout 2012, with imported electricity contributing 6% of total electricity consumption.

Previous studies have modelled interconnector flows by representing market price differentials between the All-Island system and Great Britain (Denny et al., 2010; Diffney et al., 2009). Evidence of market integration barriers shows that this approach may overstate the liquidity of interconnector trade, with trade over the interconnection capacity primarily influenced by system operation considerations (Lytvyn and Hewitt, 2013; Nepal and Jamasb, 2012). Also, due to the merit order effect of renewable electricity, the absence of renewable generation raises wholesale prices in the Single Electricity Market, all else being equal (Di Cosmo and Valeri, 2014; O'Mahoney and Denny, 2011a). This increases the economic signal to import across lines already importing close to capacity. The replacement of renewable generation with fossil-fuel alternatives in the scenarios does not change the operational imperatives or economic signals driving interconnector flows. Given these factors, and the complexities of modelling the UK system and the trading strategies and constraints on the operation of interconnectors in 2012, a fixed profile of the actual recorded flows across these lines for each 30 min period in 2012 is included in the model (SEMO, 2014).

3.4.4. Renewable electricity generation

Actual recorded wind generation and 24h-ahead wind forecast data at a 30 min time resolution is used in the modelling.[11] The available hydro resource for each month is calculated based on the output of hydro units in 2012 (SEMO, 2014). A daily limit constraint for each month is included in the model that allows the model flexibility to optimise the dispatch of hydro generation while remaining consistent with the actual energy production in 2012.

Biomass generation is comprised of landfill gas generation (LFG), some biomass CHP and biomass co-firing at a peat station representing 8.5% of fuel input in 2012. The maximum generation capacities of the individual LFG and biomass CHP units are below the 10 MW threshold for compulsory market participation and therefore can self-dispatch. These units are included in the model at a flat output level consistent with their total actual generation recorded in 2012 (Howley and Holland, 2013). Biomass combustion in the co-firing peat station is included as 8.5% fixed proportion of fuel input for each half-hour period.

3.4.5. Electricity demand, generator outages and 'must run' units

Actual recorded electricity demand and 24h-ahead forecast demand for each half-hour period in 2012 is included for the Republic of Ireland and Northern Ireland (SEMO, 2014). Planned maintenance and unexpected forced outages are included in the model as recorded by the market operator and declared by generators in 2012 (SEMO, 2014). Forced outage rates of fossil-fuel generators are assumed to be unaffected by any increase in cycling due to renewable electricity generation. This may underestimate costs, and Lew et al. (2012) have shown that unexpected breakdowns of thermal generators increase by 0.0086% per hot start.

Peat stations' 'must run' status is included as the actual recorded output for the three individual peat stations in each half-hour period in 2012 (SEMO, 2014).

3.4.6. Fuel prices

The price an electricity generator bids into the electricity market is regulated by the market authorities and is directly linked to the spot prices of input fuels. Quarterly 2012 fuel spot prices for coal, gas and oil were sourced from the IEA's fuel price database (IEA, 2014a). Distillate prices are taken from DECC (2012). The transportation cost of fuel to power stations is calculated using a fuel delivery calculator developed by the CER and Northern Ireland Authority for Utility Regulation (NIAUR) (AIP, 2012). The emissions trading sector (ETS) prices are based on recorded market prices averaged over each quarter of 2012. Table 3-3 shows fossil-fuel and CO_2 prices inputs.

[11] Wind generation and forecast data was provided on request by EirGrid for the Republic of Ireland and by SONI for Northern Ireland.

Table 3-3: Quarterly fuel and CO_2 prices for 2012

	Fuel Price (€/GJ)			
	Q1	**Q2**	**Q3**	**Q4**
Gas (NCV) – Republic of Ireland (RoI)	7.98	7.69	7.70	8.57
Gas (NCV) – Northern Ireland (NI)	8.01	7.73	7.74	8.60
Coal – RoI	3.1	2.7	2.76	2.65
Coal – NI	3.51	3.11	3.17	3.06
Distillate – RoI	21.99	21.62	22.25	20.86
Distillate – NI	21.63	21.26	21.9	20.5
Oil – RoI	17.55	16.45	17.07	15.75
Oil – NI	17.2	16.1	16.72	15.41
	CO_2 Price (€/tonne)			
	8.01	7.07	7.55	7.18

3.4.7. Dispatch decisions under uncertainty-simulation approach

Dispatch modelling approaches that incorporate forecast uncertainty employ a stochastic optimisation that aims to minimise costs over multiple possible scenarios of variable renewable output and electricity demand with multiple-stage unit commitment and dispatch (Deane et al., 2013; Denny and O'Malley, 2006; Lew et al., 2012).

This analysis uses this method and employs a two-stage generator unit commitment and dispatch to capture the impact of forecast uncertainty on generation output and fossil-fuel use. The first stage decides what generators are committed and online in advance based on 24h-ahead forecasts of wind output and electricity demand as well as information on scheduled maintenance outages of generation capacity. The real-time dispatch then takes these prior unit commitment decisions and reoptimises their output for each of the 48 half-hour periods in that day based on actual wind output, electricity demand and any unexpected generator outages. Large forecast errors will result in less optimal real-time dispatch and more fossil-fuel use. An additional look-ahead of 12 half-hour periods is included in the model to ensure that dispatch and commitment decisions include expectations for system conditions outside of the 24h simulation period. These initial conditions are fed into the next 24h-ahead simulation. The system is optimised in this way for each of the 366 days of 2012.

3.4.8. PLEXOS software

The widely used PLEXOS electricity system simulation software runs the model simulations (Energy Exemplar, 2014). A number of analyses have simulated various electricity systems and markets using PLEXOS (AIP, 2012; Calnan et al., 2013; Deane et al., 2013, 2014; Denholm et al., 2013; Di Cosmo et al., 2013; Lannoye et al., 2012; Lew et al., 2012; Malla and Wood, 2012; McGarrigle and Leahy, 2013; SEM-12-045(1), 2012). Deane et al. (2014) describe the relevant capabilities of PLEXOS software in detail.

3.5. Results and discussion

3.5.1. Model calibration

Calibration of the model compared real 2012 data, recorded by the market operator (SEMO, 2014), with the output from progressive model simulations with increasing levels of sophistication — progressing from more simplified market models to models that more adequately reflect real-time operations over the course of the year. The predicted share of each generation type from the simulations is compared to the actual shares recorded in the 2012 data. The accuracy of generator dispatch predicted in the model is also compared against actual recorded data at a daily resolution.

The CER validated market model, the starting point for the analysis, was adjusted incrementally to add more complex representations of real-time operations. The CER market model solves in a more flexible, rounded relaxation (RR) mode, which enables the model to solve in a shorter period of time. RR works by rounding the linear relaxation unit commitment solution to the "nearest" integer values, while enforcing the minimum up time (MUT), minimum down time (MDT), and minimum stability level (MSL) constraints of generators. Because of the need to enforce MUT and MDT, the algorithm is more complex than a simple rounding of individual hourly on/off decisions. In addition, the algorithm seeks to preserve as closely as possible the total commitment MW capacity in each region (as compared to the linearised solution). It uses multiple linear passes as well as decomposition similar to Lagrangian Relaxation. The CER market model dispatch results in a higher predicted use of coal and lower use of gas CCGT as compared to the real 2012 data. The modelled share of coal is 40% higher and the share of gas CCGT is 16% lower than actually recorded in 2012 data. Peaking plant have a low utilisation rate due to the combination of the optimisation settings and the absence of reserve provision and network constraints. Progressive incorporation of the network constraints and then the reserve into the model moves the balance of coal and gas towards the recorded 2012 shares and sees better prediction of peaking plant utilisation.

Incorporating mixed integer programming (MIP) allows the model to solve without breaching constraint limits. This ensures a more precise estimation of generation system flexibility and results in gas CCGTs remaining online in the low-demand periods. Coal units reduce output to allow the dispatch of this generation and to avoid the additional costs associated with stopping and starting gas CCGTs. Additional generator cycling arises, with peaking units being used to provide the flexibility to meet the electricity demand and reserve requirements at times when the output of other generators is bound by their physical limits. When MIP is applied, overall coal use is reduced further, gas CCGT generation increases and peaking plant see a much higher running duty.

The final stage of the calibration to include forecast uncertainty requires the model to make unit commitment decisions that are optimal under a range of probable scenarios. This further increases the running duty of peaking plant, reduces the

share of coal generation and increases the share of gas CCGT. More short-term peaking units are committed in real time to correct for forecast errors in wind and electricity demand, and unforeseen generator outages. Gas CCGTs also cycle more frequently and ramp more often. The inverse of the Mean Average Percentage Error (MAPE) is used to evaluate the accuracy of model prediction at a daily time resolution. The MAPE compares the actual generation across a full day with what actually occurred for each generation type and expresses the accuracy as a percentage of actual recorded generation. This metric shows that the average predictive accuracy was 95% for gas CCGTs, responsible for 61% of total predicted fossil-fuel generation; 90% for coal generators, responsible for 29% of generation, and 52% for peaking units, accounting for 0.6% of the predicted fossil-fuel generation in the model. Generation shares recorded in 2012 data were of 62% for gas CCGTs, 27% for coal and 1% for peaking generators. Peat accounts for 9% of generation in both the simulated outputs and the actual 2012 data. Figure 3-3 shows how the model prediction improves at each stage of model calibration, measured in terms of the annual share of each generation type as a proportion of total fossil-fuel generation.

The additional complexity introduced in the model to achieve the predictive accuracy results in increased running times of up to 15h for a single simulation and is not conducive to running numerous scenarios for several years' data.

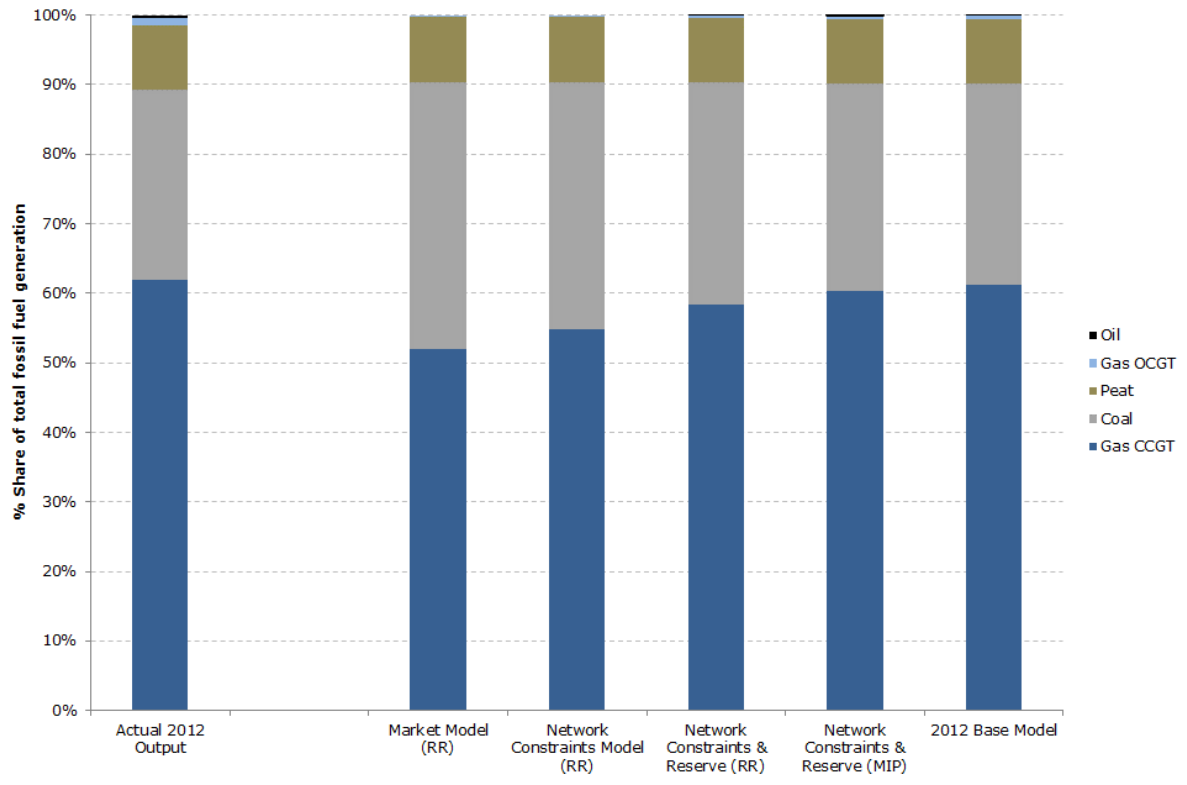


Figure 3-3: Share of fossil-fuel generation by type, actual 2012 data and model simulation predictions

3.5.2. Overall fossil-fuel use and CO_2 savings

The scenario comparisons show that renewable electricity generation is effective in replacing fossil-fuel generation and reducing CO_2 emissions. Wind generation accounted for 15.8% of total All-Island generation in 2012, averting a 20% increase in fossil-fuel use and a 14% increase in CO_2 emissions, relative to the *2012 Base Model*. All renewable electricity generation accounted for 20.4% of generation output and prevented a 26% increase in fossil-fuel use and an 18% rise in CO_2 emissions.

Natural-gas generation is typically the marginal generation source and sees the largest reduction in output with renewable electricity on the system. Some displacement of coal-fired generation is also evident at times of low net load when coal becomes the marginal generator, and at times when network constraints require other more expensive generation to remain online outside of merit order. In the *No Wind* scenario, each 10 MWh of wind generation output replaced, on average, 8 MWh of gas generation and 2 MWh of coal. In the *No RE* scenario, every 10 MWh of total renewable electricity generation replaced on average 8.3 MWh of gas generation, 1.4 MWh of coal and 0.3 MWh of peat.

Due to thermal combustion inefficiencies, fossil-fuel generation requires a higher level of primary fuel input to produce the equivalent of the absent renewable electricity output. Each unit of output from fossil-fuel generators requires between 1.8 and 4 units of primary fossil-fuel input in steady-state operation. In 2012 on the All-Island system, the *No Wind* scenario suggests that renewable electricity generation displaced 1.88 units of fossil-fuel input for each unit of electricity produced by wind. In the *No RE* scenario, total renewable electricity generation displaces 1.53 units of fossil fuel for each unit of electricity produced by renewable energy. The lower displacement ratio in the *No RE* scenario is due to the efficiency losses associated with the co-combustion of biomass in peat stations and the presence of more gas CCGT capacity.

Figure 3-4 shows the net displacement of fossil-fuels (in TJ) and CO_2 emissions (in millions of tonnes) on the All-Island system in both scenarios relative to the *2012 Base Model*. Wind generation is estimated to have saved 2.33 $MtCO_2$, equivalent to an average of 0.46 tCO_2/MWh of wind generation output. Renewable generation in total reduced CO_2 emissions by 2.85 $MtCO_2$, equivalent to 0.43 tCO_2/MWh. The displacement intensity is lower for the *No RE* scenario as less carbon-intensive gas makes up a higher proportion of the fossil fuel displaced because of the inclusion of the additional gas CCGT capacity in this scenario.

Based on the fossil-fuel prices in Table 3-1, the value of the fossil-fuel savings is estimated as €225 million on the *No Wind* scenario and €297 million in the *No RE* scenario.

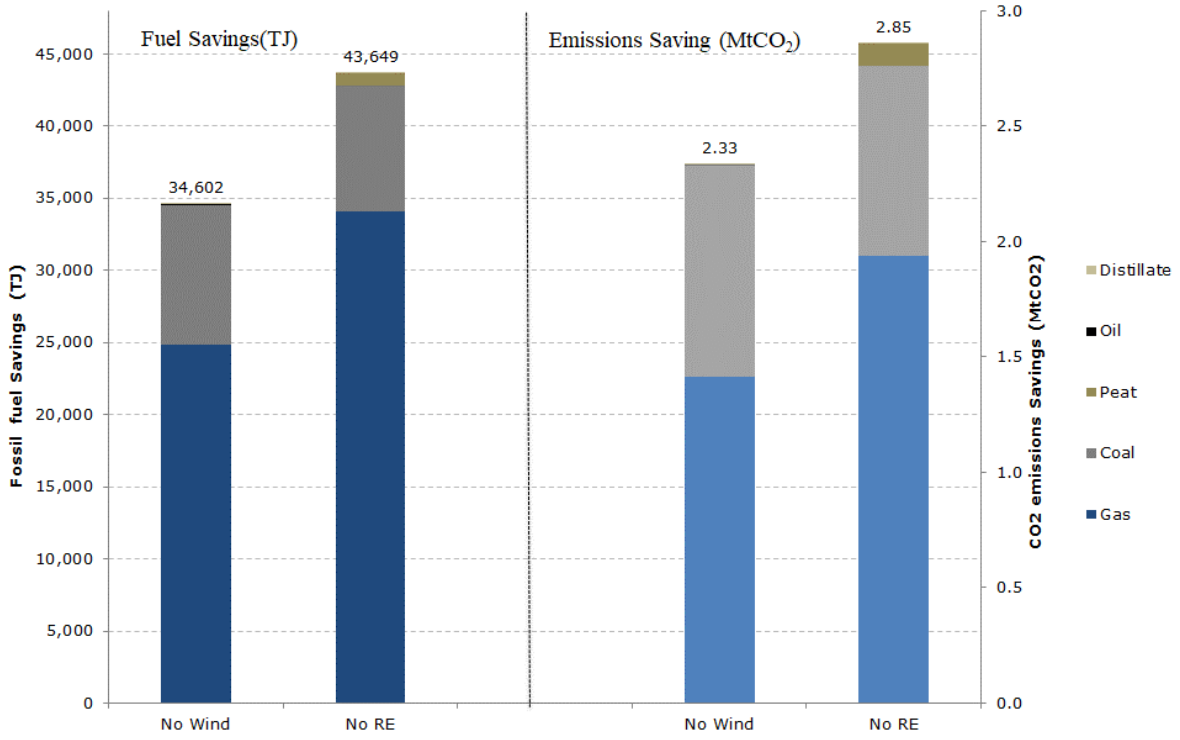


Figure 3-4: Fossil-fuel and CO_2 emissions savings by fuel source.

3.5.3. Impact of renewable generation on fossil-fuel generator operation and CO_2 production intensity

3.5.3.1. Cycling of fossil-fuel generation

Figure 3-5 shows the average amount of time fossil-fuel generators spent online for each start. Coal generators are most affected by the presence of renewable electricity generation. Renewable generation pushes coal up the dispatch curve, resulting in more cycling and a reduction in the amount of time coal units spend online for each start. As a result, coal generators use more fuel for start-ups in the *No Wind* and *No RE* scenarios.

Gas CCGT units also spend less time online for each start with renewable electricity generation on the system but the difference is less pronounced. As the marginal generator, gas units already cycle frequently to respond to daily demand variability.

As start-up energy makes up just 1% of total fossil-fuel use in all scenarios, the reduction in online time for each start due to wind and renewable electricity has little adverse impact on the total fossil-fuel and CO_2 savings.

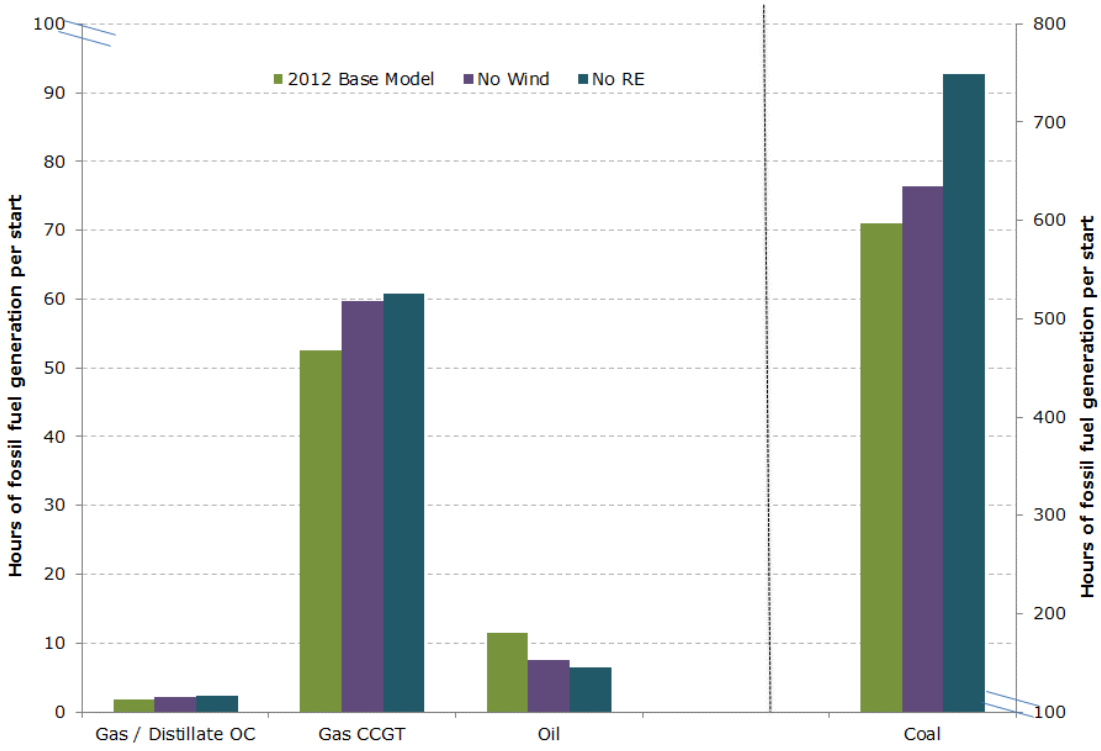


Figure 3-5: Online hours per start-up for fossil-fuel generators in the 2012 Base Model and scenarios

3.5.3.2. Ramping of fossil-fuel generation

Ramping of fossil-fuel generation can be quantified in terms of how frequently these units change output and by the intensity of these output changes. Ramping intensity is measured as the total sum of ramping output throughout the year divided by the total ramping time (Deane et al., 2014). A high ramping intensity signifies that fossil-fuel generators change output more rapidly and/or by a greater amount.

Figure 3-6 shows the average number of ramps per day by generation type (primary axis) and the intensity of the ramps (secondary axis). Coal units see an increased ramping frequency with wind generation on the system. The inclusion of wind capacity means coal deviates somewhat from a baseload running duty by responding more frequently to changes in net load. Many of these additional output changes are of a smaller magnitude in the 2012 *Base Model* and act to lower the average ramping as compared to the *No Wind* and *No RE* scenarios.

The average number of ramps per day that gas CCGTs undertake falls slightly in the *No Wind* scenario. The intensity of the ramps also falls. In the *No RE* scenario, the ramping of CCGTs increases as hydro generators are no longer available as a ramping resource. Gas and distillate open cycle (OC) turbines ramp more frequently with renewable electricity generation on the system.

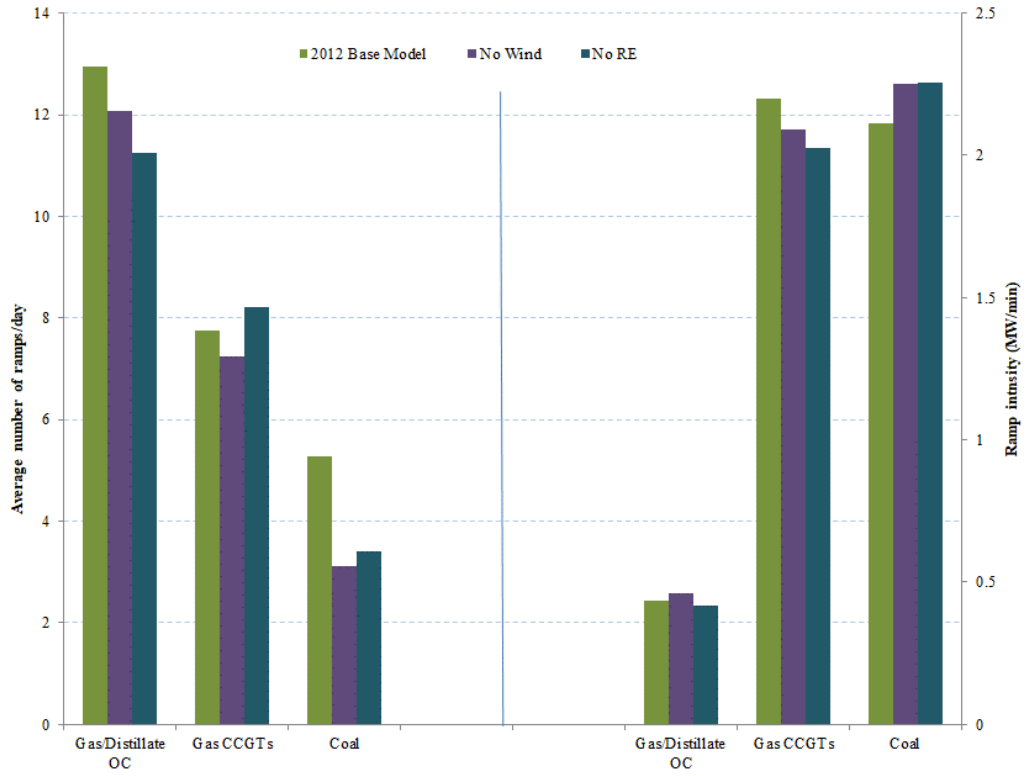


Figure 3-6: Average number of ramps per day and ramp intensity by fossil-fuel generation technology, 2012 Base Model and scenarios

3.5.3.3. Online capacity factor of fossil-fuel generators

The operating efficiency of fossil-fuel generators tends to be highest when these units operate close to or at maximum output. At lower outputs, generators tend to see a reduction in their efficiency and an increase in CO_2 production intensity. Figure 3-7 shows the average output of online generators in 2012 as a percentage of available capacity for each fossil-fuel technology type. The available capacity and output for each generator in each period is used to calculate the online capacity factor. Lower online capacity factors indicate less efficient running duties.

Gas CCGT and coal generators are responsible for over 90% of fossil-fuel generation in all scenarios. With renewable electricity on the system, these units tend to operate at lower, less efficient output levels. The 'must run' status of peat generation sees peat units run close to their maximum output when generating. Gas/distillate OC turbines and oil generators have a higher capacity factor in the *No Wind* scenario as the absence of wind generation is partly covered by an increase in output from these sources. The need for additional OC and oil output is reduced in the *No RE* scenario due to the inclusion of the additional CCGT capacity in the *No RE* scenario.

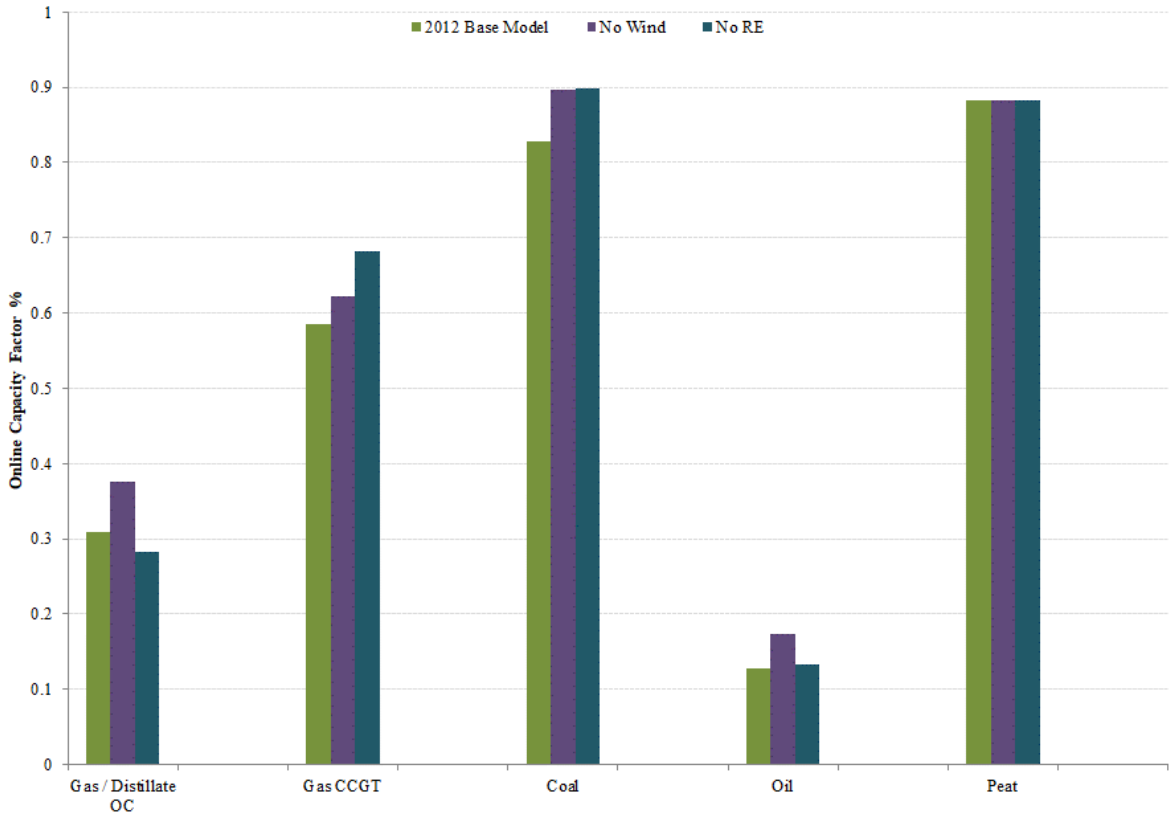


Figure 3-7: Online capacity factor of fossil-fuel generators as % of available output, 2012 Base Model and scenarios

3.5.3.4. Combined impact on CO_2 emissions

Figure 3-8 shows the combined impact of cycling, ramping and reduction in online capacity factors on the average emissions intensity of the individual fossil-fuel units across scenarios. As gas CCGTs and coal are responsible for most fossil-fuel generation, their emission production intensity is of primary concern. The results show that the impact of the operational changes because of renewable electricity generation has a minor impact on CO_2 production intensity. With wind generation removed from the system, CO_2 production intensity drops by 2% in gas CCGTs and by 1% in coal generation. Emission intensity in open-cycle generation and oil generation falls in the *No Wind* and *No RE* scenarios, reflecting their more variable running duty with renewable generation on the system, but these generation sources contribute less than 1% to total fossil-fuel generation output.

Figure 3-9 shows the positive impact of renewable generation on system-wide CO_2 emissions intensity for each scenario. With wind removed from the system, CO_2 production intensity increases by 14%, and by 17% with all sources of renewable generation removed.

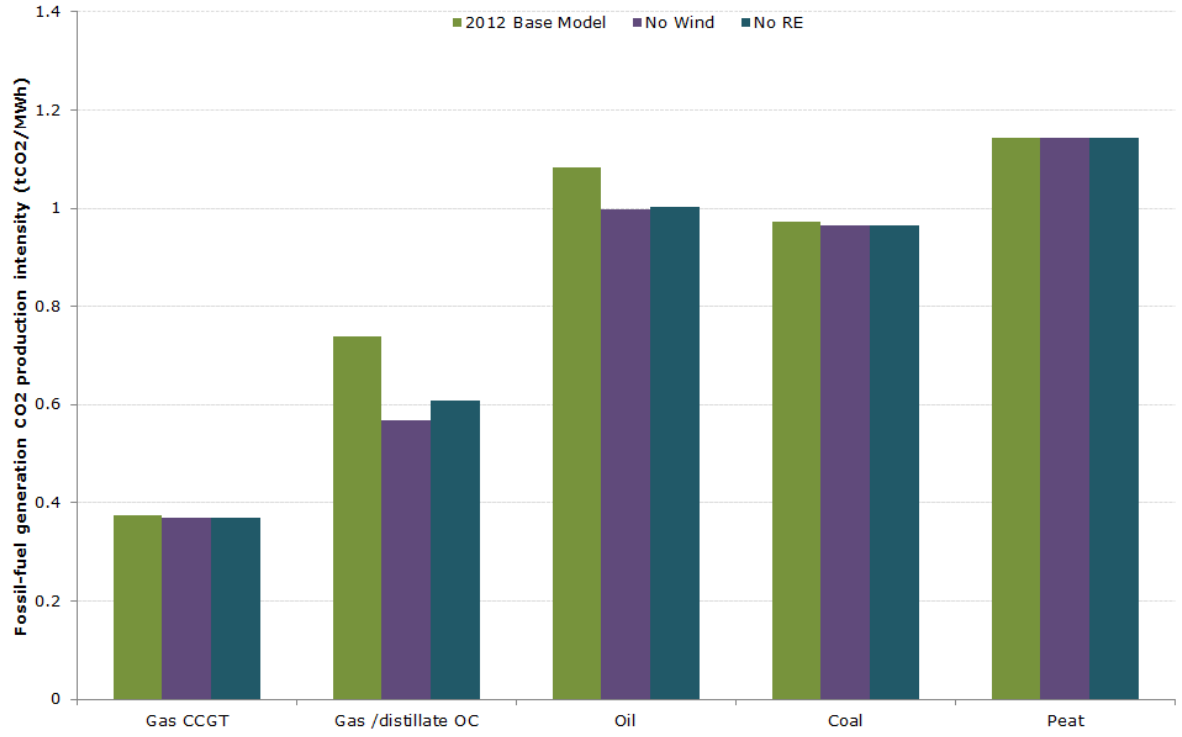


Figure 3-8: CO_2 production intensity by fossil-fuel generation type, 2012 Base Model and scenarios

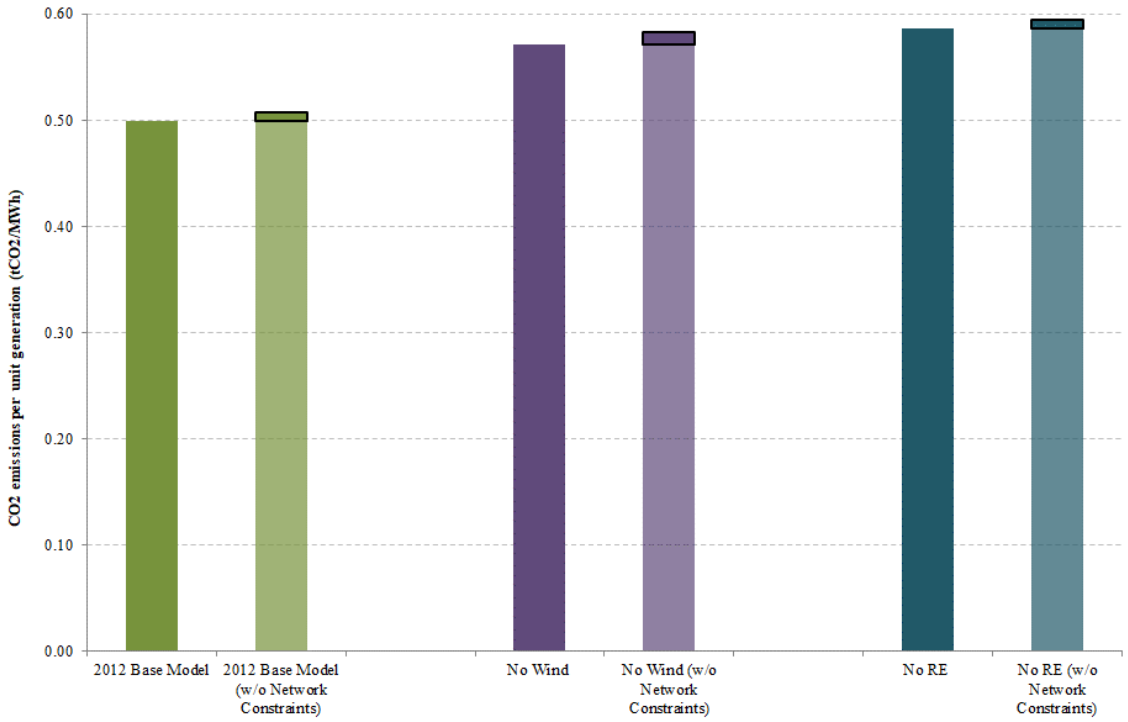


Figure 3-9: All-Island system CO_2 production intensity, 2012 Base Model and scenarios

3.5.4. Network constraints

The results of sensitivity simulations to investigate the influence of network constraints on emissions intensity are also shown in Figure 3-9. Comparing the system-wide emissions intensity levels in the same scenarios with and without constraints shows that intensity levels increase in the absence of network constraints as more expensive gas generation is run less out of merit order, with the result that more carbon-intensive coal generation makes up a greater proportion of generation output. This is a function of the location-specific impact of the constraints as they currently exist on the All-Island system. The impact of constraints on system emissions intensity is small compared to the impact of renewable electricity generation.

The effectiveness of wind generation in displacing CO_2 emissions also increases on the more flexible system. Wind saves on average 0.48 tCO_2/MWh with network constraints removed, a 5% increase. The displacement impact of all renewable electricity generation is similar with and without network constraints.

3.5.5. Seasonal CO_2 emissions

The level of fossil-fuel displacement due to renewable energy varies as system conditions change across the year. Figure 3-10 shows the changing profile of CO_2 emissions (primary axis) and total system CO_2 intensity (secondary axis) in each quarter of 2012. It emphasises that the measurement of displacement is sensitive to the conditions prevailing in the time period chosen. The availability of pumped storage and interconnection assets influenced the flexibility of the system over the course of the year. The capacity factor of wind generation was highest in the early part of the year, averaging over 45% in January and over 33% in February. The available hydro resource is also highest at these times. A number of coal units were offline for maintenance in Q3, causing a drop in overall CO_2 emissions intensity. The displacement impact was lowest during Q2 and Q3 when electricity demand was the lowest and the output from wind and hydro was lowest.

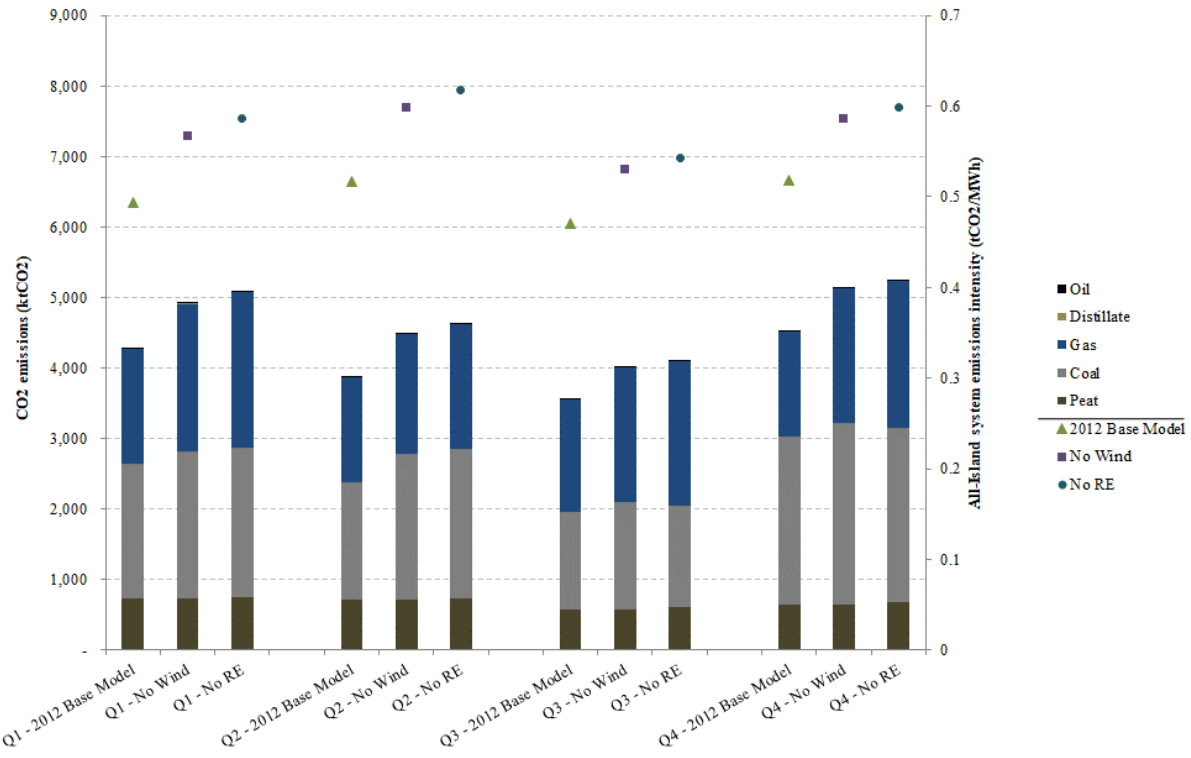


Figure 3-10: Total quarterly CO_2 emissions and CO_2 emissions intensity, 2012 Base Model and scenarios

3.6. Conclusion and policy implications

Several electricity systems now have significant proportions of electricity demand generated from weather-dependant renewable sources. Different methods of quantification have estimated the associated historical savings of fossil fuel and CO_2. Primary energy equivalent and econometric methods have limitations that can bias estimates of fossil-fuel and CO_2 savings and make explanations of contributory factors, like the impact of operational changes to fossil-fuel generation, difficult.

This chapter presented the results of a dispatch model applied to *ex-post* data for a case-study system: the All-Island system on the island of Ireland in 2012. Wind generation was responsible for 15.8% of electricity generation in 2012, averting a 20% increase in fossil-fuel use, worth €225 million, and a 14% (2.33 $MtCO_2$) increase in CO_2 emissions relative to the *2012 Base Model*. Renewable electricity generation in total accounted for 20.4% of total generation output and averted a 26% increase in fossil-fuel use worth €297 million and an 18% (2.85 $MtCO_2$) rise in CO_2 emissions. Each MWh of wind electricity is found to save an average of 0.46 tCO_2, with all renewable electricity saving 0.43 tCO_2/MWh of output.

At current prices, gas-fired generation tends to be the marginal generation in the All-Island system. Systems where coal is the marginal generation source will see higher levels of CO_2 savings per unit of renewable generation.

Additional renewable-related balancing requirements had minor impacts on fossil-fuel generation efficiency, with <2% difference in CO_2 production rates from these units in the *2012 Base Model* as compared to the *No Wind* and *No RE* scenarios. Other contributory factors have a greater influence on savings due to renewable electricity. These include network congestion, system flexibility and financial penalties for emission production. In addition, policy and market incentives can influence these factors to maximise the displacement impact of renewable sources.

These are promising results in the context of the international and EU policy direction of increased deployment of renewable electricity generation. A price increase for EU Emission Trading Scheme credits would see more carbon-intensive generation being displaced. Electricity market incentives that reduce network congestion, increase electricity system flexibility and reward more accurate forecasting of renewable electricity output can also improve the displacement impact of renewable electricity.

Chapter 4

The short-run price and CO_2 impacts of using waste heat from CCGT generators for district heating on a high-renewable electricity system

Abstract

Using waste heat from power generators is a means to reduce CO_2 emissions, but linking heat and electricity markets affects both. High levels of renewable electricity generation may affect the cost of using waste heat and influence CO_2 outcomes. This chapter examines the potential price and CO_2 impacts in both sectors of retrofitting Combined Cycle Gas Turbine (CCGT) to supply a heat network in Dublin. A detailed optimisation model is solved at five-year intervals, from 2020-2035 – with heat network and without heat network – for central and high-renewable electricity deployment. Heat revenue allows CCGT-CHPs to offset electricity production costs and increase capacity factors. Cumulative reductions of 3.5 $MtCO_2$ result: 44% in heat and 56% in electricity. While carbon prices are low, CCGT-CHP displaces some coal generation. The shadow price of electricity reduces by 4%, which increases power exports. Producing heat at CCGT-CHP units is competitive with gas boilers except at times of low electricity prices. More renewables lower the electricity price, thus reducing the competitiveness of heat production. The results are promising for the viability of CCGT-CHPs on a high-renewable electricity system but further research on the efficiency loss impact of CCGT to CCGT-CHP retrofits, system flexibility, long-run market costs and fourth-generation heat networks is necessary.[12]

[12] This chapter is based on a submission to a peer-reviewed journal:
Clancy, J.M., Gartland, D., Deane, J.P., Curtis, J., Ó Gallachóir B.P (2018), The short run price and CO2 impacts of utilising waste heat from CCGT generators for district heating on a high renewable electricity system. *Applied Energy* (in review).

4.1. Introduction

District heating can play a role in the transition to low-carbon energy systems by providing the heat requirements of buildings more efficiently and more cost-effectively than small-scale technologies installed in individual buildings (Lund et al., 2010; Werner, 2017). In areas with many buildings – and thus high heat densities – the delivery of heat through district heating networks can bring environmental and economic benefits. Relative to individual heat sources, consumers can benefit from lower-cost heat, improved reliability of heat supply, greater convenience and lower nuisance factors. Energy producers, particularly those that currently have a waste-heat source, can increase revenues by selling heat.

However, barriers to district heating networks include: long payback times, a regulatory focus on gas and electricity utilities' distinctive competence, fuel and electricity price volatility, and the priorities and experience of local government (Colmenar-Santos et al., 2015; Kelly and Pollitt, 2010). Article 14 of the EU's Energy Efficiency Directive (2012/27/EU) mandates national-level economic assessments of district heating potential (European Parliament and Council, 2012). The recommended method compares the cost of delivering heat through a network with the cost of heat-generation technologies in individual buildings, and does not examine the impacts that district heating may have on the wider energy system (European Commission, 2013). Additional potential for district heating has been identified by several member states, including Ireland (AECOM for SEAI, 2015; European Commission, 2016a). These findings align with Connolly et al., who also show that additional district heating potential exists in the EU and that district heating expansion could reduce heating and cooling costs by 15% (Connolly et al., 2014).

The long-term ambition of the EU is to reduce GHG emissions by between 80% and 95% by 2050, relative to 1990 levels (European Commission, 2011). The pathways to realising a transition from fossil-fuel-dominated systems rely on the efficient use of energy and increased renewable energy production (Chiodi et al., 2013a; European Commission, 2011; IPCC, 2015). Several studies have explored how heat networks and the operating strategies of combined heat and power (CHP) can maximise the environmental benefits and improve the flexibility of the electricity system in countries with large amounts of CHP energy production (Lund, 2005; Lund and Münster, 2003a, 2003b; Lund and Mathiesen, 2015; Nuytten et al., 2013; Sorknæs et al., 2015; Streckienė et al., 2009). Others have focused on the pricing aspects of heat delivered through district heating networks (Difs and Trygg, 2009; Li et al., 2015; Sjödin and Henning, 2004; Zhang et al., 2013), but less information is available on how both systems influence pricing in heat and electricity. For countries like Ireland, with little heat network infrastructure and CHP generation capacity, key questions remain as to what the impact of linking the heat and electricity markets through heat networks may be and how it aligns with pre-existing decarbonisation ambitions.

The research question in this chapter asks what are the price and environmental impacts of linking heat and electricity systems that have developed in isolation from each other, and how high penetrations of renewable electricity production might affect these. Specifically, the chapter explores how CHP units influence the dispatch order in the electricity market, how this influences heat and electricity prices, and what CO_2 emissions outcomes result.

Ireland can offer some useful insights. It has the lowest share of district heating in Europe, at less than 1% of the total heat demand (Euro Heat & Power, 2017) and the heat and electricity systems have developed in isolation from each other. This provides a useful benchmark to measure the impact of a large district heating system on the wider energy system. The Irish government's energy white paper commits to developing a policy framework focused on district-heating (DCENR 2015). Ireland is currently third in the world for the penetration of wind energy, measured as a proportion of electricity demand, and the decarbonisation ambitions will require continued development of wind, solar PV and other renewable sources of power generation (IEA Wind 2016). In addition, CCGT units and a waste-to-energy plant (WtE) near Dublin city, with the largest and most dense heat demand in Ireland, have significant waste heat potential (Alex Kelly and Donna Gartland, 2016a, 2016b; Donna Gartland, 2015; SEAI 2016a),. The CCGT units are currently dealing with reduced running duties due to the increased penetration of wind (AECOM for SEAI, 2015). While Ireland has made progress in decarbonising electricity, progress in decarbonising heat has been slow.

In this Chapter, an optimisation model of Ireland's electricity sector is developed and a representation of a third-generation[13] district-heating network in Dublin fed by CCGT units with retrofitted CHP capabilities (referred to as CCGT-CHP units) is included. The model optimises the dispatch and generation output from the electricity and heat units at an hourly resolution with the objective of minimising overall energy production costs at five-year intervals from 2020 to 2035. A Baseline scenario, where the electricity system continues to develop in isolation from the heat supply, is used to measure the impact of the heat network development. A central case for the deployment of variable renewable electricity generation and a sensitivity for a more rapid increase in the deployment are explored.

The chapter makes a number of contributions to the literature. Many of the previous studies have focused on Scandinavian energy systems that already have large proportions of CHP supplying extensive district heating networks (Lund, 2005; Lund and Andersen, 2005; Lund and Münster, 2003a, 2003b, 2006; Lund and Mathiesen, 2015; Sorknæs et al., 2015). This study quantifies the wider

[13] Third-generation heat networks operate at temperatures of <100°C and are characterised by the use of pre-insulated pipes, compact substations and metering and monitoring of heat use. Third-generation networks have been heat-installed since the 1980s and have replaced previous generations of heat networks operated less efficiently at higher temperatures. Fourth-generation networks that operate at temperature of <50-60°C will be possible with improvements in the thermal performance of the building stock. Lund et al. provide a detailed description of the characteristics of the various generations of heat networks (Lund et al., 2010).

energy system impacts of introducing a heat network fed by retrofitted CCGT-CHP units in the Irish energy system in a detailed way. In addition, the previous analysis has tended to focus on the operational strategies, heat-storage investments and other measures that produce the most optimal use of existing generation assets in scenarios of increasing penetrations of variable renewable generation (Lund, 2005; Lund and Münster, 2003b, 2006; Sorknæs et al., 2015; Streckienė et al., 2009). Based on the findings in previous studies, the method used here allows CHP units to regulate output and goes beyond these by exploring the link between heat and electricity production costs in CHP units and how this influences market prices for both energy types. The EnergyPLAN model has been used to examine the research questions in many of the highly cited papers in the area (Lund, 2005; Lund and Andersen, 2005; Lund and Münster, 2003a, 2003b, 2006; Lund and Mathiesen, 2015; Mathiesen et al., 2015). An additional contribution is the use of a validated power systems simulation model extended to include heat demand. This also contributes to the development of approaches to integrate modelling methods for electricity and heat systems integration. The methods and analysis provide useful insights for many regions within the EU and beyond that have high shares of CCGT electricity generation, with the potential to supply heat demands. The chapter also contributes evidence that can inform the current discussions of the District-Heating working group in Ireland and to inform district heating initiatives under the National Development Plan (Department of Public Expenditure and Reform, 2018).

Section 4.2 provides some background, Section 4.3 details the method and describes the data, Section 4.4 presents the results that are discussed in Section 4.5, and Section 4.6 concludes.

4.2. Background

4.2.1. Energy cost of heat production in power generators – the Z-factor

Power generators produce large amounts of heat as part of the electricity production process. The low temperature of the heat means it has a low exergy value and is unusable as a heating source for the current generation of district heating networks. Steam generators typically condense steam to ~30°C (Lowe, 2011) and buildings typically require water at temperatures >60°C (SEAI, 2017). Power generators located near to heat networks can retrofit CHP capabilities in order to increase the heat temperature. This comes at the expense of electrical output and efficiency.

The ratio of electricity lost to heat produced is known as the Z-factor. Lowe describes how the Z-factor is thermodynamically equivalent to the coefficient of performance of a heat pump (Lowe, 2011). Heat networks operating at higher temperatures require higher-temperature heat from CHP units. This results in a greater reduction in electricity output for each unit of heat produced and a lower Z-factor. A typical third-generation network requires heat at ~100°C (Lowe, 2011; Lund et al., 2010). At these temperatures, large-scale CCGT-CHP units achieve Z-factors of 4-7 (Poyry and AECOM, 2009; Lowe, 2011; Ricardo AEA,

2011; David Andrews et al., 2012). Fourth-generation DH networks have significantly lower input temperatures (<70°C) and offer the opportunity of higher Z-factors; some sources suggest that Z-factors as high as 12-18 may be achievable (Lund et al., 2010; William R H Orchard, 2009).

The capital costs of retrofitting CHP capabilities are not considered in this analysis but are shown here for completeness. These costs depend on the extent of the steam turbine modifications required (Andrews et al., 2012). The costs can range from 10%-20% of the original capital costs of the power station (Andrews et al., 2012) – for gas CCGT, this can be in the order of 50 to 100 €/kW_{th}. Analysis of the heat available from CCGT units in Scotland suggests a wide range from ~40 €/kW to over 300 €/kW (Ricardo AEA, 2011). The Scottish study shows that the capital costs of upgrades are not sensitive to heat output. More heat output capacity, all else being equal, lowers the cost per kW of the investments.

4.2.2. Power and heat market interaction

For CHP units with short-run costs below the electricity market price, the cost of producing heat, P_h, is equal to the market price of the forgone electricity, P_e, divided by the Z-factor.

$$P_h = \frac{P_e}{Z}$$

These CHP units can seek to maximise heat output at times of low electricity prices and maximise electricity output at times of high prices (Type I).

Units with electricity production costs above the electricity price require offsetting heat revenues in order to be dispatched in the electricity market (Type II). The combination of heat and electricity market revenues must equal the fuel burn (and other short-run costs) to meet profit maximising conditions. The profit maximising heat price for a Type II unit is:

$$P_h = \frac{P_f HR_{avg} - P_e \sigma}{Z(1-\sigma)}$$

where P_f is the fuel price, HR_{avg} is the average electrical heat rate of the unit in CHP mode, σ is the electricity output reduction factor and Z is the Z-factor.

Type II units may become more common as electricity systems decarbonise. The electricity market price tends to reduce at times of high output from variable renewable electricity generation (Lund and Mathiesen, 2015; O'Mahoney and Denny, 2011b; Sensfuß et al., 2008). CHP generators with short-run costs, previously below the market price, can move towards or above the margin.

Figure 4-1 plots marginal cost equal to marginal revenue – profit maximisation under perfect competition – in terms of short-run prices in the heat and electricity markets. The figure illustrates the potential trade-offs between power output loss

and heat market revenue. It shows how the economics are influenced by the electricity price and the generation cost as well as how higher Z-factors reduce the cost of heat production. Points A and A' show where the electricity price corresponds to the minimum heat price; the short-run marginal cost of electricity generation is equal to the electricity market price. At 30€/MWh the corresponding heat prices are 4.7€/MWh and 7.5€/MWh for Z=6.3 and Z=4 respectively. This point also represents the transition from a Type I to Type II unit. CHP generators will aim to produce as much heat output as possible at electricity market prices at or close to point A, where heat production costs are lowest.

