THE EFFECTS OF UNCERTAINTY IN THE TECHNOLOGICAL TRANSITIONS OF THE POWER SECTOR

ENDOGENOUS EMISSION SCENARIOS UP TO 2050

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text. Material included in this thesis has also been published within the following journals:

- Mercure, J.-F. and **Salas, P.**, 2012. An assessment of global energy resource economic potentials. *Energy*, 46, 322-335.
- Mercure, J.-F. and **Salas, P.**, 2013. On the global economic potentials and marginal costs of non-renewable resources and the price of energy commodities. *Energy Policy*, 63, 469-483.
- Mercure, J.-F., Pollitt, H., Chewpreecha, U., **Salas, P.**, Foley, A.M., Holden, P.B., Edwards, N.R., 2014. The dynamics of technology diffusion and the impacts of climate policy instruments in the decarbonisation of the global electricity sector. *Energy Policy*, 73, 686-700.

This dissertation does not exceed the regulation length, including footnotes, references and appendices.

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Abstract

By August 2016, 180 countries have signed the Paris Agreement and committed to holding the increase in the global average temperature to well below 2°C above pre-industrial levels. Abiding by the agreement will require a substantial reduction of emissions over the next few decades and near zero emissions of CO_2 and other long-lived greenhouse gases by the end of this century. In this context, the decarbonisation of the global power sector is of strategic importance, because low-carbon electricity has system-wide benefits that go beyond the electricity sector, enabling significant reductions of CO_2 emissions in the industry, transport and buildings sectors. To make the necessary changes depends partly on improving the analysis and estimates of the economics of climate change, and for that there is an urgent need for a new generation of models that give a more accurate picture of the potential decarbonisation pathways.

The technological transition towards a low carbon power sector depends on many uncertain factors, such as policy efficiency, renewable energy investment and availability of energy resources. The knowledge about how these uncertain factors interact, and the impacts on the technological evolution of the energy sector, are the key to creating successful policies for driving the economy towards a cleaner, low carbon society. In this context, the work presented here provides decarbonisation scenarios of the global power sector, under uncertain drivers of technological change, and in doing so, enables a better understanding of technology diffusion process in the power sector. The scenarios are created using the FTT:Power model, a representation of global power systems based on market competition, induced technological change and natural resource use and depletion. The scenarios analysed in this dissertation are focused on four drivers of technological change: energy policy, energy resource availability, learning and investment. The influence of uncertainty on each of these drivers is analysed in detail, through endogenous emission scenarios of the global power sector between 2016 and 2050. Emission pathways with uncertainty ranges, as well as policy recommendations, are presented as a result of the modelling exercise.

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Chapter 1

Introduction

1.1 Motivation

In line with the confirmed and growing human influence on the climate system (IPCC, 2014c, p. 2), 180 countries[1] have signed the Paris Agreement (UNFCCC, 2016). In doing so, they have committed to "*holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels*" (UN, 2015b, Article 2a). Abiding by the agreement will require substantial reduction of emissions over the next few decades and near zero emissions of CO_2 and other long-lived greenhouse gases by the end of this century (IPCC, 2014c, p. 20). In this context, the decarbonisation of the global power sector is of strategic importance, because low-carbon electricity has system-wide benefits that go beyond the electricity sector, enabling significant reductions of CO_2 emissions in the industry, transport and buildings sectors (IEA and OECD, 2012a, p. 10). Despite the intentions behind the Paris Agreement, however, the transition towards a low carbon economy has not yet reached a pace that will lead to the 2°C target (IEA and OECD, 2015, p. 27), let alone the 1.5°C target (Hulme, 2016).

At present, 76% of the electricity generated globally comes from fossil fuels (IEA and OECD, 2015, 584). Consequently, a radical decarbonisation represents an unprecedented policy challenge (Strachan and Usher, 2011). Present systems depending on fossil fuels display strong inertia, and tend to perpetuate the established interests (Grubb, 2014, p. 312). The path dependency generated by these kinds of systems, increases the cost of radical change

[1] Between April and August of 2016.

(Zenghelis, 2015). Therefore, to break the inertia and achieve the kind of transformation needed, stringent policies are required (Campiglio, 2016). The political will to make the necessary changes depends partly on improving the analysis and estimates of the economics of climate change, and for that there is an urgent need for a new generation of models that give a more accurate picture of the potential decarbonisation pathways (Stern, 2016).

1.2 Research questions and methodology

This research responds to the invitation made by Sir Nicholas Stern (2016), to help policy-makers by better modelling the potential for action against climate change. In order to do this, the work presented here provides decarbonisation scenarios of the global power sector, under uncertain drivers of technological change, and in doing so, enables a better understanding of the process of technology diffusion in the power sector. The scenarios are created using the **Model of Future Technology Transformation of the Power Sector** (**FTT:Power**), a representation of global power systems based on market competition, induced technological change and natural resource use and depletion (Mercure, 2012).

The decarbonisation of the power sector requires stringent energy policies to facilitate the adoption of low carbon technologies, and stimulate private-sector investment (IEA and OECD, 2012a, p. 115). However, technology diffusion and technological change are processes characterised by a high degree of uncertainty (Rogers, 1962; Rosenberg, 1998), and the evidence suggests that uncertainty deters private-sector investment (Kellogg, 2014). In terms of natural energy resources, there appears to be general consensus that the occurrence of fossil fuels and the annual renewable energy flows available far exceed global energy needs (GEA, 2012, p. 431). However, there is uncertainty regarding their actual future availability in the market place (especially for fossil fuels), and the availability of affordable technologies to manage the often low or varying energy densities and supply intermittencies associated with renewable flows (ibid.). In this context, the scenarios analysed in this dissertation are focused on four uncertain drivers of technological change:

- Energy policy
- Energy resource availability
- Learning and technological change
- Investment

The influence of uncertainty on each of these drivers is analysed in detail, through endogenous emission scenarios of the global power sector between 2016 and 2050.[2] Uncertain emission pathways and policy recommendations are presented as a result of the modelling exercise. This dissertation focuses on two types of uncertainty analysis:

Uncertainty propagation analysis using simulation based methods :[3] Using uncertainty ranges for energy policy stringency, availability of energy resources and learning coefficients, extreme decarbonisation scenarios of the power sector are analysed in this dissertation. The variation in the drivers of technological change, and the corresponding effect on energy investment and decarbonisation are studied in detail in chapters 5, 7, 8 and 9.

Decision making under uncertainty : chapter 10 introduces a new methodology to model investment decisions in FTT:Power, and chapter 11 uses the new methodology to study the effect of environmental and policy uncertainty on investment decisions. The corresponding impact on low carbon technology adoption and decarbonisation, are analysed in detail in chapter 11, and contrasted with the other uncertainty analyses in chapter 12.

The research questions and methodologies associated with each of the aforementioned drivers of technological change are presented below.

1.2.1 Energy policy

Energy policy plays an important role in steering innovation trends in clean energy, helping to accelerate commercialisation of low carbon technologies and stimulating private-sector investment (IEA and OECD, 2012a, p. 115). While traditional modelling approaches usually suggest carbon pricing as the foremost solution to spur low-carbon investment, the evidence suggest that carbon pricing represents a necessary, but not a sufficient condition for steering the economy towards a low-carbon regime (Campiglio, 2016). IEA analysis has consistently found that there are benefits when carbon pricing is accompanied by complementary policies,

[2] FTT:Power scenarios include historical data dating from 1991 until 2007, while the simulations run from 2008 until 2050. The scenarios presented in this dissertation are mostly focused in the period 2016-2050.

[3] Uncertainty propagation analysis using simulation based methods is typically based on Monte Carlo simulations (Lee and Chen, 2008). For the sake of simplicity, the analyses presented in chapters 5, 7, 8 and 9 use the extreme of the intervals of each uncertainty range, instead of using a representative sample from it. In the case of the scenario presented in section 8.4, 120 samples are taken from the uncertainty interval of the hydroelectric cost supply curve of Brazil, using the Latin Hypercube Sampling method (Helton and Davis, 2003).

and that combinations of policies improve cost-effectiveness (IEA and OECD, 2012a, p. 119-121). Moreover, the success of policy instruments such as feed-in-tariffs, which are the most popular form of renewable energy regulatory support policy worldwide (REN21, 2015, p. 88), makes a strong case for using a portfolio, instead of a single decarbonisation policy instrument. This dissertation analyses policy scenarios for different regions of the world, using four types of energy policy instruments: **carbon pricing**, **subsidies**, **feed-in-tariffs** and **direct regulation** (in the form of limitation of new electricity generation capacity for specific technologies and regions). By varying the combination of these policy instruments, with scenarios of energy demand, several decarbonisation scenarios are created. Policy sets are compared in terms of their abatement and cost, and policy efficiency implications are discussed. The research questions addressed with the analysis of these policy instruments include:

- What is the decarbonisation potential of each policy instrument, and how does it change when policies are combined?
- Are the incentives provided by market-based policy mechanisms sufficient to decarbonise the power sector?
- How are emission trajectories affected by the uncertainty in the stringency of each policy mechanism?

1.2.2 Energy resources

Natural energy resources are the first step in the chain that supplies energy services, therefore, the assessments of their potential availability is essential for planning and policy making (GEA, 2012, p. 430). To study the potential limits imposed by the physical world to the technology transition scenarios analysed in this dissertation, a database of primary energy resource potentials and a model of energy use and depletion have been built. The different energy resources are represented by cost supply curves, which describe the energy cost evolution as a function of energy use. Due to the large uncertainty surrounding the technical availability of energy resources and their cost, the mathematical formulation of the cost supply curves includes uncertainty intervals and probability density functions. The model of energy use and depletion, and its use in the formulation of the energy scenarios intends to answer questions such as:

- How does the availability of energy resources affect the performance of energy policy for decarbonisation?

- How does policy efficiency change under different sets of decarbonisation policies and scenarios of energy resource availability?
- How are emission trajectories affected by the uncertainty regarding energy resource availability and cost?

1.2.3 Learning

Given the vast amount of evidence that shows the importance of learning as a driver of economic growth and technological transitions (Audretsch, 1995; Grossman and Helpman, 1994; IEA, 2000; Kahouli-Brahmi, 2009; Kohler et al., 2006), this work incorporates an uncertainty analysis on learning rates. Based on an extensive literature review, learning rate intervals are estimated for each of the 24 FTT:Power electricity generation technologies. Emission trajectories for decarbonisation scenarios of the power sector are presented, using extreme learning rates, and different configurations of the system, regarding the capability of the grid to incorporate renewable energies. Some of the research questions addressed by this analysis include:

- How is the decarbonisation of the power sector affected by uncertainty on learning rates of renewable technologies and fossil fuels?
- How does the flexibility of the grid, regarding its capability of managing variable electricity generation from renewable energies, affect the performance of decarbonisation policies?

1.2.4 Investment

Investment drives the adoption of technology in a large scale. Therefore, to analyse the effect of uncertainty on the technological evolution of the power sector, is essential to understand how energy investment is affected by key uncertain drivers, such as policy uncertainty and environmental uncertainty. This dissertation proposes a methodology to model investment decisions, based on an innovative combination of a probabilistic model to represent preferences, and a flexible multicriteria decision-making approach. The new methodology includes a novel mathematical formulation based on two pillars: Discrete Choice Theory (DCT) and Analytic Hierarchy Process (AHP). The former captures the diversity of investors' preferences in the energy sector, using logit distributions to characterise investment choices (Ben-Akiva and Lerman, 1985; McFadden, 1973; Mercure, 2015). The latter is a flexible decision-making approach, that allows the use of conflicting and subjective criteria in investment decisions (Saaty, 1987, 2000, 2008). A new theoretical framework that combines the two mathematical theories underpinning DCT and AHP is provided in this dissertation. As a practical example of how this theory can be used to model investment decisions under uncertainty, two criteria (environmental considerations and policy uncertainty) are incorporated into the investment decision model of FTT:Power. Some of the research questions addressed with the new investment model include:

- How can quantitative and qualitative criteria be incorporated in an investment-decision model, to mimic the actual decisions-making process made by energy investors?
- How does energy investment in the power sector change, when market-based considerations are weighed against environmental considerations? What are the implications in terms of policy efficiency and decarbonisation?
- What is the effect of policy uncertainty and environmental uncertainty in power sector investment decisions?

1.3 Contribution

This dissertation provides significant theoretical and practical contributions to the literature. From a theoretical perspective, the central contributions of this dissertation are the **new approaches for modelling natural resources and investment decisions under uncertainty**. From a practical perspective, these new approaches are combined in an existing dynamic model of technology diffusion (FTT:Power), to facilitate the study of decarbonisation scenarios of the power sector. The effects of uncertainty on several drivers of technological change are analysed in this thesis, using these new approaches: on energy policy, natural resources availability, learning and investment. The specific theoretical and practical contributions of this dissertation on each of these topics are discussed below.

1.3.1 Theoretical contributions

- **A mathematical representation of energy resources, using functional forms for distributions based on statistical trends** (chapter 6). This representation of energy resources based on functional forms is a valuable contribution to the literature, because it facilitates several aspects of the modelling exercise, it allows an efficient representation of uncertainty, and simplifies the creation of large number of scenarios using a small amount of computational resources.

- **A new mathematical model for natural resources use and depletion** (chapter 6). The new model represents an important theoretical contribution, because it provides an alternative framework to the two dominant theoretical approaches for modelling the dynamics of the price of oil (Reynolds and Baek, 2012): the one based on the Hotelling Principle (Hotelling, 1931) and the one based on Hubbert Peak approach (Hubbert, 1962). Without assumptions about the underlying economic structures of the system or optimality in the use of resources, this model provides a new way to calculate the marginal cost of non-renewable energy carrier production, based on the exploitation of the underlying reserves. It was published in *Energy Policy* (Mercure and Salas, 2013b).

- **A new methodology to model investment decisions, under conflicting and subjective criteria, using heterogeneous preferences** (chapter 10). The new investment model represents a significant contribution to the literature, because it provides a novel combination of two decision making modelling theories (AHP and DCM), and that enables the modelling of investment decisions under a flexible number of criteria, using a probabilistic framework. The new model combines subjective and objective criteria, even if preferences are intransitive, with probabilistic choices, to represent diversity of agents and preferences. Using a novel mathematical formulation, the complex process of evaluating multiple options simultaneously under several criteria, is transformed into a large number of simple pairwise comparisons, but preserving the heterogeneous preferences of the investors. The new model contributes towards a more comprehensive representation of the decision-making process in general, and investment decisions in particular. The theoretical framework presented in chapter 10 can be easily adapted for other areas of decision-making, including policy-making, management, education, among many others.

1.3.2 Practical contributions

- **An assessment of global and regional energy potentials for all major natural energy resources, in the form of a database of cost supply curves for 190 countries** (chapter 6). The database of global energy resources addresses an important gap in the resources potential's literature, where abundant information exists about resource estimations, but very little attention is given to the underlying costs. In combination with the model for natural resources use and depletion, it provides a practical tool that can be used by modellers to study energy transitions in the power sector. This work supersedes outdated studies and provides a consistent update of energy resource potentials. The assessment was published in *Energy* (Mercure and Salas, 2012), and now is part of FTT:Power, in the form of a database of cost-supply curves, in terms of energy flows for renewable energy sources, or fixed amounts for fossil and nuclear resources.

- This dissertation contributes with **scenarios based on a diverse group of energy policy instruments, including carbon pricing, subsidies, feed-in-tariffs, direct regulation of newly installed capacity, and any possible combination of these, as well as energy demand reductions** (chapter 7). While economists have argued extensively in favour of a harmonised carbon tax system as the main policy instrument to mitigate climate change (Kalkuhl et al., 2013; Nordhaus, 2007), the evidence suggest that a portfolio of policies provides better results (IEA and OECD, 2012a, p. 119 & 121), especially if externalities such as pollution, imperfect competition and energy security considerations are taken into account (Fischer and Preonas, 2010; Kalkuhl et al., 2013). In this context, the use of an explicit representation of policy instruments in this work is important, because it is the basis for the analysis of the environmental and economic performance of decarbonisation policies, including emission reductions, public revenues from carbon pricing, public expenditure on subsidies and feed-in-tariffs, and private expenditure on electricity. The detailed representation of policy instruments, used in combination with the database of energy resources and the new model of investment decisions, makes FTT:Power a valuable tool for the analysis of energy policy in the power sector.

- **A detailed analysis of the impact of hydropower resources availability in the performance of decarbonisation policies in Brazil** (chapter 8). Given the current water and energy crisis in Brazil (Melo et al., 2016), this analysis represents a valuable topical contribution for policy making, in the context of the Intended Nationally Determined Contribution (INDC) towards achieving the objectives of the Paris Agreement (Brazilian Government, 2015; UN, 2015b).

- In the context of endogenous technological change modelling, chapter 9 provides **a list of learning rate intervals, based on a thorough literature review** (presented in Appendix section C.1). This is a valuable practical contribution, especially for modellers implementing learning curves. Moreover, the chapter provides an insightful quantitative analysis of the role played by the flexibility of the power grid (in terms of combining baseload, flexible and variable generation) in the performance of decarbonisation policies. This is a subject of increasing importance, because the success or failure of future decarbonisation policies will depend strongly on the capacity of national grids to absorb large quantities of variable generation from renewable energies (Boyle, 2012).

- **A new investment model that includes market-based considerations, environmental considerations and policy uncertainty as investment criteria** (chapter 11). This new model is an important contribution, because it facilitates the analysis of complex phenomena associated with investment decisions in the power sector, such as environmental policy performance and its impact on regional investment allocation, or patterns of technology uptake based on policy incentives. Moreover, the new investment decision model is presented with a step-by-step methodology for implementation, so it can be easily replicated outside the FTT:Power framework.

1.4 Thesis organisation and structure

The chapters of this thesis are organised as follows:

The **second** chapter presents some background information on the general topic studied in this dissertation: energy technology transitions. The chapter starts with historical trends and grand transitions in the energy sector, which provide insightful evidence for how the energy sector has been radically transformed in the past. The chapter then continues with an overview of the current global energy and power sectors, based on the latest available data. Finally, the chapter finishes with emission pathways and forward-looking analysis, the methodologies used in this dissertation for presenting the future technology diffusion scenarios of the power sector.

The **third** chapter presents a literature review, with an overview of methods and approaches used by models that combine the energy, climate and economic systems. The chapter divides the modelling approaches into macroeconomic models, integrated assessment models, energy sector models and power sector models. The chapter finishes with a brief description of FTT:Power, the model selected for the creation and analysis of the power sector scenarios in this dissertation, as an introduction to a more detailed description presented in the next chapter.

The **fourth** chapter describes the main components of the FTT:Power model. The description includes the modelling of natural resources, endogenous technological change and market competition. The Levelised Cost of Electricity (LCOE) framework is explained in detail in this chapter, as it is the basis of the incumbent investment decision model of FTT:Power. A new methodology to model investment-decisions is proposed later, in chapter 10. The fourth chapter also provides a description of how FTT:Power balances the amount of baseload, flexible and variable electricity in the system, using stability constraints. The role of these constraints, in the decarbonisation scenarios of the power sector, are analysed in chapter 9.

