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Deep Decarbonization Scenarios for Ireland to 2050 using a New Scenario Ensemble Tool

Thesis presented by
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Declaration

I hereby declare that this thesis is my own work and that is has not been submitted for another degree, either at University College Cork or elsewhere. Where other sources of information have been used, they have been acknowledged.

Signature: ____

Date: ____

Acknowledgement

This thesis was carried out in the Energy Policy and Modelling Group of the Marine and Renewable Energy Research (MaREI) Center, which is coordinated by the Environmental Research Institute (ERI) of University College Cork (UCC), for the project "Opportunities for Ireland In A Low Carbon Economy – Our 2050" funded by the Science Foundation Ireland (SFI) and NTR Foundation under Grant No. 12/RC/2302.

First and foremost, I'm profoundly grateful to my supervisors, Prof. Brian Ó Gallachóir and Dr. Fionn Rogan, who have guided and supported me through the course of my PhD.

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Thanks to my parents, who encouraged and supported me to pursue academic research.

Executive Summary

In response to the threat of climate change, countries of the world have signed the Paris Agreement aimed at limiting global warming to well below 2 degrees Celsius above pre-industrial levels and with an ambition to limit global warming within 1.5°C. As a member country of the European Union, Ireland is currently not on track to meet its carbon reduction targets and lacks climate policies leading towards a 1.5°C energy future. The purpose of this thesis is to develop methods, evidence and insights from energy systems modelling that can contribute to addressing the challenges of deep decarbonisation of Ireland's energy system by 2050. While scenario analysis and energy systems modelling has been widely used globally to project 2°C-consistent energy pathways, a comprehensive literature review carried out in this thesis shows that single energy system projections may result in limited or even biased insights. This thesis presents an ensemble of scenarios method, which under a wide range of assumptions captures a broader range of solution space and can better address the challenges of deep decarbonization targets towards 1.5°C. The VEDA-SET (VEDA scenario ensemble tool) system is first developed based on the user shell of the TIMES model VEDA (VErsatile Data Analyst), and allows generating, queueing and analyzing large numbers of scenarios in an efficient manner. Using the VEDA-SET system, scenario ensembles are developed to explore deep decarbonization feasibilities and pathways towards the 1.5°C target set by the Paris Agreement. The results indicate that 1.5°C compatible targets are extremely challenging in terms of cumulative emissions from now to 2050. A more realistic target is midway between 1.5°C and 2°C targets and requires much stronger mitigation efforts between 2020 to 2030 than suggested by the current Nationally Determined Contribution (NDC). The thesis then focuses on mitigation measures by deriving marginal abatement cost curves (MACCs) using scenarios with varying carbon reduction targets. The MACCs are used to identify key mitigation options with significant mitigation potential and rank them based on cost effectiveness. Compared to existing MACCs for Ireland, MACCs based on the TIMES model better capture intertemporal dynamics and interactions across different sectors. Finally, an analysis is carried out to explore pathways that achieve decarbonization through 100%

renewable energy. The analysis finds that 100% RES can be achieved through variable renewable energy (VRE) or abundant supply of bioenergy. A global sensitivity analysis using 500 scenarios reveals that energy pathways relying on bioenergy is more susceptible to uncertainties in investment costs, import costs and global bioenergy supply potentials. The scenario ensemble method adopted in this thesis enhances energy systems modeling by improving model transparency, addressing uncertainties and providing more robust policy insights. Besides journal publications and conference presentations, the findings and insights are disseminated through invited talks, policy briefs and online visualization platforms. Analysis on feasibilities of deep decarbonization is referenced by the IPCC special report on 1.5°C, providing evidence base for national mitigation pathways.

Thesis Outputs

Journal Articles

Yue, X., Pye, S., DeCarolis, J., Li, F.G., Rogan, F. and Gallachóir, B.Ó., (2018). A review of approaches to uncertainty assessment in energy system optimization models. Energy strategy reviews, 21, pp.204-217.

Yue, X, Deane, JP., Gallachóir, B.Ó., and Rogan, F. Assessing carbon mitigation options for Ireland with MACCs base on energy system analysis (In review, Applied Energy)

Yue, X. Patankar, N., DeCarolis, J., Chiodi, A, Rogan, F., Deane, JP, and Gallachóir, B.Ó., Transition pathways towards 100% renewable energy systems in Ireland by 2050 based on scenario ensembles (in preparation)

Book Chapter

Yue, X., Rogan, F., Glynn, J., & Gallachóir, B. Ó. (2018). From 2° C to 1.5° C: How Ambitious Can Ireland Be? In Limiting Global Warming to Well Below 2° C: Energy System Modelling and Policy Development (pp. 191-205). Springer, Cham.

Conference Presentations

Yue, X., Patankar, N. Rogan, Eshraghi, H. F. Decarolis, J., Rogan, F. and Gallachóir, B.Ó.,100% Renewable Energy by 2050 - Comparing Ireland and US, International Energy Workshop 2019, Paris, France, June 3, 2019

Yue, X., Rogan, F. and Gallachóir, B.Ó., Assessing mitigation feasibility and options for Ireland in 2050 with ESOM based MACCs, 10th IAMC conference, Recife, Brazil. December 5-7, 2018.

Glynn, J., Yue, X., Rogan, F. and Gallachóir, B.Ó., Direct Air Capture and the role of CDR in WB2C scenarios in ETSAP-TIAM, 10th IAMC conference, Recife, Brazil. December 5-7, 2018.

Yue, X., Rogan, F. and Gallachóir, B.Ó. Assessing carbon mitigation options for Ireland in 2050 using marginal abatement cost curves based on an energy system model, 6th Conference of Ireland Chinese Association of Environment, Resources & Energy, Galway, Ireland, April 19, 2017

Yue, X., Rogan, F. and Gallachóir, B.Ó. Techniques for Running Large Numbers of Scenarios in TIMES, ETSAP Workshop, Cork, Ireland, May 30, 2016

Invited Talks

Yue, X., Rogan, F. and Gallachóir, B.Ó. Identifying technology opportunities in the low carbon energy transition, Our 2050 – Final-Project Event, Dublin, Dec 10, 2018

Yue, X., Rogan, F. and Gallachóir, B.Ó. Assessing robust carbon mitigation opportunities for Ireland with energy system analysis and MACCs, MAREI symposium, Cork, Ireland, June 12-13, 2018

Yue, X., Rogan, F. and Gallachóir, B.Ó. Identifying Technology Opportunities, Our 2050 – Mid-Project Event, Dublin, June 19, 2017

Yue, X., Rogan, F. and Gallachóir, B.Ó. Sensitivity Analysis of Irish TIMES Scenarios using Monte Carlo Simulations, MAREI symposium, Galway, Ireland, May 5-6, 2016

Yue, X., Rogan, F. and Gallachóir, B.Ó. Multi-Scenario Analysis of Irish Energy System (poster), MaREI Scientific Advisory Committee Meeting, Ringaskiddy, Dec 15, 2016

Policy Brief

Yue, X., Rogan, F. and Gallachóir, B.Ó.., (2018). Identifying technology opportunities in the low carbon energy transition

Online Visualization

"Our 2050 – Opportunities for Ireland in a Low Carbon Economy", online visualization platform, Link: http://www.marei.ie/our-2050-visualisation/#tab-id-5

List of Abbreviations

BASE	Baseline
BAU	Business as Usual
BECCS	Bioenergy with Carbon Capture and Storage
CB	Carbon Budget
CCS	Carbon Capture and Storage
CDR	Carbon Dioxide Removal
CH4	Methane
CO2	Carbon Dioxide
COP	Conference of The Parties
E4 Models	Energy, Economy, Environment and Engineering Models
EC	European Commission
ECIU	Cost of Ignoring Uncertainty
EL	Expected Loss
EPA	Environmental Protection Agency
EPMG	Energy Policy and Modelling Group
ESD	Energy Service Demands
ESOM	Energy Systems Optimization Model
ESRI	Economic and Social Research Institute
ETS	Emissions Trading Scheme
ETSAP	Energy Technology Systems Analysis Program
EU	European Union
EVPI	Expected Value of Perfect Information
EVs	Electric Vehicles
EXPANSE	Exploration of Patterns in Near-Optimal Energy Scenarios
GAMS	General Algebraic Modelling Software
GDP	Gross Domestic Product
GFC	Gross Final Consumption
GHG	Greenhouse Gases
GIS	Geographic Information Systems
GSA	Global Sensitivity Analysis
GW	Gigawatt
GWh	Gigawatt Hours
HERMES	Irish Demographic Macro Economic Model
HP	Heat Pump
HSJ	Hop-Skip-Jump
IAM	Integrated Assessment Model
IEA	International Energy Agency
IGDT	Info-Gap Decision Theory
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency

JRC	Joint Research Centre
kt	Kilo Tonne
ktoe	Kilo Tonne of Oil Equivalent
LEAP	Long-Range Energy Alternatives Planning System
LMDI	Logarithmic Mean Divisia Index
LP	Linear Programming
MAC	Marginal Abatement Costs
MACC	Marginal Abatement Cost Curves
MARKAL Model	MARket ALlocation Model
MCA	Mont Carlo Analysis
MESSAGE Model	Model for Energy Supply Strategy Alternatives and Their General Environmental Impact Model
MGA	Modelling to Generate Alternatives
MMR	Minimax Regret Criterion
Mt	Mega Tonne
Mtoe	Mega Tonne of Oil Equivalent
MW	Megawatt
NDC	Nationally Determined Contribution
Non-ETS	Non-Emission Trading Scheme
O&M	Operation & Maintenance
OAT	One-factor-at-a-Time
PET	Pan European TIMES Model
PIH	Plug-In Hybrid
PJ	Petajoules
REF	Reference
RES	Renewable Energy System
RES-E	Renewable Energy Source - Electricity Sector
RES-H	Renewable Energy Source - Heat Sector
RES-T	Renewable Energy Source - Transport Sector
RO	Robust Optimization
SED	Structured Expert Dialogue
SFI	Science Foundation Ireland
SOW	States of The Worlds
SP	Stochastic Programming
TFC	Total Final Consumption
TIAM	The TIMES Integrated Assessment
TIMES	The Integrated Markal-Eform System
TPER	Total Primary Energy Requirement
TWh	Terawatt Hours
UCC	University College Cork
UK	United Kingdom
UNFCCC	United Nations Framework Convention on Climate Change

US	United States
VEDA	Versatile Data Analyst
VPC	Value of Policy Coordination
VRE	Variable Renewable Energy
VSS	Value of The Stochastic Solution
WWS	Water, Wind and Solar

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1 Introduction

1.1 Background

1.1.1 Global warming and the Paris Agreement

Tackling climate change is one of the greatest challenges facing humankind. According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report, human activities are the main cause of global warming with 95% certainty. The impacts of climate change on the global weather and ecosystem are unequivocal and many observed changes since 1950 are unprecedented in decades and millennia. They include but are not limited to rising sea levels causing abandonment of populated areas and extreme weather events threatening food and water security. The global mean surface warming is largely determined by the cumulative emissions of CO_2. The major source of anthropogenic CO_2 is the use of fossil fuels which contributes over 85% of total CO_2 emissions, and the rest of emissions from land use and land-use changes mainly from deforestation (Le Quéré et al., 2018). It is critical to make urgent and fundamental changes towards a low carbon future economy to stabilize the temperature increase.

Solving the global challenge of climate change will require a global effort. At the 16th session of the Conference of the Parties (COP 16) to the United Nations Framework Convention on Climate Change (UNFCCC) held in Cancun in 2010, a formal agreement was adopted that global warming should be limited to 2°C temperature rise relative to pre-industrial levels (UNFCCC, 2011). The structured expert dialogue (SED, 2015) established by COP as a review process concluded that a more ambitious global warming target of 1.5°C comes with several advantages, including reduced risks in food production and lower sea level rise. This is reflected in the Paris Agreement in 2015, which brought nearly all nations together to combat climate change. The central aim of the Paris Agreement is to keep global temperature rise to well below 2°C above pre-industrial levels and contains the ambition to limit the temperature increase to 1.5°C.

1.1.2 Climate action targets and challenges in Ireland

Nationally Determined Contributions (NDCs) are the cornerstone for implementing the Paris Agreement. Rather than negotiating and assigning legally binding national emission targets, each country is allowed to determine their own contributions in the context of their national priorities, circumstances and capabilities, and then outline and communicate their post-2020 climate actions through NDCs. Under this context, it is necessary to determine feasible decarbonization targets and optimal mitigation pathways towards those targets at a national level.

Ireland is an interesting case study in assessing national mitigation pathways. The energy system of Ireland exhibits some unique characteristics. Ireland is a small country with little impact on global emissions; however, the greenhouse gas emissions per person in Ireland are now among the highest in the world. Compared to other developed countries, the energy and land-use GHG ratio in Ireland is significantly different, making it a better representation of the global mean (Edenhofer et al., 2014, Fig. SPM.2). The agriculture sector in Ireland is the single largest contributor to overall GHG emissions and represents over one third of total emissions, while the average emissions from agriculture represents on average 10 percent of total emissions in the rest of Europe. The mitigation efforts in transport and heat sectors have been inadequate. Emissions in heat sectors are decreasing slowly with exception of cold years in 2015 and 2016. Due to tight coupling to increased economic activity, the transport sector experienced a drastic emission increase by 133% over 1990 to 2017 and now accounts for 20% of total GHG emissions. Thanks to well supported policy instruments, Ireland has made significant efforts in decarbonizing the power sector and has become one of the world leaders in wind energy, which provided over 30% of total electricity demand in 2018. As a country with a relatively isolated power system, Ireland's success in wind energy development may offer valuable insights for other countries. However, electricity only accounts for less than one fifth of total final consumption in Ireland and much stronger efforts in energy efficiency and renewable energy penetration are required for heat and transport sectors.

Such unique characteristics make decarbonization particularly challenging for Ireland, which is not on track to meet its near-term decarbonization targets. The 2020 target for Ireland is to reduce non-ETS sector emissions by 20% relative to 2005 levels (European Council, 2009a), and also to achieve a target of 40% renewable share in electricity generation, 10% in transport and 12% in heat (DCCAE, 2010). However, as of 2017, non-ETS emissions are 43.84 Mt CO2 eq, exceeding the annual limit by 2.95Mt (EPA, 2018). Renewables only contribute towards 10.6% of gross final energy consumption compared to the 16% target. Ireland is also required to contribute towards a target of reducing by at least 40% EU-wide emissions by 2030 compared to 1990 levels according to the Nationally Determined Contribution (NDC) tabled by the EU in March 2015 on behalf of Member States (European Union, 2015). The target will be delivered collectively by the EU with reductions in the Emissions Trading Scheme (ETS) and non-ETS sectors amounting to 43% and 30% by 2030 compared to 2005 respectively. The 2030 target outlined by the NDC has been ratified, but the implications are yet to percolate fully into policy.

Being aware of this gap between climate policies and decarbonization ambitions, the Irish government has developed the Climate Action Plan (Government of Ireland, 2019) that sets roadmap with timelines and steps needed to make Ireland a leader in responding to climate change. The Climate Action Plan has set more ambitious measurements than before to put Ireland in a pathway to 2030 which would be consistent with a net zero target by 2050, including increasing renewables from 30% to 70% by adding 12GW of renewable energy capacity, promotion of EVs so that 100% of all new cars and vans are EVs by 2030. The government will also evaluate in detail the changes required to adopt the commitment of net zero greenhouse gas emissions by 2050 as part of finalizing Ireland’s long-term climate strategy by the end of 2019.

1.1.3 Energy systems modelling and low carbon pathways for Ireland

Transition towards a low-carbon energy future will require a fundamental departure from the fossil fuel-based technologies through massive adoption of renewable energy and low-carbon technologies. However, existing energy infrastructure is expensive with high inertia and deploying renewable technologies requires significant capital investments. The current fossil-fuel based energy system has been described as being under the “carbon lock-in” condition (Unruh, 2002), where existing carbon intensive technologies are locked into a path dependent process due to increasing returns and scales, creating market barriers for the diffusion of renewable technologies. Evidence from past energy transitions suggests that shifting from fossil fuels to renewable energy will be a prolonged process (Smil, 2010). While rapid transitions have happened through coalitions of proactive policy planning and circumstances such as changes in costs, technologies and consumer demands (Sovacool, 2016), policy makers should not underestimate the urgency in climate actions as existing examples of rapid transitions may not be comparable with a deep decarbonization transition at the global scale (Grubler et al., 2016). While wind and solar generation has been growing rapidly in the recent years, modern renewables only accounted for 10.6% of total final energy consumption with renewable electricity from wind, solar, biomass, geothermal and ocean power supplying 2.0% of TFC by 2017 (REN21, 2019). Replacing fossil fuels with biofuels and renewable generation “will be necessarily a prolonged, multidecadal process” (Smil, 2016). Rather than waiting for energy transition taking place naturally, it is critical to speed up the pace of transitions through proactive planning and strong climate actions based on robust analysis of the vast array of possible pathways, from which insights about the preferred future pathways can be derived.

Quantitative energy models have played a critical role in developing long term mitigation pathways that guide decision making for climate and energy policies. The use of computer models in energy planning policy was first enabled in the 1970s with the rapid development in affordable computing power. Energy models were initially used to explore options in maintaining energy stability after the oil crisis

(Nakata, 2004). More recently the use of energy models shifts towards climate change policies and security in energy supply, with a focus on pathways that can deliver significant reductions in greenhouse gas emissions. Energy models are formulated using theoretical and analytical methods from several disciplines including engineering, economics, operations research, and management science, and are implemented using mathematical and statistical methods such as linear programming, econometrics and related methods of statistical analysis (Hoffman and Wood, 1976). The purpose of energy models is not to pinpoint future events, but to provide insights for addressing energy and environmental issues, with considerations in critical technical and socio-economic factors including demand growth, resource availabilities, emissions, technology costs and innovation. However, from the historical perspective, projecting 50 or 100 years into the future is inherently uncertain, and inaccuracy in forecasting energy, demand and technical projections can be demonstrated with numerous examples (Smil, 2005). The use of energy models should focus on informing decision makers by exploring energy policies which are robust under deep uncertainties. Much in the same way that explorers use maps to make navigational choices, energy economy models can be considered as tools that provide an overview of strategic decision space (Li et al., 2019).

Energy models can be classified based on underlying methodology (simulation, optimization, economic equilibrium), analytical approach (top-down, bottom-up, hybrid), or sectoral coverage (whole energy system, power system). TIMES (The Integrated MARKAL-EFOM System) (Loulou et al., 2016a) is a widely used energy systems optimization model (ESOM) that can be characterized as bottom-up optimization models covering an entire energy system. The objective function of ESOMs is to minimize the system-wide present costs based on linear programming techniques, offering insights on energy transition, economic implications and environmental impacts while capturing sectoral interactions and intertemporal dynamics. TIMES has been widely used by over 62 contracting parties (including Ireland) supported by ETSAP (Energy Technology Systems Analysis Program), an Implementing Agreement of the International Energy Agency (IEA). The original Irish TIMES dataset was extracted from the Pan European TIMES (PET36) project by the

Energy Policy and Modelling Group (EPMG) at University College Cork (UCC), and was updated with local detailed data, calibrated to the national energy system, and underpinned with macroeconomic projections from the Economic and Social Research Institute (ESRI)(Gallachóir et al., 2010). Additional inputs to the Irish TIMES model include estimates of end-use energy service demands derived from the macroeconomic model HERMES (Bergin et al., 2013), estimates of existing stocks of energy related equipment, characteristics of available future technologies, as well as present and future sources of primary energy supply and their potential.

Existing analysis with ESOM models primarily applies scenario analysis to provide policy insights in future years through exploring a spread of narrative-based what-if scenarios. A scenario can be defined as an internally consistent, plausible, and integrated description of a possible future of the human–environment system, including a narrative with qualitative trends and quantitative projections (Nakicenovic et al., 2000). Pathways are used to describe temporal evolution of scenarios in terms of emission, energy use, technology choices and associated economic implications. Scenario analysis has played a significant role in providing evidence base for policy decisions. In the context of Ireland, Scenario analysis has been carried out with Irish TIMES model to project mitigation pathways towards a low carbon future consistent with EU climate policies by 2020 (Chiodi et al., 2013b) and 2050 (Chiodi et al., 2013c), as well as addressing specific policy issues including energy security (Glynn et al., 2014), deep decarbonization carbon pathways (Glynn et al., 2019)**,** bioenergy availability (Chiodi et al., 2015a) and agriculture sector (Chiodi et al., 2016). The Irish TIMES model has also been used for informing national legislation on climate change and energy policy (Curtin et al., 2017; Deane et al., 2013).

1.2 Research Focus and Methodology

1.2.1 Exploring 1.5°C-consistent pathways with scenario ensembles

The Paris Agreement contains the ambition to limit the temperature rise to 1.5°C above the pre-industrial levels; however, existing decarbonization ambition is not strong enough to deliver this target. The global mean surface warming depends on the cumulative amount of CO_2 in the atmosphere with a near linear relationship (Allen et al., 2009; Matthews et al., 2009). Limiting global mean temperature increase at any level essentially requires global carbon emissions to become net zero at certain point (Collins et al., 2013). The feasibility in achieving 1.5°C target depends on the cumulative influence of NDCs, but the current NDCs only extend to 2030 and cumulatively imply a warming of 3°C to 4°C above pre-industrial level by 2100 (Rogelj et al., 2016a). The European Union has itself a long-term goal of reducing greenhouse gas emissions by 80%-95% when compared to 1990 levels by 2050, which was set according to the climate target of 2°C temperature rise limit prior to the Paris Agreement. It is clear that both the 2030 targets outlined by NDCs and the 2050 EU targets are not strong enough for the 1.5°C climate target set by the Paris Agreement. Therefore, it is critical to explore deep decarbonization pathways that are consistent with the 1.5°C target at a national level. While scenario analysis has played a critical role in projecting pathways with 80% reduction in CO_2 emissions consistent with 2°C target (**CO_2-80 scenario**), using small (especially single-digit) numbers of scenarios is problematic under the 1.5°C context. A spread of scenarios with varying levels of climate targets towards maximally technical feasible, under different assumptions in technology availabilities and resource constraints, captures a wider range of solution space.

The “well below 2 degrees” aim of the Paris Agreement is ambiguous and leaves a wide-open space between the 2°C and 1.5°C target. The amount of carbon emissions consistent with a certain temperature threshold is uncertain (Millar et al., 2017; Rogelj et al., 2016b). The equity principles (Clarke et al., 2014) such as responsibility based on historical emissions, capability based on GDP, equality based on population in allocating carbon budgets to individual countries lack consensus. Therefore, the exact national emission level consistent with the Paris Agreement is ambiguous and uncertain. With the ratification of the Paris Agreement, previous scenario analysis tied to a single 2°C-consistent pathway of 80% reduction by 2050 has become irrelevant. Therefore, it is necessary to explore different emission levels resilient to uncertainties in policy targets with scenario ensembles.

From the perspectives of energy systems modelling, deep decarbonization scenarios push towards the feasibility boundaries of the model and can be described as "frontier scenarios". Transitions towards a low carbon energy system typically included higher energy efficiency, deployment of renewable energy and carbon dioxide removal (CDR) technologies. Compared to 2°C-consistent pathways, 1.5°C-consistent pathways towards carbon neutrality require more profound transformations. At less ambitious reduction targets, optimization models have the freedom in choosing from a range of mitigation options to determine the cost optimal decarbonization pathways. With increased ambition in reduction targets, the model solutions push towards the feasibility boundaries. The feasibility of the "frontier scenario" depends on the portfolio of mitigation measures available in all energy using sectors of the economy (electricity, heat, and transport), including relatively uncertain technologies such as CDR technologies and resource potentials of bioenergy. It is necessary to develop a wide range of scenarios explore the feasibility of deep decarbonization under different assumptions as well as explore the roles of critical mitigation options.

Limited number of scenarios may not fully capture the inherent uncertainties and broad solution space. Scenario analysis is easy to implement and communicate but receives criticisms due to certain limitations. Simple deterministic approaches may not be suitable for complex and multi-faceted problems with inherent uncertainties (Usher and Strachan, 2012). Limited number of scenarios with detailed storylines underestimate the range of possible outcomes and lead to cognitive bias that makes them appear more probable and plausible than they are in actuality (Morgan and Keith, 2008). Scenario developers should capture a broader scope of uncertainties and facilitate the users to consider the increased range of uncertainties (Trutnevyte et al., 2016a). Ensembles of scenarios under a wide range of assumptions capture a broader scope of solution space to provide more robust policy insights.

1.2.2 Introducing the VEDA Scenario Ensemble Tool

A significant part of analysis carried out in this thesis uses the new VEDA_SET tool to explore pathways using scenario ensembles, which will demonstrate its capacity to address a number of the issues with single-digit scenario analysis that have already been mentioned.

Building an energy systems model involves a number of key components including a model generator, a solver, interfaces for handling data and results and a detailed database. TIMES is a model generator developed via the ETSAP collaboration and comprises GAMS (General Algebraic Modelling Software) source code with CPLEX and XPRESS used as solvers. The source code of the model generator is transparent and well documented (Loulou et al., 2016a). The model management "shell" VEDA (VErsatile Data Analyst) developed by KanORS is used to handle input data, invoke model generator, and examine the results. The VEDA user interface is composed of two subsystems - VEDA Front-End (VEDA-FE) which helps browse, input, and maintain the database, and VEDA Back-End (VEDA-BE) which is used to analyze the modelling outputs.

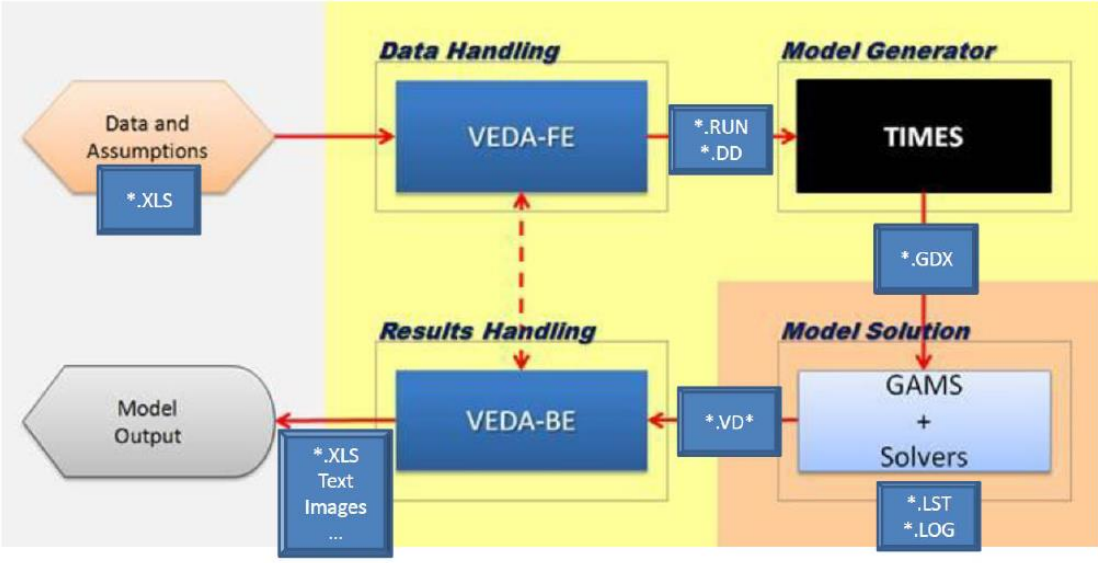
The components of the TIMES model are shown in Figure 1-1. The model inputs are datafiles in the form of spreadsheets that fully describe an energy system, including technologies, commodities, resources and demands for energy services. VEDA-FE converts the spreadsheets into *.RUN/DD (data directory) files in the format of GAMS. The TIMES model generator processes each *.RUN/DD dataset and generates a matrix with all coefficients that specify the partial equilibrium model of the energy system as a linear programming problem and outputs the *.GDX (GAMS Data eXchange) files. The model solver processes the *.GDX files and outputs the *.VD result files. The VEDA-BE interacts with the *.VD files and output model results by producing spreadsheets and other types of files.

Developing large numbers of scenarios is particularly challenging for large-scale complex models in terms of data analysis, interpretation and communication of the model results to stakeholders; these difficulties have contributed to the fact that most analysis with TIMES model has been based on scenario analysis. The current[1] VEDA system lacks the capacity to generate, import and analyze large number of scenarios. To facilitate developing scenario ensembles, I have developed the VEDA-SET (VEDA scenario ensemble tool) system. A proposal has been submitted to ETSAP that officially incorporate functions of VEDA-SET into VEDA.

Similar to VEDA user interface, VEDA-SET has two parts corresponding to VEDA-FE and VEDA-BE (Figure 1-2). The first part is a scenario generator based on VBA programming. It imports the *.RUN/DD model input files for a base case scenario and allows the user to edit parametric inputs by defining lists of input values or probability distributions. It then batch generates model input files based on user defined input values and automates the process of generating, queueing and solving the scenarios. The second part of VEDA-SET uses SQL database to replicate all functions of VEDA-BE, including importing scenarios, defining commodity and process sets, and querying the model results based on user defined attributes. While VEDA-BE can only import and process a handful of scenarios, VEDA-SET is able to process hundreds of scenarios in an efficient manner and produce data ready for analysis and visualization.

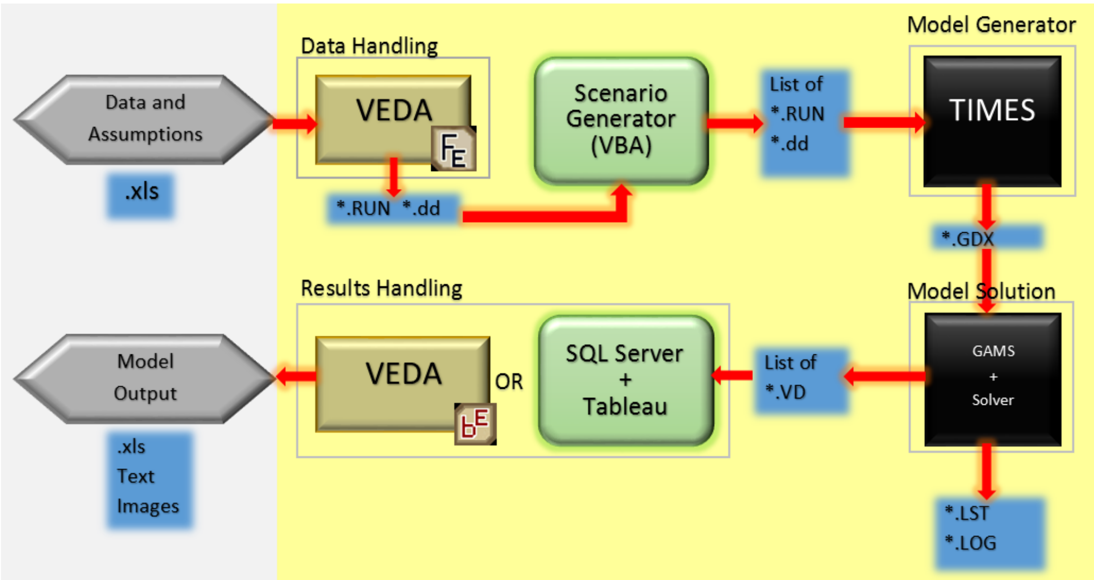
[1] VEDA-FE 2019, version 4.5.540, with most recent model documentation published in 2016. (Loulou et al., 2016b)

Figure 1-1 Schematic of VEDA (VErsatile Data Analyst) user interface



Source: (Loulou et al., 2016a)

Figure 1-2 Schematic of VEDA Scenario Ensemble Tool (VEDA-SET)



1.2.3 Thesis aim and objectives

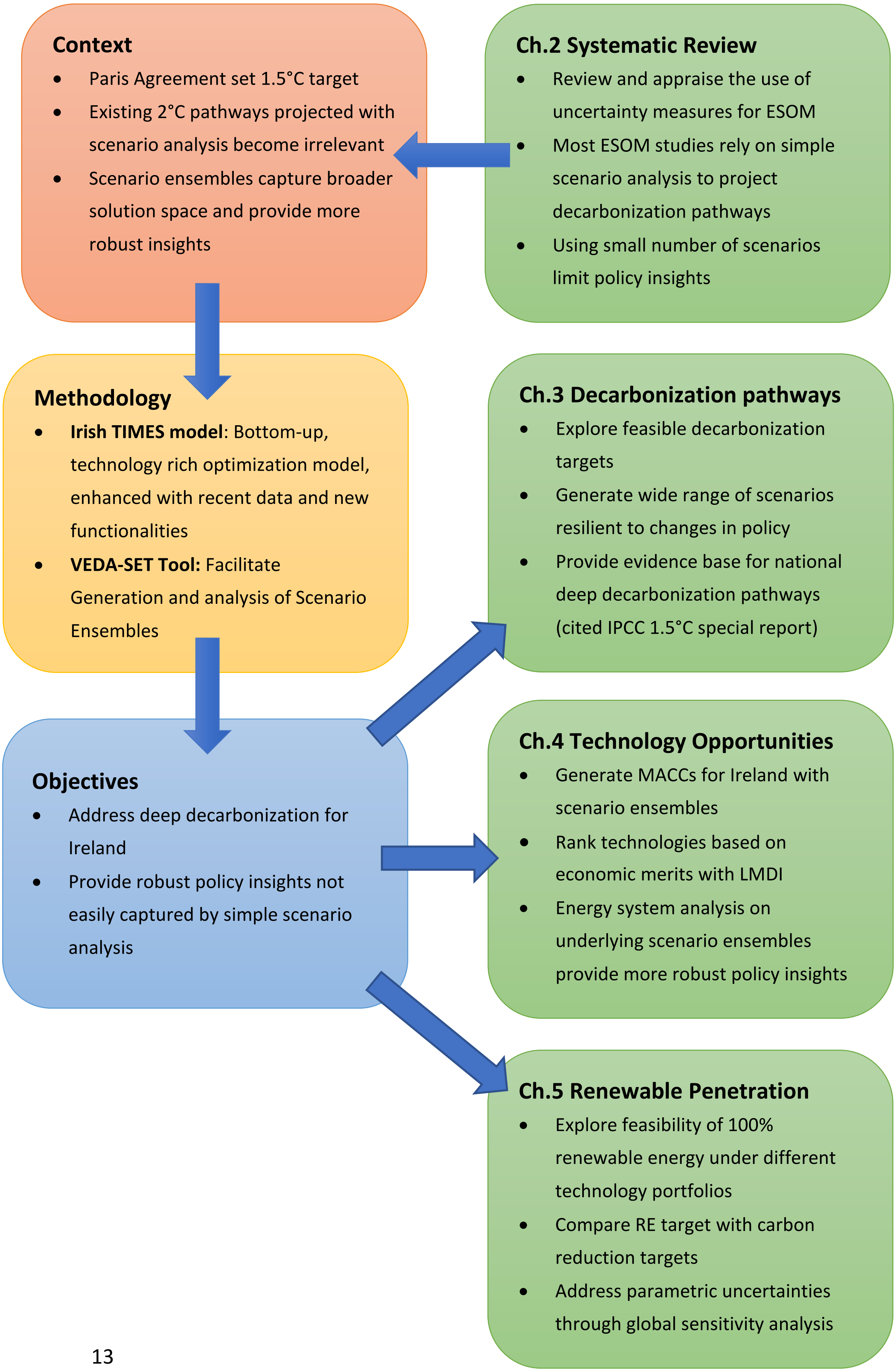
The aim of this thesis is to apply scenario ensembles to address the challenge of deep decarbonization for Ireland from different perspectives, including decarbonization pathways, technology opportunities and renewable penetration.

To achieve this aim, I have developed an innovative modelling tool to incorporate ensembles of quantitative scenarios into energy systems modelling to provide robust, well-rounded policy insights for the 1.5°C target set by the Paris Agreement.

An overview of the thesis is provided in Figure 1-3. Detailed objectives addressed by the thesis can be summarized as follows:

- Enhance the capabilities of VEDA-TIMES modelling system to facilitate generation and analysis for scenario ensembles
- Explore technical and economic feasible emission levels towards 1.5°C target set by the Paris Agreement
- Evaluate the roles of critical mitigation options under a wide range of assumptions including resource costs, technology availabilities and capital costs
- Compare economic merits of mitigation options using model based marginal abatement cost curves
- Explore feasibilities and challenges of a 100% renewable energy system with comparison to decarbonization targets
- Address the impacts from uncertainties in model assumptions though global sensitivity analysis

Figure 1-3 Thesis Overview



1.3 Thesis in Brief

In addition to the introductory chapter, this thesis is presented in four chapters: Chapter 2 has been published in the peer-reviewed scientific journal Energy Strategy Reviews. Chapter 4 has been published as a peer-reviewed chapter in the ETSAP book "Limiting Global Warming to Well Below 2 °C: Energy System Modelling and Policy Development". Chapter 3 is under review in Applied Energy. Chapter 5 is in final preparation for submission to a scientific journal. The contributions of the thesis can be summarized as follows.

Chapter 2 carries out a comprehensive review on the uncertainty analysis approaches applicable to ESOMs. The review identifies and provides a critical appraisal on the use of uncertainty analysis approaches. The review shows that while single projections of mitigation pathways may result in limited or even biased policy insights, the majority of existing analysis relies on simple scenario analysis. The review then provides a guidance in choosing systematic methods to address uncertainties and improve robustness of model results.