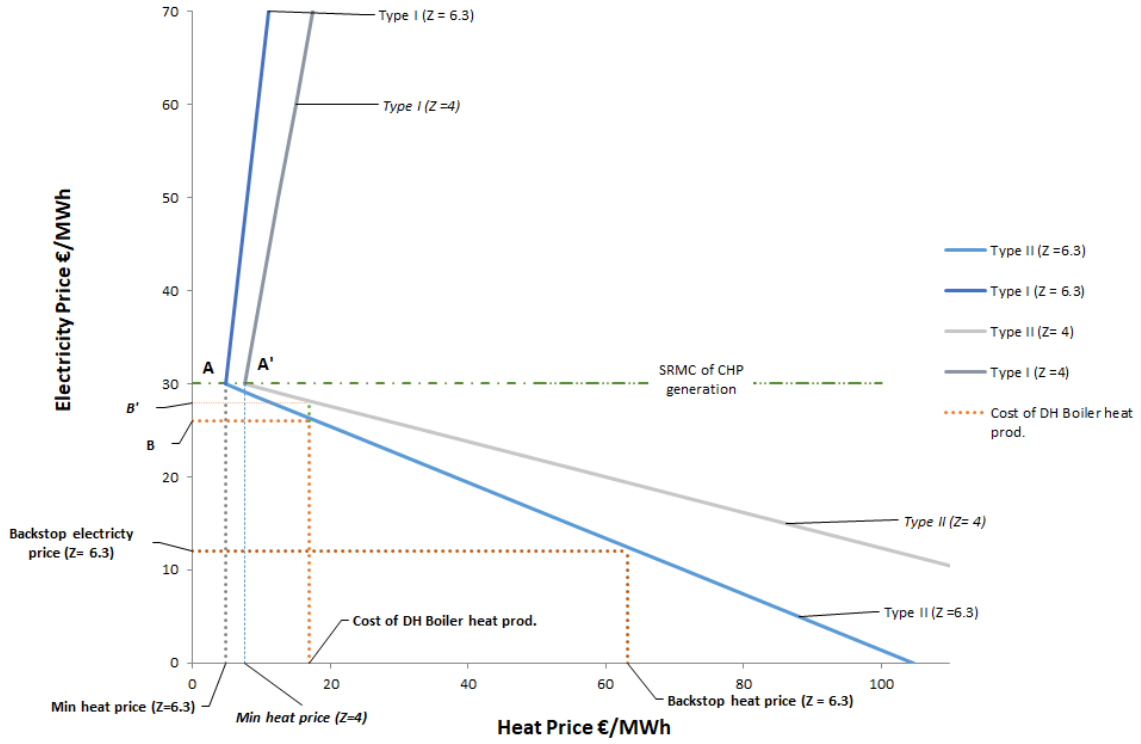


Figure 4-1: Price dynamics for CHP feeding a DH network (illustrative)

The theoretical backstop short-run price is the cost of generating heat in individual buildings. The heat generation sources connected to a heat network, including storage, must be capable of meeting heat demand peaks and have redundancy to ensure heat is available in the event of breakdowns or extreme demand peaks. Hence the typical upper-bound price on a heat network is set by these generation technologies with higher short-run costs of heat production, e.g. large gas boilers with low annual capacity factors. Points B and B' show the lowest electricity price that can allow CHP units to compete with boiler-produced heat. In this example, should electricity prices fall below 28€/MWh for Z=4, and below 26€/MWh for Z=6.3, it becomes uneconomic for CHP units to generate – the cost of heat production is above that of the large-scale boiler.

4.2.3. Allocation of CHP fuel use to heat and power

The method for distributing fuel use in CHP units between heat and power is subject to debate (Verbruggen et al., 2013; Orchard, 2009). The International Energy Agency (IEA) and Eurostat use the energy allocation method (Eurostat, 2017). Fuel use is allocated based on the proportion of energy output used for heat and power. The underlying thermodynamics of the separate heat and power products are not considered. The fuel use associated with heat production is overestimated, and underestimated for electricity production. The method is primarily used in the construction of energy balances.

The Exergy method[14] allocates fuel use on the basis of the exergy content of both energy products. This method is the most thermodynamically appropriate but requires detailed information on the parameters of the energy production cycle in question (Rosen, 2008).

The reference technology method allocates fuel based on the efficiency of producing heat and power separately. This method forms the basis for determining if a CHP unit meets the high-efficiency CHP standard in the EU's Energy Efficiency Directive (2012/27/EC). The Environmental Protection Agency in the US applies the method in the CHP emissions savings calculator (US EPA, 2017).

CHP operators can allocate based on the market value of heat and electricity (Holmberg et al., 2012; Rosen, 2008; Siitonen and Holmberg, 2012). This is known variously as the economic method or market method. While this method may not be the most appropriate for allocating fuel use from a thermodynamic point of view, it does offer most flexibility for the generators (Holmberg et al., 2012).

4.3. Data and method

The analysis uses a validated model of the Irish electricity system and generation stock, extended to include a representation of a third-generation (3G) district heat network. The model minimises the total system costs by optimising the production of electricity and heat. The electricity price is determined based on the current market rules of the Single Electricity Market (SEM) on the island of Ireland (SEMO, 2009). To link the heat and electricity markets, the analysis assumes that current electricity market rules are extended to allow CHP generators to consider the value of heat in determining their bids into the electricity market.

Baseline systems – with no district-heating network – provide benchmarks to measure the impacts of using waste heat from the power generators to supply the

[14] We use the formula suggested by Rosen (2008) as follows: $f_E = Ex_E/(Ex_E + Ex_Q)$ where f_E is the fuel share of electricity and $Ex_E$and Ex_Qdenote the exergy content of electricity and heat respectively. $Ex_E = 1$ and $Ex_Q = Q * (1 - T_0/T)$. Q is the heat output and T specifics the temperature at which heat crosses system boundary (100oC/373o K) and To is the reference environment (30oC/303oK).

network. Four primary scenarios are examined at five-year intervals from 2020 to 2035:

Central renewable deployment

- **Baseline:** no district heating system and electricity dispatch based on meeting electricity demand. Heat fuel use is based on producing heat in a 90% efficient gas boiler.
- **3rd generation district heating network (3G Scenario):** heat network supplying heat to Dublin city from CCGT units retrofitted with CHP capabilities, the existing waste-to-energy plant and centralised gas boilers.

High-renewable electricity system (HRES)

- **Baseline HRES:** annual capacity additions of variable renewable electricity installations increase by 50%. Heat fuel use is based on heat in a 90% efficient gas boiler.
- **3G HRES Scenario:** 3rd generation district heating network added to Baseline HRES.

4.3.1. Dispatch model

PLEXOS software is used to model the system and is available free of charge to academic institutions for non-commercial research purposes. PLEXOS is widely used in the literature as well as by the power sector in Ireland (Clancy et al., 2015; Collins et al., 2017; Deane et al., 2014; Di Cosmo et al., 2013; Lew et al., 2013; McGarrigle et al., 2013). This analysis is based on a data set validated and published by the market regulators on the island of Ireland (Baringa for CRU, 2016).[15]

The objective function of the model is detailed in the equation below. The objective is to minimise system costs including start costs, energy production costs including emissions costs, any unserved energy costs and interconnection wheeling charges to meet electricity and heat demand.

$$min\left\{Sc_i.S_{i,t} + (Pc_i + Ec_i).F_{i,t} + W.IF_{i,t} + UE_t.Pen\right\}$$

Start-up costs, Sc, are scaled by the unit commitment state, S, at time t for plant i. The commitment state is determined in the previous simulation period - if the unit was generating the commitment state value is 0. Start costs depend on the

[15] The validation of the model compares the model simulation to actual market outturns. The results of the validation process are published in a report by the market regulators along with the forecast model and data.

time since the unit was last running, and 'hot', 'warm' and 'cold' start costs are defined. Variable operating and maintenance costs and fuel costs are captured in Pc and emissions penalty costs are included in Ec_i. $F_{i,t}$ is the quantity of fuel used by unit *i* in time period *t*. A penalty cost, Pen, for unmet electricity demand is included to capture the cost of any unserved demand, UE_t, in time *t*. The cost of interconnector use is captured by the wheeling charges, W, and the volume of flow, $IF_{i,t}$, across interconnector *i* and time *t*.

The heat and electricity markets are linked explicitly through the production cost function for CHP units. The term $F_{i,t}$ is determined for CHP units operating in CHP mode by:

$$F_{i,t} = HR.E_{i,t} + (HR_{CHP} - HR).R.H_{i,t}$$

where HR is the heat rate of the unit in condensing mode, HR_{CHP} is the incremental heat rate in CHP mode, $E_{i,t}$ is the electrical output of unit *i* at time *t*, R is the heat to power ratio and H is the heat output of unit *i* at time *t*. Two key constraints specify electricity and heat demand. Electricity demand $D_{E,t}$ for time *t* is given by $\sum_i^N E_{i,t} = D_{E,t}$ and heat demand $D_{H,t}$ is given by $\sum_i^N H_{i,t} = D_{H,t}$. Heat demand can be met by CHP generation or by output from gas boilers.

The objective function minimises system costs by dispatching a chronologically consistent, least-cost arrangement of generation units to meet heat and electricity demands across the time horizon. An additional look-ahead of six hours into the next day is incorporated to avoid sub-optimal outcomes at the daily time step boundaries; the solutions for the look-ahead period are then overwritten by the solution for the simulation period. The model generates a maintenance schedule based on forced outage rates and repair times of electricity generators to equalise the capacity reserves for the one-year horizon. Monte Carlo simulation generates random forced outages and the frequency of time offline is determined by the forced outage rates.

Electricity demand and generation are defined at a single node and dispatch decisions are assumed to be unaffected by transmission constraints.[16] Heat demand is represented by a constraint in the model to be met by the optimal dispatch of CHP units, backup gas boilers and the heat in storage. The model represents generator capabilities through constraints on the maximum and minimum outputs, start-up times, minimum online and offline periods, and how quickly generators can change output. Constraints also define the capacities and losses on interconnector power lines and the maximum allowable instantaneous penetrations of variable renewable sources. The model contains information on: generator heat rates; forced outage rates and mean repair times, and start-up fuel and energy requirements.

[16] The Irish TSO is currently implementing a grid upgrade programme called Grid 25 aimed at strengthening the grid and eliminating sub-optimal congestion and constraints. See: https://goo.gl/yFrAJb

The model is solved at five-year intervals from 2020 to 2035. Since this study is not concerned with specific operational issues, a deterministic approach is taken; electricity and heat generators are dispatched with 'perfect foresight' of variables that may be subject to uncertainty, such as electricity and heat loads, renewable electricity outputs and generator availability.

4.3.2. Dublin heat demand

Dublin City has a population of 1.3 million (Central Statistics Office, 2016) and an estimated annual heat demand of approximately 9,000 GWh (SEAI 2016a). Gas is the primary fuel used for heating but direct electric heating is common (Element Energy and The Research Perspective for SEAI, 2015a). A small number of buildings are connected to local networks but most buildings have individual heat generation technologies installed. Analysis of heat demand density (TJ/km^2) in the Dublin city area shows 75% of mapped areas have heat demands suitable for district heating (Donna Gartland, 2015). A number of studies have shown that municipal district heating projects are economically feasible in the Dublin area (AECOM for SEAI, 2015; Byrne Ó Cléirigh for SEI, 2009; Donna Gartland and Tom Bruton, 2017; RPS and COWI, 2007). Dublin City planners require new buildings to be district-heating-enabled and are designing network development (Dublin City Council, 2016; RPS for Dublin City Council, 2016). Figure 4-2 shows a linear heat density map of Dublin and the locations of the power stations (red dots).

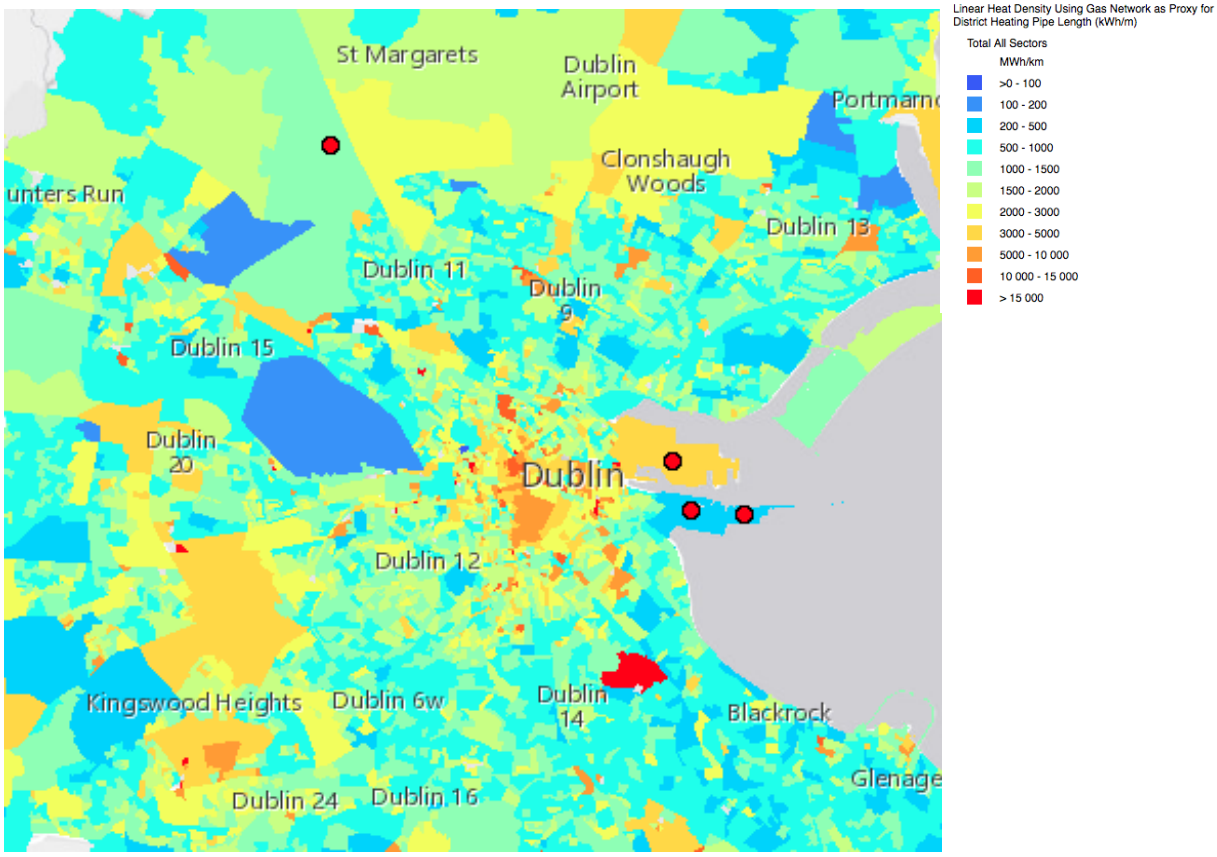


Figure 4-2: Linear heat density of Dublin City – MWh/km (Sustainable Energy Authority of Ireland, 2016a)

4.3.3. The Irish electricity system

The electricity system on the island of Ireland is interconnected with Great Britain (GB). Gas generation, provided primarily by CCGT units, accounted for 43% of gross electricity demand in 2015, followed by wind (22.8%), coal (16.9%) and other renewable generation (4.5%). Other fossil-fuel generation accounts for the remainder (Howley and Holland, 2016a). The peak demand on the all-island system has been rising slow in recent years. Peak demand in 2012 was ~6,400 MW and in 2015 was ~6,700 MW. Expectations are for this peak to increase to between 7,070 MW and 7,960 MW by 2026. In 2015, the installed wind capacity is 3,010MW (EirGrid 2016). Ireland ranks third in the world for the penetration of wind generation (IEA Wind 2016). Instantaneous wind penetration peaked at over 60% in January 2017 (EirGrid 2017a). As a small and electrically isolated system, the Irish system operator imposes a limit on the amount of non-synchronous sources of power on the system at any given moment in order to maintain control over frequency stability. This is known as the synchronous / non- synchronous pentation limit and has risen from 50% in 2012 to 75% in 2018.

CHP is a small contributor to electricity generation. There is a total of 339 MW_e of CHP, predominantly gas, with one large CHP generator responsible for 47% of this capacity. Just over 1 MW_e is connected to district heating systems. These CHP plants account for approximately 7% of electricity generation, placing Ireland 21st of the EU-28 countries in 2013, and 7% of thermal energy demand in Ireland (Howley and Holland, 2016b).

The All-Island system in Ireland has 950 MW of interconnection with GB, across two interconnectors. A simplified model of the GB system is included to simulate cross-border trade. Wheeling charges are imposed on interconnector flows. The validated model specifies a heat rate for the GB market based on the historic relationship between gas and carbon prices and market bids.

4.3.4. Generation capacity and electricity demand

The validated model time horizon is extended to 2035. The capacity additions and retirements are based on the Generation Capacity Statement published by the Irish system operator (EirGrid 2017b). An additional 450 MW gas CCGT and a 90 MW gas peaking plant are added in 2030 to maintain generation adequacy.

Wind generation capacity additions follow the trajectory published by the Irish system operator to 2026 and annual capacity additions post 2026 occur at the 2020-2026 average, 200 MW (EirGrid 2017b). In the high deployment scenario, wind capacity additions are increased by 300 MW per annum from 2025. The hourly profile for wind output uses the historical wind profile from 2009 from the validated model (Baringa for CRU, 2016). The 2009 capacity factor was 31% and represents a typical wind year (Howley and Holland, 2016a). Other renewable electricity generation capacity additions follow the expectations of the Irish system operator (EirGrid, 2017b).

The median scenario for electricity demand from the system operator is used to 2026 (EirGrid, 2017b). Post 2026, the average annual growth rate from 2020-2026 is used to project demand to 2035. The hourly demand profile uses the 2015 profile from the validated model (Baringa for CRU, 2016).

Wind and solar output is curtailed at the synchronous/non-synchronous constraint limit of 75% (EirGrid, 2017). This limit is represented by a constraint on the instantaneous generation output from non-synchronous sources.

4.3.5. Heat demand and heat network

Annual heat demand estimates are included for a 15 km zone from the main heat-supply power stations in the east of the city, encompassing all four power stations examined. The heat demand is based on energy mapping analyses carried out for the Dublin region (Kelly and Gartland, 2016a, 2016b; Gartland, 2015). The annual heat demand estimated is 9,100 GWh. Given the implications of large diurnal variations for the cost of district heating infrastructure, it unlikely that a district heating system would be designed to meet the current profile of Irish use. Hence, a more typical profile for district heat consumption, based on actual data from Norwegian heat networks, was applied to the annual heat demand to produce a diurnal profile (Pedersen et al., 2008). We assume a gradual roll-out of the network, starting from 15% of heat demand in 2020 to 85% by 2035.

Heat generation is provided from combining the heat generated from the retrofitted CCGT-CHP units, the existing waste-to-energy plant in Dublin and peaking gas boilers, equivalent to 120% of average peak heat demand (Connolly et al., 2014). The conversion efficiency of the gas boilers ranges from 85-90% (European Commission, 2013; IEA ETSAP and IRENA, 2010). The existing waste-to-energy plant has a maximum output of 67 MW_e and operates a heat to power ratio of 0.63. Heat storage is included at each of the retrofitted sites equivalent to six hours of heat production (Gartland and Bruton, 2017; IEA ETSAP and IRENA, 2013).

4.3.6. CCGT-CHP retrofits

Power generators are limited by the amount of heat that can be bled from the steam generator. Bleed point optimisation will vary for the circumstances of individual power generators. In the absence of detailed site data, we assume that the power generators are likely to limit bleeds to the Intermediate Pressure (IP) to Low Pressure (LP) reheater circuits at the final stage of steam turbines (Andrews et al., 2012). The final stage of a steam turbine typically contributes approximately 10%-25% of the total output from the steam turbine (Saqib Riaz, 2017), though this may be as high as 50% in some cases (Zachary et al., 2006). The contribution of the steam turbine to the overall output of CCGTs varies with shaft configuration, technology type and ambient atmospheric conditions. The steam turbine contributes between 33% and 47% of the maximum rated capacities of the units

considered in this analysis (Global Energy Observatory, 2017a, 2017b, 2017c). Hence, CHP retrofits could result in power output reductions of up to 12%.

The heat to power ratio can be represented by:

$$R = \frac{Z(E - \sigma E)}{\sigma E}$$

where E is the pre-retrofit power output and σ is the power reduction factor. A central Z-factor of 6.3 is used based on the mid-range of published values (AECOM for SEAI, 2015; Andrews et al., 2012; Lowe, 2011; Lund et al., 2010; Poyry and AECOM, 2009; Ricardo AEA, 2011; William R H Orchard, 2009).

Annex II of the Energy Efficiency Directive specifies a primary energy savings (PES) standard for CHP and co-generation. It compares the efficiency of CHP generation to the separate production of heat and power from efficient reference technologies, i.e. a CCGT and a gas boiler (2012/27/EC). The power reduction of the units was initially calculated based on the availability of 10% of the energy from the steam turbine. For some units this did not meet the PES standard of high-efficiency CHP. A further reduction was then made to the power output of these units to meet the 10% PES standard.

The CCGT units can operate in two modes in the model: condensing mode and CHP mode. Two separate heat rates are defined for each mode. The heat rates for the electrical output of retrofitted CCGT-CHP units are determined from:

$$HR_{CHP} = \frac{HR_{nl} + (HR_{inc,} * E)}{\sigma E}$$

where HR_{inc} is the pre-upgrade incremental heat rate in GJ/MWh. The no-load heat rate, HR_{nl}, is unaffected by a CHP upgrade.

Table 4-1 shows the maximum rated capacities, the gas and steam turbine maximum rated outputs, the power reduction factors and the average heat rates for the CCGT units.

Table 4-1: Technical details and retrofit adjustments for CCGT units

	Configuration	Max capacity (MW_e)	Gas Turbine(s) rated capacity (MW_e)	Steam Turbine rated capacity (MW_e)	Condensate mode incremental heat rate (GJ/MWh)	Estimated power reduction post retrofit* (%)	Average electrical heat rate in CHP mode (GJ/MWh)	Heat to power ratio
Dublin Bay Power	Single shaft of Alstom GT 26B & Alstom ST-1	415	265	150	5.69	-4%	5.90	0.24
Poolbeg CCGT	2 X 2 GT generator sets, Siemens V94.2 + 1 Siemens ST-1 steam turbine	512	342	170	7.04	-8%	7.68	0.57
Huntstown	Single Shaft Siemens V94.3A GT + Steam turbine	352	240	112	6.04	-5%	6.35	0.32
Huntstown Phase II	Single Shaft Mitsubishi 701F GT + Steam turbine	412	220	192	5.8	-5%	6.08	0.31

**Based on meeting the HE CHP standard for a Z-Factor of 6.3 outlined in 2012/27/EC and European Commission, 2013.*

4.3.7. Fuel and CO_2 prices

The fossil-fuel prices follow the central scenario for gas, oil and coal published by the UK government (BEIS, 2016). This trajectory does not anticipate further price growth from 2030 to 2035. Distillate and low-sulphur fuel oil prices use current Irish prices for these commodities, recorded by the IEA (IEA, 2014a), inflated at the oil price growth rate (BEIS, 2016). Transportation and other costs are included to estimate the delivered cost of fuel to the power stations based on data published by the regulator (Baringa for CRU, 2016). Carbon prices follow the trajectory outlined in the EU Reference Scenario 2016 (Capros et al., 2016). For the UK, carbon prices are based on UK government projections (Government of the UK, 2016a). There is a clear difference in the carbon prices in favour of generation assets located in the Republic of Ireland due to the implementation of the carbon floor price in the UK. Previous work has highlighted the impacts of this (Curtis et al., 2014). Table 4-2 outlines the fossil-fuel and carbon price assumptions used as inputs to the modelling.

Table 4-2: Fuel and CO_2 price assumptions

Fuel €/GJ				
	2020	**2025**	**2030**	**2035**
Republic of Ireland				
Gas (NCV)	4.42	6.31	8.20	8.20
Coal	1.58	2.30	3.03	3.023
Gasoil	14.62	18.24	21.60	21.60
LSFO	15.66	19.47	23.01	23.01
Northern Ireland				
Gas (NCV)*	4.56	6.45	8.34	8.34
Coal	2.09	2.82	3.54	3.54
Gasoil	14.24	17.86	21.21	21.21
LSFO	14.83	18.64	22.18	22.18
Great Britain				
Gas (NCV)	4.18	6.06	7.95	7.95
CO_2 price				
€/tCO2 (ROI)	10	14	35	57
€/tCO2[17] (GB & NI)	5.5	20	59	59

*NCV: Net Calorific Value

Gas prices for residential and business gas customers are used to estimate Baseline costs for the heat sector. Current prices are ex-vat and exclude gas network costs (Howley and Barriscale, 2017). Transmission and distribution costs account for 40% of the final price in the residential sector; this assumption is also applied to business prices. The prices are inflated at the gas price growth rate in (BEIS, 2016). Table 4-3 summarises the prices for household and business gas customers.

Table 4-3: Gas prices, excluding network costs, for residential and business customers

€/GJ	**2020**	**2025**	**2030**	**2035**
Households	12.69	18.64	24.59	24.59
Business	6.44	9.45	12.47	12.47

4.4. Results

4.4.1. Electricity and heat prices

The cost of electricity generation from the retrofitted gas CCGT units and the consequent effect this has on the shadow price of electricity is a key influence on the outcome. Figure 4-1 introduced the dynamics of how heat and electricity market prices can each influence the other. Table 4-4 shows how this dynamic has influenced the short-run marginal costs of the CCGT-CHP units post retrofit as well

[17] EUR/GBP FX rate on the 21/04/17 of 0.837 used to convert GBP to EUR.

as the load-weighted heat and power shadow prices in each market. The pre-retrofit information is also included.

Table 4-4: Average short-run costs of CCGT & CCGT-CHP units and shadow prices for heat and electricity (all scenarios)

Baseline electricity system (no-heat network)								
	Central renewable electricity deployment				***High-renewable electricity deployment***			
(€/MWh)	**2020**	**2025**	**2030**	**2035**	**2020**	**2025**	**2030**	**2035**
CCGT Production cost of elec.	30.90	43.99	63.23	70.99	30.91	43.99	63.20	70.96
Shadow price of electricity	37.79	51.79	66.47	71.64	37.79	51.68	64.50	67.91
Electricity system and 3rd generation heat network								
	Central renewable electricity deployment				***High-renewable electricity deployment***			
(€/MWh)	**2020**	**2025**	**2030**	**2035**	**2020**	**2025**	**2030**	**2035**
CCGT-CHP production cost elec.	29.22	40.35	55.21	61.51	29.22	40.50	55.72	61.30
Shadow price of electricity	36.14	49.61	64.05	68.81	36.14	50.52	61.86	65.64
Shadow price of heat	8.75	18.19	36.50	44.12	8.75	18.12	36.75	44.32

An important observation is the relative difference between the electricity market price and the cost of production from the CCGT pre and post retrofit. The short-run costs of the CCGT units, before the CHP capabilities are retrofitted, move towards the load-weighted average shadow price of electricity over the time horizon – and in the high-renewable deployment case, they move above the shadow price of electricity. Therefore, the cost of electricity production from these units are often above the electricity price. This means that in the 3G scenarios, the CCGT-CHP units frequently operate in Type II mode; in order to be dispatched, the value of the heat must be sufficient to reduce the short-run electricity production costs below the market price of electricity. This effect is reflected in the price of heat over the time horizon. As the cost of electricity production from the units becomes less competitive, the shadow price of heat increases and moves towards the backstop heat price. The backstop price is equivalent to the cost of producing heat from a gas boiler (~ 45 €/MWh in 2035). The modelling shows that on average CCGT-CHP units can produce heat at a cost that is competitive with heat produced from large-scale boilers feeding the same network, but that this reduces as more renewable electricity generation is connected.

Figure 4-3 shows the price duration curve for heat. The chart shows that, as more heat is connected to the network out to 2035, the price of heat increases. This is driven by increased fossil-fuel and carbon prices, increased boiler generation output to meet higher heat demand, and increased Type II operation at the CCGT-CHP units. The areas where Type II operation begins are visible as the slope between the lower price area on the chart and the higher price areas – where boilers set the marginal price. By 2030 the additional renewable deployment in the high-renewable scenarios starts to have an impact on heat price. Increased

output from variable renewable generation further reduces the shadow price of electricity and, as a result, the high-renewable system sees a slightly higher shadow price of heat. The average difference of 0.2 €/MWh in 2035 is statistically significant (p=0.05).

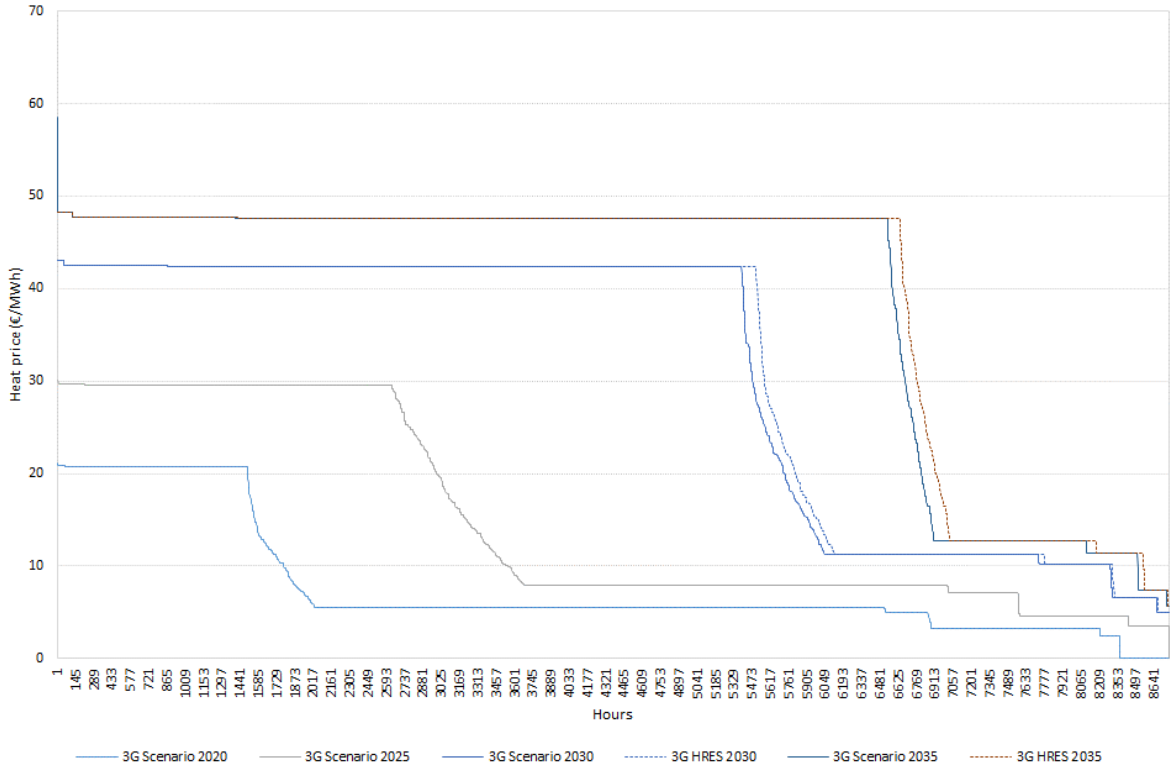


Figure 4-3: Price duration curve for heat price (all scenarios)

While the shadow price of electricity production reduces with increased CHP heat production, electricity prices increase overall. The indirect impact of CHP-CCGTs on the uplift component of the market price drives the increases. Uplift is added *ex-post* to the short-run price of electricity determined by the optimal dispatch in order to recover the other no-load and start-up costs of generators. Though the total number of start-ups and shut-downs is similar in the 3G scenarios and in the Baselines, the units providing the cycling flexibility have higher no-load and start-up costs. This outcome is sensitive to the specific circumstances of the Irish system, particularly the start-up and no-load costs of the generators that take on most of the cycling duties, and the outcome may not be applicable to other systems.

Figure 4-4 shows the market prices for each year broken into the shadow price and uplift components. The addition of CHP reduces the shadow price but increases the uplift component. For all scenarios post 2020, this results in an increase in price. Comparing the 3G scenario to the central renewable deployment Baseline, the average increase is 2%. For the high renewable scenario and Baseline the increase is 3%.

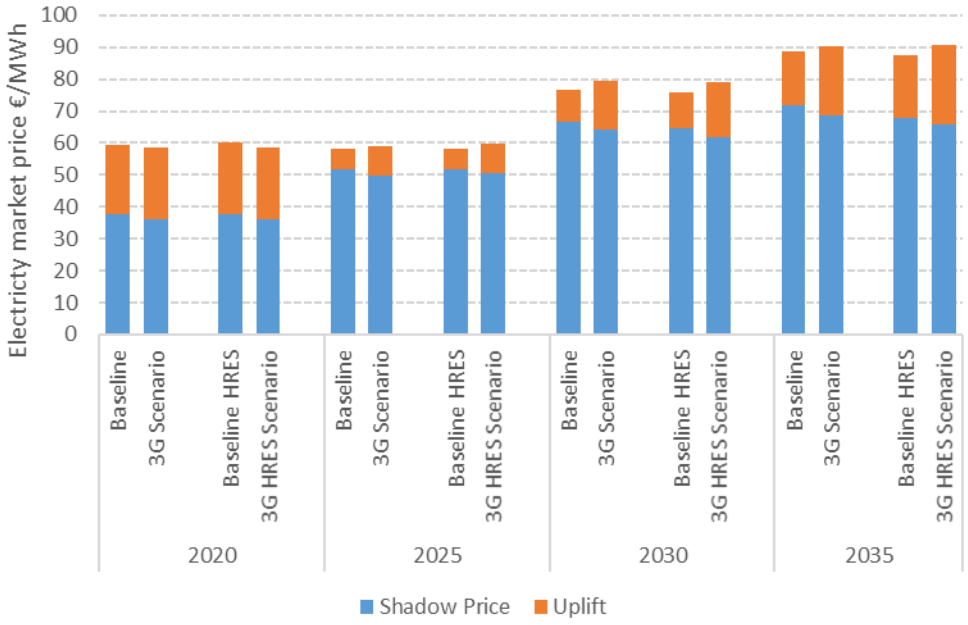


Figure 4-4: Electricity market prices by component (€/MWh$_e$)

The dynamic interaction of heat and electricity prices are explored further in Figure 4-5. The chart shows the shadow price of heat and electricity, the pre-retrofit average SRMC of the CCGT-CHP units and the heat production from CCGT-CHP units and gas boilers for a nine-day period at the start of the heating season in 2030. The chart illustrates the interplay between the electricity price, the heat price and the production of heat. When the shadow price of electricity is above the short-run cost of the pre-retrofit CCGTs, either the heat price is reduced, the production from CCGT-CHP is increased, or both. A notable period of low electricity price occurs during the weekend of 26-27th October, where electricity prices reduce to ~16 €/MWh. At this price, some of the CCGT units cannot compete with gas boilers. The output from boilers increases significantly during this period, with consequent increases in the shadow price of heat as well as reductions in the output from CCGT-CHP units.

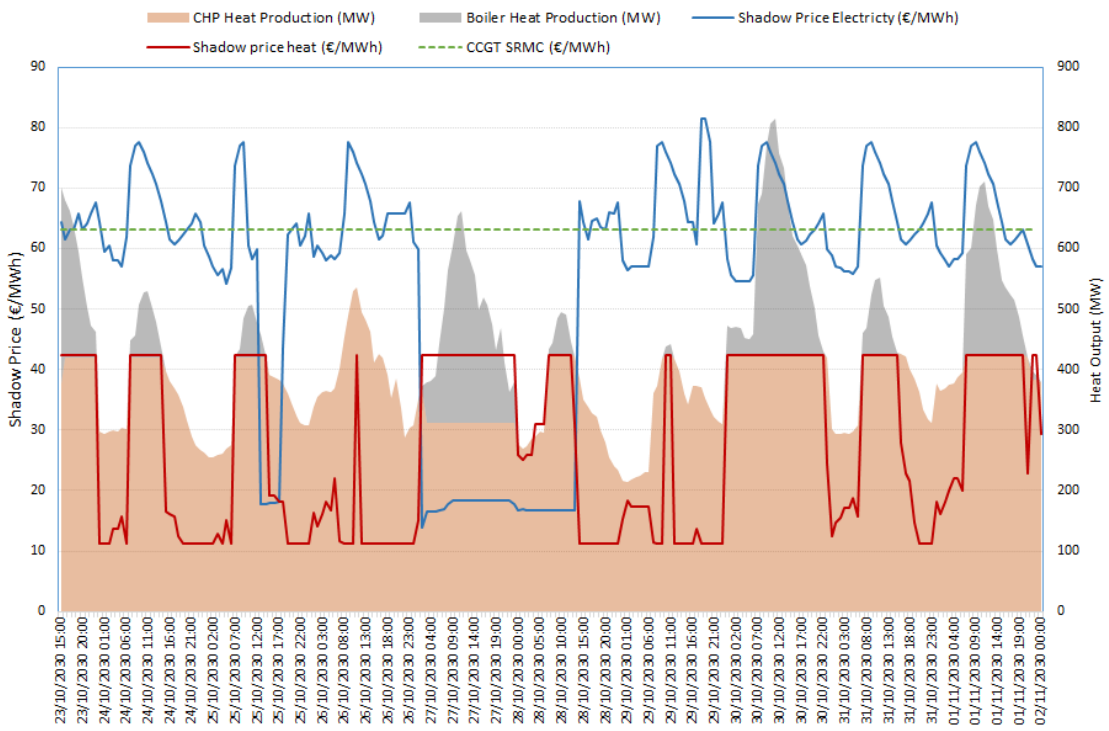


Figure 4-5: Price and heat output interactions for sample week for 3G Scenario in 2030

Heat storage is lightly used in all scenarios due to the limited arbitrage opportunities. As the CCGT-CHP units often need heat revenue to be dispatched in the electricity market, increasing heat output would add further costs to the optimisation that cannot be recovered through arbitrage.

4.4.2. Impact of prices changes

The price dynamics influence a number of outcomes, including changes in the dispatch order on the system, the volumes of electricity exported, fuel use and CO_2 production. Figure 4-8 shows the load duration curves for the Baseline scenario and the 3G scenario in 2030 and 2035 for the gas CCGT pre-retrofit, for the gas CCGT-CHP units and for coal units.

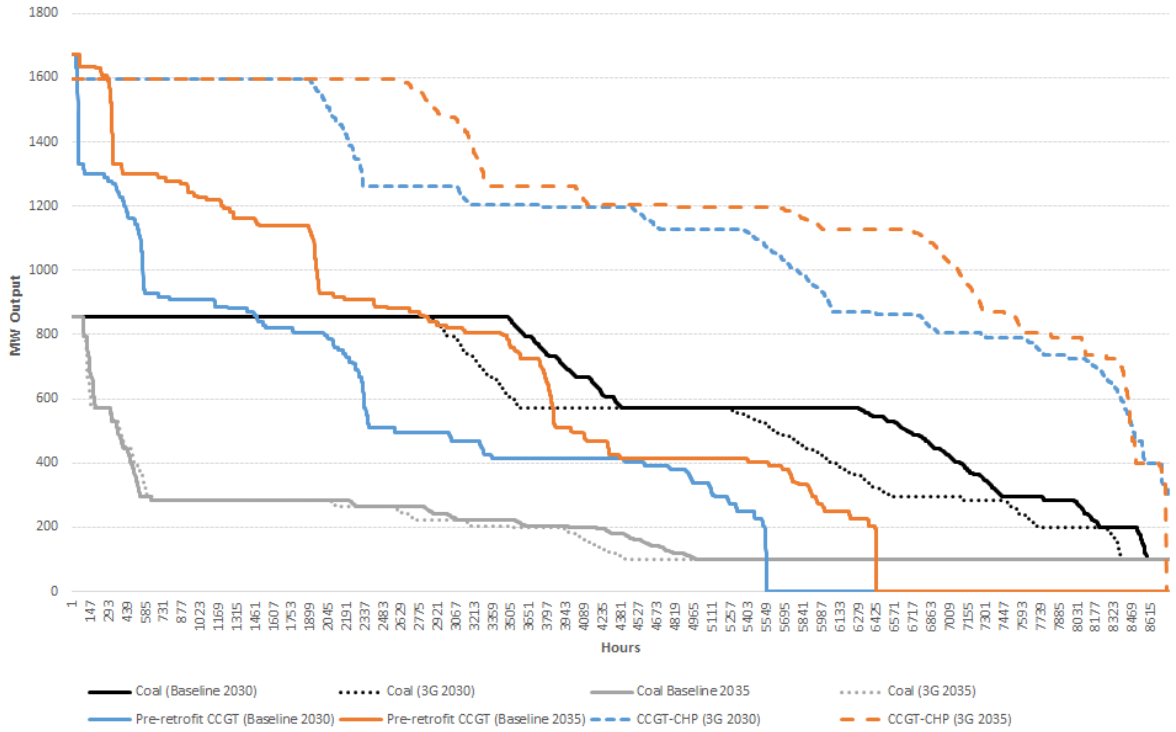


Figure 4-6: Load duration curves for coal generation and gas CCGT generation in Baseline and 3G scenarios

The addition of CCGT-CHP units to the system increases the capacity factor of these units significantly. This reduces the output at other gas stations but also reduces coal use. By 2030, with 65% of the heat demand in Dublin connected, CCGT-CHP operation leads to a ~10% reduction in coal use as compared to the Baseline. Post 2030, large increases in the projected carbon price push coal up the merit order and result in lower annual capacity factors in the Baseline scenario. This means that there is less coal available to displace in the high-renewable scenario in 2035. Figure 4-6 shows similar load duration curves for coal in the Baseline and in the other scenarios.

The overall total CO_2 savings are sensitive to the quantity of generation avoided from coal and the method used to allocate fuel use in the CHP units to the heat or electricity sectors. The IEA method allocates more fuel use to the heat sector and less to the electricity sector, while the Exergy method does the reverse. The EU EED allocation method falls between these extremes.

Figure 4-7 shows the annual savings compared to the Baseline in each year for the electricity and heat sectors. All allocation methods show savings but differ on the sector they arise in. The IEA method allocates the majority of the fuel use to the electricity sector, which results in a relatively large saving in the electricity sector but increased emissions in the heat sector. The Exergy method shows the opposite outcome: large savings accrue in the heat sector but emissions in the electricity sector increase. The EED method shows savings in both end-use sectors.

The impact of the movement of coal generation in the dispatch merit order over the horizon is evident from the change in the trajectory of the electricity sector emissions from 2025 to 2035. Using a linear interpolation between years for the central renewable deployment scenario, the EED allocation method results in an estimated 3.4 $MtCO_2$ of cumulative savings from 2020 to 2035 relative to the Baseline – 1.9 $MtCO_2$ in the electricity sector and 1.5 $MtCO_2$ in the heat sector. For the high-renewable deployment scenario, further savings accrue in the electricity sector, resulting in total cumulative savings over the horizon of 3.5 $MtCO_2$.

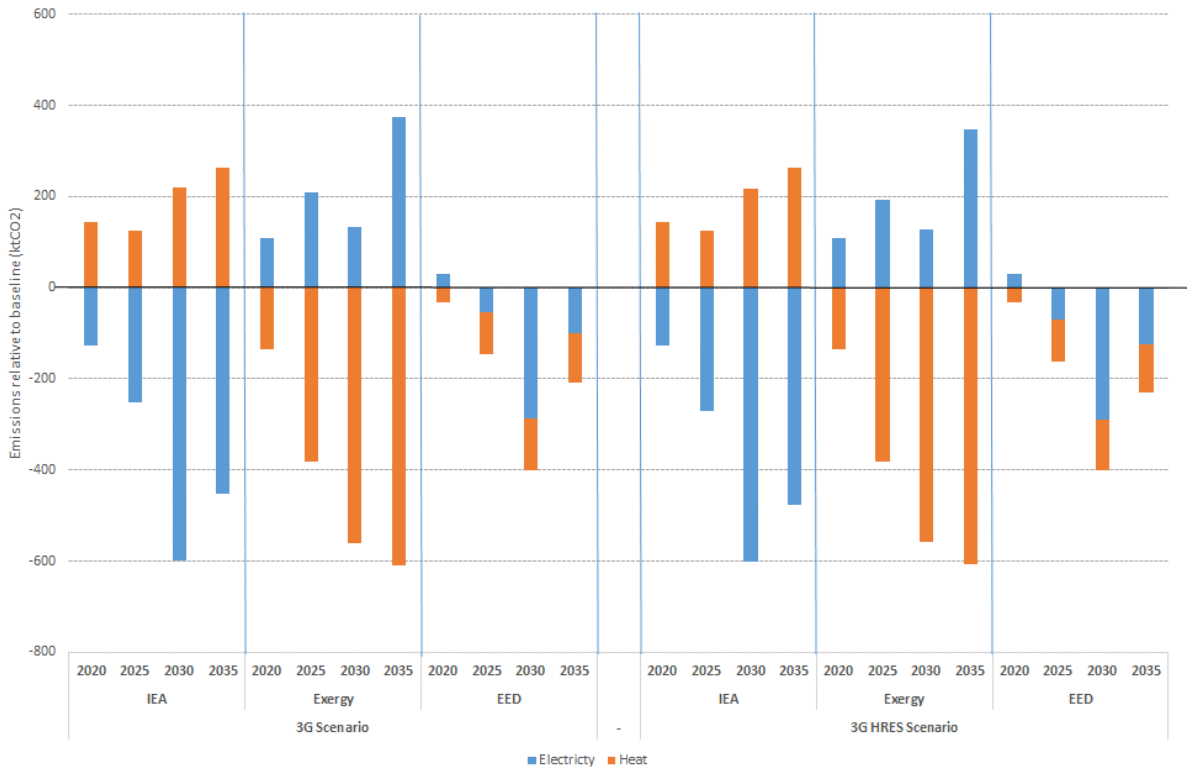


Figure 4-7: CO_2 emissions for scenarios relative to Baseline for electricity and heat production ($ktCO_2$)

These findings are sensitive to the volume of electricity trade. The reduction in the shadow price of electricity also increases the volume of exports and results in an increase in electricity generation export to the neighbouring GB system.

The increased generation to meet the increased export demand causes higher total emissions on the Irish system. Figure 4-8 presents the findings in terms of emissions intensity from electricity generation as a means to normalise the effects. The EED method shows reductions in CO_2 emissions intensity of electricity generation of 4% in 2030 and 2.7% in 2035 for the central renewable deployment electricity system. The impact is similar for both the central and high-renewable systems.

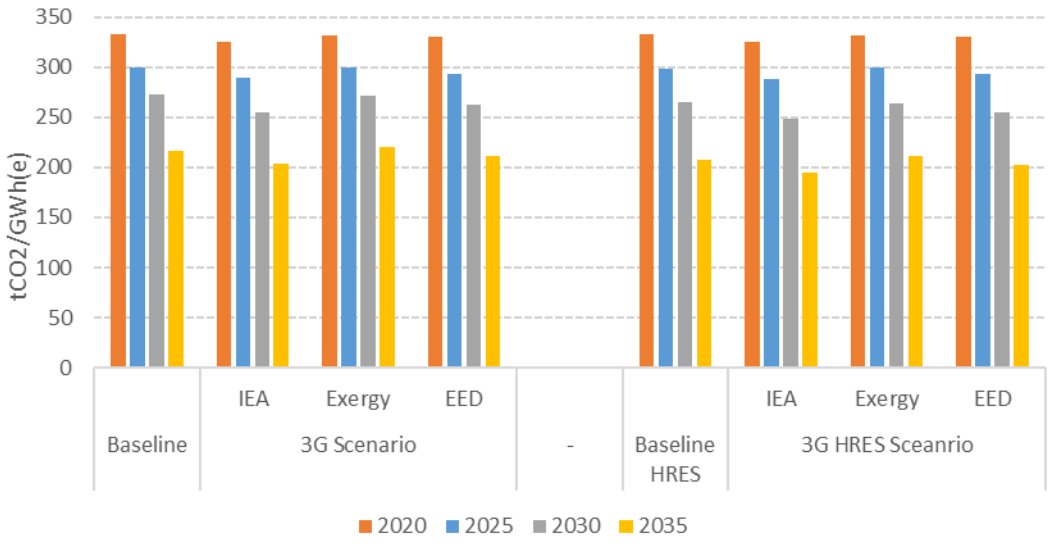


Figure 4-8: Emissions intensity of electricity production (tCO_2/GWh_e)

4.4.3. Impact of electricity trade

The simulations were rerun without any interconnection to the GB market to help understand the impact the electricity trade has on the outcome. This removes the route for generation export but also reduces the flexibility of the Irish system. Table 4-5 shows the resultant price impacts. The flexibility reduction results in higher electricity prices than those presented in Table 4-4 but the differences between the scenarios and the Baseline are similar. The shadow price of heat is also similar.

Table 4-5: Average short-run costs of CCGT and CCGT-CHP units and shadow price of heat and electricity with no interconnection (all scenarios)

Baseline electricity system (no-heat network)								
	Central renewable electricity deployment				***High-renewable electricity deployment***			
(€/MWh)	**2020**	**2025**	**2030**	**2035**	**2020**	**2025**	**2030**	**2035**
CCGT production cost of elec.								
Shadow price of electricity	31.58	57.87	67.40	74.39	31.58	57.98	66.07	70.16
Electricity system and 3rd generation heat network								
	Central renewable electricity deployment				***High-renewable electricity deployment***			
(€/MWh)	**2020**	**2025**	**2030**	**2035**	**2020**	**2025**	**2030**	**2035**
CCGT-CHP production cost of elec.								
Shadow price of electricity	30.89	60.22	65.80	71.74	30.89	57.08	63.80	68.08
Shadow price of heat	9.10	19.56	37.43	44.62	9.10	19.67	37.55	44.75

Figure 4-9 shows the emissions savings on the Irish system without connection to GB. A key difference between this and the central scenario is that all allocation methods show saving in the electricity sector. This is because the capacity factor of coal generation and less efficient gas generation increases in the Baseline. Therefore, the retrofitted gas CCGT-CHP units replace this more carbon-intensive generation in the scenarios. This hypothetical sensitivity provides some indicative results but care should be taken in drawing wider inferences. One of the reasons why the emissions outcome is better than for the actual system is that some of the savings on the GB system arising from exports from the Irish system cannot be accounted for. The GB system was not modelled in sufficient detail to make such an assessment.

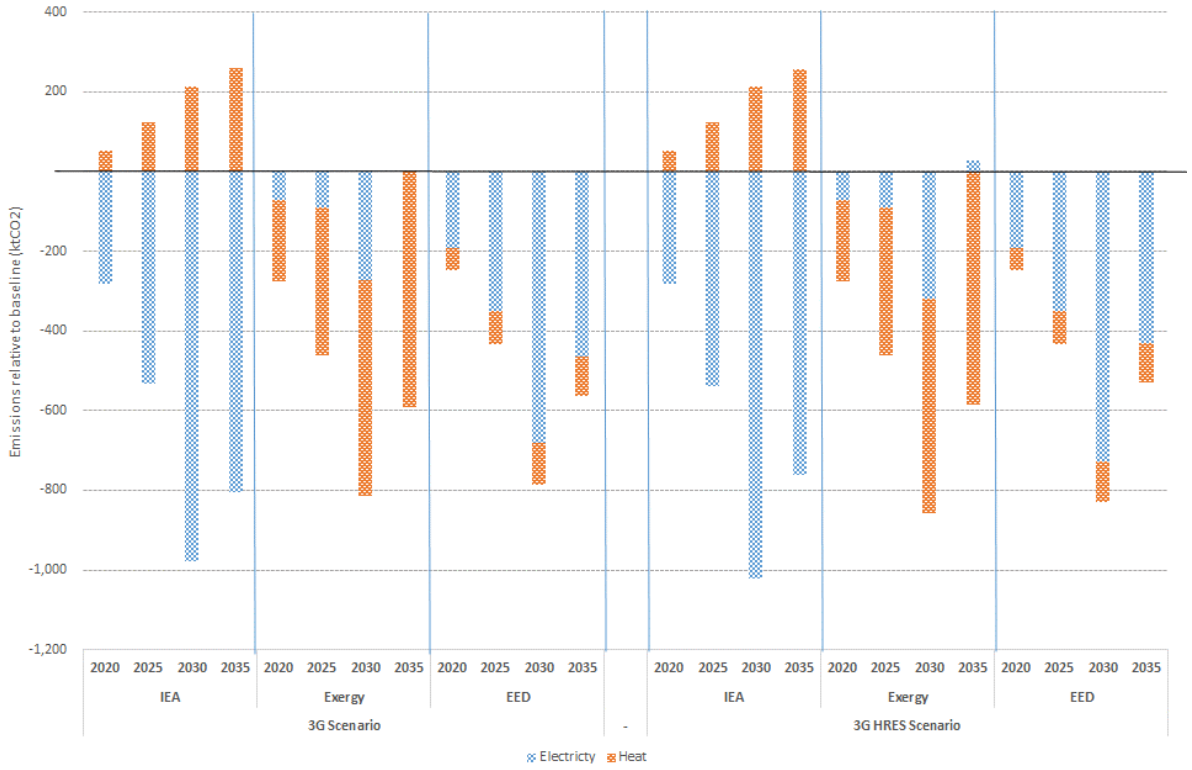


Figure 4-9: CO_2 emissions for scenarios relative to Baseline for electricity and heat production with no interconnection ($ktCO_2$)

4.4.4. Industry perspective

The modelling shows that CCGT units close to high-density heat demand in Dublin are currently out of the merit for much of the time. There is a risk that these units may become financially unviable. The revenue available from the sales of heat can offer a means for these generators to improve the long-term financial viability. As Figure 4-6 shows, the load factor of those CCGT units that can retrofit CCGT capabilities are greatly improved. Figure 4-10 shows the aggregate revenue benefit for these sites. The main benefit in terms of revenue comes from the additional running hours in the electricity market rather than the direct revenue from heat sales.

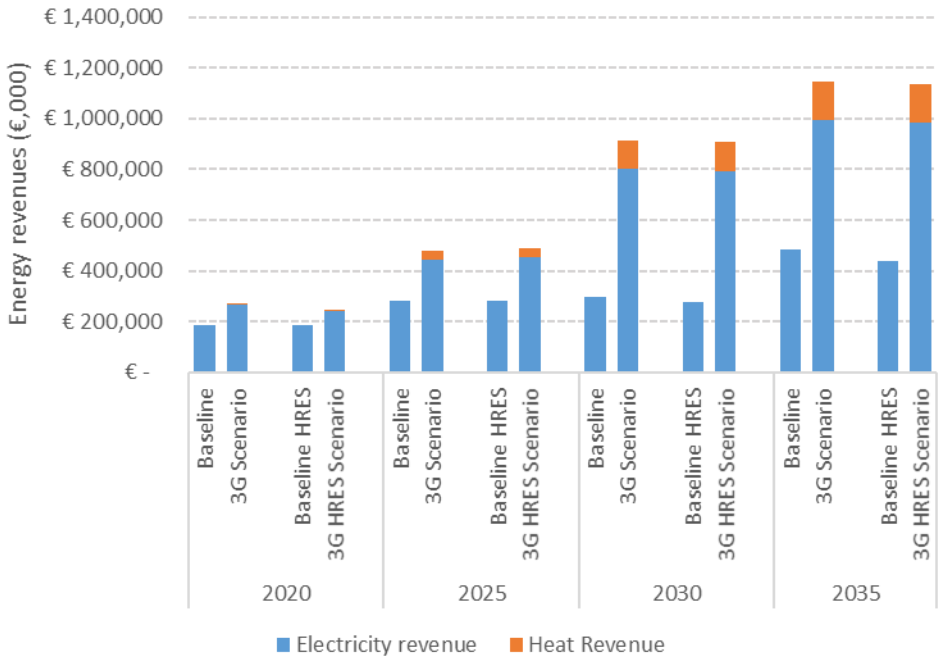


Figure 4-10: Total revenues pre and post upgrade for CCGT units

4.5. Discussion

The analysis implemented detailed simulations of the Irish power system and extended the model to include a representation of a large heat network in Dublin using the heat from CCGT units. Much of the previous analysis of CHP and high-renewable systems has focused on regions with high levels of pre-existing CHP-fed heat networks and of electrical interconnection with other systems (Lund, 2005; Lund and Münster, 2003a; Østergaard, 2015; Sorknæs et al., 2015). They have also favoured the use of the EnergyPLAN model. This chapter builds on these by employing a different methodology to examine the impact of CHP in the Irish context. The modelling approach outlined in this chapter employs a chronologically consistent, high temporal optimisation, as well as an operationally rich and validated data set. Like previous studies, the analysis of the impact of heat networks on the Irish system shows emissions reduction benefits.

Emission benefits arise from an altered dispatch order in the electricity system due to the reduction in electricity production costs at retrofitted CCGT-CHP units and through the displacement of heat produced by individual boilers. The electrical output from the CCGT-CHP units replaces coal and other gas generation. The amount of coal replaced is higher in earlier years when carbon prices are lower. Under these circumstances, coal generation is higher in the Baseline and hence there is more opportunity for coal displacement in the scenarios in the years before 2035. A lower growth rate in the carbon price increases the probability that coal would remain the cheapest fuel source and be displaced more frequently by CCGT-CHP generation. The results presented show that the CCGT-CHPs help hedge against some of the carbon price risk.