The **fifth** chapter presents the framework used throughout this thesis for the creation of scenarios of the power sector. This framework is based on a decarbonisation intensity variable, which maps a subset of the FTT:Power policy domain into the range [0 1], to facilitate the analysis of a large number of scenarios. Two extreme scenarios of the power sector are introduced in this chapter: Business as Usual (or BAU), and Decarbonisation (or DEC). These two scenarios, particularly the scenario DEC, work as a reference for all the other scenarios analysed in this dissertation.

The **sixth** chapter introduces the Natural Energy Resources (NER) module. The NER module was created as a tool for FTT:Power to include feedback with the natural world, in terms of restrictions in the use of primary energy. It includes a database of energy resources, in the form of cost supply curves, and a model of non-renewable energy resources use and depletion. The chapter presents a novel mathematical representation of energy resources, using uncertainty intervals and probability density functions based on statistical trends, which is the basis for the implementation of the NER database. A sampling of global cost supply curves is presented, for 6 types of renewable and 6 types of stock resources.

The **seventh** chapter analyses the impact of energy resource availability in the performance of energy policy. Policy efficiency, measured by the ratio between emission reductions and energy expenditure, is compared for different policy sets under extreme scenarios of energy resource availability. The resource scenarios are created using the uncertainty ranges of the NER module's database, presented in chapter 6.

The **eighth** chapter analyses the impact of hydropower resource availability in the performance of decarbonisation policies in Brazil, in the context of its Intended Nationally Determined Contribution (INDC) towards achieving the objective of the Paris Agreement. The analysis presented in this chapter builds on the methodology presented in chapter 7, and policy efficiency is compared for different policy sets under high and low availability of hydropower resources.

The **ninth** chapter provides an introduction to the subject of technological change and learning, how it is modelled in FTT:Power (in contrast with some classical approaches), and presents future decarbonisation scenarios under uncertain technological change (in the form of extreme learning rates). Moreover, the chapter provides an analysis of the impact on the performance of decarbonisation policies of the capability of the grid to incorporate variable electricity (from renewable sources). The list of learning rate intervals presented in the chapter is based on a thorough literature review (presented in Appendix section C.1), and is a valuable contribution for the creation of learning curves.

The **tenth** chapter introduces a new methodology to model investment decisions in FTT:Power. The new methodology replicates the investment dynamics of the incumbent model, and allows the incorporation of quantitative and qualitative criteria as part of the investment decision process. The methodology is based on a novel combination of a multicriteria decision-making approach called Analytic Hierarchy Process (AHP), and Discrete Choice Theory (DCT).

The **eleventh** chapter uses the methodology introduced in chapter 10, to create a new investment decision model for FTT:Power, that includes *environmental considerations* and *policy uncertainty* as investment criteria (as a complement to the incumbent investment criterion, based solely on the *levelised cost of electricity*).

Finally, the **twelfth** chapter summarises the most relevant results and conclusions presented throughout the dissertation, and combines the different scenarios in one final chart of emission trajectories, in line with the Representative Concentration Pathways approach of the IPCC IPCC (2014d, page 11).

1.5 Disclaimer

This dissertation uses the FTT:Power model as the basis for the analysis of scenarios of the power sector. The FTT:Power modelling framework, including the core part of the computer code, was developed primarily by Dr. Jean Francois Mercure (Mercure, 2012, 2015). I am author or co-author of several parts of the model, made especially for this dissertation:

- The Natural Energy Resources module (NER) is presented in detail in chapter 6. This includes a database of primary energy resource potentials, and a model of stock resources use and depletion. It was created as part of a collaborative work between Dr. Mercure and myself (50% authorship each) (Mercure and Salas, 2012, 2013b).

- Using the FTT:Power code developed by Dr. Mercure, I developed a platform to analyse uncertain scenarios, including scenarios of energy policy (chapter 5), natural resources availability (chapters 7 and 8), learning (chapter 9) and investment (chapter 11). The platform includes a Monte Carlo module, and is able to generate an arbitrary number of scenarios, using latin hypercube sampling over the FTT:Power domain (see chapter 5).

- The incumbent investment model of FTT:Power, based on the LCOE as the solely investment criterion, was devloped by Dr. Mercure. The new multicriteria investment model proposed in chapter 10, and used in chapter 11, is entirely my own work.

Chapter 2

Energy Transitions: Historical Trends and Future Pathways

2.1 Chapter summary

This chapter focuses on the technological transitions of the energy sector, how they have happened in the past, and what they can teach us about potential future scenarios. To address the imminent risks of climate change, a profound transformation of the energy sector is required. Looking at the main historical drivers of radical energy transitions in the past, key insights can be obtained regarding the possibilities (and limitations) of modelling future scenarios of radical technology transitions. The chapter discusses the importance of an appropriate treatment of uncertainty, to address some of the knowledge gaps and limitations associated with creating future scenarios of the energy sector.

The chapter is structured as follows: section 2.2 gives a brief introduction to the urgency of transforming the energy sector. Section 2.3 provides a historical perspective of major energy trends and transitions, from the industrial revolution to the end of last century. Some lessons about the past technological transitions are discussed in this section, including the time scale required for profound changes to the energy sector, and the importance of an appropriate treatment of uncertainty in forward-looking models and scenarios. Section 2.4 presents an overview of the current global energy and power sectors, in terms of energy use and emissions. Section 2.5 looks at the future of the energy and power sectors, and how they can be described using emission pathways and forward-looking analysis. Section 2.6 provides some concluding remarks.

2.2 Introduction

The technological evolution of the energy sector has provided the means for billions of people to dramatically improve their living standards over the last two centuries (Annecke et al., 2000). The unprecedented progress, however, has not reached everyone equally (UN-Energy, 2005). A large part of the global population still have no access to the most basic energy services, with the corresponding consequences for their living standards. Around 2.6 billion people rely in traditional wood and similar highly polluting biomass sources for heating and cooking, and around half of them do not have access to electricity (IEA and OECD, 2012b, p. 529). Closing that energy access gap is paramount, and for that reason the United Nations addressed it as one of the 17 Sustainable Development Goals (UN, 2015a).

Accomplishing this task will demand a double challenge: to equilibrate economic development with environmental sustainability. The development pathway followed by most of the OECD countries, based on the intensive use of fossil fuels, is not longer a viable option for developing economies, if the associated risks of climate change are considered. In the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), scientists concluded that '*continued emission of greenhouse gases will cause further warming and long-lasting changes in all components of the climate system, increasing the likelihood of severe, pervasive and irreversible impacts for people and ecosystems*' (IPCC, 2014c, p. 8). Substantial greenhouse gas (GHG) emission reductions over the next few decades are required to limit the potential risks of climate change (IEA and OECD, 2012a, p. 361). The scale of the decarbonisation needed is proportional to the fossil fuel dependence of our current energy systems. Therefore, a major technological transformation of the global energy sector is required. In order to understand how such transformation might be accomplished in the future, a good starting point is to analyse the radical transformations that the energy sector has undergone in the past.

2.3 The past: historical trends and transitions in the energy sector

The continuous process of creating new technologies, that form the basis of the products and services required to maintain and improve our living standards, was described by Schumpeter as a process of 'creative destruction' (Schumpeter, 1942). In this context, innovation and technological progress have played a vital role in modern economic development. In recent centuries, technological progress has accelerated exponentially, opening the possibility for new generations to have access to technologies that their ancestors only dreamed of. At the core of this technological revolution, is the energy sector, providing the 'blood' that fuels the increasingly complex systems under which modern societies are built.

2.3.1 The fossil fuel era and climate change

The end of the historical dominance of biomass, animal power, wind and water, as main primary energy resources globally, started with the invention of the steam engine, just before the industrial revolution (Renwick and Pambour, 1848). The steam engine was the key driver that allowed coal to become the dominant energy resource globally at the beginning of the twentieth century (see figure 2.1), despite it being part of the energy matrix for a significant period of time.[1] Coal did not only replaced biomass for heating, but it also replaced humans and animals, previously used as source of mechanical energy. The extensive adoption of the steam engine in all sort of productive activities, enabled a rapid expansion of various sectors, including agriculture, manufacturing, transport and mining (Podobnik, 2005).

The technical and economic development triggered by the industrial revolution, led to an exponential increase in global population, matched by a parallel trend in energy use (see the top charts of figure 2.2). In little more than one century, global primary energy production increased ten folds, fueled by a massive expansion in the coal and oil industries, during the 19th and 20th century, respectively (EIA, 2016; Etemad, 1991). The new fossil fuel era, marked by the access to low-cost and better energy services, led to a paradigm shift in productivity. The invention of the steam engine, followed by the internal combustion engine and the electric motor, were the basis for the development of all the technologies and

[1] The inclusion of coal in the energy matrix dates back long before the industrial revolution. For instance, Smith (1997) describes coalfields exploited by the Romans in the late 2nd century AD, while the Tiangong Kaiwu encyclopedia, published in 1637, depicts ancient coal mines in China (Elvin, 2008; Song Yingxing, 1637).

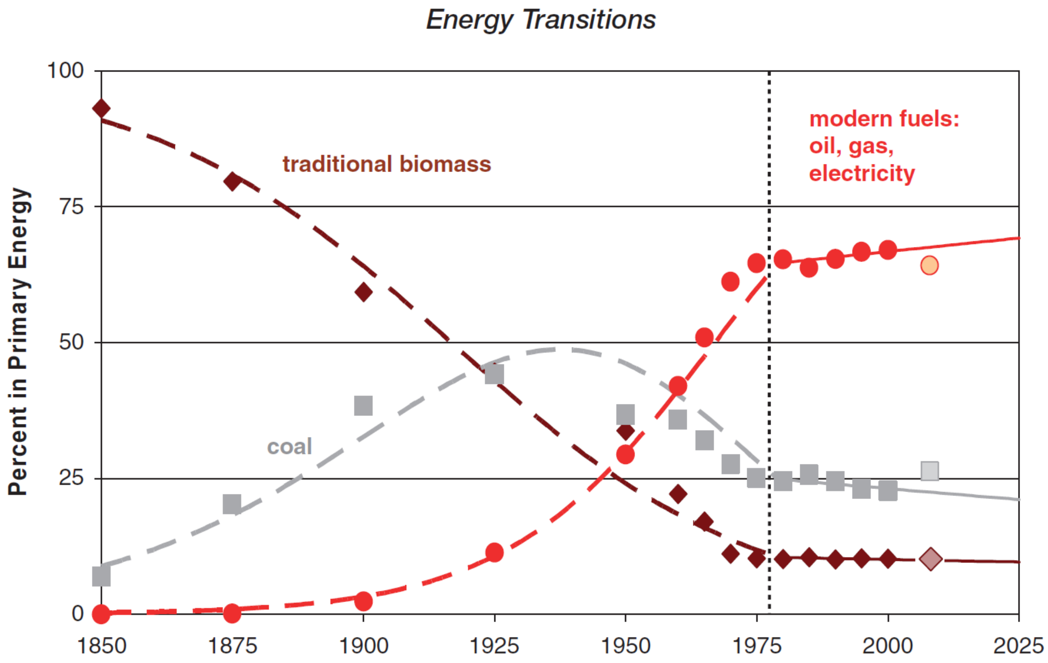

Figure 2.1 Two grand historical transitions in global energy systems, measured by market shares of primary energy use. The first transition, corresponds to the emergence of coal based steam systems, which replaced renewable energy sources. The second transition, corresponds to the displacement of the previously dominating coal-based steam technology cluster by electricity and petroleum-based technologies. The chart is taken from the book "Energy Technology Innovation" (Grubler, 2013, p. 9).

services that modern cities rely on. As a by-product of the economic development based on hydrocarbons, however, CO_2 emissions started to accumulate in the atmosphere, at a rate proportional to the burning of fossil fuels. The bottom right chart of figure 2.2 shows the rise in the level of CO_2 concentration in the atmosphere during the industrial revolution (blue) and during the last decades (red), in contrast to the historical records from the last thousand years (green).

The sharp increase in the concentration of CO_2 in the atmosphere, shown in the bottom right chart of figure 2.2, is completely aligned with the observed changes in the climate system. As stated by the IPCC, *human influence on the climate system is clear [...] Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and ocean have warmed, the amounts of snow and ice have diminished, and sea level has risen* (IPCC, 2014c, p. 2). Multiple lines of evidence indicate a near-linear relationship between net cumulative CO_2 emissions and projected global mean temperature change to the year 2100 (IPCC, 2014c, p. 62). Therefore, to meet the 2°C target stated in the Paris Agreement, it *would require*

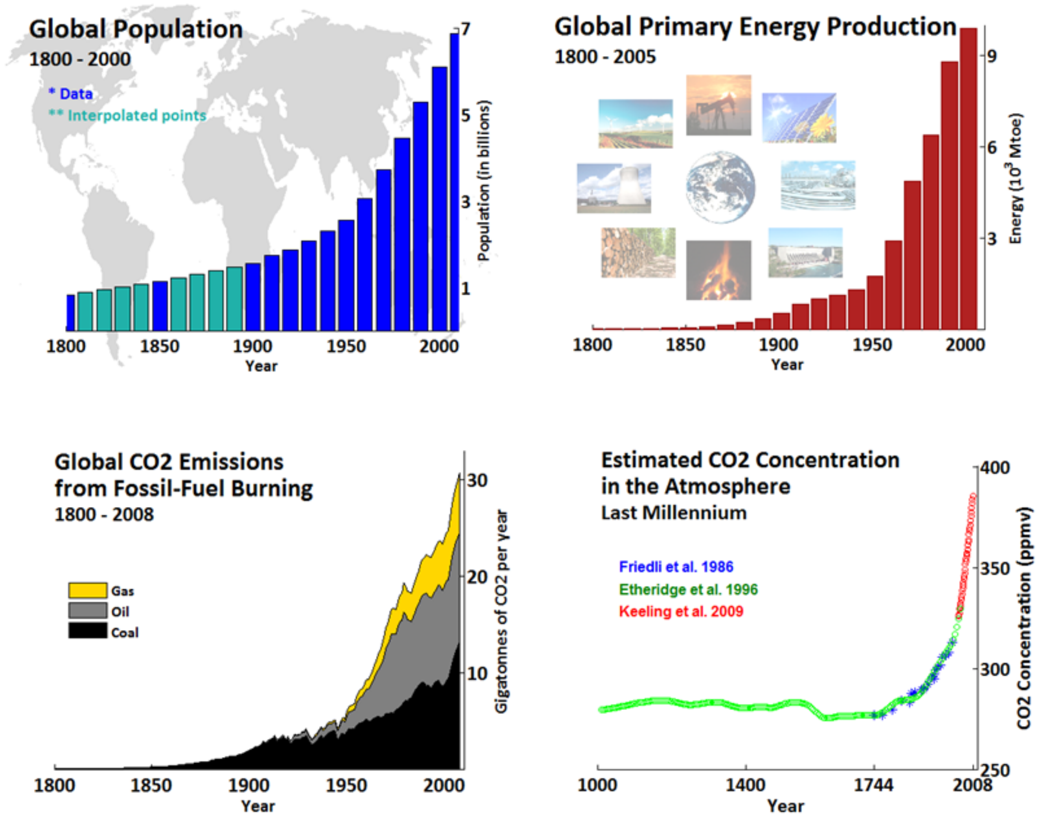

Figure 2.2 Snapshot of the era of post-industrial revolution, from the perspective of the global energy sector. In the **top left**, the exponential increase in global population over the last two centuries (data from UN (1999)). In the **top right**, the conjoined increase in global primary energy consumption over the same period (data from EIA (2016); Etemad (1991)). The bottom charts show some of the consequences of having an energy matrix dominated by fossil fuels. The **bottom left** chart shows the global CO_2 emissions from fossil fuel burning (data from Boden et al. (2016)), while the *bottom right* chart shows the historical evolution of CO_2 concentration in the atmosphere. The red line in the bottom right chart, corresponds to measurements made at the Mauna Loa observatory, in Hawaii (Keeling et al., 2009); the green and blue lines are estimations based on ice core samples (from Friedli et al. (1986) and Etheridge et al. (1998), respectively).

substantial emissions reductions over the next few decades and near zero emissions of CO_2 and other long-lived greenhouse gases by the end of the century (IPCC, 2014c, p. 20). On the contrary, if the increasing trend in emission continues, climate change will amplify existing risks and create new risks for natural and human systems, especially for disadvantaged people and communities in countries at all levels of development (IPCC, 2014c, p. 13).

2.3.2 Energy transitions from different perspectives

Before the industrial revolution, the global energy sector was dominated by renewables, as can be seen in figure 2.1. The introduction of steam power in transport and production processes during the eighteenth century boosted the development of the coal industry, generating the first grand transition in global energy systems, from biomass to coal as the main primary energy resource. This technology transition lasted more than one hundred years, and was one of the driving forces of one of the most important milestones in modern human history, the *Industrial Revolution*. In a similar way, the adoption of the internal combustion engine at the peak of the coal dominance initiated the second major transition of the global energy sector, from coal to oil as the main primary energy resource. That transition took around 50 years, although it can be argued that is not yet finished.[2] Even though the historical context during these two transitions is entirely different, it is still possible to identify some common drivers. For instance, Podobnik (1999) identified geopolitical rivalry between military powers as one of the main facilitators of the two grand technological transitions in the energy sector. From a completely different perspective, but arriving to congruent conclusions, Wilson and Grubler (2011) identified the demand for end-use applications as the main driver of technological change in the energy sector.

Major energy transitions are connected to broad social and geographical change (Bridge et al., 2013). The necessity of national military and political leaders to secure affordable and reliable access to energy resources, for instance, has driven states to intervene directly in domestic and foreign energy industries (Krasner, 1978; Podobnik, 1999). In that context, Great Britain's intervention in the coal-based cluster (including iron, rail, and shipping sectors), followed by similar efforts from other governments during the late nineteenth century, led to an exponential growth in the production and consumption of coal (Mitchell, 1984). Similarly, the arms race between political powers at the beginning of the last century was a strong stimulus for the adoption of oil-powered ships, vehicles and aircraft, that were later adopted by other sectors such as industry and energy (Podobnik, 1999). In both transitions, the expansion of the emergent energy system relied heavily on the stable support from the geopolitical and economic powers at that time (Podobnik, 2005). Not surprisingly, geopolitical factors and the availability of resources have played an important role in the diversification of the global energy matrix, as part of the energy security strategies (Ang et al.,

[2]Since the first technological transition, from biomass to coal as the main primary energy source, the share of biomass in the energy mix has experienced a sustained decline. However, while the share of coal in the primary energy mix also decreased after the second transition from coal to oil as the main primary energy source, this tendency has changed during the last decades, mainly driven by an increase in consumption of coal by developing countries such as India and China (IEA and OECD, 2011)

2015). For instance, state supported funding for R&D in low carbon energy technologies surged during the oil shocks of the 70s, and many of the renewable technologies available today are a direct consequence of some of those funds. The USA and Japan, the two largest investors in energy R&D, spent an average of 3.38 and 2.45 billion US$, respectively between 1975 and 1999 for many energy research programmes (IPCC, 2007, p. 762).