The exact level of 1.5°C-compatible carbon budget allocable to Ireland is uncertain due to lack of consensus in equity principles and uncertainties in impacts of carbon cumulation on global climate. Chapter 3 applies a spread of scenarios with different carbon budget levels and various assumptions in the mitigation options available to project a wide range of deep decarbonization pathways towards 2050. Quantitative indices are used to determine maximally feasible level of carbon budget that is technically and economically feasible. Scenarios under alternative assumptions are used to demonstrate the roles of critical mitigation options and implications from delayed actions and carbon lock-in.

With technological innovations and cost reductions, low-carbon technologies are gradually perceived as opportunities in economy development and job creation. The signing of the Paris Agreement was enabled in part due to a focus on the evidence base for seizing the technology opportunities (Schmidt and Sewerin, 2017). Chapter 4 focuses on mitigation options, which are assessed using marginal abatement cost curves (MACCs) derived using scenario ensembles from the TIMES model. The analysis presents an innovative analytical approach that combines energy systems analysis with marginal abatement costs. Decomposition analysis is used to associate mitigation measures with carbon cost levels, and the MACC is visualized in an innovative way that reflect sectoral interactions. Energy systems analysis on the ensembles of scenarios composing the MACCs provide more robust policy insights compared to simple scenario analysis.

Renewable energy technologies represent a critical low-carbon alternative to fossil fuels in all applications including electricity, heating and transport. With the ratification of the Paris Agreement, transition towards a low carbon economy through 100% renewable energy attracts increased interests. Rather than focusing on emission reductions, Chapter 5 explores pathways aiming for high renewable penetration levels for Ireland in 2050. Scenario ensembles are used to address the roles of electrification, bioenergy and renewable generation technologies. The renewable scenarios are compared with decarbonization scenarios to explore how well these targets are aligned. Global sensitivity analysis is carried out to identify which technologies remain robust under uncertainties and the most impactful source of uncertainties.

1.4 Role of Collaborations

This thesis is based on my own work. I'm the lead author and prepared the manuscript for all chapters. All aspects of this thesis have received advise and been reviewed by Prof. Brian Ó Gallachóir and Dr. Fionn Rogan as research supervisor and recognize the contributions from all co-authors and my supervisors in model development, data collaboration and elaboration, and manuscript revisions.

The analysis is based on the Irish TIMES energy systems model and I acknowledge contributions towards the development of the model from co-authors, Dr. Alessandro Chiodi, Maurizio Gargiulo, Dr. Paul Deane, Dr. James Glynn and Prof. Brian Ó Gallachóir. I programmed the VEDA_SET tool and developed techniques that facilitate scenario generation and analysis. I also gathered most up-to-date techno-economic data and added new technologies primarily on renewable and decarbonization technologies, such as bioenergy, ocean energy and power to gas. For each chapter, I performed scenarios runs for hundreds of scenarios under varying resource and technology constraints and analyzed the results using VEDA_SET. I also prepared all tables, figures and manuscripts.

Chapter 2 is a collaborative review work I led among UCC, UCL and NCSU. Dr. Steve Pye and Dr. Francis G.N. Li. suggested systematic approaches in conducting the literature search. Prof. Joseph Decarolis contributed towards the methodological descriptions on modelling to generate alternatives part. All co-authors contributed to the manuscript revision. Chapter 3 was entirely my work and received suggestions and revisions from all co-authors. Chapter 4 received revisions primarily from Dr. Fionn Rogan and suggestions from Dr. Paul Deane. Chapter 5 is a collaborative work between UCC and NCSU and received suggestions from Prof. Joseph Decarolis.

2 A Review of Approaches to Uncertainty Assessment in Energy System Optimization Models

Abstract

Energy system optimization models (ESOMs) have been used extensively in providing insights to decision makers on issues related to climate and energy policy. However, there is a concern that the uncertainties inherent in the model structures and input parameters are at best underplayed and at worst ignored. Compared to other types of energy models, ESOMs tend to use scenarios to handle uncertainties or treat them as a marginal issue. Without adequately addressing uncertainties, the model insights may be limited, lack robustness, and may mislead decision makers. This chapter provides an in-depth review of systematic techniques that address uncertainties for ESOMs. We have identified four prevailing uncertainty approaches that have been applied to ESOM type models: Monte Carlo analysis, stochastic programming, robust optimization, and modelling to generate alternatives. For each method, we review the principles, techniques, and how they are utilized to improve the robustness of the model results to provide extra policy insights. In the end, we provide a critical appraisal on the use of these methods.

Keywords

Energy system modelling; uncertainty; Monte Carlo analysis; stochastic programming; robust optimization; modelling to generate alternatives

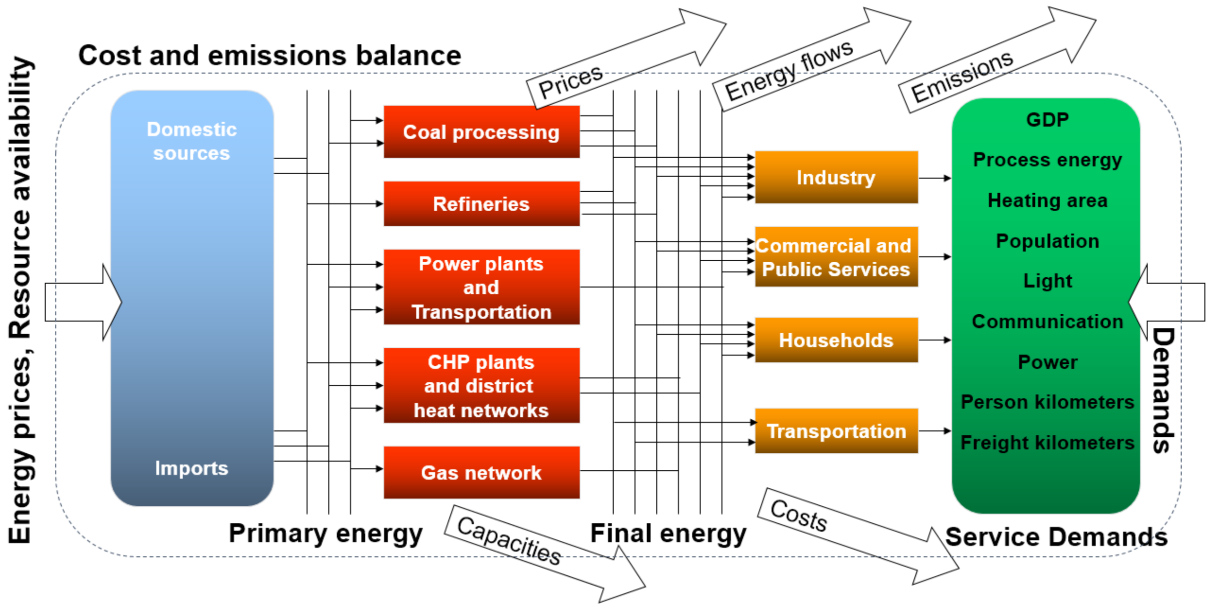
2.1 Introduction

Energy models can be categorized in various ways (Mougouei and Mortazavi, 2017). A comprehensive review by Jebaraj and Iniyan (Jebaraj and Iniyan, 2006) on existing energy models in 2006 classifies energy models into energy planning models, energy supply–demand models, forecasting models, renewable energy models, emission reduction models, and optimization models. Gargiulo and Ó Gallachóir (Gargiulo and Ó Gallachóir, 2013) classify long term energy models based on underlying methodology (simulation, optimisation, economic equilibrium), analytical approach (top-down, bottom-up, hybrid (Hourcade et al., 2006)), and sectoral coverage (energy system(Bhattacharyya and Timilsina, 2010), power system (Bazmi and Zahedi, 2011)).

As an important branch of energy models, energy system optimization models (ESOMs) can be characterised as technology-rich, optimization models covering an entire energy system. ESOMs have been widely used to offer critical climate and energy policy insights at national, global, and regional scales (Giannakidis et al., 2015). These models provide an integrated, technology-rich representation of the whole energy system for analysing energy dynamics over a long-term, multi-period time horizon. Optimal solutions are computed using linear programming techniques. The results are used to explore the least cost energy system pathways for an energy secure and low carbon future, offering insights on energy transition, economic implications and environmental impacts. One of the widely used ESOM model is the MARKAL/TIMES family of models (Loulou et al., 2016a) developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP) under the aegis of the International Energy Agency (IEA) since the 1970s. Other ESOM models include MESSAGE (Müller-Merbach, 1983), ESME (Heaton, 2014), OSeMOSYS (Howells et al., 2011) and TEMOA (Hunter et al., 2013). The schematic of a typical ESOM model is shown in

Figure 2-1 Schematic of TIMES model (Remme et al., 2002). The model inputs including energy supply, energy demand and associated economic parameters are shown on the sides, and the model outputs are shown on the top and bottom.

Figure 2-1 Schematic of TIMES model (Remme et al., 2002)



While models are becoming increasingly more complex and sophisticated, projecting 50 or 100 years into the future is inherently uncertain (Peace and Weyant, 2008a). Edenhofer et al. (2006) categorizes uncertainties into parametric and structural. *Parametric* uncertainties arise due to lack of knowledge about empirical values associated with model parameters, and *structural* uncertainties refer to uncertainties in the model equations that collectively define the model structure - examples of the latter include the default ESOM formulation that ignores the heterogeneity among decision makers in the energy system, the manner in which non-economic considerations factor into energy purchasing decisions, and the role that politics, social norms, and culture play in shaping public policy. Due to model complexity, computational intensity, and the time pressure to produce relevant policy, many ESOMs have been used in a deterministic fashion with limited attention paid to uncertainty. A review of energy system models by Pfenninger points out that assessing uncertainties has become one of the major challenges of ESOMs (Pfenninger et al., 2014). When formalizing best practices for using ESOMs, DeCarolis et al. (2017) highlight the importance of quantifying uncertainties. Ignoring uncertainty is problematic as many of the issues that ESOM analyses consider are deeply uncertain. They can be described as belonging to the area of “post-normal science”

(Ravetz and Ravetz, 1999), where both the uncertainties and the decision stakes inherent in these issues are high. As Lempert (Lempert, 2003) points out, the long-term policy analysis conducted with ESOMs requires decision making under *deep uncertainty*, where analysts and decision makers do not know or agree on (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes (i.e. as they correspond to different policy objectives). This underlines the importance of modelers carrying out uncertainty analysis in a more systematic way to improve the robustness of model outputs and their use for providing policy insights. By systematic, we mean analysis that applies a formal approach to a broad range of uncertainties, and which explicitly addresses the three aspects of *deep uncertainty* in order to provide additional policy insights beyond simple scenario analysis.

It is informative to survey the types of methods available for undertaking uncertainty assessments in different types of energy, economy, environment, and engineering (E4) models, for which a number of reviews have been undertaken. Energy models are designed with different end uses and research problems in mind. Due to the differences in model paradigm and analytical approach across various models, the uncertainty techniques available for each type of model vary. Several existing reviews focus on certain types of models, such as integrated assessment models (Kann and Weyant, 2000; Van Asselt and Rotmans, 2002, 2001), optimization models (Zeng et al., 2011), power systems models (Soroudi and Amraee, 2013), environmental models (Uusitalo et al., 2015), or energy related issues such as climate change (Peterson, 2006) and sustainable energy planning (Ioannou et al., 2017).

Given an expectation of increased global efforts to limit global warming to well below 2 degrees after the adoption of the Paris Agreement, ESOM models are likely to become critical tools that can supply an evidence base for governments, research institutions and international organizations exploring future pathways to deep decarbonization of energy systems. Therefore, it is necessary to target specifically on ESOMs and undertake a comprehensive review of the literature to identify the application of uncertainty methods. The review was done systematically, using a pre-defined search strategy. We identified four main techniques that have been applied, including Monte Carlo analysis (MCA), Stochastic

Programming (SP), Robust Optimization (RO), and modelling to generate alternatives (MGA). Besides introducing the principles and formulations of each technique, the chapter focuses on discussing how the different techniques are applied to provide additional policy insights that cannot easily be obtained from deterministic scenario runs. We also provide an appraisal and recommendations on the choice of uncertainty techniques according to the policy issue and the types of uncertainty in question. This chapter is organized as follows. In Section 2, we present the literature search methodology carried out. Section 3 thoroughly reviews the four uncertainty techniques. Section 4 provides a brief discussion and concluding remarks.

2.2 Literature Search

To capture the relevant literature on uncertainty analysis in ESOMs we carried out a systematic literature search using a three-phase search strategy based on the techniques described in (Kitchenham, 2004).

The first phase was a broad literature search for all primary studies possibly relevant to the research question using the electronic database engines Scopus and ScienceDirect. The search terms used were grouped into two lists as shown in Table 2-1. The first list includes keywords associated with ESOMs, and the second list includes those related to uncertainty. The actual search strings applied were obtained by connecting two keywords from both lists with the Boolean "AND". The search terms contained both generic search terms and specific terms. Generic terms such as "uncertainty", "stochastic" and "energy modelling" ensured a wide set of result coverage without missing key studies. More specific search terms were identified from previous search results and included model names such as "MARKAL" and "ESME", as well as uncertainty techniques like "Monte Carlo analysis" and "stochastic programming". Combining the two search term lists resulted in 42 search strings (e.g. "uncertainty and energy modelling", "Monte Carlo Analysis and MARKAL"). Search strings were searched for in titles, keywords, and abstracts. The aggregated number of results from both electronic databases totalled over 2100.

Table 2-1 Search Term Lists for Literature Search

Energy Model Related	Uncertainty Related
Energy system model	Uncertainty
Energy systems	Stochastic
Energy modelling	Sensitivity analysis
Energy modeling	Monte Carlo analysis
MARKAL	MGA
TIAM	Stochastic programming
ESME	Robust optimization

The second phase was to apply a filter on the initial search results to exclude studies unrelated to ESOM type models i.e. comprehensive pan-sectoral tools which address trade-offs through time and the transformation of whole energy systems towards sustainability. The search terms we applied are relatively generic and have been used extensively in many subject areas. For example, the term "energy system" may refer to specific sectoral models exploring building systems, power transmission systems or energy distribution systems (e.g. gas networks). We filtered the results based on a case-by-case review of individual titles and abstracts to rule out studies unrelated to ESOM models.

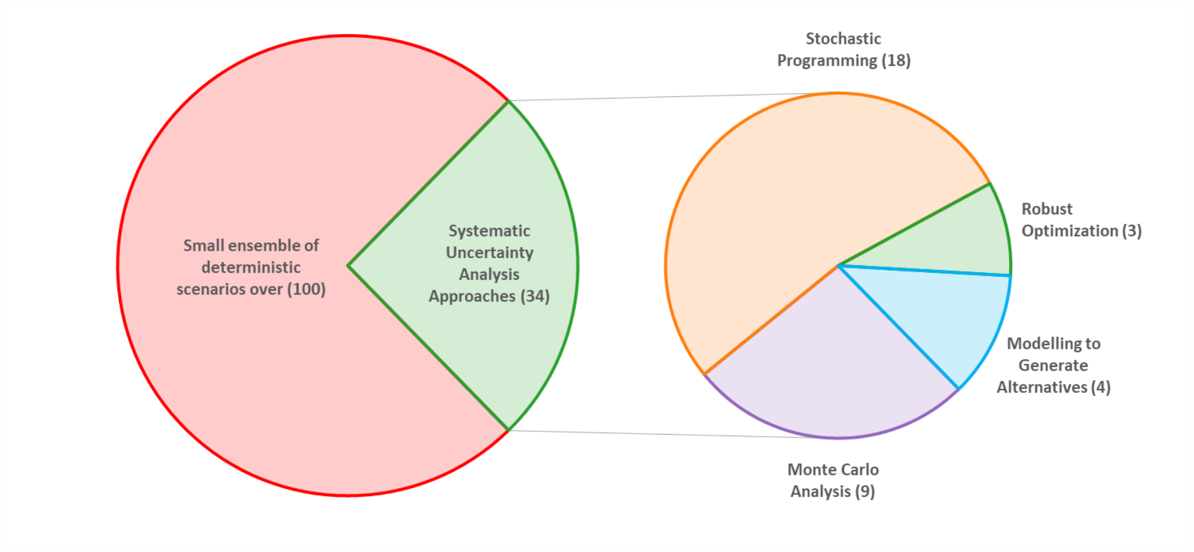
In the third phase, we closely examined the remaining studies, and selected studies under review according to the following criteria:

- First, the study explicitly addresses uncertainty as a core part of analysis.
- Second, the energy system model used is an ESOM model covering the entire energy system, and simulation models like LEAP (Rogan et al., 2014) and power systems models like PLEXOS (Deane et al., 2012) were excluded.
- Third, the uncertainty analysis is carried out in a systematic manner using formal techniques that are documented by the authors.

As the electronic databases used in our initial search may not have covered all relevant studies, we also searched the reference lists from relevant papers to look for publications that could have been missed by the academic search engines.

As shown in Figure 2-2 Number of ESOM studies that address uncertainties based on our literature search in 2017, from the literature search, we found over 100 studies that featured scenario analysis using deterministic scenarios, and only 34 studies applying formal uncertainty techniques, including MCA (9 studies), stochastic programming (18 studies), robust optimization (3 studies), and modelling to generate alternatives (4 studies).

Figure 2-2 Number of ESOM studies that address uncertainties based on our literature search in 2017



2.3 Systematic Review

The literature search shows that only a minority of ESOM-based studies apply systematic formal approaches to address uncertainties in long-term energy pathways. The majority of ESOM studies use small-ensemble scenario analysis and simple sensitivity analysis to handle uncertainties, where a base case scenario is created, and then the impacts of uncertain policy instruments or exogenous conditions are analyzed through alternative scenarios with additional constraints and assumptions. For example, Cabal et al. (Cabal et al., 2012), Calderón et al. (Calderón et al., 2014), and Føyn et al. (Føyn et al., 2011) applied additional climate policy constraints in emission targets and carbon taxes. Comodi et al. (Comodi et al., 2014), Grah et al. (Grahn et al., 2013) made alternative technological assumptions in technology efficiencies and technology costs. Gracceva and Zeniewski (Gracceva and Zeniewski, 2013) constrained resource potential on the supply side. Chiodi et al. (Chiodi et al., 2015a) compared a number of sustainable bioenergy scenarios. Czyrnek-Delêtre M.et al. (Czyrnek-Delêtre et al., 2016) assessed the impacts of including indirect land use change on mitigation pathways. Balash et al. (Balash et al., 2013), Borjesson et al. (Börjesson et al., 2014), Densing et al. (Densing et al., 2012), Gritsevskyi and Schrattenholzer (Gritsevskyi and Schrattenholzer, 2003), and Fortes et al. (Fortes et al., 2014) constructed alternative scenarios by varying assumptions in different aspects of the model. The alternative scenarios are sometimes accompanied with sensitivity analysis in a "one-factor-at-a-time" (OAT) fashion, where certain parameters are varied a few times while the other assumptions are held constant. For example, sensitivity scenarios across a range of studies are carried out by varying EV battery costs (Bahn et al., 2013), emission constraints (Cameron et al., 2014)(Contaldi et al., 2008), and discount rate (Hainoun et al., 2010). The above examples are typical of the kind of approaches to uncertainty analysis that are commonly found in the ESOM literature.

As a simple method to implement and communicate, scenario analysis with a small-ensemble of cases has played a significant role in providing policy insights in future years through exploring a spread of narrative-based what-if scenarios, and has been critical in informing policies to date on cost effective pathways towards an energy secure (Glynn et al., 2014) and low carbon (Chiodi et al., 2013a)(Chiodi et al., 2013c) future. On the other hand, due to a number of limitations, this simple approach has received many criticisms. Usher and Strachan (Usher and Strachan, 2012) argued that deterministic methodology is not suitable for complex and multi-faceted problems with inherent uncertainties. Trutnevyte et al. (Trutnevyte et al., 2016b) pointed out that simple deterministic approaches to modelling often do not anticipate real world developments in the energy system. Morgan and Keith (Morgan and Keith, 2008) argued that scenarios with detailed storylines underestimate the range of possible outcomes and lead to cognitive bias, which make them appear more probable and plausible than they are in actuality. To improve the use of scenarios for tackling uncertainties and informing decision making, many authors have suggested innovative techniques (Eline Guivarch et al., 2017; Hughes and Strachan, 2010; Trutnevyte et al., 2016a, 2016b; Trutnevyte and Guivarch, 2014), for example designing scenarios to capture a wide range of uncertainties while subsequently selecting a small subset of policy relevant scenarios.

2.4 Monte Carlo Analysis

2.4.1 Principle

Compared to scenario and sensitivity analysis, Monte-Carlo Analysis (MCA) is a more systematic way to address parametric uncertainties. The principle of MCA is to propagate uncertainties by simultaneously perturbing multiple uncertain input parameters represented by probability distributions. The collection of model outputs can be evaluated statistically using a global sensitivity analysis (GSA) approach (Saltelli et al., 2008)(Space et al., 2012), which can be defined as how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input. Saltelli and Annoni (Saltelli and Annoni, 2010) proves the statistical inadequacy of the "OAT" approach with a geometric approach and point out that GSA is a better practice in sensitivity analysis.

Carrying out a Monte Carlo simulation generally requires the following steps.

1. Assign probability distributions to multiple exogenous variables
2. Generate a sample of random values
3. Feed the sample into the model to compute a set of outputs
4. Iterate the procedure N times and collect N samples of model outputs
5. Evaluate sets of outputs using statistical techniques

The probability distributions are usually obtained through modelers' judgement or expert elicitations. For example, in some studies (Hedenus et al., 2010) and (Lehtveer and Hedenus, 2015) the uncertain parameters are assumed to vary within a certain range across the deterministic values in the base case scenarios. In another (Bosetti et al., 2015), the results from expert elicitations are aggregated to determine input range and probability distributions. In addition, the interdependencies between inputs can be defined by covariance (Fragkos et al., 2015).

Once probability distributions are assigned to inputs, the model is then run multiple times using one set of inputs for each run. Typically, one hundred to several hundred runs are considered sufficient, but the number could also be determined statistically. Generally, the number of runs required is independent of the number of uncertain parameters, and mainly depends on the level of confidence. For example, in (Alzbutas and Norvaisa, 2012) Alzbutas and Norvaisa applied Wilks' formulas (Sachs, 1984), and determined that 93 runs are required to ensure an observation has a 95% probability (u = 95%) to fall within the two sided 95%

confidence interval (v = 95%) of output distribution, where n1 and n2 are the required number of runs for one-sided and two sided tolerance limits respectively:

$$n_1 \geq \ln(1 - v)/\ln(u)$$
$$n_2 \geq (ln(1 - v) - l\,n((n_2/u) + 1 - n_2))/ln(u)$$

Morgan's formula (Morgan et al., 1990) is used by Pye et al. (Pye et al., 2015), where c is the deviation enclosing the 95% confidence interval, s is the sample standard deviation, and w is the requisite confidence interval width. The calculation showed that 475 runs are required to estimate the sample mean with less than 1% error:

$$\mathrm{n} > (\frac{2\mathrm{cs}}{\mathrm{w}})^2$$

2.4.2 Applications

In our literature search, we found 9 studies that perform uncertainty analysis through MCA. The research question, assumptions and key insights gained in each study are summarized in Table 2-2**.** As a computational intensive method, MCA method did not become widely feasible for ESOM models until the rapid development of computing power in the early 2000s. Seebregts et al. (Seebregts et al., 2002) first proposed its application for use with ESOMs, and De Feber et al. (De Feber et al., 2003) later demonstrated its feasibility in MARKAL. The key policy insights delivered by an MCA may include the likelihood in reaching a particular policy target, which technologies are more robust in an uncertain future, and insights into the relationships between the model inputs and outputs.

Table 2-2 Monte Carlo Analysis review summary

Model	Research Question	Coverage and Time Horizon	Probability Distributions	# of Runs
MARKAL (De Feber et al., 2003)	Incorporate technology learning mechanism into energy system	Western Europe All Sectors 2050	Uniform Triangular	100
GET 7.0 (Hedenus et al., 2010)	Impact of energy supply system on transport propulsion technologies	Global All Sectors 2100	Normal	100
GET (Lehtveer and Hedenus, 2015)	The role of nuclear technology on climate mitigation cost reduction	Global All Sectors 2100	Uniform	1000
MARKAL (Yeh et al., 2006)	Penetration of hydrogen fuel cell vehicle (H2-FCV) in US	US All sectors 2030	Uniform	500
MESSAGE (Alzbutas and Norvaisa, 2012)	Deployment of nuclear reactors in Lithuania	Lithuania All sectors 2025s	Uniform	100
MARKAL (Johnson et al., 2006)	Evaluate sensitivity in EPA's national MARKAL database and energy system model	US Electric Sector 2030	Uniform	1000
GCAM MARKAL_US WITCH (Bosetti et al., 2015)	Impact of technology uncertainties on a set of alternative environmental and economic metrics across models	Global & US All Sectors 2100	LogUniform Uniform (Aggregated Expert elicitations and Importance sampling)	740 for each model
ESME (Pye et al., 2015)	Impact of uncertainty on meeting UK decarbonization targets	UK All Sectors 2050	Triangular (Expert Elicitations)	500
PROMETHEUS	Introduce the stochastic model PROMETHEUS	Global All sectors	Econometric method and	

(Fragkos et al., 2015)		2050	expert judgement	

Table 2-3 Monte Carlo Analysis review summary (Continued)

Model	Key Uncertain Inputs	Result Analysis	Key Policy Insights
MARKAL (De Feber et al., 2003)	Progress ratios -solar PV -wind turbines	Histogram	Progress ratios have high impacts on the success of wind and solar technologies.
GET 7.0 (Hedenus et al., 2010)	Vehicle costs -Battery -Fuel cells -Gas storage	Scatterplot	Cost-effectiveness of propulsion technologies depend mainly on the relative price of energy carriers. Extreme vehicle costs have high impacts on the results.
GET (Lehtveer and Hedenus, 2015)	CCS capacity and costs Renewable costs and potential Gas and coal costs Nuclear technology costs Demands	Histogram	Employing nuclear technologies has potential to reduce climate mitigation costs. Compared to conventional technologies, investing in advanced nuclear technologies has greater climate costs reduction potential.
MARKAL (Yeh et al., 2006)	11 Parameters Fuel costs H2-FCV characteristics Other Vehicle characteristics	Histogram Regression	H2-FCV is only viable with cost reductions, increased oil prices and increased costs of competing vehicle technologies.
MESSAGE (Alzbutas and Norvaisa, 2012)	6 Parameters Nuclear Reactor characteristics	Partial Correlation Coefficients	Constructing nuclear reactors is economically attractive. The discount rate has highest influence on total system cost, and the nuclear fuel price has the lowest influence
MARKAL (Johnson et al., 2006)	14 Parameters Fuel Costs Hurdle Rates Nuclear Capacity Renewable Growth Rates	Normalized linear regression	The main factor that influences the electricity sector is whether specific technologies and fuels meet base or peak load electricity demands

GCAM MARKAL_US WITCH (Bosetti et al., 2015)	8 parameters Solar Nuclear Biofuel Bioelectricity CCS	Global sensitivity measures (variance, density, CDF based) Sign of Change	Cost of nuclear energy affects emissions the most in unconstrained emission scenarios In emission constrained scenarios, biofuels are also the main source of decarbonization. Policy costs most sensitive to nuclear costs
ESME (Pye et al., 2015)	Investment costs Build rates Resource Availability Resource Prices	Scatterplot Multivariate linear regression	The probability of meeting carbon reduction target is strongly dependent on the carbon price level. Biomass availability, gas prices and nuclear capital costs are critical uncertainties for achieving emission reduction targets.
PROMETHEUS (Fragkos et al., 2015)	All parameters		

One such application explored how system uncertainties might affect whether a specific carbon price level may or may not deliver emission reductions in the longer term. With the stochastic UK energy system model ESME, Pye et al. (Pye et al., 2015) found that 42% of runs failed to deliver the 80% carbon reduction target in 2050 at the reference carbon price of £421/t CO_2. The uncertainty can be mitigated by increasing the carbon price. A £30/tCO_2 increase in carbon price ensures a 100% probability in reaching the 2030 target, while controlling the probability to meet the 2050 target requires much larger carbon price increases.

The results can also be used to identify the most robust technologies under uncertainty. High penetration over a wide range of outcomes is a strong indication of robustness. A technology can then be categorized as a "no hoper", a "marginal contender" or a "no regret option" (Heaton, 2014). Yeh et al. (Yeh et al., 2006) analyzed the economic viability of hydrogen fuel cell vehicles. By plotting histograms of output distributions, it was determined that this technology is not viable in general as it has some level of penetration only in 6.4% of all simulations. The characteristics of the runs in which this technology is deployed demonstrated that this technology can be viable if its cost is reduced and oil prices and competing vehicle technology costs become higher. Lethtveer and Hedenus (Lehtveer and Hedenus, 2015) explored the role of nuclear technologies in climate mitigation cost reduction. The histogram of MCA result shows that compared to conventional nuclear technologies, investing in advanced nuclear is more likely to achieve higher cost savings.

Linear optimization models like ESOMs are often criticized as “black-box” due to their lack of transparency (Bosetti et al., 2015). Characterization of the relationships between inputs and outputs helps improve model transparency and unpacks the model structure. The scatterplot is a good starting point that provides visualization of the relationships between inputs and outputs. In (Hedenus et al., 2010), Hedenus et al. analyzed changes in energy supply and their effect on the deployment of transportation technologies. A scatterplot showed that battery cost strongly influences the electrification of road transportation. Electricity is used in the transport sector only if the battery cost is significantly reduced. However, it should be noted that the scatterplot approach is qualitative in nature (for interpretation of outputs) and requires human expertise to identify relationships (Johnson et al., 2006).

To quantify the input-output relationships, GSA can be carried out using statistical methods such as regression analysis. For example, Johnson et al. (Johnson et al., 2006) calculated correlation coefficients, where large correlation coefficients between a pair of inputs and outputs indicates a strong linear relationship. Bosetti et al. (Bosetti et al., 2015) carried out GSA to identify the key drivers of uncertainties and used the sign of change to determine whether the variation of one input parameter causes an increase or decrease in model output. Pye et al. (Pye et al., 2015) performed a multivariate linear regression and used standardized regression coefficients to rank the uncertain input factors. Biomass availability, gas prices and nuclear capital costs were identified as critical uncertainties for achieving emission reduction targets. In an analysis on the small and medium nuclear reactor viability in Lithuania, Alzbutas and Norvaisa (Alzbutas and Norvaisa, 2012) ranked the contribution of input parameters using partial correlation coefficients. The results showed that the discount rate has the strongest influence on the total system costs. Opposite to the modeler’s expectation, the nuclear fuel price actually has the weakest influence on total system costs.

2.4.3 Limitations

Even though the MCA approach is not conceptually difficult and does not require modifications in model structures or mathematical formulations, performing MCA for ESOM models suffers computationally from a heavy computational burden. ESOM models generally have thousands of variables, and take much longer processing time compared to simulation models. Typical MCA requires at least hundreds of runs to guarantee uncertainty coverage, making it impractical for very large and complex models. Sampling techniques can be used to reduce the number of runs required for statistically significant results. For example, the Latin Hypercube Sampling technique (McKay et al., 1979) evenly samples from the probability distributions, and can be used to generate a relatively small sample set that represents the real variability. Importance sampling (Glynn and Iglehart, 1989) techniques used by Bosetti et al. (Bosetti et al., 2015) sample from a different distribution and renormalize back to the original one. In this way, the areas of distributions with high interest but low probabilities can be sufficiently covered.

Another challenge for MCA is to obtain reliable probability distributions for uncertain inputs. The results from MCA can be very sensitive to distribution assumptions, and different distributions may give very different results even if they have the same mean and variance (Pindyck, 2017). However, knowledge concerning the uncertainty of model inputs is often limited. It is unreliable to derive distributions based on historical data because many uncertainties in ESOM studies have a long term, and low frequency, and do not tend to occur repeatedly. Expert elicitation (Durbach et al., 2017)(Usher and Strachan, 2013) can provide a foundation for assessing future uncertainties to support decision-making. It is important that expert elicitations to be carried out in a rigorous way and address the choice of expert, potential biases and overconfidence, convergence of different opinions, and trustworthiness in the results (Morgan, 2014)(Culka, 2014).

2.5 Stochastic Programming

MCA is able to provide additional insights compared to conventional analysis, but each scenario is assumed equally likely and the results do not suggest a single best course of action. In addition, the model assumes that all future uncertainties are resolved at the current time with perfect foresight. This "learn now then act" approach diverges with reality since policy makers need to make decisions with uncertainties revealed only at a later time in an "act now then learn" fashion Sequential decision making using stochastic programming provides one single best course action that accounts for future uncertainties. The acronyms used in this section are provided in Table 2-4.

Table 2-3 Commonly used acronyms for stochastic programming

Full Name	Acronym
State of the world	SOW
Minimax regret criterion	MMR
Expected value of perfect information	EVPI
The cost of ignoring uncertainty	ECIU
Expected loss	EL
value of the stochastic solution	VSS
value of policy coordination	VPC

2.5.1 Principle

Stochastic programming considers multiple unresolved future uncertainties and determines optimal strategies by striking a compromise between the consequences of multiple ways of "guessing wrong" (Loulou and Kanudia, 1999). The stochastic result represents a hedging strategy that provides one single best course of "here and now" actions (Hu and Hobbs, 2010). After the resolution time at which the actual values of uncertain parameters are revealed, the hedging strategy produces as many contingent strategies as the number of possible outcomes (Labriet et al., 2008). Each strategy is a recourse against the possible outcomes and the "wait and see" decisions can be made accordingly.

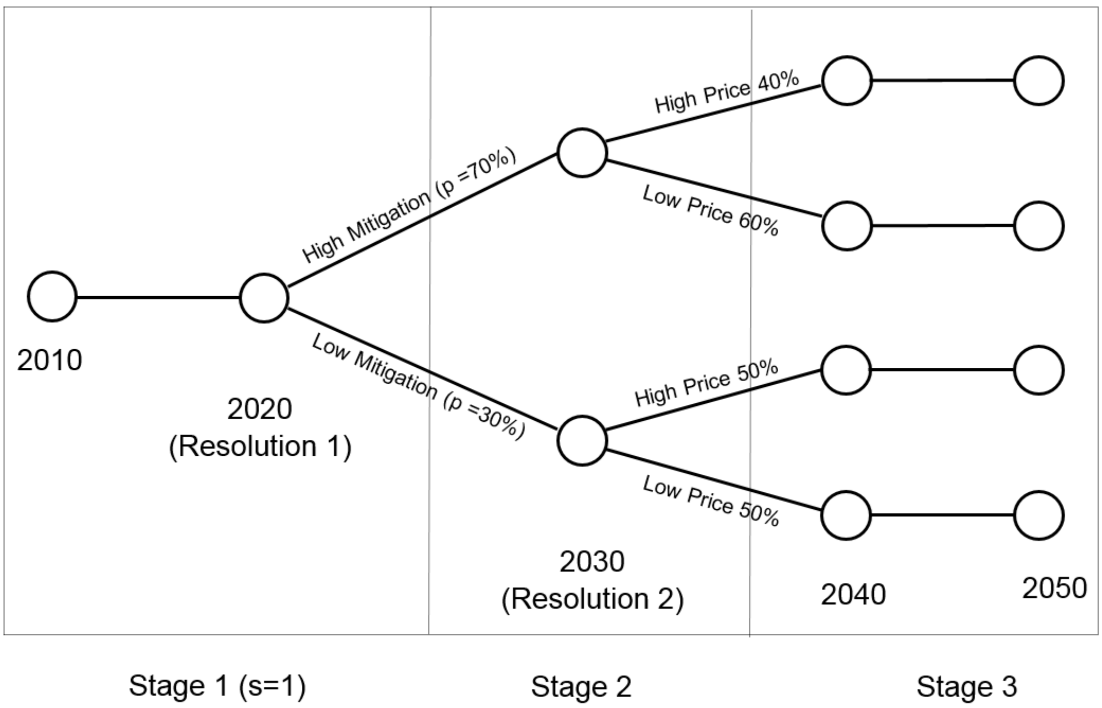
The formulation of the widely used *expected cost* criterion (Loulou, 2012) can be illustrated in Figure 2-3 Example of a three-stage Event Tree, which shows an event tree under uncertain carbon mitigation targets and energy prices. The model time horizon is divided into three time stages by two resolution times. The possible future outcomes in each stage are represented by branches known as "states of the worlds" (SOWs). The possible realizations of uncertain parameters are defined over the SOWs, while the deterministic parameters remain the same across all SOWs. The likelihood for each SOW is defined by the probability weightings shown along the branches. The optimal strategy is calculated by minimizing the expected value of total system cost over all SOWs using the formulation as shown below (Loulou, 2012).

$$minimize \sum_{s \in S(t)} \sum_{t \in T} C(t,s) * X(t,s) * p(t,s)$$

$$Subject\ to\ A(t,s) * X(t,s) \geq b(t,s)$$

- t = time period
- T = set of time periods
- s = SOW index
- S(t) = set of SOW index for time period t
- $C(t,s)$ = cost row vector
- $X(t,s)$ = decision variables
- $p(t,s)$ = probability weightings
- $A(t,s)$ = linear programming coefficient matrix
- $b(t,s)$ = right hand side column vector

Figure 2-3 Example of a three-stage Event Tree



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Anticipating a range of possible scenarios for analysis with stochastic programming is often possible, but it is difficult to reach a consensus on the likelihood of each outcome occurring. One common way to carry out the analysis under ignorance about the probability of future outcomes is to apply the Laplace expected cost criterion (Loulou and Kanudia, 1999), which simply assigns equal probability weightings at each stage. Alternatively, the minimax regret criterion (MMR) can be applied (Loulou and Kanudia, 1999). The difference between the total system cost of the hedging strategy solution and the cost of the corresponding perfect foresight scenario is defined as the "regret". The stochastic programming formulation under MMR determines the hedging strategy by minimizing the total regret between the hedging strategy and all perfect foresight scenarios. Compared to the expected cost criterion, the results under MMR mainly depend on the extreme SOWs with highest and lowest values. This approach can thus be considered as a type of risk aversion technique.