The allocation method used to divide emissions from the CCGT-CHP units between the heat and electricity sectors influences the quantity of the savings and in which sector they accrue. The method prescribed by the EU's Energy Efficiency Directive is most likely to guide policy in the area and, using this method, savings accrue in both the heat and electricity sectors. An estimated 3.4 $MtCO_2$ of cumulative savings accrue in the central renewable deployment: 56% in the heat sector and 44% in the electricity sector. Similar savings accrue in the high-renewable deployment scenario. This finding suggests that policy evaluations of emissions benefits of district heating networks may be underestimated if the electricity sector impacts are not considered (European Parliament and Council, 2012).

These findings add additional nuance to the operational strategies of CHP units in high-renewable systems. This analysis shows that the CCGT-CHP units require heat market revenue to offset the cost of electricity production in order to be dispatched. For these units, the most cost-optimal time for dispatch is when electricity market prices approach their short-run cost of electricity production. Electricity price reductions increase the cost of heat production for these units. These operation strategies can be classified as Type I and Type II. Type I is appropriate when the short-run costs of electricity production are below the shadow price of electricity and Type II is likely when the short-run costs of production, without heat revenue offset, are above the shadow price of electricity generation. As more variable renewable generation, with low or zero short-run costs, are connected to electricity systems, Type II operation become more common for CHP units (Lund and Andersen, 2005; Lund and Mathiesen, 2015; Sorknæs et al., 2015). The results show that, as more renewable electricity is added to the system, the heat output from CCGT-CHP units becomes less competitive with heat output from gas boilers. The modelling also finds that the storage of heat is found to be sub-optimal under Type II conditions. Additional heat production, at a value required to allow the CCGT-CHP units to compete in the electricity market, would increase production costs overall. Several studies have found that additional heat storage increases the flexibility of the electricity system (Lund and Andersen, 2005; Lund and Münster, 2003b; Nuytten et al., 2013; Streckienė et al., 2009). This analysis does not contradict the flexibility assessment but raises some further questions on how the valuation of heat storage should be considered.

This analysis does not consider detailed operational factors, including the impact of forecast uncertainty (Sorknæs et al., 2015). Further work is required to quantify the ancillary system value of heat storage in the Irish context, including the flexibility benefits outlined in previous studies (Lund and Münster, 2003a; Lund and Mathiesen, 2015; Streckienė et al., 2009). The inclusion of heat pumps, that can participate as demand-side units, has the potential to increase system flexibility. Further work to examine this in an Irish context can draw on similar previous work (Lund et al., 2010; Lund and Münster, 2006; Mathiesen et al., 2015). Heat pumps could produce heat during low-cost price periods in the electricity market and hedge against the higher costs of operating CHP units in Type II mode during these times. For Ireland, the availability of large sources of

waste heat from data centres, which could be used as a heat source for heat pumps, adds an additional nuance that warrants further investigation.

Type II operation at CCGT-CHP units leads to reductions in the shadow price of electricity generation of 3.7% to 4.4% in the central renewable deployment scenario and 2.6% to 4.4% in the high-renewable scenario, as compared to the Baseline. While the addition of CHP acts to reduce the shadow price of electricity, it simultaneously pushes units with higher start up and no-load costs to the margin on the All-Island market. This causes the uplift component of the market price to increase. These impacts are relatively minor compared to the annual variations in price, and the price outcome is closely tied to the issue of the misalignment of carbon pricing between the UK and Ireland (Curtis et al., 2014). The lower shadow price in the scenarios results in more exports to neighbouring electricity systems. A sensitivity that isolates these impacts results in further increases in CO_2 emissions savings. For systems with high levels of interconnection to other systems, CO_2 should be assessed across all of the interconnected systems in order to capture the true impact. The new electricity market currently in development in Ireland and the decision of Great Britain to leave the EU may both affect these results.

The modelling shows large increases in the annual revenue received by the CCGT-CHP units, which aligns with findings from similar work (Sorknæs et al., 2015; Streckienė et al., 2009). The primary benefit is from the additional revenue gained from being dispatched in the electricity market rather than from the revenue received from selling heat. Ireland has a relatively isolated electricity grid, which means that market mechanisms must support the investment costs of dispatchable capacity to support the secure operation of the grid with high amounts of variable renewable generation. Further work to examine how the improvement in the financial viability of generators could affect the total long-run costs of electricity, the cost of system security and the cost of providing capacity would add further insight to the value of large-scale CHP.

The analysis presented here uses mid-range assumptions from other studies to estimate likely Z-factors. More detailed engineering studies of the individual stations are required to understand their heat production ranges and capabilities. Z-factors below those used for this study will narrow the range of prices that a unit can viably operate in and make them less competitive with gas boilers. This suggests that, to avoid overestimation, assessments for the potential availability of waste heat should aim to incorporate economic assessments.

4.6. Conclusion

Using waste heat available from power generators in heat networks is a means to reduce CO_2 by replacing heat production from fossil-fuel heat boilers. But CHP generation, by linking heat and electricity markets, can change how other electricity generators run and affect price and emissions in both sectors. High levels of renewable electricity generation may also affect the cost of using waste heat and influence the cost and magnitude of CO_2 reduction.

Using a detailed optimisation model, this chapter finds that retrofitting CCGT units with CHP capabilities to feed a heat network in Dublin reduces emissions in both the heat and electricity sectors, and that electricity and heat are produced at competitive prices. Changes in the short-run cost of electricity production at the retrofitted CCGT-CHP units is the key driver of the emissions savings. The cost-optimal solution showed that the CCGT-CHP units use revenue from the heat market to offset electricity production costs and allow them to be dispatched more often in the electricity market. The altered dispatch order in the electricity market led to reductions in output from other gas stations and from coal generation. It also reduced the average shadow price of electricity production, leading to more exports to the GB electricity system. As more renewable electricity was added to the system, the amount of offsetting revenue required from the heat market increased. This led to a reduction in the competiveness of heat produced from the CCGT-CHP units and increased output from gas boilers feeding the heat network, but overall the average price of producing heat is competitive compared to production from gas boilers.

These findings align well with the outcomes of previous work examining CHP-fed district heating systems in the context of high-renewable electricity systems and has further defined the economic boundaries for viable use of waste heat from existing power stations in an energy system where no large-scale district heating currently exists. CHP units can produce heat at lowest cost when the price of electricity is above the short-run cost of electricity production. The addition of renewable electricity generation to the power system reduces the price of electricity, leading to more periods where offsetting heat revenue is required. These can be labelled as Type I and Type II operational modes. The analysis shows that, as more renewable electricity generation is deployed, Type II operation becomes more common. The finding is sensitive to the efficiency at which units can produce heat. This study uses a Z-factor in the mid-range of estimates from the literature. Higher Z-factors can increase the competitiveness of heat production and lessen the impact of electricity price reductions. Further modelling to explore lower temperature, fourth-generation heat networks and work to specify Z-factors achievable from the various power generation technologies would help complete the picture. Longer term, the implementation of low-temperature heat networks in conjunction with heat pumps and CHP may be required to optimise district heating on high-renewable electricity systems.

The utilities that own the CCGT generators would also see a benefit as the capacity factors and revenues increase with the addition of CHP capabilities. Capacity payments to ensure long-term generation adequacy is being considered or in place in many markets. Further analysis could examine if the additional revenue available to CHP units has an impact on total capacity payments in the electricity market. Likewise, an analysis of the impacts of CHP upgrades on the operation of the electricity system can explore if the retrofits add to or reduce system flexibility.

Part II – Mixed-method simulation of bioenergy and renewable heat policy

Chapter 5

BioHEAT: A policy decision support tool in Ireland's bioenergy and heat sectors

Abstract

Bioenergy is likely to play a key role in decarbonising the energy system. The versatility of bioenergy as a transport, heat or electricity fuel is one of its key strengths, but can add to the complexity of policy design. Policies aimed at stimulating bioenergy use in one end-use sector should consider the impacts of use and uptake in the others. This chapter details a methodology for an integrated bioenergy and heat policy decision support tool. The previous literature has focused on individual supply-chain optimisation, plant sizing and plant locations from an operator's perspective. The BioHEAT model is a techno-economic model that accounts for the co-dependencies between the end-use sectors. It extends the approach to supply-chain specification in the literature to incorporate a novel representation of consumer decision-making in the heat sector as well as the flexibility to model various policy types in heat, electricity and transport sectors from a policymaking perspective. Three scenarios are examined to demonstrate the functionality of the model, including the interaction between separate policies targeting the heat and power sectors. The results demonstrate how the model can be used to examine policy impacts against a range of metrics, including the contribution to renewable energy and carbon reduction targets; cost to the Exchequer, and the marginal cost of carbon abated. The model has helped to inform the development of a renewable heat policy instrument in Ireland.[18]

[18] This chapter is based on the published journal article: Durusut, E., Tahir, F., Foster, S., Dineen, D. and Clancy, M. (2018), BioHEAT: A policy decision support tool in Ireland's bioenergy and heat sectors. *Applied Energy*, 213, pp.306-321.

5.1. Introduction

Many countries are looking to bioenergy as a means to achieve climate and renewable energy goals (Bacovsky et al., 2016). The long-term energy system models show that bioenergy has a key part to play in meeting the climate-change mitigation goals outlined in the Paris agreement (IEA, 2016; IPCC, 2015). Biomass feedstocks are a versatile renewable energy source and can be used to produce renewable energy for heat, electricity and transport. Biomass can be converted into refined liquid, solid or gaseous fuels, and there are several production pathways possible for most feedstock types. Many countries already have policies in place to develop the use of bioenergy in all three end-use sectors (Dina Bacovsky et al., 2016). Further policy interventions will be required to make long-term decarbonisation goals a reality.

The versatility of bioenergy offers many options for policymakers but it also adds complexity and brings a significant risk of unintended consequences (Creutzig et al., 2012; Havlík et al., 2011; Muench and Guenther, 2013; Yamamoto et al., 1999). Policymakers should be aware of the impacts that policies, intended to stimulate the use of bioenergy through one particular pathway, can have on other bioenergy pathways, as well as on non-energy markets for biomass feedstock. Policy initiatives that increase bioenergy production in one sector at the expense of bioenergy output in another are counterproductive. In a recent policy design initiative for renewable heat in Ireland, several of these challenges were apparent. A modelling solution was sought to address these issues. This required the development of a novel methodology that goes beyond those previously published in the literature. The purpose of this chapter is to share the knowledge gained so as to inform similar efforts elsewhere. Bazilian et al. make the important point that, while several models are available to examine energy and other water, food and land-use questions, these are often focused on long-term policy research-orientated work rather than short-term applied policy decision support tools (Bazilian et al., 2011b).

BioHEAT is a techno-economic simulation model of bioenergy supply chains in Ireland. It follows previous approaches in incorporating a detailed representation of bioenergy supply. It goes beyond many of these by including cost-effective allocation of limited bioenergy resources between the power, transport and heat end-use sectors. Bioenergy-related demand for heat is typically treated as an external input in other approaches (Cambero and Sowlati, 2014; De Meyer et al., 2014; Freppaz et al., 2004; Mafakheri and Nasiri, 2014; Shabani et al., 2013). Bioenergy-related models that include representations of consumer behaviour seem to be absent (this review did not find any examples). The simulation of consumer behaviour and decision-making is a particularly novel approach and can have applications for heat-sector modelling beyond renewable uptake.

Much of the research and modelling to inform bioenergy decisions is focused on specific aspects of the supply chain such as:

- the most optimal way to use an individual resource or supply chain (Alex Marvin et al., 2012; An et al., 2011; Andersen et al., 2012; Chen and Fan, 2012; Cundiff et al., 1997; Dunnett et al., 2008; Freppaz et al., 2004; Frombo et al., 2009; Huang et al., 2010; Iakovou et al., 2010; O'Shea et al., 2017; Parker et al., 2010; Sacchelli et al., 2013; Walther et al., 2012);

- where to locate a bioenergy-producing plant and what size a plant should be (Comber et al., 2015; Franco et al., 2015; Höhn et al., 2014; Leduc et al., 2008, 2010; Ma et al., 2005; Natarajan et al., 2012; O'Shea et al., 2017; Rauch and Gronalt, 2010; Schmidt et al., 2010a; Shi et al., 2008; Steubing et al., 2014; Sultana and Kumar, 2012; Tursun et al., 2008; Vera et al., 2010; Vukašinović and Gordić, 2016; Zhang et al., 2011),

- and factors influencing refining costs (Mobini et al., 2013; Tittmann et al., 2010; Wetterlund et al., 2012). Others focus on what might be required from policy interventions in order to bring about uptake of a certain technology or feedstock (Gonzalez-Salazar et al., 2016; Kalt and Kranzl, 2011; Schmidt et al., 2010b; Steubing et al., 2012a; Wahlund et al., 2004).

Optimisation models for bioenergy supply chains are common. De Meyer et al. examined the use of optimisation methods in the design and management of the upstream supply chain (De Meyer et al., 2014). They conclude that models are usually developed for specific cases that address a particular part of the supply chain at one point in the hierarchical decision level. Most models address the optimisation problem from the plant or bioenergy user's point of view. Mafakheri and Nasiri (2014) reviewed the modelling of biomass to energy supply-chain operations. They point to the limited research about certain aspects of biomass supply chains. A conclusion from the review highlighted the lack of evidence on the extent of the policy impact on the design and management of biomass supply chains. Shabani et al. (2013) reviewed value-chain optimisation of forest biomass for bioenergy production. The optimisation models reviewed tended to deal with location-specific or end-use sector questions such as technology choice, plant size and location, storage location, product mix and environmental and social objectives. Cambero and Sowlati (2014) also reviewed the literature on forest biomass supply-chain assessment and optimisation. Many of the models reviewed considered energy demand as an exogenous constraint to be met in the optimisation and did not examine the cross-cutting impact on other supply chains or bioenergy end uses.

Mitchell et al. developed a decision support tool as part of a project under the International Energy Agency's Technology Collaboration on bioenergy, called the BioEnergy Assessment Model (BEAM) (Mitchell et al., 1995; Mitchell, 2000). The BEAM model allowed a techno-economic assessment of biomass-to-energy policy schemes. The model has modules that characterise the economics of feedstock supply, pre-treatment and conversion into a final product. The case studies presented in these papers inputted demand for bioenergy products – electricity and ethanol – as exogenous factors, and the model generates estimates of the costs of meeting those demands. Freppaz et al. (2004) is a often-cited example of an optimisation approach. The model seeks to minimise the costs related to plant, transportation, biomass harvesting costs and energy distribution. The

constraints to be satisfied include a requirement to meet a proportion of the thermal energy demand in a given area. The model decides on the annual biomass use and plant size. The only policy variable included is a constraint to specify the minimum amount of energy that must come from renewable sources in a given area. Some models focus on optimising the supply chain to a refinery without consideration of the final energy use (Mobini et al., 2013; Wetterlund et al., 2012). The specification of biomass supply chains in BioHEAT has mirrored the predominant approaches outlined in the literature, which include recourse costs, transport costs, refining costs and conversion costs.

A few of the modelling methods have been applied to high-level policy analysis. Kalt and Kranzl (2011) assessed the economic efficiency of bioenergy policy using a techno-economic model. The cost of energy production for clusters of bioenergy technologies is compared with a reference system. The model does not estimate uptake in a detailed way, but rather compares the costs of energy production and evaluates a mitigation cost based on this. This method helps with a broad assessment of policy but is not suitable for uptake assessments and does not tell policymakers anything on the cross-cutting impacts of a policy implementation. Wahlund et al. (2004) take a similar approach, comparing the cost of replacing a reference fossil fuel in each of the heat electricity and transport sectors, based on an evaluation of the supply-chain costs. Schmidt et al. (2010b) looked at the cost-effectiveness of various bioenergy-related policy instruments in Austria to support advanced bioenergy conversion technologies. BioHEAT focuses on the policymaker perspective.

The inclusion of energy demand, especially heat demand, has taken various high-level approaches. Schmidt et al. (2010a) developed a spatially explicit optimisation model for domestic forest biomass production and use in Austria. The model used detailed data on forest supply-chain costs and a representation of heat demand to examine the comparative cost of wood-pellet heating compared to CHP and gasification technologies. Heat demand is based on high-level factors such as number of employees for commercial and industrial demand and average consumption values by age and type of house in the residential sector. Steubing et al. (2012) implemented an optimisation model to examine the best use of residual and waste biomass in the EU. The model assesses the alternative uses of bioenergy between the heat transport and electricity generation options. Heat demand is based on aggregate energy balance data, divided simply into heat for household use and heat for industrial use. Steubing in a separate paper looked at identifying the optimal plant sizes and locations for wood-based SNG from an environmental and economic perspective (Steubing et al., 2014). Bentsen et al. (2014) developed an optimisation model to minimise the energy system emissions by allocating biomass resources to meet energy services. They use supply cost curves of biomass as inputs and include supply-chain emissions from biomass in the optimisation. Tan et al. (2012) developed a fuzzy optimisation model for biomass production and trade. Within the model, bioenergy demand in each region is an input specified by a lower limit and a tolerance level. The Global Biomass Optimisation Model (GLOBIOM) uses a partial economic equilibrium methodology to determine the land-use change implications of bioenergy policy (Havlík et al.,

2011). Demand for bioenergy resources is passed to the model, and the prices for bioenergy feedstock, and thus the supply-side response, are determined endogenously through the product balance constraint. The BioHEAT model estimates for heat demand are developed in a detailed way and the decision to move to a renewable heat technology is not solely influenced by the cost. The specification of building archetypes in BioHEAT allows a more representative analysis of the likely demands for bioenergy and other forms of renewable heat. Demand for bioenergy in the electricity and transport sectors is specified in a similar way to other models in the literature and, in the case of electricity, can also be limited by economic considerations.

The extensive barriers to heating-related investments are well documented (Clancy et al., 2017; DeCanio, 1993; Schleich, 2009; Sorrell, 2004). Heat consumers do not make choices solely on technology costs and paybacks. Models that characterise the choice preferences of consumers have shown the relative importance of technology, building and consumer characteristics on uptake decisions (Braun, 2010; Rouvinen and Matero, 2013). Horschig and Thrän suggest that hybrid models can minimise the drawbacks of using one single approach and recommend that policymakers strive to use several modelling approaches in determining a course of action. They also point to the promise of using linking approaches to combine models to answer a broader set of questions (Horschig and Thrän, 2017). Pfenninger et al. (2014) identify the development of models that represent human behaviour as a key emerging approach. The BioHEAT model incorporates consumer behaviour in the heat sector with a simulation of a range of bioenergy supply chains. The representation of consumer decision-making is a particularly novel approach.

The specification of biomass supply chains in BioHEAT has mirrored the predominant approaches outlined in the literature. The detailed way heat demand is handled and the incorporation of consumer decision-making in that sector are additional contributions to the knowledge in this area. It also connects research on bioenergy systems, consumer behaviour, and the development of policy interventions in practice.

The focus on the modelling from a policymaker perspective is also a novel aspect. Much of the literature focuses either on bioenergy from the perspective of an agent in the supply chain or on broad policy evaluations. Policymakers are concerned with understanding the impact a measure may have on uptake of specific types of technologies and how a policy in one sector may affect policy objectives in another. The method outlined here is a useful addition to the literature in this regard. The model was used as part of the design of a renewable heat incentive policy in Ireland. Pfenninger et al. (2014) identify transparency as a key way to improve some of the shortcomings of the modelling field. The description of BioHEAT in this chapter is intended to contribute to this goal as well as to contribute to literature on the modelling of bioenergy-related questions from a policymaking perspective.

In this chapter, Section 5.2 outlines the modelling method in detail; Section 5.3 describes the key data inputs; Section 5.4 presents the results of some illustrative scenarios; Section 5.5 discusses the results in the context of BioHEAT as a tool to aid policymaking, and Section 5.6 concludes.

5.2. Method

BioHEAT is a techno-economic model that combines cost-effective allocation of limited raw bioenergy resources in Ireland based on: up-to-date bioenergy resource costs and availability; refining and transportation costs; competition for bioenergy resources between the power, transport and heat sectors, and uptake of renewable heat technologies that incorporates consumer behaviour.

The model is the culmination of a number of years work in this. My initial efforts to examine the use of the bioenergy resource in Ireland involved the development of linear programming models that sought to minimise the cost of bioenergy technology deployment and use. I implemented this model, known as the BioEnergy Analysis Model, to inform Ireland's National Renewable Action Plan (NREAP) submission to the EU commission (NREAP's, 2011). The initial representation of the heat sector in the model was limited - technology cost at different sizes were represented and these were deployed to meet demand in each of the economic sub-sectors of residential, commercial, public sector and industry. Subsequently, a representation of the hidden costs faced by sites installing renewable heat technologies was developed. These costs included the space requirement for storage of wood fuels and the higher ongoing management costs associated with managing fuel deliveries. This improved the representation but predicated uptake still showed an overly optimistic trajectory for the uptake of renewable heat technologies. Previous work on technology choice had addressed this problem by examining how different consumer cohorts respond to technology attributes (Braun, 2010; Rouvinen and Matero, 2013). In collaboration with Element Energy (and some of the co-authors of this paper) an approach was used to develop a more detailed representation of the heat sector that included consumer choice. I developed a soft inking method and used both models to examine policy options for the heat sector in Ireland. The models were solved until renewable heat output converged in both models. The modelling informed the Draft Bioenergy Action Plan published in 2014 including the recommendation to implement a renewable heat incentive (Department of Communications, Climate Action and Environment, 2014). A report I authored for SEAI details the modelling method and the scenarios examined as part of the analysis for the plan (Clancy, 2015). Further work in Ireland on the potential for energy efficiency further refined the representation of heat demand and consumer decision making (Scheer et al., 2015). I initiated a further project to incorporate this approach into the heat modelling. This also allowed a full integration of both the heat and the bioenergy models. The model was developed with a focus on the design of a renewable heat incentive policy in Ireland. The model name – BioHEAT – describes the integration of the bioenergy and heat sector and highlights the detailed and novel representation of the heat sector.

BioHEAT splits energy demand into three broad sectors. Electricity generation technologies such as co-firing, landfill gas, biomass CHP, anaerobic digestion and waste to energy are referred to as "Power". The biofuels that can be used in the transport sector, such as bioethanol, biodiesel and biomethane, are included in "Transport". "Heat" includes all the heating technologies that can be used to meet the heating demand in the residential, commercial, public and industry sectors, such as ASHP (air-source heat pump), GSHP (ground-source heat pump), biomass boiler, biomass CHP (combined heat and power), gas CHP, gas boiler, oil boiler, resistive electric heating, solid-fuel boiler, district heating and biogas injection to grid.

The model can apply a range of policy interventions, which can be combined to create policy packages including upfront grant support, renewable heat incentive, low-interest loans, public procurement (mandatory uptake of renewable heat technologies in the public sector), retail tax reduction in Heat; feed-in tariffs in Power, and biofuel incentives and mandates in Transport. The model also has the functionality to add levies on fossil fuel and increase carbon tax in all sectors.

The modelling process has five key steps, which are illustrated in Figure 5-1 and explained in more detail in the subsequent sections:

1. Calculation of the cost of bioenergy pathways for Heat, Power and Transport based on bioenergy resource supply curves, bioenergy pathways that map these resources to products/technologies, and cost data on transport, refining, technology and fuel prices
2. Identification of least-cost way to meet demand in Transport and Power
3. Calculation of uptake of technologies in Heat based on a detailed representation of consumer investment behaviour in domestic, commercial, public and industry sectors, suitability of technologies for different building types, and detailed data on consumer investment behaviour
4. Prioritisation of the Heat, Power and Transport sectors to model the interactions between sectors
5. Allocation of bioenergy resource over time considering resource limitations, uptake of bioenergy and heating technologies, and competition between Heat, Power and Transport

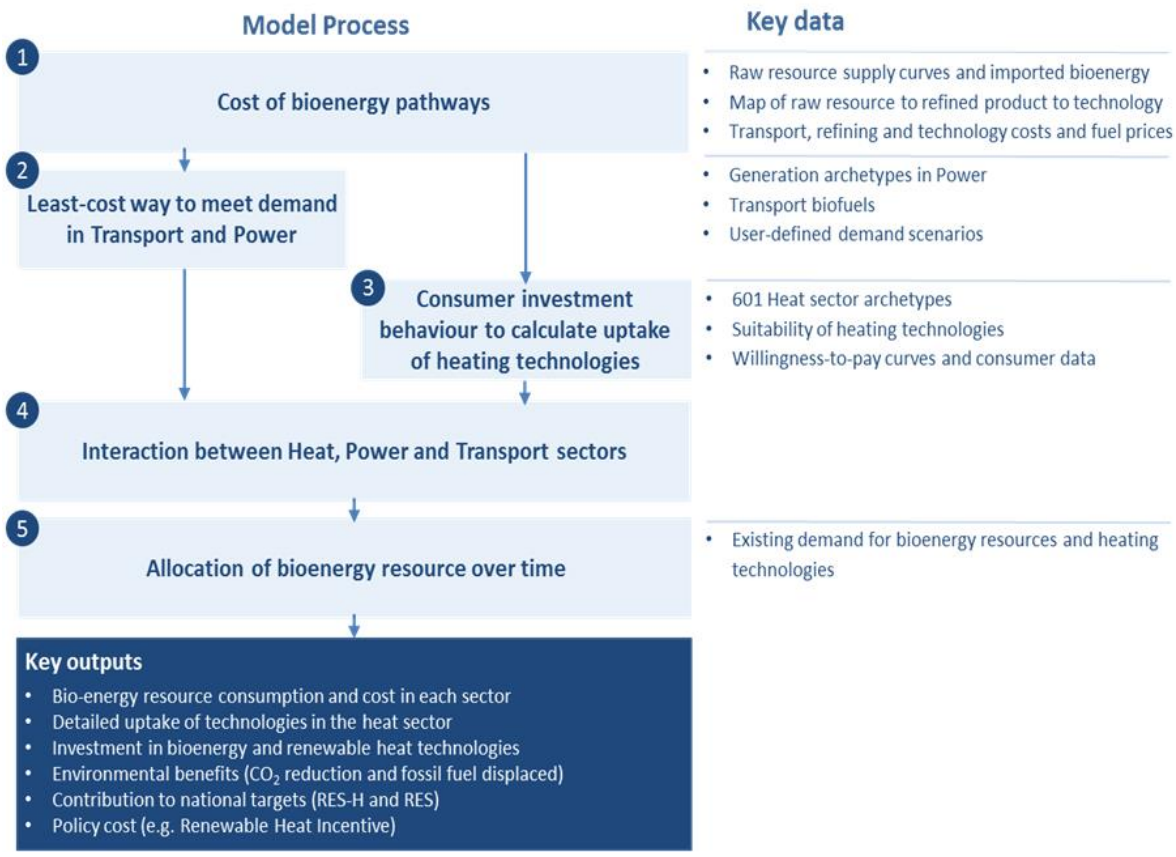


Figure 5-1: BioHEAT model diagram

5.2.1. Cost of bioenergy pathways

A bioenergy production pathway typically includes some elements of harvesting, drying or pre-treatment, transportation, refining and combustion. These elements, along with the underlying economics of the feedstock, determine the cost of producing energy from biomass through a given pathway. How these costs compare to the fossil-fuel or other renewable energy alternatives is a key factor in determining how much and in which end-use sector bioenergy is used.

The model currently includes 99 distinct bioenergy pathways that can use Irish biomass resources to meet the demand in Power, Heat and Transport, as illustrated in Figure 5-2. Imported bioenergy resources can be used directly by new pathways, or to meet bioenergy demand. It is assumed that the supply of fuel to existing demand does not change through the modelling time horizon. BioHEAT has the flexibility to add new pathways as needed. These could consist of a new resource, new refined product, new end-use technology or a new way of using an existing crop with an end-use technology. A full description of the resources is included in the table below:

Table 5-1: Resources included in the BioHEAT model

Resource	Resource category
Forest thinnings and residues (Forest)	Forestry
Sawmill residues (Sawmill)	Other by-products and waste
Post-Consumer Recycled Wood (PCRW)	Other by-products and waste
Straw	Agricultural waste and residues
Miscanthus	Energy crops
Short Rotation Coppice Willow (Willow)	Energy crops
Residual Solid Municipal Solid Waste (MSW)	Other by-products and waste
Grass Silage (Crops anaerobic)	Energy crops
Pig and cattle manure (Pig/cattle)	Agricultural waste and residues
Industrial Food waste	Other by-products and waste
Biodegradable municipal solid waste incl. separated food waste (BMSW)	Other by-products and waste
Tallow	Other by-products and waste
Oil Seed Rape (OSR)	Energy crops
Used cooking oil and recycled vegetable oil (RVO)	Other by-products and waste
Wheat	Energy crops

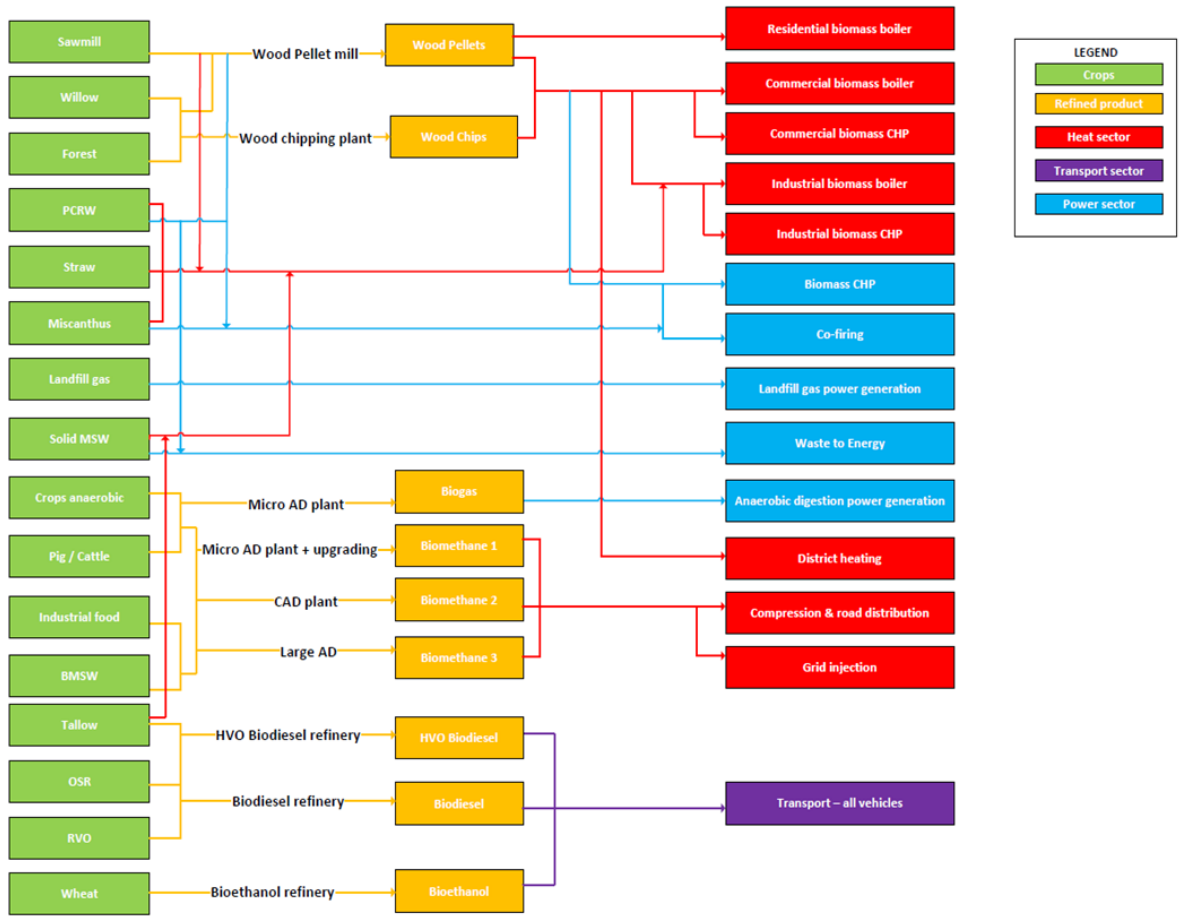


Figure 5-2: Bioenergy pathways in BioHEAT.

Bioenergy supply curves that represent the cost (€/kWh) and available potential (in TJ or GWh) for bioenergy resources for low, central and high-cost tranches[19] until 2030 provide the constraints on the availability of the bioenergy resources.

[19] This specification mirrors the Irish bioenergy supply curve data but it is possible to increase the number of tranches in the model.

Bioenergy pathways represent how these resources can be used by end users in the heat, power and transport sectors, either directly or after being converted to a refined product via refining technologies. The levelised cost of energy for each pathway (€/kWh) is calculated based on: the cost of each biomass resource in a given year for every cost tranche; the cost of refining technologies (where a resource is converted to a refined product), transportation costs, and end-use technology cost. Refining costs are based on annual output, capex, opex, discount rate and technology lifetime. Transport costs are calculated based on the transportation distances, freight capacity, fuel consumption, energy content, mass density and cost of transport fuel. Technology costs for Power are based on marginal capex, marginal opex, thermal efficiency, electrical efficiency, availability, discount rate, and economic life; for Transport are based on marginal capex and thermal efficiency; and for Heat are based on marginal capex, marginal opex, thermal efficiency, fixed capex, fixed opex, max size, electrical efficiency, discount rate, economic life, fixed hidden cost, and marginal hidden cost.

For instance, the cost of wood chip for a consumer in Heat depends on the cost of the available raw resource (e.g. willow or forest residues), the cost of refining at a wood chipping plant, and the cost of transportation based on the stock-weighted distances between raw resource and chipping plant and between chipping plant and end consumer.

The equation (1) below details how the cost of bioenergy supply pathways is calculated.

$$LC_{p,c,r} = LC_c + LC_{t,c,s} + LC_{t,c,r} + LC_{t,r,s} + LC_{rt} + LC_{et} \quad (1)$$

Levelised cost is denoted by *LC* and the subscripts identify: pathway (p), resource/crop (c), sector (s), refined product (r), transport (t), transportation fuel (f), refining technology (rt) and end-use technology (et). Levelised cost for refining/end-use technology is calculated by equation (2)

$$\mathrm{LC_{rt}} = \frac{\frac{\mathrm{C_{rt}\ x\ (1-\ d_{rt})}}{\mathrm{d_{rt}\ x\ (1-\ d_{rt}{}^{l_{rt}})}} + \mathrm{O_{rt}}}{\mathrm{S_{rt}}} \quad (2)$$

where *C*, *O, S* and *l* are capital cost (€), annual operating cost (€/y), annual output (kWh/y) and lifetime (years) of refining technology. d is the discount factor as determined by equation (3)

$$\mathrm{d} = \frac{1}{1+\mathrm{i}} \quad (3)$$

where i is the interest rate for a typical refining/end-use technology.

Transportation costs are determined by equation (4) for bioenergy resources that travel directly to an energy end-use conversion technology.

$$LC_{t,c,s} = \frac{D_{c,s} \text{ x } E_t \text{ x } LC_f}{F_{t,c}} \quad (4)$$

Equation (5) captures the case where bioenergy resources travel first to a refining process and then by equation (6) for onwards transportation to end use.

$$LC_{t,c,r} = \frac{D_{c,r} \text{ x } E_t \text{ x } LC_f}{F_{t,c}} \quad (5)$$

$$LC_{t,r,s} = \frac{D_{r,s} \text{ x } E_t \text{ x } LC_f}{F_{t,r}} \quad (6)$$

The transportation cost is calculated as the product of the distance D (km), transportation fuel consumption E (kWh/km) and transportation fuel cost LC (€/kWh) divided by the transportation crop/refined product capacity (kWh). The transportation crop/refined product capacity is based on the freight capacity (kg or m^3) and the crop/refined product energy density (kWh/kg or kWh/m^3). Equations (2), (5) and (6) go to zero in a bioenergy pathway that uses a bioenergy resource directly without a refining step.

The cost of the end-use conversion technologies is given by equation (7)

$$LC_{et} = \frac{\frac{C_{et} \text{ x } (1 - d_{et})}{d_{et} \text{ x } (1 - {d_{et}}^{l_{et}})} + O_{et}}{S_{et}} \quad (7)$$

where *C*, *O, S* and *l* are capital cost (€), annual operating cost (€/y), annual output (kWh/y) and lifetime (years) of end-use technology. d is the discount factor as determined by equation (3).

5.2.2. Least-cost way to meet demand in Transport and Power sectors

The bioenergy demands in the transport and power sectors are defined exogenously for each year and for each pathway, technology or sector. These demands are met at least cost, based on the economic ranking order of all possible bioenergy pathways available to meet the demand. The priority ranking of meeting bioenergy demands in Transport and Power is as follows:

1 First, if the exogenous inputs specify a certain demand to be met by a pathway (e.g. 10 GWh generation via co-firing using forestry residues), then that pathway is prioritised subject to availability of the bioenergy resource.

2 Second, if the exogenous inputs specify a certain demand to be met by a particular technology (e.g. 100GWh generation via co-firing), then all pathways that use that technology are ranked based on their cost, and the cheapest pathways with available raw bioenergy resource are then used to meet the technology demand.
3 Finally, the remaining pathways are ranked based on their cost, and the cheapest pathways with available bioenergy resource are then used to meet the residual sector demand (e.g. 200GWh of additional generation via bioenergy resource).

For pathways in the Power sector, an additional economic constraint can be applied to limit the generation to an amount that is economic. A pathway is only used to meet the exogenously specified demand if the cost of generation is lower than the price available for the electricity output from the technology. The price available may be defined as the market price for electricity or a policy tariff level.

If the demand is defined exogenously for a pathway, then the rank, *R,* is calculated as specified in equation (8) and utilisation, *U,* is determined by equation (9):

$$R_{p,n} = 1 + \sum_{i=1}^{t} \begin{cases} 0, \text{if } LC_{p,n} < LC_{p,i} \text{ and } D_{p,i} > 0 \\ 1, \text{if } LC_{p,n} > LC_{p,i} \text{ and } D_{p,i} > 0 \\ 0, \text{if } D_{p,i} = 0 \end{cases} \quad (8)$$

$$U_{p,R} = \min\left(D_p, A_c\right) \quad (9)$$

LC is the levelised cost in €/kWh, *D* is the exogenous demand in kWh and *A* is the availability in kWh. Subscripts are used for pathway (p), end-use technology (et), total number of pathways (t), pathway being considered (n), pathway being compared (i), pathway already utilised (j), resource (c) and sector (s).

If the demand is defined for the technology used in the pathway, then the rank is calculated as in equations (10) and (11):

$$R_{p,n} = 1 + \sum_{i=1}^{t} \begin{cases} 0, \text{if } LC_{p,n} < LC_{p,i} \text{ and } D_{p,i} = 0 \text{ and } D_{et,i} > 0 \\ 1, \text{if } LC_{p,n} > LC_{p,i} \text{ and } D_{p,i} = 0 \text{ and } D_{et,i} > 0 \\ 1, \text{if } D_{p,i} > 0 \\ 0, \text{if } D_{p,i} = 0 \text{ and } D_{et,i} = 0 \end{cases} \quad (10)$$

$$U_{p,R} = \min(D_t - \sum_{j=1}^{R-1} U_{p,j}\ , A_c) \quad (11)$$

For all other pathways, the rank is calculated as:

$$R_{p,n} = 1 + \sum_{i=1}^{t} \begin{cases} 0, \text{if } LC_{p,n} < LC_{p,i} \text{ and } D_{p,i} = 0 \text{ and } D_{et,i} = 0 \\ 1, \text{if } LC_{p,n} > LC_{p,i} \text{ and } D_{p,i} = 0 \text{ and } D_{et,i} = 0 \\ 1, \text{if } D_{p,i} > 0 \text{ or } D_{et,i} > 0 \end{cases} \quad (12)$$

$$U_{p,R} = \min(D_s - \sum_{j=1}^{R-1} U_{p,j} \ , A_c) \quad (13)$$

The available bioenergy resource and refined product resource for each sector is based on total resource in the year less the existing cumulative consumption of all sectors. The additional uptake in the higher-ranked sectors (e.g. the available bioenergy resource in 2020) is the total resource less the cumulative uptake in all sectors up to 2020. The higher ranking of the Power and Transport sectors leads to additional consumption, and thus the available resource for the Heat sector is further reduced by new uptake in 2020 in the Power and Transport sectors.

The total cost of each bioenergy pathway is compared to the cost of counterfactual energy (e.g. electricity, gasoline, diesel, etc) to calculate the savings per use of bioenergy (€/kWh). Any financial incentives such as electricity feed-in tariffs or biofuel incentives are taken into account. The pathways are ranked according to the value of the savings. Pathways are then deployed in descending order until the demand in the Transport and Power sectors is met. The remaining raw bioenergy resource is then available for use in the Heat sector uptake.

5.2.3. Consumer investment behaviour to calculate uptake of heating technologies

The representation of the heat end-use sector is a key innovation in the modelling approach. BioHEAT contains a detailed breakdown of the building and heat sector stock in Ireland. The BioHEAT model uses the heating demand of the buildings to determine the cost of heating technologies as well as the ongoing fuel costs and revenues from policy incentives if specific constraints are defined for subsidy eligibility.

The uptake of renewable heat technologies at individual building level in the model is calculated based on a model of the consumer investment decision-making process (Figure 5-3). This consists of a series of 'barriers' to the uptake of renewable heat technologies.

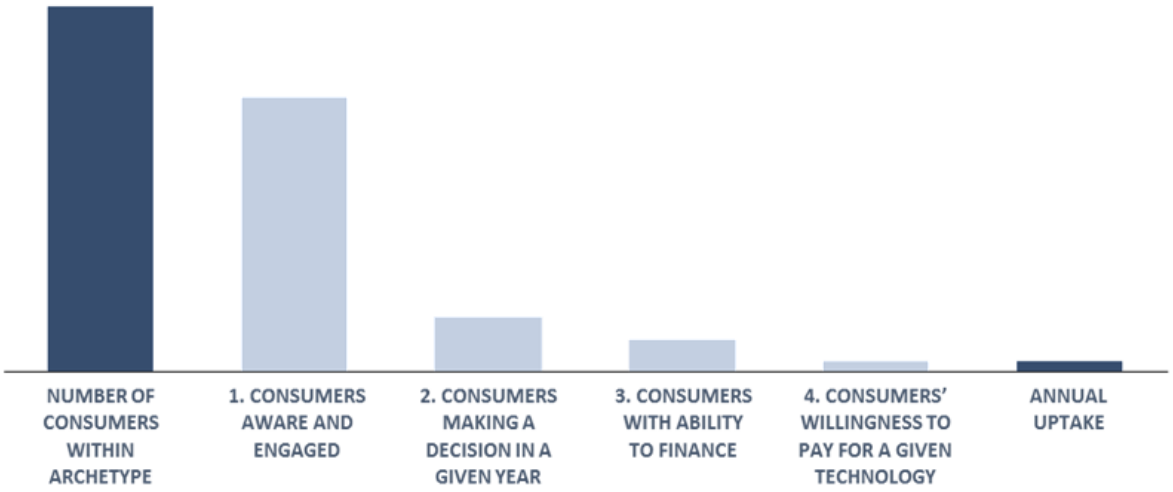


Figure 5-3: Illustration of the consumer decision-making process

The decision-making process is represented based on the results of detailed and representative surveys of consumer behaviour. Therefore, the consumer choice aspect of the BioHEAT model has been empirically determined outside of the theoretical framework of models that conceptualise consumer decision making but the approach does align with these. The work of Jackson (2005) provides a comprehensive review of the different models of consumer behaviour and behaviour change. Jackson outlines approaches ranging from the rational self-interested agent model to models that account for a more complete representation of consumer behaviour. More complete representations allow for consumer habits, attitudes and values as well as situational factors, social influences and personal capabilities to be incorporated. These more complete models have shown greater predictive power (Klöckner, 2013) and can represent the 'attitude-behaviour gap' other empirical work has identified (Young et al., 2010).

The conceptual framework for decision-making used in BioHEAT falls under this theoretical framework. Jackson (2005) mentions that: "a good conceptual model requires a balance between parsimony and explanatory completeness". Jackson also details how a representation of consumer behaviour should account for both internal (cognitive) and external (situational) factors (Jackson, 2005). BioHEAT's use of empirically determined values for consumer decision making behaviours, through a staged decision making process, approaches these aims.

The stages are described below and illustrated in Figure 5-3 are useful from a policy intervention point of view. Tools that can influence consumer behaviour can be deployed to increase awareness and engagement with the options available. For example, traditional information programmes can help bridge knowledge gaps and lower hassle factors. Newer programmes focused on consumer behaviour change can also target these early stages – for example the behavioural science on nudge theory can be effective in overcoming some of the inertia in consumer choices (Leonard, 2008). The latter stages of the decision making process can be influenced by financial incentives.

Awareness and engagement: The first aspect of the decision-making process is the segmentation of the consumer population on the basis of 'awareness and engagement'. The characteristics of consumer types make them more or less likely to engage with an energy decision. A fraction of 'laggards' for each consumer archetype is defined in BioHEAT, as explained in Section 5.5.3. This stage empirically captures some of the internal cognitive influences in an aggregate way. Jackson (2005) lists the individual factors as: motivations, attitudes, value, social influences, capabilities and habits of consumers as important internal factors.

Decision-making frequency and trigger points: The decision frequency is the frequency with which consumers make purchasing decisions (whether positive or negative) regarding their heating technology. This stage captures an important situational factor. The representation of the suitability of individual technology for specific sites also adds to the representation of situational factors.

Budget constraints: Lack of sufficient funds for renewable heating upgrade might be a key barrier, especially in the residential sector, due to the lack of accessible finance for renewable heating investments. The model has the functionality to apply budget constraints, which can limit uptake of renewable heat technologies unless loans or grants are available. This step captures the influence of the heuristic behaviours some consumers use.

Consumers' willingness to pay: The final step in the consumer decision-making process is the calculation of consumers' willingness-to-pay for each renewable heating technology based on the simple payback period of each renewable heating technology and willingness-to-pay curves for each sector, which represent the percentage of consumers willing to invest in a technology offering a given simple payback on investment. This part of the model captures the stated preferences of different consumer groups that includes the range of influential internal cognitive and external situational factors. These curves are presented in Section 5.5.3.

The payback period calculation is described in equation (14), where *C* is the capital cost in €, *H* is the hidden cost in €, *V* is the VAT reduction in €, *L* is the upfront loan in €, *G* is the grant subsidy in €, *O* is the annual maintenance cost in €/y, *F* is the annual fuel cost in €/y, *R* is the annual revenue in €/y, *P* is the annual policy payments in €/y, and *I* is the annual loan repayments in €/y. Subscripts are used for end-use technology (et), counterfactual technology (ct), electricity (e) and heat (h).

$$P_{et} = \frac{C_{et} + H_{et} - C_{ct} - V_{et} - L_{et} - G_{et}}{O_{ct} + F_{ct} + R_{et,e} + P_{et,h} - O_{et} - F_{et} - I_{et}} \quad (14)$$

A simple payback period is calculated for each heating technology and compared with the willingness-to-pay curves for each consumer type in order to identify the fraction that are likely to choose that heating technology. However, given that there is competition between several technologies, the total uptake is determined by the heating technology with the lowest payback period and hence the highest uptake fraction. The total uptake is shared between the competing technologies

weighted by their individual uptake, with the most cost-effective technology still having the highest share.

For instance, if the laggard fraction is 25% for an illustrative building/consumer archetype, which represents 100 buildings in Ireland, 75 consumers would normally consider renewable heating options. Assuming a decision-making frequency of 15 years, only five consumers would normally replace their heating systems each year. Even if we assume that all of these consumers have enough budget and 60% of the consumers are willing to invest in a given technology based on the payback period, only three consumers would install a renewable heat technology per annum. This simple example illustrates the impact of the decision-making process on the uptake of renewable heat technologies.

BioHEAT also has the functionality to consider the uptake of district heating and injection of biomethane to the gas grid. If these are defined by the user, the uptake of renewable heating in the heat sector is broken into three categories:

First, the exogenously defined uptake of district heating is applied as the rollout of such schemes reduces the remaining potential for further renewable heating uptake at consumer level. The rollout also defines the demand for bioenergy from district heating if biomass boilers or CHP technologies are used. This is a useful functionality to understand the impact of potential district heating schemes in Ireland on the uptake of renewable heat technologies.

Secondly, for some pathways no additional capex is required for an existing technology to switch from the fossil fuel to bioenergy, e.g. a gas boiler switching from grid natural gas to grid-injected biomethane. For these pathways, bioenergy will displace the fuel where the levelised cost of the equivalent biofuel is lower than that of the fuel. Exogenous inputs specify what fuels can be directly replaced for each pathway.

Finally, consumer-level uptake of renewable heating technologies is considered, as explained above. The technical potential for this uptake depends upon the remaining stock not already supplied by district heating and not already having substituted their fuel for an equivalent biofuel, as per the previous point.

5.2.4. Interaction between heat, power and transport sectors

One of the key strengths of the model is its ability to treat potential interaction between various sectors and technologies. This is an important functionality to examine the potential indirect impacts of a policy in one end-use sector on the bioenergy use in another sector.

To represent this, the model allows prioritisation of the end-use sectors for access to bioenergy resources. In this case the demands of Power, Transport and Heat are met in the order of their ranking, and the remaining bioenergy resource is then used by the next sector in each year. The default is for Power and Transport

demands to be met first, with the remaining bioenergy available for use in the heat sector.

For instance, if the power sector is prioritised in the model (assuming that power plants might be able to have access to the lowest-cost biomass resources as they offer bigger and longer contracts), BioHEAT allocates available biomass resource to the power plants cost-effectively in each year and calculates the cost of remaining biomass resource that can be used in the heat sector. Instead of meeting a pre-defined biomass demand in the heat sector at least cost, the model endogenously calculates the uptake of biomass boilers based on the costs of biomass and competition between alternative fossil fuels and other renewable heat technologies such as heat pumps. If the cost of remaining biomass resource is higher, the model estimates a lower uptake of biomass boilers as consumers consider the cost of fuel when making investment decisions in renewable heat technologies.

5.2.5. Allocation of bioenergy resource over time

The model assigns bioenergy resources to various bioenergy pathways on an annual basis. Once bioenergy resource is assigned to a pathway (due to exogenously specified demand) or to the heat sector based on consumer uptake, then at least this amount of resource is used in all of the subsequent years (since the model run years are within the lifetime of all technologies and thus decisions on fuel switching are not repeated). Thus there is no reduction of bioenergy consumption and the model only calculates the annual additional demand from pathways and consumer uptake. The available bioenergy resource for a sector in a given year is calculated using the equation (15), where *A* is the available crop resource in kWh and *U* is the historic sector utilisation in kWh. Subscripts are used for resource/crop (c), sector (s), rank of active sector (R), current year (y), rank of sectors already considered (i), historic year (j), and total number of sectors (t).

$$\mathrm{A_{c,s,R,y}} = \mathrm{A_{c,y}} - \sum_{j=2016}^{y-1} \sum_{i=1}^{t} \mathrm{U_{c,i,j}} - \sum_{i=1}^{R-1} \mathrm{U_{c,i,y}} \qquad (15)$$

5.3. Data

The key data used to populate BioHEAT to run two scenarios (i.e. Baseline and Carbon Tax) is explained in the sections below.

5.3.1. Cost of bioenergy pathways

5.3.1.1. Bioenergy supply curves

The cost and available potential for all resources for low, central and high scenarios for 2015-2030 are included in BioHEAT based on the data from the 'Bioenergy Supply in Ireland 2015-2035' report (Ricardo Energy and Environment, 2016). The report details the availability and cost of bioenergy resources based on Irish data for 14 different feedstock types. The study indicates that if market prices for

bioenergy resources are high enough and supply-side barriers are addressed, the total amount of bioenergy produced in Ireland could be as high as 138 PJ by 2035, which is substantially higher than the total primary energy demand of bioenergy of 19.6 PJ in 2014.

Imported bioenergy resources are also included in the model for refined solid biomass, biodiesel and biogasoline. The cost of imported biomass can be varied. It is assumed to be €0.038/kWh in Power and €0.069/kWh in Heat for the scenarios examined. Costs of imported biodiesel and biogasoline are assumed to be €0.11/kWh and €0.07/kWh, respectively. Around 488 GWh of imported biomass is assumed to be used for co-firing in Power, based on the Irish Energy Balance data, and all current and future demand in Transport can be met by imported biogasoline and biodiesel. Uptake of imported biomass in Heat is constrained by its price and consumers' investment behaviour.

5.3.1.2. Refining and transportation costs

Detailed data on refining and transportation are included. Specifications of the refining technologies are based on total capital cost, annual operating maintenance cost, annual fuel (oil/electricity) requirement, annual output and economic life.

The cost of transporting resources or refined products to refineries or end-use technologies is calculated based on transport vehicle fuel type, fuel consumption, maximum freight mass, maximum freight volume, resource or refined product energy density, and resource or refined product density (Fealy et al., 2012; Devlin, 2010). Weighted average distances of resource to refinery, resource to end use and refined product to end use are defined for all sectors and refined products. Wood-chip and pellet refining costs were calibrated to the delivered market prices in 2016 for these refined products (€0.039/kWh and €0.057/kWh for chips and pellets, respectively).

5.3.2. Least-cost way to meet demand in Transport and Power sectors

In the power sector, BioHEAT includes co-firing, landfill gas power generation, waste-to-energy, anaerobic digestion power generation, and biomass CHP. For each technology, capital expenditure (capex) (€/kWe), operating expenditure (opex) (€/kWe/y), fuel conversion efficiency, lifetime and fuel type are defined (Clancy, 2015).

The following sector and technology-specific demands were defined for the transport and power sectors, based on modelling carried out by SEAI on energy forecasts for Ireland (Scheer et al., 2016). Bioenergy demand in Transport is assumed to increase from ca. 8,100 TJ (2,250 GWh) in 2016 to 9,900 TJ (2,746 GWh) in 2030 based on the trajectory published in the national energy forecasts for Ireland (Scheer et al., 2016). In the power sector, bioenergy demand is defined for co-firing (236 GWh), waste-to-energy (209 GWh), landfill gas power

generation (280 GWh), and biomass CHP (803 GWh) in terms of power output, based on information from SEAI energy forecast modelling. Around 80% of existing co-firing demand is assumed to be met by imported biomass (~190 GWh).

5.3.3. Consumer investment behaviour to calculate uptake of heating technologies

5.3.3.1. Consumer archetype definition

BioHEAT is populated with best-available Irish data on building and Heat sector stock, which was developed as part of the 'Unlocking the Energy Efficiency Opportunity' study (Scheer et al., 2015). As part of the study, an extensive survey of commercial buildings was deployed and detailed datasets such as the Building Energy Rating (BER) and Non-Domestic-BER (ND-BER) databases were reviewed to identify the common characteristics of a limited number of building archetypes, which are used to represent the national stock. Building energy models such as Simplified Building Energy Model (SBEM) and Dwellings Energy Assessment Procedure (DEAP) were used to estimate the heat demands of these building archetypes. The model contains a detailed breakdown of the stock and consists of 601 building archetypes, which are used to represent the Irish heat sector, including the following:

- 115 existing and nine new-build commercial-sector archetypes characterised by: building activity (office, retail, hotel, restaurant/public house or warehouse/storage); size (large or small); HVAC type; heating fuel type; wall condition; window condition; building type (e.g. mid-terraced or detached), and purpose (commercial-only or commercial and residential). The commercial building stock model was developed by surveying a statistically representative sample of commercial buildings in Ireland (Element Energy and The Research Perspective for SEAI, 2015a); linking the survey database with ND-BER and the Irish National Calculation Methodology (NCM) databases (SEAI, 2017b); selecting a sufficient number of archetypes for use in the national stock model, based on coverage of final energy, and constructing a national stock model using building energy outputs from the Simplified Building Energy Model (SBEM). A more detailed description of the methodology is provided in the methodology and technical assumptions appendix to the 'Unlocking the Energy Efficiency Opportunity' study (Element Energy for SEAI, 2015)
- 46 existing and six new-build public sector archetypes characterised by building activity (education, healthcare or office); size; HVAC type; heating fuel type, and wall/window condition. The public buildings stock was developed by estimating the total number of public buildings based on GeoBusiness and literature including SEAI public sector programme data; obtaining detailed data from the Irish Display Energy Certificates[20] (DEC), ND-BER and NCM datasets; selecting a sufficient number of archetypes for

[20] Display Energy Certificates are required to be displayed for large buildings open to the public. They are based on the actual metered energy consumption of the building over a year. For more information, see http://www.seai.ie/Your_Building/BER/Large_Public_Buildings/DEC_FAQ/

use in the national stock model based on coverage of final energy, and constructing a national stock model using building energy outputs from SBEM.