End-use technologies, consumers, and the demand for energy services have also played a critical role in past energy transitions (Grubler, 2013). Wilson and Grubler (2011) identified the replacement of steam engines by gasoline and electric engines at the beginning of last century as one of the key factors for the transition from coal to oil, even though steam energy was more economical than oil-based energy at that time . Direct economic signals such as price, are discarded as main drivers of technological change in this view, even if these exerted an influence at various times (Grubler, 2008). In another detailed analysis of past energy transitions, Fouquet (2010) derived different conclusions regarding the influence of price on the evolution of energy technology. For instance, he identified the price of energy as one of the key factors in the diffusion of technology in several historical transitions, such as the replacement of woodfuel by coal in residential and industrial heating, or the replacement of candles by gas and kerosene appliances in lighting. However, similar to Wilson and Grubler, Fouquet also identified the services provided by end-use application, as one of the main drivers of technology diffusion (Fouquet, 2010).

From a more economic standpoint, Ayres (1990), based on the work of Schumpeter (1939), associated the transitions in the energy sector with Kondratieff waves.[3] Following the seminal work of Freeman and Perez (1988), Ayres identified that the rise and decline of coal as the main primary energy resource, was part of a long economic cycle, and that so too was the rise of oil (Ayres, 1990). The hypothesis that 50 year Kondratieff waves can explain transitions in the energy sector is further supported by de Oliveira Matias and Devezas (2007), who divided the last 250 years of the energy sector into 5 waves of technology transformation. All of them identify clustering of technologies as an important facilitator of technological evolution.

[3]Kondratieff waves are *cycles in the dynamics of the capitalist economy*, or business cycles using modern economic language. They are characterised by phases of boom, followed by phases of depression, with a frequency in the order of 50 years (Barnett, 1998; Kondratieff and Stolper, 1935).

2.3.3 Lessons from the past

One of the most important lessons that can be extracted from the past grand energy transitions, is that *profound global energy shifts can happen in a time frame of decades*. Therefore, the speed that renewable energy technologies diffuse, could potentially be accelerated, if the proper political, commercial, and social conditions were fortified. Consequently, this dissertation explores profound energy transition scenarios of the power sector in the future, aligned with the international commitment of holding the increase in the global average temperature below 2°C above pre-industrial levels (UN, 2015b). The profound energy transition scenarios analysed in this dissertation are based on a portfolio of decarbonisation policy instruments, introduced in chapter 5. These policy instruments are analysed in terms of their abatement potential and impact on expenditure at the global level (chapter 7), and the particular case of Brazil is analysed in detail (chapter 8).

The future technology diffusion scenarios analysed in this dissertation are simulated using the power sector model FTT:Power (see chapter 4 for a detailed description). While this model is able to include several types of policy instruments that influence energy transitions (including carbon pricing, subsidies, feed-in-tariffs and regulation in the construction of new power plants), the model is limited on its capacity to include more complex drivers of technology diffusion. Indeed, from an academic perspective, some of the most relevant drivers of technology transitions are, unfortunately, very difficult (if not impossible) to model. The best example is geopolitics. Despite its importance in the evolution of the global energy sector, it is not part of any of the major models considered by the IPCC for the creation of future scenarios of the energy sector.[4] Our knowledge regarding the different drivers of technology transitions in the energy sector is limited. For instance, the successful implementation of policy depends on many factors associated with human and institutional behaviour, which is prone to behavioural biases and influenced by social norms (IPCC, 2014b, p. 95). Consequently, policies to mitigate emissions are extremely complex, and arise in the context of many different forms of uncertainty (IPCC, 2014b, 114). In this context, *forward-looking models and scenarios, with underlying assumptions about policy implementation and rates of adoption of low-carbon technologies, should incorporate an appropriate treatment of uncertainty*.

Depending on the knowledge gaps to be addressed, different methodologies to deal with uncertainty are required, from a wide approach (such as modelling uncertainty), to a very specific approach (such as parametric uncertainty). The scenarios analysed in this dissertation

[4]See chapter 3 for a review of models of energy, climate and economic systems.

incorporate parametric uncertainty in several areas, including energy policy intensity (chapter 5), natural resource availability (chapters 6, 7 and 8) and learning (chapter 9). Moreover, modelling uncertainty is also addressed in this dissertation, in relation to the capabilities of the power sector to handle large amounts of renewables (chapter 9), and the influence of uncertainty in energy investment (chapter 11).

Emission reductions in line with the targets of the Paris Agreement, will require a diverse portfolio of policies that create changes in human behaviour and consumption patterns (IPCC, 2014b, 114). Decisions driving the evolution of complex systems, however, incorporate a large number of quantitative and qualitative information. Investment decisions, for instance, are the aggregation of many types of inputs, and combine well structured data (such as cost, profits, policies and others), with non-quantifiable knowledge, such as vague attitudes and opinions (Slovic et al., 1972). Therefore, together with an appropriate treatment of uncertainty, *the use of multiple and flexible criteria to model decision-making* is paramount. The combination of different decision criteria in complex systems like the global energy sector, is a very important step towards the creation of more comprehensive and realistic models and scenarios of the future. Chapter 10 proposes a methodology to model energy investment decisions under conflicting and subjective criteria, based on a probabilistic approach for representing heterogeneous preferences.

2.4 The present: an overview of the global energy and power sectors

The dominance of fossil fuels in the global energy matrix, which began at the end of the industrial revolution, still remains strong. Figure 2.3 shows how primary energy production and use (by source, sector and region) and emissions from energy use have evolved over the last decades. As shown in the top left chart, the large majority of primary energy production comes from fossil fuels: coal for producing electricity, oil for transport, and gas for various purposes.[5] Renewables represent a minor part of the global energy matrix, mostly concentrated in hydropower and biomass. Unfortunately, in the case of biomass, the vast majority corresponds to traditional, highly polluting biomass for heating and cooking in developing countries (IEA and OECD, 2012b).

[5]While the use of coal and oil is strongly concentrated in power and transport sectors, respectively, the use of gas is more balanced between buildings, industry and heat-power generation (IEA and OECD, 2012a, p. 301).

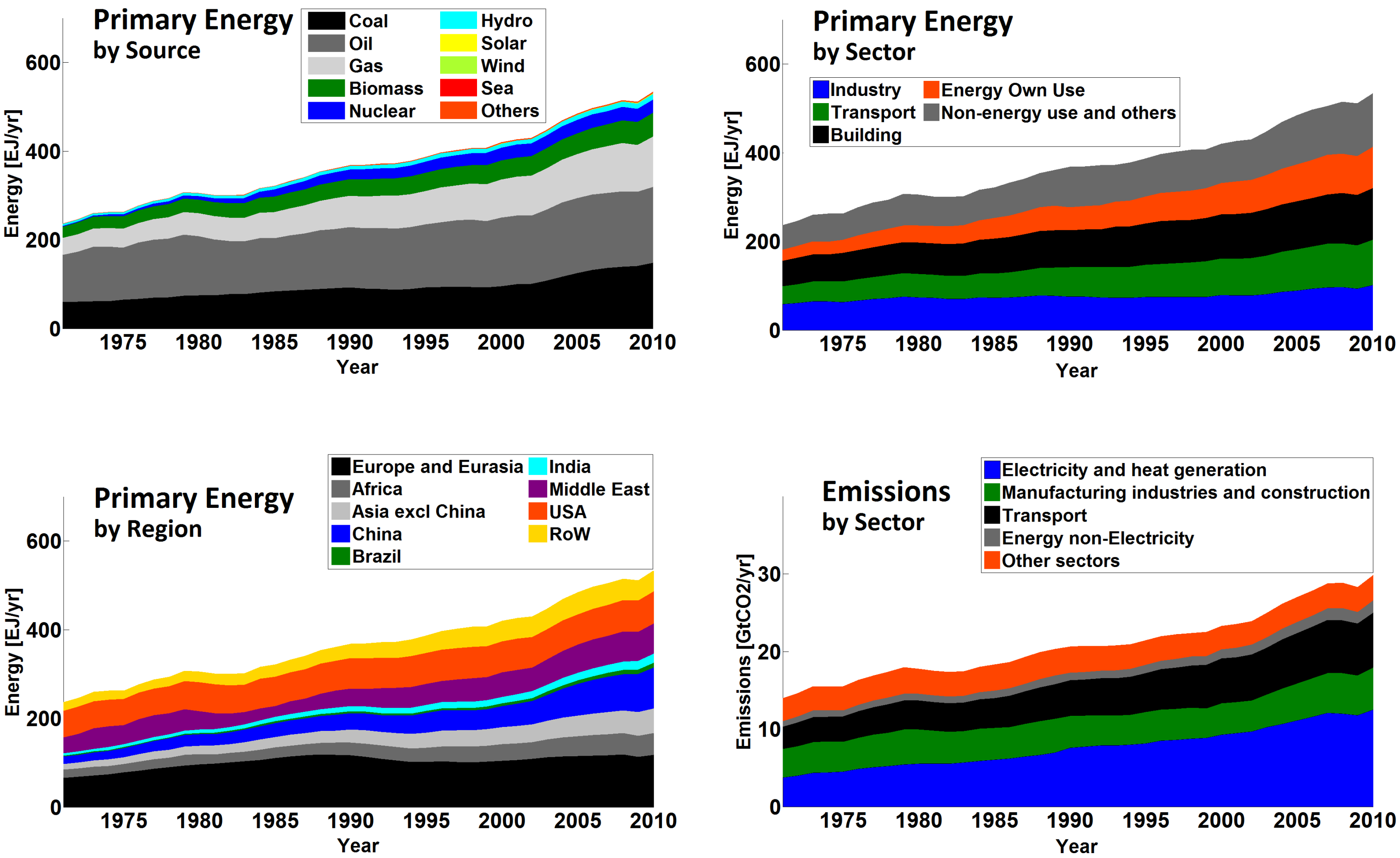

Figure 2.3 Evolution of primary energy production and use (top and bottom left), and CO_2 emissions from the energy sector (bottom right), over the last decades. Data and classification from IEA (2015).

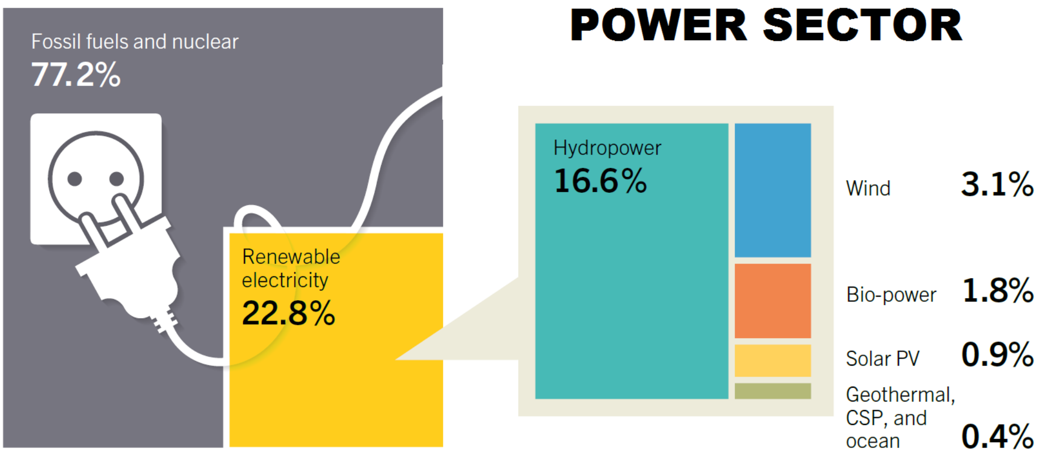

Figure 2.4 Estimated renewable energy share of global electricity production, by the end of 2014. From (REN21, 2015, p. 31).

Historically, Europe and USA have been the largest energy consumers, as shown in the bottom left chart of figure 2.3. However, the relative share in energy use has been changing since the early 1980s, with the fast economic growth of Asian countries (China in particular), who are leading the relative increase in energy consumption. Due to their intensive use of coal in electricity production, the CO_2 emissions from the power sector have strongly increased over the same period, as shown in blue in the bottom right chart of figure 2.3. As figure 2.2 shows, the concentration of GHG in the atmosphere has reached unprecedented levels, so the rapid decarbonisation of the power sector is paramount, if economic development is to be balanced with environmental sustainability (IPCC, 2014c, p. 8).

In the context of a global decarbonisation of the energy sector, the power sector is of strategic importance. As shown by the bottom right chart of figure 2.3, electricity production is the top producer of CO_2 emissions within the energy sector. Moreover, a low carbon electricity matrix is a primary condition for the decarbonisation of the transport and residential sectors, if those abatement strategies rely on the adoption of electric end use applications (such as vehicles and heaters). Therefore, low-carbon electricity is a prerequisite to reducing fossil fuel use and to mitigating emissions in the end-use sectors (IEA and OECD, 2012a, p. 361). As figure 2.4 shows, the current participation of renewables in the power sector matrix is not significant, especially for modern types such as solar and wind. A profound decarbonisation of the power sector, requires the deployment of large amounts of renewable energy technologies. Based on that premise, this dissertation focuses on the decarbonisation of the global power sector, using extreme technology diffusion scenarios for the future.

2.5 The future: emission pathways and forward-looking analysis

For the Fifth Assessment Report of the IPCC, a set of "benchmark emissions scenarios" were created, under the name of **Representative Concentration Pathways** or **RCPs**. The RCP scenarios are time-dependent projections of atmospheric GHG concentrations, designed to cover a wide range of possible magnitudes of climate change in models. They embody potential future anthropogenic climate change, underlying driving forces, and response options. Rather than being identified with one socioeconomic storyline, RCP scenarios are consistent with many possible economic futures (different combinations of emissions can lead to the same RCP) (Collins et al., 2013). Four representative scenarios were created: RCP2.6, RCP4.5, RCP6.0 and RCP8.5. They were named in terms of their target radiative forcing (or RF[6]) at 2100 or at stabilisation. Figure 2.5 shows a summary of the RCP scenarios, from IPCC (2014d, page 11).

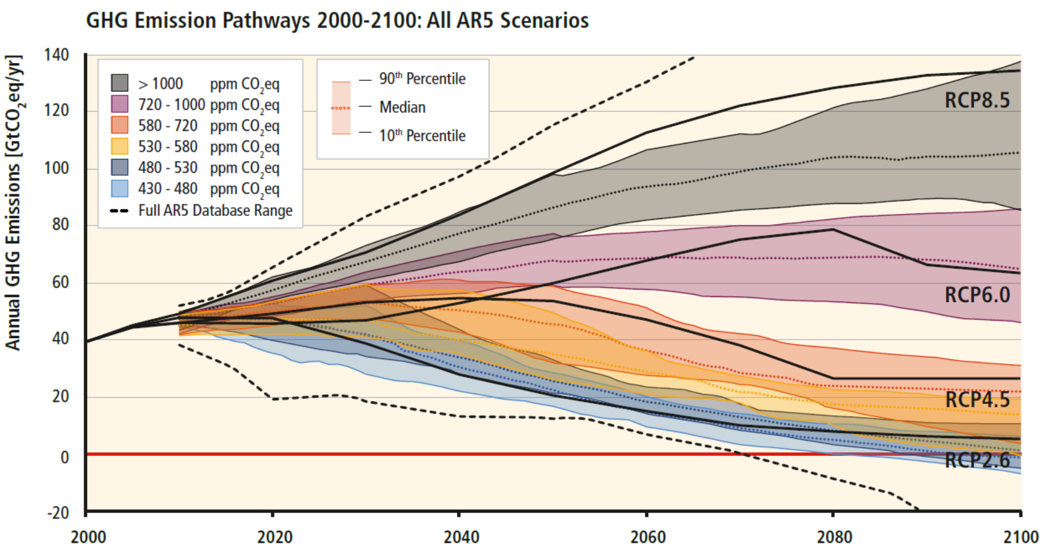

Figure 2.5 Representative Concentration Pathways scenarios, between 2000 and 2100. From IPCC (2014d, page 11).

The collection of scenarios presented in the RCP were generated as part of model intercomparison exercises, composed of specific assumptions regarding fundamental drivers such as population growth, technological progress and economic activity (Clarke et al., 2014).

[6]Radiative forcing is defined in the IPCC as the change in net, downward minus upward, radiative flux (expressed in W/m^2) at the top of the atmosphere due to a change in an external driver of climate change, such as, for example, a change in the concentration of carbon dioxide (CO_2) or the output of the sun (IPCC, 2014a).

This methodology is framed in the context of **forward-looking analysis**, where *studies construct plausible development pathways for the future and examine the ways in which development might be steered towards one pathway or another* (IPCC, 2014b, p. 311). Given the large uncertainty surrounding many of the assumptions embedded in the scenarios, emission pathways become increasingly uncertain with time, something that reflects our lack of knowledge about the future (IPCC, 2011). One important aspect to consider is "feasibility" uncertainty. Many models are unable to reproduce particularly stringent decarbonisation scenarios, something that might be associated with violation of physical laws. However, it is often the case that infeasibility arises from pushing models beyond the boundaries of what they were built to explore. In those cases, although model infeasibility cannot be taken necessarily as a lack of feasibility in an absolute sense, it highlights the challenges associated with accomplishing particular scenarios (Clarke et al., 2014).

Following the IPCC approach, this thesis uses forward-looking analysis for the development of future scenarios for the power sector, to analyse how these futures might be reached or avoided. The scenarios created using forward-looking analysis, are neither predictions nor forecasts, but are plausible description of how the future may develop based on a coherent and internally consistent set of assumptions and relationships (IPCC, 2014b, Glossary, p. 1270). In some cases *contrasting* scenarios are produced, aiming to describe the whole range of potential futures. The contrasting scenarios define, in this context, the *edges* of the plausible pathways (Bibas, 2015). Scenarios follow a story line, characterised by *policy sets*, *availability of natural resources* and assumptions about *technological change*. Different chapters of this thesis centre their attention on specific aspects of the storyline, that may steer the scenario analysis in a specific direction.

According to the IPCC, emission scenarios that are likely to maintain warming below 2°C over the 21st century relative to pre-industrial levels, have to follow a trajectory similar to the one represented by the RCP2.6 trajectory of figure 2.5 (IPCC, 2014b, p. 10). In other words, minimising the risks of climate change requires a profound transformation of the energy sector in general, and the power sector in particular. Following this premise, this dissertation includes decarbonisation scenarios of the power sector, based on stringent policy implementation in several regions of the world. The goal is to explore a wide range of the the FTT:Power domain, to generate a diverse set of emission pathways, among which the likely evolution of the power sector will lie. The goal is not to *forecast* the future evolution of the power sector, but to *analyse a wide range of potential pathways*, under different conditions of energy policy, resource availability and technological change.

2.6 Conclusion

From the analysis presented in this chapter, especially regarding the technology transitions that have shaped the global energy sector, several lessons can be learned. Firstly, and most importantly, *profound global energy shifts can happen in a time frame of decades*. For these profound transitions to happen, several circumstances have to converge, including geopolitical, commercial, and social conditions, among many others (Geels, 2002; Podobnik, 2005). Secondly, our knowledge regarding the drivers of technology transitions in the energy sector is limited, and policies to mitigate emissions arise in the context of many different forms of uncertainty (IPCC, 2014b, 114). Therefore, *forward-looking models and scenarios have to incorporate an appropriate treatment of uncertainty*. Moreover, the use of multi-criteria approaches to model decision-making are necessary, if comprehensive and realistic models and scenarios of the future are to be created. And finally, *a radical transformation of the energy sector is required*, if the potential risks of climate change are to be minimised.