Several metrics can be calculated to evaluate the uncertainties quantitatively. For example, the expected value of perfect information (EVPI) (Usher and Strachan, 2012) represents the expected cost caused by uncertainty. It can also be interpreted as the expected cost savings if all uncertainties are removed and all future values are known with certainty right now. To calculate EVPI, the weighted average cost of the deterministic perfect foresight scenarios $Cost_{PFi}$ is calculated. Then the cost of the hedging strategy $Cost_{hedge}$ is determined using SOWs corresponding to the deterministic scenarios with the same set of probability weightings p_i. The cost of the hedging strategy is always higher than the weighted average cost of the deterministic scenarios since it poses one additional constraint, namely that only one pathway is allowed before the resolution time. The difference in the hedging strategy and the expected cost of the deterministic scenarios is the EVPI.

$$EVPI = Cost_{hedge} - \sum_{i}^{n} p_i Cost_{PFi}$$

The cost of ignoring uncertainty (ECIU) (Hu and Hobbs, 2010) estimates the cost of "guessing wrong". Suppose that the decision maker faces a number of J possible future outcomes each with probability p_j. Prior to the resolution time, the decision maker takes a naïve pathway, which simply assumes certain deterministic values for uncertain parameters. At the resolution time, the actual outcome j is revealed, and the decision maker needs to adjust his decisions by re-optimizing the pathway. The conditional cost of following the naive pathway and then adjusting the strategy based on the j^{th} outcome is $Cost_{j|\,naive}$. The ECIU is the difference between the total weighted conditional cost and the hedging strategy $Cost_{hedge}$.

$$\mathrm{ECIU} = \sum_{j=1}^{J} p_j Cost_{j|\,naive} - Cost_{hedge}$$

The ECIU is also referred to as the expected loss (EL) metric (Loulou et al., 2004) if the naïve strategy is to follow one of the J pathways from the beginning. The EL of following the k^{th} pathway until resolution is:

$$EL_k = \sum_{j=1}^{J} p_j Cost_{j|k} - Cost_{hedge}$$

Another metric similar to ECIU that measures the incremental cost of the stochastic solution is the value of the stochastic solution (VSS) (Ross et al., 2011), where the naïve strategy prior to the resolution date uses the expected values of the range of deterministic scenarios.

2.5.2 Applications

Stochastic programming was originally proposed by Dantzig (Dantzig, 2011) and later expanded by Wets (Wets, 1989) and Birge (Ross et al., 2011). This approach has been applied widely after being incorporated into an enhanced version of MARKAL (Kanudia and Loulou, 1998) and MESSAGE (Messner et al., 1996) in the 1990s and later in the TIMES model (Loulou, 2012). We have reviewed 21 stochastic programming studies with ESOMs, summarized in Table 2-5.

Table 2-4 Stochastic Programming Literatures

Model	Research Question	Coverage and Time Horizon	Uncertain Inputs
TIAM World (Babonneau et al., 2012a)	Evaluate the impact of climate change on economic assessment of long-term energy policies	Global All sectors 2005-2030	Climate Sensitivity
MARKAL (Bistline and Weyant, 2013)	Analyze technological and policy-related uncertainties in the US electric sector	US Electric sector 2015-2050	Climate change policy CCS technological availability Nuclear availability
MARKAL (Condevaux - Lanloy and Fragnière, 2000)	Demonstrate the use of a specialized software SETSTOCH to solve stochastic programming problems in MARKAL	Fictitious model	CO2 Emissions
MARKAL (Dutta and Mukherjee, 2010)	Explores the potential energy reduction in steel, aluminium and cement industries	India All Sectors 2001-2031	GDP Growth
MARKAL (Hu and Hobbs, 2010)	Impact of uncertainties in electricity demand growth, natural gas prices and power sector greenhouse gas regulations on electric power sector investment	US All sectors (Power sector focused) Energy market 2000-2050	Natural gas costs CO2 cap Demand growth
Temoa (Hunter et al., 2013)	Introduces the stochastic programming feature of the Temoa model	All sectors	Energy import prices
MARKAL (Kanudia and Loulou, 1999)	Describe the stochastic programming approach with illustration on greenhouse gas abatement. In Quebec	Ontario and Quebec All sectors 1995-2035	End-use Demand GHG emission limits
MARKAL (Kanudia and Loulou, 1998)	GHG abatement in Quebec	Quebec All Sectors 2035	End-use Demand GHG emission limits
MARKAL (Kanudia and Shukla, 1998)	Impact of uncertainties in GDP growth and carbon tax in energy planning	India All Sectors 1995-2035	GDP Growth Carbon Tax

TIAM (Keppo and van der Zwaan, 2012)	Assessing the role of CCS in climate mitigation	Global All sectors 2005-2100	Climate Target CCS capacity
TIAM (Labriet et al., 2012)	impacts of long-term technology and climate uncertainties on the optimal evolution of the World energy system	Global All sectors 2010-2100	Availability and characteristics of low-carbon technologies
TIAM (Labriet et al., 2008)	Analyzed climate stabilization strategies in the long run	Global All Sectors 1998-2100	Climate Sensitivity GDP
MARKAL (Loulou and Kanudia, 1999)	Use Minmax Regret strategy to explore uncertainty in carbon reduction targets.	Quebec (Canada) All sectors 1993-2037	Cumulative GHG Abatement
TIMES (Mccall et al., 2015)	Analyze the effect of uncertainty in cumulative carbon cap to South Africa	South Africa All sectors 2015-2060	Cumulative carbon cap
TIMES (Seljom and Tomasgard, 2015)	Effect of short-term wind power uncertainty in a long-term Danish heat and electricity system.	Denmark 2010-2050 heat and electricity sector	wind power availability electricity prices,
TIAM (Sanna Syri, , Antti Lehtilä, Tommi Ekholm, Ilkka Savolainen, Hannele Holttinen, 2008)	Analyze the effect of climate sensitivity uncertainties	Global All sectors 2000-2100	Climate Sensitivity
MARKAL (Usher, 2010)	The effect of uncertainties in fossil fuel prices and biofuel availability on investment decisions	UK All Sectors 2000-2050	Fossil fuel prices Biofuel availability
MARKAL (Usher and Strachan, 2012)	Provide near-term insight under uncertainties in emission reduction target required	UK All Sectors 2000-2050	Cumulative emissions by 2050 (80% and 90%)
MARKAL (Usher and Strachan, 2012)	Provide near-term insight under uncertainties in emission reduction target required	UK All Sectors 2000-2050	Cumulative emissions by 2050 (80% and 90%)

Table 2-5 Stochastic Programming Literatures (Continued)

Model	Metrics	Stage & Scenarios	Key Insights
TIAM World (Babonneau et al., 2012a)		2 Time Stages 4 Scenarios	Climate sensitivity is the main uncertainty. Availability of carbon-free technologies is important, but there is no silver bullet
MARKAL (Bistline and Weyant, 2013)	VSS VOC EVPI	2 Time Stages 3 Scenarios	Incorporating uncertainty into capacity planning significantly reduces risks from more stringent climate policy. Nuclear and wind deployment hedges against uncertainty in CCS availability
MARKAL (Condevaux - Lanloy and Fragnière, 2000)		3Time Stages 3 Scenarios	The specialized solver requires minimal coding and is able to solve very large problems
MARKAL (Dutta and Mukherjee, 2010)		2 Time Stages 3 Scenarios	
MARKAL (Hu and Hobbs, 2010)	ECIU EVPI VPC	2 Time Stages 3 Scenarios for each uncertainty, 6 scenarios for combined analysis of CO2 cap and demand growth uncertainties	Carbon cap uncertainty is economically more important compared to electric demand and natural gas uncertainties
Temoa (Hunter et al., 2013)		2 Time Stages 81 Scenarios	
MARKAL (Kanudia and Loulou, 1999)	EL EVPI	2 Time Stages 4 Scenarios	The hedging strategy has significant lower expected system cost compared to PF strategies Significant cost saving when inter-regional cooperation is enabled
MARKAL (Kanudia and Loulou, 1998)	EVPI	3 Time Stages 4 Scenarios	Hedging decisions are different from deterministic scenarios, and do not lie on their intermediate level High EVPI shows the importance of information on uncertainties

MARKAL (Kanudia and Shukla, 1998)		2 Time Stages 9 Scenarios	Increased energy supply capacity is required to anticipate high GDP growth. Increased proportion of natural gas and decreased proportion of coal to account for possible increase in carbon tax
TIAM (Keppo and van der Zwaan, 2012)		2 Time Stages 6 Scenarios	Early actions are required for deep CO2 emission reductions CCS is important in climate mitigation and is influenced heavily by the mitigation target
TIAM (Labriet et al., 2012)		2 Time Stages 2 Scenarios	Gas is a more robust hedging option compared to nuclear and CCS
TIAM (Labriet et al., 2008)	EVPI	2 Time Stages 8 Scenarios	3°C temperature increase by 2100 can be achieved at very moderate cost, 1.9 °C target requires very high cost. Early actions are required. Climate sensitivity uncertainty has great impact, GDP growth rates have very little impacts
MARKAL (Loulou and Kanudia, 1999)		2 Time Stages 5 Scenarios	MMR is suitable when the number of outcomes of the uncertain event is large. MMR recommends early mitigation actions even without knowledge of true target
TIMES (Mccall et al., 2015)		2 Time Stages 2 Scenarios	Hedging strategy shows that investment in new generation capacity is required.
TIMES (Seljom and Tomasgard, 2015)	VSS	2 Time Stages 90 Scenarios	Compared to deterministic approach, the hedging strategy has lower system costs, investments in wind, expected electricity export, and higher expected biomass consumption.
TIAM (Sanna Syri, , Antti Lehtilä, Tommi Ekholm, Ilkka Savolainen, Hannele Holttinen, 2008)		2 Stages 4 Scenarios	Intermediate actions are required, and total emissions need to be reduced by about 40% by 2040
MARKAL (Usher, 2010)	EVPI	2 Time Stages 10 Scenarios	Hedging strategy is different from deterministic scenarios or an “average” of the deterministic scenarios. Fossil fuel

			price uncertainty is extremely expensive compared to biomass uncertainty Long-life technologies cause path dependencies and may perturb recourse strategies. A broad technology portfolio with short life-span technologies better hedges against uncertainties
MARKAL (Usher and Strachan, 2012)	EVPI	2 All Time Stages 2 Scenarios	Steep near-term decarbonization is important. The cost of uncertainty is relatively high when the scenario weightings are close, and reduces when moving away from equal weightings
MARKAL (Usher and Strachan, 2012)	EVPI	2 All Time Stages 2 Scenarios	Steep near-term decarbonization is important. The cost of uncertainty is relatively high when the scenario weightings are close, and reduces when moving away from equal weightings

Besides providing a hedging strategy and recourse actions, most stochastic programming studies compare the trend of the hedging strategy and perfect foresight pathways, and conclude that the hedging strategy differs from all perfect foresight pathways. In addition, the hedging strategy does not represent the average or the interpolation of perfect foresight strategies, and always performs better in terms of system costs compared to a naïve approach that ignores future uncertainty. This implies that stochastic programming provides insights beyond deterministic scenarios.

Comparing hedging strategies and perfect foresight strategies also helps identify "super-hedging" actions, which are robust technologies that appear more in the hedging strategy than any of the perfect foresight strategies. For example, Labriet (Labriet et al., 2012) analyzed global climate stabilization targets under uncertain GDP growth and temperature increase limits. Natural gas was identified as the most significant hedging strategy in China with 50% higher penetration in the hedging strategy than perfect foresight scenarios. Implementing gas is a "middle-of-the-road" pathway as it has moderate amount of emissions compared to other fossil fuels and relatively low capital costs compared to low-carbon options, and can be modified without severe economic consequences.

With the quantitative metric EVPI, Usher and Strachan (Usher and Strachan, 2012) evaluated the costs of uncertainties in fossil fuel prices and biomass availabilities for the UK. The EVPI is very high under uncertain fossil fuel prices, indicating a very high cost of uncertainty. The high EVPI is mainly due to the difference in near-term actions chosen under the perfect foresight and hedging strategies. The uncertainty cost can be reduced by including novel mitigation options, which improves the flexibility of the energy system against changes in fossil fuel prices. The ECIU (or EL) is not as widely used as EVPI, but it quantifies the economic value of the hedging strategy compared to the expected value associated with a naïve approach. For example, Kanudia and Loulou (Kanudia and Loulou, 1999) performed a GHG abatement analysis of Quebec and Ontario and calculated the EL for all four perfect foresight strategies, and concluded that the high EL demonstrates the significance of cost savings in following the hedging strategy. Hu and Hobbs (Hu and Hobbs, 2010) used VSS to quantify the cost of ignoring uncertainty in GHG policy, and advised energy companies to consider GHG limits when making decisions. Another closely related metric, the value of policy coordination (VPC), was also calculated to measure the difference between a naïve strategy that assumes no future policy change, and a strategy that expects future policy modifications announced by policy makers. VPC showed that avoiding unexpected policy changes and providing early information on CO_2 caps and pollution laws would result in significant cost savings.

2.5.3 Limitations

Stochastic programming is able to provide a single hedging strategy that is highly desirable by decision makers; however, this approach also suffers from similar issues as MCA in terms of calculation burden and the requirement of uncertainty-related information. The processing time for MCA increases almost linearly with the number of iterations, but does not increase with the number of uncertain parameters.

By contrast, stochastic programming suffers from the infamous "curse of dimensionality" (Shapiro et al., 2009), where the number of SOWs increase exponentially with the number of uncertain parameters and the number of stages. Since the implementation of stochastic programming is based on directly solving equivalent deterministic problems, only a small subset of uncertain parameters can be analyzed. For example, stochastic MARKAL limits the number of stages to two and number of scenarios to nine (Ross et al., 2011) , and the stochastic version of the TIMES model is in practice limited to a small number of scenarios (Loulou, 2012). All studies we reviewed have 2 or 3 time stages and most of them have no more than 10 SOWs.

2.6 Robust Optimization

2.6.1 Principle

An alternative approach called "Robust Optimization" can be used to avoid the computational burden and consider a large set of uncertain parameters while remaining numerically tractable. The uncertain parameters have set-based definitions and require minimal uncertainty information. Only the range of variation is required for each parameter and no probability distribution is needed. The principle of robust optimization is "immunizing a solution against adverse realizations of uncertain parameters within a given uncertainty set." (Labriet et al., 2015) The formulation of robust optimization may take a few different forms.

Below is the formulation used by Labriet and et al. (Labriet et al., 2015) based on Bertsimas' (Bertsimas et al., 2011) approach:

Consider the linear problem,

$$\begin{cases} \min c^T x \\ s.t.\ Ax \leq b \\ x \in \mathbb{R}^+ \end{cases}$$

The constraint coefficients matrix A represent the exogenous model parameters such as energy prices and investment costs. It is assumed that only the coefficients $a_{i,j}$ $(i \in I, j \in J)$ in matrix A are affected by uncertainty. By setting $a_{i,j} = \overline{a_{i,j}} + z_{i,j}\widehat{a_{i,j}}\, z_{i,j}$, $z_{i,j} \epsilon [-1, 1]$, the nominal value $\overline{a_{i,j}}$ of the coefficient $a_{i,j}$is allowed to vary symmetrically by $\widehat{a_{i,j}}$. The linear problem incorporates these uncertain coefficients and reformulates into another linear problem called the equivalent robust counterpart as shown below.

$$\begin{cases} \min c^T x \\ s.t.\ \sum_j \overline{a_{i,j}}\, x_j + \max_{z_{i,j}} \sum_j z_{i,j}\widehat{a_{i,j}}\, x_j \leq b_i \\ z_{i,j} \epsilon [-1, 1] \quad \forall i \in I, j \in J \\ \sum_{i,j} |z_{i,j}| \leq \Gamma \quad \forall i \in I, j \in J \\ x \in \mathbb{R}^+ \end{cases}$$

Γ is the budget of uncertainty that controls the total number of parameters that are allowed to vary. When $\Gamma = 0$ the constraints are equivalent to that of the nominal problem without uncertainties, and $\Gamma = |\mathrm{I}| + |\mathrm{J}|$ represents the worst case problem where all uncertain parameters take extreme values. By setting different Γ values the modeler is able to control the level of pessimism, where the most pessimistic case equals the worst-case scenario.

2.6.2 Applications

The robust optimization technique was first developed Soyster (Soyster, 1973) and was subject to numerous subsequent development (Bertsimas et al., 2011)(Ben-Tal and Nemirovski, 2002)(Ghaoui et al., 1998). Babonneau et al. (Babonneau et al., 2009) first proposed the use of this method in environment and energy optimization models. We reviewed 3 studies that applied this technique to ESOMs. The main policy insights include the cost to hedge against uncertainties, key hedging technologies, and quantification of uncertainty source importance.

Lourne (Lorne and Tchung-Ming, 2012) used robust optimization to analyse the impact of energy technology cost uncertainty for the French transport sector in the MIRET model, which was developed as an instance of the TIMES model. The cost deviation was set to 15% and the cost budget Γ was varied from 0% to 50%. The results show that with increasing uncertainty budgets, the model choose technologies with less cost uncertainty, and therefore result in a more diversified technology mix and a rise in total system costs to hedge against uncertainties.

A related study Labriet et al. (Labriet et al., 2015) analyzed the impacts of uncertainties in investment costs and primary energy costs, including fossil fuels and biomass on carbon mitigation under the same modeling framework. It was assumed that 120 uncertain parameters can rise by 10% and a sensitivity analysis was performed on the cost budget. The results showed that the total system cost increased by up to 11% compared to scenarios without uncertainty considerations. The cost increase can be interpreted as the cost of robustness to hedge against uncertainties in technology costs. Scenarios with higher uncertainties have a more diversified fuel usage, which proves that diversification is a good hedging strategy. Technologies like biofuel have higher penetration in scenarios with higher uncertainty budgets. These technologies can be considered robust hedging technologies against cost uncertainties. The shadow values of the robust counterpart measure the impacts of uncertain parameters on the optimum objective function and quantify the relative importance of uncertain sources. The costs of primary energy were found to be the most critical uncertainty sources.

In a methodologically oriented paper, Babonneau et al. (Babonneau et al., 2012b) demonstrated the approach in an energy security analysis of Europe with the TIAM-world model. The formulation specifies the desired level of diversification in energy supply, import dependency, and the reliability target representing the probability to guarantee energy security. A key policy insight is that with an extra 0.7% of total energy cost, near 100% reliability of EU energy supply could be guaranteed. The reliability improvement is achieved mainly through shifts from imports to indigenous resources; a relatively small contribution comes from expanding the capacity of energy import channels. In addition, four quantitative metrics were used to show that increasing reliability significantly reduces the concentration of supply sources. The contribution from expanding the capacities of energy import channel to reliability is relatively small.

2.6.3 Limitations

Robust optimization overcomes some of the shortcomings of MCA and stochastic programming approaches by offering a parsimonious way of calculating risk-averse solutions However, it loses some of the merits that the other two approaches could bring. Robust optimization can identify which strategies are more robust under uncertainties, but it fails to provide a unified hedging strategy like stochastic programming. It also contributes to the better understanding of which uncertainty sources have greater impacts on the model results; however, when probability distributions and covariance among inputs can be determined, the additional information related to uncertainty can be potentially better captured by MCA.

2.7 Modelling to Generate Alternatives

2.7.1 Principle

The uncertainty techniques we discussed in previous sections, including sensitivity analysis, MCA, stochastic programming and robust optimization, can only address parametric uncertainties. Analysts have repeatedly called for more focus on structural uncertainties in ESOMs (Hunter et al., 2013)(Trutnevyte et al., 2016b)(Pye et al., 2015), though efforts have been minimal. Modelling to generate alternatives (MGA) is a technique that can help address structural uncertainties.

Conventional ways to reduce structural uncertainty include using larger and more complex models to better represent real world dynamics, comparing different models (Riahi et al., 2015), and subjecting model relationships to expert review (O'Hagan, 2012). DeCarolis (DeCarolis, 2011) noted that increasing model complexity does not eliminate structural uncertainties. Since ESOMs attempt to model a highly complex reality under deep uncertainty, structural uncertainties and unmodeled objectives will always be present. As a result, model solutions lying within the feasible, near optimal region may be more desirable than the optimal solution when unmodelled considerations, such as unforeseen or unmodelled risks, are brought to bear on the scenario.

The principle of MGA is to relax the optimal solution and use a modified model formulation to search the near-optimal solution space for alternative solutions that are maximally different in decision space. MGA can be broadly interpreted as any method used to systematically search the near optimal solution space for alternative solutions. The Hop-Skip-Jump (HSJ) method, proposed by Brill et al. (Brill et al., 1982), represents one such MGA approach:

Step 1. Solve the original problem to obtain an initial optimal solution.

Step 2. Obtain an alternative solution using the formulation:

$$minimize \sum_{k \epsilon K} X_k$$

$$Subject\ to$$

$$f_j(\vec{x}) \leq T_j \quad \forall j$$

$$\vec{x} \in X$$

Where

K = set of indices of the decision variables that are nonzero in all previous solutions

X = set of feasible solutions based on the "technical" constraints of the model.

$\vec{x} \in X$ implies that the constraints of the original problem hold for the alternative solution

$f_j(\vec{x})$ = j^{th} objective function in the original formulation

T_j = Target value for the j^{th} modeled objective

This new formulation is designed to search for highly different solutions in decision space by minimizing the weighted sum of the decision variables that appeared in previous solutions. Each target value T_j is calculated by adding a specified amount of slack to the objective function value obtained from Step 1. Applying the adjusted objective function as a constraint ensures that the alternative solution is within a prescribed inferior region near the original optimal solution.

Step 3. Iterate the reformulated optimization in Step 2 to generate a series of alternative solutions that are different from all previous ones. The new objective function minimizes the sum of all nonzero variables in all previous solutions.

Step 4. Terminate when no significant changes to decision variables are observed.

The MGA algorithm should be adapted to suit the analysis at hand, and should consider the form of the revised objective function, the updating procedure for objective function coefficients, and the chosen slack value. The MGA-based results should be screened for plausibility and interpreted carefully in light of the study objectives.

The alternative solutions produced by MGA reveal possible future options that may be otherwise overlooked. As decision makers may be concerned with factors outside of the modelling scope, such as political tractability or equity, the alternative strategies may be preferable and more policy relevant than the optimal solution in the base case. In addition, as the alternative solutions are generated by a computer algorithm, MGA alleviates the cognitive bias issues associated with scenario analysis, whereby detailed storylines underlying different scenarios can appear cognitively compelling despite the underlying uncertainty (Morgan and Keith, 2008). Finally, MGA can help unmask “knife edge” solutions in the base case, where slight perturbations to input assumptions can produce very different solutions.

2.7.2 Applications

MGA is an emerging and innovative method for ESOMs and we have reviewed four related studies. DeCarolis (DeCarolis, 2011) first introduced this method for energy models, then later applied it to the TEMOA model (DeCarolis et al., 2016) to explore alternative energy futures in the US electric and light duty transport sectors. Four sets of MGA runs with slack values representing 1%, 2%, 5% and 10% energy supply cost were performed, and the total energy output of technologies over the model horizon were chosen as decision variables in the MGA runs. Compared to the base case scenarios and carbon-constrained scenarios, the MGA scenario results demonstrate a more diverse set of deployed technologies, and the variety increases with the slack level. Technologies such as IGCC, biomass, and wind have significantly higher penetration in MGA scenarios, indicating that they could play a significant role in achieving a low carbon future. Trutnevyte (Trutnevyte, 2013) employed the EXPANSE (Exploration of Patterns in Near-optimal energy ScEnarios) model to evaluate the economic potential of renewable energy sources for heat supply, and demonstrated the interactions among different energy sources. The EXPANSE model was also used to explore 800 different pathways for the UK power sector using a combined approach of MGA and Monte Carlo sampling (Li and Trutnevyte, 2016). The analysis considers a large number of uncertainties and produces ranges of generation capacity and investment cost in 2050. The multiplicity of near-optimal solutions with different power generation mixes supports the current UK policy of maintaining a liberalized and technology neutral electricity market. Price and Keppo (Price and Keppo, 2017) implemented a revised MGA algorithm into the TIAM-UCL model that produced solutions that are maximally different in terms of cumulative primary energy consumption by fuel type.

2.7.3 Limitations

The MGA results depend on the slack value, which is subjectively chosen. The alternative scenarios represent plausible future alternatives, but associated probabilities are not attached to the scenarios. Therefore, the findings produced from this approach do not yield a unified, near-term decision making strategy that accounts for future uncertainty. In addition, even though the alternative scenarios can be valuable in outlining future possibilities, they may also be used to justify pre-existing policy preferences. Finally, MGA allows modelers to consider structural uncertainties in a limited way. Other approaches to address structural uncertainty should be considered, particularly ones that integrate insights from models with fundamentally different structures.

2.8 Discussion and Conclusion

The value of energy system modelling is on highlighting policy implications rather than providing absolute numbers - providing insights rather than answers. Compared to conventional scenario analysis, assessing uncertainties in a systematic manner helps improve the robustness of results and provide additional insights associated with multiple outcomes. In this chapter, we carried out a comprehensive review of uncertainty techniques that have been applied to ESOM models: Monte Carlo analysis, stochastic programming, robust optimization, and modelling to generate alternatives.

A key finding arising from this review is that each of the four uncertainty analysis techniques has its own focus, advantages and limitations, and informs different aspects of decision-making. Choosing a specific uncertainty technique should involve consideration of issues such as data availability, the uncertainty space to be covered, and the type of policy questions to be answered. Figure 2-4 provides guidance and recommendations for modellers in the form of a flow chart that summarizes the key policy insights for each technique and a basis for selecting which uncertainty technique to use. It is also worth noting that uncertainty analysis approaches are not mutually exclusive and should be used in a complementary manner to provide well-rounded analysis.

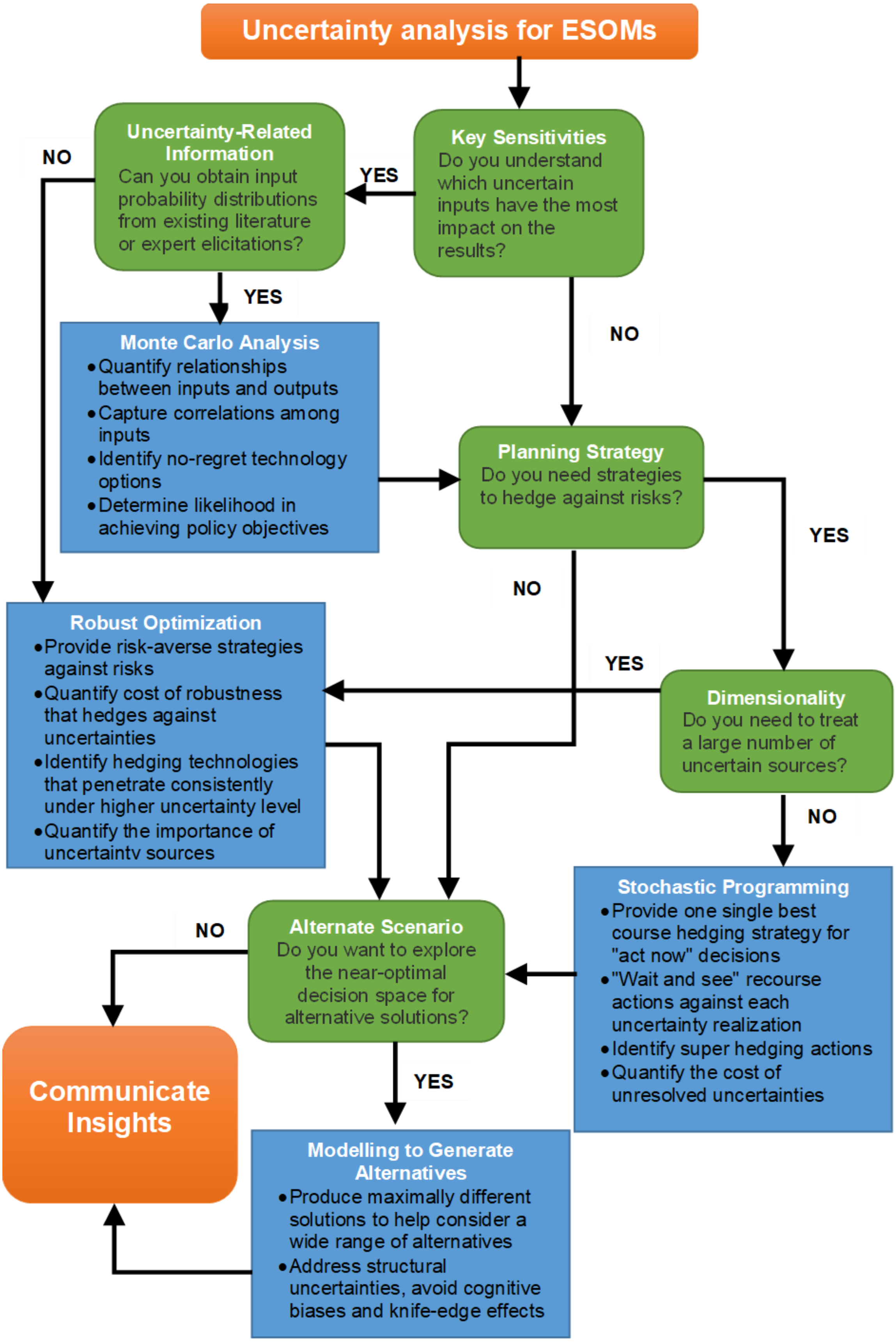
MCA can be applied when information on probability distributions could be obtained through existing studies or expert elicitation. In addition to quantifying the feasibility in reaching policy targets and identifying robust technologies, MCA can also be run in tandem with GSA to map the relationships between inputs and outputs, which improves model transparency and unpacks model structure. As the only approach for sequential decision-making, stochastic programming is best used when the number of uncertain sources under concern is small. It can be used to provide a single optimal hedging strategy that can help guide near-term action. Such an approach avoids the issue with multi-scenario approaches, where the scenario ensemble may leave the decision makers in a quandary. Robust optimization is a computationally efficient approach for handling uncertainties associated with a large set of parameters while requiring minimal information on the distribution of uncertain parameters. It computes the cost of hedging against risk at a prescribed level of uncertainty, and indicates which technologies are critical in reaching the desired policy targets. MGA is currently the only systematic approach that addresses structural uncertainties, and can be combined with other approaches.

Even though it is widely accepted that uncertainty is a key issue for energy models, the results of our literature review indicate that the number of studies that actually apply formal techniques to address uncertainties for ESOMs models is limited. For example, info-gap decision theory (IGDT) (Ben-Haim, 2006; Nojavan et al., 2017; Soroudi et al., 2017) is a well-established uncertainty analysis method for the power system; however, none of the

ESOM studies have applied IGDT, and only three studies used the alternative approach of robust optimization. One possible cause is the difficulty and additional efforts required in modifying model formulations and developing stochastic model infrastructure. The popularity of uncertainty analysis was found to be strongly related to the stochastic features that the model provides. Most of the stochastic programming analysis studies have been carried out with the MARKAL/TIMES model generators using the built-in stochastic programming feature, but only a few MCA studies have been carried out with these models. The application of MCA with the TIMES family of models may gain popularity if computational features similar to that in ESME or PROMETHEUS models is provided for queueing, processing and storing the model runs. Emerging techniques such as robust optimization and MGA also require considerable modifications in the mathematical formulation, which raises difficulties for modelers who want to apply these methods in their analysis. Deploying systematic uncertainty approaches for additional policy insights is important and therefore we recommend incorporating features that enable stochastic programming analysis into new or existing models, since these may encourage model users to go beyond simple scenarios.

Besides developing stochastic features for existing models, future research on uncertainty modelling should consider a broader range of uncertainties, explore new techniques to treat these uncertainties, address uncertainty of pertinent climate change issues, such as exploration of uncertainty around keystone technologies, and reflect on uncertainties associated with policy, politics and societal factors (Li and Pye, 2018). Currently, the majority of ESOM studies rely on historical data or expert judgements to address uncertainties for existing technologies such as electric vehicles and bioenergy. The well below 2 degrees target set by the Paris agreement necessitates the analysis of more ambitious national and global climate targets. ESOM models should therefore further consider feasibility and uncertainties of emerging technologies such as direct air capture, as well as more speculative technologies made cost-effective through potential technology breakthroughs. In addition, policy uncertainties are increasingly relevant after the US withdrawal from the Paris Agreement (Kemp, 2017). Rather than assuming a perfect foresight over the next several decades, modellers should be aware that decisions can be made myopically (Nerini et al., 2017), and constantly seek better ways to properly assess and communicate uncertainties in policy changes.

Figure 2-4 Uncertainty technique selection flowchart



3 From 2°C to 1.5°C – how ambitious can Ireland be?

Abstract

The current climate policy of Ireland was set according to a 2°C temperature rise target, and pursuing a 1.5 °C temperature increase limit requires ratcheting of decarbonisation ambition and a reduction in cumulative emissions over the century. The national carbon budget level consistent with 1.5°C is difficult to determine due to scientific uncertainties and lack of consensus in equitable effort sharing principles. A large ensemble of scenarios are generated with decreasing carbon budgets, and the challenge of not exceeding these carbon budgets are compared with the current 2°C climate policy scenario. The results indicate that the current national climate policy results in a 950MtCO_2 carbon budget, with 3.8%p.a. decline in CO_2 emissions required to achieve such a goal. Further significant reductions in carbon budget to pursue a 1.5°C consistent target of 360MtCO_2 is technically feasible, but extremely challenging with the current technology assumption. Annual emissions reductions of 10% p.a. result in a more realistic carbon budget of 530MtCO_2, which can be considered midway between 1.5°C to 2°C. Cost effective decarbonisation rates are non-linear in the near-medium term, contrary to the current policy, and more ambitious carbon budget targets can only be achieved through much stronger near-term mitigation efforts than suggested by the current NDC (nationally determined contribution). Marginal Abatement Costs (MAC) increase exponentially with decreasing carbon budgets or with increasing ambition. Delayed action causes a step change increase in MAC as well as reduces the level of feasible decarbonisation ambition.

Key messages

- The most stringent technicaly feasible carbon budget for Ireland to contribute is 360MtCO2 from 2015-2070. This target is 1.5°C compatible but extremely challenging. A more achievable carbon budget with ambitious decarbonisation rates of 10% p.a. is 530MtCO_2 between 2015-2070.
- Cost effective decarbonisation rates are non-linear in the near-medium term, contrary to current policy. Carbon budget limits more ambitious than current climate policy can only be achieved through much stronger near-term mitigation efforts than suggested by the NDC.

- Strong mitigation efforts in the near term suffer economic losses from stranded assets, but pursuing 1.5°C compatible target requires early decisions in accepting the losses to avoid carbon "lock-in" and consequences of delayed actions.

3.1 Introduction

The Paris agreement adopted in 2015 (UNFCCC, 2015) aims to keep the global temperature rise well below 2°C and contains the ambition to pursue efforts to limit the temperature increase even further to 1.5°C. As a member state of European Union, Ireland had to define a national climate target linked to the 2°C target, which is considered to translate in 80%-95% reduction in greenhouse gas emissions relative to 1990 levels by 2050 (European Council 2009a), with intermediate reduction target of 20% by 2020 (European Council 2009b), and at least 40% reduction by 2030 as outlined by the EU NDC (European Union, 2015). These targets are not sufficient to reach a 1.5°C and each country will have to propose more ambitious reduction, as agreed in the Paris Agreement on Climate Change. Ireland is currently not on track to meet the 2020 target. The total greenhouse gas emissions (GHGs) rose by 3.5% in 2016, and the cumulative emissions are projected exceed obligations by 11.5-13.7Mt of CO_2 equivalent over the period 2013-2020 (EPA 2017). This makes achieving the long-term goals and further reduction even more difficult.

The global mean surface warming has a near linear relationship with the cumulative amount of CO_2 in the atmosphere (Allen et al., 2009; Matthews et al., 2009). Pursuing efforts to remain below 1.5°C warming requires further reductions in cumulative emissions over the century. However, it is difficult to determine the national carbon budget due to scientific and political uncertainties. The global carbon budget is usually expressed with a likely chance of remaining below a temperature threshold, where uncertainty arises from interactions with non-CO_2 GHGs and climate sensitivity uncertainty. In addition, the allocation of the global carbon budget for each country has usually been considered according to certain equity principles (Clarke et al., 2014), such as responsibility based on historical emissions, capability based on GDP, equality based on population, or a combination of multiple approaches. However, the results from different approaches have significant variations, and there is no consensus on which method is most equitable.