- 112 residential sector archetypes characterised by heating fuel type (i.e. electric, gas, oil and solid fuel), Building Energy Rating (BER) and building type (detached, semi-detached, terraced or flat). The sector archetypes were developed by reviewing the BER dataset and estimating building energy demand by using the official Irish procedure for calculating and assessing energy performance of domestic buildings – the Dwelling Energy Assessment Procedure (DEAP).
- 208 space heating and 95 low-temperature process heat industrial sector archetypes characterised by 13 industrial activity subsectors,[21] EU Emissions Trading Scheme participation; participation in the national energy efficiency programme for large industry, and four heating fuel types. Note that none of the renewable heat technologies is deemed suitable to provide high-temperature process heat for industry.
- 10 agriculture sector archetypes, characterised by EU ETS status and size.

Figure 5-4 shows the resultant heat demand in residential, commercial, public and industry sectors in 2016 by fuel type (excluding the high-temperature processes in industry). This includes the impact of energy efficiency uptake as the baseline heating demand is adjusted for savings resulting from the uptake of energy efficiency measures. This results in reducing demands at building archetype levels from 2016 to 2030.

[21] Basic metals and fabricated metal products; Food, beverages and tobacco; Other non-metallic mineral products; Electrical and optical equipment; Chemicals and man-made fibres; Wood and wood products; Other manufacturing; Non-energy mining; Rubber and plastic products; Machinery and equipment; Pulp, paper, publishing and printing; Transport equipment manufacture; and Textiles and textile products.

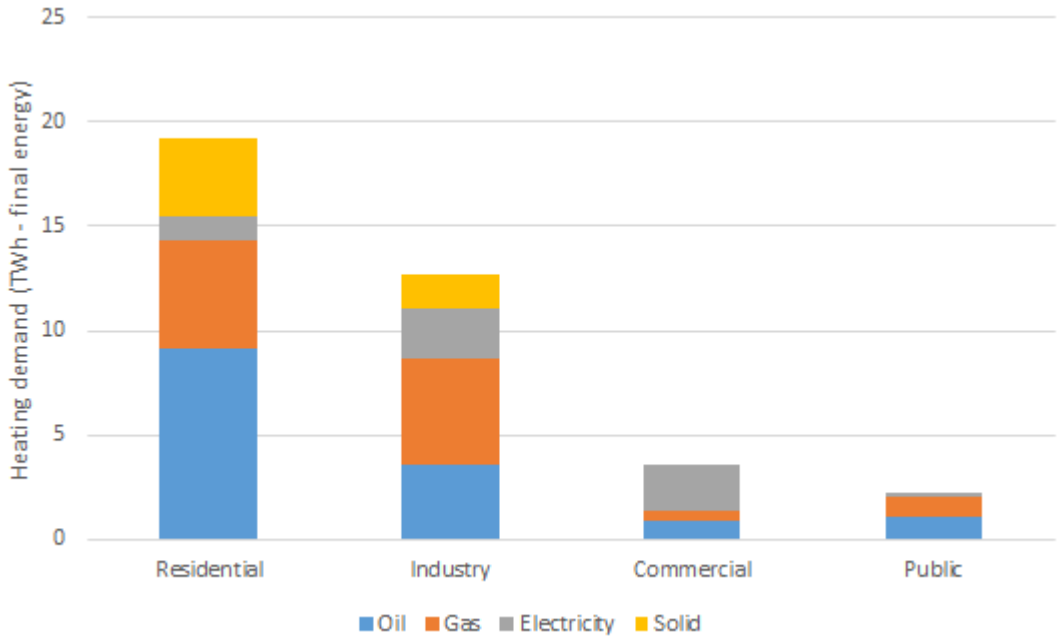


Figure 5-4: Heating demand by sector and fuel type in BioHEAT for 2016 (final energy)

Building archetypes are also disaggregated into a number of 'consumer archetypes' to better represent the main differences in the decision-making process of different consumer types based on previous surveys (Element Energy and The Research Perspective for SEAI, 2015b). These include whether companies are large or small, whether the decision-maker is owner or tenant in the commercial sector, and whether the consumer is owner-occupier or tenant/private-landlord in the residential sector. The fraction of laggards, budget limit and willingness-to-pay curves are different for different consumer groups.

Table 5-2: Existing energy production from technology pathways[22]

Technology	Bioenergy resource	Demand (GWh)
Co-firing	Miscanthus	5
Co-firing	Sawmill residue	41
Co-firing	Imported solid biomass	190
Waste to energy	Solid MSW	95
Landfill gas power generation	Landfill gas	218
Biodiesel	Imported biodiesel	779
Bioethanol	Imported bioethanol	276
Biomass CHP	Post-consumer recovered wood	15

Table 5-3: Existing uptake of renewable heat technologies

Subsector	Renewable technology	Current heating demand met (GWh)
Commercial	Biomass boiler	269
Commercial	ASHP	153
Commercial	GSHP	29
Commercial	WSHP	14
Industry	Biomass boiler	1,623

[22] Bioenergy demand for power corresponds to power output. The model calculates how much bioenergy resource is needed to meet these power demands.

Industry	Biomass CHP	69
Residential	Biomass boiler	155.2
Residential	ASHP	377
Residential	GSHP	70.7
Residential	WSHP	35.3
Residential	Solar thermal	140

The current demands and uptake are also accounted for in the model. The data on existing uptake of bioenergy and heating technologies is based on the national energy balance (Howley and Holland, 2016a). The data used to populate BioHEAT is shown in Table 5-2 and Table 5-3.

5.3.3.2. Heating technology cost, performance and suitability

As of 2016, up-to-date data on capital cost, operating cost, hidden cost, typical size, load factor, efficiency, lifetime and suitability for all heating technologies in BioHEAT is based on recent extensive stakeholder engagement carried out as part of the design of the Renewable Heat Incentive (Element Energy for DCCAE and SEAI, 2017).

5.3.3.3. Willingness-to-pay curves

The following willingness-to-pay (WTP) curves are used in BioHEAT for owner occupiers and private landlords in the residential sector, commercial buildings, public buildings and industry. WTP curves for commercial buildings were derived using the data from the survey of consumer behaviour in the commercial sector in Ireland (Element Energy and The Research Perspective for SEAI, 2015b). WTP curves for public buildings and industrial organisations were derived using cost and savings data from around 200 energy-savings projects funded by the Better Energy Programmes in 2011 and 2012 (Element Energy and The Research Perspective for SEAI, 2015b). WTP curves for residential owner-occupiers and private landlords are from the consumer surveys undertaken and household survey data in the UK (Element Energy et al., 2008; CCC 2009).

Willingness-to-pay curves represent the proportion of decision-makers who are predicted to invest in a given technology for a given payback period, as illustrated below (Figure 5-5). For example, based on the above studies it is estimated that half of residential owner-occupiers (who are aware/engaged, have sufficient budget and are considering replacing their heating technologies) will take up an investment with a payback of three years, while the corresponding number for private landlords is almost zero. For the same payback period of three years, more than 70% of companies are estimated to make an investment.

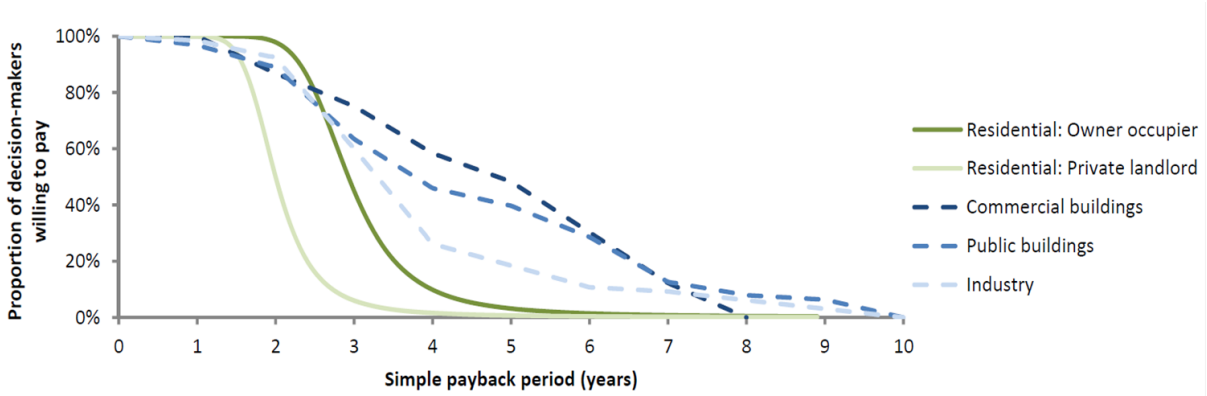


Figure 5-5: Willingness-to-pay curves used in BioHEAT

5.3.3.4. Laggards and decision-making frequency

The first aspect of the decision-making process is the segmentation of the consumer population on the basis of 'awareness and engagement'. The survey information showed that energy use is not a top priority for approximately half the consumers in the Irish commercial sector (Clancy et al., 2017; Element Energy and The Research Perspective for SEAI, 2015b). These consumers are represented in the model as 'laggards' who do not consider renewable heat technologies unless regulation is in place. The fraction of laggards is defined for each archetype in BioHEAT. For instance, the fraction of laggards is almost 60% for some of the small retail shops, but less than 20% for some of the large offices. Table 5-3 summarises the key data used and data sources.

Table 5-4: Fraction of laggards in BioHEAT

Sector	Fraction of laggards	Data sources
Commercial	Varies between 18% and 59%	Survey of consumer behaviour in the commercial sector in Ireland (Element Energy and The Research Perspective for SEAI, 2015b)
Industry	0% for LIEN[23] companies and 33% for non-LIEN companies	Survey of consumer behaviour in the commercial sector in Ireland (Element Energy and The Research Perspective for SEAI, 2015b)
Public	0%	-
Residential	Varies between 8% and 19%	Survey on energy efficiency loans in Ireland (Sustainable Energy Authority of Ireland, 2016b)

[23] The Large Industry Energy Network (LIEN) is a voluntary grouping, facilitated by SEAI focused on improving energy efficiency.

The decision frequency is the frequency with which consumers make purchasing decisions (whether positive or negative) regarding their heating technology, and is thus an important limit to the rate at which renewable heating technologies can be taken up. The decision frequency is typically related to 'trigger points' at which consumers are most likely to consider renewable heating technologies. For heating technologies, this might be a major building renovation or an end-of-life replacement of a heating system. Boilers typically have a lifetime of around 15 years, so the default assumption for the decision-making frequency in BioHEAT is every 15 years for all sectors. It is possible for policy interventions to increase the decision frequency as consumers may choose to retire an old technology early to avail of an incentive that is offered for a limited time period. On this basis, commercial, public and industry sectors' decision-making frequency is increased to every five years if incentives for renewable heat output are introduced in the model.

5.3.4. Fuel costs and emissions

Fuel costs and CO_2 prices and intensity for gas, oil, solid fossil (i.e. combination of peat and coal) and electricity are specified for domestic, commercial and industrial sectors. Gasoline and diesel prices are input for transport. The underlying commodity prices are defined for low, central and high scenarios for 2016-2030. 2016 fuel costs are based on SEAI fuel cost comparison tables (SEAI, 2017c) and the UK Department of Energy and Climate Change (DECC) fuel cost projections (BEIS 2016) are used to determine the increase in base year prices. Consumption bands for gas and electricity prices are included in the model as building owners face different prices depending on their energy consumption, which have an impact on the likely uptake of renewable heat technologies.

5.4. Illustrative scenarios and results

A number of different policy instruments can be applied in BioHEAT and assessed under a wide range of sensitivities. To demonstrate some of the capabilities and outputs of the model, a baseline scenario and two further scenarios were constructed. This section presents some of the key results from these scenarios. Note that the scenarios chosen and results shown are for illustrative purposes; they are intended to display the novel features and main outputs that the model is capable of generating. These include the interaction between separate targets for the heat and power sectors, the flexibility to model various policy types in the Heat, Electricity and Transport sectors from a policymaker's perspective, and novel representation of consumer decision-making in Heat. This chapter does not seek to examine in detail specific government policies or to forecast the development of the bioenergy sector.

5.4.1. Definition of Baseline, High-Power Sector Demand and Carbon Tax scenarios

The **Baseline** scenario shows the impact of existing policies and the additional expenditure proposed for 2017 in Ireland, but assumes no new policy is in place beyond 2020. The policies included are: a 30% grant for solar thermal technology in the residential sector; a feed-in tariff for electricity generated from biomass CHP and AD CHP until 2020; and carbon tax is assumed to remain at €20/tonne until 2030. No new policy schemes (e.g. RHI, further grants, loans schemes, etc) are included.

The **High-Power Sector Demand** scenario illustrates the impact of increased demand for bioenergy in the power sector on the heat sector. Bioenergy demand in the power sector is assumed to double from 236 GWh to 513 GWh in this scenario.

The **Carbon Tax** scenario examines the impact of an increasing carbon tax without any supporting policies over the period to 2030. Carbon tax starts at €20/tonne in 2016 and is assumed to increase over time (at the same growth rate as in the projection for carbon prices included in the Public Spending Code (CEEU, 2017)) to €40/tonne by 2025 and €100/tonne by 2030. This higher carbon tax/price is also applied to the ETS industry in this scenario.

5.4.2. Bioenergy resources used in the Baseline scenario

Bioenergy resource use in Ireland increases from 32 PJ (~9 TWh) in 2020 to 50 PJ (~14 TWh) in 2030 in the Baseline scenario, as shown in Figure 5-6. This increase is mainly driven by the uptake of solid biomass boilers in the Heat sector – which almost triples in 10 years – as well as biomass CHP uptake.

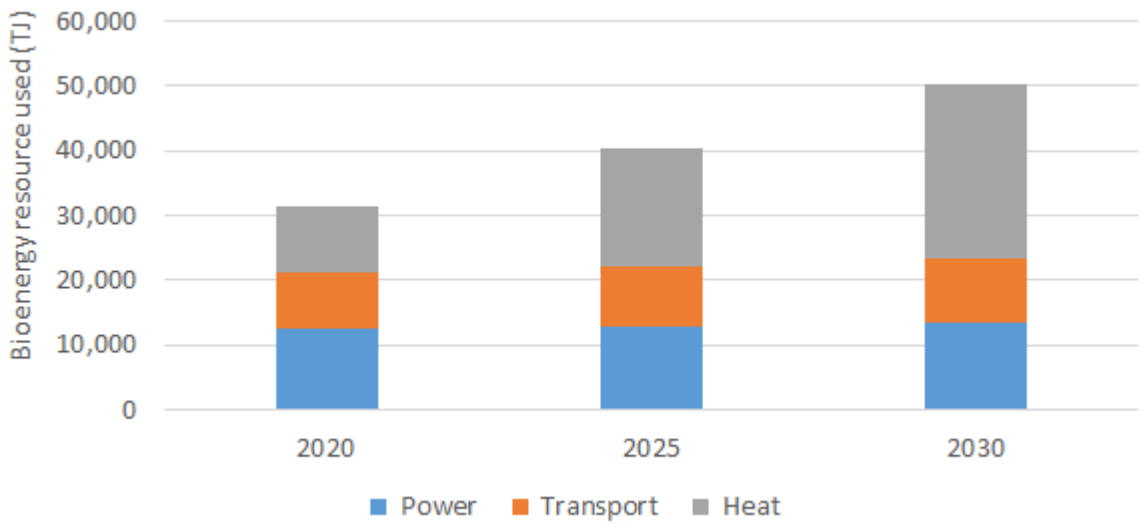


Figure 5-6: Bioenergy resource used in all sectors (Baseline scenario)

Figure 5-7 shows the bioenergy resources used in the Power sector in 2020, 2025 and 2030. The slight increase in bioenergy consumption between 2020 and 2030 is driven by the uptake of biomass CHP. Due to economic and resource constraints, the demand defined for biomass CHP in this scenario is not met in 2020. The Baseline bioenergy demand for biomass CHP does not increase between 2020 and 2030, and BioHEAT reduces the unmet demand over time as lower-cost bioenergy resource becomes available (and more biomass CHP projects become economically feasible).

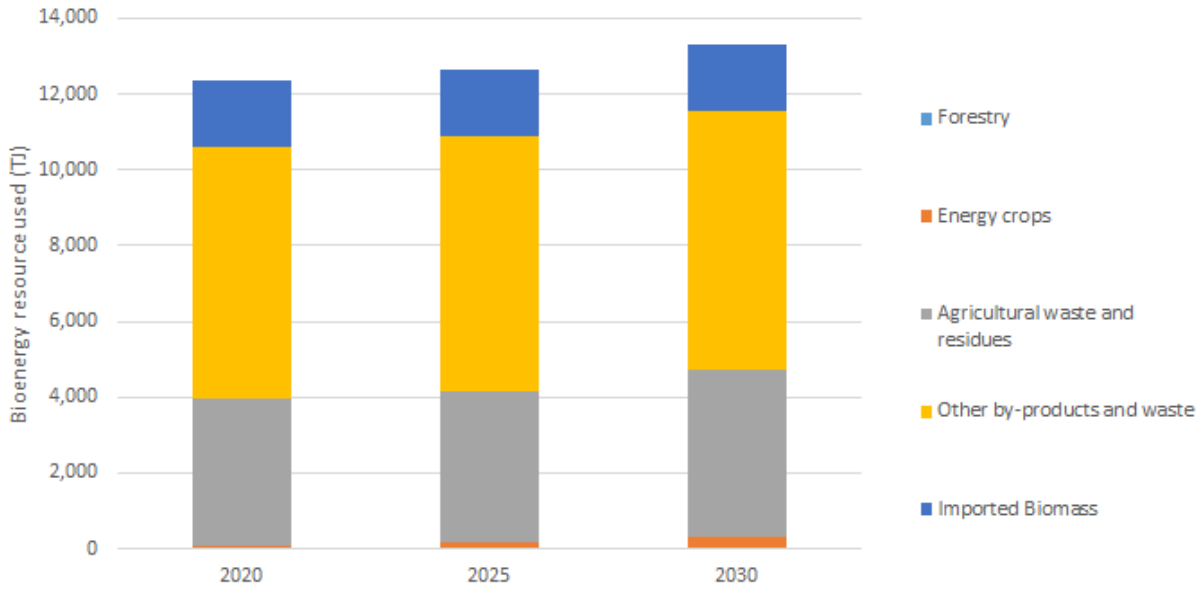


Figure 5-7: Bioenergy resource used for Power (Baseline scenario)

The amount of bioenergy demand defined and met in the power sector in the model is shown in Figure 5-8. All of the demand defined for waste-to-energy and co-firing is met; however, around 20% of landfill gas and biomass CHP demand in 2030 is not met due to economic constraints (e.g. the LCOE of biomass CHP from the higher-cost bioenergy resources and pathways is more than the 12c/kWh$_e$ REFIT incentive and the LCOE of landfill gas is higher than the electricity price).

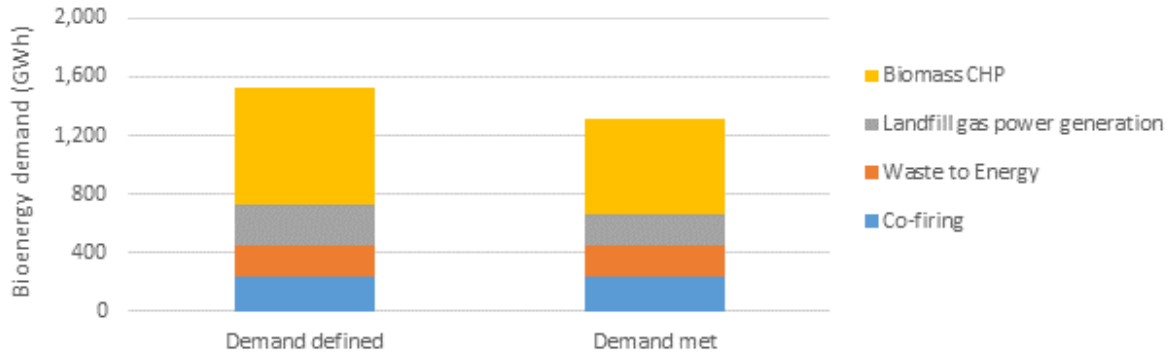


Figure 5-8: Electricity demand met by bioenergy in Power in 2030

Changes in bioenergy demand in the transport sector have no impact on power and heat sector uptake as transport demand does not compete with these for bioenergy resources. Demand is met via imported biogasoline and biodiesel as these are available at lower cost than through production pathways in Ireland.

The use of sawmill residues dominates the bioenergy resources used to generate heat energy in 2020. Sawmill residues are relatively low-cost and in 2020 there is low availability of other local biomass resources such as forest residues and willow. After 2020, more forest residues and willow energy crops are available, and the use of these resources is driven by the increased uptake of biomass boilers, mainly in the industrial sector. Total bioenergy use in Heat increases from less than 11 PJ (3 TWh) in 2020 to 27 PJ (7.5 TWh) in 2030, as shown in Figure 5-9. Imported biomass increases from 500 TJ (140 GWh) in 2018 to ~1,400 TJ (400 GWh) in 2021, but it does not increase further after 2021 as cheaper local biomass resources become available. The model estimates that uptake of biomass boilers and biomass CHP in industry could be significant if cheap local resources become available in the 2020s. The impact of resource constraints on bioenergy uptake in Heat is examined in more detail below.

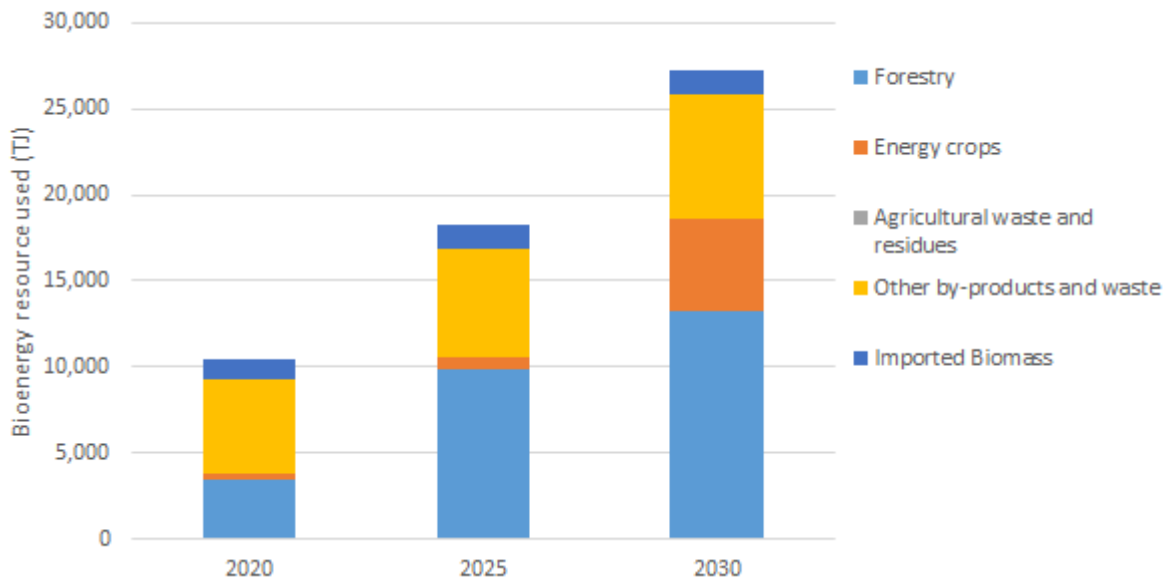


Figure 5-9: Bioenergy resource used in Heat (Baseline scenario)

Figure 5-10 shows the use of remaining forest, sawmill and willow resource (available to Heat sector) between 2018 and 2030, reflecting the underlying trends of availability and costs. Use of higher-cost imported biomass increases significantly between 2018 and 2021 due to the limited availability of cheaper domestic resources, but after 2021 the uptake of biomass is driven by the availability of low-cost domestic resources (mainly forest and sawmill). Before 2021, the utilisation rate of forest, sawmill and willow is around 100% as resource availability is the limiting factor. After 2021, the utilisation rate is generally less

than 100% as the uptake of renewable heat technologies based on consumer investment behaviour is the limiting factor.

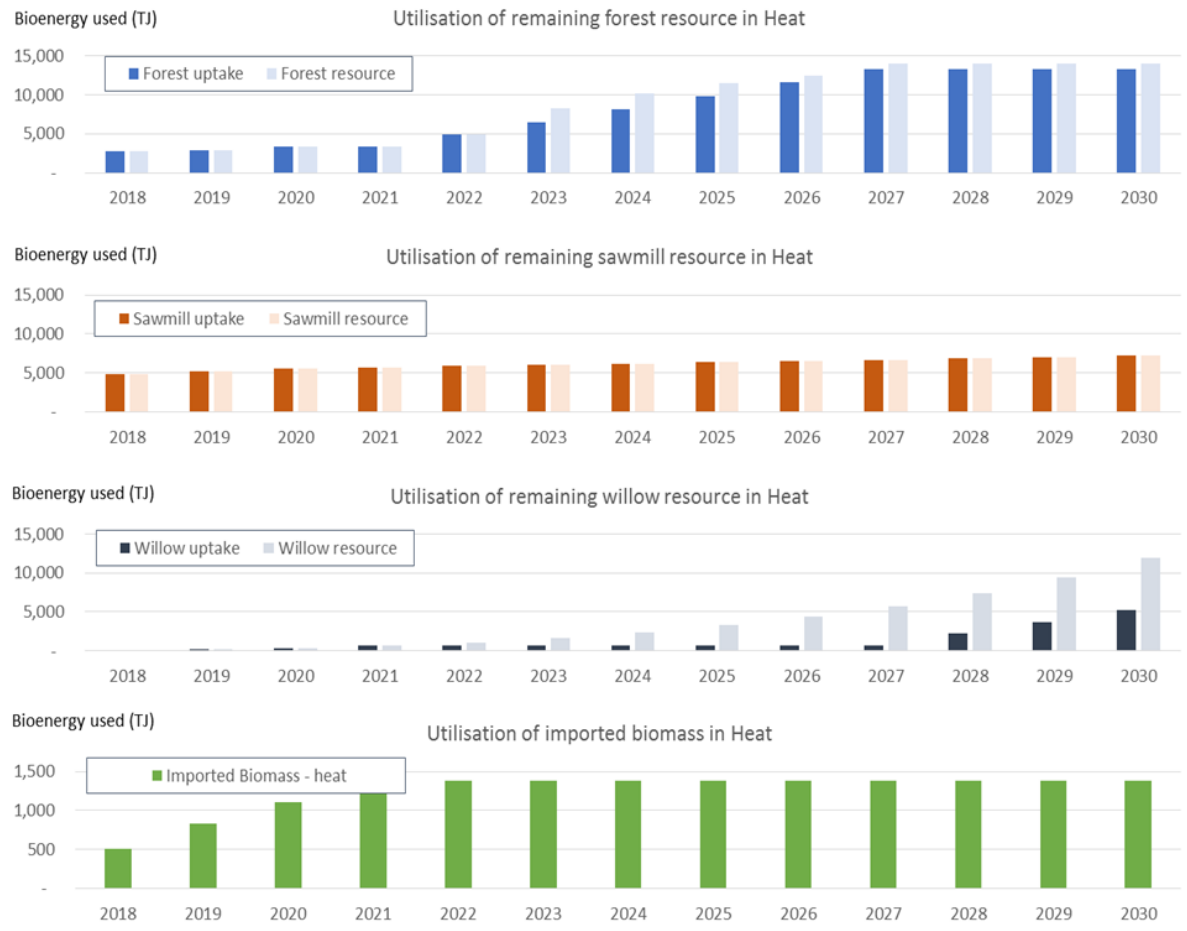


Figure 5-10: Utilisation of key bioenergy resources in Heat over time (Baseline scenario)

The uptake of biomass boilers and CHP in Heat also depends on the consumers' investment behaviour. As explained in the Method section 5.2, BioHEAT contains a detailed breakdown of the building and Heat sector stock in Ireland. The uptake of renewable heat technologies at individual building level is calculated based on a model of the consumer investment decision-making process. Consumers compare economics of different technologies and fuel types while making an investment decision. Figure 5-11 shows the fraction of each bioenergy resource that is used to replace each fossil fuel in the Baseline scenario. Due to its low price, sawmill residues could replace electricity, oil and gas, whereas imported biomass could only replace electricity. The model predicts that oil or gas-heated buildings are unlikely to invest in biomass technologies without further incentives if cheap local resources are not available.

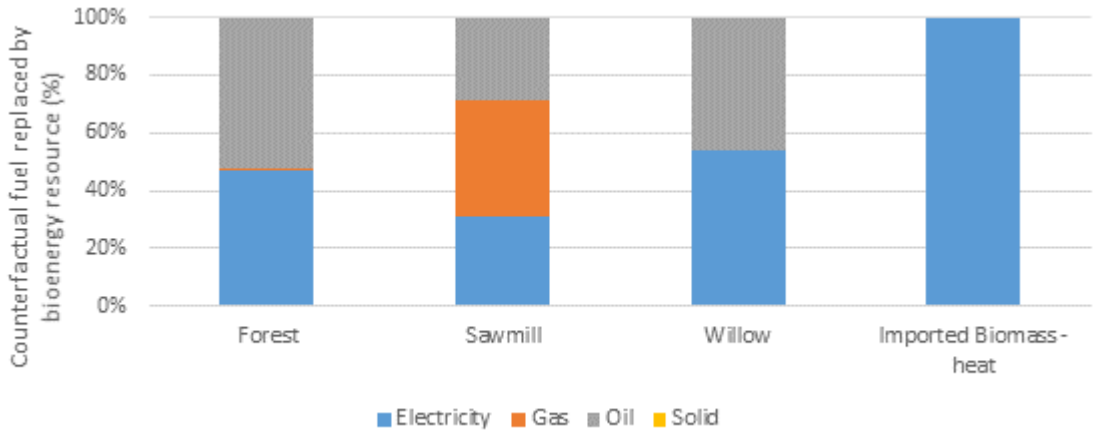


Figure 5-11: Proportion of counterfactual fuel replaced by each bioenergy resource type (Baseline scenario)

5.4.3. Impact of high bioenergy demand in Power on the Heat sector

In the High-Power Sector Demand scenario, the impact of increased bioenergy demand in the power sector on the uptake of biomass in the Heat sector is examined. Figure 5-12 shows that around 2,200 TJ (600 GWh) of additional sawmill, forest and willow is used in the power sector in 2020 to meet an assumed additional bioenergy demand arising from additional co-firing.

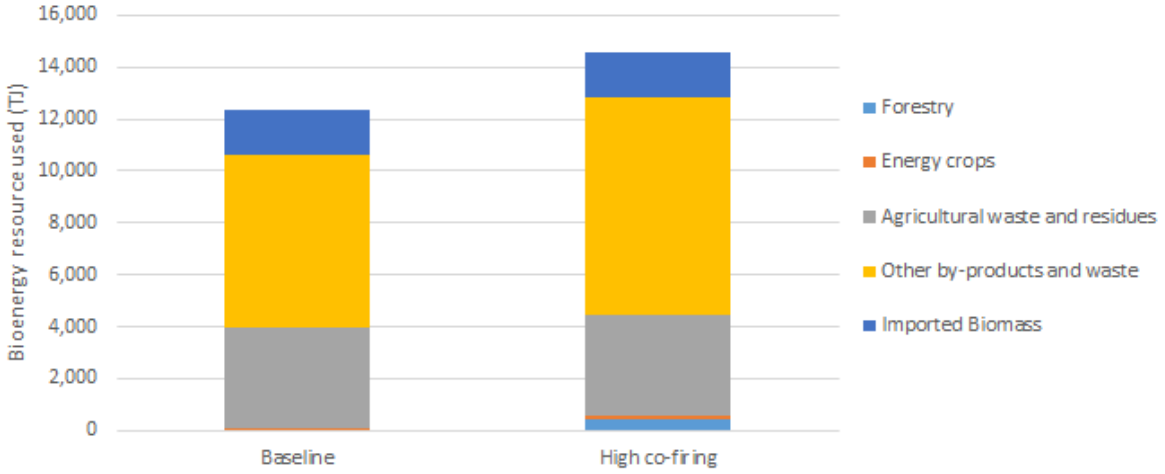


Figure 5-12: Bioenergy in Power in 2020 – comparison of Baseline and high co-firing sensitivity

Due to the reduced availability of low-cost resources for Heat, uptake in Heat is 20% lower in 2020 in the High-Power Sector Demand scenario, as shown in Figure 5-13. Imported biomass increases slightly (~180 TJ) in this scenario. This is driven by heat consumers using imported biomass where access to local resources is limited, but overall uptake is lower as the cost of imported biomass (€0.069/kWh) is higher than the costs of biomass chips and pellets (e.g. €0.039/kWh and €0.057/kWh, respectively).

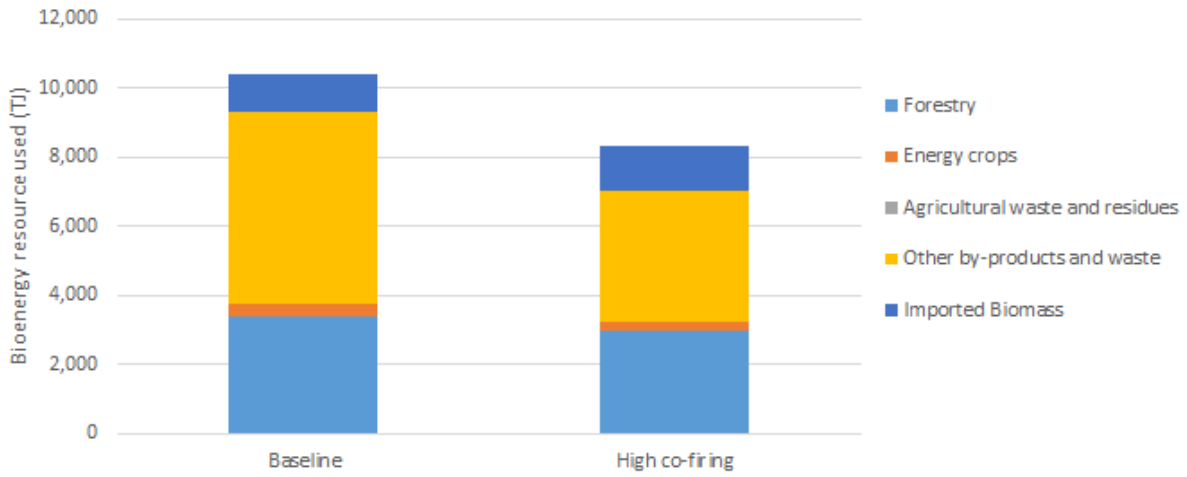


Figure 5-13: Bioenergy in Heat in 2020 – comparison of Baseline and high co-firing sensitivity

5.4.4. Uptake of renewable heat technologies in the Baseline and Carbon Tax scenarios

The objective of this section is to demonstrate the impact of higher carbon tax on the uptake of renewable heat technologies. Figure 5-14 shows the number of installations of renewable heat technologies between 2018 and 2030 by sector (residential, public, commercial, industry) and technology. Fewer than 1,000 renewable heating installations are deployed by 2020 and 3,400 by 2030 in the Baseline, mainly driven by the uptake of biomass boilers in industry and heat pumps in the commercial, public and residential sectors. In the Carbon Tax scenario, there is only a modest increase in biomass boilers and ASHPs versus the Baseline. In terms of MW_{th} installed capacity, renewable heat is dominated by biomass boilers in industry and ASHPs in the commercial and residential sector in both of the scenarios. The uptake of solar thermal is estimated to be negligible until 2030, although a grant of 30% is currently available in the residential sector as the payback periods for various consumer archetypes are higher than the acceptable levels.

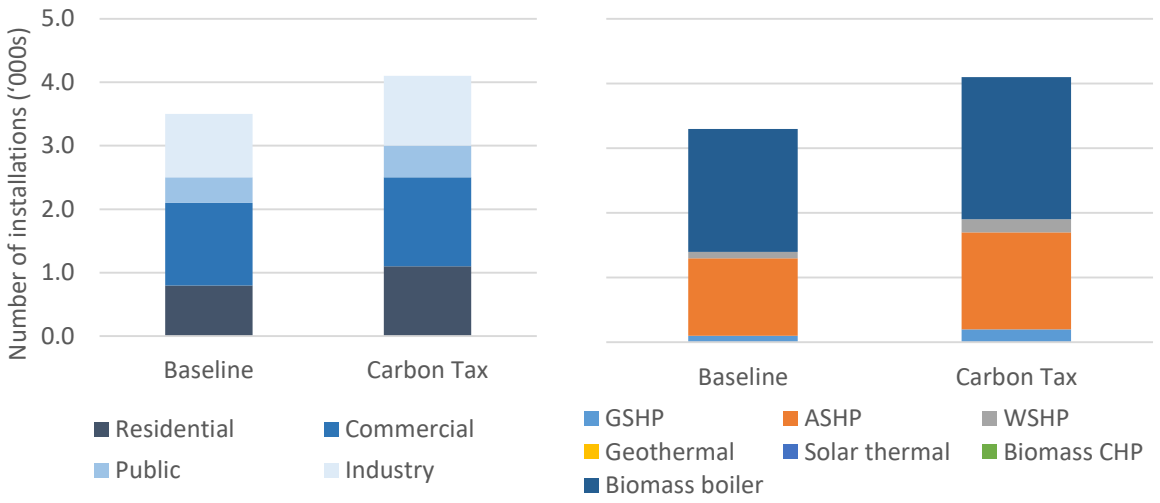


Figure 5-14: Number of installations 2018-2030 by sector and technology

The total capex in renewable heating technologies to 2030 increases from €750 million in the Baseline scenario to €800 million in the Carbon Tax scenario, mainly due to the additional investment in industry (Figure 5-15). It should be noted that both the carbon tax and EU ETS price is assumed to increase in the Carbon Tax scenario (as explained previously).

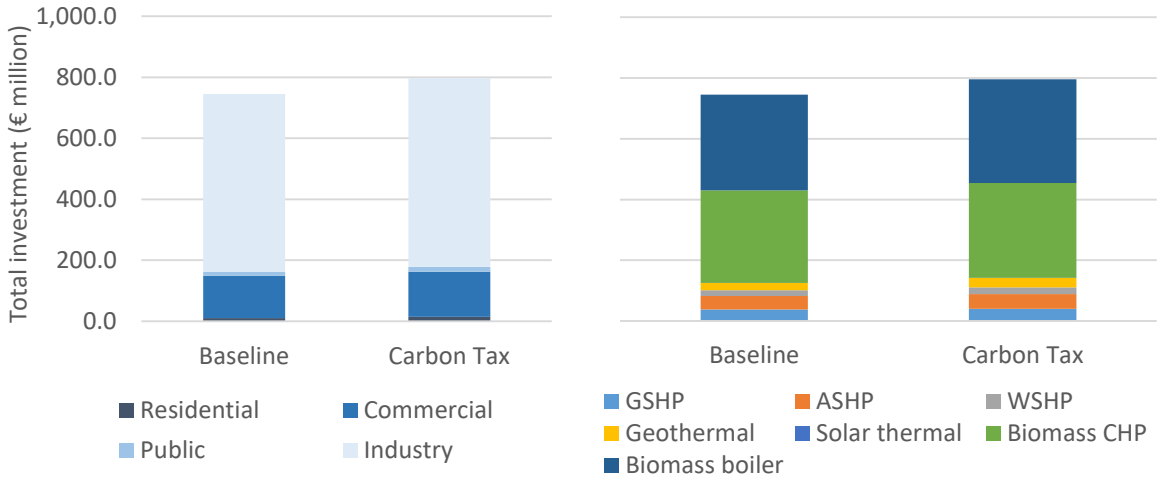


Figure 5-15: Total investment to 2030 by sector and technology (undiscounted)

Cumulative CO_2 savings between 2016 and 2030 increase from 17 $MtCO_2$ in the Baseline to 17.4 $MtCO_2$ in the Carbon Tax scenario, representing a 2.5% increase (Figure 5-16). In both scenarios, carbon savings are dominated by biomass-based heating in industry, with biomass boilers the single largest component. In terms of ETS and non-ETS split, total CO_2 savings in the non-ETS sectors are around 4 $MtCO_2$ and the rest is in the ETS sector (industry and Power).

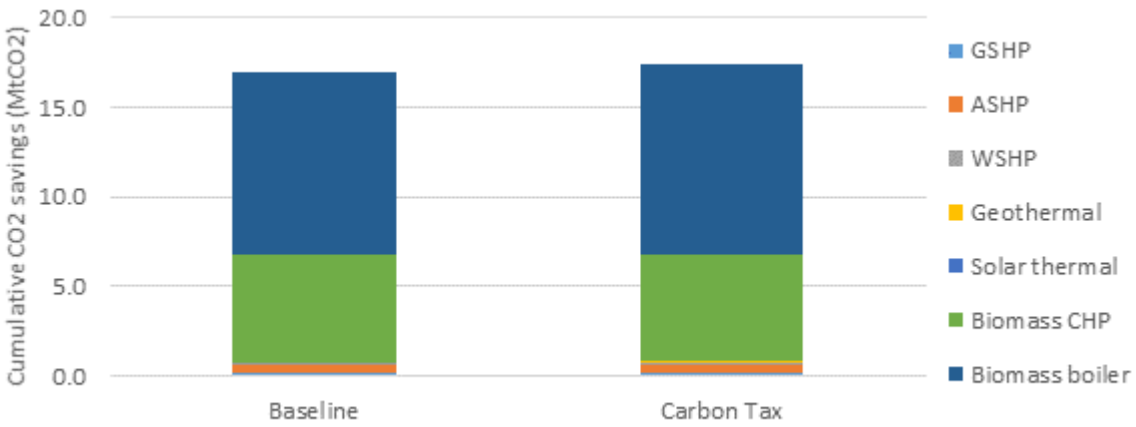


Figure 5-16: Cumulative CO_2 savings to 2030 by technology

5.5. Discussion

The BioHEAT model was developed as a decision support tool for policymakers when considering policies to support the use of bioenergy or renewable heat technologies. A number of different policy instruments can be applied in BioHEAT and assessed under a wide range of sensitivities. Sensitivity analysis can be carried out on all inputs. Important examples include sensitivity on the cost and availability of bioenergy, fossil-fuel costs, discount rates, cost of carbon, and the type, scale and duration of financial support offered by a policy measure.

The outputs of the BioHEAT model can provide a robust evidence base to assess policies against a range of important metrics – for example, the effect of a proposed policy measure on Ireland's progress towards renewable energy targets, split by Heat, Power and Transport, and towards carbon reduction targets. The model can distinguish between the ETS and non-ETS sectors, which is important when considering national carbon emissions reduction targets and the effect of targeting renewable energy policy specifically at the non-ETS sector.

BioHEAT can provide the total and annual direct cost to the Exchequer, and can give the cost profile of a scheme across the full lifetime; for instance, investigating the effects of front-loading a policy measure in the early years to help contribute to short-term 2020 targets. It can give the average and marginal cost of carbon abated and of renewable energy generated.

The model can investigate the impact of policy on the diversity of renewable heating technology mix; for example, whether a particular policy design results in over-reliance on a single technology, fuel type or sector to achieve its goals. It can also investigate the cost to the Exchequer of broadening the scheme to facilitate non-cost-optimal technologies and sectors.

The model can give an indication of the administrative burden posed by a scheme; for example, a policy that incentivises a small number of high-capacity

installations is likely to be easier to administer than one that incentivises a large number of small-capacity installations.

The detailed representation of the bioenergy sector is a key strength of the BioHEAT model due to the importance of bioenergy to the renewable heat sector and, potentially, to electricity generation. An additional goal of government policy to support renewable heat is to develop an indigenous bioenergy sector that will contribute to the economy of rural areas and to national energy security. The detailed bioenergy cost curves that underpin BioHEAT provide a robust basis on which to estimate the potential growth in supply and usage of indigenous bioenergy, and the limitations posed by cost and availability, particularly where there are competing demands for the same limited resource in multiple sectors.

As an example of how BioHEAT could be used for real applications, the model has recently been applied as part of the work being undertaken by the DCCAE and SEAI to support the design of the support scheme for renewable heat in Ireland (DCCAE, 2017a). This work provides a useful case study of the model's utility as a policy decision support tool. A wide range of key design questions for the renewable heat support scheme were studied using the model, allowing the project working group to study the potential impact of various policy design options and external scenarios on the level of deployment of renewable heating, the associated policy cost and the contribution towards national policy goals. For example, the technologies eligible for support under the support scheme were varied to consider the balance between diversity of technologies deployed and the overall policy cost; the impact of including only Non-ETS users in the scheme or both Non-ETS and ETS was assessed, and a combination of policy support mechanisms was tested, including payment per unit of heat output and payment through upfront grant support. The sensitivity of the outcome was also tested against a range of input assumptions, including the bioenergy and fossil-fuel prices; the availability of biomass imports into Ireland; the likelihood of fuel switching among cohorts using different counterfactual heating fuels, and others. The BioHEAT model is providing the capability to investigate key policy questions with a high level of robustness, flexibility and transparency.

5.6. Conclusions

This chapter presented a model of the renewable heat and bioenergy sectors in Ireland. This model was developed specifically to inform government policy in these areas and has been used to investigate policy options for the introduction of a Renewable Heat Incentive to help achieve Ireland's 2020 targets for renewable energy and carbon emissions reductions. The purpose of this chapter is to provide a detailed description of the methodology and data inputs so as to allow transparency and peer review of the model.

Three illustrative scenarios were examined to demonstrate the functionality and unique features of the model. The Baseline scenario showed the impact of existing policies on bioenergy use in the heat and power sectors. Comparing the High-Power Sector Demand scenario to the Baseline scenario illustrates the impact of

increased demand for bioenergy in the power sector on the Heat sector. In this scenario a doubling of bioenergy used for power generation led to a 20% drop in bioenergy use for heat due to a shortage of low-cost biomass resource. Finally, the Carbon Tax scenario shows the impact of higher carbon tax on the uptake of renewable heat technologies.

Together, these scenarios demonstrate the wide range of policy measures that can be modelled and how the detailed model outputs can provide a solid evidence base for policymakers when assessing policies against a range of metrics.

Chapter 6

Modelling national policymaking to promote bioenergy in heat, transport and electricity to 2030 – interactions, impacts and conflicts

Abstract

Governments must increase bioenergy use to realise the Paris agreement ambition. Most countries have limited biomass resources and policy goals beyond carbon reduction. This can lead to policy incoherence as the use of bioenergy in either heat, transport or electricity can impact on the others. Previous studies tended to focus on one end-use sector or on optimising CO_2 reduction. In this chapter, the cross-sector interactions of policy in Ireland are examined. As an EU member with ambition for increased bioenergy use, Ireland is a useful case to examine trade-offs. We simulate policy impacts using the BioHEAT policy decision support tool. Policy in the Heat and Transport sector closes the gap to Ireland's 2030 climate targets by 3%. Policy supporting co-firing of biomass increases emissions by 8.3 $MtCO_2$ overall and reduces the policy impact on national climate targets by 63% as co-firing out competes heat sector sites for the available resources. Coal conversions and the use of advanced biofuels are found to rely on high availability of imports. Overall, we find public policy supporting biomass use in the power sector can make national climate targets less achievable for EU countries. Availability of biomass imports can help reduce risks but raises security of supply questions.[24]

[24] This chapter is based on a paper currently under review in a peer-reviewed journal: Clancy, J.M., Curtis, J. and Gallachóir, B.Ó. (2018). Modelling national policy making to promote bioenergy in heat transport and electricity to 2030 – interactions, impacts and conflicts. *Energy Policy*, submitted in April 2018.

6.1. Introduction

Governments are implementing policy to stimulate the use of biomass resources for energy (Bacovsky et al., 2016). The primary focus is to reduce GHG emissions but specific policies are also influenced by considerations such as creating and protecting employment, energy security, and other environmental objectives (Berndes and Hansson, 2007; DCCAE 2014; Bacovsky et al., 2016). Over the longer term, the Intergovernmental Panel on Climate Change (IPCC), the International Energy Agency (IEA) and others show an increasing role for bioenergy in efforts to mitigate climate change (IEA, 2016; IPCC, 2015). Coherent policy measures will be required to deliver this. The range of policy objectives can be difficult to coordinate. Action in one sector may have unintended negative outcomes in another. Competition for resources between the end-use sectors can affect overall deployment, leading to more expensive policy interventions. Therefore, the modelling of bioenergy policy must consider the system-wide and cumulative impacts of policy interventions.

Examples of policies that encourage bioenergy use in one or more of the three end-use sectors of Heat, Transport and Power are already commonplace. In North America the policy focus has been on liquid biofuels. Through the Energy Independence and Security Act of 2007, the US aims to produce 36 billion gallons (136 Gigalitres) by 2022 (United States Congress, 2007). Canada has also had a focus on biofuel use. The Federal Renewable Fuels Regulations require a 5% bioethanol blend and a 2% renewable content in diesel (Government of Canada, 2010). In Asia, Japan is focused on the use of bioenergy to produce electricity (METI, 2014) and China has policy measures for liquid biofuels and for power generation (Jiang et al., 2017). Policy in the Republic of Korea is also oriented towards supporting biofuels for transport, though recent measures have increased the use of bioenergy in the power sector (Bacovsky et al., 2016). In Europe, policy measures have been implemented to encourage bioenergy use for heat, transport and electricity; many countries have policy instruments in place for bioenergy in each sector (Bacovsky et al., 2016). Germany, for example, has feed-in tariff support for bioenergy production from solid biomass and biogas (Bundestag, 2008) as well as mandates for CO_2 reductions though blending liquid biofuels into petrol and diesel (FNR, 2015). The UK has bioenergy supports and regulations in place for heat (Government of the UK, 2009), transport (Government of the UK, 2015) and electricity (Government of the UK, 2016b, 2017a). UK government support has enabled some coal generation units to convert to using wood pellets to produce electricity (Government of the UK, 2017a), while support for bioenergy through the Renewable Heat Incentive has led to increased use of solid biomass for heat and increased production biogas, for direct combustion and for injection into the gas grid as biomethane (Government of the UK, 2017b).

As an EU country with several renewable energy policies in place, Ireland is a useful case study to examine the policy trade-offs and the importance of national considerations (Tonini et al., 2017). Like the EU as a whole, Ireland has limited domestic biomass resources and ambitious decarbonisation goals. As is the case

at a global level, Ireland's decarbonisation pathways are likely to see an increasing role for bioenergy (Chiodi et al., 2013a). Ireland's Energy White Paper outlines the ambition to reduce Ireland's energy-related GHG emissions by 80% by 2050, as compared to 1990 levels (DCENR, 2015). A number of Irish government documents set out policy aspirations in the area. These point to measures in all three end-use sectors but also set out some principles for policymaking, including: "*policy should be economic, bioenergy delivers genuine carbon reductions, policy contributes to wider environmental policy objectives, policy aims to optimise enterprise and employment opportunities, and energy citizens play an active role in the transition"* (DCENR, 2015; DCCAE, 2014).

Much of the previous literature has focused on specific elements of the bioenergy supply chain or climate mitigation optimisation with limited consideration of the other policy objectives (Berndes and Hansson, 2007). Assessments of the optimal use for a specific resource, the optimal size and location of bioenergy plant and factors that influence the cost of feedstock refinement are common. Some studies have taken a broader view and examined energy security implications (Chiodi et al., 2015; Glynn et al., 2017), or the optimal allocation of feedstock to bring about the largest overall CO_2 emissions reduction impact. Several literature reviews discuss these approaches in more detail (Bentsen et al., 2014; Graham et al., 2011; Schmidt et al., 2010b; Steubing et al., 2012b; Wahlund et al., 2004) but few studies deal with the simulation of policy in all end-use sectors, and examinations of the use of bioenergy in the heat sector are rare. This chapter aims to add to the literature in this regard, using Ireland as a case study.

The BioHEAT model, which is a techno-economic simulation model that integrates bioenergy and heat – including allowing for co-dependencies between the heat, power and transport end-use sectors – is used for our analysis (Durusut et al., 2018). Using the BioHEAT model presented in Chapter 4, this chapter examines the interactive and cumulative impacts of separate policy instruments aimed at increasing renewable energy output through bioenergy supply chains. Scenarios examine the impact of converting existing generation units from fossil fuel to biomass fuel, the mandated use of advanced biofuels in transport, and the extension of the support for renewable heat to 2030. Impacts such as the total renewable energy production from bioenergy, energy-related CO_2 reductions, energy security, and the overall resource efficiency of bioenergy use in Ireland are evaluated. Several studies have noted the variability in outcomes of national-level analyses (Berndes and Hansson, 2007; Steubing et al., 2012b; Bentsen et al., 2014). These analyses sought to inform policy development rather than examine the impact of policy instruments. The contribution of this chapter is to show how various policy proposals interact, to highlight the interdependencies and trade-offs, in the context of actual policy goals and considerations at a national level. The modelling employed is applicable to other jurisdictions and can help develop targeted and more effective bioenergy policy supports.

Section 6.2 provides background, Section 6.3 presents methodology and data, Section 6.4 shows the results discussed in Section 6.5 and Section 6.6 outlines the policy conclusions.

6.2. Background

6.2.1. EU policy context

The EU has set a target to reduce GHG emissions by 40% as compared to 1990 levels by 2030 (UNFCCC, 2015b) and to increase the share of renewable energy to at least 27% of energy consumption (European Council, 2016). To achieve this, the Emissions Trading Scheme (ETS), which covers electricity generation and other energy-intensive producers, is undergoing changes with the aim of increasing the price signal to prompt increased mitigation action (European Commission, 2016b). In addition, CO_2 reduction targets have been agreed for each member state to share the effort of reducing emissions in those sectors that are outside the ETS (non-ETS) by 30% as compared to 2005 levels by 2030 (DCCAE, 2017b). A large majority of the energy-related non-ETS emissions come from transport and heating fuel combustion (EEA, 2017). The draft second EU Renewable Energy Directive proposes legislation to meet the 27% renewable energy target (European Council, 2016). Specific targets are proposed for transport, with the proposed directive setting a limit on the amount of biofuels that can come from first-generation biofuels as well as minimum amounts that must come from advanced biofuels.

The combination of these proposals should increase the focus of national climate policy on the heat and transport sectors, with the revamped ETS guiding investment in the electricity generation and energy-intensive industry.

6.3. Drivers of policy in Ireland

6.3.1. Electricity sector

There are three peat-fired power stations with 346 MW of generation capacity in Ireland, owned and operated by two state utilities (EirGrid, 2017b). In 2015, electricity generation at the peat-fired plants accounted for 8.8% of Ireland's electricity demand (SEAI, 2016a). Co-firing biomass with peat is supported though a feed-in tariff at one of the peat stations, and the combustion of peat is supported at the other two (CER, 2017). Security of fuel supply and the protection of local employment are the primary justifications for the policy support (Tuohy et al., 2009).

Bord na Móna – a state utility that harvests, supplies and uses peat – has a strategy to further diversify into other energy sources (Bord na Móna, 2016). This includes the continued co-firing at the Edenderry power station and the ambition to move to 100% renewable energy sources by 2030 (Bord na Móna, 2016). The Edenderry power plant was granted a planning permission extension to continue to operate to 2023 subject to a number of conditions, including the requirement to co-fire with biomass (An Bord Pleanála, 2016). The two peat stations owned by the Electricity Supply Board (ESB) have planning permits until 2020. In the absence of a planning permission extension, they must decommission by 2022 (An Bord Pleanála, 2002). The precedent of the planning authorities' decision on

the Edenderry plant implies that the remaining peat stations will also need to co-fire in order to retain planning consent. Both state companies have agreed to keep the peat-fired stations open beyond this closure date and to co-fire them with biomass (Joint Committee on Transport and Communications, 2015). Due to the uncompetitive cost of producing electricity at these sites, policy support will be required to make the extension viable.