Chapter 3

Literature Review

3.1 Chapter summary

This chapter provides an overview of methods and approaches used by energy, climate and economic system models. The literature review includes an extensive list of macroeconomic, energy sector, power sector and integrated assessment models, and a list of the most prominent cross-model comparison exercises in the area of energy and climate change over the past few years. This chapter provides an overview of the modelling landscape in the area of energy economics and climate change, and identifies where FTT:Power stands with respects to the main modelling approaches in the field. The chapter also identifies some of the key gaps in the modelling literature, and discuss how are they addressed in this dissertation. The chapter ends with a brief description of FTT:Power, the model selected for the creation and analysis of the power sector scenarios in this dissertation, as an introduction to a more detailed description presented in the next chapter.

3.2 A large spectrum of modelling approaches

During the energy crisis in the 1970s, research funds provided by several countries created a virtual explosion in the area of energy economics modelling (Griffin, 1993). A widely diverse group of researchers were attracted to study the major policy questions at that time. The topics included modelling of exhaustible resources, cartel theory applications to OPEC, environmental economics, and a variety of energy supply/demand models designed to address specific questions. With the growing concern for climate change in the 1990s, an important part of the energy economics community decided to direct their efforts towards the analysis of long-term scenarios of the economy, the environment and the energy sector. Since then, a vast number of models have been created, following a variety of approaches. For instance, there has been an extensive development of macroeconomic models, with energy-economy-environment (E3) components. Some groups have incorporated this type of models into integrated assessment platforms, combining highly aggregated models of climate change, economic activity, energy systems and emissions. Other approaches are more specifically focused in the energy sector and/or climate change policy, as in the case of energy sectoral and technology models. Following the categorisation made by Grubb et al. (2002), models that combine the energy, climate and economic systems, can be classified in three large groups: macroeconomic models, integrated assessment models (IAMs) and energy sector models.[1] These three groups, plus a fourth group corresponding to power sector models, are briefly described below. The next section provides an overview of the modelling landscape in the area of energy economics and climate change, and identifies where FTT:Power stands with respects to the main modelling approaches in the field. A list of models (classified by the aforementioned categories) is summarised in table 3.2, and a list of cross model comparison exercises is provided in table 3.1.

3.2.1 Macroeconomic models

Macroeconomic models are particularly focused on the economy, and may or may not incorporate an endogenous representation of the energy sector and/or the climate. Because technological evolution is a phenomenon very difficult to model, most models incorporate exogenous assumptions about technological change (Grubb et al., 2002). In the study of energy technologies, particularly popular is the use of the autonomous energy efficiency index (AEEI), which describes changes in energy demand associated with a decline in energy intensity, even when energy prices are stable or falling (Webster et al., 2008). Among the macroeconomic models that use exogenous technological change stand **EPPA** (recursive-dynamic multi-regional general equilibrium model of the world economy, part of the MIT

[1] The number of model categories existing in the literature varies, depending on the specific approach taken by the author. For instance, Edenhofer et al. (2006) groups them in four categories: optimal growth models, energy system models, simulation models and general equilibrium models. In contrast, Després et al. (2015) grouped them in two categories: energy-economy-environment (E3) models and integrated assessment models (IAM).

Integrated Global Systems Model (IGSM) (Paltsev et al., 2005)), **GEM-E3**[2] (General Equilibrium Model for Energy-Economy-Environment interactions, an applied model for the European Union member states developed by Capros et al. (2010)), **GREEN** (GeneRal Equilibrium ENvironments model, a dynamic multi-region, multi-sector, general equilibrium model developed by Burniaux et al. (1992)) and **WorldScan** (a multi-sector, multi-region, global computable general equilibrium (CGE) model, developed by the CPB in The Netherlands (Bollen, 2015)). Also using exogenous technological change, but in the particular form of a backstop technology,[3] Nordhaus' **DICE** (Dynamic Integrated Climate-Economy Model (Nordhaus and Boyer, 2003)) and **RICE** (Regional Integrated model of Climate and the Economy (Nordhaus, 2008)) stand among the most prominent models in the field. In both cases, fossil fuels are assumed to be replaced by an unknown backstop technology, that at some point will be more competitive than the incumbent options, and consequently will dominate the market.

Among macroeconomic models that include endogenous technological change, stands **IMACLIM-R** (Computable General Equilibrium (CGE) model, developed at CIRED, France (Waisman et al., 2012)) and **WARM** (World Assessment of Resource Management, a general equilibrium econometric model of the European economy, developed by Carraro and Galeotti (1997)). In the former, electricity, transport, industry and residential sectors have endogenous technological change, while the macro-economy has exogenous learning based on labour productivity (Kriegler et al., 2015a). In the latter, capital stock is separated in environmentally friendly and polluting capital, and their respective growths depend endogenously on explanatory variables such as R&D spending, output demand, factor prices and the number of imported patents. A more disaggregated macroeconomic model with endogenous technological change is **E3MG/E3ME** (Energy-Environment-Economy Model at the Global level, developed by Cambridge Econometrics). E3MG/E3ME incorporates technological progress in gross investment enhanced by R&D expenditure. Technological progress is then used to calculate energy demand, which also depends on industrial output, consumers' income and trade and relative prices (Barker et al., 2012, 2006; Barker and Scrieciu, 2010; Cambridge Econometrics, 2016).

[2]In the standard setup of GEM-E3, technical change is defined exogenously. Alternatively, a semi-endogenous learning by doing option can be activated, in which labour productivity of a sector increases as a result of the increase in capacity (Kriegler et al., 2015a).

[3]In the DICE and RICE models of Nordhaus, the backstop technology is defined as "*a technology that can replace all fossil fuels. The backstop technology could be one that removes carbon from the atmosphere or an all-purpose environmentally benign zero-carbon energy technology. It might be solar power, or nuclear-based hydrogen, or some as-yet-undiscovered source. The backstop price is assumed to be initially high and to decline over time with carbon-saving technological change*" (Nordhaus, 2008, p.42).

3.2.2 Integrated assessment models

Integrated Assessment Models (or IAMs) of climate change are an amalgam of economics, energy and climate models, with the aim of combining physical and socio-economic information to examine the key interactions between the climate system and society (Mastrandrea, 2010). They have the advantage of including the feedbacks between the economy and the environment, but they have to face a trade-off between an elaborate representation of these two systems and the tractability of the model (Grubb et al., 2002). It implies that in general, these models give little attention to technology and technological change, and therefore technological transitions are mostly modelled using exogenous approaches. Some macroeconomics models are also considered IAMs because they have an environmental component (typically a GHG emissions module), such as **GREEN**, **DICE** and **RICE** (Grubb et al., 2002). Mastrandrea (2010) categorised IAMs in two large groups: *policy optimization* and *policy evaluation* models.

Policy optimisation IAMs

The policy optimisation IAMs are models designed to calculate optimal trajectories of future carbon emission reductions, and they are typically based on minimisation of costs or maximisation of utility or consumption. Due to the mathematical difficulty of finding the solution for optimality problems, the complexity included in this type of models tend to be limited. Examples are **DICE**, **RICE**, **GREEN**, **FUND** (Waldhoff et al., 2014), **MERGE** (Manne and Richels, 2005), **PAGE** (Hope, 2011) and **REMIND** (Luderer et al., 2015).

The model **WITCH** (World Induced Technical Change) deserves a particular mention, because even though it has a neoclassical optimal growth structure (top-down approach), it also includes a detailed energy module based on I/O tables (bottom-up approach). It is self-called an hybrid model (a combination of top-down and bottom-up approaches), and includes an endogenous technological change module, based on R&D investment as well as learning curves (Bosetti et al., 2007).

Policy evaluation IAMs

The policy evaluation IAMs are designed to model scenarios based on specific sets of policies. They do not necessarily use optimisation algorithms, and therefore they can make more complex and detailed representations of social and environmental phenomena. Examples of this type of models are **AIM** (Kainuma et al., 2003), **ETSAP-TIAM**[4] (Loulou and Labriet, 2008), **GCAM** (Zhou et al., 2014), **IGSM** (Sokolov et al., 2005) and **IMAGE** (Bouwman and Kram, 2006).

While many IAMs use autonomous energy efficiency indices (AEEI),[5] **IMAGE** uses a combination of AEEI and price-induced energy efficiency improvements, the latter depending on various endogenous variables such as energy prices, cost of improving energy efficiency, among others. As mentioned above, **WITCH** uses an hybrid approach. In the bottom up part of the model, it encompasses the learning-by-doing effects by bringing in experience curves for all energy technologies, while in the top down part it accounts for the accumulation of knowledge (via R&D), and for its effects on energy efficiency and the cost of advanced biofuels (Bosetti et al., 2007). In the case of **ETSAP-TIAM**, the model uses learning curves, combined with Mixed Integer Programming (MIP) technique for solving the optimisation, due to the non-linear, non-convex behaviour associated with the incorporation of learning-by-doing (Loulou and Labriet, 2008).

3.2.3 Energy sector models

Grubb et al. (2002) characterised energy sector models as those specifically oriented to analyse the energy sector and the emissions from energy production and consumption in detail. In contrast with their high resolution representation of the energy sector, the representation of the economy in this type of models is simple, typically using exogenous projections of economic activity. The asymmetry in the level of details in these models between the energy sector and the rest of the economy has the disadvantage of underestimating some important feedback effects, such as the demand response to changes in energy prices. However, energy sector models can analyse complex phenomena associated with the energy industry that cannot be studied with more simple representations of this sector, such as the energy modules existing in macroeconomic models or IAMs.[6]

[4] ETSAP-TIAM is an acronym for the Energy Technology Systems Analysis Programme (ETSAP), TIMES Integrated Assessment Model (TIAM). Is the "global incarnation" of the TIMES model, which in turns is the successor of the MARKAL model (Loulou and Labriet, 2008).

[5] In the case of climate-energy models, with simulations over several decades, there is evidence that model outputs are extremely sensitive to small variations in the AEEI. It poses the question of how to calibrate the model, or even if AEEI is an appropriate way of modelling technological change at all (Yates, 1995).

[6] Due to the increasing complexity of the models, many of them can be considered as part of several categories. For instance, ETSAP-TIAM, IMAGE and WITCH have a detail representation of the energy sector, so they could also be considered as energy sector models. Moreover, AIM and ETSAP-TIAM can work in a policy optimisation setting, so they could also be considered as policy optimisation IAMs.

Examples of energy sector models include **MARKAL**, **MESSAGE**, **DNE21+**, **POLES** and **FTT**. **MARKAL** is a dynamic linear programming model developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA). The model includes production, trading, transformation, distribution and end-uses of various energy forms. It computes supply-demand partial economic equilibrium on energy markets, while it minimises the net discounted total cost of the system. MARKAL is very detailed in terms of energy technologies, and includes endogenous learning, although an external technological path can be defined for different technologies. Even though MARKAL optimises over the entire modelling horizon, it can also be run in a time-stepped manner (myopically), in which case investment decisions are made at each period without knowledge of future events (Labriet and Loulou, 2005). As mentioned earlier, the TIMES model was developed as a successor of MARKAL, and incorporates some of its features, such as the detailed description of technologies, and the equilibrium properties. In additions, some of the specific features of TIMES include vintaged technologies, stochastic programming with risk aversion, a climate module, endogenous trade and endogenous technological change. The TIMES model is wider in scope that MARKAL, and therefore is considered as IAM, especially in the context of the ETSAP-TIAM implementation (Loulou and Labriet, 2008).

The Model for Energy Supply Strategy Alternatives and their General Environmental Impact (**MESSAGE**) developed at International Institute for Applied Systems Analysis (IIASA), is also based on optimisation algorithms. The evolution of the energy system is defined by scenarios developed through minimisation of total costs, under the constraints imposed on supply and demand structures, resource extraction profiles and international trade. The energy demand is exogenous to the model, which is the reason why it is often connected to macroeconomic models that can give demand feedback for increase in energy prices. Technological change is incorporated in MESSAGE using learning curves, so technological improvement rates are modelled as a function of accumulated experience (Messner and Schrattenholzer, 2000; Rao et al., 2006).

The model **DNE21+** is an optimisation model, with 77 regions and eight types of primary energy sources explicitly modeled (natural gas, oil, coal, biomass, hydro and geothermal, photovoltaics, wind, and nuclear). The model was developed at the Research Institute of Innovative Technology for the Earth (RITE), in Japan (Oda et al., 2009). DNE21+ minimises energy system costs between 2000 and 2050, under constraints such as global emissions path, electricity demand, or steel production. DNE21+ takes into account the vintages and lifetimes of the technologies, modelling the energy supply systems in a bottom-up fashion, while the end-use sectors are treated in a top-down fashion, using long-term price elasticities for four types of secondary energy carriers: solid fuel, liquid fuel, gaseous fuel, and electricity (Oda et al., 2007).

The **POLES** model is a world simulation model for the energy sector and industrial GHG emitting activities. It works in a year-by-year recursive simulation (up to 2100) and partial equilibrium framework, with endogenous international energy prices and lagged adjustments of supply and demand by 47 world regions (Kitous et al., 2010). POLES is a partial equilibrium simulation model, with special emphasis on the role of technology improvement via innovation and dissemination processes. It includes 32 power generation technologies, 14 hydrogen production technologies, six types of vehicle in the transport sector and three building types. The model simulates non-linear technology trajectories with path-dependency and lock-in/lock-out effects by combining permanent inter-technology competition and cumulative effects (Criqui et al., 2015).

The Price-Induced Market Equilibrium System model (**PRIMES**), developed by the National Technical University of Athens, simulates the European energy system. The model provides detailed projections of energy demand, supply, prices, emissions and investment, on a country-by-country basis and for Europe-wide. The distinctive feature of PRIMES is the combination of a behavioural agent-based modelling framework, following a microeconomic foundation, with a descriptive approach following macro interactions and dynamics. The model produces projections over the period from 2015 to 2050 in 5-years intervals, using data based on Eurostat statistics for the years 2000-2010 (E3MLab, 2013).

Not based on recursive dynamics or intertemporal optimisation algorithms, but using a dynamic set of coupled logistic differential equations, the Future Technology Transformation (**FTT**) family of models represents a different way of modelling the energy sector. FTT is a family of sectoral bottom up models of technology diffusion, developed at the Cambridge Centre for Climate Change Mitigation Research (4CMR) of the University of Cambridge. The current version has three components: **FTT:Power**, **FTT:Transport** and **FTT:Agriculture**.[7] Technological change is modelled in FTT through logistic transitions based on demographic theory, using replicator dynamics (Mercure, 2015; Saviotti and Mani, 1995). The FTT modeling suite, in combination with the macroeconomic model E3MG/E3ME (described earlier), are now part of a new IAM project. A first modelling exercise was published in 2014, using only the power sector branch of FTT (FTT:Power). A more comprehensive modelling exercise, that includes the whole FTT platform, is currently under development.[8]

[7]FTT:Agriculture is still under development.

[8]The modelling exercise, available in Mercure et al. (2014), included the models FTT:Power, E3MG, an emulator of the climate system (PLASIM-ENTSem (Holden et al., 2014)) and an emulator of the the carbon cycle (GENIEem (Holden et al., 2013)).

3.2.4 Power sector models

While some of the models presented above include representations of the energy and the power sectors, with different degrees of explicitness, there exist a vast group of models focused specifically in the power sector. While academics and utility companies began electricity modelling in the 1950's, the liberalisation of electricity markets and the rapid growth of renewables have led to the development of a number of proprietary off-the-shelf type and custom built electricity market models in the last 10 years (Foley et al., 2010). Electricity systems modelling is typically based on optimisation algorithms. Stochastic optimisation and dynamic programming are the two main approaches, while less used techniques including neural networks, genetic algorithms, game theory, fuzzy logic and analytic hierarchy process (Dreyfus, 2002; Foley et al., 2010; Kim and Ahu, 1993; Park et al., 1998; Spall, 2012; Zhu and Chow, 1997). Some of the most extensively used electricity sector models include **EMCAS**, **GTMax**, **PRIMES Power and Steam** and **WASP**.[9]

Designed with a very practical focus, typically in the context of utility operation or integrated resources planning, power sector models are usually much more detailed than energy sector models. The high level of resolution creates a natural limitation in terms of geographical scope, reason why most of these models are not global. One of the largest power sector models, in terms of geographical scope, is **PRIMES Power and Steam**, which provides projections of detailed electricity trading for the European markets, as a whole and per country. PRIMES Power and Steam is a detailed model of electricity and steam generation, trade and supply, part of the energy sector model PRIMES. The model incorporates in detail feed-in-tariff and other supporting schemes for renewables, as well as regulation, such as the large combustion plant directives and other European regulation/schemes. Non-linear cost-supply curves are part of the investment and operation optimisation, for all types of fuels, including fossil fuels, renewables, CCS and nuclear energy (E3MLab, 2013).

Models with a more limited geographical scope, but with a higher level of detail, include the Electricity Market Complex Adaptive Systems (**EMCAS**) and the Generation and Transmission Maximization (**GTMax**) models, developed at the Argonne National Laboratory. EMCAS uses an agent based modelling approach, to represent market participants who operate with their own objectives and apply their own decision rules. Agents include generation companies, demand aggregators, consumers, and independent system operators. They share a minimum amount of information, so decisions are taken in a framework of uncertainty and

[9]For a review of computer tools for analysing the integration of renewables into the energy system, which includes a large number of power sector models, please refer to Connolly et al. (2010).

incomplete information. Using a complex adaptive systems approach, agents in EMCAS are able to learn and adapt their strategies, on the basis of the success or failure of their previous actions. The EMCAS modelling system operates at six time scales, from hourly (real time) dispatch, up to 2-10 years ahead (considered mid to long term planning) (Veselka et al., 2002). The model is mostly used in USA, but has also been used in a number of studies in Europe, South America and Australasia (Foley et al., 2010).

The GTMax model simulates a detailed regional or national generation and transmission systems operation, maximising net revenues under physical and institutional constraints (Koritanov and Veselka, 2003). It was referenced by the World Bank, European Union, and U.S. Agency for International Development (USAID) as a preferred tool for use in regional interconnection, electricity market analysis, and generation and transmission planning studies (Foley et al., 2010). GTMax has detailed representation of hydropower, and is able to optimise the scheduling of hydro/thermal power plants, taking into consideration transmission constraints, ramp rates, system hydrology, scheduling of maintenance, bilateral contracts, and opportunities for trading on the spot market. Due to its detailed level of resolution (it determines optimal hourly power plant operations), the model is suited for short-term modelling, with hydro focus, and not for mid or long term planning (Wang, 2013).

Among the most prominent power sector models, stand the Wien Automatic System Planner **WASP**, a comprehensive planning tool for electric power system expansion analysis. It was developed in 1972 by the Tennessee Valley Authority (TVA) and the Oak Ridge National Laboratory (ORNL) in the USA, to meet the IAEA's needs to analyse the economic competitiveness of nuclear power (IAEA, 2001). Being one of the oldest and most widely used long term generation capacity expansion tool for integrated resources planning, WASP is recognised as a standard approach by the World Bank (Foley et al., 2010; Hertzmark, 2007). The main inputs of the model are demand forecast, existing and committed plants, and technical requirement such as loss of load probability (LOLP), energy not served (ENS) and reserve margin. Using these inputs, WASP is able to provide generation expansion planning for medium to long term, with a planning period of 15-30 years. The model has a wide variety of plant types and technologies, and includes economic uncertainties such as fuel price and investment costs (Foley et al., 2010; IAEA, 2001).