In this analysis, instead of attempting to share out a portion of the remaining global CO_2 budget for Ireland, we explore how far Ireland can reduce the carbon budget level and pursue effots to remain below 1.5°C. A high granularity analysis on the carbon budget over the period 2015 to 2070 was carried out. Starting from a carbon budget level with no emission constraint, the carbon budget is gradually reduced with small step changes in each subsequent scenario until the model becomes infeasible, resulting in over 100 scenarios. The feasibility of reaching different levels of mitigation target (Gambhir et al., 2017) is assessed based on the degree of challenge measured by model solvability, rate of decarbonization, carbon price and energy system cost. The challenge levels of the carbon budget scenarios are then compared with the current 80% reduction target to determine feasible carbon budgets. Alternative set of carbon scenarios are generated with different assumptions to explore the role of bioenergy imports and carbon capture and sequestration (CCS) technologies.

3.2 Methodology

3.2.1 Irish TIMES model

TIMES (The Integrated MARKAL-EFOM System) (Loulou et al., 2016a) is an economic model generator for local, national, multi-regional, or global energy systems, which provides a technology-rich basis for representing energy dynamics over a multi-period time horizon. TIMES assumes that each agent has perfect foresight on the market's parameters, and computes the inter-temporal dynamic equilibrium by maximizing the total surplus over the entire time horizon with decisions made on equipment investment and operation, primary energy supply and energy trade for each region. TIMES is thus a vertically integrated model of the entire extended energy system.

The original Irish TIMES dataset was extracted from the Pan European TIMES (PET36) project by the Energy Policy and Modelling Group (EPMG) at University College Cork (UCC), and was updated with local detailed data, calibrated to the national energy system with macroeconomic projections from the Economic and Social Research Institute (ESRI). The inputs to the Irish TIMES include estimates of end-use energy service demands derived from the macroeconomic model HERMES (Bergin et al., 2013), estimates of existing stocks of energy related equipment, characteristics of available future technologies, as well as present and future sources of primary energy supply and their potential.

The Irish TIMES model has been used to provide detailed insights on the possible pathways in achieving the challenging emission reduction targets for Ireland, and inform the development of national legislation on climate change and energy policy. Scenario analysis has been carried out to explore energy system trajectories to meet emission reduction targets (Chiodi et al., 2013c, 2013b), the security of supply dimensions of a decarbonized energy system (Glynn et al., 2017a) , and bioenergy availability (Chiodi et al., 2015a). To facilitate scenario generation for sensitivity analysis, we developed the VEDA_SET (VEDA scenario ensemble tool) (Yue, 2016) on top of the existing TIMES model data handling system VEDA. This tool allows users to perform parametric sensitivity analysis by batch generating, queueing, and executing a large number of scenarios.

3.2.2 A series of diverse scenarios

In this chapter, two single scenarios and five carbon budget (CB) scenario sets have been developed. The Reference (REF) scenario and CO_2_80 scenario represents the pathways with and without climate policies, and provides a benchmark of comparison with carbon budget scenairos. Each of the carbon budget scenario set, including CB, CB15, NOCCS, NOBECCS, NOBIO, consists of large number of scenarios with different level of carbon budget.

REF scenario: The Reference Energy System scenario is the least cost pathway that delivers energy service demands without any climate policies. Cumulative CO_2 emissions from the energy system from 2015 to 2070 is 2100MtCO_2. These emissions do not include agriculture process (CH_4) emissions. This scenario includes the current macro-economic outlook, but does not explicitely include any carbon constraint policies on the energy system.

CO_2_80 scenario: The CO2_80 scenario sets linearly declining annual emission constraint according to to the EU climate & energy package and EU low-carbon economy roadmap from 2020 to 2050, achieving an 80% reduction in all energy related CO_2 emissions by 2050 on 1990 levels. ETS sectors are included in the total energy system CO_2 annual cap constraint. Beyond 2050 no further policy instrument is assumed and the emission level remains constant. This scenario has a cumulative emission of 950MtCO_2.

CB: The carbon budget scenarios apply decreasing levels of carbon budget constraints from 2015 to 2070. The model is free to choose the optimal emission pathways that reach the given carbon budgets. The carbon budget level starts from the REF scenario of 2100Mt. Each subsequent scenario reduces the carbon budget by 10Mt until the model is no longer feasible. This approach, rather than the opposite one (start with a very small budget and increase it) was followed in order to be able to analyse the evolution of the energy system with increasing ambition until infeasibility. Based on the historical emission trends and future projections of Ireland, significant mitigation actions are unlikely to be taken in the near future. Therefore, it is assumed that mitigation efforts will not start until 2020, and the emission pathways of CB scenarios are assumed to adhere with the pathway of REF scenario until 2020.

Besides the CB scenarios, alternative carbon budget scenarios including NOBECCS, NOCCS and NOBIO scenarios are generated using the same approach to quantify the impacts if certain technology options on the carbon budget feasibility, usually considered as key in emission mitigation, are no longer available.

NOBECCS: The NOBECCS carbon budget scenario set disables bioenergy carbon capture and sequestration for power generation.

NOCCS: This set of carbon budget scenarios disables all carbon capture and sequestration technologies for power generation. It should be noted that only CCS in the power sector is disabled, and CCS usage in the industry sector is still allowed.

NOBIO: This set of carbon budget scenarios disables all bioenergy imports, and only allows bioenergy from indigenous sources.

CB15: This set of carbon budget scenarios assume that significant mitigation efforts have been taken 2015 instead of 2020.

3.3 Model results

Even though there is uncertainty and lack of consensus on equity principles when determining a share of the remaining carbon budget, global estimates on carbon budget (Millar et al., 2017; Rogelj et al., 2016b) and national level analysis (Pye et al., 2017) suggest that 1.5°C consistent carbon budget is in general at least 50% lower relative to the 2°C target. The carbon budgets for limiting temperature rise by 1.5°C and 2°C with 66% certainty are 400GtCO_2 and 1000GtCO_2 respectively from 2011 onward to net-zero emissions (IPCC, 2014). Based on the equity standard by population, the carbon share of Ireland is 766MtCO_2 for 2°C target and 376MtCO_2 for 1.5°C target (Glynn et al., 2017b), which is approximately 20% and 60% less than the cumulative emission of 950MtCO_2 under the current climate policy. The analysis on the feasibility of the carbon budget scenarios indicate that reducing cumulative emissions to 360MtCO_2 is technically feasible (compatible with a 1.5°C carbon budget), while 530MtCO_2 is a more realistic carbon budget level.

3.3.1 Feasible carbon budget levels for Ireland

To determine feasible carbon budget targets, the carbon budget scenarios are assessed based on multiple criteria that measure level of challenge, which include the model feasibility, decarbonization rate from 2020 to 2030, timing of carbon neutrality, marginal abatement costs in 2050 and energy system cost.

Whether or not the model can produce a solution is a key indicator of low carbon pathway feasibility under the techno-economic assumptions reflected in the model. As increasingly more stringent emission constraints are applied, the capacity of available mitigation options is gradually exhausted, and the model needs to deploy very expensive backstop options for further mitigation. The results from the carbon budget scenarios show that the minimum feasible carbon budget for Ireland is 360MtCO_2. This would correspond to a fair budget based on population to reach the 1.5°C target. However, this budget level is extremely challenging. Reaching the 360MtCO_2 carbon budget requires 80% annual emission reduction to be delivered by 2030, and the carbon cost is €1600/tCO_2 in 2030 and €5200/tCO_2 in 2050.

Since it is assumed that no significant amount of carbon reduction can be achieved before 2020, the 2020 emission level is fixed (Figure 3-1). The gap between the milestone year trendlines measures the required reductions in annual emissions over each 10-year period, and indicates that achieving a more stringent carbon budget mainly depends on stronger near-term mitigation efforts between 2020 and 2030. Compared to the constant 3.8% per annum decarbonization rate under the current policy framework, the annual decarbonization rate rises significantly to 7% in the CB_730Mt scenario and 10% in CB_540Mt scenario (Figure 3-2). High decarbonization rates indicate significant challenge as phasing out fossil fuels and early retirement of existing technologies may raise concerns in terms of social acceptance, stranded assets and economic losses.

Figure 3-1 Annual emission levels for milestone years for 175 carbon budget scenarios from REF scenario to CB_360Mt

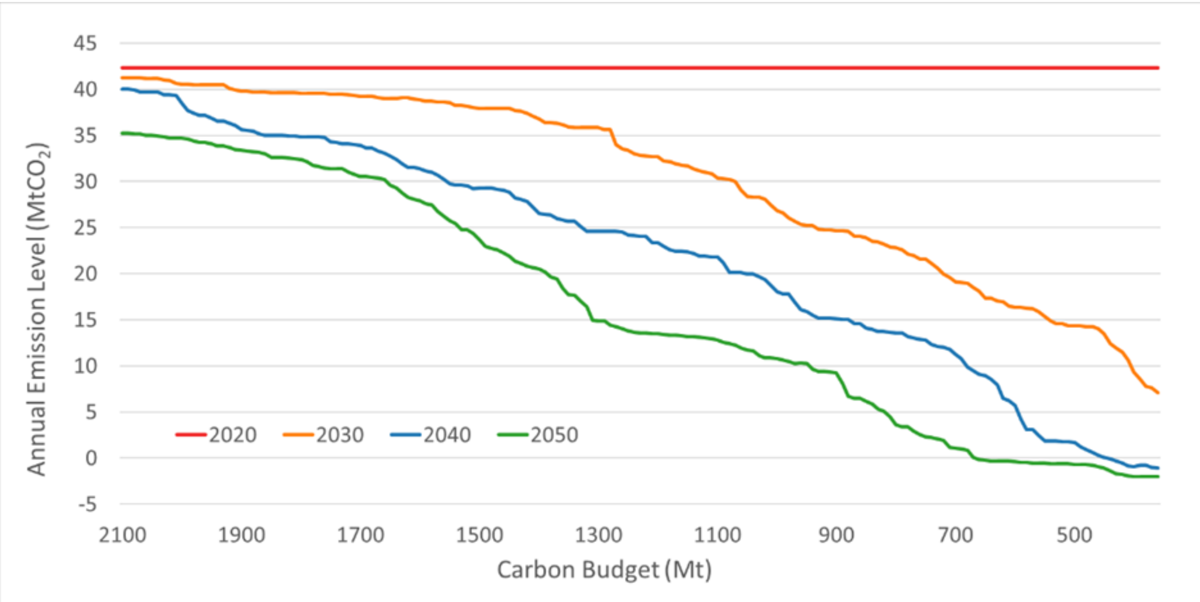
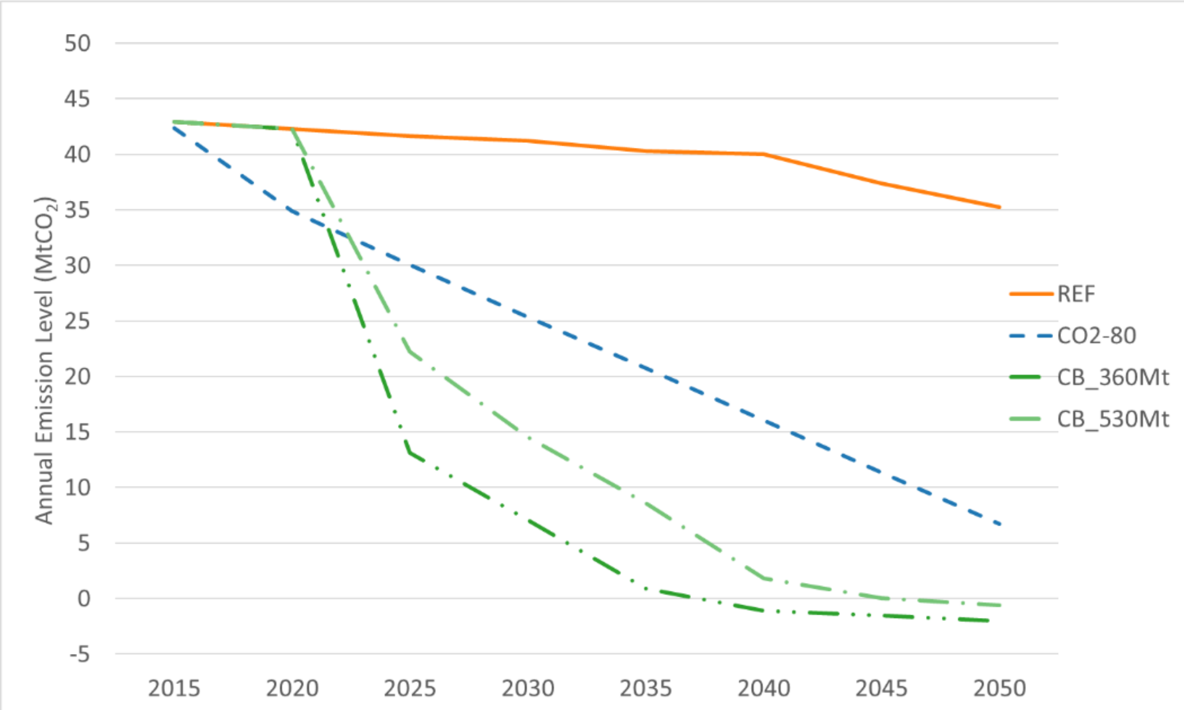


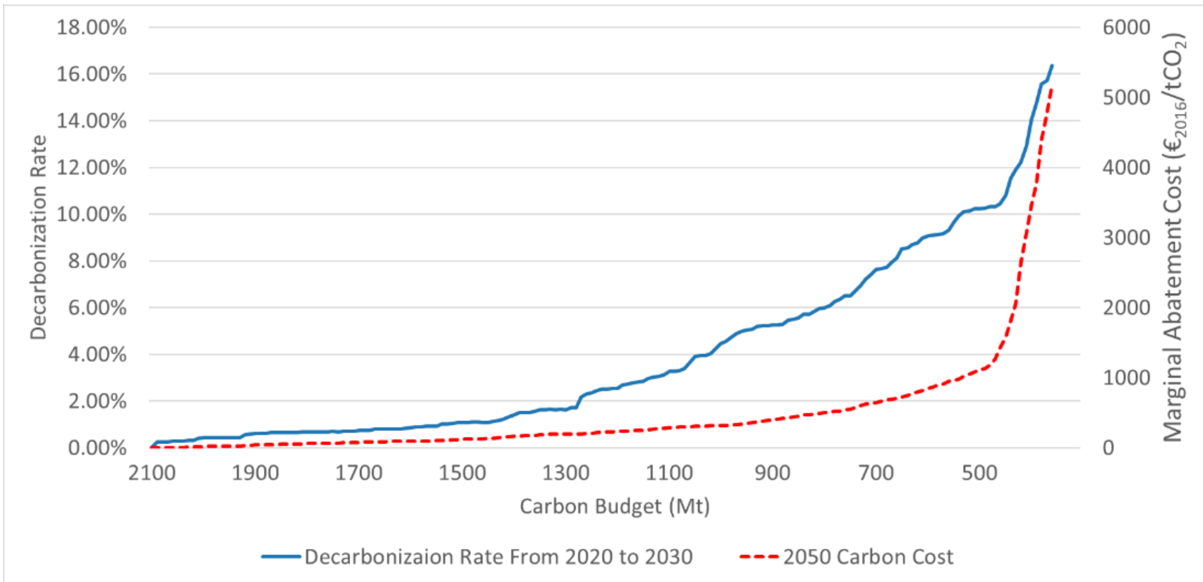
Figure 3-2 Optimal annual emission pathways for REF, CO2-80, CB_540Mt (10% annual decarbonization rate from 2020 to 2030), and CB_360Mt (minimum feasible carbon budget) scenario



Stabilizing temperature essentially requires net-zero anthropogenic carbon emissions (Matthews and Caldeira, 2008). The timing of carbon neutrality is important and 1.5°C consistent targets need to reach net-zero carbon emissions by mid-century (Rogelj et al., 2016b). The milestone years emission levels (Figure 3-1) show that reaching 660$MtCO_2$ carbon budget requires negative emissions by 2050. Further reduction in carbon budget requires earlier carbon neutrality. The CB_440Mt scenario has net-zero emission by 2040, and CB_510Mt scenario reaches carbon neutrality by 2045.

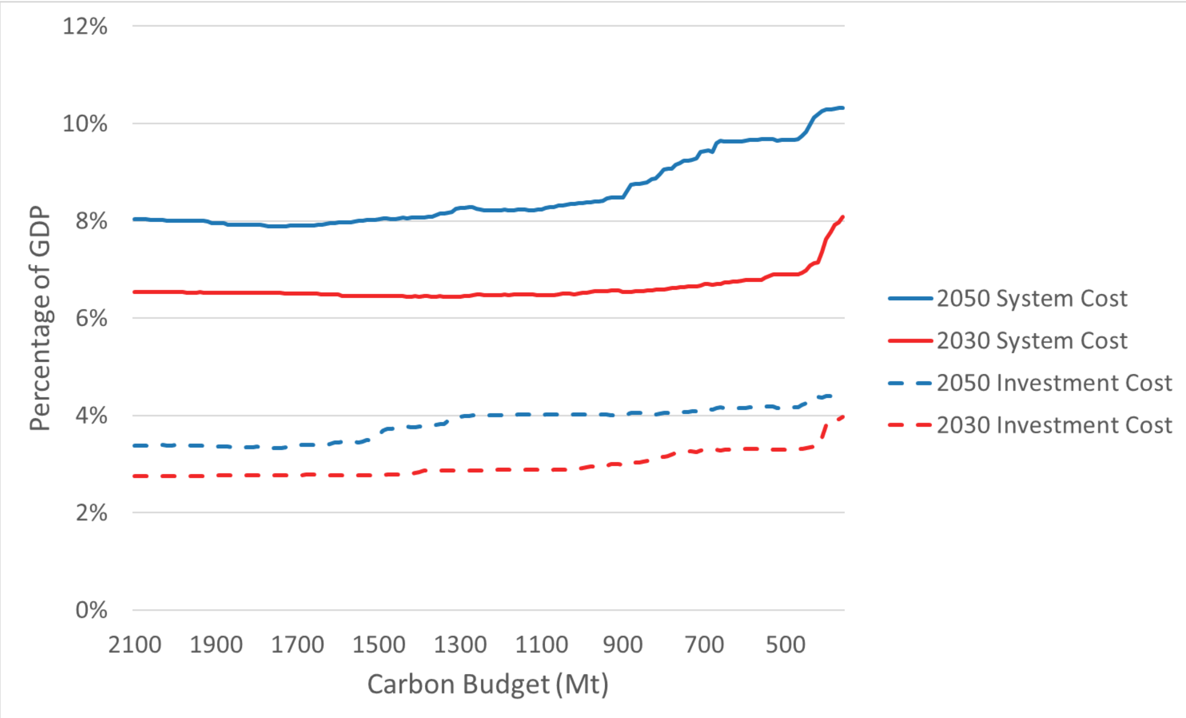
Deep decarbonization involves drastic energy system transformation and poses significant long-term challenges. The level of difficulty can be assessed with the CO_2 mitigation prices, which measures the marginal effort in mitigating an additional tonne of CO_2. A very high CO_2 price indicates a lack of available mitigation options in delivering the required mitigation level. The CO_2 price in the CO2-80 scenario is €114/tCO_2 in 2030, rising to €484/tCO_2 in 2050 (2016 prices). Due to stronger early actions, with the same CO_2 price in 2050 the total emissions can be reduced from 950$MtCO_2$ to 820$MtCO_2$ as a result of an optimised mitigation pathway rather than a linearly declining emissions cap. At a carbon cost of €1000/tCO_2, the total emissions can be cut to 530MtCO_2. The carbon cost has a nonlinear relationship with the carbon budget level (Figure 3-3). Further reductions beyond 530MtCO_2 requires significantly higher marginal costs, which increases to €2000/tCO_2 in the CB_430Mt scenario. Comparing carbon costs across scenarios shows that achieving the same level of annual emissions reduction in 2030 requires much higher carbon cost than in 2050. For example, the CB_360Mt scenario has 80% annual emissions reduction by 2030 with a carbon cost of €1600/tCO_2, tripling the 2050 CO_2 price of the CO2-80 scenario.

Figure 3-3 Marginal abatement cost in 2050 and decarbonization rate over 2020 to 2030 for 175 carbon budget scenarios from REF scenario to CB_360Mt



Another key indicator of the carbon budget feasibility is the annual energy system cost (Figure 3-4). The system cost accounts for 6.5% of GDP in 2030 and 8.0% in 2050 for the REF scenario, increasing to 6.9% in 2030 and 9.7% in 2050 for the 530MtCO_2 scenario, indicating that reducing total emissions from 2100MtCO_2 to 530MtCO_2 requires an additional 1.7% GDP total costs. The energy system cost includes investment costs, fuel costs, and operation and maintenance costs. The proportion of investment costs in energy system cost remains relatively stable across scenarios. The investment cost as a percentage of GDP rises from 2.8% (2030) and 3.4% (2050) for the REF scenario, to 3.3% and 4.2% for the CB_530Mt scenario. Compared to the marginal abatement cost, the rise of energy system cost and the investment cost with emission constraint level is not as drastic. Pushing from the current policy to an ambitious mitigation target of 530MtCO_2 only requires 27% additional investment cost to the energy sector in 2050.

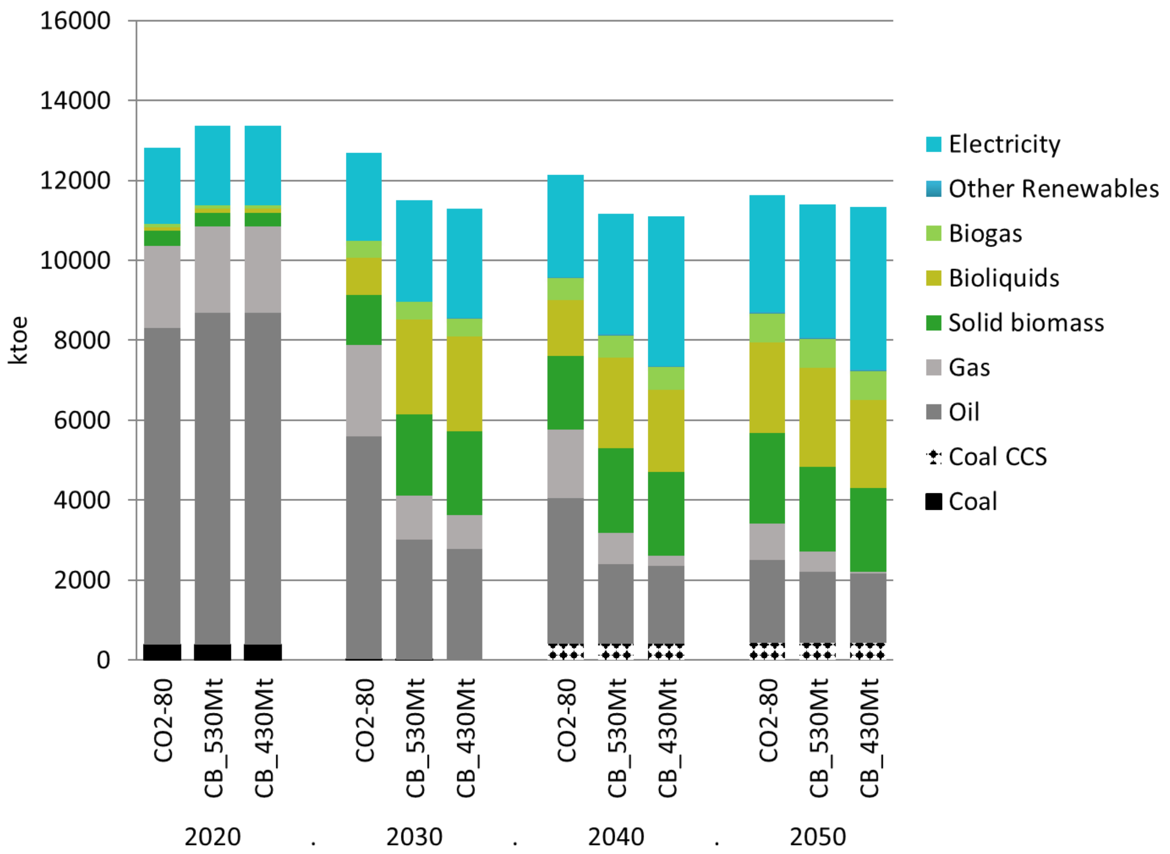
Figure 3-4 Energy system cost and the investment portion as a percentage of GDP in 2030 and 2050 for 175 carbon budget scenarios from REF scenario to CB_360Mt



3.3.2 Energy system transformation

In 2015, the total final energy consumption (TFC) in Ireland was 11.3 Mtoe, with 77% fossil fuels consumption and an electrification level of 19% (SEAI, 2016). The energy demand of the CO2-80 scenario is characterized by significant reductions in fossil fuel consumption that decreases to 20% by 2050, as well as an increased level of electrification to 24%. The remaining energy demand is provided by renewable sources primarily from bioenergy. The TFC results of more amibitious carbon budget scenarios with 2050 carbon prices of €1000/tCO_2 (CB_530Mt) and €2000/tCO_2 (CB_430Mt) indicate that transition towards more ambitious emission targets requires higher levels of electrification and bioenergy consumption that replace fossil fuels (Figure 3-5). Overall fossil fuel consumption declines with mitigation stringency as a result of efficiency gains from electrifying private cars and reduced demands due to higher carbon costs.

Figure 3-5 Final energy consumption by fuel for CO2-80, CB_530Mt and CB_430Mt scenarios.



The choice of mitigation options in the carbon budget scenarios are similar to the CO2_80 scenario and the sectoral proportions in TFC remain relatively stable (Figure 3-6). Cost effective mitigation options include switching to electric vehicles and plug-in hybrids for private cars; bioenergy for navigation and freight transportation; replacing gas with biomass for industrial boilers; switching to coal CCS for cement and lime production; increased penetration of biogas and biomass for the residential sector. Transition towards more stringent carbon budget constraints consistent with a 1.5C goal mainly requires replacing gas by electrifying the residential and services sectors, and large deployment of BECCS technology (Figure 3-7).

Figure 3-6 Final energy consumption by sector for CO2-80, CB_530Mt and CB_430Mt scenarios.

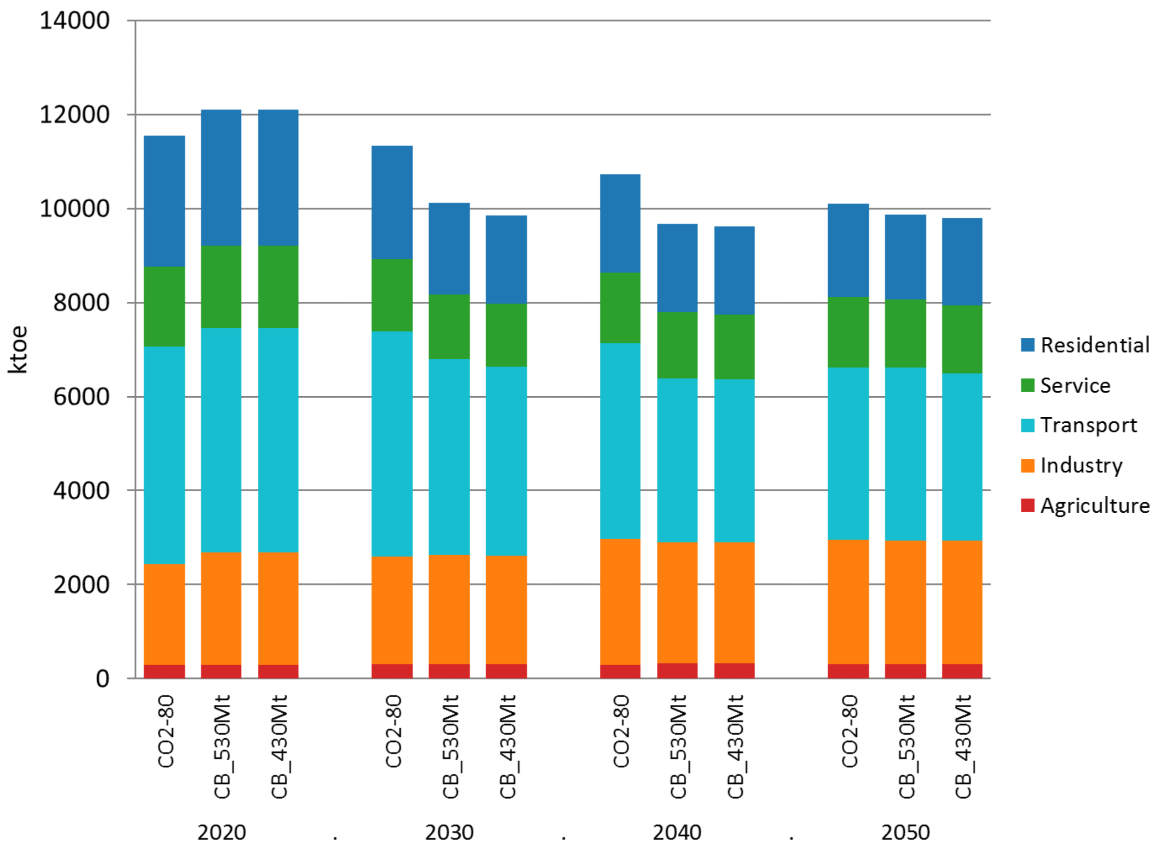
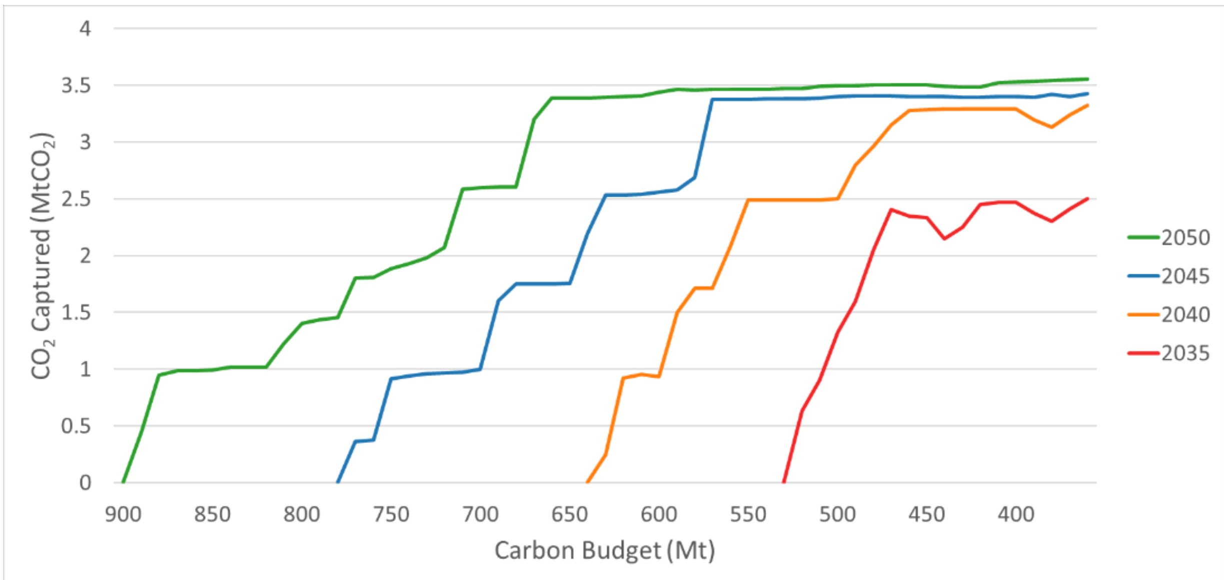


Figure 3-7 Total amount of CO_2 captured by BECCS technology for 54 carbon budget scenarios from CB_890Mt scenario to CB_360Mt scenario



Negative emission technologies are critical for carbon neutrality due to emissions from unmitigable sources, such as cement and lime production, passenger trains, hybrid vehicles. In the Irish TIMES model, BECCS is able to capture as much as 3.5MtCO_2, which is essential to bring the minimum achievable annual emissions level from 1.7MtCO_2 (96% reduction) to a level of negative emissions of -2MtCO_2. More stringent carbon budget levels require earlier deployment of BECCS technology, which starts to penetrate in 2035 for CB_520Mt scenario and in 2040 for CB_640Mt scenario.

Due to limited mitigation options, reduction of annual emission beyond -2MtCO_2 is extremely costly. Attaining ambitious carbon budget level therefore relies on strong efforts in the near term. As shown in Figure 3-8 and Figure 3-9, at ambitious carbon budget levels, the TFC trend in 2030 decreases at a fast rate, while the 2050 trend stays relatively stable after reaching net-zero emission. The timing of technology deployment is closely related to the level of annual emission reduction. For example, the 360MtCO_2 budget scenario has a similar energy system configuration in 2030 as the system of CO2_80 scenario in 2050. Results in the levels of technology penetration also show that early transition into a low carbon economy requires phasing out of fossil fuel based technologies before the end of their lifetime and create stranded assets. Technologies with heavy investments and long lifetime have higher risks of being stranded, and such technologies include gas-fired power plants, space and water heating in residential and commercial sectors.

Figure 3-8 Final energy demand in 2030 for 175 carbon budget scenarios from REF scenario to CB_360Mt

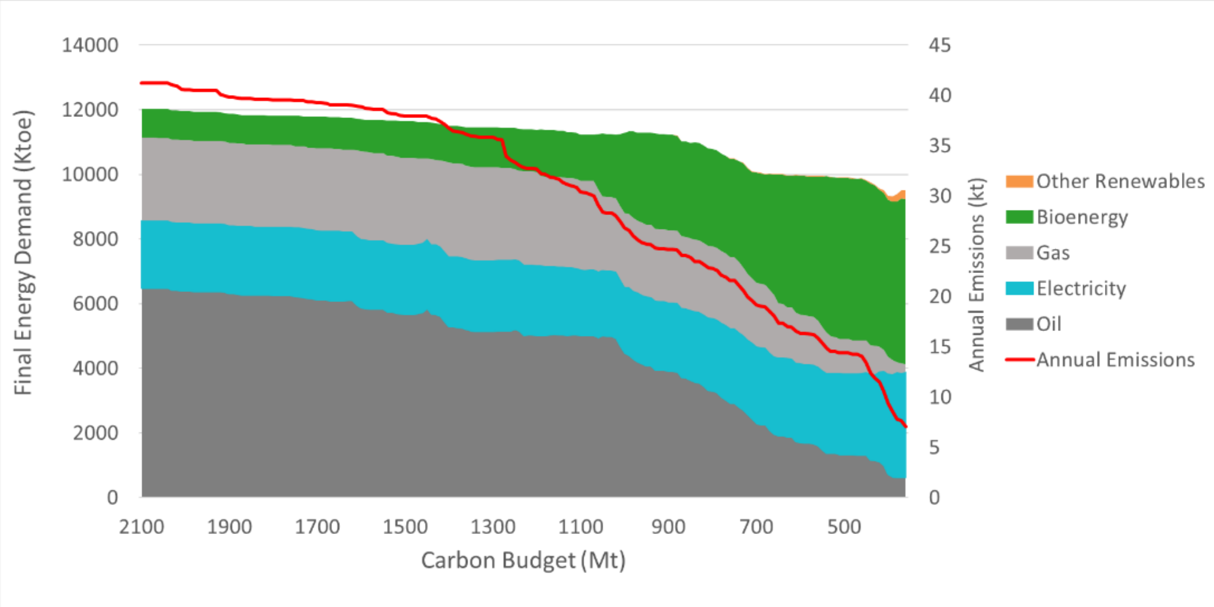
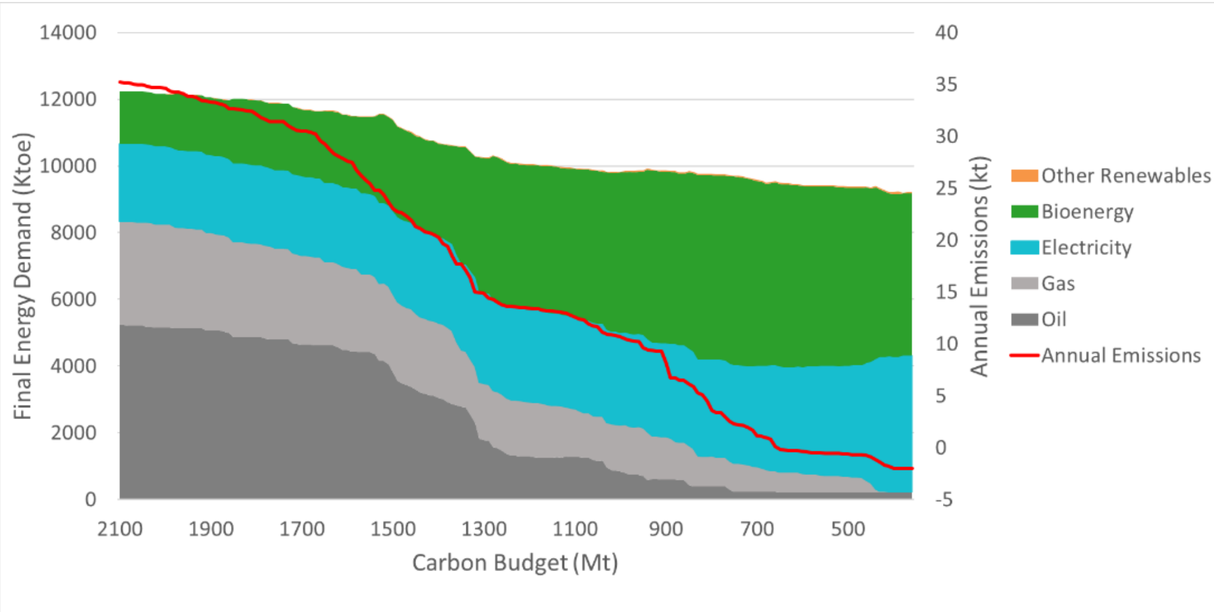


Figure 3-9 Final energy demand in 2050 for 175 carbon budget scenarios from REF scenario to CB_360Mt



3.3.3 Implications from variant scenarios

Table 1 compares the carbon budgets for different CO_2 mitigation costs and associated rates of decarbonisation under alternative assumptions. The importance of key mitigation options can be quantified by the difference in carbon budget level attainable at the same degree of challenge (i.e. CO_2 mitigation cost and rate of decarbonisation). For example, if the availability of BECCS technology is disabled, the minimum feasible level of carbon budget is increased from 360MtCO_2 to 480MtCO_2, and the carbon budget that can be achieved at the same level of difficulty is increased by approximately 100MtCO_2. Compared to the BECCS technologies, CCS power plants have less impacts on the carbon budget feasibility. Without CCS technologies, the energy system can deploy more biomass power plants for deep decarbonization, and the change in carbon budget level attainable at the same degree of challenge is within 20MtCO_2 from NOBECCS scenarios.