Coal is the lowest-cost fossil-fuel generation source on the Irish system (Baringa for CRU, 2016). The 895 MW of generation export capacity provided 17% of electricity demand in 2015 (SEAI, 2016a). The Moneypoint station has coal storage equivalent to three months of running and is a key security-of-supply asset. The station is due to come to the end of its operating life in its current configuration in 2025 (DCENR 2015). Options for the future of the Moneypoint station are being examined, including the potential to convert from coal to biomass. Some key financial and technical challenges have been identified (O'Sullivan, 2017).

The carbon intensity of the counterfactual generation source is a key determinant of how much CO_2 emissions savings will accrue (Clancy et al., 2015; Ó Gallachóir et al., 2006). National energy projections suggest that reduced output from peat stations is offset by increased output from gas combined-cycle gas turbines (CCGTs) (SEAI, 2017a). In order for the output from a peat station to reach carbon intensity parity (in terms of gCO_2 per kWh generated) with a typical gas-fired CCGT plant, co-firing rates must reach an average of 65%.[25] While biomass co-firing can increase renewable output, this result means co-firing will increase CO_2 emissions if co-firing rates are less than 65%. Projections for the Irish energy system also show coal moves out of its baseload position by 2025 due to projected increases in carbon prices and an increase in coal prices relative to gas (SEAI, 2017a). Hence, a switch from coal to biomass is also likely to displace gas rather than coal.

6.3.2. Heat sector

In 2015, 6.5% of demand in the heat sector in Ireland was met by renewable energy (SEAI, 2016a). In this chapter, heat use includes all energy used (excluding electricity) to meet the thermal energy needs of all sectors of the economy, i.e. heating of homes and other buildings, cooking, hot water, manufacturing processes, etc. Bioenergy is the largest source of renewable heat, though heat delivered through heat pumps is growing fastest (SEAI, 2016a). The support scheme for renewable heat (SSRH) supports renewable installations at non-residential sites that are outside the EU ETS. The SSRH aims to meet the national target, which requires 12% of heat demand from renewable sources by

[25] The average efficiency of the peat power stations is 35% and for a typical CCGT is 54%, based on data published by the electricity market operator (Baringa for CRU, 2016). The carbon intensity of milled peat is 1,077.4 tCO2/GWh and for gas it is 203.7 tCO2/GWh (SEAI, 2016a). The proportion of peat output to achieve equivalence is equal to {(Carbon intensity of gas/efficiency of CCGT)/(Carbon intensity of peat fuel/efficiency of peat generation)}

2020 (DCENR, 2015). Tariffs are offered across a number of output tiers for biomass and biogas technologies that replace oil, gas or solid fuel. Should the consumers opt to install a heat pump in their building then capital grant support is available in lieu of the ongoing support.

6.3.3. Transport sector

Some 5.7% of road and rail transport demand in Ireland came from biofuels in 2015 (SEAI, 2016a). The EU Renewable Energy Directive (RED) sets a binding target of 10% of transport demand to come from renewable energy by 2020. Ireland has policy measures that mandate the use of biofuels and incentivise the uptake of electric vehicles (EVs). The renewable contribution from EVs is currently small as the numbers of vehicles on the road are at a low, but increasing, levels (SEAI, 2016a).

The blending rate for biofuel in Ireland is set at 8.695% by volume and is implemented though an obligation on the suppliers of mineral oil (NORA, 2010). A high share (46%) of the biofuel placed on the Irish market is from used cooking oil (UCO), most of which is imported. As a by-product, UCO (along with other biofuels from waste) receives double-weighted certification (NORA, 2017). This allows the energy output to be counted twice towards the renewable transport target under the rules of the (2009/28/EC). A recent consultation sought views on increasing the blending rate to a level sufficient to meet the 2020 targets (Department of Communications, Climate Action and Environment, 2017c). The proposed requirement to including more advanced biofuels out to 2030 in the recast of the EU Renewable Energy Directive will require further policy action at national level.

6.4. Methodology

6.4.1. BioHEAT techno-economic decision support model

The full detail of the BioHEAT model was presented in Chapter 4 and is summarised here again for context. The versatile nature of biomass means that many individual feedstocks can be used in solid, liquid or gaseous form to meet energy needs in the heat, transport or electricity sectors. The BioHEAT model is a techno-economic simulation model that integrates bioenergy pathway optimisation with demand for bioenergy in the heat, transport and electricity sectors. A novel aspect of the model is the inclusion of a detailed bottom-up representation of heat demand as well as a lifelike representation of how consumers in the heat sector make decisions. The background, method and data have been peer-reviewed and published (Durusut et al., 2018). This decision support tool was developed in Ireland to help with bioenergy policy design.

BioHEAT divides energy demand into heat, transport and electricity. For the electricity sector, the renewable output for individual technologies determines the bioenergy demand. This is an exogenous input linked to other models or sources of data. For example, the renewable output from a converted coal power station

is determined based on the capacity of the station and annual load factor. The biomass feedstock demand is determined within the model based on the pathway efficiency. The model determines if the electricity demand is economic, based on a comparison of the cost of the renewable output from a pathway and the market price or a policy tariff. Bioenergy demand is limited to pathways that provide renewable output at a cost lower than the market price or policy tariff.

Transport demand is also an exogenous input – determined at the sector rather than the technology level. Transport demand inputs are based on energy projections for future transport demand growth and renewable policy targets (SEAI, 2017a). In addition, demands for specific pathways can be mandated. For example, the requirement for advanced biofuel is imposed on advanced biofuel pathways, which also contributes to the overall demand for bioenergy in the transport sector.

The bioenergy demand in the heat sector is determined endogenously. The model calculates the uptake of biomass boilers based on the costs of biomass and competition between alternative fossil fuels and other renewable heat technologies. If the cost of biomass resource is higher, the model estimates a lower uptake of biomass boilers as consumers consider the cost of fuel when making investment decisions. The detailed and representative description of building heat demand and technology is one of the key strengths of the model. The uptake of technologies is calculated at an individual building level based on a model of the consumer decision-making process that captures factors beyond cost alone. The decision-making process starts with the probability of a consumer type being aware of the options available to replace existing technologies. The characteristics of a consumer type make them more or less likely to investigate the options. Of those consumers that are aware of the options, only a fraction of these will make an investment decision in any given year. As boilers typically have a lifetime of 15 years, this means only 7% of consumers will make an investment decision (DCCAE and SEAI, 2017). The payback periods of the various technologies examined depends on the competitiveness of that technology in a given building type and the willingness-to-pay curve for that sector (residential, commercial, public sector and industry). The data to calibrate the stages of the decision-making process is based on statistically representative surveys of Irish consumers and buildings (Durusut et al., 2018; Scheer et al., 2015)

The BioHEAT model has a detailed representation of the cost of bioenergy pathways across all the end-use sectors. The costs of refining and conversion supply-chain stages are determined by the capital, investment and operating costs as well as the technology-specific performance characteristics. The cost of resources, including the costs of transportation, is also accounted for. The heat sector includes the hidden costs associated with aspects of renewable heat production, such as the storage space for wood fuel or the management of fuel deliveries. Financial incentives such as electricity feed-in tariffs are taken into account. The pathways are ranked according to the value of the savings. Pathways are then deployed in order of least cost to meet demand power and transport and all economic uptake has happened in the heat sector. The model

allows sectors to be prioritised or considered together (e.g. resources deployed to meet demand in the power sector first) – in this analysis the sectors are considered together without prioritisation.

6.4.2. Scenarios examined

Scenarios are developed based on the current policy context in Ireland. The policy signals from the emerging climate and energy legislation focus on those sectors outside the EU ETS (i.e. non-ETS sectors). Action in the heat and transport sectors will contribute most to national targets that result from the EU legislation. Hence, the scenario analysis examines the impacts of policy in these sectors and evaluates the impact of further policy action in the electricity sector supplementary to these. All impacts are compared to a business-as-usual Baseline scenario to assess the differences in renewable energy output, CO_2 emissions, policy support cost, bioenergy use and resource efficiency. The impact on investment in the heat sector is also examined. Table 6-1 summaries the detail of the scenarios examined.

Baseline: acts as a benchmark to measure the impacts of policy interventions. It captures the current state of policy.

Scenario 1 (S1): examines the impact of the extension of the support scheme for renewable heat to 2030 along with the implementation of the proposed requirements for advanced biofuels and limits for first-generation biofuels from the proposed revised EU Renewable Energy Directive.

Scenario 2 (S2): This peat co-firing scenario builds on S1 and examines the additional impact of co-firing at the three peat stations to 2030. As the available policy supports up to 30% co-firing, further growth in co-firing rates is linked to growth in the ETS carbon price projections.

Scenario 2 accelerated increase of co-firing rates (S2 aggressive): This scenario examines a more rapid increase in co-firing rates to reflect the stated ambitions of industry.

Scenario (S3): This coal conversion scenario assumes the Moneypoint station converts to biomass combustion from 2025, with all three units converted to biomass by 2030.

Table 6-1: Summary of scenarios examined

	Heat policy	Transport policy	Power policy
Baseline	Support scheme for renewable heat runs to 2020 and supports non-domestic installations at sites outside of the ETS	Current levels of mandated blending and advanced target of 0.25 % of biofuels to come from advanced sources	Co-firing at one peat plant rising from current rate of 40% in line with growth in ETS price receiving feed-in tariff of 100 €/MWh
Scenario 1 (S1)	Extension of SSRH to 2030	Mandates to reach targets of proposed Renewable Energy Directive[26] by 2030 including: Advanced fuel penetrations of 0.25 % in 2020; 1% in 2025; 3% in 2030.	As Baseline
Scenario 2 (S2)	As S1	As S1	Co-firing rate reaching 60% at all 3 peat stations by 2030 receiving feed-in tariff of 100 €/MWh
Scenario (S2 aggressive)	As S1	As S1	Edenderry converts fully to biomass by 2025 Full conversion achieved at remaining 2 stations by 2030 All receiving feed-in tariff of 100 €/MWh
Scenario 3 (S3)	As S1	As S1	Peat co-firing as S2 Coal converts incrementally from 2025. 1st unit converts to biomass in 2025, 2nd unit in 2027 and 3rd unit in 2029. Receives feed-in tariff of 130 €/MWh

6.5. Data

6.5.1. Biomass supply

The cost and availability of Irish biomass resources are taken from 'Bioenergy Supply in Ireland 2015-2035' (SEAI, Ricardo Energy and Environment, 2016). Availability of imported solid biomass resources is adapted from the UK's biomass feedstock availability report (Ricardo Energy & Environment, 2017a). When scaled by the relative size of UK and Irish energy consumption, the availability of imports to Ireland is circa 70 PJ in 2020 and in the range 36 – 77 PJ in 2030 (BEIS, 2016; SEAI, 2016a).

Accessing these import quantities represents a significant increase in the imported volumes of material into Ireland; in 2016 the import volumes of solid biomass were ~2 PJ. Port infrastructure constraints may limit rapid increases in imported volumes (Ricardo Energy & Environment, 2017b). Our central assumption is that imports can grow by a maximum of 30% per annum up to a value equal to 50 PJ.

[26] The directive proposes a 14% RES-T target for 2030, with a limit of 7% on first-generation biofuels. Advanced and second-generation fuels count double in the RES-T calculation; this means that the actual blending rate by energy in 2030 would be 10.5%. Current blending rates (2016) by energy in Ireland are 3% (5% when weightings are applied).

This (50 PJ) is the median value from the UK analysis, scaled to Ireland's energy demand. For sensitivity analysis, the allowable annual increase in import volumes is assumed to be 70% per annum and import availability increase up to the value determined to be available internationally for import to Ireland in 2030. Figure 6-1 shows the quantities of imports available for solid biomass in both cases.

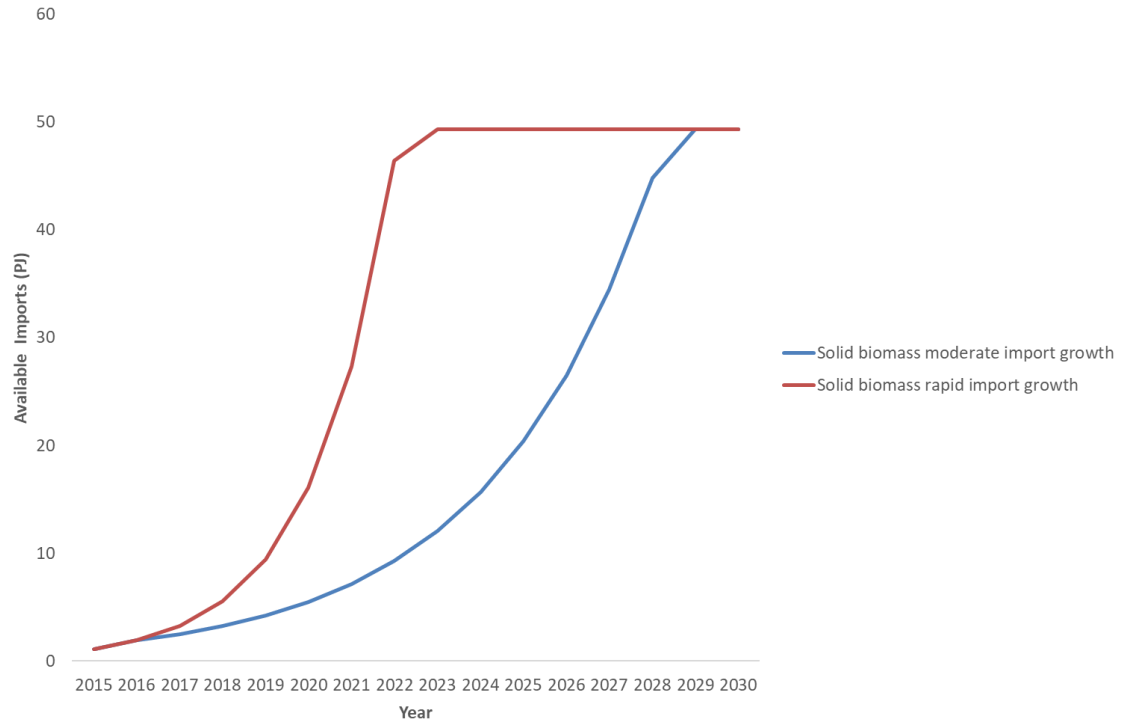


Figure 6-1: Imported biomass availability

A similar approach is taken for first-generation biofuels and advanced biofuel, with international estimates scaled to Ireland's energy demand (IEA, 2017b; Veum et al., 2016).

There is considerable uncertainty as to how the price of internationally traded solid biomass may develop (Thrän et al., 2017; Ricardo Energy & Environment, 2017b). Recent analysis for Ireland recommended a price range of 5.5 c/kWh to 6.5 c/kWh (15-18 €/GJ), applicable to solid biomass imports in the heat sector (Ricardo Energy & Environment, 2017b). The lower end of this range is used for the central case. Power generation sites may be able to access material at lower cost. A low-price sensitivity where the power sector can access imports at a price of 3.5 c/kWh (9.7 €/GJ) is also examined.

The price of first-generation imported biodiesel and biogasoline are included, based on information from Platts at 11 c/kWh (30 €/GJ) and 7 c/kWh (19 €/GJ) respectively (Platts, 2017). Much less certainty is available on the price of advanced biofuels. Individual costs for drop-in-biodiesel, drop-in-bioethanol and other advanced biofuels are included. The low-end cost estimates of the pathways examined in the IRENA report on advanced biofuels are used, with an average

price for all advanced fuels equivalent to 80 c/kWh (220 €/GJ) (Alberts et al., 2016) .

6.6. Bioenergy demand

6.6.1. Power sector demand

Table 6-1 outlines the assumptions on the electricity generation technologies supported. Peat stations can access the current feed-in tariff support scheme that offers 100 €/MWh for co-firing rates up to 30% (DCCAE, 2017d). There is no support available for conversion of pulverised coal stations at present, but a forthcoming auction scheme will allow bids from all renewable sources (DCCAE, 2017e). The assumed level of support for the conversion of pulverised coal stations is 130 €/MWh based on the average strike price agreed for this type of units in the UK market (Low Carbon Company, 2017)

The exogenous input for renewable electricity output from peat and coal is based on an annual load factor of 75%. While a full conversion may affect the export capacity and efficiencies of these units, no site-specific data is available. Hence, the characteristics of the units are assumed to remain in place post conversion.

Table 6-2: Power generation key technical parameters (Baringa for CRU, 2016)

		Peat		Coal
Station name:	**Edenderry:**	**West Offaly Power**	**Lough Ree Power**	**Moneypoint**
Average heat rate (GJ/MWh) (Baringa for CRU, 2016)	12	9.5	9.9	11.46
Export capacity (MW)(Baringa for CRU, 2016)	118	140	93	855 (285 X 3)

Other bioenergy-related power generation comes from landfill gas generation and waste-to-energy (WtE) and continue to generate at current levels of energy production (EirGrid, 2017b).

Solid biomass CHP and anaerobic digestion CHP are available for use by heat consumers in the model. The BioHEAT model determines the uptake of these units based on the suitability and economics of the CHP technologies, including financial support to service individual consumer heat loads.

6.6.2. Transport sector

For the Baseline scenario, the current blending mandate of 8.695% by volume is assumed to remain in place to 2030 (NORA, 2010). The limits imposed by EU indirect land-use change (ILUC) rules are captured by limiting the use of first-generation fuels to maximum of 7% of total road and rail transport energy use and requiring 0.5% of transport energy to come from advanced biofuels. Regarding the latter, Ireland has received a derogation to 0.25% for advanced biofuels based on the availability of qualifying resources (2009/28/EC).

The demand for fuel in road and rail transport is taken from the national energy projections, and the proposed transport target of 14% renewable fuel by 2030 is imposed in the scenarios (SEAI, 2017a). The latest version of the directive proposed continuation of the 7% cap on first-generation biofuels, a double multiplier for fuels refined from feedstocks such as used cooking oil and other residues, and a requirement to increase the use of feedstocks suitable for advanced biofuels to 1% of transport demand by 2025 and 3% by 2030. As biofuels from these feedstocks are double-counted, the actual energy required from these feedstocks is 0.5% by 2025 and 1.5% by 2030 (European Council, 2016).

6.6.3. Heat demand

In the heat sector, a renewable heat incentive policy is assumed to be in place from 2018. A tiered tariff structure is available to biomass and biogas[27] technologies that replace fossil fuel in commercial, public sector, agricultural and non-ETS industrial sites. The c/kWh tariff offered reduces as annual output increases, with the highest output band having the lowest tariff level (DCCAE, 2017a). A grant of 30% is available for sites that choose to install heat pumps. In the scenarios, these tariffs remain in place beyond 2020, up to 2030. The uptake of bioenergy arises from the impact of this policy on the relative economics of these technologies in for consumers in individual building archetypes.

Table 6-3: Details of tariffs offered under the support scheme for renewable heat

Tier	Lower Limit (MWh/yr)	Upper Limit (MWh/yr)	Biomass Heating Systems (c/kWh)	Anaerobic Digestion Heating Systems (c/kWh)
1	0	300	5.66	2.95
2	300	1,000	3.02	2.95
3	1,000	2,400	0.50	0.50
4	2,400	10,000	0.50	0.00
5	10,000	50,000	0.37	0.00
6	50,000	N/A	0.00	0.00

6.6.4. Pathway costs

Bioenergy pathways are defined within the model. The delivered energy cost of each possible pathway is calculated based on the biomass feedstock cost, the cost of transporting feedstock to a refining plant, the refining costs, transport of a

[27] In phase I of the SSRH, there is no subsidy for biomethane grid injection. This is currently under review for Phase II. In the absence of guidance on the tariff rates, biomethane is excluded from this analysis.

refined product and the conversion costs. Detail on the pathway cost calculation and data is available in Durusut et al. (2018).

Some further pathways have been added for this analysis. Biogas and biomethane pathways[27] are determined based on surveys of Irish industry active in the supply chain (Ricardo Energy & Environment, 2017c). Advanced liquid biofuel pathways are based on a report by IRENA (Alberts et al., 2016). Pulverised coal conversion costs are based on the range of published international values and the strike prices for this technology established in recent renewable support auctions in Great Britain (IEA, 2012a; IRENA, 2012; Low Carbon Company, 2017).

6.6.5. Fossil-fuel and carbon prices

Fossil-fuel and electricity prices in the heat sector vary by usage band and are based on data recorded in 2017 (SEAI, 2017c). From this starting point, these prices expand at the growth rate of the appropriate underlying commodity price projection. Low, central and high trajectories for future prices are taken from projections published by the UK government for oil, gas and coal (BEIS, 2016). As gas is the price-setting fuel in the Irish electricity market, future electricity prices – wholesale and retail – are grown at the same rate as gas prices. A projected price for carbon is also applied to the price of each fossil fuel (CEEU, 2017).

6.7. Results

The Baseline scenario results in a renewable energy output of 10,720 GWh in 2030 – 69% coming from renewable heat, 26% in the transport sector and 5% from power generation.

Figure 6-2 shows the biomass resources used in each sector. Much of the resources used come from domestic sources. The potential resource available from forest residues and energy crops increases across the horizon, and this drives much of the uptake in the heat sector. Biomass boilers are competitive with oil for many consumers, particularly in the industry sector. The Baseline simulation shows ongoing uptake of these technologies as fossil-fuel and CO_2 prices increase over the horizon.

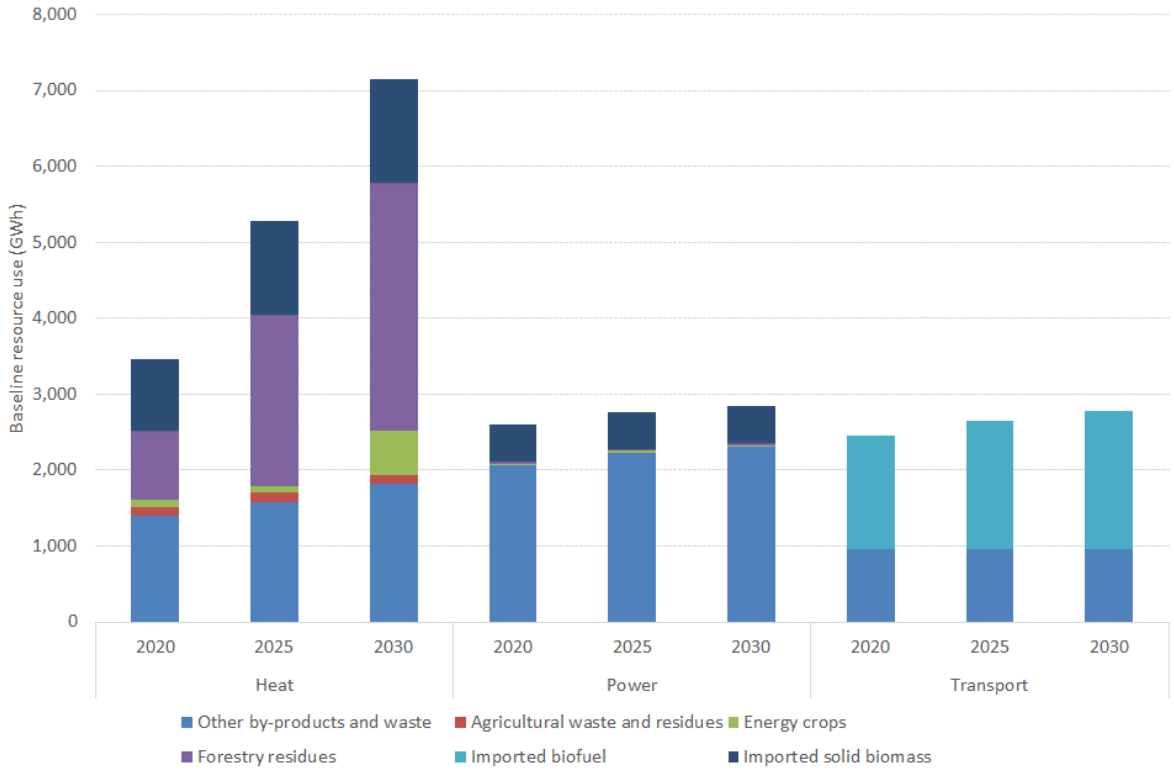


Figure 6-2: Biomass fuel use for each end-use sector in the Baseline (GWh primary)

6.7.1. Renewable energy production

Policy support in the power sector results in the largest increases in renewable output but there are trade-offs with output in the heat sector.

Figure 6-3 shows the change in renewable output in each end-use sector for each scenario as compared to the Baseline. The extension of the support scheme for renewable heat and the additional requirement for advanced biofuels in S1 lead to an increase in renewable output of 1,687 GWh in 2030 – an increase of 15% compared to the Baseline. Heat policy increases renewable heat output by 570 GWh (8%) and the advanced biofuel requirements increase renewable use in the transport sector by 1,116 GWh (40%). By 2030, the share of renewables in heat (RES-H) increases by 1.5% points as compared to the Baseline and the transport share (RES-T) increases by 4% points. The overall, renewable share increases by 1% point.

The additional co-firing in S2 increases renewable output further. In 2030, S2 renewable output is 2,070 GWh (22%) higher than the Baseline. The additional co-firing crowds out some of the renewable output in the heat sector. The renewable output in the power sector is 840 GWh higher in S2 than in the Baseline but the renewable heat output increases by the lower amount of 115 GWh (2%). The more rapid increase in co-firing rates in scenario S2 aggressive leads to further increases in output in the electricity sector but also to further reductions

in the heat sector. Co-firing increases the share of renewables in the electricity sector (RES-E) by 3% points in 2030 but reduces the contribution towards RES-H to 0.6%.

S3 includes the renewable output from the conversion of the coal station to biomass, beginning in 2025. This results in a large increase in renewable output without any additional further negative impact on the heat sector. The coal conversion requires a higher standard of fuel than the peat stations. Imported wood pellets are favoured due to the lower cost relative to the wood pellets available through domestic supply chains. S3 has the largest overall impact on RES, which increases to 4% by 2030.

Table 6-4 shows the difference in the renewable heat shares in each sector in 2030. The trade-offs between co-firing and heat are demonstrated again, and the S3 scenario results in the highest overall share of renewable energy in 2030.

Table 6-4: Renewable shares overall and in each end-use sector as compared to Baseline in 2030

2030	**RES-E**	**RES-T**	**RES-H**	**Overall RES**
Difference v Baseline in 2030				
S1	0%	4.1%	0.4%	1.0%
S2	3%	4.1%	-0.3%	1.4%
S2 aggressive	5%	4.1%	-1.0%	1.7%
S3	16%	4.1%	-0.3%	5%

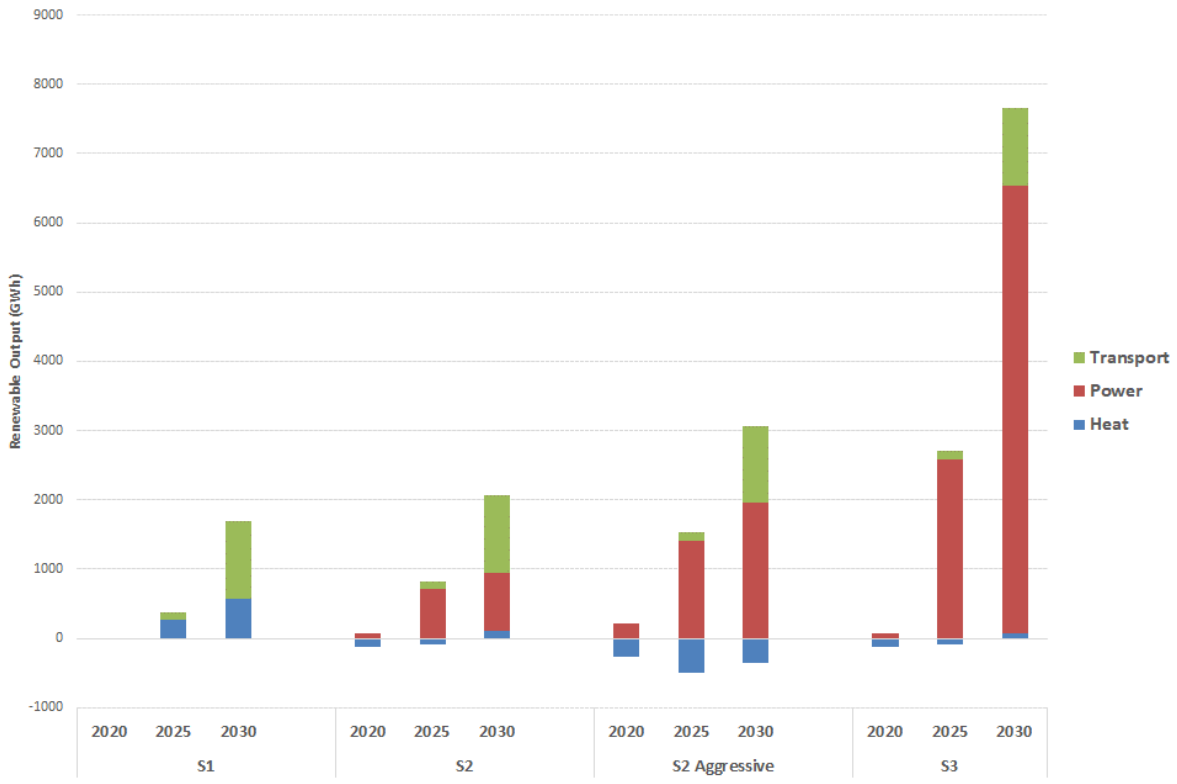


Figure 6-3: Renewable output in each end-use sector compared to the Baseline (GWh)

The impact of competition for biomass resources between co-firing stations and biomass boilers on uptake in the heat sector is explored further in Figure 6-4 and Figure 6-5.

The extension of support for renewable heat in S1 results in an increased uptake of biomass boilers providing heat, primarily at industrial sites. In scenario S2, the additional demand in the power sector draws the lower-cost material out of the heat sector and into use for co-firing. The more forceful ramp up of co-firing in S2 aggressive compounds this negative impact. Early in the time horizon, the reduced availability of lower-cost resources – particularly forest residues – and the reduced capacity to import biomass fuels means that the impact on the heat sector is more severe. As more potential from forestry resources becomes available post 2025 and as the import capacity for biomass grows, the impact of competition is less severe and the negative impact on renewable heat output eases. The conversion of the coal units in S3 has no additional impact beyond S2 as the coal stations import all of their biomass fuel requirement.

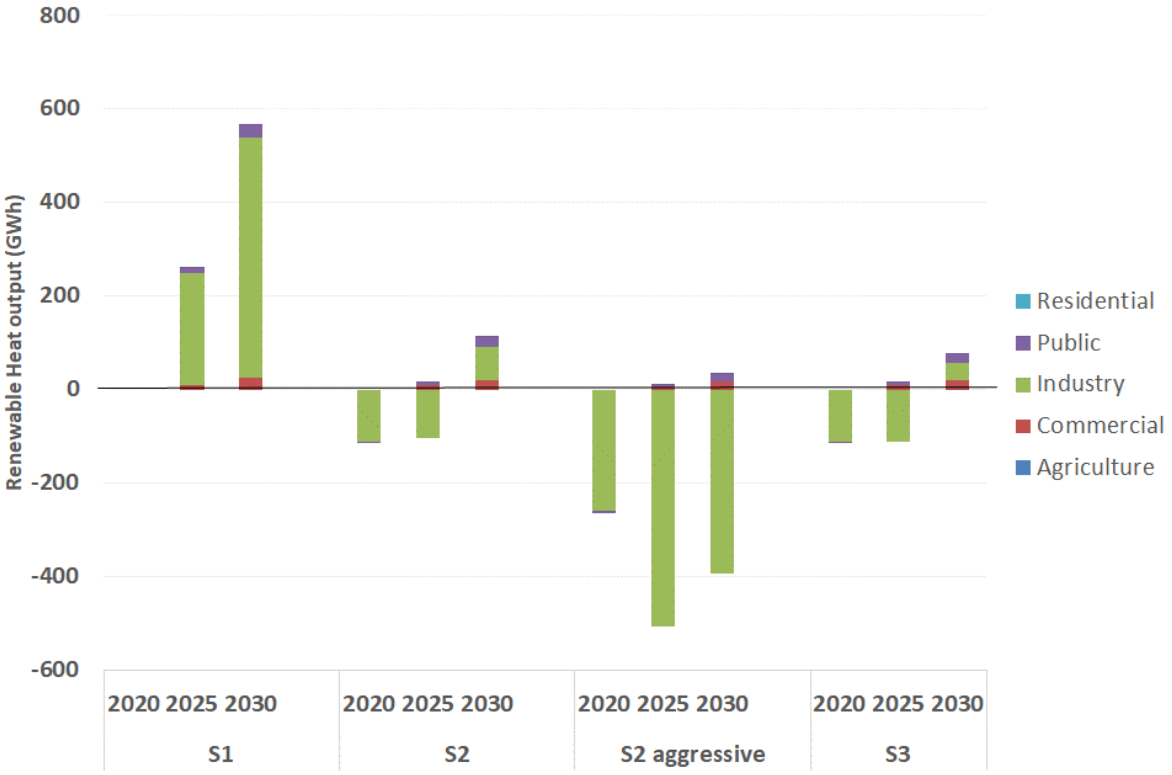


Figure 6-4: Difference in renewable heat output by sector as compared to the Baseline – all scenarios (GWh)

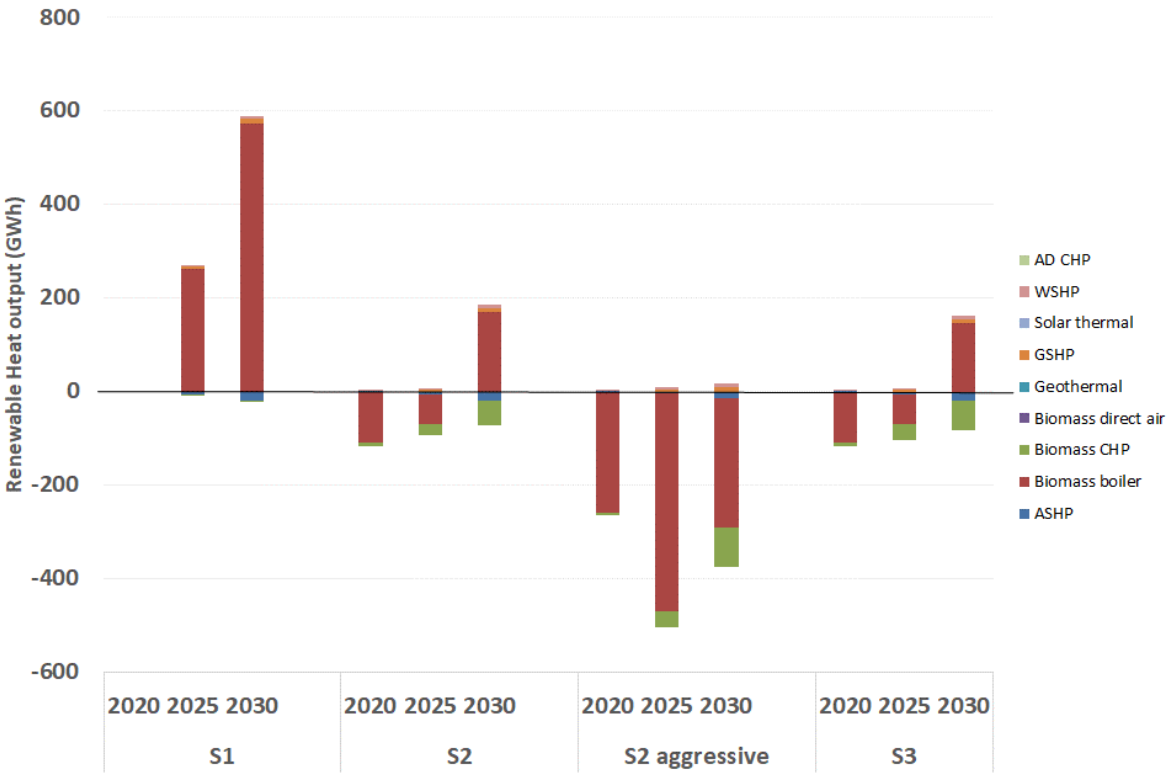


Figure 6-5: Difference in renewable heat output by technology as compared to the Baseline – all scenarios (GWh)

Figure 6-6 shows the impact of policy on fuel displacement as compared to the Baseline. Sites switching from oil account for ~70% of the fuel saved by renewable technologies in the Baseline. The extension of policy support in the heat sector to 2030 in S1 causes additional replacement of natural gas, with some additional replacement of oil also occurring. With the addition of co-firing in S2, fuel savings reduce with oil fuel use increasing. Further increases in the rate of co-firing in the S2 aggressive scenario result in more fuel use than in the Baseline.



Figure 6-6: Difference in fuel replaced by renewable technologies in the heat sector as compared to the Baseline (GWh primary)

6.7.2. CO_2 emissions

The picture for CO_2 emissions is more nuanced. Figure 6-7 shows what the various policy configurations mean for CO_2 emissions.

By 2030, total annual emissions in S1 are 440 kt CO_2 lower than in the Baseline, with cumulative savings from 2020-2030 of 1.8 $MtCO_2$.[28] The additional co-firing in scenario S2 results in an increase in CO_2 emissions. In the Baseline, the current support scheme for peat generation expires in 2020, at which point those peat stations not already co-firing cease to generate. Support for renewable output from co-firing at these stations allows for the continued use of peat post 2020, which displaces gas CCGT generation. This increases CO_2 emissions in the power sector. Annual emissions in 2030 are 348 $ktCO_2$ higher than in the Baseline and cumulative emissions increase by 8.3 $MtCO_2$ from 2020 to 2030. The crowding-out of the heat sector results in cumulative emissions in the heat sector that are higher in S2 than in the Baseline.

[28] The official national GHG emissions projections indicate that cumulative total energy-related emissions for the period 2021-2030 in the 'With Measures' scenario are 472.29 $MtCO_2$ and 47.14 $MtCO_2$ in 2030.

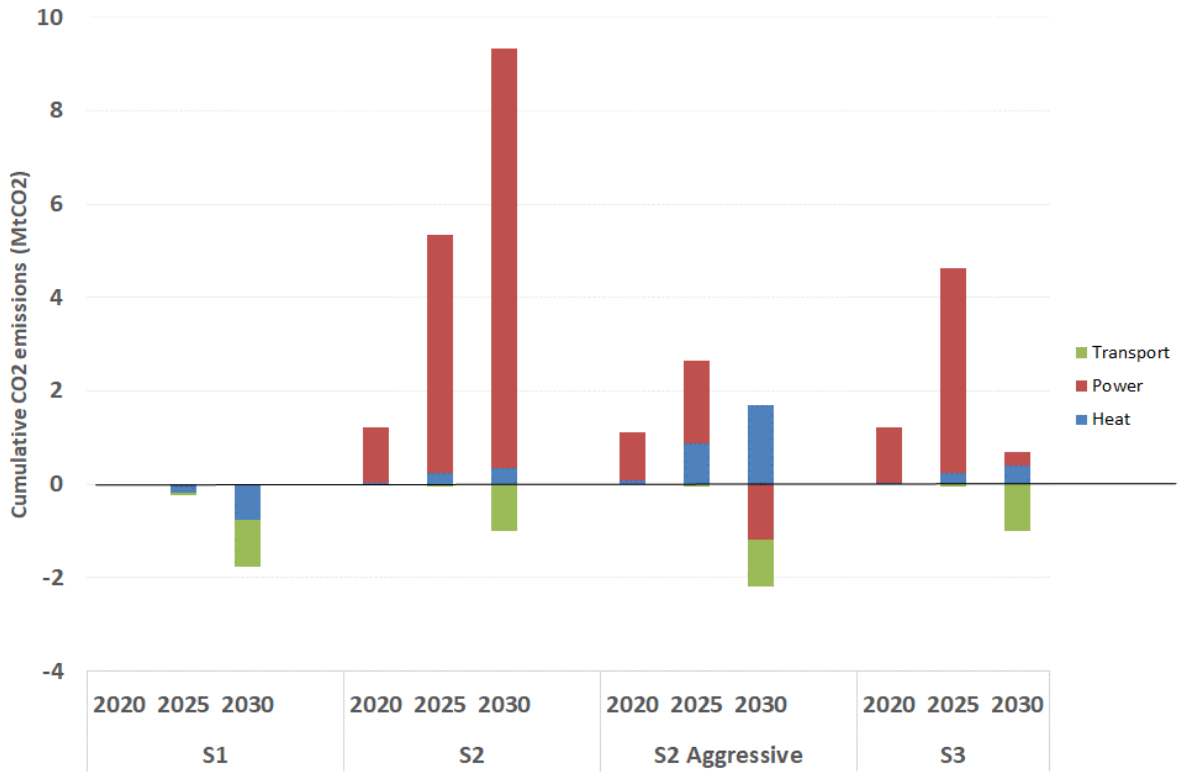


Figure 6-7: Cumulative CO_2 emissions impacts in each scenario for each end-use sector ($MtCO_2$)

The outcome of S2 does not align with wider policy objectives to decarbonise the electricity grid. Accelerated increases in co-firing rates at the peat stations mean the peat stations can reach emissions parity with gas CCGTs faster and begin to save emissions earlier. In S2 aggressive, all stations achieve full conversion to biomass by 2030. The in-year savings in 2030 compared to the Baseline for S2 aggressive are 1,049 $ktCO_2$ and cumulative savings are estimated as 493 $ktCO_2$. The cumulative savings are lower as the co-firing rate in the first four years is not high enough to result in net emissions savings. The more aggressive co-firing trajectory also results in further crowding-out of emissions savings in the heat sector; cumulative emissions from the heat sector are 344 $ktCO_2$ higher than in the Baseline. This offsets most of the emissions saving benefit from the more accelerated co-firing trajectory.

Scenario S3 sees additional reductions in CO_2 emissions. The savings from the conversion of the coal station offset the impact of co-firing shown in S2 and result in cumulative savings of 298 $ktCO_2$ from 2020-2030. Cumulative savings attributable to the coal station conversion to 2030 are 6.5 $MtCO_2$. The coal conversion does not result in any additional negative impact on emissions in the heat sector.

6.7.3. CO_2 emissions outside of the ETS

The distinction between those CO_2 emissions covered by the ETS and those emissions falling outside of this (non-ETS) is important from a policy perspective

for member countries of the European Union. National targets and associated penalties for shortfalls relate to the non-ETS sector. Ireland must reduce emissions from 44.54 $MtCO_2$ in 2019 to 33.20 $MtCO_2$ by 2030 to meet the target.[29] National emissions projections published by the Environmental Protection Agency (EPA) suggest a cumulative gap to the target of 51 $MtCO_2$ (EPA, 2017b).

Table 6-5 and Figure 6-8 show the cumulative emissions impact in the heat sector. Scenario S1 is the only scenario that results in non-ETS emissions savings – the 1.8$MtCO_2$ cumulative reduction. Scenario S2 aggressive results in more non-ETS emissions than in the Baseline. Emissions increase in the heat sector and add a further 1% to the gap to the non-ETS target. As the conversion of the coal station to biomass does not compete strongly for resources with the heat sector, the additional negative impact of S3 on non-ETS emissions is negligible.

Table 6-5: Cumulative non-ETS emissions in each scenario compared to the Baseline and the contribution to the estimated gap to target

	Difference in cumulative Non-ETS CO_2 v Baseline (2020-2030)	**% contribution to non-ETS gap to target $MtCO_2$**
S1	-1.75	3%
S2	- 0.64	1%
S2 aggressive	0.70	-1%
S3	- 0.60	1%

[29] A starting point of May 2019 is used to calculate the emissions starting point of 44.54 $MtCO_2$. The starting point for Ireland is based on a 2016-2018 average of total non-ETS emissions and includes non-energy sectors such as agriculture. The static gap, before economic growth and other factors are accounted for, is 11.43 $MtCO_2$. The projected cumulative gap is estimated as 51 $MtCO_2$ based on the With Measures Scenario in EPA projections (EPA, 2017b).

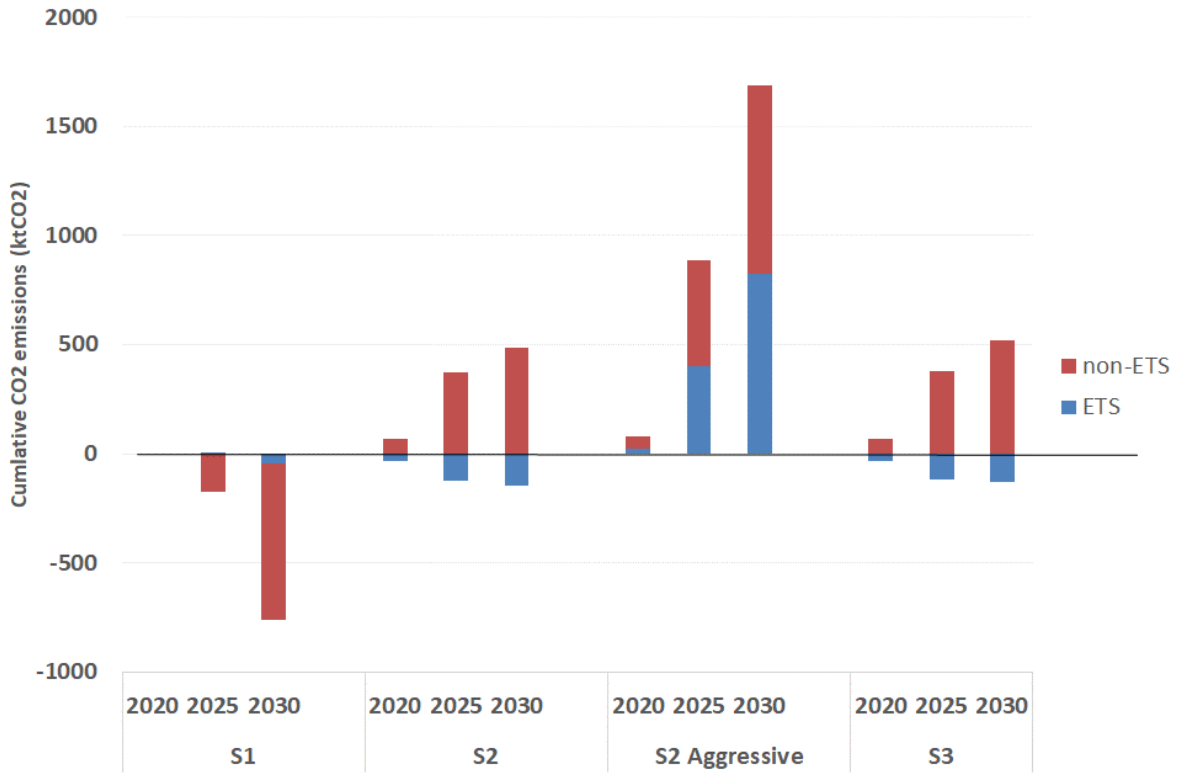


Figure 6-8: Cumulative CO_2 emissions impact in each policy scenario for ETS and non-ETS sectors ($ktCO_2$)

6.7.4. Biomass resource use

Figure 6-9 presents the resource use in each of the scenarios. Domestic resources are categorised as energy crops, forestry residues, agricultural wastes and residues and other by-products and wastes. Imports are categorised as imported solid biomass and imported biofuel.

The chart shows the majority of the increase in renewable heat output in S1 comes from imported biomass, with a small increase in the use of forestry residues. The increase in biofuels use in the transport sector relies on the availability of imported biofuels.

Co-firing in S2 uses forestry residues, with some contribution from energy crops. However, this is not a net increase in the use of domestic resources but rather a transfer from the heat sector. The heat sector moves to imports to partly replace the shortfall. Within the model, biomass boilers face higher costs due to the fuel refining necessary to ensure an adequate fuel standard. The fluidised bed boilers at the peat stations allow for more heterogeneity in biomass fuel and hence lower fuel refining costs.

Co-firing in scenario S2 aggressive uses all of the available forest resource as well as some of the energy crop potential, i.e. SRC willow. To meet the demand of the increased co-firing rates, imported biomass is also used.

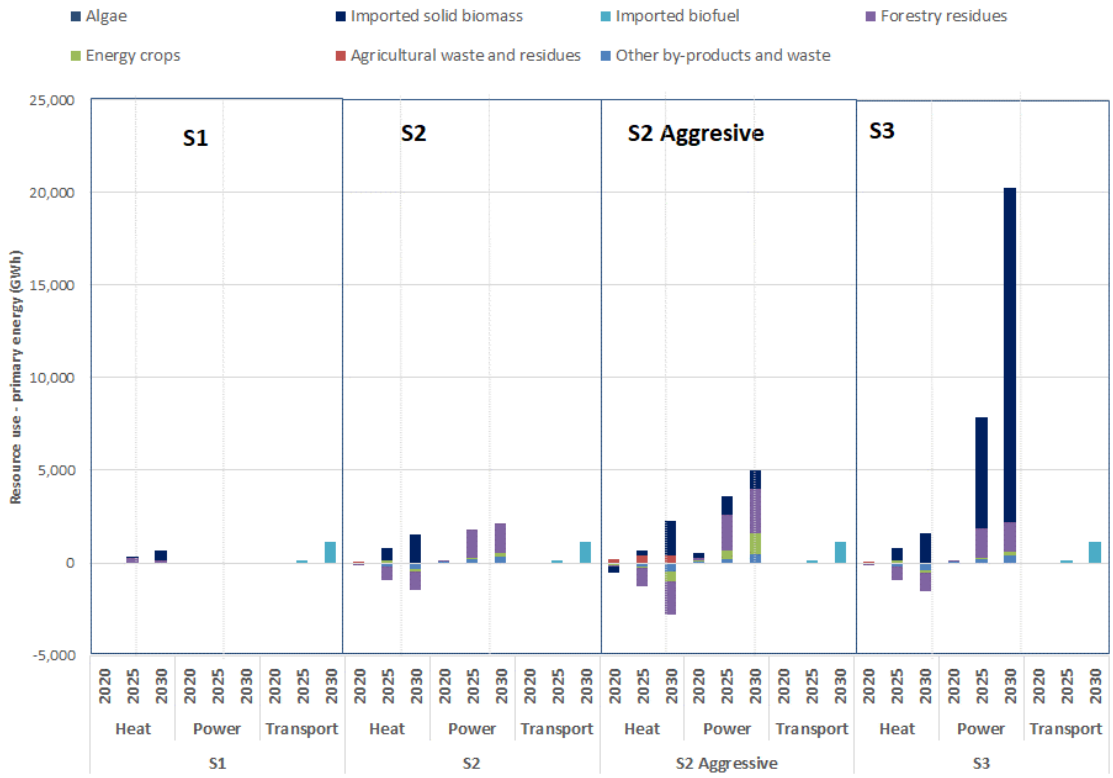


Figure 6-9: Resource use by sector in each scenario (GWh primary)

The conversion of the coal stations to solid biomass results in a large increase in imported solid biomass. Imported wood pellet costs are below the cost of production from domestic resources. As Moneypoint station has major port infrastructure already in place, it is not subject to the limits of port capacity growth that the heat sector and the co-firing plants face. Pulverised coal conversions using wood pellets have similar fuel quality requirements as the heat sector technologies. By 2030, the quantity of imports is above the median estimate for international biomass import availability of 50 PJ but just within the estimate for the maximum available imports of 77 PJ. Table 6-6 summaries the conversion efficiency in each scenario.

Table 6-6: Conversion efficiency in each scenario (GWh/PJ)

Scenario:	Resource efficiency (GWh/PJ)
Scenario S1	227
Scenario S2	216
Scenario S2 aggressive	195
Scenario S3	149

6.7.5. Sensitivity analysis – fossil-fuel price and biomass availability

Sensitivities on the high and low fossil-fuel prices and on the price and availability of biomass resources were also examined. For changes in fossil-fuel prices, the

trends that emerged were similar. In the low fossil-fuel price scenario, the negative impact of co-firing on the heat sector were less pronounced and in the high fossil-fuel price scenario they were more evident.

Changing the availability and price of biomass imports had a more significant impact. In scenario S1, the overall increase in renewable output, as compared to the Baseline, is similar at 1,556 GWh. In the subsequent scenarios, the overall renewable energy output increases as the availability of low-price domestic resources is less limiting to the uptake of renewable heat. In scenario S2 renewable energy output is 2,300 GWh higher than the Baseline in 2030. For scenario S2, aggressive renewable output is 3,150 GWh higher and 8,985 GWh for scenario S3.

Cumulative emissions reduce in scenario S1 by 1.7 $MtCO_2$. This is lower than the reduction in the central case as the uptake in the Baseline increases due to higher availability of resources. For scenario S2, emissions increase by a lower amount – 7.5 $MtCO_2$ cumulatively to 2030 – and S2 aggressive sees substantially increased savings of 2.6 $MtCO_2$ to 2030.

6.8. Discussion

Previous literature finds that optimal use of resources is linked to the efficiency of the technologies and fossil fuels displaced; that use of woody biomass has the largest impact on CO_2 savings; and that separation of woody biomass from agricultural residues is optimal (Graham et al., 2011; Steubing et al., 2012b; Bentsen et al., 2014). However, Bentsen et al. further conclude that some country-specific analyses may differ from the wider consensus in the literature. Our analysis at a national level for Ireland finds that support for renewable heat and transport results in increased renewable output and emissions savings. Renewable heat technologies are among the most efficient, and use woody biomass. Policy to stimulate increased use of biomass in less efficient technologies in the power sector has several risks related to CO_2 emissions, import dependence and resource efficiency – including negative impacts on the effectiveness of policy in the heat sector. Policy in the transport sector leads to more importation of biofuels and does not compete with heat or power for resources.

6.8.1. Heat and power – policy implications

The use of resources to maintain the commercial viability of the state-owned peat plants, and associated employment, does not align with either high-level climate policy objectives nor national efforts to meet climate targets. Under a scenario where significant amounts of peat continue to be combusted with biomass to produce power to 2030, a total of 8.3 $MtCO_2$ additional emissions are produced. Co-firing policy is already in place at one of the peat stations and the co-firing and the other stations have been accepted into the existing feed-in tariff scheme. To prevent emissions increases, a more aggressive increase in co-firing rates is required to achieve emissions savings by 2030. Such a policy would ideally require

a minimum co-firing rate of 65% biomass to ensure that the emissions from a co-firing unit are at least equivalent to the counterfactual electricity generation technology of gas-fired CCGTs.

The fluidised bed boilers at the peat stations are capable of using heterogeneous and unrefined biomass fuel sources (Koppejan and Van Loo, 2012). This means that peat stations are able to access resources at lower cost than the heat sector. Hence, increases in biomass demand in the power sector come with the risk of reducing the uptake of renewable technologies in the heat sector and the quantity of CO_2 emission savings that count towards national targets for member countries of the EU. Non-ETS emissions savings decline as co-firing increases. Further increases in co-firing increases the negative impact on the heat sector and leads to an increase in non-ETS emissions. This agrees with Berndes and Hansson (2007) who found that use of resources to achieve divergent policy objectives does not result in coherent outcomes.

Despite this context, a number of policy measures are focused on enabling co-firing in the power sector (Bacovsky et al., 2016). In addition, several studies highlight the potential for co-firing in Europe and North America (Agbor et al., 2014; Hansson et al., 2009; Roni et al., 2017). These studies have tended to evaluate climate and other benefits based on the counterfactual fuel being coal and have not examined the impact on other sectors of using limited resources at these sites. The analysis presented here suggests that policymakers should examine these impacts in their own national context and across all end-use sectors when considering co-firing support, as there is the potential for negative climate outcomes – particularly where resources are limited.

As the availability and cost of solid biomass imports increase, the coherence of between policy in the heat and power sector improves. High availability of solid biomass imports allows the heat sector to replace with imported fuels some of the domestic resource that is diverted to the power sector. This reduces the negative indirect impact of co-firing policy on the heat sector. Full conversion of coal to biomass also depends on the availability of low-cost solid biomass. The quantities of imports required are above the estimates of what may be available for import to Ireland. This does not help policy ambitions to increase security of supply, and the low resource conversion efficiency in the power sector leads to risks of high lifecycle GHG emissions.

The electrification of heat demand, to benefit from a high renewable share in the electricity sector, is a potential route to overcome the negative impact on renewable heat production. However, this route also needs deeper consideration. The majority of the renewable heat uptake in our modelling occurred in the industry sector. These sites are not suitable candidates for electrification via heat pumps due to the higher heat temperatures typically required. Hence, electrification as a means to decarbonise heat may not be the most optimal route if using biomass in the power sector crowds out the low-cost renewable process heat and replaces it with higher-cost space heat delivered by heat pumps.