Table 3.2 summarises the list of models presented above. Most models, particularly integrated models, are a simplified, stylised, numerical representation of enormously complex physical and social systems. Modelling approaches can be very different, and these differences can have important implications for the variations among scenarios that emerge from different models. In order to address these differences, and incorporate them as part of the uncertainty analysis, the Intergovernmental Panel on Climate Change (IPCC) uses large ensembles of scenarios from different models, different studies, and different versions of individual models. For the Working Group III of the Fifth Assessment Report of the IPCC, almost 1,200 scenarios from more than 300 different integrated models were generated (IPCC, 2014b). Table 3.1 shows a selected list with some of the most prominent cross-model comparison exercises in the area of energy and climate change over the past few years.

Project	# Models	Source
RoSE - Roadmaps towards Sustainable Energy Futures.	5	(Kriegler et al., 2016)
AMPERE - Assessment of Climate Change Mitigation Pathways and Evaluation of the Robustness of Mitigation Cost Estimates	11	(Kriegler et al., 2015b)
EMF27 - Stanford Energy Modeling Forum Study 27	18	(Kriegler et al., 2014)
LIMITS - Low Climate Impact Scenarios and the Implications of Required Tight Emission Control Strategies	7	(Kriegler et al., 2013)
AME - Asian Modeling Exercise	23	(Calvin et al., 2012)

Table 3.1 Selected list with some of the most prominent cross-model comparison exercises in the area of energy and climate change over the past few years. Based on Bibas (2015, p. 68) and IPCC (2014b, p. 421).

The models presented in table 3.2 are classified according to their representation of **technological change**, and their **intertemporal solution methodology**. Models with *endogenous technological change* are those on which the technological development of the system is influenced over time by energy market conditions and expectations. Therefore, models with *No endogenous technological change* (or *exogenous technological change*) are those on which technological development is viewed either as an autonomous process, or as a product primarily of government research and development.[10]

[10]This classification follows the definition of endogenous technological change from Grubb et al. (2002).

Model Name	Model Type	Intertemporal Solution Method.	Endogenous Tech. Change	Source
AIM	IAM	Recursive dynamic	No	(Kainuma et al., 2003)
DNE21+	Energy	Intertemporal optimisation	No	(Sano et al., 2011)
DICE/RICE	Macro/IAM	Intertemporal optimisation	No	(Nordhaus, 2008)
E3MG/E3ME	Macro	Econometric / dynamic	Yes	(Cambridge Econometrics, 2016)
EMCAS	Power	Agent Based Modelling	No	(Veselka et al., 2002)
EPPA	Macro	Recursive dynamic	No	(Paltsev et al., 2005)
ETSAP-TIAM	IAM	Intertemporal optimisation	Yes	(Loulou and Labriet, 2008)
FTT	Energy	Dynamic dif. equations	Yes	(Mercure, 2015)
GCAM	IAM	Recursive dynamic	No	(Zhou et al., 2014)
GEM-E3	Macro	Recursive dynamic	Yes	(Capros et al., 2010)
GREEN	Macro/IAM	Recursive dynamic	No	(Burniaux et al., 1992)
GTMax	Power	Intertemporal optimisation	No	(Koritanov and Veselka, 2003)
IGSM	IAM	Recursive dynamic	No	(Sokolov et al., 2005)
IMACLIM-R	Macro	Recursive dynamic	Yes	(Waisman et al., 2012)
IMAGE	IAM	Recursive dynamic	Yes	(Bouwman and Kram, 2006)
MARKAL	Energy	Intertemporal optimisation	No	(Labriet and Loulou, 2005)
MERGE	IAM	Intertemporal optimisation	Yes	(Manne and Richels, 2005)
MESSAGE	Energy	Intertemporal optimisation	Yes	(Messner and Schrattenholzer, 2000)
PAGE09	IAM	Stochastic simulation	Yes	(Hope, 2011)
POLES	Energy	Recursive dynamic	Yes	(Criqui et al., 2015)
PRIMES	Energy	Eq. problems/const. EPEC	Yes	(E3MLab, 2013)
PRIMES P&S	Power	Eq. problems/const. EPEC	Yes	(E3MLab, 2013)
ReMIND	IAM	Intertemporal optimisation	Yes	(Luderer et al., 2015)
WARM	Macro	Recursive dynamic	Yes	(Carraro and Galeotti, 1997)
WASP	Power	Intertemporal optimisation	No	(IAEA, 2001)
WITCH	IAM/Energy	Intertemporal optimisation	Yes	(Bosetti et al., 2007)
WorldScan	Macro	Recursive dynamic	Yes	(Bollen, 2015)

Table 3.2 Non-exhaustive list of models, following the categorisation made in section 3.2, which in turn is based on Grubb et al. (2002). Information based on the listed sources, as well as on Kriegler et al. (2015a) and Bibas (2015).

In the case of the intertemporal solution methodology, the models are classified as *intertemporal optimisation* models (agents have complete foresight), *recursive dynamic* models (agents have myopic expectations), *equilibrium problem with equilibrium constraints* or *Eq. problems/const. EPEC* (each agent solves an optimisation problem with equilibrium constraints), *agent based modelling* (agents have their own objectives and apply their own decision rules), *stochastic simulation* (simple equations run using stochastic samples from triangular probability distributions), *econometric/dynamic* (behavioural equations solved using regressions) and *dynamic dif. equations* (dynamic system of first order differential equations).

Some of the key gaps in the modelling literature highlighted by the cross-model comparison exercises presented in table 3.1, that are addressed in this dissertation, include:

- Weak near-term decarbonisation actions to 2030 lead to aggressive energy transformation requirements after 2030, causing significant transitional economic impacts (Kriegler et al., 2016; Luderer et al., 2016). This result casts doubt on the political feasibility of keeping the 2°C target within reach, unless mitigation efforts are significantly strengthen before 2030 (Luderer et al., 2016). These findings are relevant for the review of the INDCs proposed under the Paris Agreement (Kriegler et al., 2016), a subject discussed for the case of Brazil in chapter 8.

- Capital stock inertia hinders the accomplishment of stringent emission reductions in the power sector (Kriegler et al., 2015b). Therefore, a better understanding of the mechanism that can break this inertia is paramount. This phenomenon is discussed in this dissertation in chapters 7 and 8.

- Deployment levels for wind and solar power vary considerably across models, due to differences in assumptions about costs and resource potentials, and the representation of integration challenges related to fluctuating supply (Kriegler et al., 2014; Luderer et al., 2013). In this dissertation, the effect of uncertainty in the potential of wind and solar energy is studied in chapter 7. The impact of the capacity of the grid to manage variable electricity on decarbonisation is analysed in chapter 9.

3.3 Natural resources

The performance of decarbonisation policies and the corresponding uptake of low carbon technologies, are constrained by limitations imposed by the natural world. For instance, if a

1 GW coal power station was to be replaced by wind energy, it would require around 700 to 1,100 turbines, covering an area of between 500 to 1,500 km^2 (Mercure and Salas, 2013a). If solar power was used instead, this would require an area of between 50 and 500 km^2 (ibid.), depending on the latitude, and in the case of biomass this would require a piece of land in the order of 5,000 km^2 (ibid.). Depending on the context, such limitations may create a fundamental difference, especially for large scale energy policies. Therefore, accounting for these types of constraints can be as important as accounting for energy costs differences or the decarbonisation potential. In this context, assessment of energy resources and their cost are a relevant tool for modellers and policy makers. Many reviews and studies have been published that summarise what was known of global energy potentials at time of their publication. Among the most prominent studies published recently, stand:

- Energy Study 2015. Reserves, Resources and Availability of Energy Resources, by the Federal Institute for Geosciences and Natural Resources (BGR, 2015).
- World Energy Resources: 2013 and 2010 Surveys, by the World Energy Council (WEC, 2010, 2013).
- Global Energy Assessment, by IIASA (GEA, 2012).
- Special Report on Renewable Energy Sources and Climate Change Mitigation, by the IPCC (IPCC, 2011).
- The Energy Report, 100% Renewable Energy by 2050, by WWF (WWF et al., 2011).
- Role and Potential of Renewable Energy and Energy Efficiency for Global Energy Supply, by the German Federal Environment Agency (Krewitt et al., 2009).

These studies gather valuable information about the amount of stock resources available (such as fossil fuels), the potential for deployment of renewable energies (typically in the form of technical potentials), and current trends of energy use. However, without detracting from their valuable contribution, the aforementioned studies provide very limited information (if any) about the economic structure of the energy resources available. Natural resource limits without individual cost information, are of limited use for energy systems modelling and policy-making. Among the assessments that include cost representations (typically in the form of cost supply curves[11]), stand the work on fossil fuels from Rogner at IIASA, and McGlade and Ekins at UCL. The work of Rogner is primarily summarised in an influential article in which reserves and resources of conventional oil, natural gas and coal are presented

[11] In this context, a cost supply curve corresponds to the cost function of a particular type of energy resource, given the amount of it that has been already exploited. See section 6.2.2 for more details.

(Rogner, 1997). The work from McGlade and Ekins has been recently published in *Nature*, and includes cost supply curves for oil, gas and coal (McGlade and Ekins, 2015).[12] In the area of renewable energies, the PBL Netherlands Environmental Assessment Agency provided a series of publications with cost supply curves for wind, solar PV, biomass and biofuel energy sources, estimated using the IMAGE model (de Vries et al., 2007; Hoogwijk, 2004; Hoogwijk et al., 2009; van Vuuren et al., 2009). Also using the IMAGE model, a more recent study provides long-term cost supply curves for offshore wind, and explores its regional and global potential to contribute to global electricity production (Gernaat et al., 2014). For onshore wind, Zhou et al. (2012) developed an updated global estimate of the potential using wind speed data, along with updated wind turbine technology performance, land suitability factors, cost assumptions, and explicit consideration of transmission distance in the calculation of transmission costs. In the area of biomass, Koornneef et al. (2012) analysed the global technical and economic potential for combining biomass with carbon dioxide capture, transport and storage up to 2050, while Yemshanov et al. (2014) estimated the technical potential and financial costs of post-harvest forest residue biomass supply in Canada.

From the aforementioned studies, those that include global data with regional disaggregation (such as the literature from PBL), unfortunately are becoming increasingly outdated, especially in terms of the costs associated with renewable energies. And from the other studies, most of them do not provide geographical disaggregation or they are only focused on a particular world region. Based on these considerations, Dr. Mercure and I developed a methodology for, and produced an updated assessment of global economic energy potentials (with a regional disaggregation) for all major natural energy resources for the power sector (Mercure and Salas, 2012).[13] The study reflects the latest knowledge about the potential of all the energy resources analysed (seventeen), and it includes a theoretical model of resource distribution according to observed statistical trends. This assessment was incorporated in FTT:Power, in the form of a database of energy resources, and is used in this work to analyse the impact of energy resources availability in the performance of energy policy. The main characteristics of the database are presented in chapter 6, while the scenarios of energy resources are analysed in chapters 7 and 8.

[12] McGlade and Ekins (2015) cited the work of Rogner, which has been partially replicated in (GEA, 2012).

[13] Mercure and Salas (2012) was submitted on early 2012, consequently, the studies published in 2012 or after were not included.

3.4 Energy policy, technological change and uncertainty

The effective decarbonisation of the energy sector, requires policies working in coordination, particularly in the areas of carbon pricing, energy efficiency and technology deployment (Hood, 2011). Unfortunately, even when the appropriate policies are chosen, their actual implementation does not always make them mutually reinforcing. They can be redundant, or even work against one another. Therefore, it is very important to understand both the effect that each of these policies has on the objective sector (in this case, power sector), as well as the effect of these policies combined.

Several of the models mentioned in section 3.2 identify learning-by-doing as an important driver of technological change. However, it is not clear that market incentives are the most effective way of stimulating learning, particularly for some of the less advanced technologies. For instance, Kalkuhl et al. (2012) shows that small market imperfections may trigger a several decades lasting dominance of an incumbent energy technology over a dynamically more efficient competitor, given that the technologies are very good substitutes. Therefore, to stimulate the right amount of investment on the appropriate technologies, a far wider range of policies may be required (IEA and OECD, 2012a, p. 119 & 121). Consequently, an appropriate decarbonisation analysis of the power sector requires the use of modelling tools that include both, and appropriate representation of technological change and a variety of policy mechanisms to stimulate low carbon investment, combining market-based and non-market-based policy instruments.

Uncertainty in regulatory policies remains as a relevant obstacle to boost private financing for innovation (Bistline, 2014; Shahnazari et al., 2014), and failure to set up decarbonisation policies is delaying investment in low carbon technologies (Fabrizio, 2012). The importance of including endogenous technological change and uncertainty in energy models has been noted by several authors, and important progress in the area has been done (Grubb et al., 2006; Popp et al., 2010). Among the pioneers in the modelling of technological change under uncertainty is the IIASA group. Gritsevskyi and Nakicenovic (2000) used the linear programming optimisation model MESSAGE to stochastically generate 520 alternative technological scenarios, assuming increasing returns to scale for the costs of new technologies, induced learning on cluster technologies, and uncertain costs based on a log-normal distribution function. They concluded that lock-in effects and increasing returns to adoption, result in near term investment decisions under uncertainty deciding the direction of long-term development of the energy system. Also based on an optimisation approach, Grubler et al. (2002) introduced a multi-region multi-actor model of uncertain increasing returns on technological innovations. The main difference with respect to the previous approach is that, instead of finding the optimum from the social planner perspective (total cost minimisation), this model also finds the optimal solution from the individual agents perspective (independent actors optimise their own part of the system, and interact between each other through trade flows).

Based on the work done in IIASA, Ma (2010) also discussed the effect of uncertain technological change using an intertemporal optimisation approach, but introducing a new risk-constrained optimisation algorithm. The new methodology is applied to a hypothetical energy system of three technologies (namely existing, incremental, and revolutionary), and the computational benefits of the new algorithm with respect to the approach used by Gritsevskyi and Nakicenovic are discussed.

Also using an optimisation approach, Rout et al. (2009) studied the effect of uncertainty in the learning rates of energy technologies, using the TIMES-G5 model (based on the MARKAL framework). In this case, learning is divided into two components: global learning (in which all regions participate in a common learning process) and regional learning. The large uncertainty in the progress ratio (PR[14]) of technologies at their early stage of development, is addressed in this case using the floor-cost approach. In this method, same technologies witness the same specific cost at the initial and final stages (floor cost) of development, which are calculated exogenously. The authors concluded that uncertainty in the learning rates has a big impact on the diffusion of energy technologies, and therefore they advocate for policy support for some particularly high potential technologies (such as IGCC, CCGT, wind onshore and geothermal energy).[15]

Using a stochastic version of the WITCH model, Bosetti and Tavoni (2009) analysed the optimal investments in a backstop technology when dealing with a stringent climate target and with uncertain effectiveness of R&D. They concluded that uncertainty in the cost of the backstop technology leads to a higher optimal investment in R&D, with lower policy costs. Also centred on investment in R&D under uncertainty, Baker and Adu-Bonnah (2008) analysed how the socially optimal technology R&D investment depend on both the risk-profile of the R&D program and the uncertain climate damages. Their analysis (theoretical model) and their simulations were based on a variation of the DICE model of Nordhaus. In the same area of investment in R&D under uncertainty, Blanford (2009) proposed an analytic framework for determining optimal R&D investment allocation and presented some

[14] $PR = 1 - LR = 2^{-b}$, being b the learning elasticity of a particular technology.

[15] Using a similar approach to Rout et al. (2009), chapter 9 of this dissertation presents decarbonisation scenarios for the power sector under uncertain learning rate coefficients. Following a dynamic instead of an optimisation approach, and assuming global spillovers, scenarios of extreme learning rate coefficients for fossil fuels and renewables are analysed in chapter 9.

numerical results to demonstrate the implementation of the methodology. He used the MERGE model under three policy scenarios: business as usual, 450 ppmv and 550 ppmv,[16] assuming that market participants know the policies constraint with certainty, while R&D decision-makers (who act at the beginning of the time horizon) are uncertain as to which scenario will result. While the numerical results may be taken as speculative, that study offered insights into the nature of an optimal technology strategy for addressing climate change, given the uncertainty surrounding the real impact of investing in R&D.

One of the major challenges that policy makers face, particularly in the area of climate change, is knowing how to address the uncertainties associated with these long term problems, using the currently available policy instruments (Popp et al., 2010). While in "pure" environment issues, uncertainty is about the behavior of natural systems, in technological environments, uncertainty is exacerbated by the interaction of human and social systems (ibid.). Indeed, Mercure et al. (2016) identified the interaction between human and environmental systems as one of the four major areas where uncertainty contributes to climate policy indecisiveness.[17] Consequently, an appropriate treatment of uncertainty, to study future scenarios of technological transitions, is paramount to understand the role of the different policy instruments in the decarbonisation of the power sector.

3.5 Use of FTT:Power in this dissertation

The model selected for the creation and analysis of endogenous emission scenarios of the power sector in this dissertation, is **FTT:Power**. The choice of model is closely connected with its main characteristics, which include an explicit representation of uncertainty, a descriptive (in contrast to a normative) approach, inclusion of endogenous technological change, availability of policies beyond carbon pricing, and an explicit representation of natural resources.

3.5.1 Uncertainty

To effectively decarbonise the global power sector, it is necessary to understand how technology diffusion works. Energy technology transitions depend on many uncertain factors,

[16] The acronym *ppmv* stands for *parts per million volume*, and it corresponds to a unit of gas concentration (in this case, GHG concentration in the atmosphere).

[17] The other three areas are the dynamics of technology adoption and diffusion, macroeconomic impacts of low-carbon policies and policy implementation and effectiveness (Mercure et al., 2016).

such as energy policy, investment and resource availability. The knowledge about how these factors interact, and the impacts on the technological evolution of the power sector, are the key to creating successful policies, to move the economy toward a cleaner, low carbon regime. Because uncertainty is at the core of the analysis, the model selected for this dissertation requires an explicit representation of uncertainty. In this context, FTT:Power was especially amended to include:

- variable energy policy stringency (defined by a *decarbonisation intensity* range, see chapter 5).
- distributions of energy resources and costs (in the form of cost-supply curves), which are the basis for the creation of scenarios of energy resources availability (see chapters 6, 7 and 8).
- ranges of learning rates, which are used for creating scenarios of extreme learning coefficients for fossil fuels and renewables (see chapter 9).
- a flexible model of investment decisions, that includes criteria with explicit representation of uncertainty (such as investment under policy uncertainty or under environmental uncertainty, see chapters 10 and 11).

3.5.2 Descriptive approach

Most of the model presented in section 3.2 use optimisation algorithms to simulate the energy sector. In that context, endogenous policies obtain the maximum environmental benefits, using the minimum amount of resources. In reality, however, policy implementation works differently. The process of low-carbon technology diffusion can be inhibited, despite its environmental and economic advantages, by issues such as market failures, technological lock-in, path dependence and inertia (Arthur, 1989).