In the CO2-80 scenario, import accounts for 100% of bio liquids and 32% of the biomass, rising to 100% and 59% in the CB_530Mt scenario. The NOBIO scenarios measured has a minimum solvable carbon budget of 660MtCO2, over 200MtCO_2 higher budget levels compared to the original carbon budget scenarios under the same degree of challenge, indicating that bioenergy imports have a more critical role than CCS technologies. With no bio liquids supply, the navigation and road freight transportation can no longer be fully decarbonized and has significantly higher penetration of hydrogen and biogas. BECCS has no penetration in any of the NOBIO scenarios due to limited supply of biomass. The decarbonization of the power sector relies on gas CCS, and the biomass is primarily used by industrial boilers, residential heat and commercial heat. This result implies that even though BECCS is critical for negative emissions, it is comparatively more cost intensive and should only be deployed when sufficient biomass supply can be secured.

The mitigation feasibility is also strongly impacted by the timing of mitigation efforts. The results of the CB15 scenarios (Table 3-1 Carbon budget level (MtCO2) for carbon budget scenarios under different level of challenge measurement) show that with strong early actions starting from 2015, 100MtCO_2 emissions can be further mitigated at the same degree of challenge. The minimum level of carbon budget with a model solution for the CB15 scenarios is 260MtCO_2. The 2050 carbon price is €1000/tCO_2 for the CB15_450Mt scenario and

€2000/tCO_2 for the CB15_350Mt scenario.

Table 3-1 Carbon budget level ($MtCO_2$) for carbon budget scenarios under different level of challenge measurement

Scenario	Minimum Solvable	2050 Carbon Price (€$_{2016}$/tCO2)			Annual Average Decarbonization Rate from 2020 to 2030		
		€500	€1000	€2000	5%	7%	10%
CB	360	800	530	430	960	730	540
NOBECCS	480	880	670	570	990	800	650
NOCCS	490	870	660	560	1020	820	670
NOBIO	660	1010	810	710	1000	810	740
CB15	260	750	450	350	640	450	300

3.4 Conclusion

The aim of the chapter is to explore how ambitious can Ireland be in constraining its carbon budget towards a 1.5°C consistent level, and to provide insights in the degree of challenge and required actions at ambitious reduction targets. The sensitivity analysis on the carbon budget constraints shows that the cumulative emissions can be cut significantly, and constraining the carbon budget from the current 950$MtCO_2$ climate target down to 360$MtCO_2$ is technically feasible. Even though 360$MtCO_2$ can be considered as a 1.5°C consistent carbon budget level, it requires over 80% emission reduction to be delivered by 2030 and €5000/tCO_2 carbon cost by 2050. R&D that provide cost effective new mitigation options, particularly in carbon intensive industries, can be important in reducing the economic impacts and making the roadmap to 1.5°C carbon budget more economically feasible.

Analysis on the level of challenge for carbon budget scenarios suggests that the 530$MtCO_2$ carbon budget, which lies approximately midway between 1.5°C and 2°C target, is a more economically feasible carbon budget target with current technologies. However, compared to the current climate policy scenario CO2-80, the 530$MtCO_2$ scenario is still much more challenging, and requires a 10% p.a. emissions rate decline to 2030, resulting in a 57% emission reduction below 1990 levels by 2030, which is significantly higher than the 40% reduction target set by the EU NDC. The decarbonization rate from 2020 to 2030 is tripling the rate of the scenario corresponding to the current policies, and the carbon cost in 2050 is twice as much as that of CO2-80 scenario at €1000/tCO_2.

With the current technological assumptions, reducing the net annual emission level of Ireland below -2MtCO_2 is extremely costly. Pushing towards more ambitious long-term climate target therefore relies on much stronger mitigation efforts by 2030 than the reduction target suggested by the NDC. However, strong mitigation efforts in the near term suffer economic losses from stranded assets such as gas-fired power plants and space and water heating in residential and commercial sectors. Decisions as to whether Ireland should accept such losses and pursue a 1.5°C compatible carbon budget target should be made early. Investment in energy system are often capital intensive. Adhering to the existing near-term emission target may raise risks of "lock-in" to an energy system configuration that meets the near-term target but is unsuitable for a long-term 1.5°C roadmap.

4 Assessing decarbonization options for 2050 using marginal abatement cost curves based on energy systems optimization model with a new analytical approach

Abstract

The European Union has a target to reduce greenhouse gas emissions to 80% below 1990 levels by 2050 to keep global warming within 2°C relative to pre-industrial levels. The more recent Paris climate agreement has a more ambitious target of limiting the temperature rise to well below 2°C. This research aims at addressing decarbonization options with an innovative analytical approach that combines energy systems analysis and marginal abatement cost curves (MACCs). System-wide MACCs are derived using scenario ensembles from Irish TIMES energy systems model. Decomposition analysis is used to associate decarbonization options with carbon costs and rank them based on economic merit into categories of resilient, tipping-point, and niche technologies. Energy systems analysis on the underlying scenario ensembles that constitute MACCs is carried out to capture more technological details and reflect interactions among technologies across sectors. MACCs with alternative assumptions in technology availability highlight the critical role of bioenergy and carbon capture and sequestration (CCS) technologies in achieving deep decarbonization.

Keywords

Energy systems modelling; marginal abatement cost curve; technology uncertainty; CO2 mitigation; Carbon Price

4.1 Introduction

At the 16th Conference of the Parties (COP) meeting in Cancun in 2010, it was formally agreed that global warming should be limited to 2°C temperature rise relative to pre-industrial levels (UNFCCC, 2011). The structured expert dialogue (SED, 2015) established by COP as a review process concluded that the consideration of a 1.5°C global warming target should continue as it comes with several advantages, including reduced risks in food production and lower sea level rise. This is reflected in the Paris Agreement, where the aim is to limit the global temperature rise to "well below 2°C" above pre-industrial levels and contains the ambition to "limit the temperature increase to 1.5°C". Prior to the Paris Agreement, the European Union had set ambitious targets to reduce greenhouse gas emissions by 80% - 95% in 2050 relative to 1990 levels (European Council, 2009b), together with intermediate country targets for 2020 (European Council, 2009a) and (in their current form, draft targets) for 2030 (European Council, 2014). In response to the Paris Agreement, the European Union has submitted the Nationally Determined Commitment in March 2015 on behalf of Member States (European Union, 2015). The target will be delivered collectively by the EU with reductions in the Emissions Trading Scheme (ETS) and non-ETS sectors amounting to 43% and 30% by 2030 compared to 2005 respectively. An Effort Sharing Regulation (European Council, 2018) was proposed to translate this commitment into binding annual greenhouse gas emission targets for each Member State for the period 2021–2030, based on the principles of fairness, cost-effectiveness and environmental integrity.

The signing of the Paris Agreement was enabled in part due to a focus on the evidence base for seizing technology opportunities (Schmidt and Sewerin, 2017). Technological innovations and cost reductions were achieved much faster than previously estimated and policy makers have become increasingly more aware of the potentials from low-carbon technologies in developing local industries and creating jobs. This has contributed to stronger incentives for more ambitious national climate and energy policies. Climate negotiations are no longer framed as sharing the economic burden of mitigation, with negotiated national emission targets now replaced by national determined contributions (NDCs), allowing each country to determine their own contribution in the context of their national priorities, circumstances and capabilities.

This study intends to assess mitigation options for one EU member country Ireland with a focus on policy insights for maximizing technology opportunities. As an EU member country, Ireland has set decarbonization targets progressively up to 2050 in line with the EU policies. However, the greenhouse gas emissions per person in Ireland are among the highest in the world and Ireland is not on track to meet its ambitions due to specific challenges it faces. For example, the agriculture sector is the single largest contributor to overall emissions and represents over one third of total emissions, while the average emissions from agriculture represents on average 10 percent of total emissions in the rest of Europe. In addition, energy-related emissions increase over the past decade driven by fast economic growth. In particular, the transport sector experienced a drastic emission increase by 133% over 1990 to 2017 and now accounts for 20% of total emissions

The marginal abatement cost curve (MACC) is a widely used climate and energy policy analytical tool in assessing mitigation technologies and has proven popular with policy makers. MACCs graphically relate different levels of emissions reduction to the marginal abatement cost, which measures the additional costs accrued for an additional unit of carbon abatement, providing an estimate of the tradeoff between the reduction level and the abatement costs required to make further reduction. The origin of MACCs date from the oil crisis in the 1970s, where the first cost curve was developed to evaluate savings in energy consumption (Meier, 1982). The policy tool was later applied to address climate change problems in 1990s (Jackson, 1991).

According to a review (Huang et al., 2016), MACCs can be classified according to the underlying methodologies. While the top-down approach uses economic models such as CGE to explore the impacts of economic issues such as energy prices (Klepper and Peterson, 2006) or GHG policies (Morris et al., 2012), the bottom-up approach is more frequently used to assess mitigation measures by quantifying carbon mitigation potentials and cost effectiveness for each abatement option using detailed technology charactersitics. The most famous example of a MACC is the global MACC published by the McKinsey and Company (Nauclér, T., & Enkvist, 2009). This type of MACCs applies financial accounting methods to assess the cost and emissions reduction potential of a portfolio of policy measures individually ranked by cost from lowest to highest. The MACCs are presented in a stepwise graph that links mitigation potential with costs for a range of mitigation technologies. The McKinsey type MACCs are relatively simple and easy to communicate; however, this financial-accounting type MACC has been criticized as they evaluate each mitigation measure individually at a static timeframe and may not capture the interactions across different energy sectors or the temporal dynamics in technologies, policies and end use demands over time (Kesicki and Strachan, 2011).

Another bottom-up approach is to derive MACCs using energy systems optimization models (ESOM) (DeCarolis et al., 2017). ESOMs represent an important branch of energy models and can be characterized as bottom-up optimization models covering an entire energy system. Examples of ESOM models include TIMES (Loulou et al., 2016a), MESSAGE (Müller-Merbach, 1983), ESME (Heaton, 2014), OSeMOSYS (Howells et al., 2011) and TEMOA (Hunter et al., 2013). In ESOM models, an economic optimizer is combined with a technology-rich database to provide a consistent accounting framework for the techno-economic characteristics of all modelled technologies. Cost optimal solutions are determined based on linear programming techniques for the whole energy system over the entire time horizon. ESOM models have been widely used to provide policy insights for the energy transition, including the economic implications and environmental impacts of decarbonization technologies (Chiodi et al., 2015b). ESOM based MACCs can be generated by running an ESOM multiple times with increasingly more stringent CO2 targets or applying increasingly higher CO2 tax. Compared to ESOMs derived from financial accounting methods, ESOM based MACCs better capture technology interactions and temporal dynamics. Uncertainties can also be assessed by deriving MACCs under different underlying assumptions.

A number of research gaps can be identified within the existing literature.

From the perspective of energy system modelling, deriving MACCs from ESOMs has the potential to improve the robustness of model results from ESOMS. Existing ESOM based studies primarily rely on projecting energy transition pathways through simple scenario analysis to support their policy making process (Yue et al., 2018a). While scenario analysis is an established analytical tool that is useful in informing policies, analyzing the energy system with a limited number of scenarios is not without problems. Scenarios with detailed storylines can cause cognitive biases to make them appear probable (rather than exploratory) and lead to an underestimation of the associated uncertainties and range of possible outcomes (Morgan and Keith, 2008). Besides, a narrow set of scenarios may not meet the needs of all users under all policy contexts (Trutnevyte et al., 2016c). The usage of models for long term policy making should focus on drawing insights rather than providing numbers (Peace and Weyant, 2008b). Evaluating the energy system with an ensemble of scenarios is advantageous for robust decision making as it considers a multiplicity of alternative possibilities which provides scope for more robust policy insights (Lempert, 2003). Analysis on scenario ensembles constituting MACCs may help provide more robust policy insights compared to focusing on a limited number of scenarios focusing solely on climate policies in place. However, existing studies on model-based MACCs only address the economic implications of the MACCs without assessment on the underlying scenarios that constitute the MACCs. Majority studies only focus on the cost curves themselves (Chen, 2005; Chen et al., 2007; Gao et al., 2004; Kesicki, 2013a). Kesicki (Kesicki, 2013b) and Tomaschek (Tomaschek, 2015) associate carbon costs and mitigation measures in the transport sector by deriving step-wise graphs similar to McKinsey type MACCs; however, these step-wise graphs may not fully reflect the dynamics of the ESOM model and cover technological details contained in the underlying energy system model scenarios.

Existing MACCs for Ireland have been developed based on financial accounting methods for the agriculture sector by Teasgsc (Schulte et al., 2012) and for the whole economy by the McKinsey company (Motherway and Walker, 2009). Relying on one single oversimplified tool could lead to suboptimal decision-making.

The aim of this study is therefore to fill this research gap by assessing mitigation opportunities for Ireland with a more nuanced and robust version of MACC based on the Irish TIMES energy systems model. The TIMES model captures more techno-economic details and considers mitigation options across all sectors over the entire time horizon in an integrated manner. MACCs are derived by applying increasingly more stringent targets to the TIMES model, resulting in hundreds of scenarios. Using decomposition analysis, key mitigation technologies are identified and ranked according to their cost-effectiveness into resilient technologies (cost effective), tipping point technologies (drives up the marginal abatement cost) and niche technologies (requires further cost reductions). Multiple MACCs are developed to capture the impacts of uncertainties in the portfolio of mitigation measures available.

Besides exploring economic implications of MACCs, we also apply innovative analytical approaches to enhance model-based MACCs and draw policy insights beyond what is typically possible with simple scenario analysis from ESOM models. Energy system analysis is carried out on the underlying scenarios that constitute MACCs to capture more technological details. The combination of MACC and energy system analysis reveals how the penetration of low carbon technologies drive up the economy-wide marginal abatement costs and identify tipping points where further emission reduction requires significantly higher abatement costs. Over 500 scenarios are used to derive MACCs to improve granularity of MACCs which helps explore changes of energy transformation pathways towards incremental increase in carbon mitigation targets. MACCs are visualized in a new way to better reflect technology interactions and impacts of technology penetration on abatement costs. To the knowledge of the authors, this study is the first study that carries out a whole-system MACC with a focus on technological details on all mitigation measures.

The chapter is organized as follows: Section 2 describes the scenario setup with Irish TIMES energy systems model and the methodology used to assess mitigation options. Section 3 presents the results of MACCs and the energy system analysis on the scenarios that form the MACCs with a focus on carbon mitigation measures. Section 4 presents a more detailed discussion of the modelling and policy implications based on the results in Section 3, and Section 5 provides concluding remarks.

4.2 Methodology

4.2.1 Irish TIMES model

TIMES (The Integrated MARKAL-EFOM System) (Loulou et al., 2016a) is an economic model generator for local, national, multi-regional, or global energy systems, which provides a technology-rich basis for representing energy dynamics over a multi-period time horizon. It is usually applied to the analysis of the entire energy sector, but may also be applied for sectoral analysis in industry (Chen et al., 2014), transport, power sector, as well as analysis in low carbon technologies (A Sgobbi et al., 2016). TIMES assumes that each agent has perfect foresight of the market's parameters and computes the inter-temporal dynamic equilibrium by maximizing the total surplus over the entire time horizon. Decisions are made on equipment investment and operation, primary energy supply and energy trade for each region. The choice by the model of the generation equipment is based on analysis of the characteristics of alternative generation technologies, on the economics of the energy supply, and on environmental criteria. TIMES is thus a vertically integrated model of the entire extended energy system. TIMES is now widely used by over 62 contracting parties supported by ETSAP (Energy Technology Systems Analysis Program), an implementing agreement of the International Energy Agency (IEA).

The original Irish TIMES dataset was extracted from the Pan European TIMES (PET36) project by the Energy Policy and Modelling Group (EPMG) at University College Cork (UCC), and was updated with local detailed data, calibrated to the national energy system, and underpinned with macroeconomic projections from the Economic and Social Research Institute (ESRI)(Gallachóir et al., 2010). The resulting national model for Ireland is called Irish TIMES. The inputs to the Irish TIMES model include estimates of end-use energy service demands derived from the macroeconomic model HERMES (Bergin et al., 2013), estimates of existing stocks of energy related equipment, characteristics of available future technologies, as well as present and future sources of primary energy supply and their potential.

To provide detailed insights on the possible pathways to achieve challenging emission reduction targets for Ireland, the Irish TIMES model has been used to inform the development of national legislation on climate change and energy policy. Scenario analysis has been carried out to explore energy system trajectories to meet emission reduction targets (Chiodi et al., 2013c, 2013b), the security of supply of a decarbonized energy system (Glynn et al., 2014), GHG for agriculture sector (Chiodi et al., 2016) and bioenergy availability (Chiodi et al., 2015a). Multi-model approaches have also been carried out for detailed sectoral analysis. For example, Deane (Deane et al., 2012) soft-linked the Irish TIMES model with the power systems model Plexos to add higher levels of technological details and enhanced time resolution. The TIMES model has also been linked with a transport model for analysis of the freight sector (Mulholland et al., 2016) and the private car sector (Mulholland et al., 2017). Already published research describes in detail some of the scenarios referred to in this analysis, principally the **REF scenario** (the least cost optimal pathway that delivers the energy service demands in the absence of emissions reduction targets) and the **CO2-80 scenario** (the energy system is required to achieve at least an 80% CO_2 emissions reduction below 1990 levels by 2050)(Chiodi et al., 2013c).

Building an energy systems model involves a number of key components including a model generator, a solver, interfaces for handling data and results, and a detailed database. TIMES is a model generator developed via the ETSAP collaboration and written in GAMS (General Algebraic Modelling Software) code with CPLEX and XPRESS typically used as solvers. The code of the model generator is transparent and well documented (Loulou et al., 2016a). The database includes both supply side and demand side energy technologies, and contains technical, environmental and economic data. The user shell of TIMES model VEDA (VErsatile Data Analyst) developed by KanORS. The VEDA system is composed of two major subsystems - VEDA Front-End (VEDA-FE) which helps browse, input, maintain the large database, and VEDA Back-End (VEDA-BE) which helps to analyze the output and gain insights.

The VEDA system lacked the capacity in generating, importing and analyzing large number of scenarios, which is a contributing factor to most analysis with TIMES being based on simple scenario analysis. To facilitate developing scenario ensembles, the authors have developed the VEDA-SET (VEDA scenario ensemble tool) system (Yue, 2016). Similar to VEDA, VEDA-SET has two subsystems corresponding to VEDA-FE and VEDA-BE. The first subsystem applies VBA programming and allows the user to define inputs by lists or stochastic values. It then automates the process of generating, queueing and solving the scenarios based on user defined values. The second part of VEDA-SET corresponds to VEDA-BE and contains all functions of VEDA-BE. Using the SQL database, VEDA-SET allows the importation and process of large number of scenarios in an efficient manner and produces data ready for visualization and analysis. The integration of scenario generation techniques that facilitate Monte Carlo analysis have also been integrated into TIMES model by the ETSAP community (ETSAP, 2019).

4.2.2 Derivation of MACCs and scenario set up

This MACC is derived by generating an ensemble of scenarios with increasing levels of emission constraints with very small step changes and can be considered as performing a high granularity sensitivity analysis on the system wide emission constraint:

BASE-MACC: The BASE MACC starts from the **REF scenario** and imposes increasingly higher emission reduction targets. The REF scenario represents the least cost optimal energy system trajectory without emission reduction targets; in 2050 the emission level of energy related CO_2 is 4% above 1990 levels. The REF MACC scenario ensemble consists of over 100 scenarios, including all scenarios between the REF scenario and the 100% decarbonization scenario (MACC_100%) with 1% step change in 2050 carbon reduction target. The intermediate targets in 2020, 2030 and 2040 are linearly interpolated. The model determines the cost optimal pathways that meets the carbon constraints. The optimal carbon costs in 2050 are graphically related to derive the MACC.

Multiple MACCs are developed to explore the role of critical mitigation measures. Each alternative MACC is generated with similar procedure but with different technological assumptions.

NO-BIO-MACC: Previous scenario analysis (Chiodi et al., 2013c) of the Irish energy system has shown that CCS technologies for power generation and bioenergy imports are critical in achieving 2050 reduction targets. The NO-BIO-MACC explores the impacts if bioenergy imports are not available and only indigenous resources can be utilized.

NO-CCS-MACC: The carbon capture and storage (CCS) technologies for power generation are disabled for this MACC.

NO-BIO/CCS-MACC: Both bioenergy imports and CCS technologies are disabled for this MACC.

BECCS-MACC: Many analyses have concluded that carbon dioxide removal (CDR) technologies such as bioenergy with CCS (BECCS) is critical in removing CO_2 from the atmosphere to achieve deep decarbonization. (Carbo et al., 2011; IPCC, 2014; Tavoni and Socolow, 2013). The BECCS MACC explores the impacts of deploying BECCS on the MACC as well as the feasibility to reach negative emissions consistent with well below 2 degrees target for Ireland.

4.2.3 Decomposition Analysis

Decomposition analysis is used to associate mitigation measures with MACCs. Decomposition analysis is a well-established analysis tool widely used in energy and emission studies for policy making. In this analysis, we applied the type I Logarithmic Mean Divisia Index (LMDI-I) using the additive decomposition procedure and quantitative indicator following the methods by (Ang, 2015) (Eq. 1).

$$\Delta CO_2 = \Delta\text{Activity Effect} + \Delta\text{Structure Effect} + \Delta\text{Intensity Effect} \quad (1)$$

In the Irish TIMES model, the activity levels of each technology can be measured by the energy service demands they produce. Energy service demands (such as residential space heating, industrial steel, and transport car distances) are exogenous demand projections that must be met by the least-cost technology mixes and are only affected by their own price elasticity. The three factors that influence carbon mitigation can thus be defined as:

Activity effect: reduced end use energy service demands with price increases (i.e. demand elasticity)

Structure effect: reduced emissions from switching from high carbon technologies to low carbon technologies as measured by the amount energy services they produce

Intensity effect: reduced emission intensities, measured by the reduction in emissions per energy services produced by each technology

As multiple technologies may provide the same type of energy service demands, technologies are first categorized based on the energy service demands they produce so that the emission reductions from phasing out carbon intensive technologies can be attributed to low carbon technologies. To illustrate the LMDI calculations in detail, the carbon reduction from phasing out diesel vehicles is shown as an example. Comparing the **CO2-80 scenario** with the **REF scenario**, the emission reduction can be attributed to three LMDI effects: activity effect from reduced demands for private vehicles measured in passenger mileage (Eq.2), the intensity effect from reduced emissions per unit of passenger mileage provided by diesel vehicles (Eq. 3), and structure effect of lower share of diesel vehicles over all private vehicles in terms of passenger mileage provided (Eq. 4).

$$\Delta\text{Activity Effect} = \frac{{CO_2}_{\text{Diesel}}^{80\%} - {CO_2}_{\text{Diesel}}^{REF}}{\ln {CO_2}_{\text{Diesel}}^{80\%} - \ln {CO_2}_{\text{Diesel}}^{REF}} * \ln\left(\frac{ESD_{Cars}^{80\%}}{ESD_{Cars}^{REF}}\right) \quad (2)$$

$$\Delta\text{Intensity Effect} = \frac{{CO_2}_{\text{Diesel}}^{80\%} - {CO_2}_{\text{Diesel}}^{REF}}{\ln {CO_2}_{\text{Diesel}}^{80\%} - \ln {CO_2}_{\text{Diesel}}^{REF}} * \ln\left(\frac{{CO_2}_{\text{Diesel}}^{80\%}}{ESD_{Diesel}^{80\%}} \Bigg/ \frac{{CO_2}_{\text{Diesel}}^{REF}}{ESD_{Diesel}^{REF}}\right) \quad (3)$$

$$\Delta\text{Structure Effect}$$
$$= \frac{{CO_2}_{\text{Diesel}}^{80\%} - {CO_2}_{\text{Diesel}}^{REF}}{\ln {CO_2}_{\text{Diesel}}^{80\%} - \ln {CO_2}_{\text{Diesel}}^{REF}} * \ln\left(\frac{ESD_{Diesel}^{80\%}}{ESD_{Cars}^{80\%}} \Bigg/ \frac{ESD_{Diesel}^{REF}}{ESD_{Cars}^{REF}}\right) \quad (4)$$

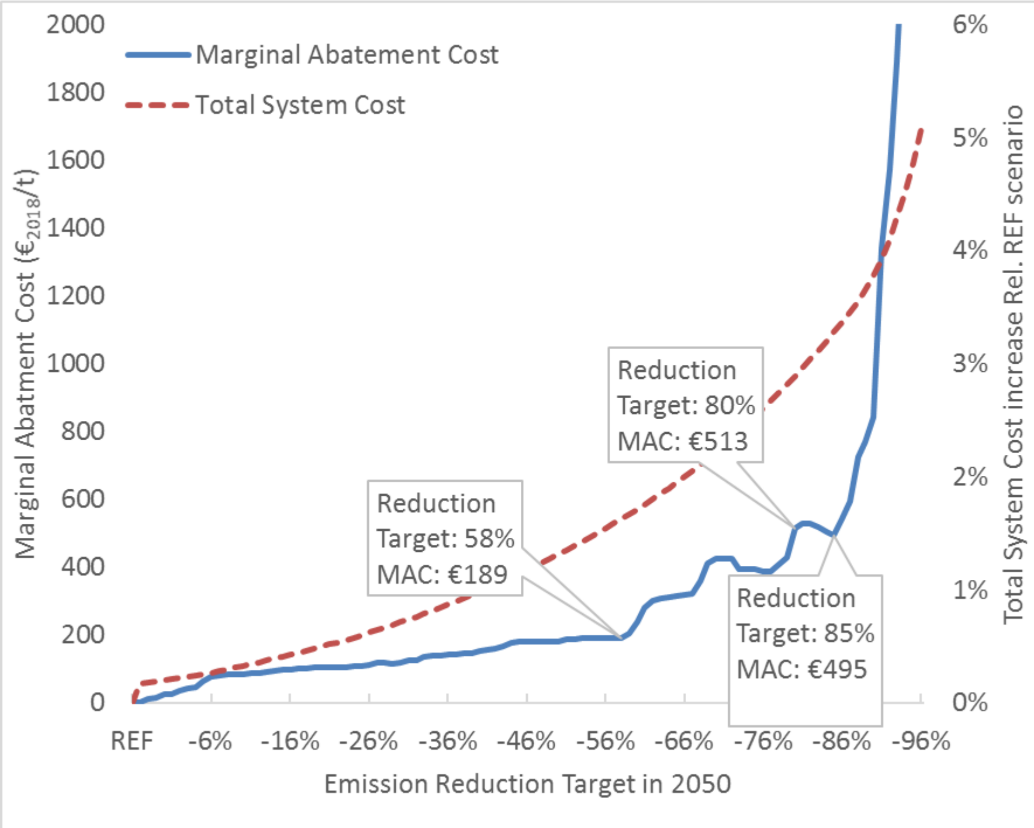
The calculation is then repeated for all other carbon intensive private vehicles including gasoline cars and LPG cars. The total structure effects from all carbon intensive vehicles are then aggregated and attributed back to low-carbon technologies including electrical vehicles, biofuel-based cars and hydrogen cars according to their activity level. This procedure is then repeated for all other technology groups such as freight transport, industrial heating and home heating.

4.3 Results

4.3.1 Marginal abatement cost curve

Figure 1. shows the REF-MACC in 2050, where the carbon costs calculated in all scenarios from REF scenario to 96% (maximally feasible decarbonization target) are graphically linked together. The graph also presents the total system costs for the whole energy system. As the objective of the TIMES model is to minimize total system costs over the entire time horizon, the total cost increases with higher mitigation targets. This can be reflected by the smooth and strictly increasing total system cost curve (Figure 4-1). However, the cost in a particular model year may not necessarily be strictly increasing. The model may choose similar yet not incremental pathways over time to reach a 1% additional carbon mitigation target, resulting in fluctuations in the 2050 MACC. Such fluctuations can be attributed to the “penny switching” or the “razor-edge” effect of linear programming models (Labriet et al., 2012), where small changes in inputs assumptions result in significant changes in outputs.

Figure 4-1 REF-MACC and total system cost in 2050 for REF-MACC scenarios



This graph shows the non-linear relationship between overall system cost, marginal abatement cost (MAC), and the level of ambition, underscoring the importance of a system approach to understand these dynamics. The MACC characterizes the tradeoff between economic feasibility and incremental levels of emission reduction targets in 2050. The increase of MACC can be divided into different regions separated by step changes in the marginal abatement costs. These changes can also be characterized as “tipping points”. Initially the marginal abatement cost has a steady and low rate of increase. From MACC_6% to MACC_58% the marginal abatement cost increases from €77/tCO_2 to €189/tCO_2. In this region, the model is able to deploy and expand the capacities of many cost-effective mitigation options. As these cheaper sets of technologies reach their maximum potential, more expensive options need to be deployed causing the marginal abatement cost to increase. From MACC_58% to MACC_85% the marginal abatement cost increases at a much higher rate from €189 to €495. Beyond a tipping point at MACC_85%, the marginal abatement cost increase dramatically, reaching €840/tCO_2 at MACC_90% and €2769/tCO_2 at MACC_95%. The model becomes infeasible in the MACC_96% scenario. This is because certain technologies have limited mitigation options in the model (such as passenger trains and cement production) and some mitigation technologies (such as plug-in hybrid vehicles and CCS) are not completely carbon free. Therefore, it is impossible to reach carbon neutrality without negative emission technologies such as BECCS.

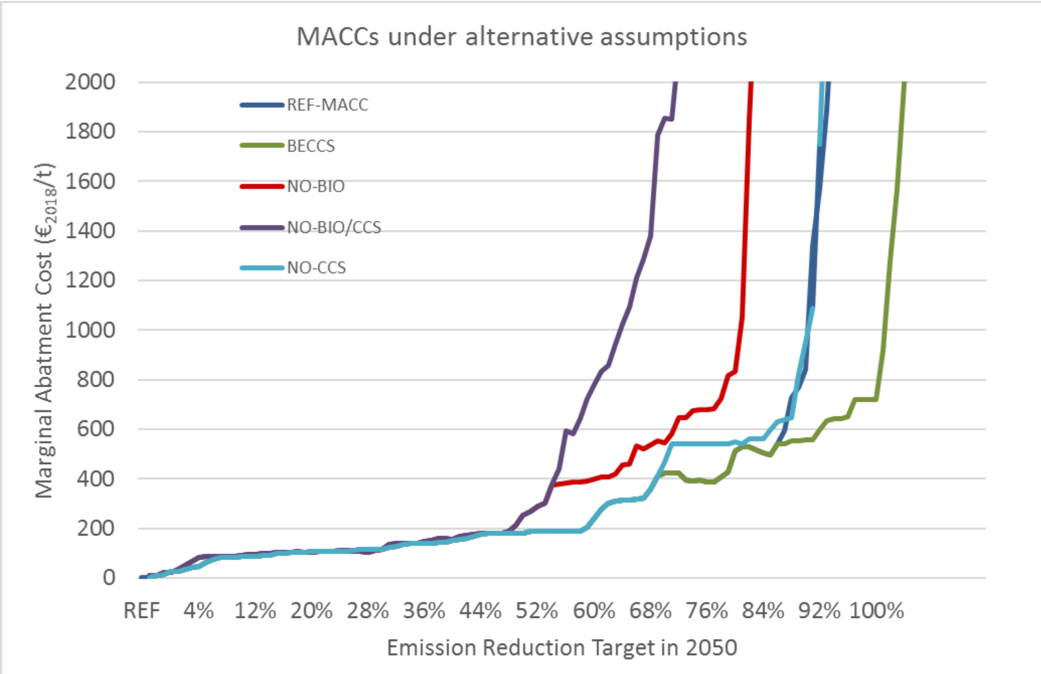
4.3.2 MACCs under alternative assumptions

MACCs derived under alternative assumptions provide quantitative measurements for the impacts on the MACCs from uncertainties in the availabilities of critical mitigation measures. The MACCs under alternative assumptions of technology availabilities are shown in Figure 4-2 Sensitivity of MACCs to availabilities in mitigation options in 2050 for scenarios with CO2 emission 4% above to 104% reduction relative to 1990 level and the abatement costs at varying reduction levels are summarized in Table 4-1.

Table 4-1 Marginal abatement costs (€$_{2018}$) at different reduction levels for sensitivity MACCs

MACC	REF	NO-CCS	NO-BIO	NO-BIO/CCS	BECCS
20%	106	106	104	104	106
40%	154	154	156	156	154
60%	240	240	400	780	240
80%	513	550	816	12232	513
95%	2759	4237	Infeasible beyond 83%	Infeasible beyond 80%	641

Figure 4-2 Sensitivity of MACCs to availabilities in mitigation options in 2050 for scenarios with CO_2 emission 4% above to 104% reduction relative to 1990 level



All alternative MACCs have similar shapes as the REF-MACC with relatively steady increase until reaching a tipping point. The MACCs also follow very similar pathways until 50% reduction targets, showing that the availability of bioenergy imports and CCS have little impact for less ambitious climate targets. The NO-BIO-MACCs show that the bioenergy imports have significant impacts on the MACC. The cost of 80% reduction target increases from €513/tCO_2 of REF-MACC to €832/tCO_2 of NO-BIO-MACC, and the maximum feasible reduction target is reduced to 83%. Compared to bioenergy imports, the availability of CCS technologies has much less impact on the MACCs. The NO-CCS-MACC does not differ much from REF-MACC. Without CCS plants for power generation, decarbonization in the power sector can still be achieved through biomass plants. However, if both CCS and bioenergy imports are disabled, the NO-BIO/CCS-MACC shows that 80% reduction target cannot be reached, and achieving 57% reduction requires higher mitigation cost (€583/tCO_2) than reaching the 80% reduction for REF-MACC.

The BECCS-MACC demonstrates the critical role BECCS plays in reaching deep decarbonization. With BECCS, 100% reduction can be achieved at €720/tCO_2, a cost level comparable to the 80% reduction target (€513/tCO_2) of the REF-MACC. Achieving the well below 2°C target mainly depends on the cumulative carbon level in the atmosphere, and the window is small and rapidly closing (Rogelj et al., 2015). According to Irish EPA projections, the share of non-energy agriculture emissions accounts for a total of 33% GHG (EPA, 2015) and is expected to grow by 1.4% over the period 2018 – 2020 (EPA, 2019). The major GHG emissions are from enteric fermentation and manure management which have limited mitigation options. Therefore, it is crucial for the energy system to achieve negative emissions to offset the GHG emissions from the agriculture sectors. The results from BECCS-MACC show that BECCS is an expensive mitigation option that does not penetrate below 87% reduction targets. However, it is a critical option in achieving deep decarbonization pathways consistent with the 1.5°C pathway.

4.3.3 Ranking of mitigation measures

This section presents the results of decomposition analysis described in Section 2.3. Decomposition analysis is carried out between the REF scenario and all underlying carbon constraint scenarios of REF-MACC. The collection of decomposition analysis results across all scenarios are used to identify key mitigation measures and to associate mitigation measures with carbon costs.