6.8.2. Transport sector – policy implications

Increases in the demand for bioenergy in the transport sector are met through additional importation of biofuels. Ireland's size and demand for biofuels relative to the economic scale of a biofuels refinery mean that advanced biofuel refineries are uncompetitive with imports. For larger countries, increases in biofuel production may affect other sectors more. Several studies have found that using woody biomass to make advanced biofuels can counteract the emissions reduction potential as material is diverted from other sectors (Bentsen et al., 2014; Schmidt et al., 2010b; Wahlund et al., 2004). For Ireland, the modelling shows that all additional demand for first-generation and advanced biofuels is imported. The move to high shares of biofuels may see a reliance on a much smaller market, from fewer sources, and one that is exposed to regulatory risk. For example, a change in the sustainability rules affecting non-EU countries could leave Ireland exposed to lack of supply. In this context, the option to increase the use of biomethane and compressed natural gas in the transport sector maybe an import enabler to allow Ireland to meet the obligations of the proposed Renewable Energy Directive for advanced biofuels from domestic feedstock. Further work to examine the implementation costs of a biomethane transport policy would help guide policy in the area, and the gasification of transport fleets may also overcome some of the resource competition found in other studies.

6.9. Conclusions

Policymaking for bioenergy is complex. Biomass can be used as a fuel to produce heat, transport or electricity outputs, and many alternative pathways to end-use energy are possible. In addition, the reduction of CO_2 emissions is rarely the only objective of government policy. Rural employment, security of supply, bolstering agricultural, industry and semi-state enterprises, and other individual national issues are often part of the policy mix. For many countries, the availability of biomass for energy is limited. This means that policy options chosen for one end-use sector may have consequences for the outcomes in another. These require careful consideration in policy formation. The analysis undertaken in this chapter uses the BioHEAT model to simulate the impact of policy action in the heat, power and transport sectors in Ireland.

The results show that policies for the heat and transport sectors increase renewable energy and save emissions in the non-ETS sectors counting towards Ireland's binding obligations under EU legislation. The policies modelled in these sectors contribute a 15% reduction in the gap to 2030 climate targets. Policy to enable co-firing at the peat stations increases emissions in Ireland – directly through enabling peat combustion beyond 2020 and indirectly through crowding out biomass use in the heat sector. A more accelerated path to full conversion of the peat stations can prevent an increase in direct emissions but has additional negative impacts on the emissions outcome in the heat sector. In the latter case, emissions in the heat sector increase and add 6% to the gap to national targets. Co-firing policy is being pursued in a number of countries, and this analysis shows

that the wider system impacts need to be explored and risks assessed to ensure similar outcomes are avoided.

The conversion of the pulverised coal station to biomass combustion does not result in any further crowding-out of the heat sector. The results show a conversion may rely on imported wood pellets that are lower-cost than the domestic market can provide. The Moneypoint coal station is not constrained by import volumes as it has a large port infrastructure in place.

Most domestic supply chains for biofuels are uncompetitive with imports, with the transport sector relying on imports to meet increasing bioenergy demand in the sector. Advanced biofuels have high production costs. There may be options for Ireland to reduce the cost associated with advanced fuels and increase the use of domestic resources by moving to biomethane in the transport sector. Further work that incorporates supply and demand-side costs can help inform the options.

Part III – Empirical analysis

Chapter 7

What are the factors that discourage companies in the Irish commercial sector from investigating energy-saving options?

Abstract

To implement an energy-saving measure, companies must first decide to investigate the options available. Representative survey data shows that almost half of companies in the Irish commercial sector do not take this step. This chapter explores the barriers and drivers of this. Two logit models are fitted to data to estimate the influence of variables, representing company and building characteristics, on the likelihood of a company investigating either a fabric upgrade or a behaviour change measure. Companies are more likely to investigate a fabric upgrade where they own the building they operate from, make energy-related decisions locally, have more than 10 employees, have had a recent renovation, accept longer paybacks, and apply a case-by-case approach to budget decisions. Hotels and offices were found to have a higher likelihood of investigating fabric options. Lack of knowledge of building floor area reduced the likelihood of investigation of both fabric upgrade and behavioural options. Much of the previous research is concerned with the final adoption of measures; this analysis adds additional insights by identifying the factors that determine if a company is likely to investigate the options available.[30]

[30] This chapter is based on a published journal paper: Clancy, J.M., Curtis, J. and O Gallachóir, B.P. (2017), What are the factors that discourage companies in the Irish commercial sector from investigating energy saving options? *Energy and Buildings*, 146, pp.243-256.

7.1. Introduction

The International Energy Agency has shown that action to increase efficiency can halve energy demand growth to 2035 (IEA, 2012b; Oettinger, G., Rosenfeld, A, 2013). Unlocking this potential is a key policy challenge facing governments' efforts to reduce GHG emissions (IEA, 2012b; Chiodi et al., 2013b; Edenhofer et al., 2014). Along with the direct climate and energy cost reduction benefits, energy efficiency has been shown to deliver tangible co-benefits for nations, industry, businesses and individuals (IEA, 2014b). These include improved security of supply, higher productivity, GDP increases, less exposure to fuel price volatility, increased comfort in buildings and improved human health outcomes.

The services sector is not a large consumer of energy, even in economies where it is responsible for the majority of economic activity. The services sector includes both commercial (comprising banking, retail, hotels, etc) and public (education, health, local government, etc) services. Energy use in the services sector represented 13% (5,911 PJ) of final energy consumption in the EU in 2014 (European Commission, 2016c). In comparison, the transport (14,755 PJ), industry (11,505 PJ) and residential (11,019 PJ) sectors have much higher annual energy demand. Future energy projections suggest that the services sector is likely to maintain that share (Capros et al., 2016).

Analyses of the energy-savings potential, however, indicates that the commercial sector has significant potential to reduce energy consumption. The Ecofys and Fraunhofer ISI (2010) examination of the marginal savings curve for energy efficiency investments shows that such investment in the services/commercial sector offers some 100 Mtoe (4,187 PJ) of savings (~25% of total potential savings available in all sectors) (Wesselink et al., 2010). This confirms earlier analysis conducted by Fraunhofer ISI et al. for the European Commission that found the tertiary sector holds 22% of the total savings potential to 2030 across all sectors (Eichhammer et al., 2009). Almost half of these savings comes at a negative cost if the necessary policy instruments act to remove the barriers to investment in energy efficiency measures. Analysis of the energy efficiency potential and costs in Ireland shows similar results (Scheer et al., 2015).

In Ireland, the commercial sector accounts for 7% of final energy consumption but 11% of the total primary energy requirement. The relatively high proportion of electricity use in the Irish commercial sector drives the higher share of primary energy (Howley et al., 2015). Projections for the Irish energy system show that the sector is likely to increase its share in final energy demand to 13% (SEAI, 2016c). The services sector in Ireland accounts for 70% of GDP, 54% of all active companies (EU average is 45.5%) and employs 51% of the working population (Central Statistics Office, 2014). In addition, the sector is one of the largest indigenous exporters, and competitiveness is a key concern (National Competitiveness Council, 2016). The technical potential for energy savings in the

Irish commercial sector represents 26% of the total available across all sectors to 2020. The value of the savings available over the full lifetime of most measures is greater than the investment costs for these measures – i.e. negative cost over the full lifetime (Scheer et al., 2015).

The observation of a gap between the actual uptake of energy efficiency measures and the economic potential predicted by engineering-economic models is common in the literature on energy efficiency. A body of theoretical and empirical literature has explored the barriers contributing to this phenomenon. Using representative survey data from Ireland, this chapter aims to identify the characteristics of commercial companies that are likely or unlikely to engage with energy efficiency actions in the context of the barriers to, and drivers of, energy efficiency. Two distinct categories of measures are possible for companies to implement: behavioural measures that lead to changes in how employees use and conserve energy (e.g. reducing room temperature or turning off appliances when not in use), and building upgrade measures (e.g. insulating walls, installing lighting controls or a more efficient heating source). Two separate logit models are fitted to the data on relevant factors, including company activity, number of employees, tenure, building size and stated approach to financial decision-making. This adds to the limited empirical evidence on energy efficiency in the commercial sector and contributes new information on the factors that discourage companies from engaging with the available energy-saving opportunities. Representative data on energy use and attitudes in the commercial sector are rare, and the data set that underpins this analysis is notable as being representative of the Irish commercial building stock and the attitudes of commercial sector companies to energy efficiency actions.

Section 7.2 provides an overview of the literature. A full description of the data and the model specification are given in Section 7.3, Section 7.4 presents the results, Section 7.5 discusses the key insights in the context of the relevant previous empirical research, and Section 7.6 concludes.

7.2. Literature background

The difference between the actual level of energy efficiency action and the rate implied by these models has been labelled the 'energy efficiency gap' (Hirst and Brown, 1990; Jaffe and Stavins, 1994; Backlund et al., 2012). Theoretical investigations into the causes of the gap have shown a range of barriers to investment in commercial organisations. Sorrell (2004), a key reference, has identified and categorised the barriers to energy efficiency into economic, behavioural and organisational. Economic barriers include market failures such as imperfect and asymmetric information, adverse selection, principal agent relationships subject to moral hazard, split incentives and heterogeneity (Blumstein et al., 1980; Howarth and Andersson, 1993; Jaffe and Stavins, 1994; DeCanio, 1994; Sorrell et al., 2000; Brown, 2001; IEA., 2007). Non-market failures also present barriers in the form of hidden costs, uncertainty/risk and access to capital (Fisher and Rothkopf, 1989; Jaffe and Stavins, 1994; Golove and Eto, 1996). Human behaviour barriers such as bounded rationality in decision-

making, trust and credibility, the form and timing of how information is communicated, resistance of consumers to change (inertia) and the personal values of decision-makers have been shown to diminish the uptake of energy efficiency technology (Stern and Aronson, 1984; Eyre, 1997; Almeida, 1998; Sanstad and Howarth, 1994; Sorrell et al., 2000; Sathaye et al., 2001). At the organisation level, the power or status of divisions and/or individuals with responsibility for energy decisions and how conservation and environmental issues are viewed in the organisational culture can act as barriers to uptake (DeCanio, 1993, 1998; Brown, 2001; Worrell et al., 2003; Sorrell, 2004; Rohdin and Thollander, 2006; Schleich and Gruber, 2008; Cagno and Trianni, 2013; Cagno et al., 2013). In practice, these barriers overlap and energy-related decisions in a commercial organisation will have aspects of economic, behavioural and organisational barriers (Weber, 1997; Cagno et al., 2013).

The literature on the drivers for energy efficiency in the sector is less developed. Reddy and Assenza (2007) and Cagno and Trianni (2013) list the drivers of energy efficiency that also include energy management practices as well as energy efficient technology. The classification of drivers lists management sensitivity to environmental issues, external pressures on the bottom line from rising fuel and CO_2 prices or other regulatory penalties, having clients who consider environmental behaviour in decisions, and having access to information from case studies of interventions by similar companies. Additional drivers include access to low-cost expert advice (particularly for small companies), internal competence in energy management, availability of public financing, a focus on long-term benefits, availability of new solutions, anticipation of environmental regulations and an entrepreneurial culture within the company. The literature on business engagement with wider environmental issues reports similar classifications of drivers (Simpson et al., 2004; Studer et al., 2006; Revell et al., 2010).

The empirical literature has used a number of methods to investigate the impact and importance of the barriers to energy efficiency in practice. These have examined barriers in the industrial sector, small and medium enterprises (SMEs) and various sub-sectors within this. Given the relatively low number of empirical analyses and lack of studies that examine the commercial sector in isolation, all relevant studies are considered here.

A number of case studies, based on interviews with a smaller sample of companies, have provided insight into the energy-related decision-making processes within organisations (Almeida, 1998; Ostertag, 2002; O'Malley and Scott, 2004; Rohdin and Thollander, 2006; Cooremans, 2012a). Econometric and other statistical analyses, based on larger data samples, have sought to establish the significance and importance of the barriers and company factors that impede uptake of energy efficiency (Gruber and Brand, 1991; Velthuijsen, 1993; DeCanio and Watkins, 1998; Harris et al., 2000; de Groot et al., 2001; Diederen et al., 2003; Anderson and Newell, 2004; Sorrell, 2004; Aramyan et al., 2007; Rohdin et al., 2007; Thollander et al., 2007; Schleich and Gruber, 2008; Thollander and Ottosson, 2008; Trianni and Cagno, 2012).

Sorrell et al. (2011) and Fleiter et al. (2012) contain detailed literature reviews of the various empirical studies on the barriers to energy efficiency. Both reviews point to the difficulty of comparing results across studies due to the different methods employed and the variations in time horizons, sectors and sub-sectors examined, as well as the barriers considered.

Sorrell et al. (2011) assessed the relative importance of the barriers based on a simple count of the barriers identified in the empirical research on energy efficiency in the services sector. The findings identify differences between developed and developing countries. Imperfect information was the most identified barrier in developed countries, while access to capital was the most frequently identified barrier in developing countries. Hidden costs, risk/uncertainty and bounded rationality were also identified frequently. The review points to the greater obstacles faced by SMEs. Sorrell et al. (2011) suggest that this is due to a lack of information about the opportunities available and a lack of implementation expertise where opportunities have been identified. Obtaining relevant data on energy consumption is relatively more expensive for SMEs, and energy costs typically account for a small proportion of total production costs. The high option cost of a large capital investment for SMEs heightens the sensitivity to the risk and uncertainty surrounding capital investments.

Fleiter et al.'s (2012) comprehensive review of previous empirical literature shows that SMEs tend to face more barriers to the implementation of energy-efficient measures than their industrial counterparts. The most common barriers are access to capital and, for energy-intensive SMEs, the technical risk associated with a production outage. In less energy-intensive SMEs, the lack of time and lack of information show up as significant barriers to energy efficiency. Other frequently identified factors were the number of available employees, bounded rationality and split incentives. The relevance of the empirical literature in informing the specification of the model used for our analysis is described in more detail in Section 7.3.

7.3. Data and methods

7.3.1. Data

In recognition of the data and information deficit in the commercial sector – and the difficulties it causes for effective policymaking – the Sustainable Energy Authority of Ireland (SEAI) undertook a survey of energy use in the commercial sector and the attitudes of commercial sector companies to energy projects (Element Energy and The Research Perspective for SEAI, 2015a, 2015b). This data set is notable as a statistically representative dataset of the commercial building stock and the attitudes of commercial sector companies to energy efficiency actions.

A total of 750 phone interviews were conducted in March 2014 across a statistically representative sample of commercial business activities in Ireland. The survey

collected data relating to the behaviour and decision-making process of commercial sector companies as well as physical information on their buildings.

Figure 7-1 shows the primary and final energy use estimated from the building survey data, broken down by fuel and by commercial activity categories. Electricity accounts for 73% of final energy consumption. The conversion losses in generating electricity are greater than for other fuel sources, and about 2.5 units of primary energy are required for each unit of electrical end use. Electricity accounts for 86% of the 70 PJ of primary energy used in the commercial sector. Table 7-1 shows the number of buildings in each category in the commercial sector in Ireland.

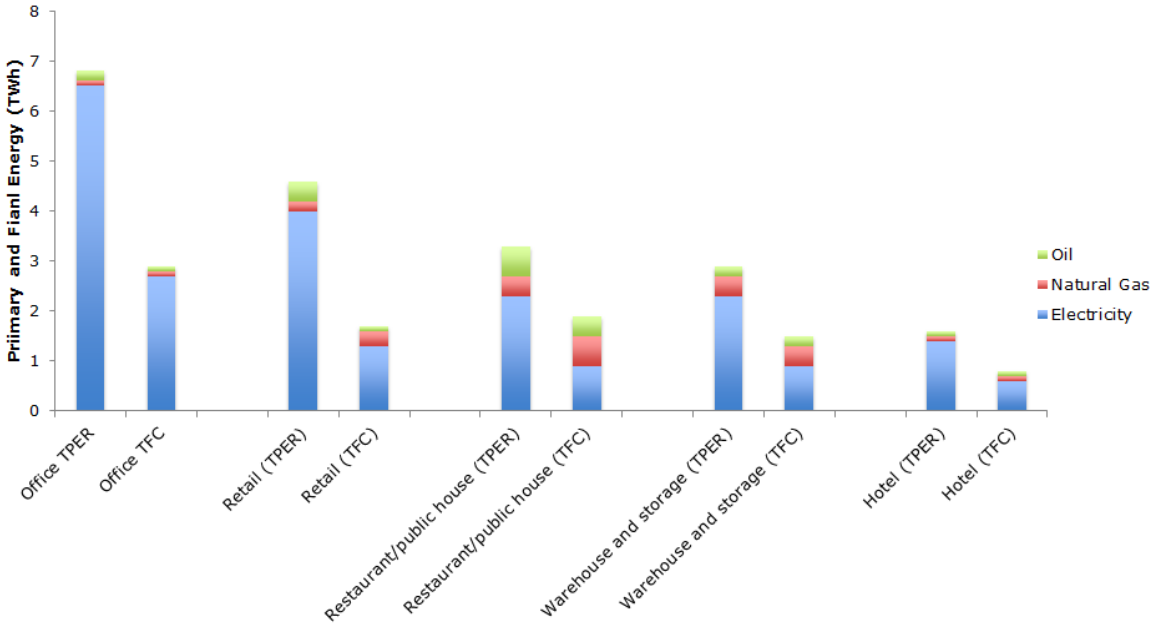


Figure 7-1: Primary and final energy in the Irish commercial sector by building activity (Element Energy and The Research Perspective for SEAI, 2015a)

Table 7-1: Number of buildings by commercial activity

	Office	Retail	Restaurant/public house	Warehouse/ storage	Hotel
No. of buildings (,000)	42	40	16	8	4

Table 7-2 summarises the survey information collected in more detail, showing the frequency of the responses by business activity type. The sampling method across the sectors is calibrated against the distribution of business types recorded in the Geodirectory – a database of all commercial business active in Ireland – to provide a statistically representative sample of business types. There are some notable differences in the distributions across the business types for several variables. For example, hotels and restaurants/public houses tend to be owned by

the occupant while retail premises and offices tend to be rented. Similarly, the proportion of companies where energy-related decision-making responsibilities reside within the business unit are notably higher for hotels and public houses than in other business activity areas.

Table 7-2: Summary of survey data by variable and by business activity

		Total (n=750)	Retail (n-255)	Hotel (n=95)	Restaurants/ Pubs (n=136)	Office (n=194)	Warehouse (n=70)
Number of employees	≤10	66%	73%	38%	72%	66%	66%
	>10	34%	27%	62%	28%	34%	34%
Tenure type	Owner	67%	62%	85%	80%	52%	73%
	Tennant	33%	38%	15%	20%	48%	27%
Respondent status in energy-related decisions	Decision maker	70%	64%	96%	82%	57%	70%
	Not a decision-maker	30%	36%	4%	18%	43%	30%
Budgeting approach	<€10,000	49%	50%	32%	54%	49%	56%
	≥€10,000	6%	4%	19%	4%	5%	4%
	Depends on business case of individual measure	45%	46%	49%	41%	46%	40%
Floor area	< 1,000 m2	38%	44%	17%	38%	41%	33%
	≥ 1,000 m2	23%	25%	28%	13%	19%	34%
	No reply	40%	31%	55%	49%	40%	33%
Recently renovated	Yes	17%	14%	38%	15%	17%	9%
	No	83%	86%	62%	85%	83%	91%
Heating fuel type	Electricity	44%	58%	20%	26%	53%	33%
	Gas, Oil or Other	56%	42%	80%	74%	47%	67%
Investigated fabric upgrade	Did not investigate	42%	50%	28%	39%	37%	53%
	Investigated but did nothing	7%	7%	5%	10%	6%	4%
	Investigated, took action but think more to do	21%	18%	29%	23%	23%	17%
	Investigated, took action, think no more to do	30%	26%	37%	29%	35%	26%
Investigated behaviour measure	Did not investigate	35%	41%	22%	33%	35%	40%
	Investigated but did nothing	6%	7%	7%	4%	7%	4%
	Investigated, took action but think more to do	31%	26%	39%	36%	30%	30%
	Investigated, took action, think no more to do	28%	26%	32%	27%	29%	26%

Differences are also evident across the types of fuel used for heating. Building size and retail business and restaurants/public houses have a relatively high percentage of business with fewer than 10 employees.

Overall, the majority of organisations reported having considered either behaviour or a fabric upgrade measure. A large proportion of those companies that said they had investigated a measure considered themselves to have done everything that was possible. This category may well be less engaged in the future and are not aware that significant potential likely remains. Half of the retail and warehouse companies surveyed reported not having investigated fabric upgrade measures and over 40% of the same categories had not investigated the savings available through behavioural measures.

Figure 7-2 shows the payback period that a company is willing to accept on an energy-related investment for each business activity. More hotels are willing to accept a longer payback on investment than is the case in the other commercial activities.

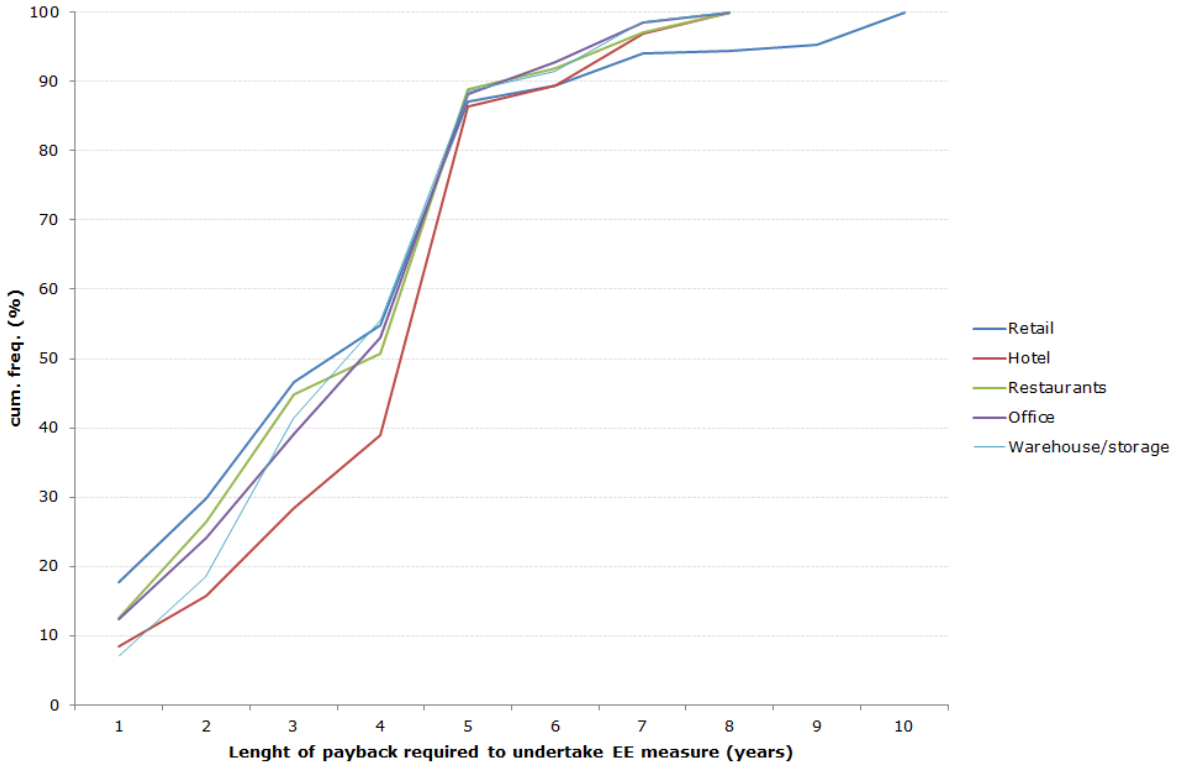


Figure 7-2: Maximum time an energy efficiency measure must pay back in, by business activity

Respondents who stated they had not investigated an energy efficiency upgrade were asked the follow-up question: what was the primary reason for not investigating a measure? The fabric upgrade choices were:' a) we do not think we need to reduce our energy use as a top priority, b) we do not think there are any ways to reduce our energy use, c) we think there are ways to reduce but need more information, d) we think there are ways to reduce but it's not our responsibility, e) we are planning to investigate in the near future'. These reasons,

summarised in Table 7-3, provide a context for the model results presented in the next section. A full description of the survey and results is available from Element Energy and The Research Perspective for SEAI (2015b). The low priority of energy is the primary reason reported by commercial organisations for not engaging with energy efficiency. Lack of information and lack of trust in the savings available are also reported frequently as the most important barrier.

Table 7-3: Reasons given for not investigating energy efficiency upgrade, number of responses

	Retail	Hotel	Public houses and restaurants	Offices	Warehouse and storage	Total
Behaviour						
Sceptical that reductions in energy use through behavioural change are possible	13%	10%	9%	6%	7%	10%
Reducing energy use is not a top priority	69%	81%	71%	73%	75%	72%
Planning to investigate	6%	0%	4%	9%	0%	5%
Need more information on possible measures	12%	10%	16%	12%	18%	13%
Fabric Upgrade						
Sceptical that reductions in energy use through fabric upgrades are possible	5%	11%	8%	4%	3%	5%
Reducing energy use is not a top priority	79%	70%	75%	73%	86%	77%
Planning to investigate	5%	4%	4%	3%	3%	4%
Need more information on possible measures	5%	0%	6%	15%	3%	7%
Fabric improvements are not responsibility of occupant	7%	15%	8%	4%	5%	7%

7.3.2. Model

As companies that do not investigate potential energy efficiency measures cannot deliberately implement energy efficiency actions, the data suggests a selection bias problem – i.e. only those companies that have investigated will implement a measure. Initially, a Heckman selection model was fitted to the data in an effort to control for selection bias. For both the behaviour change measures and fabric upgrade models, there was no statistical support for a selection bias and consequently we proceeded with a standard logit model. Two separate logit models are estimated to examine the factors that discourage engagement with behaviour change measures, and the factors that discourage investigation of building fabric upgrade options. Both models include variables that describe building-specific and business-specific characteristics of the respondents. The

dichotomous dependent variables are equal to 1 if a business investigated an energy efficiency measure.[31]

The explanatory variables included in the regression equations are guided by the findings of previous empirical analysis from the literature on barriers to energy efficiency, discussed further below. The general model specification is as follows:

$$\Pr(Y_{i,j} = 1) = \frac{1}{1 + \exp(f(Z_{i,j}, X_{i,j})}$$

where $Y_i = 1$ if the company has investigated a fabric upgrade measure and $Y_j = 1$ if a company has investigated a behaviour change measure. Z captures the company-specific factors such as business activity, tenure, number of employees and approach to financial decision-making, while X refers to the building-specific factors such as floor area, fuel used for heating and recent renovations.

Access to capital both internally within a company and though external sources has been frequently identified as an important barrier in empirical research (Velthuijsen, 1995; Ostertag, 2002; Anderson and Newell, 2004; Thollander et al., 2007; Trianni and Cagno, 2012). The BUDGET variable captures the impact of capital restrictions by differentiating between companies that have fixed maximum budget amounts and those companies that consider the business case for each measure on its own merits. Bounded rationality in financial decisions has also been found to influence energy-related decision-making (de Almeida, 1998; DeCanio and Watkins, 1998). In order to capture this, the BUDGET variable categorises companies into those that apply fixed budget rules (i.e. they will not consider a project above a certain predefined cost) and those that implement a business case approach for projects. The *a priori* expectation is that fixed budgets will impede engagement with energy efficiency options.

PAYBACK requirements also reflect bounded rationality barriers. It captures uncertainty and risk considerations. Uncertainty and risk have been identified in previous empirical analysis as a primary barrier to energy conservation (Velthuijsen, 1995; Harris et al., 2000; Diederen et al., 2003; Anderson and Newell, 2004; Rohdin et al., 2007; Fleiter et al., 2012b).

The number of EMPLOYEES may positively affect the expertise and time available in the organisation to investigate the options for energy-saving measures. A company with fewer employees may face higher hidden costs in gathering the information required to implement an energy efficiency project (Gruber and Brand, 1991; Sorrell, 2004; Anderson and Newell, 2004; Rohdin and Thollander, 2006; Thollander et al., 2007; Schleich, 2009; Trianni and Cagno, 2012). Companies

[31] Multinomial logit models were initially fitted to the data so as to divide the dependent variables into companies that investigated behaviour change, companies that investigated fabric upgrade, companies that looked at both fabric and behaviour, and companies that did neither. It was found that these models were unsuitable due to the sample size, leading to lack of data required to assess the interaction of independent variables within sectors.

with more employees may have more time and expertise available, and hence more opportunities to engage in research of energy efficiency options. Companies with a larger number of employees may also suffer negatively from organisational barriers such as complex decision-making chains, status of energy and strategic value of energy projects and principal/agent, and split incentive barriers that occur in larger organisations (Gruber and Brand, 1991; de Groot et al., 2001; Sorrell, 2004; Thollander et al., 2007; Cooremans, 2012b). Given these potentially opposing effects, no *a priori* expectations on the sign of the coefficient were established.

The DECISION_MAKER variable also captures some organisational barriers. Companies where energy decisions occur at the business unit level may be more likely to have investigated and implemented energy efficiency measures as they have more ownership over the outcome and may see more of the resultant energy cost-saving benefits, comfort and other benefits. Hence a positive coefficient is expected. The OWNER variable captures the barriers of split incentives and principal/agent moral hazard between landlords and tenants. If a company owns the building from which they operate, they will reap the full benefits of any investment in building upgrades, hence a positive estimated coefficient is anticipated. The interaction of these variables is also likely to have a positive influence on engagement with energy efficiency.

Building-specific variables include the energy source for heat energy (ELECTRICITY) and the floor area of the building (M2). Companies with large floor area and companies that use electricity as their main heating fuel are likely to have more expensive energy bills, but may also have lower per unit energy prices as a result of the pricing tariffs of energy suppliers. It is expected that larger buildings and buildings with more expensive heat sources are more likely to investigate energy demand reduction options. The M2 categorical variable includes responses with no information. This may imply a lack of awareness of the built environment a company is operating from; if basic information like floor area was not provided, then it may be likely that questions on the less obvious information such as type of lighting or the u value of the walls would also go unanswered. For this cohort, the expectation is that the estimator will have a negative relationship to the likelihood of investigating an energy efficiency measure. The 'lack of information' barrier has frequently been identified in previous empirical studies (Fleiter et al., 2012b; Gruber and Brand, 1991; Kostka et al., 2013; Schleich, 2009; Schleich and Gruber, 2008; Velthuijsen, 1993).

A cohort of respondents did not reply to the survey question on floor area. This cohort can be said to be missing at random (MAR) as the lack of response is likely related to some observed characteristics of the company and building, but this does not depend on the organisation's overall attitude to energy efficiency opportunities. To examine how this affects overall engagement with energy efficiency and how this information barrier may affect engagement, three separate methods are used to estimate the logit models: 1) The No Reply cohort from the survey data is estimated as a category in the M2 variable, 2) with the listwise deletion of the No Reply observations, and 3) with multiple imputation of the No

Reply using the Multivariate Imputation by Chain Equations (MICE) method (as described by Schafer and Graham, 2002; Horton and Kleinman, 2007; Graham et al., 2007; Graham, 2009).[32] The listwise deletion can provide some insight into how firms that have provided basic information about their building engage with energy efficiency options relative to those that did not provide basic information on floor area. The Multiple Imputation model recategorises the 'no reply' respondents into large buildings (floor area >1,000m^2) and small buildings (floor area <1,000 m^2), based on the imputed likelihood that the fall into either category is based on the observed relationship with other survey variables.

Premises that have had some form of building RENOVATION may be more aware of the options for energy efficiency as a natural consequence of engaging with building contractors with knowledge of energy efficiency technologies and the requirement to consider the wider impacts of building-related design decisions. Fleiter et al. (2012b) show that information provided to companies though an energy audit programme in Germany led to increased awareness of energy consumption.

The business ACTIVITY variable controls for implicit information on the sub-sector-specific barriers that affect energy efficiency decisions. Some empirical evidence has shown that the impact of barriers to energy efficiency varies by business activity (Velthuijsen, 1995; DeCanio and Watkins, 1998; Schleich and Gruber, 2008; Trianni and Cagno, 2012). Table 4 summarises the variables included in the models.

[32] A multinomial logit with the dependent variable as M2=1 if the data is missing, M2=0 if data report estimated over 20 imputations.

Table 7-4: Information collected in commercial sector attitudes survey

	Variable	Freq	Mean	Std. Dev.	Min	Max	Description
BEHAVIOUR	Organisation investigated behaviour change measure	750	0.647	0.478	0	1	1= The organisation has investigated ways to reduce energy use through behaviour change
FABRIC	Organisation investigated fabric upgrade measure	750	0.580	0.494	0	1	1 = The organisation has investigated ways to reduce energy use through improving the building fabric
BUDGET	Budgeting rules	750	0.451	0.498	0	1	0= Fixed budget for energy efficiency investments 1= No fixed budget – it would depend on the business case for the measure
ELECTRICITY	Primary heating source	750	0.436	0.496	0	1	0= Oil or gas, LNG, solid fuel or wood chips is the primary means of heating the building 1= Electricity is the primary means of heating the building
EMPLOYEES	No. of employees	750	0.343	0.475	0	1	1= More than 10 employees
RENOVATED	Building renovated in the last 10 years	750	0.656	0.475	0	1	1= Premises has undergone maintenance, renovation, fit-out or upgrade of the fuel system in the last 10 years
OWNER	Organisation owns the building	750	0.667	0.472	0	1	0 = Organisation is a tenant in the building 1= Organisation owns the building
DECISION_MAKER	Respondent is decision-maker for energy-related decisions in the building	750	0.701	0.458	0	1	1= Respondent is responsible for energy-related decisions
PAYBACK	Payback requirements	750	3.997	2.003	1	10	The maximum number of years an organisation is willing to wait for the savings to cover the investment costs
ACTIVITY	Business activity undertaken in the building	750					The primary business activity undertaken in the building
	Retail	*255*					
	Hotel	*95*					
	Public Houses and Restaurants	*136*					
	Offices	*194*					
	Warehouse and Storage	*70*					
M2	Floor area	750					The floor area taken up by an organisation in the building
	Small: <1,000 M2 floor area	*282*					
	Large: >1,000 M2 floor area	*169*					
	No reply	*299*					

7.4. Results

Table 7-5 and Table 7-7 show the outcomes of the logit regressions for both behaviour measures and fabric upgrade measures. The odds ratios (OR) and marginal probabilities discussed are from the models fitted to the raw survey data. Results from listwise deletion and imputation methods are mentioned where appropriate. The characteristics that influence the decision to investigate a fabric upgrade are presented first. A subsequent section deals with the factors found to influence decisions to investigate a behaviour change measure.

7.4.1. Fabric upgrade logit model result

Table 7-5: Logit regression with odds ratios of likelihood of having investigated a fabric upgrade

Investigated fabric upgrade		**Survey data**	**Listwise deletion**	**Multiple Imputation**
(Robust SE)		n=750	n=451	n=750
ACTIVITY	Hotels	1.638*	1.610	1.530
		(0.484)	(0.714)	(0.450)
	Restaurants/public houses	1.241	0.878	1.172
		(0.302)	(0.280)	(0.281)
	Office	1.605**	1.460	1.552**
		(0.346)	(0.396)	(0.334)
	Warehouse and storage	0.848	0.791	0.859
		(0.244)	(0.287)	(0.248)
EMPLOYEES	>10 employees	2.796***	3.314***	2.662***
		(0.876)	(1.446)	(0.859)
BUDGET	No fixed budget – it would depend on the business case for the measure	1.513**	1.461*	1.429**
		(0.255)	(0.323)	(0.235)
M2	Large (>1,000 m2)	0.895	0.917	0.931
		(0.202)	(0.217)	(0.195)
	No reply	0.661**		
		(0.126)		
RENOVATED	Some building upgrade in the last 10 years	1.900***	1.598**	1.971***
		(0.327)	(0.370)	(0.341)
ELECTRICITY	Uses electricity for heat	1.073	0.938	1.108
		(0.189)	(0.210)	(0.194)
OWNER	Business owns the building	0.309*	0.197**	0.286**
		(0.192)	(0.152)	(0.177)
DECISION_MAKER	Respondent is responsible for energy-related decisions	0.316*	0.189*	0.295*
		(0.221)	(0.179)	(0.204)
OWNER X DECISION_MAKER		16.321***	33.106***	17.984***
		(14.906)	(39.449)	(16.239)
PAYBACK	Minimum payback requirement	0.873*	0.847*	0.872*
		(0.063)	(0.084)	(0.063)
OWNER X EMPLOYEES		0.306***	0.184***	0.321***
		(0.114)	(0.094)	(0.120)
OWNER X DECISION_MAKER X PAYBACK	Owner and responsible for energy-related decisions	1.171*	1.246*	1.173*
		(0.106)	(0.159)	(0.107)
	Owner and not responsible for energy-related decisions	1.356**	1.349*	1.375**
		(0.184)	(0.218)	(0.187)
	Tenant and responsible for energy-related decisions	1.299*	1.425*	1.322*
		(0.202)	(0.295)	(0.203)
Constant		0.618	1.034	0.553
		(0.243)	(0.517)	(0.213)

Significant at *90%, **95%,***99%

The nature of a company's tenure and the decision-making responsibility of the survey respondent show a strong association with the likelihood of investigating a fabric upgrade measure. Companies that own the building they operate from and where the respondent is responsible for energy-related decision-making are over 16 times more likely to engage with energy efficiency options. Companies with more than 10 employees are found to be over 2.5 times more likely to investigate a fabric upgrade. The interaction of EMPLOYEES and OWNER is also significant in the model. Companies that rent their commercial space and that have more than 10 employees were significantly more likely to investigate the options as compared to tenant companies with fewer than 10 employees. No statistical difference in the likelihood of investigation was found between those companies with more than 10 employees that own their building, and those that rent.

PAYBACK and BUDGET variables were both found to be significant in the model. Companies that implement a case-by-case approach to budgeting decisions are 1.5 times more likely to investigate a fabric upgrade. Companies willing to wait longer for the energy savings to cover the cost of investment are also significantly more likely to investigate a fabric measure.

Figure 7-3 shows how the interaction of payback expectations has a significant influence in this dynamic. The slope of the marginal probability for PAYBACK is significantly different across the combinations of TENURE and DECISION_MAKER. The marginal probability for companies that own their building and where the respondents are responsible for energy-related decisions does not vary as payback time increases; PAYBACK does not seem to influence the decision to investigate a fabric upgrade for this cohort. Overall, this cohort is more likely than the other interaction categories to investigate a fabric upgrade at all payback levels.

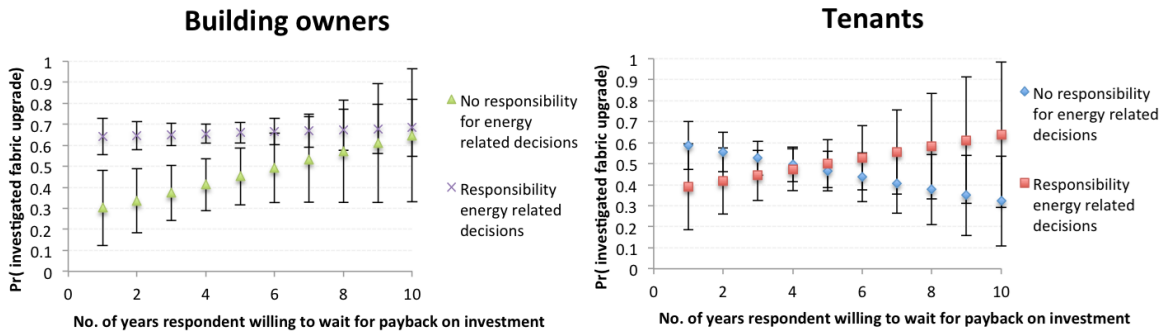


Figure 7-3: Marginal probability of fabric investigation at each year of acceptable PAYBACK by tenure and by decision-making responsibility of the respondent

For companies that own the building and where the respondent is not the decision-maker, the likelihood of investigation increases for companies that accept longer paybacks. Tenants with energy-related decision-making responsibility have a similar slope to the latter category, with no statistical difference evident between the two categories. A counter-intuitive outcome is evident for companies that are tenants and that are not responsible for energy-related decisions: as the stated acceptable period of payback in years increases, this cohort becomes less likely to

have investigated an energy efficiency upgrade. As more energy efficiency measures become economic with an increasing payback period, it could be expected that building occupants accepting higher payback periods would be more likely to investigate these opportunities. This is the case with the other cohorts presented. It is unclear from the data what is driving this result but perhaps the distance of this cohort from financial and building-related decisions leads to less considered responses.

The types of commercial activity undertaken in a building are significant, and there are differences in likelihood found between some sectors. Figure 7-4 shows the marginal probabilities for each business activity. Offices and hotels are most likely to have investigated an upgrade, with warehouses and retail companies least likely. These differences are statistically significant for offices compared to retail and to warehouses, and also for hotels compared to warehouses – all at the 95% significance level.

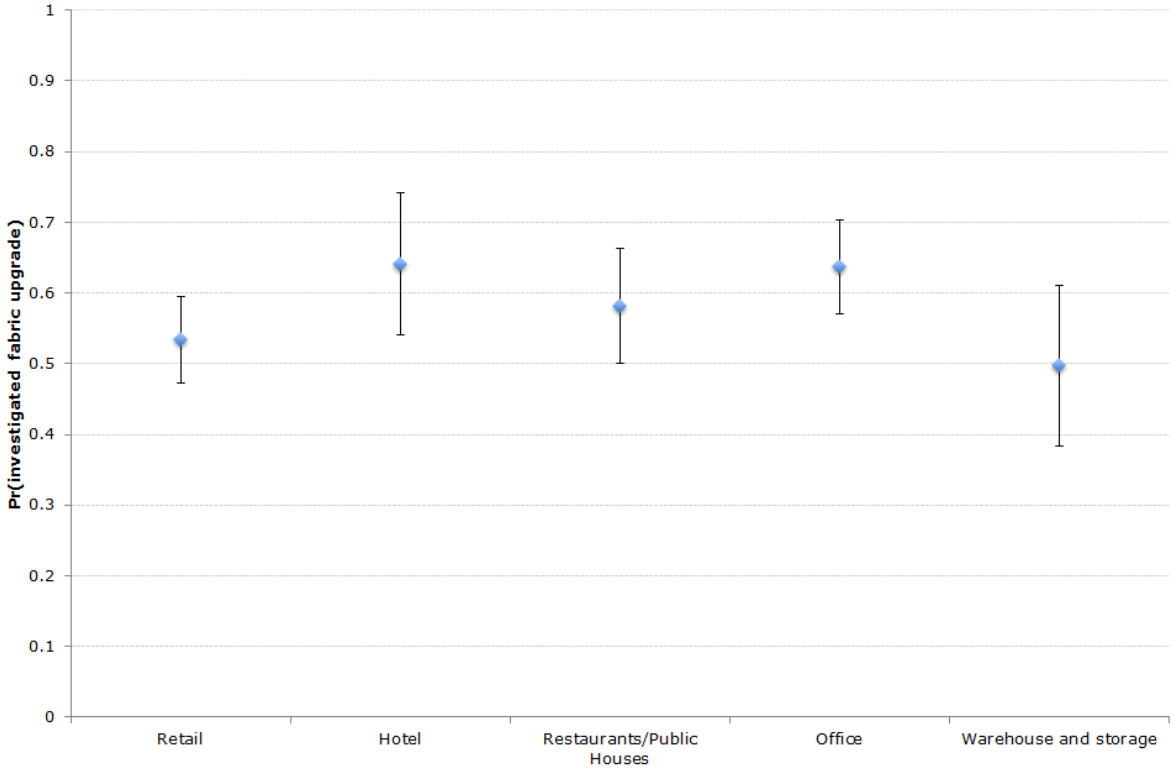


Figure 7-4: Marginal probabilities by company ACTIVITY of investigating a fabric upgrade (95% interval)

Respondents that did not reply to the question on the floor area of the building are significantly less likely to have investigated a fabric upgrade. A listwise deletion of the 'no reply' cohort resulted in a change of magnitude and significance of a number of variables, with the marginal probabilities of investigation increasing across most variables. Companies that owned their own building and where the respondent is the decision-maker were over 30 times more likely to investigate a fabric upgrade. Furthermore, the likelihood for companies with more than 10 employees increased in the listwise model. The

odds ratio for companies that have had a building renovation at some time over the past 10 years is 1.598 lower than the results from the other models for the same variable shown in Table 7-5. In addition, previously significant categories in the ACTIVITY variable in the other models lose their significance in the listwise model. An examination of the no-reply cohort using a separate logit equation showed some significant associations. No replies are more likely from hotels, restaurants/public houses and offices that have not renovated recently, that use oil, gas or other as the primary heating fuel and that apply fixed budget rules to investment decisions. The logit results for this equation are shown in Table 7-6.

Table 7-6: Results of logit regression on likelihood of company to not provide a response to question on floor area

Did not reply to Q on floor area =1			
(Robust SE)		**n=750**	**Odds ratio**
ACTIVITY	Hotels		2.479*** (0.678)
	Restaurants/public houses		2.000*** (0.465)
	Office		1.537** (0.324)
	Warehouse and storage		0.940 (0.284)
BUDGET	No fixed budget – it would depend on the business case for the measure		1.918*** (0.305)
EMPLOYEES	> 10 employees		1.041 (0.222)
ELECTRICITY	Uses electricity for heat		0.564*** (0.117)
DECISION_MAKER	Respondent is responsible for energy-related decisions		0 .929 (0.279)
OWNER	Company owns the building		1.183 (0.382)
RENOVATED	Some building upgrade in the last 10 years		0.590*** (0.102)
DECISION_MAKER X OWNER			1.097 (0.453)
ELECTRICITY X EMPLOYEES			1.735* (0.584)
Constant			0.687 (0.238)

Significant at *90%, **95%,***99%

The RENOVATED variable was also found to be significant. Businesses operating from buildings that were renovated sometime in the previous 10 years are almost twice as likely to have investigated a fabric energy efficiency measure. The underlying data set includes information on the energy use or costs faced by the companies surveyed. To try to estimate this impact, the initial model specification included an interaction term combing floor area, type of heating fuel and the number of employees as a proxy for energy use and energy costs. The interaction was not significant and did not affect the significance of other terms in the model; hence it was dropped from the final specification.

7.4.2. Behaviour change logit model results

Analysis of the factors that influence a company to investigate a behaviour change measure differ somewhat from those factors that influence fabric upgrade. Similar to the fabric upgrade case, a lack of knowledge of the size of the building is a strong predictor of lack of engagement, but the company business activity, the company's tenure in the building operated from, the decision-making responsibility of the respondent and the number of employees differ in their effect.

Table 7-7: Logit odds ratios for likelihood of a company investigating a behaviour change

Investigated behaviour change		**Untreated data**	**Listwise deletion**	**Multiple Imputation**
(Robust SE)		n=750	n-451	n=750
ACTIVITY	Hotels	1.462	1.147	1.234
		(0.605)	(0.640)	(0.505)
	Restaurants/public houses	1.183	1.842	1.008
		(0.356)	(0.795)	(0.308)
	Office	0.961	0.877	0.896
		(0.271)	(0.297)	(0.249)
	Warehouse and storage	0.572	0.415*	0.580
		(0.226)	(0.192)	(0.223)
BUDGET	No fixed budget – it would depend on the business case for the measure	0.653	0.423*	0.560
		(0.241)	(0.198)	(0.204)
ACTIVITY X BUDGET	Hotel X BUDGET	0.875	0.438	0.902
		(0.505)	(0.347)	(0.513)
	Restaurants/public houses X BUDGET	1.421	0.346	1.530
		(0.701)	(0.246)	(0.739)
	Office X BUDGET	2.644**	3.105**	2.731**
		(1.142)	(1.784)	(1.177)
	Warehouse and storage X BUDGET	3.714**	8.180**	3.683**
		(2.432)	(7.544)	(2.390)
M2	Large (> 1,000 m2)	0.923	0.878	1.020
		(0.265)	(0.258)	(0.278)
	No reply	0.486***		
		(0.108)		
		[0.107]		
EMPLOYEES	>10 employees	1.040	1.049	1.382
		(0.378)	(0.392)	(0.429)
EMPLOYEES X M2	>10 employees X Large (>1,000 m2)	3.053**	3.455**	1.958
		(1.606)	(1.871)	(0.900)
	>10 employees X No reply	2.454**		
		(1.121)		
ELECTRICITY	Uses electricity for heat	1.582	1.749	1.666*
		(0.478)	(0.696)	(0.493)
DECISION_MAKER	Respondent is responsible for energy-related decisions	1.615	1.597	1.530
		(0.533)	(0.682)	(0.503)
ELECTRICTY X DECISION_MAKER		0.468**	0.433*	0.471**
		(0.172)	(0.211)	(0.170)
RENOVATED	Some building upgrade in the last 10 years	1.455**	1.420	1.557**
		(0.259)	(0.352)	(0.275)
BUDGET X DECISION_MAKER		2.442**	4.353***	2.513**
		(0.925)	(2.211)	(0.943)
OWNER	Business owns the building	1.426*	1.432	1.375
		(0.291)	(0.382)	(0.275)
Constant		0.687	0.767	0.569*
		(0.238)	(0.328)	(0.195)

Significant at *90%, **95%,***99%

The interaction between ACTIVITY and BUDGET is significant for a number of business activities. Companies that make budget decisions on the basis of the

individual business case of each measure, and that operate from office buildings or warehouses, are more likely than hotels, retail premises and restaurants/public houses to investigate behaviour change. Figure 7-5 summarises the marginal probabilities of the budget approaches across the business activities.

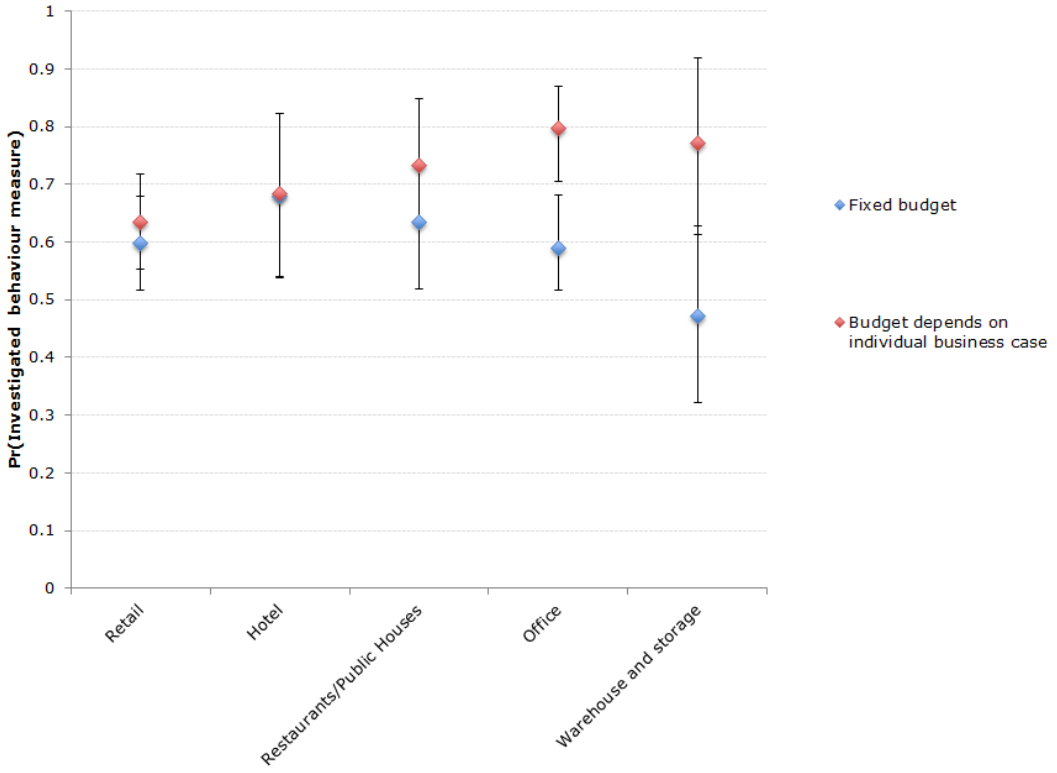


Figure 7-5: Marginal probabilities by company ACTIVITY and BUDGET approach of investigating a behaviour change measure (95% interval)

Office buildings with a case-by-case budgeting approach are over 2.6 times more likely than office buildings that apply fixed budget rules of thumb to investment decisions to report investigating a behavioural measure. The same is true of warehouse and storage businesses. Office-based businesses with a 'business case' approach have an 80% marginal probability of saying they have investigated a behaviour change as compared to a 59%–73% probability range for retail, hotels and restaurants/public houses and a 59% probability for offices that use fixed budget rules of thumb.

The answer respondents gave to the question on the size of the business premises was significant in explaining the likelihood of investigating a behaviour change energy efficiency measure. Those respondents who did not respond to the question on the size of the business premises were also significantly less likely to report having investigated a behaviour change. As described in the fabric upgrade results and as shown in

Table 7-7, this cohort of business shares defining characteristics that set them apart: hotels, restaurants/public houses and offices that have not renovated

recently, use oil, gas or other as the primary heating fuel and apply fixed budget rules to investment decisions are less likely to respond to the floor area question.

The number of employees alone was not a significant indicator of the likelihood to investigate a behaviour change measure. When the interaction with floor area is considered, companies with more than 10 employees and with floor areas greater than 1000 m^2 are significantly more likely to have investigated a behaviour change measure. This category is over three times more likely to report investigating behaviour change as compared to the base category: the cohort with fewer than 10 employees and a floor area of under 1000 m^2.

The interaction of ELECTRICITY and DECISION_MAKER is significant in all models. Companies that use electricity as the main heating fuel, and where the respondent to the survey is responsible for energy-related decisions, are about half as likely to have investigated a behaviour upgrade compared to companies that use other fuels for heating and where the respondent is the decision-maker. Company units using oil, gas or other fuel sources and where the respondent is not responsible for energy-related decisions are significantly less likely to investigate a behaviour change measure when compared to the base category. Owning the building tends to favour engagement with a behaviour change investigation, although this is significant only in the raw survey data model. The decision-making responsibility of the respondent does not have a significant association with behaviour change investigation. In contrast to the fabric upgrade model, the interaction of both variables is insignificant, and was dropped from the final specification of the behaviour measure model.

Companies where the respondent is responsible for energy-related decisions and where a business case approach is applied to budget decisions are between 2.4 times and 4.3 times more likely to have investigated a behaviour change. The marginal probabilities for companies where the respondent is not the decision-maker and where a case-by-case budgeting approach is taken (pr 57%) show no statistical difference in comparison with companies where a fixed budget approach is taken (pr 60%).

Companies that occupy buildings that have been renovated or upgraded in the last 10 years are significantly more likely to have considered a behaviour change. When those respondents that did not reply to the floor area question were excluded, the significance dropped below the 90% level.

7.5. Discussion

In order for a company to undertake a measure, they must first invest the time in investigating the options available. The representative survey data shows that almost half of Irish companies operating in the commercial sector do not take this first essential step in accessing the energy efficiency measures available to them. The findings presented identify the company factors associated with a likelihood of investigating an energy efficiency measure. This section reflects on the findings

of this chapter in the context of other empirical analyses and mentions the theoretical background where relevant.

The influence of tenure and localised energy-related decision-making responsibilities are perhaps the most definitive insight from this analysis. Companies that own the building they operate from and where energy-related decisions are made by local management are found to be much more likely to investigate a fabric upgrade measure. These findings are consistent with the split-incentive barrier and organisational barriers identified in the theoretical literature. These findings may tentatively indicate that energy efficiency drivers may also be influencing companies with these favourable characteristics. The literature that explores the drivers for energy efficiency cites improved working environments, greater comfort, increased asset values and productivity as reasons for companies to take up these measures.