Without detracting from their valuable contribution, some of the main shortcomings associated to optimisation-based approaches include:

- The underlying assumption of a social planner, which is able to minimise total costs and coordinate society (Mercure et al., 2016).
- The use of representative agents with rational expectations, which are able to carry out exhaustive rankings of their preferences over all possible alternatives, and take

optimum decisions that either maximise their utility or minimise their cost (Kirman, 1992).

- The neglect of phenomena such as increasing returns, path dependence and non-convex preferences, due to the underlying mathematical difficulties of finding optimum solutions under such conditions (Mercure et al., 2016).

Cost-optimisation technology models, in normative mode, are a powerful tool for finding detailed, lowest-cost future technology pathways that reach particular objectives (Mercure et al., 2014). However, in this dissertation I am not looking for optimal pathways, but for a descriptive view of the power sector. The goal is not to find the least-cost decarbonisation pathways, but to understand how technology transitions are actually affected by energy policy, resources availability, and other uncertain drivers, and how uncertain incentives may affect the behaviour of heterogeneous groups of investors.

In this context, FTT:Power represents the right alternative for studying future scenarios of the power sector, at the light of the research questions stated in section 1.2. Instead of assuming rational expectations, decisions in FTT:Power are taken under *bounded rationality* (Mercure, 2015; Simon, 1984)[18]. The investment process in FTT:Power aggregates a diverse set of preferences, without assumptions regarding optimality or coordination between agents. This is a critical difference with respect to optimisation models, which assume a high level of coordination, typically based on access to perfect information and foresight (Mercure et al., 2016). Moreover, phenomena such as path dependence, positive feedbacks and increasing returns are embraced as part of the system dynamics. The use of a dynamic simulation instead of an optimisation algorithm facilitates the representation of complexity, given the lack of constraints in terms of convexity of the domain space. Consequently, through the use of FTT:Power, this thesis presents scenarios of the power sector using non-optimal dynamics, without assuming perfect market conditions, and accounting for the use (and potential depletion) of natural resources.

3.5.3 Endogenous technological change

The complexities associated with modelling the process of technological change, added to the difficulties of measuring learning rates, drives part of the modelling community to avoid the implementation of endogenous technological change models. However, such approach

[18] In FTT:Power, agents have diverse preferences and face limited information. See section 4.6 for more details on technological choices within the FTT:Power framework.

is in contradiction with a vast amount of evidence that shows the importance of learning as driver of economic growth and technological transitions (Grossman and Helpman, 1994; Grubb et al., 2006; IEA, 2000; Kahouli-Brahmi, 2009; Kohler et al., 2006; McDonald and Schrattenholzer, 2001). Given the importance of technological change in the decarbonisation of the power sector, this dissertation analyses the impact that uncertainty in the values of the learning rates (due to over or underestimation) may have in technology uptake. For that reason, an endogenous representation of technological change is required, such as the one implemented within FTT:Power.

3.5.4 Policies beyond carbon pricing

In 2015, an estimated 145 countries had renewable energy support policies in place, being Feed-in-Tariffs (FiT) and Renewable Portfolio Standards (RPS) the most commonly used worldwide (REN21, 2015). There is evidence of the significant impact that FiTs have on renewable energy deployment, helping bring the countries that have implemented them successfully to the forefront of the global renewable energy industry (Couture et al., 2010). It is reasonable to expect, then, that energy sector models incorporate a variety of policy mechanism to describe this phenomenon, and not rely on the traditional approach of using carbon pricing as the only solution to spur low-carbon investment.

In the case of FTT:Power, the model includes an explicit representation of a variety of policy instruments. Carbon pricing, subsidies, feed-in-tariffs, direct regulation of new installed capacity, energy demand reductions and any possible combination between them can be defined in detail on every region of the model. For this reason, FTT:Power was selected in this dissertation to study the effect of the different policies in the decarbonisation of the power sector (in chapter 5), and the efficiency of the market based policy instruments under uncertain scenarios of energy resources (in chapters 7 and 8).

3.5.5 Natural resources constraints

Realistic scenarios of the power sector are constrained by physical limits imposed by nature, such as maximum resources productivity or extraction limitations. Under extreme decarbonisation policies, these limitations become ever more important, if unfeasible or unrealistic scenarios are to be avoided. In this context, a database of energy resources was implemented within FTT:Power, with the intention of providing a tool to study the diffusion of energy technologies, addressing the corresponding feedbacks with the natural world in terms of primary energy use and depletion. This is another reason why FTT:Power was selected for the creation and analysis of the power sector scenarios in this dissertation.

3.6 Conclusion

The literature review presented in this chapter, shows some of the methods and approaches used by energy, climate and economic system models, and highlights key factors to be addressed by the power sector scenarios analysed in this thesis. The model chosen for the representation of the power sector is FTT:Power, for the following reasons:

- It uses a descriptive (in contrast to a normative) representation of the power sector, which is required to answer the research questions stated in chapter 1.
- It has an endogenous representation of the technology diffusion process.
- It includes an explicit treatment of uncertainty.
- It includes market-based and non-market based policy instruments.
- It has an updated database with information on natural resources limits and costs.

The decarbonisation analysis presented in this thesis addresses some of the key issues found in the literature, which include:

- The impact of energy resource availability in the performance of energy policy (see section 3.3).
- The differentiated effect of each policy instrument (and all possible combinations) in the decarbonisation of the power sector (see section 3.4).
- The impact of the different policy mechanisms on technology diffusion, and how they can help to break the capital stock inertia of the power sector (see sections 3.2 and 3.4).
- The importance of near-term stringent decarbonisation policies to meet the targets of the Paris Agreement, and the implications for INDCs (see section 3.2).
- How resources availability and the capacity of the grid to manage variable electricity can affect the deployment of renewable energies (see section 3.2).

The next chapter provides a more detailed description of FTT:Power.

Chapter 4

The FTT:Power Model

4.1 Chapter Summary

The modelling platform used throughout this thesis to analyse the global electricity sector, is introduced in this chapter: the **Future Technology Transformation Model of the Power Sector** (**FTT:Power**). The main components of the model are introduced here, based on their original implementation. In the next chapters, different parts of the model are presented in detail (and sometimes modified), to study the effect of uncertainty on specific areas of the power sector. A full description of the original FTT:Power model can be found in Mercure (2012, 2015).

This chapter starts with an introduction to the FTT family of models, in section 4.2. Section 4.3 introduces FTT:Power, its main components and general structure. The model of natural resources use and depletion (NER), part of FTT:Power, is briefly presented in section 4.4. The endogenous technological change approach used in the model, based on learning curves, is introduced in section 4.5. Section 4.6 presents the market competition framework, where technologies compete against each other for market shares. Technologies are compared pairwise using the Levelised Cost of Electricity (LCOE) as the main investment decision criterion. The LCOE approach is explained in detail in section 4.6.1. Section 4.6.2 introduces the stability constraints of FTT:Power, which are a representation of the capabilities of the system to balance the amount of baseload, flexible and variable electricity generation technologies. Finally, section 4.7 concludes with a list of the main components of the model that are analysed (and sometimes modified) in the following chapters, to study how uncertainty on specific areas can influence future decarbonisation scenarios of the power sector.

4.2 Introduction to the FTT Family

The Future Technology Transformation (FTT) modelling suite is a family of sectoral bottom-up models of technology diffusion, developed at the Cambridge Centre for Climate Change Mitigation Research (4CMR), by Dr. Jean Francois Mercure (Mercure, 2012, 2015). The current version has three components, each of them representing a part of the global energy sector:[1]

- **FTT:Power**, developed by Dr. Jean Francois Mercure and Pablo Salas
- **FTT:Transport**, developed by Dr. Jean Francois Mercure and Aileen Lam
- **FTT:Agriculture**, developed by Dr. Jean Francois Mercure and Dr. Siyuan He

The FTT modelling suite combines elements from different theoretical backgrounds, including discrete choice theory(Ben-Akiva and Lerman, 1985; McFadden, 1973), mathematical ecology (Kot, 2001) and evolutionary economics (Freeman and Perez, 1988; Rogers, 1962), to represent the dynamics of technology diffusion from a non-equilibrium perspective (Mercure, 2012). At the core of FTT is the assumption of *bounded rationality*, with agents (investors) facing limited information and having diverse preferences. In reality, when people have to choose between technologies (for example mobile phones, cars or power stations), their decisions are based on many different factors. These factors include the technical characteristics of the technologies involved (especially cost), but also include their own personal preferences, their previous experience with similar technologies and their level of risk aversion, just to name a few elements influencing their decisions. From an aggregate perspective, diversity in the preference of agents translates into logistic patterns of technology diffusion, a phenomenon extensively studied in the literature (Grubler et al., 1999; Marchetti and Nakicenovic, 1978; Rogers, 1962). Logistic transitions are modelled in FTT through Lotka-Volterra system of equations, a methodology that is presented in section 4.6, and analysed in more detail in chapter 10.

[1]At the time of writing this dissertation, FTT:Power was the only FTT model completely finished. FTT:Transport was in an advanced stage of development, while FTT:Agriculture was in an early stage of development.

The FTT:Power model is used in this dissertation to analyse technology diffusion scenarios of the power sector. The main characteristics of the model are presented throughout this chapter. The information presented here is complemented with a compilation of tables, equations and mathematical derivations in the Appendix section A. For a thorough analysis of the model and its different submodules, please refer to Mercure (2012, 2015); Mercure et al. (2014); Mercure and Salas (2012, 2013b).

4.3 Introduction to FTT:Power

FTT:Power is a *'dynamic representation of global power systems based on market competition, induced technological change and natural resource use and depletion. The model uses a dynamic coupled set of logistic differential equations, which offer an appropriate treatment of the times and structure of change involved in sectoral technology transformations'* (Mercure, 2012). Technology diffusion in FTT:Power is fueled by investment, which can go to any of the 24 power generation technologies represented in the model.

Figure 4.1 shows the main components of the model. Simulations in FTT:Power are based on exogenous scenarios of energy policy and electricity demand. Energy policy has a direct impact on the cost of producing electricity (LCOE), or in the amount of new installed capacity, while the demand for electricy determines the amount of resources required, given a specific electricity matrix. Policies are implemented in FTT:Power using the following approach:

- **Carbon price** is defined independently in each region, as an arbitrary amount of euros per ton of carbon. Its impact in the levelised cost of electricity of a specific technology, is calculated as the net present value of operational costs, estimated at each time step as the amount of fuel used times the carbon intensity of the fuel (see equation 4.7 below).
- **Subsidies** are defined independently for each technology and region. They are characterised as a percentage of the net present value of the investment cost, payed by the regulator to the investors.
- **Feed-in-tariffs** are defined independently for each technology and region. Feed-in-tariffs are granted to investors and are ascertained based on the difference between the cost of electricity of a specific technology, and the retail price of electricity, times a premium.
- **Direct regulation** is defined independently for each technology and region, as an exogenous cap in installed capacity (which can be zero).

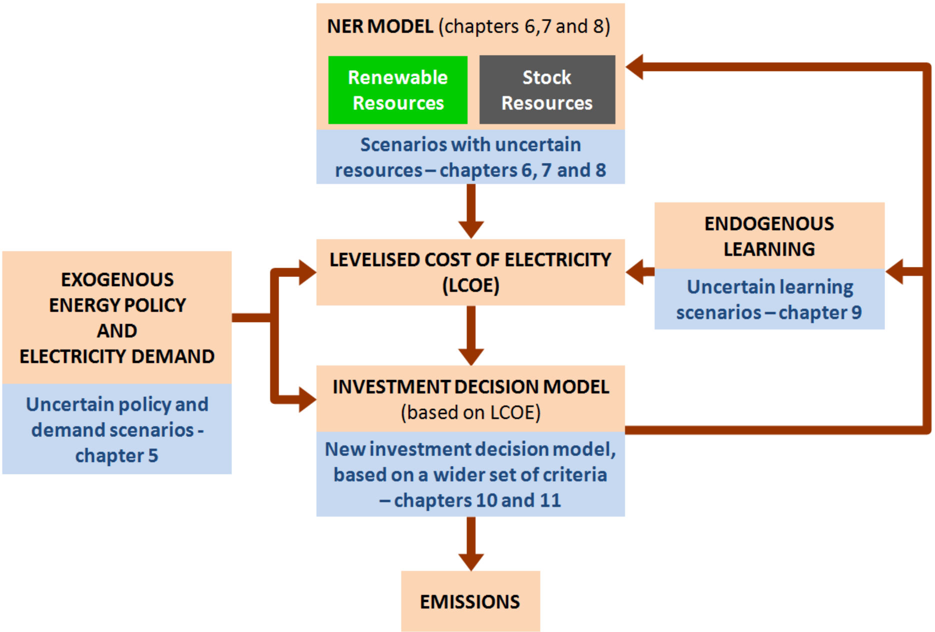

Figure 4.1 Diagram showing the main components of FTT:Power. In beige, the original components of the model. In blue, the main modifications, made in the context of this dissertation. Exogenous energy policy and electricity demand scenarios (left) are the starting point for producing scenarios of the power sector. The Natural Energy Resources model(NER, top), provides the information required to calculate the levelised cost of electricity (LCOE), based on the policy scenarios, the electricity demand and the availability and cost of the required resources. Using the LCOE information, together with the exogenous policy scenario and electricity demand, investment is allocated on each technology. Investment decisions fuel technology adoption, with a direct impact in carbon intensity and emissions. The technologies that are favoured by investors increase their market share, and benefit from economies of scale, through learning-by-doing.

- **Electricity demand** is defined independently in each region, in terms of an exogenous amount of MWh/yr.

The exogenous definition of energy policy and electricity demand, represent the starting point for producing scenarios of the power sector. Given the amount of primary resources required to meet the demand, the Natural Energy Resources module (top of figure 4.1) provides the corresponding energy carrier costs. The process of use and depletion of natural energy resources, modelled through the NER, is introduced in section 4.4, and explained in detail in chapter 6. Scenarios of uncertain energy resources are presented in chapters 7 and 8.

The policy instruments in FTT:Power are implemented independently, using a modular approach. In this way, complex combination of policy packages can be analysed. Chapter 5 includes a detailed explanation of how the policy instruments are implemented in the

FTT:Power, and which energy policy and electricity demand scenarios are analysed in this dissertation. The use of an explicit representation of a variety of policy instruments is important, because it allows to study in detail the environmental and economic performance of all the possible policy combinations (see chapters 7 and 8).

The levelised cost of electricity is calculated combining the energy carrier costs, with the exogenous energy policies. This results in a portfolio of options presented to investors, based on exogenous energy policies, electricity demand, availability of energy resources and their cost, all summarised in a single indicator: the LCOE. Technologies that are favoured by investors increase their market share, and benefit from economies of scale, which in turn directly impacts on the cost of electricity. This phenomenon is called *learning-by-doing*, and is incorporated in FTT:Power through learning curves. The effect of learning in FTT:Power scenarios is presented in section 4.5, and explained in detail in chapter 9.

Investment allocation in FTT:Power has a direct impact on new installed capacity, and consequently on the carbon intensity of the grid and CO_2 emissions. Investment decisions are based on the LCOE, as the main parameter to compare the different technologies. A new model is proposed in chapters 10 and 11, to incorporate other drivers of investment, beyond the LCOE.

The next sections briefly introduce the main components of FTT:Power: the Natural Energy Resources (NER) module, technological change and market competition.

4.4 Natural Energy Resources (NER) module

Realistic energy scenarios of the future can only be designed in a way that does not exceed the natural sources and flows of energy available in all regions of the world. Therefore, assessments of the potential of natural energy resources, including their cost structures, are essential to energy planning and policy. Unfortunately, most of the literature regarding energy potentials does not provide information about the underlying costs structures, and therefore, its practical relevance for modelling purposes is limited. Aiming to fill that gap, Dr. Mercure and I produced a thorough assessment of global economic potentials[2] for all major natural energy resources (Mercure and Salas, 2012). As part of this assessment, a database of energy

[2]Economic potential is defined in this work as the quantity of energy stock or flow estimated to exist or stem from a particular natural process, recoverable at exploitation costs that are competitive compared to all other alternative ways of producing the same energy carrier (Mercure and Salas, 2012). See section 6.2.1 for more details.

resources was built, for 17 types of energy resources in 190 countries. Economic potentials for all the major energy resources were calculated and stored in the form of cost supply curves. Figure 4.2 shows, as example, the global cost supply curve of hydroelectricity.

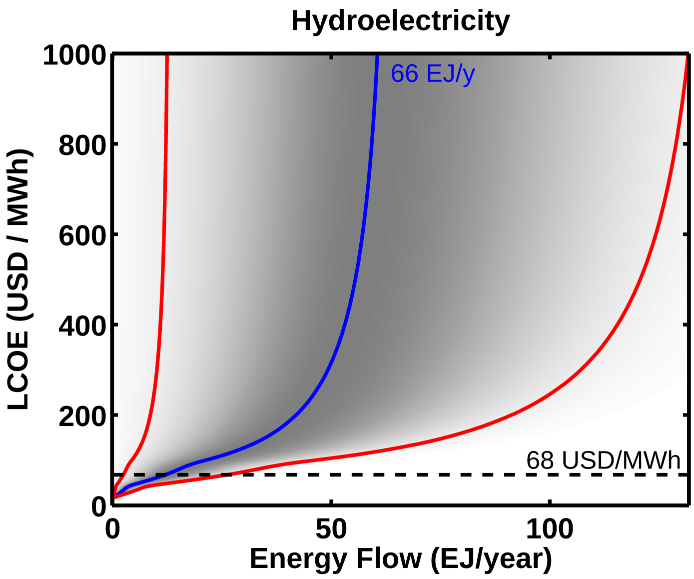

Figure 4.2 Global aggregation of the regional cost supply curves for hydroelectricity used in FTT:Power. In blue, the most likely cost supply curve, while in red the lower and upper limits of the confidence interval (96% of confidence). The red curves are based on pessimistic (lower limit) and optimistic (upper limit) assumptions about the availability of hydroelectric resources. The abscissa is the energy flow (annual electricity generation), while the ordinate is the Levelised Cost of Electricity. The dashed line represents today's (2010) LCOE, given the current use of hydroelectricity. The theoretical framework behind the cost supply curves is explained in detail in chapter 6. Figure reproduced from Mercure and Salas (2012).

The database of energy resources was incorporated in FTT:Power, as part of the Natural Energy Resources (NER) module, shown at the top of figure 4.1. The NER module provides a tool for the study of the diffusion of energy technologies in FTT:Power, addressing the corresponding feedbacks with the natural world in terms of primary energy use and depletion. Natural resources are represented by distributions based on statistical trends, using a novel mathematical representation in the productivity/quantity space. The details about the assessment, the cost supply curves and the methodology to compare the different energy resources is explained in detail in chapter 6.

The NER module also includes a dynamic model of gradual resource depletion, to represent the evolution of stock resources under exogenous scenarios of energy cost and demand. This model is explained in detail in section 6.7. The NER module, including the energy resources database and the model of gradual resource depletion, is used in chapters 7 and 8 to analyse the impact of energy resources availability on the performance of energy policy. A complete description of the NER module, and other potential applications, can be found in Mercure and Salas (2012) and Mercure and Salas (2013b).