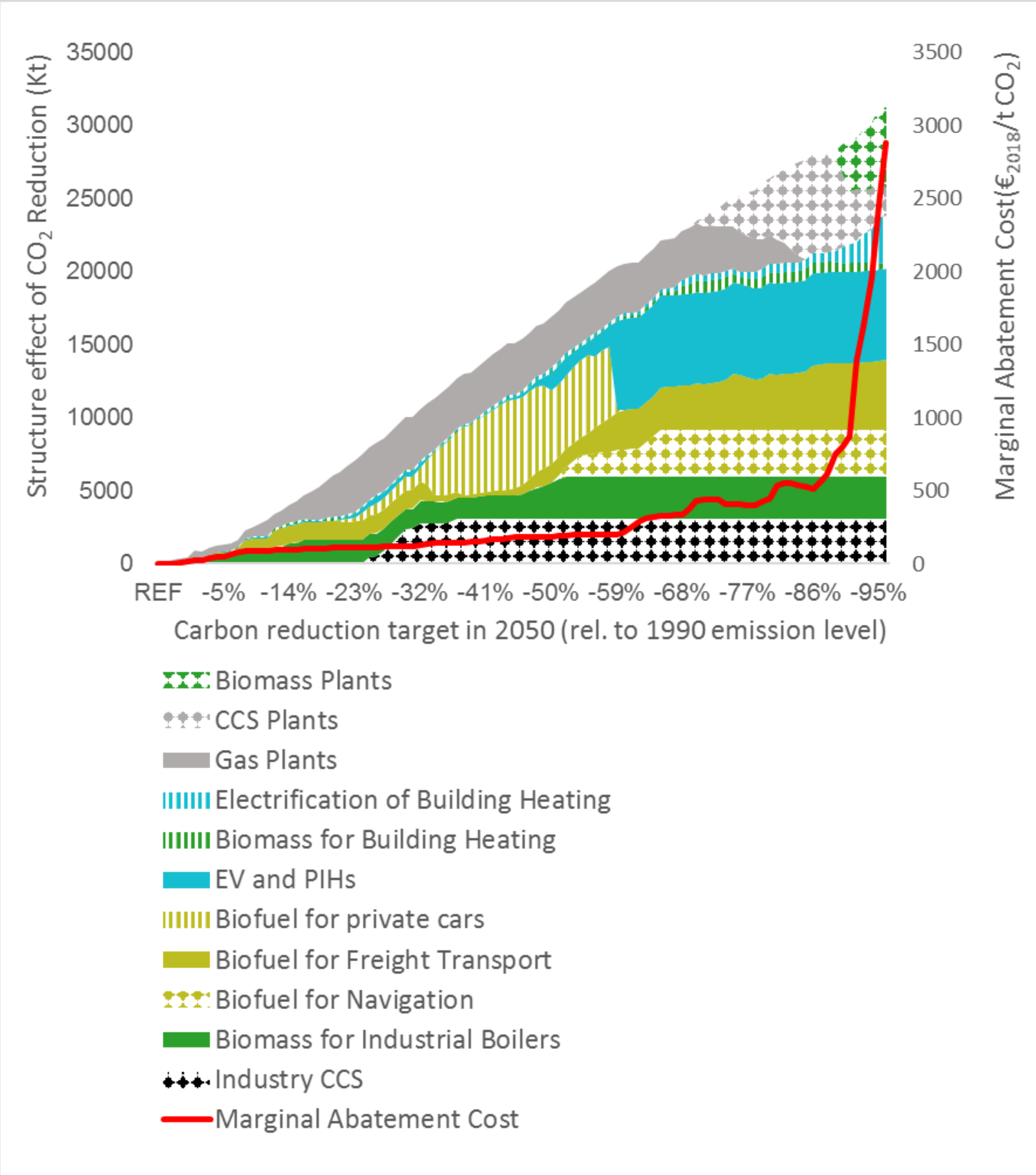
The results show that the intensity effect across all scenarios are close to 0, indicating that improving energy efficiency is cost-effective without any climate targets. Activity effect increases with carbon reduction targets due to price elasticity and represents 5% of total emission reductions at most ambitious decarbonization targets. The structure effect of switching from fossil fuels to low carbon technologies is the major factor of CO_2 reduction and represents 95% of total emission reduction.

As described in Section 2.3, the structure effect from the decomposition analysis is defined as the carbon mitigation from replacing carbon intensive technologies with low carbon technologies. Therefore, here we consider the mitigation amount contributed from the low carbon technologies as their penetration level. Figure 3 shows the change of penetration of key mitigation options over different levels carbon reduction targets. The highest carbon reduction amount from each mitigation option across all scenarios is identified as its mitigation potential. Options with mitigation potential greater than 1% of total emission in REF scenario are classified as key mitigation options and are presented on the graph. The MACC is shown alongside with the technology penetration in Figure 3 to reveal how the penetration of low carbon technologies impact the abatement costs.

As the optimal solution of the TIMES model is based on the least cost principle, mitigation options that penetrate in scenarios with lower marginal abatement costs are relatively more cost effective than those that penetrate at higher reduction targets. However, unlike financial-accounting MACCs where each technology is assessed individually, MACCs derived from ESOMs consider the whole energy system in an integrated manner. The ESOM based MACC thus captures interactions among different technologies, which can be reflected in Figure 4-3 Penetration of key mitigation options in 2050 for REF-MACC scenarios. For example, the penetration of bio-liquids for private transport and freight trucks demonstrates the "flip-flop" behavior due to resource constraint at 59% reduction. In addition, certain mitigation options may be further replaced by those with less emissions. For example, in the power sector the gas plants can be further decarbonized by gas CCS plants, which again can be further decarbonized by biomass or BECCS plants at more ambitious targets.

Figure 4-3 Penetration of key mitigation options in 2050 for REF-MACC scenarios

The penetration of a mitigation option is measured by the structure effect of carbon mitigation from shifting away from carbon intensive technologies to the low-carbon option. Energy efficiency measures, wind and solar power generation are cost-effective and reach their full potential in the REF scenario without any carbon constraints, and are therefore not reflected in the graph.



Due to model dynamics, the model does not simply exhaust one mitigation option before deploying another to achieve higher reduction targets. It is impossible to associate a single carbon cost level with each technology to produce a stepwise graph. The cost range of each mitigation option is therefore measured by the carbon costs of the scenarios between which the measure starts to penetrate and reaches its full mitigation potential. The CO_2 mitigation potentials and the related costs for key mitigation options are summarized in Table 4-2 Relative cost of key mitigation options for REF-MACC. It should be noted that the MACC derived with ESOM is highly dependent on the type of approach, the assumptions in technoeconomic data and technology availability. As pointed out by Huang et al., the MACC is best used to rank the cost effectiveness of technologies rather than focusing on the absolute prices (Huang et al., 2016).

Table 4-2 Relative cost of key mitigation options for REF-MACC

Mitigation Measure	Technology Group	MAC Range (€$_{2014}$/tCO_2)	Mitigation Potential Rel. REF Scenario (kt)
Biomass Boilers	Industrial Heating	15-189	2900
Gas Power Plants	Power Generation	35-107	3600
Industrial CCS	Cement Production	107-141	3100
PIH and EV	Private cars	180-240	6250
Navigation Biofuel	Navigation	188-316	3200
Freight Biofuel	Freight Transport	159-541	4800
Biomass	Building Heating	279-425	800
Gas CCS Plants	Power Generation	425-495	6800
Electrification	Building Heating	528-3964	3300
Biomass Plants	Power Generation	769-3964	5600

The mitigation technologies are therefore categorized according to their corresponding marginal abatement costs. Measures like wind power, utility-scale solar power, and improving energy efficiency are already adopted in the REF scenario and cannot be reflected in the graph. These measures are *cost-effective* even without any mitigation targets and can therefore be considered as low-hanging fruit. Options that penetrate at lower reduction targets corresponds to lower marginal abatement costs, including switching from coal and peat to gas for power generation, gas to biomass for industrial boilers, diesel cars to PIH, replacing diesel with biofuels for freight and navigation. Deploying these mitigation measures do not cause drastic increase in marginal abatement cost, and they can be classified as *resilient technologies* that should receive sufficient policy supports to maximize their potential. Replacing gas with electric appliances for residential and commercial heating, and biomass power plants are measures that only penetrate with ambitious mitigation targets. They are classified as *tipping point technologies* that cause significantly increases in the marginal abatement cost. Technologies such as wave energy do not penetrate in any scenarios, implying that significant cost reduction is required to make them economically competitive, and are therefore classified as *niche* technologies.

4.3.4 Energy system analysis

Compared to projecting pathways for climate policies in place with limited number of scenarios, analyzing the scenario ensembles that compose MACCs provides a more nuanced understanding of the economic implications and dynamics of the energy system in response to different levels of decarbonization. The response of the energy system to decarbonization ambition levels are described with trends in emissions, energy mix and technology penetration levels with high granularity. This helps add more technological details to MACCs, identify technological interactions, and understand the driving forces that increase MACCs.

In the REF scenario, the total amount of energy related CO2 emissions in 2050 is 34.6Mt, where the transport sector accounts for the highest amount of emissions (14.7Mt), followed by power generation (7.9Mt), industry (6.9Mt), residential (3.0M), and commercial sector (1.6Mt). The trends in sectoral emission for increasing levels of reduction targets (Figure 4-4) show that each sector decarbonizes at different rates. Table 4-3 Decarbonization profile of subsectors in 2050 of REF-MACCs scenarios. summarizes the decarbonization profiles of each sector by showing the marginal abatement costs at which each sector reaches 50%, 80% and 95% carbon reduction.

Table 4-3 Decarbonization profile of subsectors in 2050 of REF-MACCs scenarios.

Subsector	Emissions in REF scenario	Mitigation Measure	MAC at 50% reduction €/tCO_2	MAC at 80% reduction €/tCO_2	MAC at 95% reduction
Navigation	3192kt	Biofuel	189	310	316
Freight	4684kt	Biofuel	189	393	541
Public Transport	155kt	Biofuel	15	42	77
Private Cars	6466kt	Electrification	139	153	180
Power Generation	7790kt	Biomass CCS	393	518	3964
Industry cement production	3110kt	Industrial CCS	117	125	141
Industrial Boilers	2940kt	Biomass	90	180	280
Residential Heating	2934kt	Biomass Electrification	359	1573	2364
Commercial Heating	1259kt	Biomass Electrification	359	1573	2769
Cooking	205kt	Electrification	1341	1573	1888

Figure 4-4 Sectoral Emission Trends in 2050 for REF-MACC scenarios

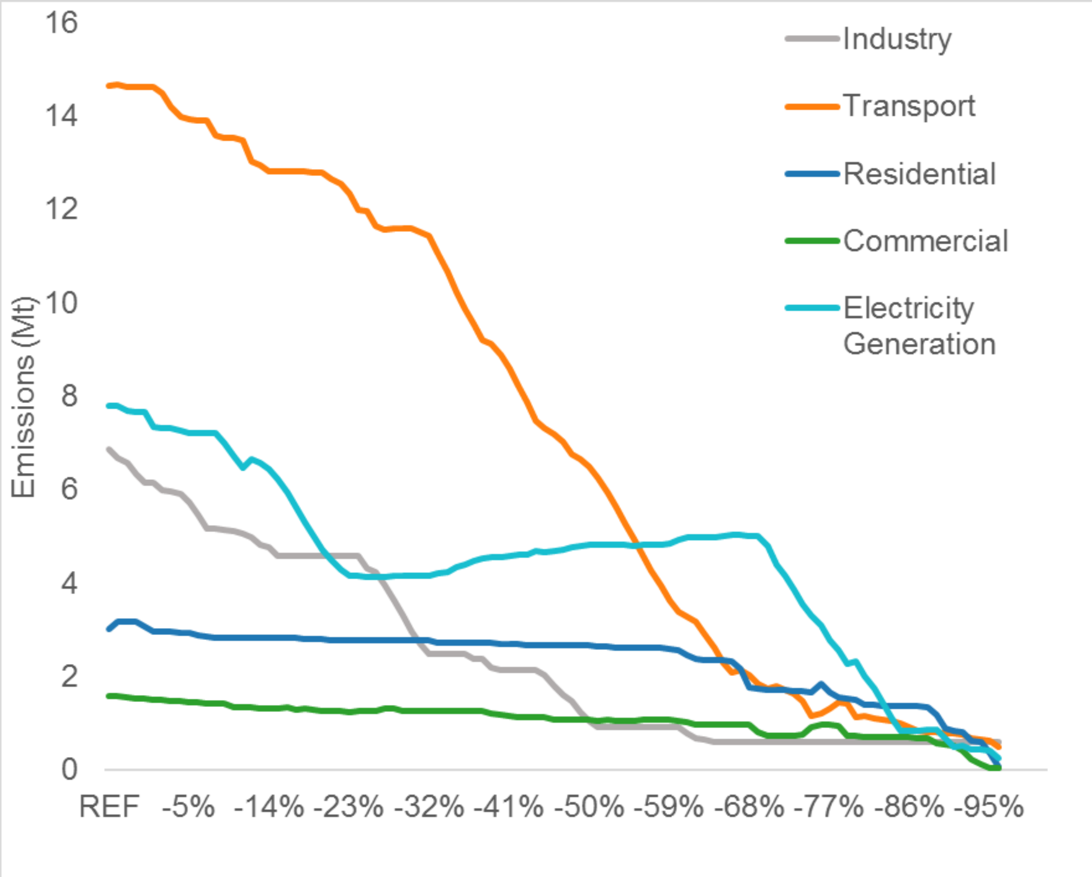
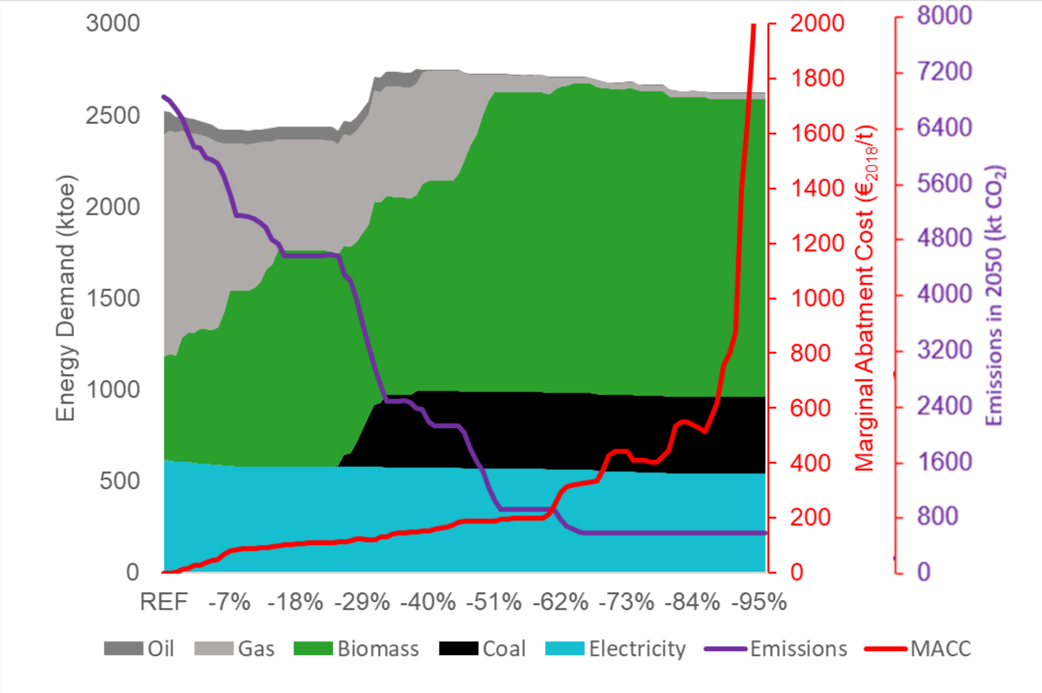


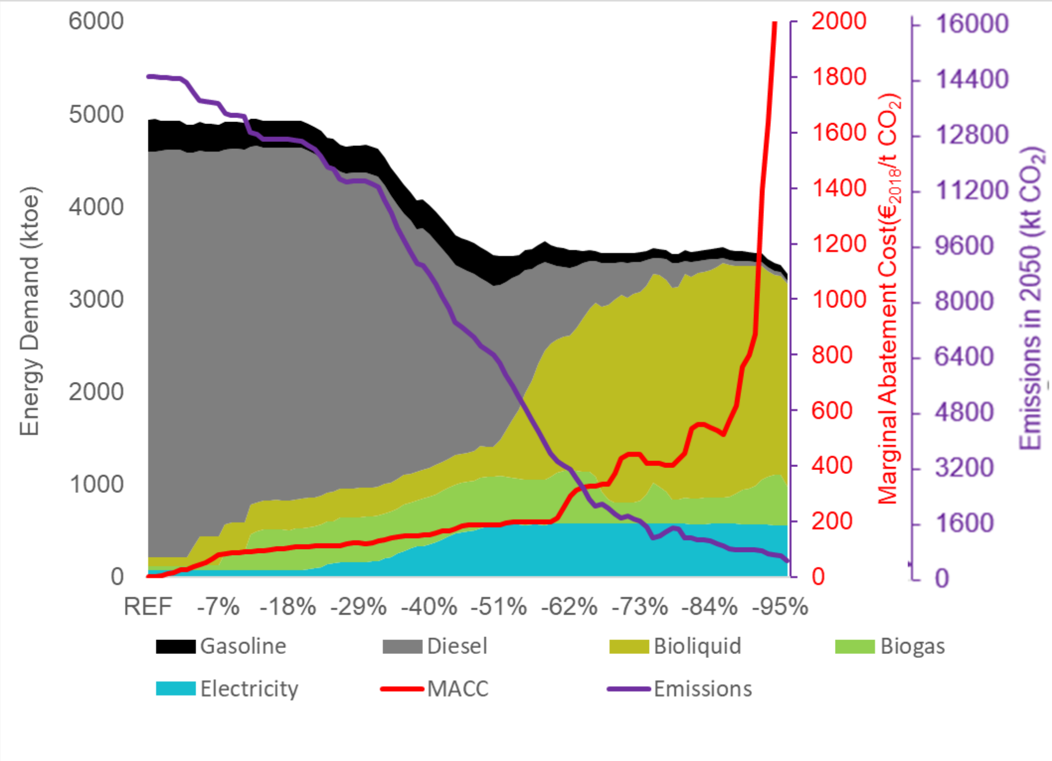
Figure 4-5 to Figure 4-9 shows sectoral trends in total final consumption (TFC) with comparison to system wide MACCs and sectoral emissions. The industry sector (Figure 4-5) accounts for 20.2% of emissions in 2050; in the REF scenario the majority of emissions are from fossil fuel consumption for cement and lime production (52.1%) and industrial boilers (42.7%). Industrial boilers switch from oil and gas to biomass at relatively low marginal abatement costs (0-€239/tCO_2). Cement and lime production switches from gas to coal CCS between €107/tCO_2 and €141/tCO_2. The cement and lime production sub-sectors have residual emission from industrial CCS of 0.58 Mt, equivalent to 1.7% of total system emissions in 1990.

Figure 4-5 Industry Sector energy demand, emission trends and system-wide MACC for REF-MACC scenarios



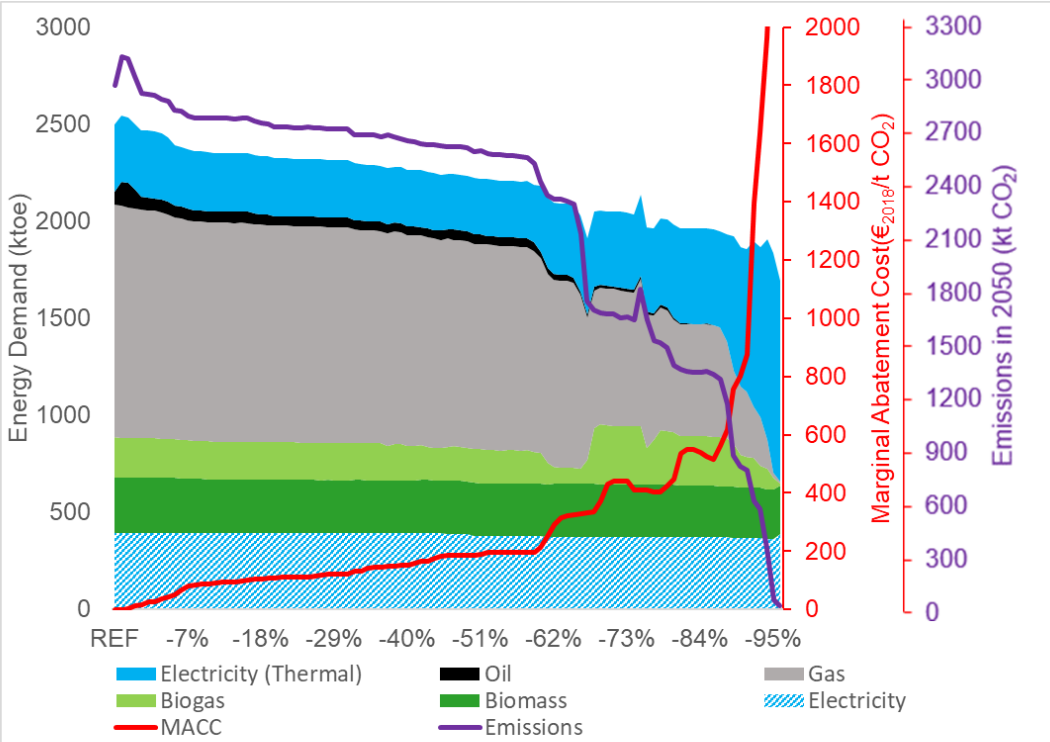
The transport sector (Figure 4-6) accounts for 43.1% of total CO_2 emissions in 2050 in the REF scenario, including private car (44.3%), road freight trucks (32.1%), navigation (21.6%), and public transport (2.0%). In the REF scenario, fuel consumption for the transport sector is dominated by fossil fuels (95.5%). Public transport decarbonizes at very low marginal abatement costs by switching to bio-liquids. At €180/tCO_2 the private car sector fully decarbonizes through biofuels (19%), EV (9%) and plug-in hybrid (72%). However, due to constraints in biofuel supply, the bioliquids are allocated to freight sector and private cars are fully electrified at €240/tCO_2. Full decarbonization for the navigation and freight sector is achieved at €518/tCO_2.

Figure 4-6 Transport Sector energy demand, emission trends and MACC in 2050 for REF-MACC scenarios



The residential sector (Figure 4-7) and commercial sector (Figure 4-8s) account for 8.8% and 4.6% of total emissions in the REF scenario. Due to similarities in technology characteristics these two sectors have similar emission and energy consumption profiles at different levels of decarbonisation ambition. Most emissions are from gas and oil consumption for space and water heating (97%). Decarbonization occurs at relatively high marginal abatement cost above 85% reduction targets through electrification with electric boilers, electric radiators and heat pumps (€494 - €2364/tCO_2), and solar panels (€2379 - €3964/tCO_2).

Figure 4-7 Residential sector energy demand, emission trends and system-wide MACC for REF-MACC scenarios



Decarbonization in the power sector starts at the lowest marginal abatement costs but finishes at the highest MACCs. The fuel mix in power generation (Figure 2-1) in the REF scenario is a mix of wind (42.0%), hydro (4.1%), solar (6.5%), coal/peat (21.6%), gas (23.2%), and municipal waste (1.4%). Decarbonization starts at low marginal abatement cost by replacing carbon intensive municipal waste (0-€15/tCO_2) and coal/peat (€84-€108/tCO_2) with gas. From €108/tCO_2 to €425/tCO_2, higher electrification levels for private cars causes a steady increase in electricity demand, but this does not change the fuel mix in power generation. The majority of emissions abatement is achieved between €358/tCO_2 and €495/tCO_2 by replacing gas plants with gas CCS plants, which is further replaced by biomass plants between €769/tCO_2 and €3964/tCO_2.

Figure 4-8 Commercial sector energy demand, emission trends and system-wide MACC for REF-MACC scenarios

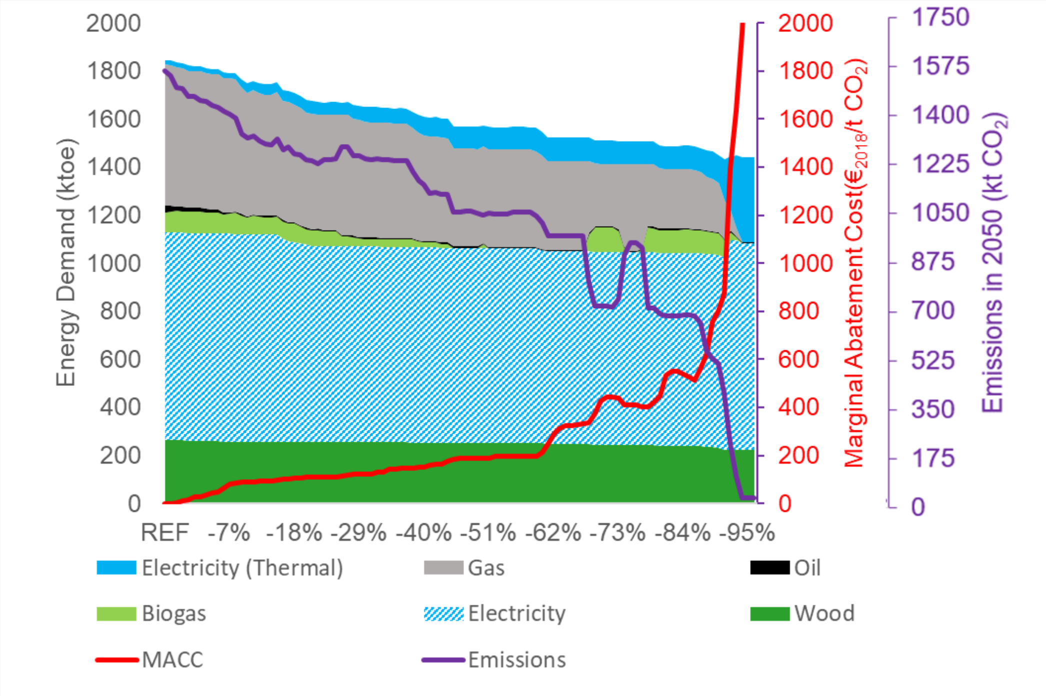
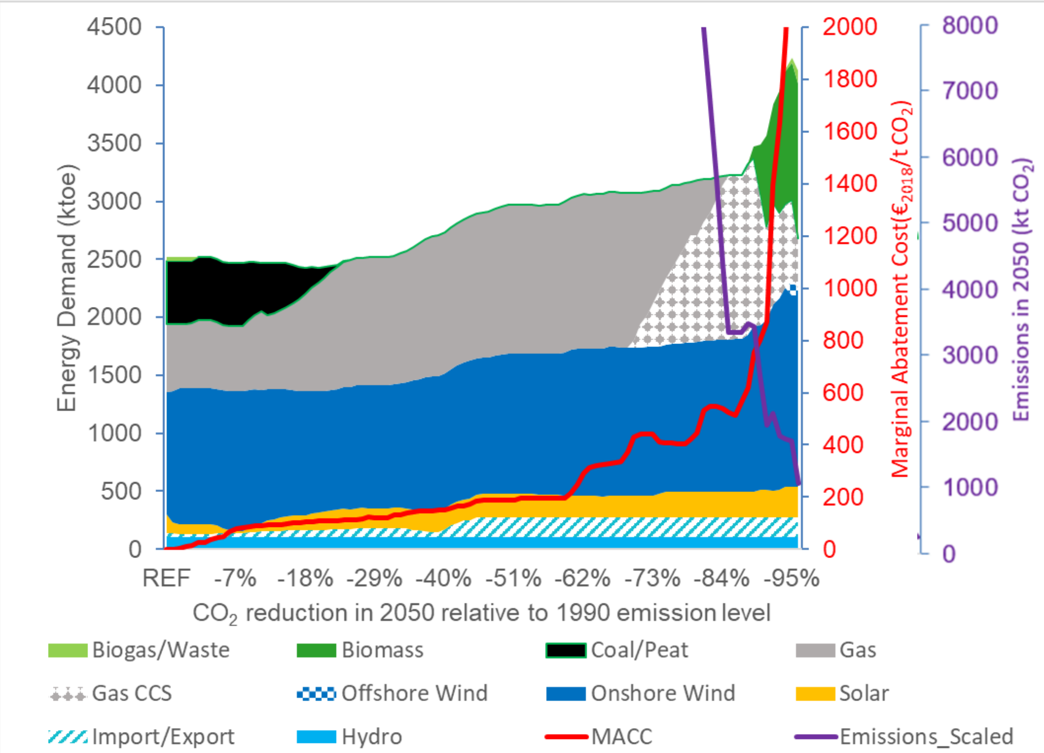


Figure 4-9 Electricity generation energy demand, emission trends and system-wide MACC in 2050 for REF-MACC scenarios



Comparison in energy consumption trends across different sectors indicates that the electrification of building heating significantly drives up the marginal abatement cost and causes the step change of the MACC in the MACC_85% scenario. At less ambitious reduction targets, building heating can be decarbonized through increasing biogas penetration. However, due to limited supply in biogas, gas consumption needs to be replaced by electrification beyond CO_2 85% reduction, driving up the electricity demand and investment costs in power generation. This finding implies that biogas could be more cost effective in decarbonizing building heating compared to electrification. Biogas offers the same fuel source as natural gas at zero net CO_2 emissions and requires no specialized equipment for existing gas consumers. Higher biogas supply allows building heating to decarbonize without extra investment costs. Currently six European countries have set up the target to reach 100% carbon-neutral gas supply in 2050 (Murphy, n.d.). Ireland has no green gas targets for 2050, but future research on exploring new sources of biogas (Allen et al., 2013; Wall et al., 2013) will play a critical role for deep decarbonization in Ireland.

4.4 Conclusions

In this study, we derive MACCs from the Irish TIMES energy systems model by applying increasingly stringent emission constraints. Besides ranking the cost-effectiveness of mitigation measures, we also assess MACCs and energy systems of the scenario ensembles that form the MACCs in an integrated manner. This new analytical approach improves existing energy policy tools by adding more technological details to MACCs and providing more robust policy insights with energy systems models compared to conventional scenario analysis.

The system-wide MACCs demonstrate the tradeoff between economic feasibility and mitigation ambition and shows that the marginal efforts towards higher ambition targets are nonlinear with tipping points at which the marginal abatement costs increase significantly. With decomposition analysis, the relationships between MACCs and CO_2 reductions contributed from mitigation options are visualized while capturing the interactions and switching effects among decarbonization technologies. Key mitigation measures are ranked based on their economic merits and categorized into cost-effective technology, resilient technology, tipping point technology, and niche technology. Energy efficiency measures, wind and solar power are cost effective even without any carbon constraint. Mitigation options such as electric vehicles and biogas industrial boilers penetrate at lower marginal abatement costs and are identified as resilient measures. On the other hand, electrifying residential heat and commercial heat requires significantly more marginal efforts and causes a tipping point at 85% reduction. Niche technologies such as wave energy and hydrogen for transport do not penetrate in the highest reduction targets, implying that significant cost reduction is required to make them economically competitive.

The finding about the marginal abatement cost step changes can be made into a more general observation, namely, that as the level of mitigation ambition increases, the number of mitigation options decreases and that at certain points this narrowing of options contributes directly to a tipping point in the marginal abatement cost. Without a system perspective, it is impossible to determine in advance which technologies will lead to such a spike in the overall marginal abatement cost.

The energy systems analysis on scenarios that form the MACCs combined with sectoral patterns in emissions and fuel consumption help draw more nuanced policy insights beyond what is typically possible with simple scenario analysis. With the ratification of the Paris Agreement which essentially requires zero emissions by mid-century, previous scenarios tied to 2°C-consistent pathways have become irrelevant. A multiplicity of pathways is more resilient towards changes in policy targets. Compared to single projections of low carbon energy pathways, results from a spread of scenarios help improve model transparency by demonstrating how the energy system changes over increase in reduction targets.

The observation in the “flip-flop” behavior among technologies indicates that focusing on a handful of scenarios is problematic and may ignore important policy implications. If only the pathway towards current climate policy (CO2-80) is examined, it is likely to conclude that full electrification is the most cost-effective pathway to decarbonize private car sector. Compared to deploying few types of technologies, a diversified technology portfolio better hedges against uncertainties (Labriet et al., 2015). The energy system analysis on the scenario ensembles shows that compared to electrification, using biofuels is more cost-effective in decarbonizing private transport sector. The main reason for full electrification under the 80% policy target is due to limitation in overall biofuel supply and lack of mitigation options for freight transport and navigation. Rather than targeting 100% electrification in private vehicles, policy makers could also seek a more diversified strategy including electricity, biofuels and hydrogen. Further analysis may apply the modelling to generate alternatives (MGA) approach (DeCarolis, 2011) to systematically explore alternative pathways that do not incur a significant increase in overall costs.

5 Least cost energy system pathways towards 100% renewable energy systems by mid-century

Abstract

Studies focussing on 100% RE have emerged in recent years. Within the existing 100% RE literature however, certain gaps exist in terms of both the modelling framework and sectoral focus. Existing 100% renewable energy system studies tend to focus on the power sector based on exploratory approaches. This paper addresses these key gaps by undertaking a whole energy systems approach and exploring how to achieve a 100% RE system by 2050 at least cost. The analysis is carried out using the Irish TIMES energy systems optimization model for an EU member country Ireland, which currently has the highest share of variable electricity on a synchronous power system. A broad range of scenarios are developed to address impacts from VRE levels, bioenergy costs and availabilities and cost assumptions. The results show that the current rate of renewable development needs a boost and indigenous bioenergy needs to be exploited to its full potential. The paper also compares 100% RE pathways with deep decarbonisation pathways and finds that focussing on renewable energy rather than decarbonisation is a more costly way to achieve CO2 emissions reduction. A further innovation is that global sensitivity analyses with stochastic input assumptions are used to capture critical uncertainties.

Keywords:

100% Renewable Energy, Electrification, Energy System Optimization Model, Uncertainty Analysis

5.1 Introduction

5.1.1 Policy Context

At the 16th Conference of the Parties (COP) meeting in Cancun in 2010, it was formally agreed that global warming should be limited to 2°C temperature rise relative to pre-industrial levels (UNFCCC, 2011). The Paris agreement adopted in 2015 (UNFCCC, 2015) aims to keep the global temperature rise well below 2°C and contains the ambition to pursue efforts to limit the temperature increase even further to 1.5°C. While the exact amount of carbon emissions that remains global warming below a certain temperature threshold is under uncertainties (Millar et al., 2017; Rogelj et al., 2016b), limiting global mean temperature increase at any level essentially requires global carbon emissions to become net zero at certain point in 21st century (Collins et al., 2013).

Recently, more ambitious climate actions towards zero emissions pathways are gaining momentum. The European Union has set an 80%-95% reduction target in greenhouse gas emissions relative to 1990 levels by 2050 (European Council 2009a) and is considering further reducing emissions to net zero GHG emissions by 2050 (Rankin, 2019). In the United States, the Green New Deal was proposed in the 116th Congress with goals of achieving net-zero greenhouse gas emissions (Ocasio Cortez, 2019). In June 2019, UK became the first G20 economy to legislate for a legally binding net zero 2050 target (Walker et al., 2019).

Renewables such as wind, solar, hydro, ocean and bioenergy represent a critical decarbonization option. With the rapid cost reductions in wind and solar energy, renewable electricity has become the preferred source of electricity generation over the past few years (Motyka et al., 2018). Renewables will need to account for 52%-67% of primary energy by 2050 under the 1.5°C-consistent pathways projected by IPCC (Rogelj et al., 2018). The energy consumption comprises large amounts of renewable electricity but also renewable fuels for heating and transport, and negative emissions technologies. The global energy transformation pathway towards well below two degrees projected by IRENA also indicates over two-thirds of total energy consumption from renewables (IRENA, 2018). Besides avoiding greenhouse gas emissions, the transition towards a high renewable energy system comes with several other co-benefits, such as addressing the challenge of fossil fuel depletion (Höök and Tang, 2013), ensuring security of energy supply, stabilizing energy prices, as well as reducing pollutants and health risks (International Energy Agency, 2017).

Renewables are well recognized as critical tools in climate mitigation, and policies that support renewable energy are present in nearly all countries in the world. Over half of the Nationally Determined Contribution (NDC) (UN Climate Change, 2019) submitted to the United Nations Framework Convention on Climate Change (UNFCCC) set specific renewable energy targets (Wuester and Strinati, 2017). The European Union is committed to a binding target of 32% renewable by 2030 (European Commission, 2018). The Green New Deal also contains the goal of meeting 100% power demand with renewable electricity.

However, renewable energy targets under current policy framework are not ambitious enough compared with decarbonization targets, and have significant variation in scope and comprehensiveness (REN21, 2019).Many countries and regions have set 100% renewable targets in electricity generation, which include Bangladesh, Cambodia, Colombia, Portugal, Sweden, California. However, policy targets on renewables outside the power sector are far less ambitious. Targets in 100% total renewable energy are mainly taking place in cities, such as Frankfurt, Hamburg, Vancouver and Hague (REN21, 2019). Denmark thus far is the only country with 100% renewable target in total final energy consumption by 2050.

5.1.2 Status of Research

A number of studies focusing on 100% RE have emerged in recent years. Within the existing 100% RE literature, certain gaps exist in terms of both the sectoral focus and modelling framework.

Currently there is no uniform definition of 100% RE and majority of 100% RE studies focus on the power sector as a starting point (Hansen et al., 2019). Most studies find that 100% renewable electricity primarily from variable renewables feasible with technologies available now. It is pointed out the major barriers towards 100% renewable electricity are political, institutional and cultural

(Diesendorf and Elliston, 2018). The importance of flexibility measures (Lund et al., 2015) (Deason, 2018) (Reedman, 2012), storage (Lazkano et al., 2017) and interconnectors (Pean et al., 2016), centralised and decentralised electricity (Kaundinya et al., 2009; Lilliestam and Hanger, 2016; Mclellan et al., 2015) are also addressed within the current literature. Some challenges are also addressed in regional studies, such as high investment cost in flexibilities and new capacities (Krakowski et al., 2016), extreme weather conditions (Ye et al., 2017), summer peak demand (Esteban et al., 2018), management of low-demand periods (Mai et al., 2012), access to renewable data (Akuru et al., 2017), government regulations (Aghahosseini et al., 2018), constraints on geographical allocation of storage technology (Bussar et al., 2014). Few studies have argued against 100% RE. A review study based on a scoring system (Heard et al., 2017) points out that existing studies cannot meet criteria in consistency with demand forecast, reliability in meeting in-time demand, identifying transmission and distribution requirements, and provision of essential ancillary services. This finding was criticized by another review (Brown et al., 2018), which argues that the methodology is problematic and the feasibility criteria chosen are critical but can be addressed at low economic costs.