The empirical studies reviewed did not examine the interaction of tenure with energy-related decision-making responsibility, as is done here. Some empirical literature has examined the impact of renting on uptake while other studies have looked at the impact of internal investment decision processes. Schleich and Gruber found that renting commercial space was a barrier to organisations in over half the sub-sectors they examined (Schleich and Gruber, 2008; Schleich, 2009). Fleiter et al. (2012b) examined the impact of tenure on uptake and found no significant relationship. They hypothesise that the provision of information through building energy ratings may have mitigated the impact of this and other barriers identified elsewhere in the literature. Muthulingam et al. (2011) found that managerial attention requirements influence the adoption rate of energy efficiency measures. Trianni and Cagno (2012) and Thollander et al. (2007) identify lack of access to internal capital as a barrier. While the control variables used in these studies are not directly comparable to the decision-making responsibility variable used here, they do support the finding that the investment decision process can present organisational barriers to energy efficiency measures.

Companies with more than 10 employees are found to be more likely to investigate both fabric upgrades and behavioural options. This finding is consistent with several other empirical studies, including Anderson and Newell (2004), Aramyan et al. (2007) and Schleich (2009). Some studies that have included variables representing the number of employees have not found a significant relationship with likelihood to take up an energy efficiency measure; Fleiter et al. (2012b) postulate that the effect may be captured in other control variables included in the model. Several of the analyses report lack of time to investigate measures as an important factor (Gruber and Brand, 1991; Sorrell, 2004; Rohdin and Thollander, 2006; Thollander et al., 2007; Trianni and Cagno, 2012). The data this analysis relies on does not allow for the inclusion of a control variable for lack of time, though it is probable that the effect may be captured by the variable for number of employees. Analysis by Velthuijsen (1995) (reported in Fleiter et al., 2012b) finds an additional nuance: as the size of a firm increases, decision-making complexity begins to negatively affect uptake. Commercial sector companies of

100 employees or more are rare in Ireland. This may partially explain why no such negative relationship was found in this analysis.

This analysis found that companies that did not provide a response to the question on floor area were less likely to investigate a fabric upgrade or a behavioural measure. Lacking basic information, such as floor area and energy use, has been found to negatively affect the uptake on energy efficiency measures (Gruber and Brand, 1991; Kostka et al., 2013; Schleich, 2009; Schleich and Gruber, 2008; Velthuijsen, 1993). Some empirical analyses have shown how information campaigns and energy audits can remove the impact of information barriers (Harris et al., 2000; Anderson and Newell, 2004; Thollander et al., 2007; Fleiter et al., 2012b). For example, Fleiter et al. (2012b) examined the uptake of measures in German SMEs after an energy audit was completed and the firm was provided with information on energy-saving options. They found that lack of information was not a significant variable for these companies. This analysis finds, companies that had undergone some form of a renovation in the previous 10 years were more likely to have investigated a fabric upgrade. This may suggest a similar effect. It is interesting to note that, having undergone a renovation, companies were also more likely to have investigated a behaviour change measure. The Cagno et al. (2013) review of the literature on barriers to industrial energy efficiency explains the role of building designers, building contractors and trusted independent third parties in disseminating information on energy-saving measures. The energy agency in Ireland (SEAI) has been active in providing information as well as mentoring in the past decade and runs a tax rebate scheme for companies that install equipment listed as highly energy-efficient. The energy agency and wider market activity may be helping companies to access information on energy efficiency as part of the renovation process.

The empirical evidence shows that lack of capital, both internally within the company and from external sources, is a significant barrier to the uptake of energy efficiency measures (Velthuijsen, 1993, 1995; Fleiter et al., 2012b; Anderson and Newell, 2004; Thollander et al., 2007; Rohdin et al., 2007; Muthulingam et al., 2011; Trianni and Cagno, 2012). The findings in this chapter expand on this and examine the impact of bounded rationality in budgeting decisions. The analysis found that the use of heuristics – through the application of budget expenditure limits – was associated with a lower likelihood of investigating fabric upgrade options. The approach to budget decisions also had some impact on the likelihood of investigating a behavioural measure when the interaction with decision-making responsibility and commercial activity were considered.

The payback duration required was also found to be significant. Companies that accept longer payback times were found to be more likely to investigate fabric upgrade measures. This agrees with Harris et al. (2000), Diederen et al. (2003) and Anderson and Newell (2004), who found payback and hurdle rates to be relevant to the uptake of energy efficiency measures. The findings on budget approach and payback lengths are notable given that little or no capital commitment is required to investigate a measure, but yet those companies with budget limits and short payback requirements are less likely to investigate energy-

saving options. This may reflect organisational barriers or a focus of investment options related to core business only.

The various sub-sectoral business activities undertaken in a building has a significant association with the likelihood of having investigated a fabric upgrade measure. Offices and hotels were found to be more likely to have considered such options as compared to retail and warehouse/storage. DeCanio (1998) examined the influence of variables including sub-sectoral classification on the profitability of lighting upgrade projects and found that the type of business activity is significant. De Groot et al. (2001) and Schleich (2009) examined barriers at a sub-sector level for German and Dutch data sets respectively. They found differences in the significance and magnitude of barriers within the sub-sectors. These broadly align with our findings and may suggest that individual sub-sectors respond to the drivers in different ways. It is plausible that hotels and offices may value the co-benefits from upgrade measures, such as increased internal comfort and noise reduction, more than retail or warehouse sub-sectors.

The underlying data set for our analysis did not have information on energy bills. A proxy for energy costs was examined through the interaction of building size, number of employees and heating fuel type, but was not found to be significant in the decision to investigate. The empirical findings differ on this point. Some studies have not found a significant link between energy costs and the uptake of energy efficiency measures, while others found, in a number of empirical studies, that the share of energy costs in total operating costs was found to influence upgrade activity. Schleich (2009) found that a higher annual energy use per employee positively influenced the likelihood of an organisation investigating and implementing a measure. Anderson and Newell (2004) found that increases in energy costs increased the likelihood of a measure being implemented in manufacturing plants. In contrast, de Groot et al. (2001) found no significant relationship between companies' prioritisation of energy and the uptake of energy efficient measures. Similarly, Fleiter et al. (2012b) found no significant relationship between the variable capturing energy costs and likelihood of uptake. The findings in this chapter should be viewed in the context that energy use is a relatively minor cost for most commercial sector companies in Ireland. In addition, as Table 7-3 shows, the low priority of energy use was cited by over 77% of those respondents as the reason for not investigating an upgrade.

7.6. Conclusion

This chapter examined the factors associated with the likelihood that a commercial sector company will investigate a fabric upgrade or behaviour change energy efficiency measure. The analysis is based on an internationally rare example of a statistically representative data set, for the commercial sector in Ireland. The data set is compiled from a survey of commercial sector business units and captures building-specific and company-specific characteristics as well as their behaviours and attitudes towards energy efficiency.

The profile of companies was represented in the regression models by the type of commercial activity undertaken in the building, the number of employees normally at work at the premises on a typical day, the floor area of the building, the fuel used for heating, if the building is owned or rented, and if energy-related investment decisions are made locally. Factors representing the company's approach to determining capital expenditure budgets and their acceptable payback lengths were also included. Two logit models were specified separately to examine the influence these factors have on decisions to investigate a fabric upgrade measure, and a behaviour change measure.

The results show that companies that rent the building they occupy and where decision-making responsibilities are not made locally are unlikely to investigate a fabric upgrade measure, suggesting that spit incentives and organisational barriers are acting to prevent engagement for this cohort. Hotels and offices were significantly more likely to have investigated a measure relative to companies in retail and warehouse sub-sectors, perhaps suggesting that some additional energy efficiency drivers are promoting engagement in these sectors. Lack of time, internal expertise and the hassle of investigating the available options have been reported in the literature as barriers to energy efficiency. The results also show larger companies with more than 10 employees were more likely to have investigated a fabric upgrade measure.

Lack of information on energy use and on the intervention measures available are frequently identified in the literature as preventing adoption of measures. These results resonate with this, with respondents that did not know the floor area of their business premises significantly less likely to investigate upgrade options. In addition, the results show that companies that recently had a renovation were more likely to have investigated a fabric upgrade measure, perhaps due to the availability of information during this process. Companies that apply a fixed-limit budgeting approach and have short payback requirements are less likely to engage with fabric upgrades options. This is an interesting finding given that relatively little budget commitment is required to investigate the available measures.

Companies with more employees, larger floor areas, that own their own building, operate as offices or warehouses and apply a business-case evaluation for each individual project were more likely to investigate behaviour change measures. Interestingly, those companies that had a recent renovation were also more likely to have investigated a behaviour change, suggesting that the information on and awareness of the building can motivate wider interest in energy savings. Respondents who did not report floor area, were not the energy decision-makers and who use electricity as a heating source were less likely to investigate behaviour change measures.

The findings are consistent with the previous empirical and theoretical literature on the barriers and drivers to energy efficiency. Much of the previous research is concerned with the final adoption of measures; this analysis adds additional insights by identifying the factors that determine if a company is likely to

investigate the options available. The focus of previous research has been on the adoption of appliance and fabric upgrade options; this work also contributes additional information by extending the analysis to identify factors that influence the decision to investigate behaviour change options. The robustness of the statistically representative data set underlying the analysis is also a useful and rare aspect of this work.

This chapter examines the barriers and drivers across the decision-making process by focusing on the first step in the process of implementing a saving measure, the investigation step. Further research that separates the effect of barriers at the investigation step from their effect at the implementation phase would add an additional layer of understanding into how the barriers act to impede energy-savings uptake at the various stages of the decision-making process. The initial model specification looked at examining the adoption of measures by first controlling for the self-selection bias of companies that investigated measures but the data set did not support this two-stage analysis. Future data collection efforts can keep in mind the usefulness of these staged approaches during survey design.

Chapter 8

Conclusions

The climate-change mitigation ambition agreed at the 2015 Conference of Parties (COP) in Paris represents a substantial challenge. Energy generation continues to be dominated by carbon-based fossil fuels. Well-informed policy design and implementation, at national and regional levels, is required to decarbonise the energy sector and to maintain global temperature increases to well below 2^0C in this century. Governments, and those who vote for them, often seek more than climate mitigation benefits from the policy they implement. Factors such as policy cost, economic growth, market distortion, energy prices, energy security, employment and social cohesion are also important. Policymakers need to understand the trade-offs and effectiveness of policy, both existing and planned.

The aim of this thesis was to provide evidence and insights based on transparent methods in order to inform policy decisions as well as the wider societal debate on sustainable energy. To meet the aim, four research questions were addressed, using three main modelling approaches, as follows:

Part I – Power system modelling

RQ1 (a): RQ1 (a): What are the methods available to assess the emissions saving contribution of renewable electricity generation?

RQ1 (b): What fossil-fuel and emissions savings impacts have resulted from the renewable power generation already deployed in Ireland?

RQ2: What are the short-run price and CO_2 impacts of using waste heat from CCGT generators for district heating on a high-renewable electricity system?

Part II – Mixed-method simulation of bioenergy and renewable heat policy

RQ3 (a): How can demand for bioenergy in the heat, power and transport sectors be represented in a decision support tool to aid policymaking?

RQ3 (b): What are the interactive and cumulative impacts of bioenergy policy options for the heat, transport and power sectors in Ireland?

Part III – Empirical analysis

RQ4: What are the factors that discourage commercial businesses from considering energy-related decisions?

Each chapter set out to address a part of these research questions, with a focus on the policy implications. This final chapter summarises the findings relevant to policy and modelling methodology.

8.1. Policy

The decarbonisation of the energy sector raises many questions for policy. Among these: what has the impact of current policy been, what can enabling infrastructure deliver, what end-use sector should bioenergy resource be used in, and how can policy be better tailored to overcome the specific barriers faced by citizens and businesses.

Many countries have already implemented policy that has resulted in substantial change to the energy sector. Policy supporting the deployment of variable renewable power generation sources of wind and solar have resulted in significant penetration of these technologies (IEA, 2017a). Establishing the impact of existing policies allows policy design to learn and evolve. It also can inform the wider debates and allow governments to present credible evidence to those citizens affected by infrastructure development and those working in industries negatively affected by decarbonisation efforts. RQ1 was focused on examining the impact of renewable electricity development in Ireland and evaluating the most appropriate methods for assessing this.

Continued decarbonisation of the energy system will require enabling infrastructure to support technology deployment. The infrastructure required is frequently assessed within the boundaries of the electricity, heat or transport system in which it is deployed. This approach can miss the benefits and costs that such infrastructure may have across all end-use sectors. A wider view is often more appropriate. RQ2 examined the wider impacts of district heating networks on both the heat and electricity sectors.

Similarly, bioenergy has a key role in decarbonising the energy system, but policy evaluation is often limited to the end-use sector on which it is focused. Bioenergy resources in the short term are restricted in availability, and policy incentivising demand in one end-use sector may negatively affect the aims of bioenergy policy in another. RQ3 focused on developing the appropriate tools to analyse bioenergy policy and investigating the impact of future policy options in Ireland.

Much of the move to a low-carbon energy system will require energy consumers to choose energy-efficient and low-carbon technologies. To reach different cohorts of consumers effectively, tailored policy development is required to incentivise or mandate low-carbon and energy-efficient choices based on the individual circumstances of a citizen or business. RQ4 looked at the factors that discourage businesses in the Irish commercial sector from investigating the options available to reduce energy use.

RQ1 (a) ***What are the methods available and how well equipped are they to assess the emissions saving contribution of renewable electricity generation?***

The methods used to evaluate the fossil-fuel and CO_2 saving from renewable electricity generation are explored in Chapter 2. A primary policy driver for the investment in wind and other renewable energy has been the promise of CO_2 reductions from the generation of renewable electricity. This is not a straightforward exercise as the impact of renewable generation must be isolated from the other complex interactions on the power system. The primary parameters affecting emissions intensity can vary significantly across short timescales and no 'natural experiment' exists to facilitate conclusive empirical analysis.

Four main methods, which vary in complexity and approach, have been used to examine this question. Each method has its benefits and drawbacks. For example, detailed simulation is the correct approach for studies seeking to isolate the impact of wind generation and to quantify the impact of any additional cycling and ramping introduced by wind and solar, but these models are characterised by detail and complexity. The models can lack transparency and also be time-consuming to build and run. Econometric techniques can capture the emissions reduction impact but require several years of high-resolution historic data for the relevant dependent variables in order to give a reliable result. These models have limited explanatory and predictive power due to the difficulty of representing the complex relationship between variables within the power system. The simplicity of the displacement method is a useful first-order approach to estimating savings but it cannot provide additional insights beyond emissions and fuel savings.

The literature review showed that the magnitude of the savings was the relative proportion of electricity generated from coal or gas on the system in question, regardless of the method used. Power systems that have high penetrations of gas CCGTs record savings in the range of 0.26 to 0.502 tCO_2/MWh of renewable generation. Systems with large amounts of coal have estimated savings in the range 0.489 to 0.847 tCO_2/MWh of renewable generation. Simulation studies tend to focus on future scenarios while econometric analysis is applied to historic data only.

RQ1 (b): What fossil-fuel and emissions savings impacts have resulted from the renewable power generation already deployed in Ireland?

In Chapter 3 a dispatch model is applied to *ex-post* data for the 2012 All-Island system in Ireland to determine the fossil-fuel and CO_2 savings. Renewable electricity accounted for 20.4% of total generation, 15.8% from wind, on the Irish system in 2012. The results show renewable generation averted a 26% increase in fossil fuels (valued at €297 million) and avoided an 18% increase in CO_2 emissions (2.85 $MtCO_2$), as compared to the simulated 2012 system without renewable generation. Wind generation on its own averted a 20% increase in fossil-fuel generation and a 14% increase in CO_2 emissions (2.33 $MtCO_2$).

Each MWh of renewable electricity generation avoided on average 0.43 tCO_2, with wind generation avoiding 0.46 tCO_2/MWh. This was at the higher end of the range for electricity systems with high amounts of natural-gas generation. Many of the studies that have found lower savings point to a loss of efficiency in the fossil-fuel generators induced by a more variable operating profile required to balance the wind generation on the system. Chapter 3 shows that the additional renewable-related balancing requirements had minor impacts on fossil-fuel generation efficiency – CO_2 production rates increased by less than 2%. Other contributory factors have a greater influence on savings. Policy measures to alleviate network congestion, increase system flexibility and increase financial penalties on emissions can increase savings from renewable generation.

RQ2: What are the short-run price and CO_2 impacts of using waste heat from CCGT generators for district heating on a high-renewable electricity system?

Using waste heat available from power generators in heat networks is a means to reduce CO_2 by replacing heat production from fossil-fuel heat boilers. But CHP generation, by linking heat and electricity markets, can change how other electricity generators run, and affect price and emissions in both sectors. High levels of renewable electricity generation may also affect the cost of using waste heat and influence the cost and magnitude of CO_2 reduction. Chapter 4 also uses a power systems model to simulate the short-run impacts of using waste heat from existing power generators on heat and electricity systems. The model is solved at five-year intervals, from 2020-2035 – with heat network and without heat network – for central and high-renewable electricity deployment.

The findings show that retrofitting CCGT units with CHP capabilities to feed a heat network in Dublin resulted in cumulative reductions of 3.5 $MtCO_2$ – 44% in heat and 56% in electricity. The CCGT-CHP units were found to produce electricity and heat at competitive prices. The average shadow price of electricity reduces by 4% and producing heat at CCGT-CHP units is competitive with gas boilers except at times of low electricity prices. The cost-optimal solution showed that the CCGT-CHP units use revenue from the heat market to offset electricity production costs and allow them to be dispatched more often in the electricity market. As more renewable electricity was added to the system, the amount of offsetting revenue required from the heat market increased. Chapter 4 labels these offsetting periods as Type II operational modes and finds that the CCGT-CHP units operating in these modes tend not to produce heat for storage.

The findings are sensitive to the efficiency at which units can produce heat. In this study, a Z-factor in the mid-range of estimates from the literature is used. Higher Z-factors can increase the competitiveness of heat production at times of lower electricity prices. Further modelling to explore lower-temperature, fourth-generation heat networks and work to specify Z-factors achievable from the various power generation technologies would help complete the picture. Longer term, the implementation of low-temperature heat networks in conjunction with heat pumps and CHP may be required to optimise district heating on high-

renewable electricity systems. Further analysis could also examine if the additional revenue available to CHP units has an impact on total capacity payments in the electricity market. Likewise, an analysis of the impacts of CHP upgrades on the operation of the electricity system can explore if the retrofits add to or reduce system flexibility.

RQ3 (a): How can demand for bioenergy in the heat, power and transport sectors be represented in a decision support tool to aid policymaking?

Bioenergy is likely to play a key role in decarbonising the energy system. The versatility of bioenergy as a transport, heat or electricity fuel is one of its key strengths, but it can add to the complexity of policy design. Policies aimed at stimulating bioenergy use in one end-use sector should consider the impacts of use and uptake in the others.

Chapter 5 detailed a methodology to account for these interactions, and the decision support tool was used in the development of a renewable heat incentive policy in Ireland. Much of the published modelling methods focus on supply-chain optimisation and plant sizing and location from an operator's perspective. The BioHEAT model described in Chapter 5 focuses on a policymaker's perspective and accounts for the co-dependencies between the end-use sectors. The model is a techno-economic model with the novel approach that it accounts for consumer behaviour in the heat sector.

Three illustrative scenarios were examined to demonstrate the functionality and features of the model. The Baseline scenario showed the impact of existing policies on bioenergy use in the heat and power sectors. A doubling of bioenergy used for power generation led to a 20% drop in bioenergy use for heat due to a shortage of low-cost biomass resource. A further scenario demonstrates the impact of higher carbon tax on the uptake of renewable heat technologies. Together, these scenarios show the wide range of policy measures that can be modelled and how the detailed model outputs can provide a solid evidence base for policymakers when assessing policies against a range of metrics.

RQ3 (b): What are the interactive and cumulative impacts of bioenergy policy options for the heat, transport and power sectors in Ireland?

Chapter 6 used the BioHEAT policy support decision tool to examine the climate energy and security-of-supply impacts of bioenergy policy for several bioenergy policy options available to Ireland. Scenarios simulated policy supports for renewable heat and renewable electricity as well as mandates for the use of biofuels. As an EU member country, Ireland is obligated to meet national climate and renewable energy targets. The policy options examined are influenced by these targets but also by broader policy goals. For example, policy to support the co-firing of biomass for heat would help the viability of the state company that supplies peat fuel and maintain employment in the Irish Midlands. But policy at an EU level is pushing national climate policy towards action in the heat and transport sectors.

Chapter 6 concludes that policy action in the heat and transport sectors saves a cumulative total of 1.8 $MtCO_2$ by 2030, most of which counts towards the national emissions reduction target. Supporting low to moderate rates of co-firing in Ireland's peat power stations has a negative emissions impact and adds a cumulative total of 8.3 $MtCO_2$ to the system by 2030. Much of this is from the additional peat combustion at these stations, but a significant proportion is due to a reduction in uptake of renewable heat technologies. Co-firing stations out-compete installations in the heat sector for biomass resources. Emissions from the peat stations are covered by the Emissions Trading Scheme (ETS) but the majority of emissions from heat use occur in those sectors outside of the trading scheme. Non-ETS emissions count towards the national targets of EU countries.

To mitigate the impact of additional peat combustion, a scenario with an accelerated path to full conversion at the peat stations was examined. This resulted in some emissions savings overall but led to a net increase in emissions from the heat sector of 0.4 $MtCO_2$. Sensitivities on the availability and price of imported biomass show that a trend that sees imports increase by 70% year on year reduces the negative impacts. The chapter concludes that a policy to support co-firing has negative risks for the national climate targets in Ireland.

The conversion of a large pulverised coal station to biomass is also examined. The scenario finds that a conversion would rely on quantities of imported biomass in the upper range of estimates of international availability. The cost of producing wood pellets from native feedstock is above the price at which a converted station can import wood pellets, hence no domestic resource is used to generate power in the converted station. Most domestic supply chains for biofuels are uncompetitive with imports, with the transport sector relying on imports to meet increasing bioenergy demand in the sector. There may be options for Ireland to reduce these costs and increase the use of domestic resources by moving to biomethane in the transport sector.

RQ4: What are the factors that discourage commercial businesses from considering energy-related decisions?

Many policy measures are focused on incentivising or mandating end-use consumers to choose more efficient and low-carbon technologies. Policy tailored and timed to the circumstances of consumers is likely to have a larger impact. Before an energy measure can be implemented, it first must be investigated and representative survey data from Ireland's commercial sector shows that half of businesses do not take this first step. Chapter 7 examined the factors associated with a company's decision to investigate an energy-related investment or behaviour change in this context. The analysis used a statistically representative data set of the commercial sector in Ireland based on a survey of business units. Both building-specific and company-specific characteristics as well as their behaviours and attitudes towards energy are captured.

The chapter concludes that companies that rent the building they occupy and where energy decision-making responsibilities are not made locally are relatively

unlikely to investigate a fabric upgrade. Split incentives and organisational barriers are limiting the engagement of this cohort. Policy may need to rely on regulation to improve the energy performance of these buildings. Companies that have more than 10 employees, had a recent renovation, accept longer paybacks and apply a case-by-case approach to budgeting decisions were more likely to investigate a measure. Lack of time and expertise and the hassle factors of investigating a measure are often reported as a barrier; having more employees may help overcome these. Lack of knowledge of the building floor area was associated with a lower likelihood of investigation. Lack of information on energy consumption is a barrier cited in several other studies, and the results in Chapter 7 align with this finding. Government policies can help small companies and companies with low awareness of energy to engage by requiring building energy audits or providing information services. An interesting outcome was the significance of financial considerations in lowering the likelihood of investigation given the minimal financial commitment involved in investigating a measure. Companies that applied fixed-budget limits to capital spending and had more stringent payback requirements were less likely to investigate. Regulation may have a role to play in encouraging this cohort to examine the energy options available. Chapter 7 also shows that there may be an additional benefit to companies that undertake energy upgrades in how they manage energy use from a behavioural standpoint. Companies that had a recent renovation were more likely to examine a behaviour change option.

8.2. Recommendations

A key objective of the work presented in this thesis is to provide policymakers with evidence to help with the decision-making process. A number of findings from the work are relevant:

- Wind and other renewable generation have reduced carbon emissions. For systems with high proportions of coal, lignite or other carbon-intensive fuel, the benefit is likely substantial. Policymakers, through measures such as carbon floor pricing, can help ensure that the most carbon-intensive fuels stay near the margin on the system. This will increase the benefit from the renewable electricity installed. In addition, grid operators and policymakers should aim to incentivise the development of more flexible electricity systems. Market mechanisms that reward higher forecast accuracy for wind and solar output along with measures that promote newer, more flexible generators will also maximise the CO_2 benefit from wind and other renewable electricity sources.

- Policymakers often limit consideration of the benefits of district heating to the emissions saved in the heat sector. Chapter 4 shows that the electricity sector impacts should also be considered. District heating in Dublin can make a large contribution to CO_2 emissions reduction in both the heat and electricity sectors. The use of waste heat is economic and can improve the profitability of CCGT stations that retrofit CHP

capabilities. Further work to explore how the improved revenue of CCGT-CHP units may affect capacity auctions and how heat networks affect the electricity system flexibility can add to the evidence base for policymakers.

- Policy measures for bioenergy in the electricity sector can have negative impacts for the uptake of bioenergy in the heat sector. For EU countries, the implementation of policy to support the use of less refined solid biomass in the electricity sector could make national climate targets for greenhouse-gas reduction more difficult to achieve. In addition, the co-firing of fossil fuel with biomass fuel can lead to an increase in emissions overall. The low-risk approach for policymakers is to prioritise the use of the available renewable solid biomass resources for heat.

- Individual energy consumers are impacted by situational and internal factors in different ways. Financial incentives are unlikely to have an impact without other supporting measures and, for some business types, regulation may be the most effective way to deliver engagement. Policy packages tailored to individual circumstances, that addresses the various barriers faced by individual companies, have the potential to increase uptake of energy efficiency options. For example, consumers that rent their building face significant split-incentive barriers. Regulation along with financial support, could see more landlords engaging. Also, consumers that are owner occupiers and that make investment decisions locally could benefit by more targeted impartial information followed by well-developed financing options.

8.3. Modelling

Three distinct modelling approaches were applied to answer the research questions and meet the aims of the thesis. The choice of modelling approach was based on the literature in each of the topic areas, and the implementation has drawn upon existing methods and added to these approaches in some cases.

8.3.1. Power system modelling

Power system modelling was used to examine RQ1(b) and RQ2. The decision to implement a simulation of the power system to examine RQ1(b) was based on a review of the methods carried out for RQ1(a). Simulation models of power system operation can provide detailed insights into how the deployment of variable renewable electricity generation affects other parts of the electricity system, but are generally applied to future scenarios. Criticism of this method points to the simplifying assumptions that forward-looking simulation models tend to implement and to the lack of transparency that can be associated with such detailed models. The approach outlined in Chapter 3 addresses this by implementing a novel dispatch model calibrated with publically available *ex-post* data.

The approach calibrates the model based on historic data, with high temporal resolution, and implements a two-stage model. The first stage of the model captures the impact of forecast uncertainty for wind output and electricity demand. The second stage uses the unit commitment starting point to meet actual electricity demand less actual wind energy output in each hour for a full year. A hypothetical Baseline – where all renewable generation is removed – acts as a benchmark to compare the impact of the actual 2012 system. This approach allowed detailed impacts to be evaluated, including the impact of wind on the emissions intensity of other units on the system.

Chapter 4 also uses the power systems modelling approach to investigate RQ2. An hourly demand profile is included in the model. Heat produced from gas CCGTs that retrofit CHP capabilities can meet the heat demand along with gas boiler peaking capacity and storage capacity. The use of this method allowed the short-run price and emissions impacts on the electricity and heat sectors to be investigated. The model produces a chronologically consistent, least cost dispatch of heat and power generators using high resolution data. This adds to previous approached that use more aggregated representations of generating units and chronology.

In addition, evaluations of district heating infrastructure that are internal to the heat sector are unlikely to capture the full costs and benefits of building the network infrastructure. Some studies make simplifying assumptions about the price of heat delivered from retrofitted CHP units based on the value of electricity production forgone and about the fuel and efficiency of generation that is replaced. For systems with low penetrations of renewable electricity, these assumptions are reasonable approximations, but they do not necessarily hold for systems with higher penetrations of variable renewable electricity generation. The method used in Chapter 4 allowed the type of fuel displaced to be quantified and the variability in the price of heat explored.

An important methodological aspect, separate to the power system modelling, explored in Chapter 4 is the method used to split fuel use in co-generation. Three primary methods are used and lead to large differences in the estimated impact on the heat and electricity systems. The analysis provides insight into the differences and potential policy implications of using individual methods.

8.3.2. Mixed-method simulation of bioenergy and renewable heat policy

A review of the literature on modelling on the use of biomass for energy was carried out in Chapter 5 and Chapter 6 to identify the approaches taken to examine bioenergy use. Optimisation modelling at an annual resolution has been the predominant approach, while a sub-section of the literature focuses on incorporating the spatial characteristics of biomass use. The hybrid techno-economic model developed in Chapter 5 takes some elements from the optimisation and simulation approaches previously used and adds a representation of heat consumer decision-making to build a decision support tool for policymaking. Bioenergy pathways are represented based on the typical approach

in the literature. An additional capacity to represent policy interventions to encourage bioenergy use in the heat, transport and power sectors is included. An important improvement in the approach is the representation of the heat sector as well as a representation of how energy consumers make decisions on the choice of heat-producing technologies. Heat demand is represented based on a detailed bottom-up representation of the building stock, and consumer decision-making preferences are based on detailed and statistically representative data of consumer preferences related to energy. This moves the resulting uptake results away from the 'winner takes all' phenomenon that other techno-economic optimisation models are prone to and gives a more lifelike representation of the impact of energy policy.

8.3.3. Empirical analysis

Chapter 7 examines the factors that influence consumer decisions to investigate the energy-saving options available to them. A logistic model is fitted to a statistically representative sample of business in the Irish commercial sector. Logistic models are a well-established method for examining the association of dependent variables with the probability of a particular binary outcome. In this case, the association between the building and consumer characteristics and the decision to investigate an energy-saving measure was determined. The decision to use a logistic model was determined by the sample size. Initially the possibility of using a Heckman model to investigate consumer investment decisions was examined. A Heckman approach would allow the factors that influence the decision to investigate options to be determined and then, controlling for this, the factors that influence the decision to invest in an energy measure to be established. The analysis in Chapter 7 used a pre-existing data set. A data collection approach that allows a more sophisticated model – such as a Heckman model – to be specified could allow further insights to be gained.

8.4. Limitations and further work

The research presented in this thesis has some limitations and raises questions with potential for further research:

- The power system simulation model developed to explore RQ1(b) requires detailed data and the implementation of a multi-stage simulation model that includes uncertainty. The regulatory authorities and system operators in Ireland publish the information. This is not available for all electricity systems and where it is substantial analytical effort is required. Further work to develop a more accessible assessment method that is verified by more detailed simulation could help policymakers to more easily assess the impacts of renewable electricity investments on CO_2 emissions.

- The Z-factor achievable at a CHP plant is a key factor in determining the competitiveness of the energy output from the unit. The analysis in this thesis used a single Z-factor for each hypothetical CCGT configuration, based on the best available information. Further work is required to better

quantify Z-factors under various circumstances and technology configurations. In addition, the temperature requirement of a heat network influences the Z-factor, and analysis to explore the impact of fourth-generation heat networks would also be useful. Further work is also required to assess the impact of CCGT-CHP upgrades on system flexibility and on wider energy market aspects such as the valuation of capacity.

- The location of biomass supply-chain elements is an important factor in locating bioenergy infrastructure, particularly at larger scales. Additional work to extend the transport distance methodology in the BioHEAT model to incorporate actual spatial data could improve the insights available from the modelling. In addition, the heat service demand in the BioHEAT model is based on a representation of the current building stock. Further work to incorporate the impact of energy efficiency policy on reducing heat demand and the underlying economic drivers for heat demand increases could also improve the model. Further work to link the model more directly with power and transport sector models would also yield more dynamic insights.

- The logit model used in Chapter 7 is limited to an examination of the factors that encourage or discourage companies from investigating an energy efficiency option. Further efforts in data collection could allow the modelling method to extend to an examination of the factors that also influence the decision to invest in an energy upgrade.

Bibliography

2009/28/EC, 2009a. DIRECTIVE 2009/28/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC.

2009/28/EC, 2009b. Directive 2009/28/EC European Parliament and of the Council of 23 April 2009 on the Promotion of the Use of Energy from Renewable Sources and Amending and Subsequently Repealing Directives 2001/77/EC and 2003/30/ EC. Off. J. Eur. Union 46.

2012/27/EC, 2012. Directive 2012/27/EU of the European Parliament and the Council of the 25 October 2012 on energy efficiency, 2012/27/EU.

AECOM for SEAI, 2015. Cost Benefit Analysis of the potential for High-Efficiency Cogeneration and Efficienct District Heating and Cooling in Ireland. The Sustainable Energy Authority of Ireland (SEAI), Wilton Palce, Dublin.

Agbor, E., Zhang, X., Kumar, A., 2014. A review of biomass co-firing in North America. Renew. Sustain. Energy Rev. 40, 930–943. https://doi.org/10.1016/j.rser.2014.07.195

Alex Kelly, Donna Gartland, 2016a. Fingal Spatial Energy Demand Analysis. Codema, Dublin.

Alex Kelly, Donna Gartland, 2016b. Dún Laoghaire–Rathdown Spatial Energy Demand Analysis. Codema, Dublin.

Alex Marvin, W., Schmidt, L.D., Benjaafar, S., Tiffany, D.G., Daoutidis, P., 2012. Economic Optimization of a Lignocellulosic Biomass-to-Ethanol Supply Chain. Chem. Eng. Sci., Dynamics, Control and Optimization of Energy Systems 67, 68–79. https://doi.org/10.1016/j.ces.2011.05.055

All Island Project (AIP), 2012. PLEXOS Validation RAs Validated SEM PLEXOS Forecast Model 2012-2013 [WWW Document]. Isl. Proj. URL http://www.allislandproject.org/en/market_decision_documents.aspx?article=261a5576-bd83-4544-b250-7b18b55bd9ba (accessed 7.28.14).

Almeida, E.L.F. de, 1998. Energy efficiency and the limits of market forces: The example of the electric motor market in France. Energy Policy 26, 643–653. https://doi.org/10.1016/S0301-4215(98)00023-8

Amor, M.B., Billette de Villemeur, E., Pellat, M., Pineau, P.-O., 2014. Influence of wind power on hourly electricity prices and GHG (greenhouse gas) emissions: Evidence that congestion matters from Ontario zonal data. Energy 66, 458–469. https://doi.org/10.1016/j.energy.2014.01.059

An Bord Pleanála, 2016. Planning Register Reference Number: PL2/15/129.

An Bord Pleanála, 2002. Planning Register Reference Number: 01/187.

An, H., Wilhelm, W.E., Searcy, S.W., 2011. A mathematical model to design a lignocellulosic biofuel supply chain system with a case study based on a region in Central Texas. Bioresour. Technol. 102, 7860–7870. https://doi.org/10.1016/j.biortech.2011.05.060

Andersen, F., Iturmendi, F., Espinosa, S., Diaz, M.S., 2012. Optimal design and planning of biodiesel supply chain with land competition. Comput. Chem. Eng., FOCAPO 2012 47, 170–182. https://doi.org/10.1016/j.compchemeng.2012.06.044

Anderson, S.T., Newell, R.G., 2004. Information programs for technology adoption: the case of energy-efficiency audits. Resour. Energy Econ. 26, 27–50. https://doi.org/10.1016/j.reseneeco.2003.07.001

Aramyan, L.H., Lansink, A.G.O., Verstegen, J.A., 2007. Factors underlying the investment decision in energy-saving systems in Dutch horticulture. Agric. Syst. 94, 520–527.

Australian Energy Market Operator, (AEMO), 2014. Carbon Dioxide Equivalent Intensity Index [WWW Document]. Aust. Energy Mark. Oper. URL http://www.sciencedirect.com/science?_ob=DownloadURL&_method=finish&_eidkey=1-s2.0-S0301421513007398&count=1&_docType=FLA&md5=8959fea5e228d3f59139f9f67d8cd7b9 (accessed 10.11.14).

Backlund, S., Thollander, P., Palm, J., Ottosson, M., 2012. Extending the energy efficiency gap. Energy Policy, Renewable Energy in China 51, 392–396. https://doi.org/10.1016/j.enpol.2012.08.042

Balling, L., 2011. Fast cycling and rapid start-up: new generation of plants achieves impressive results. Mod. Power Syst. San Franc. CA 31, 35–41.

Baringa for CRU, 2016. Baringa SEM PLEXOS Forecast Model for 2016-17 [WWW Document]. SEM Comm. URL https://www.semcommittee.com/news-centre/baringa-sem-plexos-forecast-model-2016-17 (accessed 4.21.17).

Bazilian, M., Rogner, H., Howells, M., Hermann, S., Arent, D., Gielen, D., Steduto, P., Mueller, A., Komor, P., Tol, R.S.J., Yumkella, K.K., 2011a. Considering the energy, water and food nexus: Towards an integrated modelling approach. Energy Policy, Clean Cooking Fuels and Technologies in Developing Economies 39, 7896–7906. https://doi.org/10.1016/j.enpol.2011.09.039

Bazilian, M., Rogner, H., Howells, M., Hermann, S., Arent, D., Gielen, D., Steduto, P., Mueller, A., Komor, P., Tol, R.S.J., Yumkella, K.K., 2011b. Considering the energy, water and food nexus: Towards an integrated modelling approach. Energy Policy, Clean Cooking Fuels and Technologies in Developing Economies 39, 7896–7906. https://doi.org/10.1016/j.enpol.2011.09.039

Bentsen, N.S., Jack, M.W., Felby, C., Thorsen, B.J., 2014. Allocation of biomass resources for minimising energy system greenhouse gas emissions. Energy 69, 506–515. https://doi.org/10.1016/j.energy.2014.03.045

Berndes, G., Hansson, J., 2007. Bioenergy expansion in the EU: Cost-effective climate change mitigation, employment creation and reduced dependency on imported fuels. Energy Policy 35, 5965–5979. https://doi.org/10.1016/j.enpol.2007.08.003

Blumstein, C., Krieg, B., Schipper, L., York, C., 1980. Overcoming social and institutional barriers to energy conservation. Energy 5, 355–371.

Bord na Mona, 2016. Sustainability 2030.

Braun, F.G., 2010. Determinants of households' space heating type: A discrete choice analysis for German households. Energy Policy, The socio-economic transition towards a hydrogen economy - findings from European research, with regular papers 38, 5493–5503. https://doi.org/10.1016/j.enpol.2010.04.002

Brown, M.A., 2001. Market failures and barriers as a basis for clean energy policies. Energy Policy 29, 1197–1207.

Bundestag, D., 2008. Gesetz zur Neuregelung des Rechts der Erneuerbaren Energien im Strombereich und zur Änderung damit zusammenhängender Vorschriften (Erneuerbare-Energien-Gesetz, EEG 2009), amtliche Fassung vom 25. 10 2008. Bundesgesetzblatt 49, 2074–2100.

Burton, J., Hubacek, K., 2007. Is small beautiful? A multicriteria assessment of small-scale energy technology applications in local governments. Energy Policy 35, 6402–6412. https://doi.org/10.1016/j.enpol.2007.08.002

Byrne Ó Cléirigh for SEI, 2009. Combined Heat and Power (CHP) Potential in Ireland. Sustainable Energy Authority of Ireland (SEAI), Dublin.

Byrne Ó Cléirigh, LHM Casey McGrath, 2017. THE BIOFUELS OBLIGATION SCHEME ANNUAL REPORT 2016 (No. 457-X0174). National Oil Reserves Agency (NORA).

Cagno, E., Trianni, A., 2013. Exploring drivers for energy efficiency within small- and medium-sized enterprises: First evidences from Italian manufacturing enterprises. Appl. Energy 104, 276–285. http://dx.doi.org/10.1016/j.apenergy.2012.10.053

Cagno, E., Worrell, E., Trianni, A., Pugliese, G., 2013. A novel approach for barriers to industrial energy efficiency. Renew. Sustain. Energy Rev. 19, 290–308. https://doi.org/10.1016/j.rser.2012.11.007

Calnan, P., Deane, J.P., Ó Gallachóir, B.P., 2013. Modelling the impact of EVs on electricity generation, costs and CO2 emissions: Assessing the impact of different charging regimes and future generation profiles for Ireland in

2025. Energy Policy 61, 230–237. https://doi.org/10.1016/j.enpol.2013.05.065

Cambero, C., Sowlati, T., 2014. Assessment and optimization of forest biomass supply chains from economic, social and environmental perspectives – A review of literature. Renew. Sustain. Energy Rev. 36, 62–73. https://doi.org/10.1016/j.rser.2014.04.041

Capros, P., De Vita, A., Tasios, N., Papadopoulos, D., Siskos, P., Apostolaki, E., Zampara, M., Paroussos, L., Fragiadakis, K., Kouvaritakis, N., others, 2013. EU Energy, Transport and GHG Emissions: Trends to 2050, reference scenario 2013.

Capros, P., De Vita, A., Tasios, N., Siskos, P., Kannavou, M., Petropoulos, A., Evangelopoulou, S., Zampara, M., Papadopoulos, D., Nakos, C., others, 2016. EU Reference Scenario 2016-Energy, transport and GHG emissions Trends to 2050.

Central Economic Evaluation Unit, Department of Public Expenditure and Reform, 2017. The Public Spending Code: E. Technical References Shadow Price of Carbon. Department of Public Expenditure and Reform, Dublin.

Central Statistics Office, 2016. Census 2016 Summary Results - Part 1 - CSO - Central Statistics Office, Census 2016. Central Statistics Office, Dublin.

Central Statistics Office, 2014. Business Demography 2014 [WWW Document]. URL http://www.cso.ie/en/releasesandpublications/er/bd/businessdemography2014/ (accessed 1.21.17).

Chen, C.-W., Fan, Y., 2012. Bioethanol supply chain system planning under supply and demand uncertainties. Transp. Res. Part E Logist. Transp. Rev., Select Papers from the 19th International Symposium on Transportation and Traffic Theory 48, 150–164. https://doi.org/10.1016/j.tre.2011.08.004

Chiodi, A., Deane, P., Gargiulo, M., Gallachóir, B.Ó., 2015. The Role of Bioenergy in Ireland's Low Carbon Future – is it Sustainable? J. Sustain. Dev. Energy Water Environ. Syst. 3, 196–216. https://doi.org/10.13044/j.sdewes.2015.03.0016

Chiodi, A., Gargiulo, M., Rogan, F., Deane, J., Lavigne, D., Rout, U.K., Gallachóir, B.P.Ó., 2013a. Modelling the impacts of challenging 2050 European climate mitigation targets on Ireland's energy system. Energy Policy 53, 169–189.

Chiodi, A., Gargiulo, M., Rogan, F., Deane, J.P., Lavigne, D., Rout, U.K., Ó Gallachóir, B.P., 2013b. Modelling the impacts of challenging 2050 European climate mitigation targets on Ireland's energy system. Energy Policy 53, 169–189. https://doi.org/10.1016/j.enpol.2012.10.045

Chris Heaton-Harris et al., 2012. Full letter from MPs to David Cameron on wind power subsidies. The Telegraph.

Clancy, J.M., Curtis, J., O'Gallachóir, B.P., 2017. What are the factors that discourage companies in the Irish commercial sector from investigating energy saving options? Energy Build. 146, 243–256. https://doi.org/10.1016/j.enbuild.2017.04.077

Clancy, J.M., Gaffney, F., Deane, J.P., Curtis, J., Ó Gallachóir, B.P., 2015. Fossil fuel and CO2 emissions savings on a high renewable electricity system – A single year case study for Ireland. Energy Policy 83, 151–164. https://doi.org/10.1016/j.enpol.2015.04.011

Collins, S., Deane, J.P., Poncelet, K., Panos, E., Pietzcker, R.C., Delarue, E., Ó Gallachóir, B.P., 2017. Integrating short term variations of the power system into integrated energy system models: A methodological review. Renew. Sustain. Energy Rev. 76, 839–856. https://doi.org/10.1016/j.rser.2017.03.090

Colmenar-Santos, A., Rosales-Asensio, E., Borge-Diez, D., Mur-Pérez, F., 2015. Cogeneration and district heating networks: Measures to remove institutional and financial barriers that restrict their joint use in the EU-28. Energy 85, 403–414. https://doi.org/10.1016/j.energy.2015.03.088

Comber, A., Dickie, J., Jarvis, C., Phillips, M., Tansey, K., 2015. Locating bioenergy facilities using a modified GIS-based location–allocation-algorithm: Considering the spatial distribution of resource supply. Appl. Energy 154, 309–316. https://doi.org/10.1016/j.apenergy.2015.04.128

Commission for Energy Regulation, 2017. CER17241 PSO Levy 2017-18 Decision Paper (No. CER/17/241). CER.

Connolly, D., Lund, H., Mathiesen, B.V., Werner, S., Möller, B., Persson, U., Boermans, T., Trier, D., Østergaard, P.A., Nielsen, S., 2014. Heat Roadmap Europe: Combining district heating with heat savings to decarbonise the EU energy system. Energy Policy 65, 475–489. https://doi.org/10.1016/j.enpol.2013.10.035

Cooremans, C., 2012a. Investment in energy efficiency: do the characteristics of investments matter? Energy Effic. 5, 497–518.

Cooremans, C., 2012b. Investment in energy efficiency: do the characteristics of investments matter? Energy Effic. 5, 497–518.

Creutzig, F., Popp, A., Plevin, R., Luderer, G., Minx, J., Edenhofer, O., 2012. Reconciling top-down and bottom-up modelling on future bioenergy deployment. Nat. Clim. Change 2, 320–327. https://doi.org/10.1038/nclimate1416

Cullen, J., 2013. Measuring the Environmental Benefits of Wind-Generated Electricity. Am. Econ. J. Econ. Policy 5, 107–133. https://doi.org/10.1257/pol.5.4.107

Cundiff, J.S., Dias, N., Sherali, H.D., 1997. A linear programming approach for designing a herbaceous biomass delivery system. Bioresour. Technol. 59, 47–55. https://doi.org/10.1016/S0960-8524(96)00129-0

Curtis, J., Di Cosmo, V., Deane, P., 2014. Climate policy, interconnection and carbon leakage: The effect of unilateral UK policy on electricity and GHG emissions in Ireland. Econ. Energy Environ. Policy 3. https://doi.org/10.5547/2160-5890.3.2.jcur

Daniela Thrän, David Peetz, Kay Schaubach, Sofia Backéus, Luca Benedetti, Lena Bruce, Suani Teixeira Coelho, Laura Craggs, Rocio Diaz-Chavez, Javier Farago Escobar, Jose Goldemberg, Ruben Guisson, Morten Tony Hansen, Jussi Heinimö, Bo Hektor, J. Richard Hess, Martin Junginger, Patrick Lamers, Thuy Mai-Moulin, Gordon Murray, Olle Olsson, Alessandro Pellini, Svetlana Proskurina, Fabian Schipfer, Peter-Paul Schouwenberg, Wolfgang Stelte, Ute Thiermann, Erik Trømborg, Lotte Visser, Michael Wild, 2017. Global Wood Pellet Industry and Trade Study 2017 (No. ISBN 978-1-910154-32-8). IEA Bioenergy Task 40.

David Andrews, Anna Krook Riekkola, Evangelos Tzimas, Joana Serpa, Johan Carlsson, Nico Pardo-Garcia, Ioulia Papaioannou, 2012. Background Report on EU-27 District-Heating and Cooling Potentials, Barriers, Best Practice and Measures of Promotion (No. Report EUR 25289 EN), JRC Scientific and policy reports. Joint Research Centre, European Commission, Luxembourg: Publications Office of the European Union.

DCENR (Department of Communications, Energy and Natural Resources), 2015. White Paper on Ireland's Transition to a Low Carbon Energy Future. DCENR, Dublin.

DCENR (IE) / DETI (UK), 2008. All Island Grid Study, Work Stream 4, Analysis of Impacts and Benifits, All-Island Grid Study. Department of Communications, Energy and Natural Resources / Department of Enterprise, Trade and Investment, Dublin / Belfast.

de Groot, H.L.F., Verhoef, E.T., Nijkamp, P., 2001. Energy saving by firms: decision-making, barriers and policies. Energy Econ. 23, 717–740. https://doi.org/10.1016/S0140-9883(01)00083-4

De Meyer, A., Cattrysse, D., Rasinmäki, J., Van Orshoven, J., 2014. Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review. Renew. Sustain. Energy Rev. 31, 657–670. https://doi.org/10.1016/j.rser.2013.12.036

Deane, J., McKeogh, E., Gallachóir, B., 2013. Derivation of intertemporal targets for large pumped hydro energy storage with stochastic optimization. IEEE Trans Power Syst Doi 10, 1109.

Deane, J.P., Drayton, G., Ó Gallachóir, B.P., 2014. The impact of sub-hourly modelling in power systems with significant levels of renewable generation.

Appl. Energy 113, 152–158. https://doi.org/10.1016/j.apenergy.2013.07.027

DeCanio, S.J., 1998. The efficiency paradox: bureaucratic and organizational barriers to profitable energy-saving investments. Energy Policy 26, 441–454.

Decanio, S.J., 1994. Agency and Control Problems in US Corporations: The Case of Energy-efficient Investment Projects. Int. J. Econ. Bus. 1, 105–124. https://doi.org/10.1080/758540502

DeCanio, S.J., 1993. Barriers within firms to energy-efficient investments. Energy Policy 21, 906–914.

DeCanio, S.J., Watkins, W.E., 1998. Investment in Energy Efficiency: Do the Characteristics of Firms Matter? Rev. Econ. Stat. 80, 95–107. https://doi.org/10.1162/003465398557366

DECC, 2012. Quarterly Energy Prices. Department of Energy and Climate Change, London.

Denholm, P., Wan, Y.H., Hummon, M., Mehos, M., 2013. Analysis of Concentrating Solar Power with Thermal Energy Storage in a California 33% Renewable Scenario (No. NREL/TP-6A20-58186). National Renewable Energy Laboratory (NREL), Golden, CO.

Denny, E., O'Malley, M., 2007. Quantifying the Total Net Benefits of Grid Integrated Wind. IEEE Trans. Power Syst. 22, 605–615. https://doi.org/10.1109/TPWRS.2007.894864

Denny, E., O'Malley, M., 2006. Wind generation, power system operation, and emissions reduction. IEEE Trans. Power Syst. 21, 341–347. https://doi.org/10.1109/TPWRS.2005.857845

Denny, E., Tuohy, A., Meibom, P., Keane, A., Flynn, D., Mullane, A., O'Malley, M., 2010. The impact of increased interconnection on electricity systems with large penetrations of wind generation: A case study of Ireland and Great Britain. Energy Policy 38, 6946–6954. http://dx.doi.org/10.1016/j.enpol.2010.07.011

Department for Business, Energy & Industrial Stragety, 2016. Digest of United Kingdom Energy Statistics. Department for Business, Energy & Industrial Stragety.

Department for Business, Energy & Industrial Strategy, 2016. Fossil Fuel Price Assumptions: 2016.

Department of Communications, Climate Action and Environment, 2017a. Support Scheme for Renewable Heat.

Department of Communications, Climate Action and Environment, 2017b. 2030 EU Targets [WWW Document]. URL https://www.dccae.gov.ie/en-ie/climate-action/topics/eu-and-international-climate-action/2030-eu-targets/Pages/default.aspx (accessed 3.30.18).

Department of Communications, Climate Action and Environment, 2017c. Public Consultation on the Biofuel Obligation Rate Scheme [WWW Document]. URL https://www.dccae.gov.ie/en-ie/news-and-media/consultations/Pages/Biofuel-Obligation-Rate-Consultation.aspx (accessed 3.30.18).

Department of Communications, Climate Action and Environment, 2017d. REFIT Schemes and Supports [WWW Document]. REFIT Schemes. URL http://www.dccae.gov.ie/en-ie/energy/topics/Renewable-Energy/electricity/renewable-electricity-supports/Pages/REFIT-Schemes-and-Supports.aspx (accessed 4.19.17).

Department of Communications, Climate Action and Environment, 2017e. Renewable Electricity Support Scheme - Design Consultation [WWW Document]. URL https://www.dccae.gov.ie/en-ie/energy/consultations/Pages/Renewable-Electricity-Support-Scheme-Design-Consultation.aspx (accessed 2.7.18).

Department of Communications, Climate Action and Environment, 2014. Draft Bioenergy Plan. Department of Communications, Climate Action and Environment, Dublin.

Department of Public Expenditure and Reform, 2018. –National Development Plan 2018-2027. DPER, Dublin.

Di Cosmo, V., Curtis, J., Deane, P., 2013. Climate policy, interconnection and carbon leakage: the effect of unilateral UK policy on electricity and GHG emissions in Ireland (Working Paper). ESRI.

Di Cosmo, V., Valeri, L.M., 2014. The Effect of Wind on Electricity CO2 Emissions: The Case of Ireland, Working Paper No. 493. Economic and Social Research Institute, Dublin., Dublin.

Diederen, P., Van Tongeren, F., Van Der Veen, H., 2003. Returns on investments in energy-saving technologies under energy price uncertainty in Dutch greenhouse horticulture. Environ. Resour. Econ. 24, 379–394.

Diffney, S., Gerald, J.F., Lyons, S., Valeri, L.M., 2009. Investment in electricity infrastructure in a small isolated market: the case of Ireland. Oxf. Rev. Econ. Policy 25, 469–487. https://doi.org/10.1093/oxrep/grp022

Difs, K., Trygg, L., 2009. Pricing district heating by marginal cost. Energy Policy 37, 606–616. https://doi.org/10.1016/j.enpol.2008.10.003

Dina Bacovsky, Nikolaus Ludwiczek, Christian Pointer, Vijay Kumar Verma, 2016. IEA Bioenergy Countries' Report. Bioenergy policies and status of implementation (796 TR N4102901601). IEA Bioenegry.

Donna Gartland, 2015. Dublin City Spatial Energy Demand Analysis. Codema, Dublin.

Donna Gartland, Tom Bruton, 2017. A Guide to District Heating in Ireland, SEAI RD&D funded. Codema / IrBEA, Dublin.

Dublin City Council, 2016. Dublin District Heating System [WWW Document]. URL http://www.dublincity.ie/ddhs (accessed 7.15.17).

Dunnett, A.J., Adjiman, C.S., Shah, N., 2008. A spatially explicit whole-system model of the lignocellulosic bioethanol supply chain: an assessment of decentralised processing potential. Biotechnol. Biofuels 1, 13. https://doi.org/10.1186/1754-6834-1-13

Durusut, E., Tahir, F., Foster, S., Dineen, D., Clancy, M., 2018. BioHEAT: A policy decision support tool in Ireland's bioenergy and heat sectors. Appl. Energy 213, 306–321. https://doi.org/10.1016/j.apenergy.2017.12.111

ECN, 2011. Data on renewable energy in the European Union Member States [WWW Document]. URL https://www.ecn.nl/projects/nreap/home/ (accessed 5.5.14).

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., others, 2014. Climate change 2014: mitigation of climate change. Contrib. Work. Group III Fifth Assess. Rep. Intergov. Panel Clim. Change 511–597.

Eichhammer, W., Fleiter, T., Schlomann, B., Faberi, S., Fioretto, M., Piccioni, N., Lechtenböhmer, S., Schüring, A., Resch, G., 2009. Study on the energy savings potentials in EU member states, candidate countries and EEA countries.

EirGrid, 2017. All-Island Generation Capacity Statement 2017-2026, Generation Capacity Statement. Dublin / Belfast.

EirGrid, 2013. 2012 Curtailment Report. EirGrid/SONI, Dublin.

EirGrid, 2012. 2011 Curtailment Report. EirGrid/SONI, Dublin.

EirGrid, 2007. Wind Powered Generation An analytical framework to assess generation cost implications. EirGrid, Dublin.

EirGrid Group, 2017. Wind Record Broken [WWW Document]. URL http://www.eirgridgroup.com/newsroom/wind-record/index.xml (accessed 4.29.17).

EirGrid Group, 2016. Generation Capacity Statement 2016-2025. EirGrid Group, Dublin/Belfast.