4.5 Technological Change

Numerous attempts have been made to model technological change as an endogenous factor of economic growth. These models are discussed in the vast number of existing literature reviews (Kahouli-Brahmi, 2008; Kohler et al., 2006; van der Zwaan and Seebregts, 2004). One of the most commonly accepted ways of modelling technological change is by using learning curves, using a power relation between unit cost and experience (the latter typically measured through sales, installed capacity or investment). FTT:Power incorporates learning curves to model the process of technological evolution, using a power relation between cumulative investment and the unit cost of the respective technology. This approach is known as the 'one-factor learning curve', and it is by far the most common model used in the literature on energy to forecast changes in technology cost (Rubin et al., 2015). In its simplest form, the logarithm of the cost of production of technology i varies linearly with respect to the logarithm of its initial production cost and the cumulative investment in that technology:

$$\log C_i(t) = \log C_i(0) + b * \log W_i(t) \tag{4.1}$$

where $C_i(0)$ and $C_i(t)$ are the costs of production in time 0 and t respectively, b is the learning index, and $W_i(t)$ is a measure of cumulative investment between time 0 and t. The learning rate, which is the fractional reduction in cost associated with a doubling of experience, is represented by:

$$LR = 1 - 2^b \tag{4.2}$$

The use of learning curves in FTT:Power produces path dependent scenarios of technology adoption. In this context, early investment decisions connected with technological lock-ins produce inertia in the system, constraining its potential adaptability to scenarios radically different to business as usual (Grubb, 2014). The nature of the technology evolution process, which is path dependent and extremely non-linear, makes it very uncertain. Unsurprisingly then, estimated learning rates found in the literature exhibit large variations, which can differ as much as one order of magnitude (Rubin et al., 2015). Based on a thorough literature review, chapter 9 presents a compilation of learning rate uncertainty intervals for all the 24 FTT:Power technologies. Using these ranges, decarbonisation scenarios under uncertain technological change are analysed in section 9.8.

4.6 Market Competition

The market competition in FTT:Power is represented by coupled logistic differential equations. This framework is the same as that used to model evolutionary dynamics and competition in biological systems (Kucharavy and De Guio, 2011; Lotka, 1910; Volterra, 1927). Electricity generation technologies compete for market share at a regional level.[3] Technologies in FTT:Power are compared on a pairwise basis. Switches between the two technologies within each pair is measured based on the flow of market share in electricity generation capacity (Mercure et al., 2014).

The rate at which shares of one type of technology (j) can be replaced by shares of another type (i) is proportional to:

1. The rate at which units of technology j come to the end of their lifetime and how many old units require replacement.
2. The rate at which the construction capacity for technology i can be expanded.
3. The market position of technologies i and j (in terms of shares of installed capacity).
4. Investors' preferences (see figure 4.4).
5. Other technical constraints.

Items 1 and 2 are constraints that define the growth rate limits for the market shares, based on the life cycle specifications of the underlying technologies. So, for instance, the long construction time required for nuclear power stations, as well as the long lifetime of hydroelectric dams, create natural limits for the maximum rate of installation and replacement of these technologies.

[3]The regions in FTT consist either of countries (such as UK, Germany, USA or Brazil) or groups of countries (such as OPEC).

The size of an industry also constrains the speed at which new power stations of that technology can be built. Very small industries face growth limitations, connected to the size of the underlying manufacturing capacity. As the industry grows, the manufacturing capacity to support that industry expands. This phenomenon is addressed by the third constraint in the list.

The main driver for the installation of new power stations is, of course, investment. This is captured by the four constraint in the list. If investors allocate more resources in a particular technology, the market size of that technology expands. The investment decision model inside FTT:Power is analysed in detail in chapter 10, and expanded in chapter 11.

Finally, the last item in the list, corresponds to technical constraints. The maximum amount of energy that can be produced from a specific source in FTT:Power, is limited by stability constraints. The stability constraints of FTT:Power are analysed in section 4.6.2.

Equation 4.3 describes, in a simplified case with only two alternatives, how the market share S_i of technology i evolves over time, when faced with competition from technology j. This is a logistic differential equation from the Lotka-Volterra family, with the analytical solution shown in equation 4.4.

$$\frac{dS_i}{dt} = \alpha \cdot S_i \cdot S_j = \alpha \cdot S_i \cdot (1 - S_i) \tag{4.3}$$

$$S_i(t) = \frac{1}{1 + e^{-\alpha(t-t_0)}} \tag{4.4}$$

In equations 4.3 and 4.4, α is a measure of the speed at which technology S_i can take market share from technology S_j.[4] If only two technologies were available, as in the case presented in equation 4.3, then the evolution of market share follows a perfect logistic pattern, described by the functional form of equation 4.4 and the left-hand chart of figure 4.3. In a more general case, when there are more than two options, the pattern of technology diffusion is more complex, but follows the same principles. The right-hand chart of figure 4.3 shows a simple example with three technologies.

The dynamics associated with the evolution of shares in FTT:Power is presented in equation 4.5. It is called the "shares equation".[5]

[4]In mathematical ecology, the equation 4.3 represents the population dynamic for a species with an 'intrinsic rate of growth' α (Kot, 2001).

[5]For more detail about the theoretical background of the shares equation, please refer to Mercure (2012)

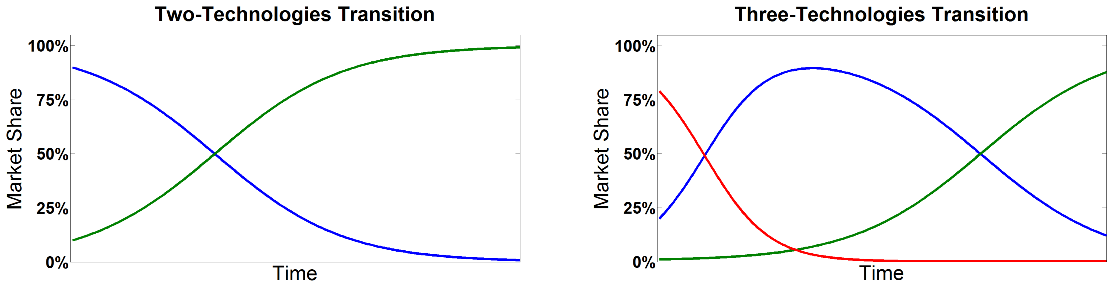

Figure 4.3 Example of technology diffusion patterns, modelled using logistic differential equations from the Lotka-Volterra family. On the left, a perfectly logistic transition from the blue technology to the green technology. On the right, a more complex (not perfectly logistic) transition involving three technologies. Early on in that simulation, the red technology (incumbent) is replaced by the blue technology, on a fast transition. The green technology, which enters the market later on, replaces the blue technology, with a more gradual transition. The slopes of the transitions are governed by the equivalent of the parameter α_{ij} in equation 4.5.

$$\Delta S_i = \sum_j S_i S_j \left(A_{ij} G_{ij} F_{ij} \left(\Delta C_{ij} \right) - A_{ji} G_{ji} F_{ji} \left(\Delta C_{ji} \right) \right) \frac{\Delta t}{\bar{\tau}} = \sum_j S_i S_j \alpha_{ij} \tag{4.5}$$

The speed at which technology i can capture market share from technology j (measured by the parameter α_{ij}, the equivalent to the parameter α in equations 4.3 and 4.4) in FTT:Power depends on several factors, including:

A_{ij} **Technology diffusion rates,** that define the speed at which technology i can be deployed, and technology j can be replaced. They depend on the construction time and lifetime of the different alternatives. For instance, technologies such as hydroelectricity and nuclear energy have a small diffusion rate (given by their long construction time and lifetime), while technologies such as thermoelectric power plants and wind farms have faster diffusion rates.

G_{ij} **Technical constraints,** to ensure grid stability and balance of baseload with flexible and variable generation technologies. These technical constraints are particularly important in scenarios with large amount of variable renewable energy (such as solar or wind), because the system is required to balance the growth of variable generation with flexible alternatives. This phenomenon is analysed in detail in chapter 9.

ΔC_{ij} **Cost difference between technologies i and j,** measured as the difference in the LCOE (see section 4.6.1 for more details).

F_{ij} **Investors' preferences,** based on the cost structure of technologies i and j. This term provides the likelihood of a switch from technology j to i, given the difference in the relative cost of both technologies (ΔC_{ij}). In chapter 10, investor's preferences are analysed in detail, to see how the inclusion of other criteria (beyond the cost of producing electricity) might influence investment allocation.

Δt is the time interval in which the change in market shares takes place, and $\bar{\tau}$ is the average sectoral rate of technology turnover. To calculate the aggregated changes in market share of technology i (ΔS_i in equation 4.5), the technology has to be compared with all the other technologies, using pairwise comparisons. In a simple system with only two options, equation 4.5 leads to a logistic pattern of diffusion, with $\alpha = A_{ij}G_{ij}F_{ij}\left(\Delta C_{ij}\right) - A_{ji}G_{ji}F_{ji}\left(\Delta C_{ji}\right)$. In the case of FTT:Power, the interaction of the 24 different technologies generates a complex pattern of diffusion. The equation cannot be solved analytically, but is straightforward to solve numerically.[6]

As mentioned at the beginning of section 4.6, the size of an industry constrains the speed at which new power stations of that technology can be built. In mathematical terms, this is defined by the proportionality of ΔS_i (change in shares of technology i) and S_i (size of industry associated to technology i) in the shares equation. This constraint reflects the fact that the manufacturing capacity of the supply chain of technology i is limited, and grows in parallel with the market expansion of the technology itself. While this approach provides a good representation of a market driven technology diffusion process, it has some caveats:

- This approach does not account for drivers beyond market considerations, such as technology diffusion driven by geopolitical change. As analysed in section 2.3, drivers such as direct state intervention have had a strong influence in energy transitions in the past (e.g. adoption of coal during the Industrial Revolution and oil after the Second World War).

- Incumbent technologies (those with large S_i) tend to perpetuate their dominance, while at the same time new entrants have limited growth rate. The dominance of the incumbents could be considered as a constraint for studying rapid technology diffusion scenarios. However, it can also be argued that this modelling approach is a realistic representation of the current limitations in the development of innovation systems around renewable energy technologies (Negro et al., 2012).

[6] In FTT:Power, the scenarios are simulated on a discrete time step, not solved using a differential equation solver.

In the context of the stylised modelling framework provided by FTT:Power, in which technology diffusion is driven by market interactions, there is room for exogenous definition of technology uptake. Non market driven scenarios, such as those driven by geopolitical forces, which are beyond the scope of the model, can be analysed in this way. In every region it is possible to specify the capacity installed for each technology at every time step. This capability of the model is the basis to define policies that regulate the use of specific technologies, something that is addressed in detail in section 5.2.3.

In FTT:Power, technologies are divided in three main groups, based on their electricity generation characteristics:

Baseload : technologies that are expected to produce a steady flow of electricity.

Flexible : technologies that rapidly increase or decrease the amount of electricity they produce.

Variable : technologies that cannot precisely manage the production of electricity, due to the intermittent availability of the underlying primary energy resource, such as wind blowing or sun shining.

Due to the unpredictable nature of some renewable energy sources, it is necessary to complement the installed capacity of variable technologies with some flexible capacity, that can be made rapidly available on demand. The composition of the electricity matrix is, therefore, constrained by lower and upper limits of baseload, flexible and variable technologies. The specific requirements in terms of baseload, flexible and variable generation and installed capacity in FTT:Power, are analysed in section 4.6.2. Table 4.1 lists the technologies with their respective classification.

4.6.1 Levelised Cost of Electricity - LCOE

The term F_{ij} in equation 4.5 corresponds to the preference of investors when comparing technologies i and j. In order to make such a comparison, investors in FTT:Power require a metric to compare the 24 available electricity generation technologies. This metric has to incorporate as much information as possible, including lifetime of the power stations, energy produced, investment cost, operation costs, fuel use and environmental impact. The metric chosen for FTT:Power was the **Levelised Cost of Electricity** or **LCOE**, a standard methodology used extensively for the comparison of power sector investment projects (IEA et al., 2010, 2015).

Index	**Technologies**	**Group**	Index	**Technologies**	**Group**
1	Nuclear	Baseload	13	Biogas	Flexible
2	Oil	Flexible	14	Biogas + CCS	Flexible
3	Coal	Baseload	15	Tidal	Baseload
4	Coal + CCS	Baseload	16	Hydroelectricity	Flexible
5	IGCC	Baseload	17	Onshore Wind	Variable
6	IGCC + CCS	Baseload	18	Offshore Wind	Variable
7	CCGT	Flexible	19	Solar PV	Variable
8	CCGT + CCS	Flexible	20	CSP	Variable
9	Solid Biomass	Baseload	21	Geothermal	Baseload
10	Solid Biomass + CCS	Baseload	22	Wave	Variable
11	BIGCC	Baseload	23	Fuel Cells	Baseload
12	BIGCC + CCS	Baseload	24	CHP	Baseload

Table 4.1 Technologies in FTT:Power. **Baseload** technologies are those typically used as base load supply. **Flexible** technologies are those able to respond to changes in peak demand, and **Variable** technologies are wind, solar and wave, technologies under variable conditions of electricity production during the day. +CCS indicates the use of Carbon Capture and Storage

Some electricity generation technologies, such as hydroelectric dams and nuclear power stations, are characterised by capital intensive investment and long installation periods, but low fuel and maintenance costs. Others, such as gas or coal power stations, require less investment capital and have shorter installation periods, but have higher fuel and maintenance costs. In order to be able to compare these technologies, it is necessary to normalise the values in time and per energy produced. The most common way of doing this is using net present values per unit of energy, which is the approach on which the LCOE is based.

Inequality 4.6 is a very basic criterion on which investors might base a decision to allocate resources in a new power plant: the net present value of revenues have to be higher or equal to the net present value of the costs of producing electricity.

$$\sum_{t=0}^{T} \frac{\mathrm{P}_i(t) \cdot \mathrm{EP}_i(t)}{(1+r)^t} \leq \sum_{t=0}^{T} \frac{\mathrm{TI}_i(t) + \mathrm{OM}_i(t) + \mathrm{FC}_i(t) + \mathrm{CC}_i(t)}{(1+r)^t} \tag{4.6}$$

P denotes the price of electricity, *EP* is the energy expected to be produced, *TI* corresponds to the specific technology investment cost, *OM* the operation and maintenance costs, *FC* the fuel costs, *CC* the carbon cost component associated with emissions allowances or taxes where applicable, r the technology or region specific discount rate, t is time and T is the lifetime of the project. The subscript i represents either technology or region, depending on the context (Mercure, 2012).[7] The LCOE is the price of electricity that balances the net present value of revenues and costs. In other words, it corresponds to the minimum long term price of electricity such that investors do not face losses, assuming perfect foresight of costs and energy production. From inequality 4.6, LCOE is calculated as the constant price of electricity that makes both sides equal:

$$\mathrm{LCOE} = \mathrm{P}_i = \frac{\sum_{t=0}^{T} \frac{\mathrm{TI}_i(t)+\mathrm{OM}_i(t)+\mathrm{FC}_i(t)+\mathrm{CC}_i(t)}{(1+r)^t}}{\sum_{t=0}^{T} \frac{\mathrm{EP}_i(t)}{(1+r)^t}} \tag{4.7}$$

In FTT:Power, the LCOE terms are normalised by unit of energy. So, the equation 4.7 can be expressed as:

$$\mathrm{LCOE} = \mathrm{LCOE}_{TI/EP} + \mathrm{LCOE}_{OM/EP} + \mathrm{LCOE}_{FC/EP} + \mathrm{LCOE}_{CC/EP} \tag{4.8}$$

Each of these terms (except $\mathrm{LCOE}_{C/E}$ which is based on specific carbon price policies) are based on the International Energy Agency values published in IEA et al. (2010).

The LCOE framework is typically used for comparing specific projects (for instance, one power plant versus another). In the case of FTT:Power, however, investment allocation represents aggregated investment decisions at the regional level. In this context, the LCOE framework is used in FTT:Power to compare aggregated regional investment. The aggregation process conceals large variations related to aspects of local nature, such as the cost of land and labour, and decisional issues which may or may not lead to the rational choice of the option with the lowest LCOE. From a behavioural economics perspective, these variations are a representation of the heterogeneity of the system. Investment decisions are taken at the firm level, with no expected coordination among agents, access to limited information and bounded rationality (Simon, 1984), as opposed to system level optimisation, where full coordination and foresight is assumed. In this context, is appropriate to use a probabilistic representation of costs. Figure 4.4 shows a representation of two technologies, with different LCOE distributions. The use of distributions instead of single values captures the uncertain nature of the LCOE estimation.[8] The variance of the distributions partly determines the time of diffusion given the price differential, i.e. for an average cost difference, the narrower the

[7] Due to the discounting, the net present value of decommissioning costs are assumed to be negligible in this context.

[8] Details about the data used for the estimation of the LCOE distributions are presented in the Supplementary Material of Mercure and Salas (2012).

distributions (the more identical agent perceptions are), the faster diffusion takes place, given the specific technology diffusion rates (Mercure et al., 2014).

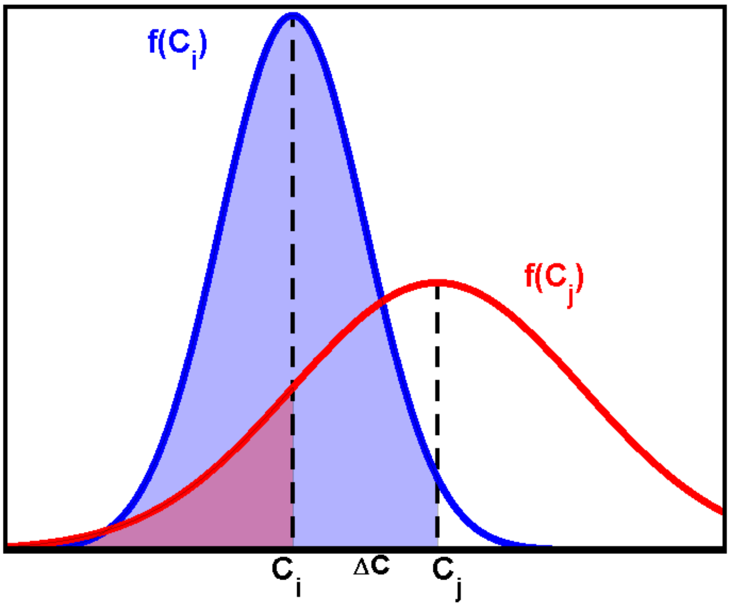

Figure 4.4 Distribution of LCOE values for two technologies i and j. At the firm level, technologies are compared through single values, corresponding to the LCOE calculations from the perspective of the single investor. Due to the variability among conditions and preferences that different investors face, the comparison of technologies at the aggregate level is represented by the comparison of distributions. The probability of technology i being chosen over technology j in the aggregate, is proportional to the frequency in which technology i is less costly than technology j. This comparison is represented by the shaded areas in the chart: the number of units of technology j that emerge as less costly than the median value of the distribution of technology i corresponds to the red shaded area, a value much smaller than the reverse, which is the blue area. Therefore, technology i is preferred over j in aggregate terms. Based on Mercure (2012).