Achieving a 100% RE power system is a key starting point and then electrifying the parts of heat and transport that can be electrified, with electro-fuels used for sectors that cannot be electrified. Some 100% renewable energy studies propose a 100% renewable power system and electrify all energy sectors. For example, Jacobson has proposed a 100% renewable energy system solely based on water, wind and solar (WWS) for the 50 US states (Jacobson et al., 2015) and 139 countries in the world (Jacobson et al., 2017). The study finds that a 100% RE based on WWS is technically and economically feasible and will reduce overall energy costs, provide net new jobs and avoid significant climate costs. However, the scale of this challenge is apparent against the current situation where electricity accounts for just 20% of energy end use, with heat and transport accounting for the remaining 80%. The WWS energy system proposed by Jacobson was met with criticism (Clack et al., 2017) stating that there were key methodological oversight, including invalid modelling tools, modelling errors and implausible assumptions.

Another research gap in 100% RE is that analysis is usually carried out in an exploratory manner. The energy mixes and technology portfolio are based on exogenous assumptions rather than optimizing the transition pathways. For example, the input-output model EnergyPLAN has been used in numerous studies to explore feasibilities of 100% RE system (Connolly et al., 2016)(Zakeri et al., 2015)(Child and Breyer, 2016)(Ćosić et al., 2012)(Lund and Connolly, 2012) (Lund and Mathiesen, 2009). The model is able to account for intermittency from renewable sources by performing hourly simulation over one year. However, exogenous assumptions in energy supply and demand may overlook cross-sectoral interactions and cannot determine optimal levels of bioenergy consumption and electrification levels, which is a major challenge for studies using EnergyPLAN model (Vad et al., 2015).

It is noteworthy that studies focussing on deep decarbonisation have tended to take a different approach, in particular, focussing on i) system wide solutions and on ii) least cost optimisation modelling. Deep decarbonisation analyses generally take a systems approach with integration between electricity heat and transport systems. These analyses seek a least cost optimal balance between electrification, renewables and other low and negative carbon technologies, and point to the long-term transition pathways. For example, the Integrated Assessment Models (IAMs) have been widely used to project long-term global low carbon transition pathways, including the IPCC SR1.5 report on 1.5 °C global warming (Rogelj et al., 2018), 2050 energy roadmaps by (IRENA, 2018) and energy technology perspectives from IEA (IEA, 2017). Besides high renewable penetration, deep decarbonization pathways are also characterized by nuclear and carbon dioxide removal technologies (CDR) such as CCS power plants and direct air capture. Pathways of 100% renewable energy has rarely been considered by IAM modelling before and was first mentioned in the IPCC SR1.5 report (Rogelj et al., 2018). It is pointed out that 100% RE pathways have significantly higher wind, solar and electrification levels compared to existing decarbonization pathways, and may expand range of possible pathways given that the underlying assumptions are plausible.

Renewable energy targets should be set in line with carbon reduction targets within a robust climate policy framework. This is because emissions reduction ambitions are the primary driver for large scale development of renewable energy. The approaches of i) system solutions and ii) least cost optimisation are not sufficiently addressed within the current 100% RE literature. Without properly addressing these gaps, insights from 100% RE analysis may be limited and inconsistent with insights from deep decarbonization pathways, leading to suboptimal policy decisions.

This paper addresses the key research gaps by taking an energy systems analysis approach to address the challenge of how to achieve a least cost 100% RE system. It also addresses a further weakness in that it compares 100% RE pathways with deep decarbonisation pathways. These studies are normally undertaken separately, with little comparison of the two approaches in the literature.

5.1.3 Chapter Objective

This paper focuses on one EU member country Ireland and analyzes the long-term decarbonization targets and renewable energy targets under a single modelling framework. Ireland is an interesting case study for high renewable study as the energy system is relatively small and isolated with characteristics that well represent developed country. Ireland is currently missing its national target of 16% (European Union, 2009) share of gross final consumption GFC by 2020. As of 2016, the total final energy consumption (TFC) in Ireland is 11,680 ktoe, with only 9.5% contribution from renewables. Wind generation accounts for 22.3% total electricity generated, and total renewable generation accounts for 27.2% of gross electricity consumption; however, electrification only accounts for 18.8% of TFC (SEAI, 2018) and more efforts are required in the transport and heat sector. The current energy consumption and renewable targets are summarized in Table 5-1.

A first step in exploring feasibilities of 100% RES in Ireland was carried out with EnergyPLAN model based on exogenous assumptions in technology mixes, with bioenergy share in total primary energy ranging from 71%-95% (Connolly et al., 2011). In this paper, the bottom-up energy systems optimization model (ESOM) is applied to determine cost-optimal level of electrification and bioenergy consumption from a whole system perspective based on techno-economic assumptions, demand projections and resource constraints.

The usage of energy models should focus on the policy insights rather than numbers (Peace and Weyant, 2008a). One way to improve robustness of model results and the policy insights is through systematic assessment of uncertainties (Yue et al., 2018a). In this analysis, rather than using a few scenarios, scenario ensembles are applied to capture a wide range of possibilities and address parametric uncertainties to draw more robust policy insights. A broad range of scenarios under different assumptions are used to identify the role of bioenergy and VRE under 100% RE pathways. Sensitivity analysis on RES targets is carried out to determine the incremental impact of different levels of renewable penetration and find out feasible renewable energy targets. Global sensitivity analysis is performed on key techno-economic assumptions such as bioenergy costs and availabilities and investment costs of renewable technologies to identify critical sources of uncertainties and assess robustness of renewable technologies.

The paper is outlined as follows. Section 2 provides detailed description of the model used, the assumptions on RES and scenario setup. Section 3 presents the results and discussions. Section 4 provides a concluding remark.

Table 5-1 Ireland's current energy consumption and progress towards RES targets Source: (SEAI, 2018)

	2005	2017	2020 Target
TPER (ktoe)	15803	14413	
Fossil Fuels	15306 (96.6%)	13058 (90.2%)	
Hydro	54 (0.3%)	59 (0.4%)	
Wind	96 (0.6%)	640 (4.4%)	
Biomass	180 (1.1%)	378 (2.6%)	
Other Renewables	40 (0.3%)	270 (1.9%)	
Import Dependency	89%	66%	
TFC (ktoe)	12606	11821	
Fossil Fuels	10324 (81.9%)	9055 (76.6%)	
Renewables	188 (1.5%)	472 (4.0%)	
Wastes (Non-Renewables)	0	70 (0.6%)	
Electricity	2094 (16.6%)	2223 (18.8%)	
Renewable share (GFC)	2.8%	10.6%	16%
RES-E	7.2%	30.1%	40%
RES-T	0	7.4%	10%
RES-H	2.8%	6.9%	12%
Emissions (Mt/% Rel. 2005)	45.7	36.8/-18%	20%

5.2 Methodology

5.2.1 Model Description

TIMES (The Integrated MARKAL-EFOM System) (Loulou et al., 2016a) is an economic model generator for local, national, multi-regional, or global energy systems, which provides a technology-rich basis for representing energy dynamics over a multi-period time horizon. It includes a technology-rich database that allows the model to estimate based on the objective function to maximise the surplus (minimise total discounted energy system cost) and numerous constraints that can include both environmental emission to technological or policy constraints over a multi-period time horizon. The cost that is being minimized takes into consideration investment costs of energy technologies, operation and maintenance costs, the cost of imports, profits from energy exports and the residual value of technologies at the end of the horizon considered within the model. TIMES assumes that each agent has perfect foresight on the market's parameters and computes the inter-temporal dynamic equilibrium by maximizing the total surplus over the entire time horizon with decisions made on equipment investment and operation, primary energy supply and energy trade for each region. TIMES is thus a vertically integrated model of the entire extended energy system. TIMES is now widely used by over 62 contracting parties supported by ETSAP (Energy Technology Systems Analysis Program), an Implementing Agreement of the International Energy Agency (IEA).

In this study the Irish TIMES model is used. The model has been used to provide detailed insights on the possible pathways in achieving the challenging emission reduction targets for Ireland and inform the development of national legislation on climate change and energy policy. The Irish TIMES model has been used in many studies including in informing the Irish White Paper that set out a framework to guide policy and the actions that Government intends to take in the energy sector from now up to 2030 and published by the Department of Communications, Climate Action and Environment (DCENR, 2015).Other analysis include energy system trajectories to meet emission reduction targets (Chiodi et al., 2013c, 2013b), the security of supply dimensions of a decarbonized energy system (Glynn et al., 2017a) , impacts of bioenergy availability (Chiodi et al., 2015a), as well as decarbonization feasibility in achieving well below 2 degrees target (Yue et al., 2018b).

5.2.2 Technoeconomic Assumptions

The original Irish TIMES dataset was extracted from the Pan European TIMES (Pan European TIMES model that includes EU27, Iceland, Norway, Switzerland and Balkans countries) project by the Energy Policy and Modelling Group at University College Cork, and was updated with more detailed local data, calibrated to the national energy system with macroeconomic projections from the Economic and Social Research Institute (ESRI). The time horizon in the Irish TIMES model used is from 2005 to 2050 with a time resolution of four seasons, each is comprised of day, night and peak time slice. The inputs to the Irish TIMES include estimates of end-use energy service demands derived from the macroeconomic model HERMES (Bergin et al., 2013), estimates of existing stocks of energy related equipment, characteristics of available future technologies, as well as present and future sources of primary energy supply and their potential.

The potential for additional large hydro plants in Ireland is limited but further deployment of small hydro plants is possible (ESBI, 1997). The resource potentials for wind is assumed to be 6.9GW and 7.5GW for onshore and offshore generation (Chiodi, 2010). The level of intermittent (non-dispatchable) renewable generation – namely wind, solar and ocean energy is limited to 50% at annual level and 70% at time slice level according to the report by Ireland's transmission system operator EirGrid (Boemer et al., 2010). The use of geothermal energy in Ireland is limited only to small installations in the residential and services sector mostly for space and water heating purposes.

The potential of bioenergy available for import is set according to the analysis of (Clancy et al., 2012), where the estimate of bioenergy import potential available for Ireland is estimated according to the current share of primary energy demand of Ireland as a fraction of EU's primary energy demand. The potentials of domestic bioenergy is projected to 2,887 ktoe for the year 2030 and at 3,805 ktoe by 2050 (Chiodi et al., 2015a). Additional details on how demand is driven and technoeconomic inputs can be found in (Chiodi et al., 2013b, 2013c).

The original cost assumptions in Irish TIMES model are from the values in the PET model used in the Intelligent Energy— RES2020 project (RES2020). In this analysis, the input assumptions for renewable technologies are updated and refined according to the most recent data available and summarized in Table 5-2. Renewable technologies including solar, wind, ocean energy are updated according to JRC data (Tarvydas, 2018). The cost of residential and commercial heat pumps are updated with data from (Hofmeister and Guddat, 2017). In addition, the hydrogen energy system is also added to the model using assumptions in production, storage and transmission from (McDonagh et al., 2018; Alessandra Sgobbi et al., 2016). Some of the model assumptions in technology deployment rates are relaxed to allow all energy service demands to be met using renewables and electricity by 2050.

Table 5-2 Technoeconomic assumptions of capital cost for renewable technologies

Euro/kW	2020	2030	2040	2050	2050 Low	2050 High
Power to Gas (Electrolysis)	1420	1169	935	935	-20%	+30%
Wave Energy	6310	5320	4040	3240	-54%	+76%
Tidal Energy	4920	4140	3150	2520	-54%	+57%
Solar Energy (Utility Scale)	600	480	440	390	-28%	+105%
Offshore Wind	2870	2570	2430	2330	-45%	+33%
Onshore Wind	1020	980	950	910	-20%	+14%
COM Solar	720	430	350	350	-17%	+131%
RSD Solar	920	600	490	420	-17%	+131%
COM HP Air	405	366	350	350	-15%	+20%
COM HP Ground	299	266	233	233	-15%	+20%
RSD HP Air	679	614	586	586	-15%	+20%
RSD HP Ground	1014	937	861	861	-15%	+20%
COM HP Air to Water	509	509	459	459	-15%	+20%
RSD HP Air to Water	700	700	631	631	-15%	+20%
Bioenergy import price					-60%	+80%
Bioenergy Import					-49%	+20%

5.2.3 Scenario Definition

Core Scenarios

As pointed out by Ó Gallachóir et al., equating the electricity generated from renewable sources with the primary energy supply is inaccurate in representing the contributions from renewables in replacing fossil fuels (Ó Gallachóir et al., 2006). Therefore, the constraint of the level of renewable energy penetration rate is applied to the model based on the gross final consumption (GFC) instead of primary energy, and is based on the Directive1 2009/28/EC (European Parliament, 2009), which is the sum of (a) gross final consumption of electricity from renewable energy sources; (b) gross final consumption of energy from renewable sources for heating and cooling; and (c) final consumption of energy from renewable sources in transport. In this analysis, the calculation of renewable share excludes non-energy fuel use and oil consumption for aviation. The core scenarios in this analysis include the following.

REF The reference scenario represents the cost optimal energy system pathway that delivers energy service demands without any policy instruments. This scenario projects a 25% renewable share by 2050.

RES(X) The renewable energy system scenarios apply constraints to the minimum share of renewable energy in total final energy consumption. The number in scenario names represent level of RES share. For example, RES100 scenario has 100% constraint in renewable share in 2050. The constraints in intermediate model years are linearly interpolated.

CO2-80 The CO2-80 scenario sets annual emission constraints according to the EU climate & energy package and EU low-carbon economy roadmap from 2020 to 2050, achieving an 80% reduction in all energy related CO2 emissions by 2050 on 1990 levels. This scenario does not have any constraints applied on the renewable levels and is used to compare differences in renewable energy targets and decarbonization targets.

Alternative Constraints

Besides RES scenarios, a range of alternative constraints are applied to address the critical factors that may impact the renewable energy pathways.

HighBIO: The bioenergy potential in baseline scenarios are projected under the global context that assumes “High demand/Medium supply” that assumes the current trend of bioenergy development will prevail. The RES-HighBIO assumption assumes that the global bioenergy availability is projected based on “High demand/Ambitious supply” assumption under an optimistic view of bioenergy potential due to increased planting and removal of barriers by investment.

HighVRE: The current assumption in VRE share is 50% at annual level and 75% at time slice level. HighVRE assumption assumes that 100% VRE is allowed.

NoBIOIMP: The level of bioenergy available for comes with a high degree of uncertainties and high reliance on energy import may cause negative impacts on energy security. Under NoBioIMP assumption, international import of bioenergy is not available, and bioenergy can only be produced from indigenous sources.

NoBIOELC: Under NoBioELC assumption renewable electricity can only be generated from WWS sources and biomass power plants are not allowed.

Multiple alternative constraints may be applied to one scenario. For example, scenario with 75% RES level and no bioenergy import is named as **RES_75_NoBioIMP**. Scenario with 100% RE constraint, 100% VRE and no bioenergy import is named as **RES100_HighVRE_NoBioIMP**. The assumptions made in core scenarios and alternative constraints are summarized in Table 5-3.

Table 5-3 Scenario assumptions

Core Scenarios	Global Bioenergy Supply	VRE	Biomass Plants
REF/RES/CO2-80	Medium	50%	Allow
Alternative Constraints			
HighBIO	Ambitious		
NoBioIMP	Disabled		
HighVRE		100%	
NoBIOELC			Disabled

5.2.4 Sensitivity Analysis

In addition to scenario analysis, local sensitivity analysis is carried out on renewable energy targets to explore technical feasibilities and incremental impact of increasing renewable targets. Starting from the 25% renewable share corresponding to the renewable penetration level in REF scenario, each RE scenario increases the renewable target by 1% from the previous scenario. The resulting set of scenarios range from 25% (RES25) renewable share to 100% RES (RES100) resulting in a total of 76 scenarios. The sensitivity analysis is carried out under alternative assumptions as well.

Besides sensitivity analysis on RE targets, carbon constraint scenarios corresponding to each RE scenario are developed to explore differences between policy targets that focus on decarbonization and targets that focus on RE penetration. For each RES scenario, emission levels for each model year obtained from the model results are applied to a CO2 scenario as exogenous emission constraint. For example, emission constraints in **RES95_CO2** scenario is set equal to the emission levels of the **RES95** scenario.

5.2.5 Global sensitivity Analysis

Projection into decades from now is inherently uncertain. In this study we use Monte Carlo analysis (MCA) to address parametric uncertainties in a systematic manner. The principle of MCA is to propagate uncertainties by simultaneously perturbing multiple uncertain input parameters represented by probability distributions. The collection of model outputs are then evaluated statistically using a global sensitivity analysis (GSA) approach (Saltelli et al., 2008), which is used to determine how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input. The MCA is carried out with constraint of 100% renewable energy share and the assumption of 100% VRE. The MCA is carried out in the following steps.

1. Triangular probability distributions are assigned to techno-economic parameters including capital costs of renewable technologies, bioenergy import prices and availability. The uncertainty ranges are summarized in Table 5-2.
2. A sample of random values is generated based on the probability distributions.
3. The randomly generated sample is fed into the model to compute a set of outputs.
4. The procedure is repeated 500 times and 500 samples are generated.
5. The outputs are evaluated using global sensitivity analysis. Standard correlation coefficients are calculated to determine the correlations among input uncertainties and key energy system metrics such as system costs, bioenergy consumption and technology penetrations

5.3 Modelling Results

This section presents the cost optimal energy systems configurations of a high renewable energy system in 2050. 100% RE under various assumptions are explored using over 1000 scenarios, addressing multiple aspects including optimal mixes of electrification and bioenergy usage, the relationships among decarbonization and renewable, and the roles of key renewable technologies.

5.3.1 Technical feasibility of high RE penetration

The technical feasibility of 100% RES depends on the availabilities of bioenergy and renewable electricity. Under assumptions in medium bioenergy projection and VRE limitation of 50%, **RES100** scenario fails to find a solution. Sensitivity analysis on RE penetration levels show that the maximum feasible RE level is 94%.

Scenarios with alternative constraints show that the technical feasible level of RES increases to 100% under the **RES100_ HighVRE** scenario where 100% VRE in the power system is assumed feasible, and the **RES100_HighBIO** scenario where more ambitious global bioenergy supply is available. Bioenergy import has significant impact on the technical feasibility of high RE. Without bioenergy import, the maximally feasible level is reduced to 75% (**RES75_NoBIOIMP**).

5.3.2 Energy supply and demand

Figure 5-1 shows the total primary energy required (TPER) in 2050. Figure 5-2 shows the system wide total final consumption (TFC) in 2050 with shares of renewables shown in Figure 5-3. The large shares of bioenergy energy supply demonstrate its critical role under high RE energy system. In **REF scenario**, the amount of bioenergy supply in 2050 is 1700ktoe which accounts for 12.7% of TPER. Targeting higher renewable penetration is characterized by higher amount of bioenergy usage. Bioenergy supply rises to 9360ktoe in **RES90** scenario accounting for 68.8% TPER, and further to 11930ktoe (80.8% TPER) in **RES100_HighBIO** scenario.

Another important source of energy supply for 100% renewable energy is renewable electricity. Figure 5-4 shows electricity production by source and Figure 5-5 presents electricity consumption with overall electrification levels. The electrification level is calculated by percentage share of electricity consumption in total energy consumption. It should be noted that the electricity input into power-to-x processes is included in the calculation of total electricity consumption. This should be distinguished from hydrogen consumption presented in the TFC graph, which presents final hydrogen consumption by end-use technologies.

Figure 5-1 Total primary energy required (TPER) in 2050

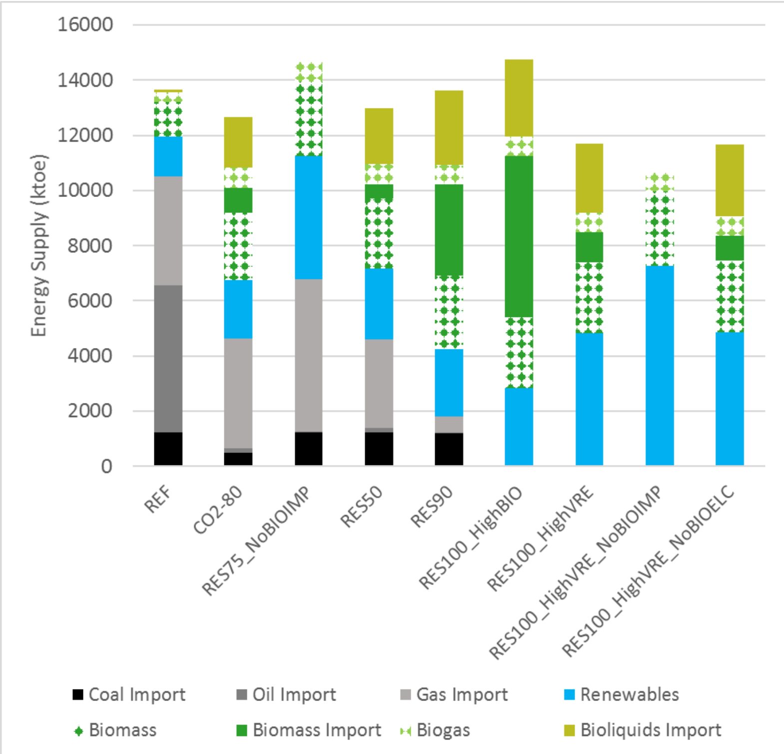


Figure 5-2 Total final energy consumption (TFC) in 2050

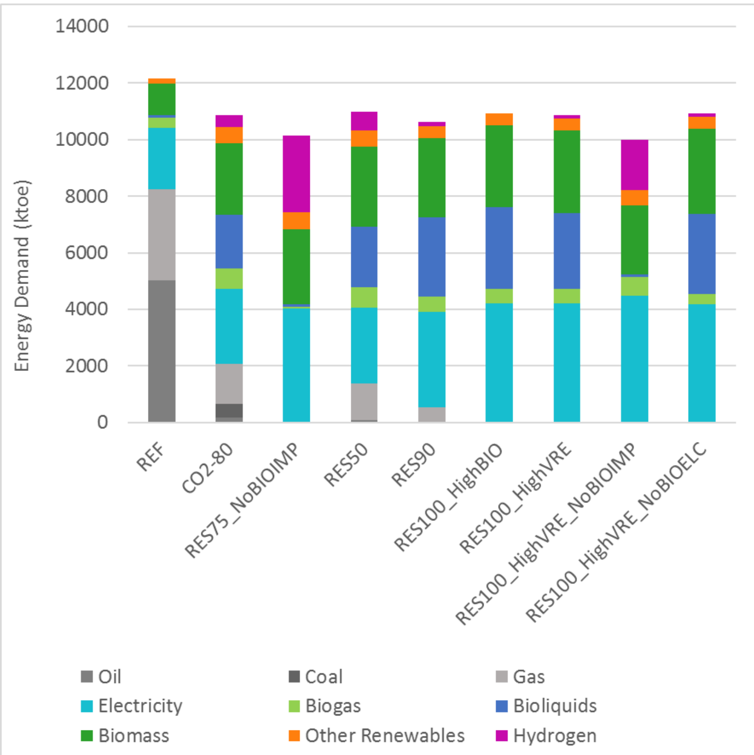


Figure 5-3 Renewable share by mode of application in 2050

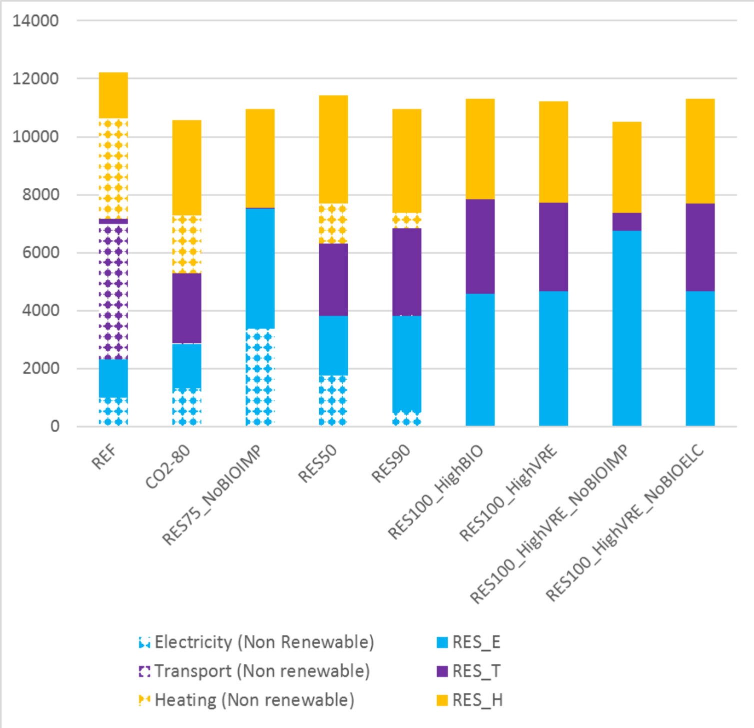


Figure 5-4 Electricity production by fuel use in 2050

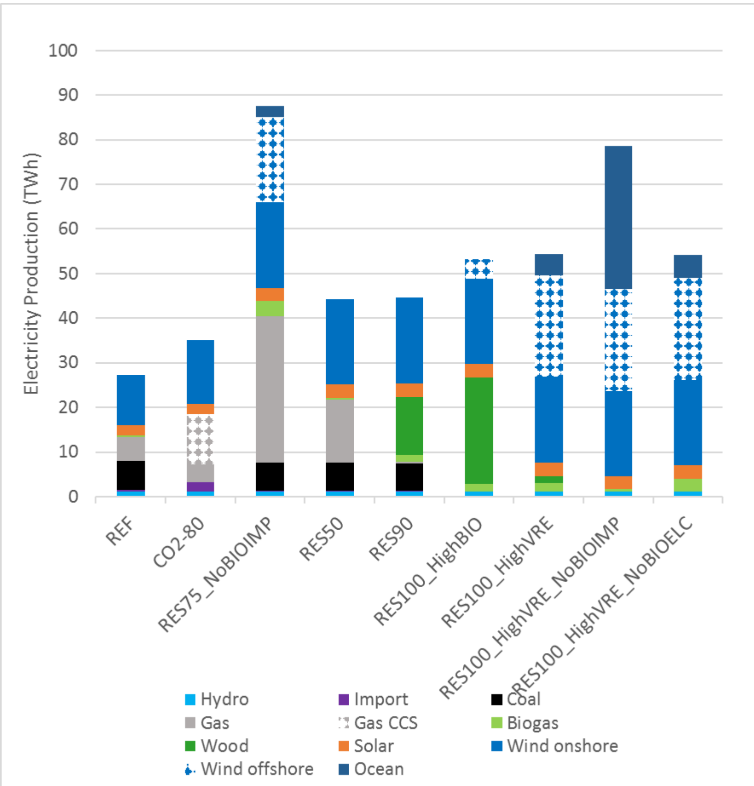
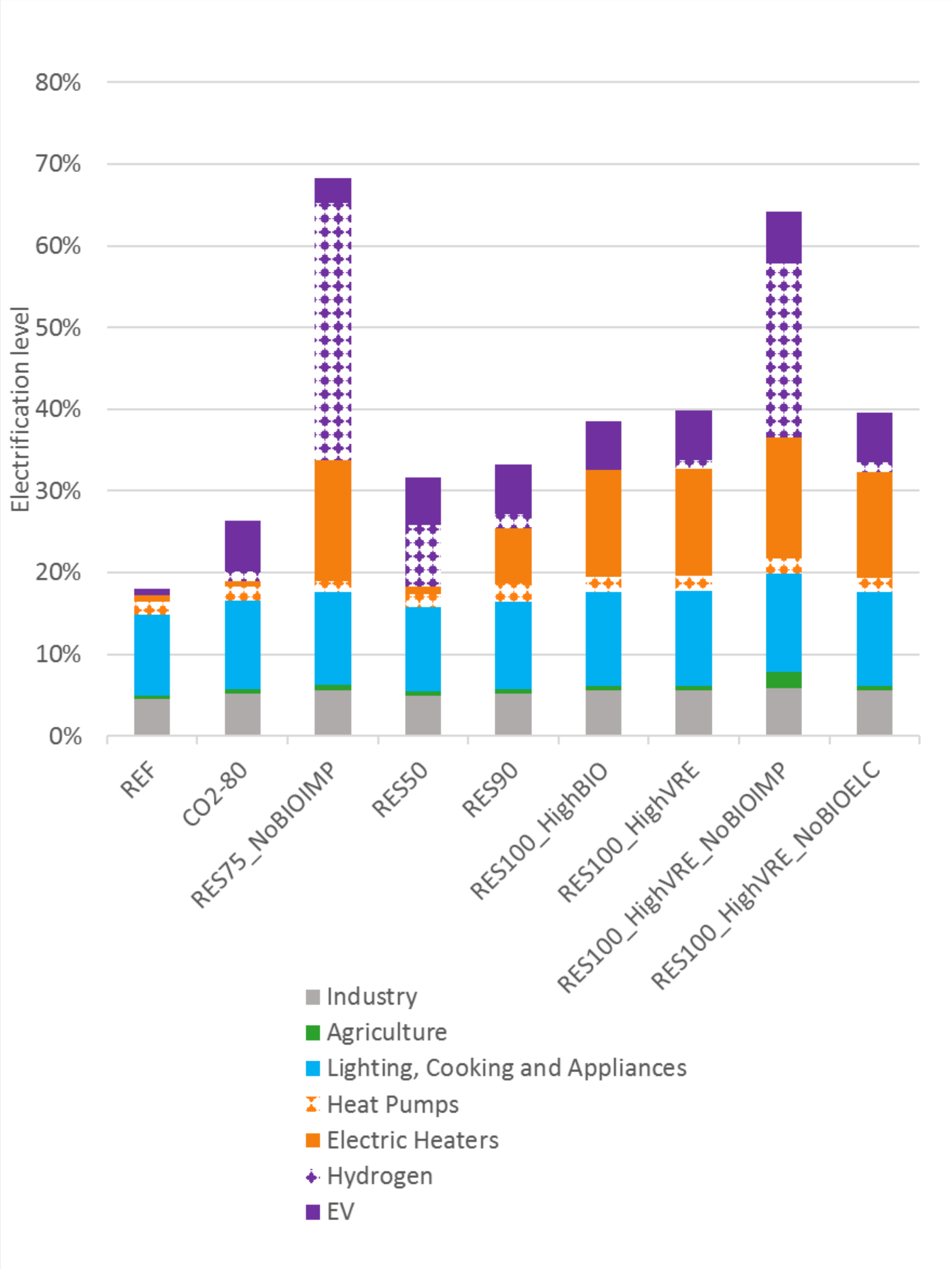


Figure 5-5 Electrification level by applications in 2050



Under the REF scenario where no policy constraints are applied, the electricity demand in 2050 remains similar and is projected to 27.2TWh with an overall electrification level of 18.4%. The electricity demand increases significantly from REF scenario to 43.1TWh (25.8%) in **RES50** scenario, and further increases to 53.3TWh (38.8%) in **RES100_HighBIO** scenario.

Comparison between **RE100_HighBIO** and **RE100_HighVRE** scenarios show that increasing VRE levels has little impacts on overall electrification levels. Increasing the VRE levels mainly causes switching from dispatchable biomass plants towards intermittent renewable generation including offshore wind and ocean energy. This results in reduction in bioenergy consumption from 80.9% share in TPER in **RES100_HighBIO** scenario to 58.8% in **RES100_HighVRE** scenario. The electricity demand significantly increases when bioenergy import is not available, which drives up the demand in hydrogen to replace biofuel consumption in freight and navigation. Under the **RES100_HighVRE_NoBIOIMP** scenario, electricity demand increases to 78.5TWh and the overall electrification level increases to 64.1%. Bioenergy supply reduces to 3420ktoe accounting for 32.1% TPER.

The **RES75_NoBIOIMP scenario** shows that 75% RE can be reached without bioenergy import or high VRE. Achieving this target requires high electrification (68.2%) to produce hydrogen for the transport sector. A large share of electricity is produced from natural gas, resulting in both high carbon emissions and energy system costs.

In the building sector (Figure 5-6), transition towards 100% RES is characterized by switching from gas to biomass and electricity for heating. Electricity consumption for lighting, appliances, and energy saving from insulation remain relatively the same in RES scenarios compared to the REF scenario. The increase in electricity consumption is driven by high penetration of electric heaters and radiators for building heating. Due to high investment costs, penetration of heat pumps remains relatively low compared to electric heaters and radiators.

In the transport sector (Figure 5-7), it is assumed that compared to private vehicles, freight and navigation have a less diverse portfolio of energy supply as they require energy-dense fuels such as oil, hydrogen and biofuels. The transition towards high renewable energy in the transport sector is achieved through electrifying the private cars and replacing fossil fuels with biofuels for freight transport and navigation. Increasing the VRE level (**RES100_HighVRE**) does not have much impact on the transport sector. However, limited biofuel supply (**RES100_HighVRE_NoBIOIMP scenario**) entails higher electrification of the transport sector and increases the share of electricity and hydrogen from power-to-gas to 80%.

The industry sector in Ireland is small and has a relatively simple representation in Irish TIMES model compared to other sectors. In high RE scenarios, biomass replaces gas in producing industrial heat. The sectoral emissions (Figure 5-8) shows that the industry sector is the major source of residual emissions in 100% RE scenarios. Comparison between **RES** scenarios and the **CO2-80** scenario shows that industrial CCS is required to reduce residual emissions from cement and lime production.