EirGrid Group, 2013. Annual Renewbale Report 2013 Towards a Smart, Sustainable Energy Future (Annual Report). EirGrid Group, Dublin/Belfast.

EirGrid, SONI, 2010. All Island TSO Facilitation of Renewables Studies. Final Report. EirGrid/SONI, Dublin/Belfast.

EirGrid/SONI, 2014. Wind Forecast Accuracy Statistics [WWW Document]. URL http://www.eirgridgroup.com/site-files/library/EirGrid/All_Island_Wind_Forecast_Accuracy_Report_March_2013.pdf

EirGrid/SONI, 2013a. Generation Capacity Statement 2013-2022. EirGrid/SONI, Dublin/Belfast.

EirGrid/SONI, 2013b. Operational Constraints Update. Dublin/Belfast.

Ela, E., Milligan, M., Kirby, B., 2011. Operating reserves and variable generation (No. 303).

Element Energy and Frontier economics for DCCAE and SEAI, 2017. Economic analysis for the RHI in Ireland [WWW Document]. URL https://www.dccae.gov.ie/documents/Economic%20analysis%20for%20the%20RHI%20in%20Ireland.pdf (accessed 1.19.18).

Element Energy and The Research Perspective for SEAI, 2015a. Extensive survey of the commercial buildings stock in the Republic of Ireland, Insights Report. Sustainable Energy Authority of Ireland (SEAI), Dublin.

Element Energy and The Research Perspective for SEAI, 2015b. Survey of consumer behaviour in the commercial sector in the Republic of Ireland, Insights Report. Sustainable Energy Authority of Ireland (SEAI), Dublin.

Element Energy for SEAI, 2015. Energy efficiency investment pathways in Ireland. Appendix: Methodology and technical assumptions.

Element Energy on behalf of Committee on Climate Change, 2009. Uptake of Energy Efficiency in buildings. Committee on Climate Change.

Element Energy, TNS, Ken Willis, Riccardo Scarpa, Alistair Munro, 2008. The growth potential for Microgeneration in England, Wales and Scotland. BERR, Cambridge.

Energy Exemplar, 2014. PLEXOS® Integrated Energy Model [WWW Document]. URL http://energyexemplar.com/software/plexos-desktop-edition/ (accessed 5.14.14).

EPA, 2017a. Ireland's Provisional Greenhouse Gas Emissions. Environmental Protection Agency.

EPA, 2017b. Ireland's Greenhouse Gas Emission Projections. Environmental Protection Agency.

ESB National Grid, 2004. Impact of Wind Power Generation In Ireland on the Operation of Conventional Plant and the Economic Implications. ESB National Grid, Dublin.

Euro Heat & Power, 2017. Country by Country. Euro Heat and Power.

European Commission, 2016a. Cogeneration of heat and power [WWW Document]. Energy. URL /energy/en/topics/energy-efficiency/cogeneration-heat-and-power (accessed 7.11.17).

European Commission, 2016b. Market Stability Reserve [WWW Document]. Clim. Action - Eur. Comm. URL https://ec.europa.eu/clima/policies/ets/reform_en (accessed 8.25.17).

European Commission, 2016c. EU Energy in Figures. Publications Office of the European Union, Luxembourg.

European Commission, 2013. Guidance note on Directive 2012/27/EU on energy efficiency, amending Directives 2009/125/EC and 2010/30/EC, and repealing Directives 2004/8/EC and 2006/32/EC Article 14: Promotion of efficiency in heating and cooling.

European Commission, 2011. The roadmap for transforming the EU into a competitive, low-carbon economy by 2050. European Commission, Brussels.

European Council, 2016. 2030 climate & energy framework [WWW Document]. Clim. Action - Eur. Comm. URL https://ec.europa.eu/clima/policies/strategies/2030_en (accessed 2.16.18).

European Environment Agency, 2017. Total greenhouse gas emission trends and projections [WWW Document]. Eur. Environ. Agency. URL https://www.eea.europa.eu/data-and-maps/indicators/greenhouse-gas-emission-trends-6/assessment-1 (accessed 2.16.18).

European Parliament, 2017. Effort sharing regulation, 2021-2030. Legislation in Progress Briefing.

Eurostat, 2017. Energy Statistics Manual - Product - Eurostat [WWW Document]. URL http://ec.europa.eu/eurostat/en/web/products-manuals-and-guidelines/-/NRG-2004 (accessed 5.6.17).

EWEA, 2011. Wind Energy and Climate Change Policy, Achieving 30% lower emissions by 2030.

Eyre, N., 1997. Barriers to energy efficiency: more than just market failure. Energy Environ. 8, 25–43.

Fay, D., Ringwood, J., 2010. On the Influence of Weather Forecast Errors in Short-Term Load Forecasting Models. IEEE Trans. Power Syst. 25.

Fealy, R., O'Donoghue, C., Hanrahan, K., Martin, M., Shulte, R.P., 2012. Modelling the Gross Cost of Transporting Pig Slurry to Tillage Spread Lands in a Post Transition Arrangement within the Nitrates Directive. (Working Paper). Teagasc, Oak Park, Carlow, Ireland.

Fisher, A.C., Rothkopf, M.H., 1989. Market failure and energy policy A rationale for selective conservation. Energy Policy 17, 397–406. https://doi.org/10.1016/0301-4215(89)90010-4

Fleiter, T., Schleich, J., Ravivanpong, P., 2012a. Adoption of energy-efficiency measures in SMEs—An empirical analysis based on energy audit data from Germany. Energy Policy, Renewable Energy in China 51, 863–875. https://doi.org/10.1016/j.enpol.2012.09.041

Fleiter, T., Schleich, J., Ravivanpong, P., 2012b. Adoption of energy-efficiency measures in SMEs—An empirical analysis based on energy audit data from Germany. Energy Policy 51, 863–875.

FNR, 2015. Biokraftstoffquotengesetz [WWW Document]. URL https://bioenergie.fnr.de/rahmenbedingungen/gesetze-verordnungen-richtlinien/gesetzeslage/biokraftstoff-quotengesetz/ (accessed 3.21.17).

Foley, A.M., Ó Gallachóir, B.P., McKeogh, E.J., Milborrow, D., Leahy, P.G., 2013. Addressing the technical and market challenges to high wind power integration in Ireland. Renew. Sustain. Energy Rev. 19, 692–703. https://doi.org/10.1016/j.rser.2012.11.039

Fragkos, P., Tasios, N., Paroussos, L., Capros, P., Tsani, S., 2017. Energy system impacts and policy implications of the European Intended Nationally Determined Contribution and low-carbon pathway to 2050. Energy Policy 100, 216–226. https://doi.org/10.1016/j.enpol.2016.10.023

Franco, C., Bojesen, M., Hougaard, J.L., Nielsen, K., 2015. A fuzzy approach to a multiple criteria and Geographical Information System for decision support on suitable locations for biogas plants. Appl. Energy 140, 304–315. https://doi.org/10.1016/j.apenergy.2014.11.060

Freppaz, D., Minciardi, R., Robba, M., Rovatti, M., Sacile, R., Taramasso, A., 2004. Optimizing forest biomass exploitation for energy supply at a regional level. Biomass Bioenergy 26, 15–25. https://doi.org/10.1016/S0961-9534(03)00079-5

Frombo, F., Minciardi, R., Robba, M., Rosso, F., Sacile, R., 2009. Planning woody biomass logistics for energy production: A strategic decision model. Biomass Bioenergy 33, 372–383. https://doi.org/10.1016/j.biombioe.2008.09.008

Genevieve Alberts, Maria Ayuso, Ausilio Bauen, Francisco Boshell, Claire Chudziak, Jan Peer Gebauer, Lizzie German, Martin Kaltschmitt, Lucy Nattrass, Ralph Ripken, Paul Robson, Richard Taylor, Hannes Wagner, 2016. Advanced Liquid Biofuels (No. ISBN 978-92-95111-52-3). International Renewable Energy Agency.

Ger Devlin, 2010. Fuel consumption of timber haulage versus general haulage (COFORD Connects No. 22), Coford Connects Harvesting / Transportation No. 22. COFORD, Dept. Agriculture, Fisheries & Food Agriculture House, Kildare Street Dublin 2, Ireland, Dublin.

Global Energy Observatory, 2017a. Poolbeg CCGT Power Plant Ireland [WWW Document]. URL http://www.globalenergyobservatory.org/geoid/43924 (accessed 8.15.17).

Global Energy Observatory, 2017b. Dublin Bay (Ringsend) CCGT Power Plant Ireland [WWW Document]. URL http://www.globalenergyobservatory.org/geoid/43926 (accessed 8.15.17).

Global Energy Observatory, 2017c. Huntstown CCGT Power Plant Ireland [WWW Document]. URL http://www.globalenergyobservatory.org/geoid/43933 (accessed 8.15.17).

Glynn, J., Chiodi, A., Ó Gallachóir, B., 2017. Energy security assessment methods: Quantifying the security co-benefits of decarbonising the Irish Energy System. Energy Strategy Rev. 15, 72–88. https://doi.org/10.1016/j.esr.2016.11.005

Golove, W.H., Eto, J.H., 1996. Market barriers to energy efficiency: a critical reappraisal of the rationale for public policies to promote energy efficiency. LBL-38059 Berkeley CA Lawrence Berkeley Natl. Lab.

Gonzalez-Salazar, M.A., Venturini, M., Poganietz, W.-R., Finkenrath, M., Kirsten, T., Acevedo, H., Spina, P.R., 2016. A general modeling framework to evaluate energy, economy, land-use and GHG emissions nexus for bioenergy exploitation. Appl. Energy 178, 223–249. https://doi.org/10.1016/j.apenergy.2016.06.039

Government of Canada, 2010. Renewable Fuels Regulations, SOR/2010-189.

Government of the UK, 2017a. Contracts for Difference [WWW Document]. URL https://www.gov.uk/government/publications/contracts-for-difference/contract-for-difference (accessed 3.30.18).

Government of the UK, 2017b. Renewable Heat Incentive statistics [WWW Document]. URL https://www.gov.uk/government/collections/renewable-heat-incentive-statistics (accessed 3.21.17).

Government of the UK, 2016a. Updated short-term traded carbon values used for modelling purposes [WWW Document]. URL

https://www.gov.uk/government/publications/updated-short-term-values-used-for-modelling-purposes-2016 (accessed 4.21.17).

Government of the UK, 2016b. Feed-in tariffs: get money for generating your own electricity [WWW Document]. URL /feed-in-tariffs/overview (accessed 3.21.17).

Government of the UK, 2015. The Renewable Transport Fuel Obligations (Amendment), 2015 No. 53.

Government of the UK, 2009. Non-domestic Renewable Heat Incentive (RHI) [WWW Document]. URL https://www.gov.uk/non-domestic-renewable-heat-incentive (accessed 3.21.17).

Graham, J.W., 2009. Missing data analysis: Making it work in the real world. Annu. Rev. Psychol. 60, 549–576.

Graham, J.W., Olchowski, A.E., Gilreath, T.D., 2007. How many imputations are really needed? Some practical clarifications of multiple imputation theory. Prev. Sci. 8, 206–213.

Graham, P.W., Brinsmead, T., Reedman, L.J., others, 2011. An assessment of competition for biomass resources within the energy and transport sectors, in: 55th Annual National Conference of the Australia Agricultural & Resources Economics Society. Melbourne, Australia.

Gruber, E., Brand, M., 1991. Promoting energy conservation in small and medium-sized companies. Energy Policy 19, 279–287.

Hansson, J., Berndes, G., Johnsson, F., Kjärstad, J., 2009. Co-firing biomass with coal for electricity generation—An assessment of the potential in EU27. Energy Policy 37, 1444–1455. https://doi.org/10.1016/j.enpol.2008.12.007

Harris, J., Anderson, J., Shafron, W., 2000. Investment in energy efficiency: a survey of Australian firms. Energy Policy 28, 867–876.

Havlík, P., Schneider, U.A., Schmid, E., Böttcher, H., Fritz, S., Skalský, R., Aoki, K., Cara, S.D., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., Obersteiner, M., 2011. Global land-use implications of first and second generation biofuel targets. Energy Policy, Sustainability of biofuels 39, 5690–5702. https://doi.org/10.1016/j.enpol.2010.03.030

Hirst, E., Brown, M., 1990. Closing the efficiency gap: barriers to the efficient use of energy. Resour. Conserv. Recycl. 3, 267–281. https://doi.org/10.1016/0921-3449(90)90023-W

Hodge, B.-M., Lew, D., Milligan, M., Holttinen, H., Sillanpää, S., Gómez-Lázaro, E., Scharff, R., Söder, L., Larsén, X.G., Giebel, G., Flynn, D., Dobschinski, J., 2012. Wind Power Forecasting Error Distributions : An International Comparison, in: NREL/CP-5500-56130. Presented at the The 11th Annual

International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants Conference, Lisbon.

Höhn, J., Lehtonen, E., Rasi, S., Rintala, J., 2014. A Geographical Information System (GIS) based methodology for determination of potential biomasses and sites for biogas plants in southern Finland. Appl. Energy 113, 1–10. https://doi.org/10.1016/j.apenergy.2013.07.005

Holmberg, H., Tuomaala, M., Haikonen, T., Ahtila, P., 2012. Allocation of fuel costs and CO2-emissions to heat and power in an industrial CHP plant: Case integrated pulp and paper mill. Appl. Energy, (1) Green Energy; (2)Special Section from papers presented at the 2nd International Enery 2030 Conf 93, 614–623. https://doi.org/10.1016/j.apenergy.2011.11.040

Holttinen, H., 2005. Impact of hourly wind power variations on the system operation in the Nordic countries. Wind Energy 8, 197–218. https://doi.org/10.1002/we.143

Holttinen, H., O'Malley, M., Dillon, J., Carlini, E.M., Vergine, C., Kondoh, J., Gibescu, M., Tande, J.O., Estanqueiro, A., Gomez, E., Söder, L., Smith, J.C., Milligan, M., Lew, D., 2013. Design and operation of power systems with large amounts of wind power Final summary report, IEA WIND Task 25, Phase two 2009–2011 (No. Phase 2), VTT Technology 75. VTT, Espo.

Horschig, T., Thrän, D., 2017. Are decisions well supported for the energy transition? A review on modeling approaches for renewable energy policy evaluation. Energy Sustain. Soc. 7, 5. https://doi.org/10.1186/s13705-017-0107-2

Horton, N.J., Kleinman, K.P., 2007. Much ado about nothing. Am. Stat. 61.

Howarth, R.B., Andersson, B., 1993. Market barriers to energy efficiency. Energy Econ. 15, 262–272.

Howley, M., Holland, M., O'Rourke, K., 2014. Renewable Energy in Ireland 2012 Update. Sustainable Energy Authority of Ireland (SEAI), Dublin.

Huang, Y., Chen, C.-W., Fan, Y., 2010. Multistage optimization of the supply chains of biofuels. Transp. Res. Part E Logist. Transp. Rev. 46, 820–830. https://doi.org/10.1016/j.tre.2010.03.002

Iakovou, E., Karagiannidis, A., Vlachos, D., Toka, A., Malamakis, A., 2010. Waste biomass-to-energy supply chain management: A critical synthesis. Waste Manag., Anaerobic Digestion (AD) of Solid Waste 30, 1860–1870. https://doi.org/10.1016/j.wasman.2010.02.030

IEA, 2017a. World Energy Outlook. Paris.

IEA, 2017b. Tracking Clean Energy Progress 2017., Energy Technology Perspectives 2017 Excerpt Informing Energy Sector Transformations. International Energy Agency, Paris.

IEA, 2016. World Energy Outlook 2016 [WWW Document]. URL https://www.iea.org/newsroom/news/2016/november/world-energy-outlook-2016.html (accessed 8.22.17).

IEA, 2014a. Energy Prices and Taxes. OECD/IEA, Paris.

IEA, 2014b. Capturing the Multiple Benefits of Energy Efficiency. OECD/IEA.

IEA, 2013a. The Power of Transformation -- Wind, Sun and the Economics of Flexible Power Systems. OECD/IEA, Paris.

IEA, 2013b. Medium -Term Renewable Energy Market Report 2013 -- Market trends and projections to 2018. OECD/IEA, Paris.

IEA, 2012a. Publication: Technology Roadmap: Bioenergy for Heat and Power [WWW Document]. URL http://www.iea.org/publications/freepublications/publication/technology-roadmap-bioenergy-for-heat-and-power-.html (accessed 5.11.17).

IEA, 2012b. World Energy Outlook 2012.

IEA., 2007. Mind the Gap: Quantifying Principal-Agent Problems in Energy Efficiency. Organisation for Economic Co-operation and Development.

IEA ETSAP, IRENA, 2013. Thermal Energy Storage (No. E17), Technology Brief. International Renewable Energy Agency and Enegry Technology Systems Analysis Programme.

IEA ETSAP, IRENA, 2010. Industrial Combustion Boilers (No. I01), Technology Brief. International Renewable Energy Agency and Enegry Technology Systems Analysis Programme.

IEA Wind, 2017. IEA Wind TCP Annual Report 2016. Executive Committee of the Implementing Agreement for Co-operation in the Research, Development, and Deployment of Wind Energy Systems of the International Energy Agency.

IEA Wind, 2013. IEA Wind 2012 Annual Report. Paris.

IEA Wind ExCo, 2016. IEA Wind Technology Colaboration Programme Annual Report (No. 978- 0-9905075-3–6), IEA Wind Annual Reports. IEA Wind TCP.

International Renewable Energy Agency, 2012. RENEWABLE ENERGY TECHNOLOGIES: COST ANALYSIS SERIES. Biomass for Power Generation (No. 1/5). International Renewable Energy Agency, Bonn.

IPCC, 2015. Climate Change 2014: Mitigation of Climate Change. Cambridge University Press.

IRENA, 2014. REmap 2030: A Renewable Energy Roadmap. Abu Dhabi.

Jackson, T., 2005. Motivating sustainable consumption. Sustain. Dev. Res. Netw. 29, 30.

Jaffe, A.B., Stavins, R.N., 1994. The energy paradox and the diffusion of conservation technology. Resour. Energy Econ. 16, 91–122.

Jiang, Z., Dai, Y., Luo, X., Liu, G., Wang, H., Zheng, H., Wang, Z., 2017. Assessment of bioenergy development potential and its environmental impact for rural household energy consumption: A case study in Shandong, China. Renew. Sustain. Energy Rev. 67, 1153–1161. https://doi.org/10.1016/j.rser.2016.09.085

Jim Scheer, Matthew Clancy, Fiac Gaffney, 2016. Ireland's Energy Targets. Progress, Ambition & Impacts. The Sustainable Energy Authority of Ireland (SEAI), Dublin.

Kaffine, D.T., Mcbee, B.J., Lieskovsky, J., 2013. Emissions Savings from Wind Power Generation in Texas. Energy J. 34, 155–175.

Kalt, G., Kranzl, L., 2011. Assessing the economic efficiency of bioenergy technologies in climate mitigation and fossil fuel replacement in Austria using a techno-economic approach. Appl. Energy 88, 3665–3684. https://doi.org/10.1016/j.apenergy.2011.03.014

Karina Veum, Ayla Uslu, Jaap Jansen, Marc Londo, Marcel Weeda, Francesco dalla Longa, Dierk Bauknecht, Veit Bürger, Christoph Heinemann, Markus Haller, David Ritter, Moritz Vogel, Robert Brückmann, Jan-Coen van Elburg, Eline Kleiwegt, Irene Pohl, Fabian Pause, Markus Kahles, Stefanie Wizinger, Doerte Fouquet, Jana Nysten, 2016. Study on the impact assessment for a new Directive mainstreaming deployment of renewable energy and ensuring that the EU meets its 2030 renewable energy target Final task 1 & 2 report: "Mainstreaming RES" (No. ENER/C1/2014-668). European Commission DG Energy, Amsterdam.

Kartha, S., Lazarus, M., Bosi, M., 2004. Baseline recommendations for greenhouse gas mitigation projects in the electric power sector. Energy Policy, An economic analysis of climate policy: essays in honour of Andries Nentjes 32, 545–566. https://doi.org/10.1016/S0301-4215(03)00155-1

Kelly, S., Pollitt, M., 2010. An assessment of the present and future opportunities for combined heat and power with district heating (CHP-DH) in the United Kingdom. Energy Policy, Energy Efficiency Policies and Strategies with regular papers. 38, 6936–6945. https://doi.org/10.1016/j.enpol.2010.07.010

Kiviluoma, J., Meibom, P., 2010. Influence of wind power, plug-in electric vehicles, and heat storages on power system investments. Energy 35, 1244–1255. https://doi.org/10.1016/j.energy.2009.11.004

Klessmann, C., Held, A., Rathmann, M., Ragwitz, M., 2011. Status and perspectives of renewable energy policy and deployment in the European Union—What is needed to reach the 2020 targets? Energy Policy, Clean Cooking Fuels and Technologies in Developing Economies 39, 7637–7657. https://doi.org/10.1016/j.enpol.2011.08.038

Klöckner, C.A., 2013. A comprehensive model of the psychology of environmental behaviour—A meta-analysis. Glob. Environ. Change 23, 1028–1038. https://doi.org/10.1016/j.gloenvcha.2013.05.014

Koppejan, J., Van Loo, S., 2012. The handbook of biomass combustion and co-firing. Routledge.

Kostka, G., Moslener, U., Andreas, J., 2013. Barriers to increasing energy efficiency: evidence from small-and medium-sized enterprises in China. J. Clean. Prod. 57, 59–68. https://doi.org/10.1016/j.jclepro.2013.06.025

Kriegler, E., Weyant, J.P., Blanford, G.J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., others, 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Clim. Change 123, 353–367.

Kubiszewski, I., Cleveland, C.J., Endres, P.K., 2010. Meta-analysis of net energy return for wind power systems. Renew. Energy 35, 218–225. https://doi.org/10.1016/j.renene.2009.01.012

Kumar, N., Besuner, P., Lefton, S., Agan, D., Hilleman, D., 2012. Power plant cycling costs. National Renewable Energy Laboratory (NREL), Golden, CO.

Lang, S., McKeogh, E., 2010. Verification of wind power forecasts provided in real-time to the Irish Transmission System Operator, in: Power and Energy Society General Meeting, 2010 IEEE. pp. 1–6. https://doi.org/10.1109/PES.2010.5590032

Lannoye, E., Flynn, D., O'Malley, M., 2012. Evaluation of Power System Flexibility. IEEE Trans. Power Syst. 27, 922–931. https://doi.org/10.1109/TPWRS.2011.2177280

Leduc, S., Schwab, D., Dotzauer, E., Schmid, E., Obersteiner, M., 2008. Optimal location of wood gasification plants for methanol production with heat recovery. Int. J. Energy Res. 32, 1080–1091. https://doi.org/10.1002/er.1446

Leduc, S., Starfelt, F., Dotzauer, E., Kindermann, G., McCallum, I., Obersteiner, M., Lundgren, J., 2010. Optimal location of lignocellulosic ethanol refineries with polygeneration in Sweden. Energy, 7th International Conference on

Sustainable Energy Technologies 35, 2709–2716. https://doi.org/10.1016/j.energy.2009.07.018

Leonard, T.C., 2008. Richard H. Thaler, Cass R. Sunstein, Nudge: Improving decisions about health, wealth, and happiness. Const. Polit. Econ. 19, 356–360. https://doi.org/10.1007/s10602-008-9056-2

Lew, D., Brinkman, G., Ibanez, E., Hodge, B.M., Hummon, M., Florita, A., Heaney, M., 2013. The Western Wind and Solar Integration Study Phase 2 (No. NREL/TP-5500-55588). National Renewable Energy Laboratory (NREL), Golden, CO.

Lew, D., Brinkman, G., Kumar, N., Besuner, P., Agan, D., Lefton, S., 2012. Impacts of wind and solar on fossil-fueled generators, in: Proc. IEEE Power and Energy Society General Meeting.

Li, H., Sun, Q., Zhang, Q., Wallin, F., 2015. A review of the pricing mechanisms for district heating systems. Renew. Sustain. Energy Rev. 42, 56–65. https://doi.org/10.1016/j.rser.2014.10.003

Lind, A., Rosenberg, E., Seljom, P., Espegren, K., Fidje, A., Lindberg, K., 2013. Analysis of the EU renewable energy directive by a techno-economic optimisation model. Energy Policy 60, 364–377. https://doi.org/10.1016/j.enpol.2013.05.053

Low Carbon Company, 2017. CFD Register | Low Carbon Contracts [WWW Document]. URL https://lowcarboncontracts.uk/cfds?title=&field_cfd_technology_type=Biomass+Conversion&field_cfd_applicant_name=Drax&field_cfd_target_comm_date_value_1%5Bdate%5D=&field_cfd_target_comm_date%5Bdate%5D=&field_cfd_unique_id=&field_cfd_agreement_type=All&field_cfd_strikeprice=All (accessed 4.11.17).

Lowe, R., 2011. Combined heat and power considered as a virtual steam cycle heat pump. Energy Policy 39, 5528–5534. https://doi.org/10.1016/j.enpol.2011.05.007

Lund, H., 2005. Large-scale integration of wind power into different energy systems. Energy 30, 2402–2412. https://doi.org/10.1016/j.energy.2004.11.001

Lund, H., Andersen, A.N., 2005. Optimal designs of small CHP plants in a market with fluctuating electricity prices. Energy Convers. Manag. 46, 893–904. https://doi.org/10.1016/j.enconman.2004.06.007

Lund, H., Möller, B., Mathiesen, B.V., Dyrelund, A., 2010. The role of district heating in future renewable energy systems. Energy 35, 1381–1390. https://doi.org/10.1016/j.energy.2009.11.023

Lund, H., Münster, E., 2006. Integrated energy systems and local energy markets. Energy Policy 34, 1152–1160. https://doi.org/10.1016/j.enpol.2004.10.004

Lund, H., Münster, E., 2003a. Modelling of energy systems with a high percentage of CHP and wind power. Renew. Energy 28, 2179–2193. https://doi.org/10.1016/S0960-1481(03)00125-3

Lund, H., Münster, E., 2003b. Management of surplus electricity-production from a fluctuating renewable-energy source. Appl. Energy, Energex 2002 - Energy Policies and Economics and Rational Use of Energy of Energy Topics VI and VII 76, 65–74. https://doi.org/10.1016/S0306-2619(03)00048-5

Lund, R., Mathiesen, B.V., 2015. Large combined heat and power plants in sustainable energy systems. Appl. Energy 142, 389–395. https://doi.org/10.1016/j.apenergy.2015.01.013

Lytvyn, I.V., Hewitt, N., 2013. Barriers to increased electricity interconnection between neighboring markets, in: European Energy Market (EEM), 2013 10th International Conference on The. pp. 1–8. https://doi.org/10.1109/EEM.2013.6607332

Ma, J., Scott, N.R., DeGloria, S.D., Lembo, A.J., 2005. Siting analysis of farm-based centralized anaerobic digester systems for distributed generation using GIS. Biomass Bioenergy 28, 591–600. https://doi.org/10.1016/j.biombioe.2004.12.003

Mafakheri, F., Nasiri, F., 2014. Modeling of biomass-to-energy supply chain operations: Applications, challenges and research directions. Energy Policy 67, 116–126. https://doi.org/10.1016/j.enpol.2013.11.071

Malla, K., Wood, A., 2012. Economic significance of Basslink in the Australian National Electricity Market, in: 2012 IEEE International Conference on Power System Technology (POWERCON). Presented at the 2012 IEEE International Conference on Power System Technology (POWERCON), pp. 1–3. https://doi.org/10.1109/PowerCon.2012.6401466

Martin Howley, Amanda Barriscale, 2017. Electricity & Gas Prices in Ireland 2nd Semester (July – December) 2016, Electricity & Gas Prices in Ireland. Sustainable Energy Authority of Ireland (SEAI), Cork/Dublin.

Martin Howley, Mary Holland, 2016a. Energy in Ireland 1990-2015; 2016 report, Energy in Ireland. Sustainable Energy Authority of Ireland (SEAI), Cork/Dublin.

Martin Howley, Mary Holland, 2016b. Combined Heat and Power in Ireland, 2016 update. The Sustainable Energy Authority of Ireland (SEAI), Cork/Dublin.

Martin Howley, Mary Holland, 2013. Energy in Ireland 1990 – 2012, 2013 Report. Cork/Dublin.

Martin Howley, Mary Holland, Denis Dineen, Eimear Cotter, 2015. Energy in Ireland 1990-2014; 2015 report, Energy in Ireland. Sustainable Energy Authority of Ireland (SEAI), Cork/Dublin.

Mathiesen, B.V., Lund, H., Connolly, D., Wenzel, H., Østergaard, P.A., Möller, B., Nielsen, S., Ridjan, I., Karnøe, P., Sperling, K., Hvelplund, F.K., 2015. Smart Energy Systems for coherent 100% renewable energy and transport solutions. Appl. Energy 145, 139–154. https://doi.org/10.1016/j.apenergy.2015.01.075

Mc Garrigle, E.V., Deane, J.P., Leahy, P.G., 2013. How much wind energy will be curtailed on the 2020 Irish power system? Renew. Energy 55, 544–553. https://doi.org/10.1016/j.renene.2013.01.013

McGarrigle, E.V., Leahy, P.G., 2013. The value of accuracy in wind energy forecasts, in: Environment and Electrical Engineering (EEEIC), 2013 12th International Conference On. pp. 529–533. https://doi.org/10.1109/EEEIC.2013.6549572

Michael Colreavy, Barry Cowen, Michael Fitzmaurice, Noel Harrington, Seán Kenny, Michael McCarthy, Helen McEntee, Brian Walsh, Paschal Mooney, JOHN O'MAHONY, 2015. Parliamentary Debates. Irish Government, Houses of the Oireachtas.

Milligan, M., Porter, K., DeMeo, E., Denholm, P., Holttinen, H., Kirby, B., Miller, N., Mills, A., O'Malley, M., Schuerger, M., Soder, L., 2009. Wind power myths debunked. IEEE Power Energy Mag. 7, 89–99. https://doi.org/10.1109/MPE.2009.934268

Mitchell, C., Bridgwater, A., Stevens, D., Toft, A., Watters, M., 1995. Technoeconomic assessment of biomass to energy. Biomass Bioenergy, International Energy Agency Bioenergy Agreement Progress and Achievements 1992/94 9, 205–226. https://doi.org/10.1016/0961-9534(95)00092-5

Mitchell, C.P., 2000. Development of decision support systems for bioenergy applications. Biomass Bioenergy 18, 265–278. https://doi.org/10.1016/S0961-9534(99)00099-9

Mobini, M., Sowlati, T., Sokhansanj, S., 2013. A simulation model for the design and analysis of wood pellet supply chains. Appl. Energy 111, 1239–1249. https://doi.org/10.1016/j.apenergy.2013.06.026

Muench, S., Guenther, E., 2013. A systematic review of bioenergy life cycle assessments. Appl. Energy 112, 257–273. https://doi.org/10.1016/j.apenergy.2013.06.001

Muhammad Saqib Riaz, 2017. Steam Turbine Retrofits.

Muthulingam, S., Corbett, C.J., Benartzi, S., Oppenheim, B., 2011. Investment in Energy Efficiency by Small and Medium-Sized Firms: An Empirical Analysis

of the Adoption of Process Improvement Recommendations. Decis. Oper. Technol. Manag.

Mutual Energy, 2011. Moyle Interconnector Limited Interconnector Capacity Calculation.

Natarajan, K., Leduc, S., Pelkonen, P., Tomppo, E., Dotzauer, E., 2012. Optimal Locations for Methanol and CHP Production in Eastern Finland. BioEnergy Res. 5, 412–423. https://doi.org/10.1007/s12155-011-9152-4

National Competitiveness Council, 2016. Ireland's Competitiveness Scorecard 2016. Department of Jobs, Enterprise and Innovation.

National Oil Reserve Agency, 2010. Biofuels Obligation Scheme [WWW Document]. URL http://www.nora.ie/biofuels-obligation-scheme.141.html (accessed 4.19.17).

National Renewable Energy Action Plans (NREAPs), 2011. Renewable Energy: Action Plans & Forecasts [WWW Document]. URL http://ec.europa.eu/energy/renewables/action_plan_en.htm (accessed 5.5.14).

Nelson, T., Nelson, J., Ariyaratnam, J., Camroux, S., 2013. An analysis of Australia's large scale renewable energy target: Restoring market confidence. Energy Policy 62, 386–400. https://doi.org/10.1016/j.enpol.2013.07.096

Nepal, R., Jamasb, T., 2012. Interconnections and market integration in the Irish Single Electricity Market. Energy Policy 51, 425–434. http://dx.doi.org/10.1016/j.enpol.2012.08.047

No, D., 2009. 406/2009/EC of the European Parliament and of the Council of 23 April 2009 on the effort of Member States to reduce their greenhouse gas emissions to meet the Community's greenhouse gas emission reduction commitments up to 2020. Off. J. Eur. Union 5.

Nuytten, T., Claessens, B., Paredis, K., Van Bael, J., Six, D., 2013. Flexibility of a combined heat and power system with thermal energy storage for district heating. Appl. Energy 104, 583–591. https://doi.org/10.1016/j.apenergy.2012.11.029

O Gallachoir, B.P., Gardner, P., Snodin, H., McKeogh, E.J., 2007. Wind energy and system security – the grid connection moratorium in Ireland. Int. J. Energy Technol. Policy 5, 633–647.

Ó Gallachóir, B.P., O'Leary, F., Bazillan, M., Howley, M., McKeogh, E.J., 2006. Comparing Primary Energy Attributed to Renewable Energy with Primary Energy Equivalent to Determine Carbon Abatement in a National Context. J. Environ. Sci. Health Part A 41, 923–937. https://doi.org/10.1080/10934520600614561

Oettinger, G., Rosenfeld, A, 2013. Visualising the hidden fuel of energy efficiency. J. Int. Energy Agency 1–48.

O'Mahoney, A., Denny, E., 2011a. The Merit Order Effect of Wind Generation on the Irish Electricity Market [WWW Document]. URL http://mpra.ub.uni-muenchen.de/56043/ (accessed 10.12.14).

O'Mahoney, A., Denny, E., 2011b. The Merit Order Effect of Wind Generation on the Irish Electricity Market [WWW Document]. URL http://mpra.ub.uni-muenchen.de/56043/ (accessed 7.28.14).

O'Malley, E., Scott, S., 2004. Production must go on: barriers to energy efficiency in the Irish mechanical engineering industry. Econ. Energy Effic. Edw. Elgar Chelten.

O'Shea, R., Wall, D.M., Kilgallon, I., Browne, J.D., Murphy, J.D., 2017. Assessing the total theoretical, and financially viable, resource of biomethane for injection to a natural gas network in a region. Appl. Energy 188, 237–256. https://doi.org/10.1016/j.apenergy.2016.11.121

Østergaard, P.A., 2015. Reviewing EnergyPLAN simulations and performance indicator applications in EnergyPLAN simulations. Appl. Energy 154, 921–933. https://doi.org/10.1016/j.apenergy.2015.05.086

Ostertag, K., 2002. No-regret Potentials in Energy Conservation: An Analysis of Their Relevance, Size and Determinants; with 51 Tables. Springer Science & Business Media.

Parker, N., Tittmann, P., Hart, Q., Nelson, R., Skog, K., Schmidt, A., Gray, E., Jenkins, B., 2010. Development of a biorefinery optimized biofuel supply curve for the Western United States. Biomass Bioenergy 34, 1597–1607. https://doi.org/10.1016/j.biombioe.2010.06.007

Pedersen, L., Stang, J., Ulseth, R., 2008. Load prediction method for heat and electricity demand in buildings for the purpose of planning for mixed energy distribution systems. Energy Build. 40, 1124–1134. https://doi.org/10.1016/j.enbuild.2007.10.014

Pfenninger, S., Hawkes, A., Keirstead, J., 2014. Energy systems modeling for twenty-first century energy challenges. Renew. Sustain. Energy Rev. 33, 74–86. https://doi.org/10.1016/j.rser.2014.02.003

Platts, 2017. Biodiesel Price Assessment Explained [WWW Document]. URL https://www.platts.com/price-assessments/agriculture/european-biodiesel (accessed 3.30.18).

Poyry, AECOM, 2009. The Potential and Costs of District Heating Networks. A report to the Department of Energy and Climate Change.

Rauch, P., Gronalt, M., 2010. The Terminal Location Problem in the Forest Fuels Supply Network. Int. J. For. Eng. 21, 32–40. https://doi.org/10.1080/14942119.2010.10702596

Reddy, B.S., Assenza, G., 2007. Barriers and drivers to energy efficiency. WP2007-003 IGIDR Work. Pap. Ser.

Revell, A., Stokes, D., Chen, H., 2010. Small businesses and the environment: turning over a new leaf? Bus. Strategy Environ. 19, 273–288. https://doi.org/10.1002/bse.628

Ricardo AEA, 2011. A study into the recovery of heat from power generation in Scotland. Scottish Government.

Ricardo Energy & Environment, 2017a. Biomass Feedstock Availability Final report (No. ED 662421043, Issue 3). Department for Business, Energy & Industrial Strategy.

Ricardo Energy & Environment, 2017b. Potential Biomass Prices in Ireland. The Sustainable Energy Authority of Ireland (SEAI).

Ricardo Energy & Environment, 2017c. Assessment of Cost and Bene_ts of Biogas and Biomethane in Ireland. The Sustainable Energy Authority of Ireland (SEAI), Dublin.

Ricardo Energy and Environment, 2016. Bioenergy Supply Curves 2015-2035. The Sustainable Energy Authority of Ireland (SEAI).

Rogelj, J., den Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., Schaeffer, R., Sha, F., Riahi, K., Meinshausen, M., 2016. Paris Agreement climate proposals need a boost to keep warming well below 2 °C. Nature 534, 631–639. https://doi.org/10.1038/nature18307

Rogelj, J., Luderer, G., Pietzcker, R.C., Kriegler, E., Schaeffer, M., Krey, V., Riahi, K., 2015. Energy system transformations for limiting end-of-century warming to below 1.5 °C. Nat. Clim. Change 5, 519–527. https://doi.org/10.1038/nclimate2572

Rohdin, P., Thollander, P., 2006. Barriers to and driving forces for energy efficiency in the non-energy intensive manufacturing industry in Sweden. Energy 31, 1836–1844.

Rohdin, P., Thollander, P., Solding, P., 2007. Barriers to and drivers for energy efficiency in the Swedish foundry industry. Energy Policy 35, 672–677.

Roni, M.S., Chowdhury, S., Mamun, S., Marufuzzaman, M., Lein, W., Johnson, S., 2017. Biomass co-firing technology with policies, challenges, and opportunities: A global review. Renew. Sustain. Energy Rev. 78, 1089–1101. https://doi.org/10.1016/j.rser.2017.05.023

Rosen, M.A., 2008. Allocating carbon dioxide emissions from cogeneration systems: descriptions of selected output-based methods. J. Clean. Prod., Papers selected from the 7th conference - Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction- PRES 2004 16, 171–177. https://doi.org/10.1016/j.jclepro.2006.08.025

Rouvinen, S., Matero, J., 2013. Stated preferences of Finnish private homeowners for residential heating systems: A discrete choice experiment. Biomass Bioenergy 57, 22–32. https://doi.org/10.1016/j.biombioe.2012.10.010

RPS, COWI, 2007. Dublin District Heating project feasibility study. Dublin City Council, Dublin.

RPS for Dublin City Council, 2016. Dublin District Heating System. Technical Information Pack for Developers.

Sacchelli, S., De Meo, I., Paletto, A., 2013. Bioenergy production and forest multifunctionality: A trade-off analysis using multiscale GIS model in a case study in Italy. Appl. Energy 104, 10–20. https://doi.org/10.1016/j.apenergy.2012.11.038

Sanstad, A.H., Howarth, R.B., 1994. Markets for energy efficiency'Normal' markets, market imperfections and energy efficiency. Energy Policy 22, 811–818. https://doi.org/10.1016/0301-4215(94)90139-2

Sathaye, J., Bouille, D., Biswwas, D., Crabbe, P., Geng, L., Hall, D., Imura, H., Jaffe, A., Michaelis, L., Peszko, G., others, 2001. Barriers, opportunities, and market potential of technologies and practices. Clim. Change 345–398.

Schafer, J.L., Graham, J.W., 2002. Missing data: our view of the state of the art. Psychol. Methods 7, 147.

Scheer, J., Durusut, E., Foster, S., 2015. Unlocking the Energy Efficiency Opportunity. Sustainable Energy Authority of Ireland (SEAI), Dublin.

Schleich, J., 2009. Barriers to energy efficiency: A comparison across the German commercial and services sector. Ecol. Econ., Methodological Advancements in the Footprint Analysis 68, 2150–2159. https://doi.org/10.1016/j.ecolecon.2009.02.008

Schleich, J., Gruber, E., 2008. Beyond case studies: Barriers to energy efficiency in commerce and the services sector. Energy Econ. 30, 449–464. https://doi.org/10.1016/j.eneco.2006.08.004

Schmidt, J., Leduc, S., Dotzauer, E., Kindermann, G., Schmid, E., 2010a. Potential of biomass-fired combined heat and power plants considering the spatial distribution of biomass supply and heat demand. Int. J. Energy Res. 34, 970–985. https://doi.org/10.1002/er.1623

Schmidt, J., Leduc, S., Dotzauer, E., Kindermann, G., Schmid, E., 2010b. Cost-effective CO2 emission reduction through heat, power and biofuel

production from woody biomass: A spatially explicit comparison of conversion technologies. Appl. Energy 87, 2128–2141. https://doi.org/10.1016/j.apenergy.2009.11.007

SEAI, 2017a. Ireland's Energy Projections Progress to targets, challenges and impacts. The Sustainable Energy Authority of Ireland (SEAI), Dublin.

SEAI, 2017b. National Calculation Methodology [WWW Document]. URL http://www.seai.ie/Your_Building/BER/Non_Domestic_buildings/Download_SBEM_Software/Download_SBEM_Software.html (accessed 8.8.17).

SEAI, 2017c. Fuel Cost Comparison. The Sustainable Energy Authority of Ireland (SEAI).

SEAI, 2015. Renewable Heat in Ireland to 2020. Achieving Ireland's 2020 renewable heat target: Analysis of policy options. The Sustainable Energy Authority of Ireland (SEAI), Dublin.

SEM-12-045(1), 2012. Forecast Imperfections Revenue Requirment for Tariff ear 1st October 2012 - 30th September 2013. EirGrid/SONI, Dublin.

SEMO, 2014. Market Data [WWW Document]. Httpwwwsem-Ocom. URL http://www.sem-o.com/marketdata/Pages/default.aspx (accessed 7.28.14).

SEMO, 2009. Market Rules [WWW Document]. Httpwwwsem-Ocom. URL http://www.sem-o.com/MarketDevelopment/Pages/MarketRules.aspx (accessed 10.21.17).

Sensfuß, F., Ragwitz, M., Genoese, M., 2008. The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36, 3086–3094. https://doi.org/10.1016/j.enpol.2008.03.035

Shabani, N., Akhtari, S., Sowlati, T., 2013. Value chain optimization of forest biomass for bioenergy production: A review. Renew. Sustain. Energy Rev. 23, 299–311. https://doi.org/10.1016/j.rser.2013.03.005

Shane O'Sullivan, 2017. Moneypoint and Ireland's low carbon future.

Shi, X., Elmore, A., Li, X., Gorence, N.J., Jin, H., Zhang, X., Wang, F., 2008. Using spatial information technologies to select sites for biomass power plants: A case study in Guangdong Province, China. Biomass Bioenergy 32, 35–43. https://doi.org/10.1016/j.biombioe.2007.06.008

Siitonen, S., Holmberg, H., 2012. Estimating the value of energy saving in industry by different cost allocation methods. Int. J. Energy Res. 36, 324–334. https://doi.org/10.1002/er.1794

Simpson, M., Taylor, N., Barker, K., 2004. Environmental responsibility in SMEs: does it deliver competitive advantage? Bus. Strategy Environ. 13, 156–171. https://doi.org/10.1002/bse.398

Single Electricity Market Committee, SEM-11-062, 2011. Single Electricity Market,Principles of Dispatch and the Design of the Market Schedule in the Trading and Settlement Code,. Commission for Energy Regulation (CER) / Utility Regulator, Dublin/Belfast.

Sjödin, J., Henning, D., 2004. Calculating the marginal costs of a district-heating utility. Appl. Energy 78, 1–18. https://doi.org/10.1016/S0306-2619(03)00120-X

Soder, L., Abildgaard, H., Estanqueiro, A., Hamon, C., Holttinen, H., Lannoye, E., Gomez-Lazaro, E., O'Malley, M., Zimmermann, U., 2012. Experience and Challenges With Short-Term Balancing in European Systems With Large Share of Wind Power. IEEE Trans. Sustain. Energy 3, 853–861. https://doi.org/10.1109/TSTE.2012.2208483

Soimakallio, S., Kiviluoma, J., Saikku, L., 2011. The complexity and challenges of determining GHG (greenhouse gas) emissions from grid electricity consumption and conservation in LCA (life cycle assessment)–a methodological review. Energy 36, 6705–6713.

Sorknæs, P., Lund, H., Andersen, A.N., 2015. Future power market and sustainable energy solutions – The treatment of uncertainties in the daily operation of combined heat and power plants. Appl. Energy 144, 129–138. https://doi.org/10.1016/j.apenergy.2015.02.041

Sorrell, S., 2004. The economics of energy efficiency: barriers to cost-effective investment. Edward Elgar Publishing.

Sorrell, S., Mallett, A., Nye, S., 2011. Barriers to industrial energy efficiency: A literature review. United Nations Industrial Development Organization (UNIDO).

Sorrell, S., Schleich, J., Scott, S., O'malley, E., Trace, F., Boede, E., Ostertag, K., Radgen, P., 2000. Reducing barriers to energy efficiency in public and private organizations. Retrieved Oct. 8, 2007.

Stern, P.C., Aronson, E., 1984. Energy use: The human dimension.

Steubing, B., Ballmer, I., Gassner, M., Gerber, L., Pampuri, L., Bischof, S., Thees, O., Zah, R., 2014. Identifying environmentally and economically optimal bioenergy plant sizes and locations: A spatial model of wood-based SNG value chains. Renew. Energy, World Renewable Energy Congress – Sweden, 8–13 May, 2011, Linköping, Sweden 61, 57–68. https://doi.org/10.1016/j.renene.2012.08.018

Steubing, B., Zah, R., Ludwig, C., others, 2012a. Heat, electricity, or transportation? The optimal use of residual and waste biomass in Europe from an environmental perspective. Environ. Sci. Technol. 46, 164–171.

Steubing, B., Zah, R., Ludwig, C., others, 2012b. Heat, electricity, or transportation? The optimal use of residual and waste biomass in Europe from an environmental perspective. Environ. Sci. Technol. 46, 164–171.

Streckienė, G., Martinaitis, V., Andersen, A.N., Katz, J., 2009. Feasibility of CHP-plants with thermal stores in the German spot market. Appl. Energy 86, 2308–2316. https://doi.org/10.1016/j.apenergy.2009.03.023

Studer, S., Welford, R., Hills, P., 2006. Engaging Hong Kong businesses in environmental change: drivers and barriers. Bus. Strategy Environ. 15, 416–431.

Sultana, A., Kumar, A., 2012. Optimal siting and size of bioenergy facilities using geographic information system. Appl. Energy 94, 192–201. https://doi.org/10.1016/j.apenergy.2012.01.052

Tan, R.R., Aviso, K.B., Barilea, I.U., Culaba, A.B., Cruz, J.B., 2012. A fuzzy multi-regional input–output optimization model for biomass production and trade under resource and footprint constraints. Appl. Energy, Energy Solutions for a Sustainable World, Special Issue of International Conference of Applied Energy, ICA2010, April 21-23, 2010, Singapore 90, 154–160. https://doi.org/10.1016/j.apenergy.2011.01.032

The Ministry of Economy, Trade and Industry (METI), 2014. Strategic Energy Plan (2014).

The Sustainable Energy Authority of Ireland, 2017. A contractor's guide to sizing of radiators with a condensing boiler.

The Sustainable Energy Authority of Ireland, 2016a. SEAI Heat Demand Map of Ireland [WWW Document]. URL http://maps.seai.ie/heatdemand/ (accessed 3.24.17).

The Sustainable Energy Authority of Ireland, 2016b. Behavioural insights on energy efficiency in the residential sector. The Sustainable Energy Authority of Ireland (SEAI), Dublin.

The Sustainable Energy Authority of Ireland, 2016c. Energy Portal [WWW Document]. Energy Data Portal. URL http://www.seai.ie/InteractiveEnergyCharts/# (accessed 1.21.17).

Thollander, P., Danestig, M., Rohdin, P., 2007. Energy policies for increased industrial energy efficiency: evaluation of a local energy programme for manufacturing SMEs. Energy Policy 35, 5774–5783.

Thollander, P., Ottosson, M., 2008. An energy efficient Swedish pulp and paper industry–exploring barriers to and driving forces for cost-effective energy efficiency investments. Energy Effic. 1, 21–34.

Tittmann, P.W., Parker, N.C., Hart, Q.J., Jenkins, B.M., 2010. A spatially explicit techno-economic model of bioenergy and biofuels production in California. J. Transp. Geogr., Special Section on Alternative Fuels and Vehicles 18, 715–728. https://doi.org/10.1016/j.jtrangeo.2010.06.005

Tonini, D., Vadenbo, C., Astrup, T.F., 2017. Priority of domestic biomass resources for energy: Importance of national environmental targets in a climate perspective. Energy 124, 295–309. https://doi.org/10.1016/j.energy.2017.02.037

Trianni, A., Cagno, E., 2012. Dealing with barriers to energy efficiency and SMEs: some empirical evidences. Energy 37, 494–504.

Tuohy, A., Bazilian, M., Doherty, R., Gallachóir, B.Ó., O'Malley, M., 2009. Burning peat in Ireland: An electricity market dispatch perspective. Energy Policy 37, 3035–3042. https://doi.org/10.1016/j.enpol.2009.03.049

Tuohy, A., O'Malley, M., 2011. Pumped storage in systems with very high wind penetration. Energy Policy 39, 1965–1974. https://doi.org/10.1016/j.enpol.2011.01.026

Tursun, U.D., Kang, S., Onal, H., Ouyang, Y., Scheffran, J., 2008. Optimal Biorefinery Locations and Transportation Network for the Future Biofuels Industry in Illinois (No. 53502), Environmental and Rural Development Impacts Conference, October 15-16, 2008, St. Louis, Missouri. Farm Foundation, Transition to a Bio Economy Conferences.

UNFCCC, 2016. Report of the Conference of the Parties on its twenty-first session, held in Paris from 30 November to 13 December 2015. Part two: Action taken by the Conference of the Parties at its twenty-first session.

UNFCCC, 2015a. Intended Nationally Determined Contributions - All Countires [WWW Document]. URL http://www4.unfccc.int/ndcregistry/Pages/All.aspx (accessed 2.7.18).

UNFCCC, 2015b. INDC - Submissions [WWW Document]. URL http://www4.unfccc.int/submissions/indc/Submission%20Pages/submissions.aspx (accessed 2.7.18).

UNFCCC, 2006. Clean Development Mechanism (CDM) [WWW Document]. URL http://unfccc.int/kyoto_protocol/mechanisms/clean_development_mechanism/items/2718.php (accessed 4.2.18).

United States Congress, 2007. 'Energy Independence and Security Act of 2007, 121 STAT.1492.

US EPA, O., 2017. CHP Energy and Emissions Savings Calculator [WWW Document]. URL https://www.epa.gov/chp/chp-energy-and-emissions-savings-calculator (accessed 5.6.17).

Valentino, L., Valenzuela, V., Botterud, A., Zhou, Z., Conzelmann, G., 2012. System-Wide Emissions Implications of Increased Wind Power Penetration. Environ. Sci. Technol. 46, 4200–4206. https://doi.org/10.1021/es2038432

Velthuijsen, J.W., 1995. Determinants of investment in energy conservation.

Velthuijsen, J.W., 1993. Incentives for investment in energy efficiency: an econometric evaluation and policy implications. Environ. Resour. Econ. 3, 153–169.

Vera, D., Carabias, J., Jurado, F., Ruiz-Reyes, N., 2010. A Honey Bee Foraging approach for optimal location of a biomass power plant. Appl. Energy 87, 2119–2127. https://doi.org/10.1016/j.apenergy.2010.01.015

Verbruggen, A., Dewallef, P., Quoilin, S., Wiggin, M., 2013. Unveiling the mystery of Combined Heat & Power (cogeneration). Energy 61, 575–582. https://doi.org/10.1016/j.energy.2013.09.029

Vukašinović, V., Gordić, D., 2016. Optimization and GIS-based combined approach for the determination of the most cost-effective investments in biomass sector. Appl. Energy 178, 250–259. https://doi.org/10.1016/j.apenergy.2016.06.037

Wahlund, B., Yan, J., Westermark, M., 2004. Increasing biomass utilisation in energy systems: A comparative study of CO2 reduction and cost for different bioenergy processing options. Biomass Bioenergy 26, 531–544. https://doi.org/10.1016/j.biombioe.2003.09.003

Walther, G., Schatka, A., Spengler, T.S., 2012. Design of regional production networks for second generation synthetic bio-fuel – A case study in Northern Germany. Eur. J. Oper. Res. 218, 280–292. https://doi.org/10.1016/j.ejor.2011.09.050

Wang, Y., Chen, C., Wang, J., Baldick, R., 2016. Research on resilience of power systems under natural disasters—A review. IEEE Trans Power Syst 31, 1604–1613.

Weber, L., 1997. Some reflections on barriers to the efficient use of energy. Energy Policy 25, 833–835. https://doi.org/10.1016/S0301-4215(97)00084-0

Werner, S., 2017. International review of district heating and cooling. Energy. https://doi.org/10.1016/j.energy.2017.04.045

Wesselink, B., Harmsen, R., Eichhammer, W., 2010. Energy savings 2020: How to triple the impact of energy saving policies in Europe. Contrib. Stud. Roadmap 2050, 2–1.

Wetterlund, E., Leduc, S., Dotzauer, E., Kindermann, G., 2012. Optimal localisation of biofuel production on a European scale. Energy, 23rd International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, ECOS 2010 41, 462–472. https://doi.org/10.1016/j.energy.2012.02.051

Wheatley, J., 2013. Quantifying CO2 savings from wind power. Energy Policy 63, 89–96. https://doi.org/10.1016/j.enpol.2013.07.123

William R H Orchard, 2009. EXERGY & MARGINAL FUEL USE, AN ANALYSIS OF HEAT FROM CHP & HEAT FROM ELECTRIC HEAT PUMPS.

Worrell, E., Laitner, J.A., Ruth, M., Finman, H., 2003. Productivity benefits of industrial energy efficiency measures. Energy 28, 1081–1098.

Yamamoto, H., Yamaji, K., Fujino, J., 1999. Evaluation of bioenergy resources with a global land use and energy model formulated with SD technique. Appl. Energy 63, 101–113. https://doi.org/10.1016/S0306-2619(99)00020-3

Yasuda, Y., Ardal, A.R., Carlini, E.M., Estanqueiro, A., Flynn, D., Gomez-Lázaro, E., Holttinen, H., Kiviluoma, J., Van Hulle, F., Kondoh, J., 2013. Flexibility chart: Evaluation on diversity of flexibility in various areas.

Young, W., Hwang, K., McDonald, S., Oates, C.J., 2010. Sustainable consumption: green consumer behaviour when purchasing products. Sustain. Dev. 18, 20–31. https://doi.org/10.1002/sd.394

Zachary, 12/15/2006 | Dr Justin, Koza, D.J., Corp, B.P., 2006. The long and short of last-stage blades. POWER Mag.

Zhang, F., Johnson, D.M., Sutherland, J.W., 2011. A GIS-based method for identifying the optimal location for a facility to convert forest biomass to biofuel. Biomass Bioenergy 35, 3951–3961. https://doi.org/10.1016/j.biombioe.2011.06.006

Zhang, J., Ge, B., Xu, H., 2013. An equivalent marginal cost-pricing model for the district heating market. Energy Policy 63, 1224–1232.