Figure 5-6 Final energy demand in building sector in 2050

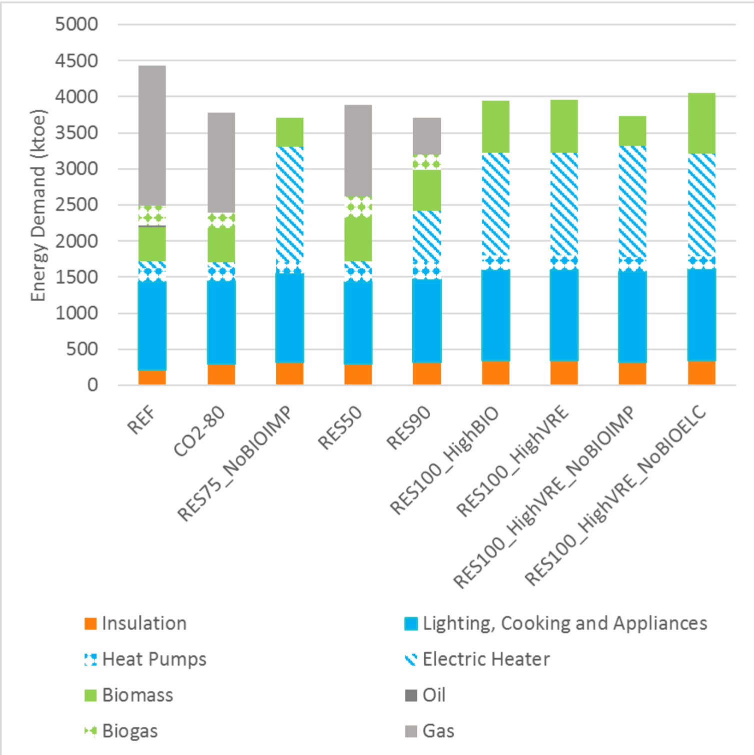


Figure 5-7 final energy demand in transport sector in 2050

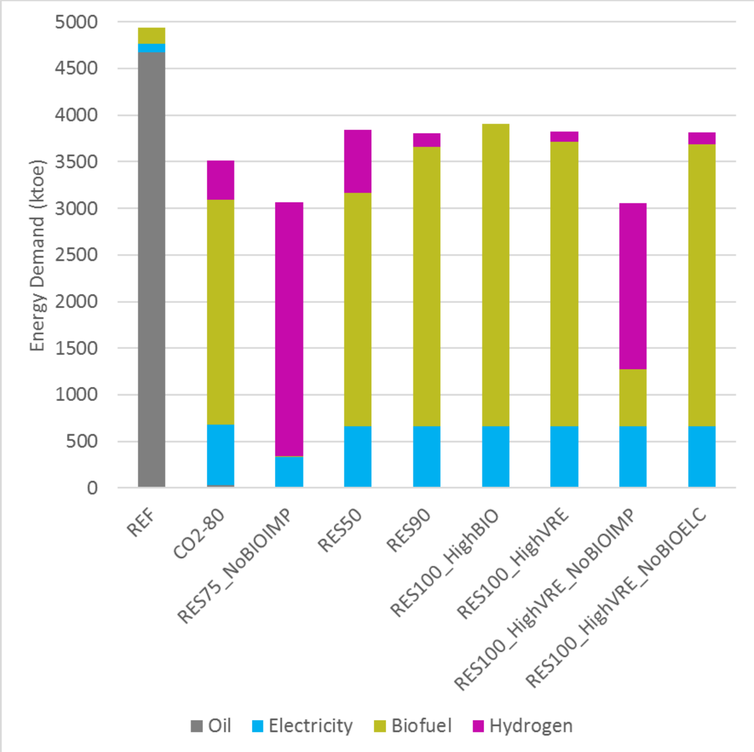
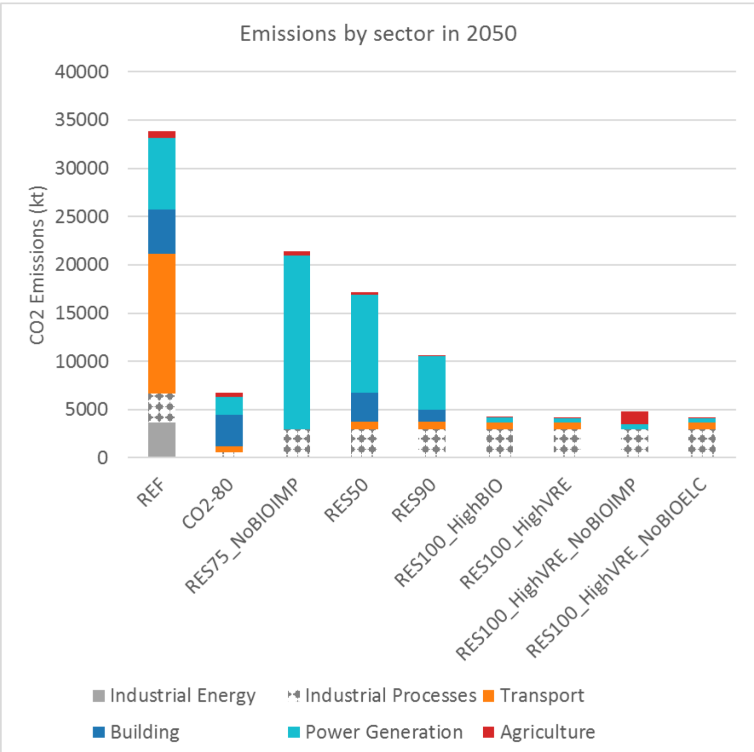


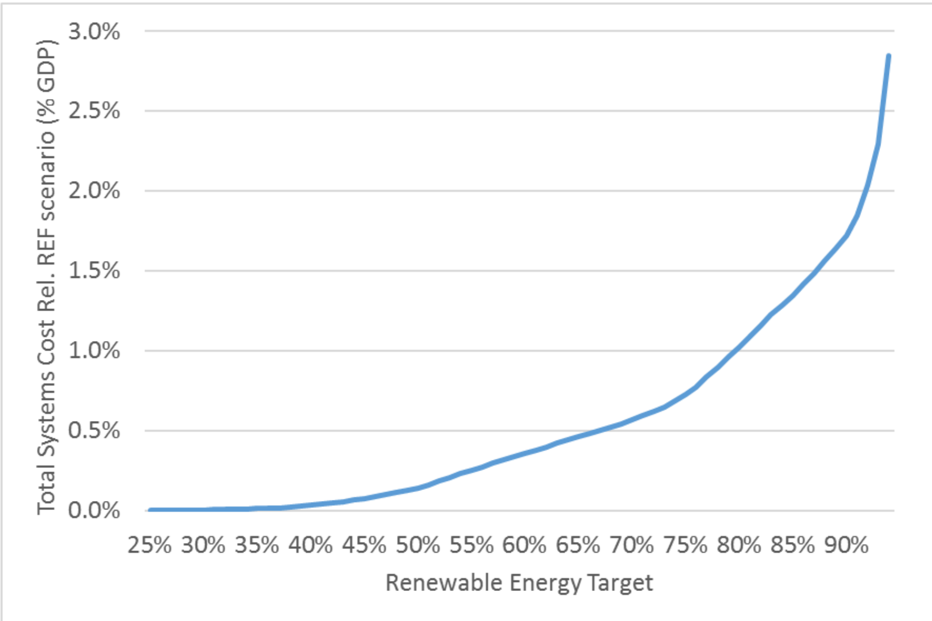
Figure 5-8 Emissions by sector in 2050



5.3.3 Economic Implications

The technical feasibility only indicates whether 100% RES can be achieved under different model assumptions. A better measurement of the difficulties in achieving 100% RES is the total system cost. As explained in Section 3.1, the principle of the TIMES model is to minimize the total discounted energy system cost over the entire time horizon. The total system cost includes energy import costs, capital investments and operation and maintenance costs. A higher total system cost implies additional efforts required to achieve more ambitious renewable energy targets. Figure 5-9 shows total systems cost in 2050 expressed in terms of percentage of projected GDP in 2050. The incremental effort in targeting for higher ambitious renewable penetration levels is non-linear. The increase in total system cost from 25% to 50% RES level is less than 0.3% of total GDP and reaching 90% RES level requires total system cost equivalent to 1.7% of total GDP in 2050.

Figure 5-9 Total system cost in 2050



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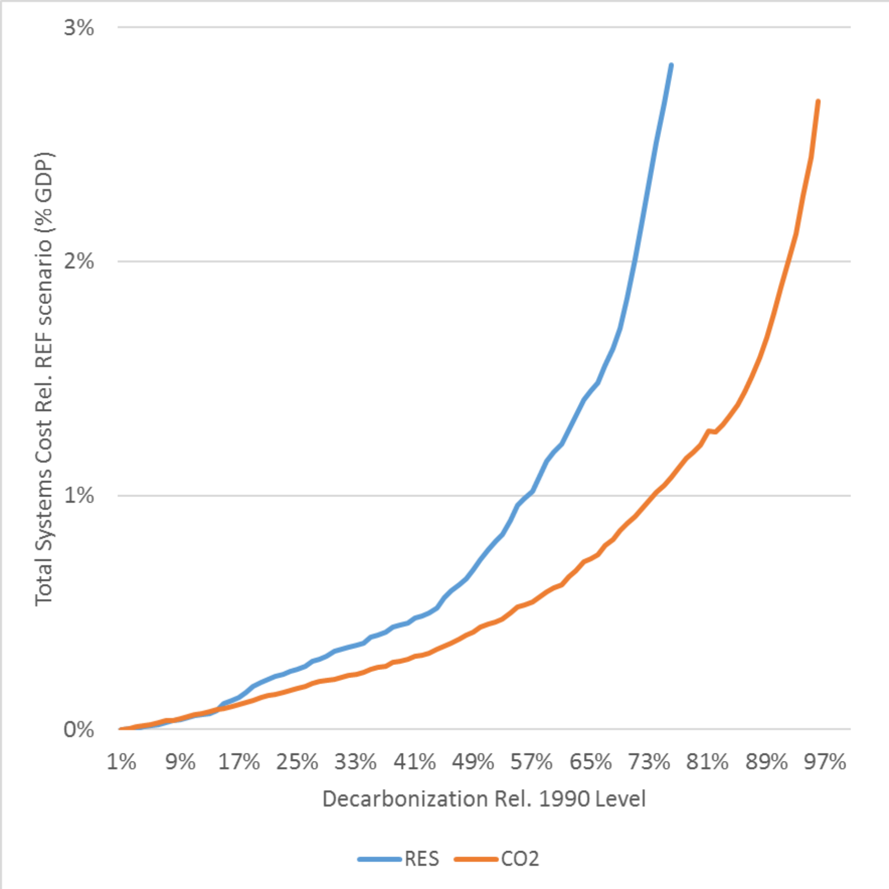
5.4 Renewable and decarbonization targets

Comparison between sensitivity scenarios on RE targets (**RES** scenarios) and corresponding carbon constraint (**RES_CO2**) scenarios reveal differences in energy pathways and decarbonization costs between the two policy targets. At less ambitious policy targets, decarbonization and renewable targets lead to very different energy pathways. For example, when focusing on CO_2 reduction, carbon intensive coal plants phase out rapidly at 20% reduction target. On the other hand, when focusing on RE penetration, coal plants remain under cost optimal pathways at 70% RE targets. At more ambitious policy targets, pathways towards renewable and decarbonization targets are broadly aligned as many of renewable technologies are carbon free. However, without deploying CCS technologies, emissions from industrial processes cannot be mitigated and only 88% carbon reduction can be reached when 100% renewable energy penetration is achieved.

The difference between renewable targets and decarbonization targets can also be reflected by energy system costs (Figure 5-10). In linear programming models like TIMES models, the marginal abatement costs in carbon reduction are determined by the shadow price of CO_2. Under RE scenarios, CO_2 emissions are model outputs rather than applied constraints, which makes the shadow prices under RE scenarios 0. Therefore, the model cannot directly compare the marginal abatement costs between RE scenarios and carbon constraint scenarios. Figure 5-10 compares the total system costs at each emission level between **RES** scenarios and **RES_CO2** scenarios. The RES scenarios have higher systems costs compared to **RES_CO2** scenarios, indicating that focusing on renewable energy targets is less cost effective in decarbonization. With an additional energy system cost equivalent to 1% GDP, emission reduces by 73% under CO_2 targets, but only reduces by 55% when focusing on RE targets. Similarly, the energy system cost of **CO2-80** scenario only reduces emissions by 60% when focusing on RE targets.

Figure 5-10 Total systems cost for sensitivity scenario in 2050



5.5 Global Sensitivity Analysis

Projections in techno-economic assumptions towards 2050 are inherently uncertain. It is critical to understand the economic and technological implications of uncertainties on the energy pathways. Global sensitivity analysis is applied to determine the correlations among model inputs and outputs and quantify the robustness of technology choices. In this analysis we focus on the uncertainties in key factors related to renewable energy, namely bioenergy, renewable generation technologies and power to gas.

Table 5-4 presents the standardized correlation coefficients between the input parameters and output parameters. The standard correlation coefficients are statistical measurements on the relationships between the input parameters and model outputs. A higher value indicates stronger impacts from input uncertainties on the model results. Parameters with p value greater than 0.05 are considered lack of statistical evidence in any relations between inputs and outputs. The correlation coefficients with high p values are left as blank in Table 5-4. A positive correlation coefficient indicates that increasing the input parameter is likely to cause increases on the corresponding output. Similarly, a negative value indicates that the increase in input value is likely to cause decreases on the output.

The correlation coefficients reveal the strong impacts of uncertainties in bioenergy imports on 100% RE pathways. Compared to other sources of uncertainties, uncertainties in bioenergy import price and availabilities have the strongest impacts on the total system costs and are also influential on the electrification levels and deployment of renewable generation technologies. On the other hand, uncertainties in investment costs of renewable generation technologies mainly affect the level of deployment of themselves and have relatively weak impacts on other model outputs. For example, an increase in offshore wind costs has strong negative impacts on the capacity of offshore wind and moderate impacts on the capacity of ocean energy and biomass power plants.

Figure 5-11 presents the pathways from 2015 to 2050 of key renewable options under uncertainties. The pathways demonstrate optimal investment timings as well as robustness against uncertainties. For example, pathways of hydrogen show that the penetration of hydrogen over time has a wide span and are therefore susceptible to uncertainties. The correlation coefficients in Table 5 show that the import price of biofuels has significant impacts on the penetration of hydrogen, and uncertainties in the investment cots of power-to-x and renewable energy technologies have much less influences. On the other hand, onshore wind has a much narrow span and reaches maximum resource potential by 2050 across all scenarios and can therefore be considered as “no-regret” options.

Table 5-4 Standard Correlation Coefficient of global sensitivity analysis

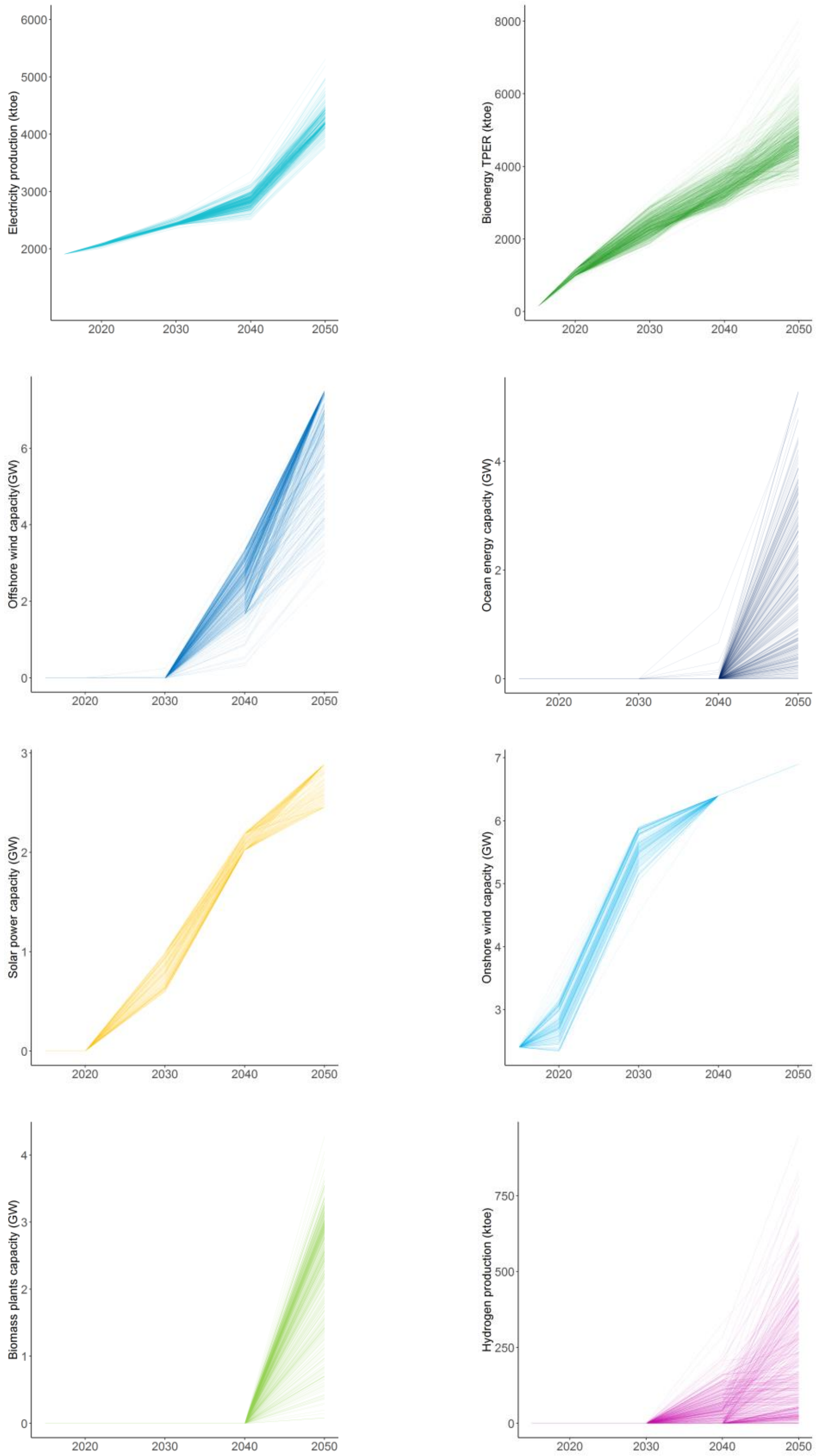
Outputs / Inputs	System Cost	Level of Electrification	Bioenergy Consumption
Bioenergy Import Availability	-0.33	-0.44	-0.15
Bioenergy Import Price	0.88	0.69	-0.66
Onshore Wind Cost	0.06		
Offshore Wind Cost	0.23		0.28
Electrolysis Cost	0.01	-0.06	
Wave Energy Cost	0.05	-0.20	0.38
Heat Pump Cost	0.03		
Commercial Solar Cost		-0.06	
Residential Solar Cost	0.06	0.25	0.19
Solar Power Plant Cost	0.03		

Outputs / Inputs	Offshore Wind	Solar Plant	Ocean Energy	Biomass Plants
Bioenergy Import Availability	-0.18	-0.17	-0.30	0.44
Bioenergy Import Price	0.27	0.25	0.37	-0.58
Onshore Wind Cost				
Offshore Wind Cost	-0.57		0.22	0.21
Electrolysis Cost				
Wave Energy Cost	0.36	0.25	-0.57	0.35
Heat Pump Cost				
Commercial Solar Cost				
Residential Solar Cost		-0.08		0.26
Solar Power Plant Cost		-0.51		

Outputs / Inputs	Electric Vehicles	Transport Biofuel	Transport Hydrogen
Bioenergy Import Availability	-0.30	0.31	
Bioenergy Import Price	0.60	-0.66	0.76
Onshore Wind Cost			
Offshore Wind Cost		-0.06	-0.07
Electrolysis Cost			-0.14
Wave Energy Cost			-0.18
Heat Pump Cost			
Commercial Solar Cost			
Residential Solar Cost			
Solar Power Plant Cost			

Outputs / Inputs	Heat Pumps	Biomass Heating	Solar heating
Bioenergy Import Availability	-0.37	0.44	
Bioenergy Import Price	0.38	-0.39	
Onshore Wind Cost			
Offshore Wind Cost			
Electrolysis Cost			
Wave Energy Cost			0.08
Heat Pump Cost	-0.10	0.15	
Commercial Solar Cost	-0.17	0.19	
Residential Solar Cost	-0.09		-0.83
Solar Power Plant Cost			

Figure 5-11 Pathways of renewable technology penetrations and fuel consumption under uncertainties



5.6 Discussions

The major advantage of TIMES model is the capabilities in optimizing the bioenergy consumption and electrification level while considering power generation, heat and transport sectors in an integrated manner. Bioenergy and renewable electricity are the primary energy supplies under 100% RES. Decision making should strike a balance between the use of bioenergy and electrification with considerations in feasibilities, uncertainties and technical challenges. The roles of bioenergy and electrification under 100% RES can be demonstrated by comparing advantages and challenges between pathways dependent on bioenergy (**RES100_HighBIO** scenario) and pathways with bioenergy import disabled and dependent on electrification (**RES100_HighVRE_NoBIOIMP** scenario).

The bioenergy and electrification pathways are similar in terms of economic feasibility. The 2050 total system costs of both pathways are 29% higher relative to the REF scenario and the difference in total system cost between these pathways is less than 1%. However, the cost composition of the system costs in these scenarios differ significantly. Bioenergy pathways rely heavily on the bioenergy import. Ireland's import dependency remained around 85% to 90% until 2016 when it fell to 69% in 2016 and 66% in 2017 due to the new gas field and increases in wind energy. The total import cost in 2017 was €4 billion accounting for 1.2% total GDP. The import dependency in the **RES100_HighBIO** scenario is 58% by 2050. The import cost rises to €9.9 billion import cost accounting for 26.3% of the system cost. This amount is higher than the fossil fuel import cost of €9.3 billion in 2050 projected by the REF scenario.

High dependency on bioenergy import poses significant challenges in energy security. A review study by (Slade et al., 2014) suggests that under different technical and sustainability assumptions the estimate in global bioenergy supply ranges widely from 100EJ per year to over 1200EJ per year(Slade et al., 2014)(Slade et al., 2014) and estimate of over 600EJ is based on extreme assumptions and should not be considered as socially acceptable or environmentally responsible. The current world population share of Ireland is 0.06% and the share of primary energy demand is about 0.1% (Birol, 2017). If the share of global bioenergy supply for Ireland (12700ktoe) remains at a similar level to its current share of primary energy demand, the world bioenergy supply should exceed 530EJ, which is roughly similar to the current global primary energy supply (550EJ). As shown in Section 3.3, the global sensitivity analysis indicates that the uncertainties in bioenergy import has strongest impacts on the energy pathways. Therefore, locking into a bioenergy dependent pathway is susceptible to uncertainties and poses risks for energy security.

When the bioenergy import is disabled, the 100% RE pathways rely on renewable electricity and electro-fuels such as power-to-x. Under the **RES100_HighVRE_NoBioIMP** scenario, all energy supply is from indigenous sources including indigenous bioenergy production and renewable electricity. By 2050, electricity accounts for 64.1% of final energy demand and VRE reaches 97.9%. Even though this electrification pathway is robust in terms of energy import dependency, the high installation rate in power generation poses challenges in investment, acquiring materials and labour. By 2050 the annual investment cost requirements in new generation is €8.4 billion, which is significantly higher than the €1.3 billion under the REF scenario and €3.4 billion under the **RES100_HighBIO** scenario**.** The capacity of renewable generation is projected to 30.8GW under the **RES100_HighVRE_NoBIOIMP** scenario implying annual average installation rate over 800MW in onshore and offshore wind, solar and ocean energy, which is more than 50% higher compared to the installation rate of 532MW in wind energy as of 2017.

Another key challenge of the electrification pathway is the integration of 100% intermittent generation in power sector. From the literature review we find that the technical feasibility of power systems with 100% renewable electricity remains controversial. As discussed in Section 1.2, many studies indicate that 100% renewable energy systems are feasible at reasonable costs while other studies conclude differently. This analysis is not intended to address the feasibilities and costs associated with integrating 100% VRE into the power system. An EU project in exploring solutions and costs for high VRE power system are currently underway (Hillberg et al., 2019). On the other hand, as a relatively small isolated Ireland country, integrating high VRE into the power system could be particularly challenging for Ireland due to lack of interconnection (Collins et al., 2017). One way to address high VRE is through improving system flexibility with demand side management (DSM) techniques. The modelling results point to significant potentials of DSM. Under the **RES100_HighVRE_NoBIOIMP**, electricity consumption from electric vehicles and power to gas account for over 40% share of total electricity consumption under.

It should be noted that the cost estimate related to energy storage within the current modelling frame is underestimated. Long term energy systems models are best suited in projecting long term optimal pathways and may not properly validate feasibility of power system under 100% VRE or determine the associated costs. In the Irish TIMES model, each milestone year contains 12 time slices (seasonal, day, nights and peak for four seasons). Using a small number of time slices cannot properly capture variation in intermittent generation and may result in underestimate in the capacity of hydrogen storage required (Alessandra Sgobbi et al., 2016) (Krakowski et al., 2016). Our model results show that energy storage mainly capture day/night variabilities in power generation and does not sufficiently account for variation in wind energy. To address this underestimate in storage capacity and usage, in this analysis we leave some reserve for energy storage by crudely increasing the assumption in capital cost of power to gas by 20%. Future work on Irish TIMES model will focus on more accurate estimates in the costs associated with higher temporal resolution and dispatching features. The results from this analysis can be soft linked to power systems model (Deane et al., 2012) with higher temporal resolution to determine more accurate requirements in energy storage, as well as interconnection and associated costs for 100% VRE power system.

Another important area related to 100% RE that requires further research is the estimates in renewable source potential, which vary significantly within the current literatures. For example, Estimates from SEAI (SEAI, 2011) projects onshore wind potential between 11GW – 16GW and 30GW of offshore wind by 2050, which is more than twice as much as our assumptions (6.9GW on onshore wind and

7.5GW offshore wind). In our model the constraints applied on renewable resource potentials are based on relatively conservative assumptions. Compared to analysis assuming wind and solar power can provide all renewable electricity (Jacobson et al., 2017), the generation portfolio from our modelling results is more diversified with combinations of wind, solar, offshore wind, wave and tidal energy, which is also more energy secure compared to 100% WWS power system as ocean energy is more predictable than wind and solar. This diversified generation portfolio requires much higher investment cost as the costs for wave, tidal and offshore wind are significantly higher, which could somehow account for the underestimate in the cost for integrating high VRES into the power system.

5.7 Conclusions

The use of renewable energy is a critical decarbonization option with co-benefits in environment, economics and energy security. In this analysis, we carry out the first assessment of 100% renewable energy system in 2050 for Ireland using the Irish TIMES energy system optimization model. Scenario ensembles under a broad scope of assumptions are used to explore technical and economic feasibilities towards 100% RES while assessing the roles of electrification, bioenergy and key renewable technology options.

The results show that under current technology assumptions and resource potentials with an annual limit of 50% on VRE generation, a maximum of 94% renewable can be reached, where electricity accounts for one third of energy consumption with over 85% from renewables. Without bioenergy import, maximum feasible renewable reduces to 75%. 100% RE can be reached with more ambitious bioenergy supply or integrating higher shares of variable renewable energy. Scenarios with 100%RE requires additional system cost equivalent to more than 2% GDP relative to the REF scenario. Incremental cost in targeting for higher ambitious renewable penetration levels is non-linear. Extra system cost from 25% to 50% RE level is less than 0.3% of total GDP and reaching 90% RES requires 1.3% of total GDP.

Focusing on RE targets is more costly in achieving carbon mitigation compared to CO_2 targets. The energy system cost required for 80% CO_2 reduction targets will only deliver a 60% reduction in CO2 emissions when achieved using RE targets.

Bioenergy plays a critical role under cost-optimal 100% renewable pathways. Indigenous bioenergy consumption is close to maximally resource potentials across all 100% renewable pathways, indicating that efforts in maximizing indigenous bioenergy resources should be made. Pathways relying on high bioenergy import are more cost effective and requires less upfront investments and infrastructural transformation. However, under these pathways up to 58% of TPER will come from imported biofuel with only 25% to 31% come from indigenous production. Global sensitivity analysis demonstrates that bioenergy dependent pathways could be more susceptible to uncertainties as uncertainties in bioenergy import have much greater impacts compared to uncertainties in investment costs.

When bioenergy import is disabled, the optimal pathways depend more heavily on renewable electricity from indigenous biomass and 100% renewable electricity from wind, solar, ocean and offshore wind. The overall electrification level increases from 39% to 61% while bioenergy consumption reduces from 81% to 32%. These pathways require integrating high shares of VRE combined with high penetration of power-to-gas technologies, which may confront challenges in high upfront investment cots and integration of intermittent generation. Given that the current electrification level is less than 20%, much stronger efforts and faster progress is required than the current renewable energy plan (DCCAE, 2017). The current fast development on wind energy should continue with an aim for at least 40% overall electrification level. If higher share of electrification levels and lower bioenergy import dependency are desired, the development in renewable electricity should speed up, with additional efforts made on electrifying heat and transport sectors through heat pumps, EVs and power to gas.

6 Conclusion

The aim of this thesis is to incorporate quantitative scenarios into energy system modelling and provide robust, well-rounded policy insights for 1.5°C target set by the Paris Agreement with the development of an innovative modelling tool. The VEDA-SET modelling systems have been developed on top of the modelling system of TIMES model to facilitate scenario generation and analysis. Ensembles of scenarios capture a wide range of assumptions in decarbonization ambitions and techno-economic parameters are used to provide insights that may not be easily captured by simple scenario analysis.

Chapter 2 carried out a comprehensive literature search that screens over 2000 scientific journal papers. It was found that vast majority of ESOM studies rely on a few deterministic scenarios to address climate and energy policy. Limited number of deterministic scenarios provide limited insights and can be misleading. Addressing uncertainties in a systematic manner using formal approaches such as linear programming, robust optimization, modelling to generate alternatives and global sensitivity analysis can improve robustness of model results and improve model transparency.

Chapter 3 explored deep decarbonization feasibilities and pathways towards 1.5°C target set by the Paris Agreement. The analysis carried out a high-granularity sensitivity analysis on the carbon budget to determine how much can Ireland reduce its cumulative carbon emissions towards the well below 2°C target. The results showed that given the current technological and economic assumptions, 1.5°C compatible targets are extremely challenging. Without overshoot and return, an ambitious decarbonisation rate of 10% per year can only lead to a carbon budget level midway between 1.5°C and 2°C targets. Achieving negative emissions and relying on BECCS for overshoot and return is extremely costly. Compared to 80% reduction target by 2050, deep decarbonization pathways towards carbon neutrality by 2050 is similar during the later period of the time horizon quality but requires much stronger mitigation efforts between 2020 to 2030 than suggested by current NDC. It is critical to take climate actions as early as possible to avoid consequences from carbon lock-in.

In Chapter 4 mitigation measures were evaluated using marginal abatement cost curves with an innovative analytical approach. With decomposition analysis, the marginal abatement costs are associated with CO_2 reductions contributed from each mitigation option. Mitigation measures were ranked based on cost effectiveness in decarbonization and categorized into low hanging fruit, resilient technologies, tipping point technologies and niche technologies. The innovative combination of energy systems modelling and marginal abatement cost curves strengthens both energy policy tools. From the perspective of MACCs, compared to existing financial-accounting MACCs for Ireland, MACCs derived from energy systems model captures intertemporal dynamics and interactions among technologies across different sectors. From the perspectives of energy systems modelling, evaluating ensembles of scenarios composing the MACCs helps gain more robust insights that cannot be captured by simple scenario analysis.

Chapter 5 explored the feasibilities and optimal pathways towards a high renewable energy future with a focus on addressing uncertainties. Scenario ensembles with different underlying assumptions showed that 100% RES can be reached with multiple pathways, ranging from pathways dependent on bioenergy that accounts for 80% of TPER, to those more reliant on renewable electricity with 60% overall electrification level. Bioenergy-dependent pathways rely on high import dependency while the electrification pathways face challenges in high capital investments and incorporation of 100% intermittency in the power system. Comparison between renewable energy targets and decarbonization targets showed that focusing on renewables is significantly less cost effective in carbon mitigation. A global sensitivity analysis with 500 scenarios were carried out to quantify input-output relationships and robustness of renewable technologies. It was found that the uncertainties in bioenergy imports and import availabilities have much stronger impacts on the mitigation pathways and total system costs compared to techno-economic assumptions in low carbon technologies.

6.1 Dissemination

The results from the analysis has been disseminated through peer reviewed publications and conferences such as International Energy Workshop and Integrated Assessment Modeling Consortium. The innovation of VEDA-SET was presented in the ETSAP workshop (Yue, 2016) and initiated the development of Monte Carlo analysis capacity in VEDA-TIMES modelling tool. The assessment in carbon budget scenarios (Yue et al., 2018b) was published in the ETSAP book "Limiting Global Warming to Well Below 2 °C: Energy System Modelling and Policy Development" (Giannakidis et al., 2018), which was referenced in the IPCC special report on global warming of 1.5°C (Rogelj et al., 2018), providing evidence base for national mitigation pathways towards well below 2°C target. Part of the modelling results was also published on the online visualization platform "Our 2050 – Opportunities for Ireland in a Low Carbon Economy" (Yue and Rogan, 2018).

6.2 Policy Insights

The key take-away from the thesis is that using scenario ensembles provide much more robust policy insights for energy systems modelling and the methodology should be applied for future regional or global analysis on deep decarbonization pathways. From the perspective of policy insights, the thesis shows that targeting a 1.5°C-consistent pathway is extremely challenging and points to the importance of early actions, necessity in fully deploy indigenous bioenergy, as well as faster development in renewable electricity than current pace. A list of key policy insights and recommendations are summarized as follows:

- Deep decarbonization pathways towards 1.5°C target are qualitatively similar to 2°C-consistent pathways but require carbon neutrality by 2050 and (compared to the current NDC) much stronger mitigation efforts between 2020 and 2030, which would require accepting the economic losses from stranded assets such as coal and gas power plants.
- Specific long-term mitigation targets should be decided with actions carried out as early as possible to avoid locking in a carbon intensive pathway and the consequences of delayed actions.
- The increase in carbon costs with higher reduction targets is nonlinear. Exhaustion of cheaper mitigation options lead to dramatic increases in carbon costs and tipping points in the marginal abatement cost curves.

- Based on the marginal abatement costs and decomposition analysis, the mitigation measures can be classified based on economic merits into low hanging fruit (energy efficiency, wind energy), resilient technologies (EVs, biofuel vehicles, gas CCS), tipping point technologies (biomass plants, offshore wind), and niche technologies (ocean energy).
- Biomass and biofuels can be used as the primary energy source for a decarbonized economy. However, besides concerns about sustainability and competition with food production, a bioenergy dependent mitigation pathway is susceptible to uncertainties in availabilities and the costs of bioenergy imports.
- Pathways with a high level of electrification have better energy security and are more robust against uncertainties. Electrification-dependent pathways have a 60% level of electrification combined with power-to-gas and energy storage. The major challenge is to incorporate high variable renewable generation.
- Given that the current electrification level is less than 20%, besides focusing on the development on wind energy, additional efforts should be put on electrification of heat and transport through heat pumps, EVs and power to gas.

6.3 Modelling Insights

From the perspective of energy modelling, this thesis demonstrated that energy models should capture a wider range of solution space through scenario ensembles to provide more robust and well-rounded insights. The literature review found that majority of existing ESOM models apply scenario analysis to project transition pathways; however, using scenario analysis with single-digit number of scenarios to project energy pathways limit the solution space, fail to provide robust policy insights, and could even be misleading by causing stakeholders underestimate the range of possibilities. Scenario ensembles with hundreds of scenarios were applied in the thesis to provide policy insights that may not be easily captured by simple scenario analysis, including exploring technically and economically feasible decarbonization targets, quantifying cost effectiveness of critical mitigation technologies, and identifying tipping points where significant changes in energy pathways and extra systems costs are required for additional carbon reduction.

The use of scenario ensembles also contributes towards improving model transparency, which is widely recognized as a critical criterion for responsible use of modelling to support decision-making. ESOM models have complex model structures and large technology data set and requires deep modelling knowledge for understanding the model assumptions. Local sensitivity analysis can help stakeholders better understand the response of the model outputs towards incremental changes in input assumptions. Monte Carlo analysis combined with statistical approaches can be used to characterize relationships between inputs and outputs by quantifying impacts from input uncertainties on energy pathways. Modelling results from large number of scenarios may baffle scenario users and therefore need to be appropriately analyzed, visualized and communicated. This thesis presented innovative methods through analyzing MACCs and energy system trends over different reduction targets to demonstrate interactions across different sectors and competition among technologies in pushing for increasingly more ambitious decarbonization targets.

6.4 Future Work

The modelling tools and methodologies developed in this thesis could be applied to other regions with broader geographical coverage, such as applying global sensitivity analysis to EU and global TIMES model to address uncertainties. The research presented in this thesis also suggests a number of areas for future research:

Discover scenarios with systematic and innovative approaches

In this thesis, scenario ensembles were developed based on the policy questions need to be addressed and the modeler’s judgement. For example, in Chapter 3 a spread of scenarios with different carbon constraints were developed to explore deep decarbonization scenarios in line with the 1.5 °C target set by the Paris Agreement. In Chapter 4 alternative scenarios were developed to explore the impacts of availabilities of bioenergy and CCS technologies due to their high penetration.

While a broad range of possible pathways were captured through hundreds of scenarios, it is impractical to develop scenarios that exhaustively capture all possibilities. Future work should apply innovative methodologies to discover and develop scenarios. One method is the story-and-simulation approach, which is to conduct expert elicitations with stakeholders to create storylines of future developments with considerations in the aggressiveness of emissions reductions, preferences on overall emission reduction targets, and reliance on bioenergy and controversial technologies such as CCS and DAC. The TIMES model can then be applied to translate the qualitative storylines of interest into transition pathways. While developing scenarios and communicating policy insights with decision makers is important, co-designing scenarios with non-experts such as companies and financial institutions with emerging interests in mitigation scenarios can also help improve modelling assumptions and connect model outputs with users in economy. Different methods in presenting and communicating model results and insights can be explored, such as presenting results on interactive data platforms.

Elaborate and explore uncertainties analysis approaches

This thesis applied scenario ensembles to address parametric uncertainties and overcome shortcomings of simple scenario analysis. In Chapter 5, global sensitivity analysis was carried out to address uncertainties for a high renewable energy system by simultaneously perturbing multiple uncertain parameters related to renewable technologies, such as bioenergy costs and capital costs of renewable generation technologies. However, energy systems analysis requires decision making under deep uncertainties. It is impossible to get accurate or widely acceptable probability distributions of uncertain parameters. While probability distributions can be elaborated through expert elicitations, projection into the future decades from now is inherently uncertain. Future analysis should aim at minimizing the impacts from inaccurate representation of uncertain sources. Possible approaches include the robust optimization method discussed in Chapter 2 or carrying out global sensitivity analysis runs with different probability distributions to explore their impacts on model results.

The main focus of the thesis is on parametric uncertainties. Besides elaborating existing uncertainty analysis approach, future analysis should explore innovative methodological approaches and address uncertainties from different perspectives and multiple sources, most notably the epistemological uncertainties. For example, stochastic programming is a hedge-based approach and can be used to project a pathway that strikes a balance among uncertainties. Modelling to generate alternative approach can be applied to explore near optimal solution space under structural uncertainties. Uncertainty analysis approaches applied to ESOM models are limited due to the complexity of the models.

This thesis developed the scenario ensemble tool VEDA-SET to facilitate scenario generation for carrying out global sensitivity analysis. Future work should explore feasibilities of applying innovative uncertainty analysis approaches for the TIMES model and incorporating the approach into the modelling interface to encourage modelers to address uncertainties in their analysis.

Improve spatial and temporal resolution

Temporal resolution of ESOM models is generally coarse due to complexity and length of time horizon. The Irish TIMES model includes 12 time slices that capture daily and seasonal variations in energy supply and demand. Modelling results in Chapter 5 indicate that this level of temporal resolution is not sufficient for capturing implications for high variable renewable generation and underestimate the additional systems costs for a high VRES power system and the amount of energy storage required.

The modelling results indicate potential future improvements on the Irish TIMES model in terms of spatial and temporal granularity. Irish TIMES model is relatively smaller and less computationally intensive compared to global models and is a good starting point for exploring the feasibility of integrating of high temporal resolution in ESOM models. The current model is a single region model, which could be further disaggregated into multiple regions to better represent energy infrastructure and provide insights for regional decision making. With innovation and new techniques in data science, the data available to energy models has become more abundant. Big data and geographic information systems (GIS) can be applied to the model to improve quality of data in areas such as travel patterns, renewable energy resource potentials and improved representation of population and energy consumption.

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