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Figure 4.4 shows an example of LCOE median values C_i and C_j for technologies i and j respectively. Under the scenario depicted by figure 4.4, technology i is less costly, and is therefore preferred over j by the investors in aggregate terms. However, that is not always the case, because there is a probability larger than zero that technology j might be less costly than technology i in some particular cases. If the distributions of figure 4.4 are interpreted using a frequentist approach, then the blue area represents the fraction of the total amount of cases in which technology i is less costly than the median value of technology j. Equivalently, the red area represents the fraction of the total cases in which technology j is less costly than the median value of technology i. While, in aggregate, i is less costly than j (the blue area is larger than the red area), there is a fraction of investors that will prefer technology j over i. Following this approach, given that the median value of technology i is less costly than the median value of technology j, over time the system moves towards the technology with the lowest cost. This probabilistic framework of incomplete overlapping of investor's preferences is the starting point for the development of a more complex model of investment decisions, which is explained in detail in chapter 10.

4.6.2 Stability constraints and storage in FTT:Power

In the past, electricity was produced mainly by two types of power plants: **baseload** generators, which run at nearly constant output, and **load-following** (or **flexible**) units, which meet the variation in demand as well as provide operating reserves. With the adoption of wind and solar energy, **variable** electricity was incorporated into the system. The limited control of the output coming from variable generators has brought new challenges to national energy grids, particularly in Europe, where several countries are deploying large amount of wind and solar energy (Weitemeyer et al., 2015). In places like Germany, where the share of non-hydropower renewable generation reached 24% in 2014, the maximum share of variable generation that the system can handle is subject of debate (REN21, 2015; Weitemeyer et al., 2015).

The constraints of the current power sector to balance the amount of baseload, flexible and variable technologies are modelled in FTT:Power as **stability constraints**. These stability constraints depend on the peak demand pattern of electricity consumption, on the amount of energy storage available on the system, and the current energy mix. So, based on these technical considerations, there are some limits associated with the amount of renewable energy that the system can adopt. The rationales behind these constraints are explained below:

Minimum flexible and maximum variable

In a system with a large amount of variable resources (for instance, wind turbines), flexible technology has to be in place to produce electricity when the variable resources are not available (for instance, when wind does not blow). Therefore, the minimum amount of flexible installed capacity required in the system, as well as the maximum amount of variable installed capacity that the system can handle, depend on each other. The interdependence of flexible and variable installed capacity is also connected with the availability of energy storage systems (more storage, less interdependence), and the peak-demand patterns (larger the ratio between peak and average demand, more interdependence).

On each region, two independent requirements have to be met to guarantee the stability of the system, one for energy production and one for installed capacity:[9]

Energy requirement: the peak energy demand plus the missing energy from renewables (variable electricity) must be covered by the sum of flexible electricity generation and energy storage.

$$\Delta D + U_{Var} \cdot T_D - G_{Var} \leq G_{Flex} + E_S \tag{4.9}$$

where ΔD is the difference between peak and average energy demand, $U_{Var} \cdot T_D - G_{Var}$ is the difference between the maximum variable electricity generation ($U_{Var} \cdot T_D$) and the actual variable electricity generation (G_{Var}), G_{Flex} is the electricity produced with flexible sources and E_S is the energy produced from storage sources.

Installed capacity requirement: the total capacity of flexible sources plus storage generation capacity must at least be able to cover for possible variations of power demand and variable output.

$$U_{Flex} + U_S \geq \Delta U_D + U_{Var} \tag{4.10}$$

where U_{Flex} is the installed capacity of flexible sources, U_S is the storage generation capacity, ΔU_D is the maximum potential variation in power demand (in terms of capacity, due to the specific demand profile of the region) and U_{Var} is the installed capacity of variable sources.

The variables associated to the storage capacity of the region (E_S and U_S) can be found in tables A.2 and A.3 of the Appendix section A, while the peak demand variables (ΔD and ΔU_D) can be found in tables A.1 and A.4 of the same Appendix section.[10]

<u>**Maximum baseload and variable**</u>

The off-peak demand for electricity represents an upper limit for the baseload electricity of the system. If the installed capacity of baseload rises over the off-peak demand requirements, electricity would have to be either stored or curtailed. Moreover, baseload could potentially be replaced by a very large amount of variable, that would have to be complemented by flexible

[9]The constraints presented in this section are the most relevant subset of technical constraints of FTT:Power, in relation to the scenarios analysed in this thesis. For a full detail of all the technical constraints of the model, please refer to Mercure (2011, 2012).

[10]The variable in the Appendix section are normalised, and therefore presented as ratios: E_S/D, U_S/U_T, $\Delta D/D$ and $\Delta U_D/U_T$, being D and U_T total demand and total installed capacity, respectively.

capacity (see previous constraint). Such scenario would be economically feasible under low prices of renewable technologies (driven, for instance, by strong decarbonisation policies). However, flexible technology would have to work under very low capacity factors, something that is unrealistic. Therefore, FTT:Power constrains the maximum share of baseload and variable installed capacity, based on the amount of flexible capacity already installed, the peak-demand pattern of the system and the amount of energy storage capability.

In mathematical terms, this constraint can be written as:

$$S_{Base} + S_{Var} \leq \left(\overline{CF} - \frac{\Delta U_D}{2U_T} + \frac{U_S}{U_T} \right) \tag{4.11}$$

where S_{Base} and S_{Var} are the market shares of baseline and variable electricity, respectively, and $\overline{CF}$ is the average capacity factor of the system, calculated as:

$$\overline{CF} = \sum_{i=1}^{24} S_i \cdot CF_i \tag{4.12}$$

where S_i is the market share of technology i, and CF_i is the capacity factor of the same technology (the sum is over the 24 FTT:Power technologies). Over time, the shares S_i change, having an effect on the average capacity factor, and therefore on the limits of baseload, variable and flexible electricity that the system can handle. As in reality, in FTT:Power the flexible electricity generation sources adapt to changes in demand, in order to maintain the stability of the system. The effect of such changes in the capacity factors is explained in detail in the Appendix section A.3.

In scenarios of extreme decarbonisation, a rapid increase of variable electricity in the system activates the control mechanism described above (security constraints). Under these conditions, investment preferences in FTT:Power are weighted by "probability of investment" factors. These factors limit the capability of switching from one technology to another (Mercure, 2011, p. 21). In this way, the system is maintained in a stable configuration of baseload, variable and flexible electricity. As a consequence of this security measure, if there are policies in place that regulate the construction of new coal power stations, these policies are superseded by the control mechanism. Therefore, the expected replacement of coal power stations can be stopped, as a way of controlling the stability of the system.

The stability constraints in FTT:Power are a stylised representation of a complex phenomena, driven by the interactions between baseload, flexible and variable electricity. As it might be expected, this stylised representation has some limitations, mainly related to the storage requirements of the regional grids. In rapid decarbonisation scenarios, the stability constraints might induce an overestimation of storage requirements. For this reason, the standard storage capacity on FTT:Power is assumed to be in the order of 18% of the global installed capacity for electricity generation,[11] higher than the actual global storage capacity of around 3% (approximately 127GW in 2010 (Beaudin et al., 2010; Denholm and Hand, 2011; Dunn et al., 2011)). In reality, there exists several ways of increasing grid flexibility, beyond increasing storage capacity or flexible generation (Denholm et al., 2010). Some of the most common mechanisms include:

- Supply and reserve sharing: greater aggregation of loads and reserves through market mechanisms is one of the less expensive ways of dealing with demand variability.
- Demand flexibility: Responsive demand (to price variations, for instance) can increase grid flexibility.
- Variable generation curtailment: while excess on installed capacity of variable generators leads to curtailment of low-value springtime generation, it also allows for a greater overall contribution of variable electricity. Curtailment capabilities can also provide operating reserves to the system.
- New loads: new controllable loads can be added to the system to absorb excess of variable generations. Examples include space and process heating, fuel production such as hydrogen via electrolysis or electric vehicles. Availability of these controllable loads increases the system flexibility.

Because these mechanisms are not included in FTT:Power, the requirements of storage in the model are higher than in reality. For instance, in the scenarios analysed in chapter 9, the storage capacity of the system is assumed to increase to 90% in order to obtain high variable electricity penetration levels. In reality, however, there are substantial diminishing returns for greater amount of storage (Denholm et al., 2010). For instance, combination of short term storage with load shifting technologies is more cost efficient than pure short term storage increase (ibid.). Moreover, short term storage is not able to address the limited seasonal correlation of the combined variable generation mix and demand. This seasonal mismatch would need to be addressed by extremely long-term storage, which is less efficient (more costly) than a combination of the mechanisms described above (ibid.). Another limitation of

[11] Detailed values per region are presented in tables A.2 and A.3 of the Appendix section A, under the column "low grid flexibility". In the column "high grid flexibility" are the values used in the high grid flexibility scenario presented in chapter 9.

the storage modelling approach in FTT:Power is its cost. In the model, the difference between the cost of energy produced by storage units and the cost of producing electricity with other technologies is not internalised in the LCOE. Consequently, investors do not internalise the fact that energy storage is more expensive than the average price of electricity. For a more realistic representation of the interactions between energy storage, baseload, flexible and variable electricity, a detailed dispatch model would be required. This model would have to match supply and demand at every moment, and calculate the corresponding marginal cost variations between the different sources. This is something that is beyond the capabilities of the current version of FTT:Power. For a detailed analysis of the impact of the stability constraints on rapid decarbonisation scenarios, please refer to sections 9.8.2 and 9.8.3 in chapter 9.

4.7 Conclusions

This chapter provided an introduction to the dynamic technology diffusion model of the power sector FTT:Power. The main components of the model were briefly discussed, including the representation of phenomena such as natural resources use and depletion, technological change, market competition and policy instruments. FTT:Power includes three types of market-based policy instruments (carbon price, subsidies and feed-in-tariffs), direct regulation in the form of cap on installed capacity, and exogenous electricity demand. In the following chapters, each of the main components of the model are analysed (and sometimes modified), to study how uncertainty on specific areas can influence future decarbonisation scenarios of the power sector. This includes:

Scenarios of policy uncertainty : variations in the stringency of policy and in the combination of policy instruments create different emission trajectories (chapter 5).

Scenarios of natural resource availability uncertainty : variations in the availability of natural resources, in the form of extreme assumptions regarding the technical potential of specific resources, have an impact in the cost of electricity.[12] Scenarios of uncertainty on natural resource availability are analysed for different combinations of policy, to determine the impact of resource availability on policy performance (chapters 6, 7 and 8).

[12] See chapter 6 for an explanation of the cost supply curve approach.

Scenarios of learning uncertainty : decarbonisation scenarios under extreme learning rate assumptions (in the form of maximum and minimum learning rate coefficients, based on a thorough literature review summarised in Appendix section C), are presented in chapter 9.

Investment under uncertainty : Chapter 10 proposes a new methodology to model investment decisions in FTT:Power, based on multicriteria analysis. Using this new methodology, chapter 11 analyses scenarios for the power sector using environmental uncertainty (uncertainty about the environmental impacts associated with atmospheric pollution) and policy uncertainty (uncertainty about the effect of policy instruments in the price of electricity), as counterparts to purely market based investment considerations.

Chapter 5

Energy Policy Scenarios

5.1 Chapter Summary

This chapter presents a framework for the creation of scenarios of the power sector, using the FTT:Power model introduced in chapter 4. This framework is based on a **decarbonisation intensity** variable, which maps a subset of the FTT:Power policy domain into the range [0 1], to facilitate the analysis of a large number of potential pathways. The limits of the range correspond to extreme scenarios of the power sector, based on pessimistic (lower limit) and optimistic (upper limit) assumptions about future decarbonisation efforts. The methodology presented here is the basis for the scenarios analysed in chapters 7, 8, 9 and 11.

The concept of decarbonisation intensity is explained in section 5.2. Using this concept, the domain space of FTT:Power is sampled and mapped into the range [0 1]. The sampling of the FTT:Power domain includes variations in the following areas:

- Carbon price, section 5.2.1.
- Subsidies and feed-in-tariffs, section 5.2.2.
- Direct regulation in the use of specific technologies, section 5.2.3.
- Electricity demand, section 5.2.4.

Based on the variations of these variables, two extreme scenarios of the power sector are introduced: **Business as Usual** (or **BAU**, section 5.4), and **Decarbonisation** (or **DEC**, section 5.5). These two scenarios, particularly the scenario DEC, work as a reference for all the other scenarios presented in the rest of the thesis.

Section 5.7 extends the decarbonisation intensity framework presented in this chapter, to explore the domain of other FTT:Power variables, including:

- Technical potential of natural resources, section 5.7.1, analysed in detail in chapters 7 and 8.
- Learning rates, section 5.7.2, analysed in detail in chapter 9.

5.2 Exploring the Policy Domain Space in FTT:Power

The likelihood of staying below a threshold temperature increase of 2°C over the 21st century, relative to 1900 depends on key driving factors of potential energy futures, many of which are uncertain. Issues such as technological progress, availability and cost of energy resources, and rate of implementation and success of decarbonisation policies, are just a few of the uncertain aspects that will play a relevant role in the future of our energy systems (O'Neill et al., 2014). It is, therefore, appropriate to use a range of scenarios to represent potential futures of the power sector, that allow an appropriate uncertainty analysis. Using FTT:Power, two extreme emission scenarios for the power sector were created, to define the range of plausible futures to be analysed. This is presented in figure 5.1 in the form of a range of potential emission trajectories.

The trajectory with the upper limit of emissions in figure 5.1 is **BAU**, and the trajectory with the lower level of emissions is **DEC**. A middle ground scenario (**MID**) is also presented in figure 5.1, as a dashed line. The two extreme trajectories represent limits of what could be achieved in the power sector, in an environmentally friendly (DEC) or fossil fuel intensive (BAU) context. They represent the upper and lower limits in terms of emissions, within a range of scenarios that can be considered feasible in the FTT:Power model domain. To produce the range of scenarios represented in figure 5.1, the policy domain space of FTT:Power was divided into the following sets of variables:

- Carbon pricing, in $US\$/tonC$ per region.
- Subsidies and feed-in-tariffs, as a percentage of the overnight cost of investment and the price of electricity, respectively, per region per technology.
- Regulation in the form of a cap in units of new installed capacity (in GW) for some electricity generation technologies (per region per technology).
- Electricity demand, in GWh/yr per region.

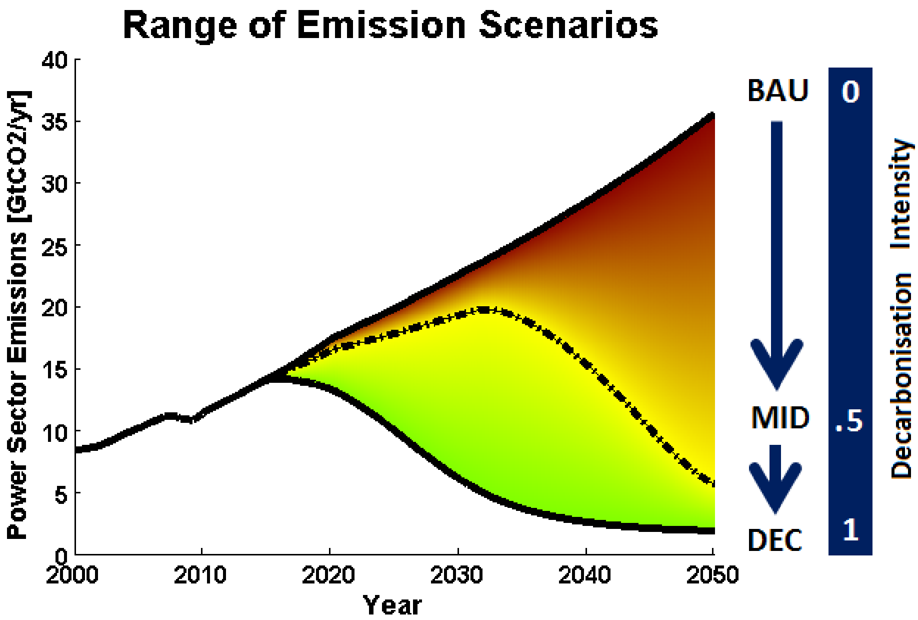


Figure 5.1 Range of emission's trajectories, based on two extreme FTT:Power scenarios. The top curve represents the emission's trajectory of the Business As Usual (BAU) scenario, which depicts a fossil fuel intensive future. The bottom curve represents the emission's trajectory of the Decarbonisation (DEC) scenario, which depicts a future where strong efforts are made to decarbonise the global power sector. The dashed line in the middle represents a middle ground scenario (MID), which is a trade-off between the two extremes. The shading represents the decarbonisation intensity: BAU (decarbonisation intensity equal 0) is brown, MID (decarbonisation intensity equal 0.5) is yellow, and DEC (decarbonisation intensity equal 1) is green.

All of these variables work on different units and have a different scope. With the aim of simplifying the scenario analysis, the domain range was normalised between zero and one for each one of these sets of variables, using a **decarbonisation intensity** variable. The minimum decarbonisation intensity scenario (intensity equal zero) corresponds to the case of minimum decarbonisation efforts, in terms of energy policy (no support for low-carbon technologies) and energy demand (no energy efficiency policies in place). In figure 5.1, it corresponds to the upper limit of the emission trajectories. The maximum decarbonisation intensity scenario (intensity equal one) corresponds to the case of maximum decarbonisation efforts, in terms of energy policy and energy demand. In figure 5.1, it corresponds to the lower limit of the emission trajectories. In the maximum decarbonisation effort scenario, emissions in 2050 are less than half the emission in 2000, in line with the RCP2.6 trajectory (IPCC, 2014b, p. 52).

The minimum decarbonisation intensity scenario corresponds to the BAU scenario, and the maximum decarbonisation intensity scenario corresponds to the DEC scenario. The MID scenario was formulated such that it coincides with the middle of the range (intensity equal 0.5). The next sections describe the way that these sets of variables are mapped into the decarbonisation intensity ([0 1] range), and how the range of scenarios described by figure 5.1 was created.[1]

5.2.1 Carbon Pricing

FTT:Power assumes that each region has its own independent carbon price, which can (but it does not have to) be the same for all (or some) regions. From a mathematical perspective, the price of carbon is accounted in the model as the carbon cost component of the Levelised Cost of Electricity (see equation 4.6 in the previous chapter). Mathematically, there is no difference if the price of carbon comes from a cap-and-trade system, from taxation, or any other policy mechanism. Therefore, in the context of the stylised version of the power sector within the model, it is not required the specification of the type of instrument behind the carbon price.

Naturally, reality is more complex than stylised models. When imperfect markets, incomplete access to information and uncertainty are taken into account, then taxes and cap-and-trade mechanisms do not produce the same results, and therefore the policy instrument matters. On the one hand, a cap ensures an upper limit for emissions, but generates uncertainty on the price. On the other hand, a tax generates a certain price, but its impact on emissions is uncertain (Grubb, 2014, p. 223). The efficiency and effectiveness of both mechanism (or any hybrid combination of them), will depend on various factors, including short versus long term objectives, industry expectations on investment and how consumers may perceive the different instruments (ibid.). Despite these important differences, the FTT:Power model does not differentiate between a carbon price defined by taxation, by a cap-and-trade system, or any other policy instrument. It is, therefore, relevant to keep in mind this limitation when

[1]The mapping of the policy variables into the range [0 1] facilitates the creation of a large number of scenarios, within the context of the policies analysed in this dissertation. For instance, the emission scenarios for Brazil presented in figure 8.8 (chapter 8: "Hydropower Resources and Policy Performance in Brazil") correspond to 120 samples of the decarbonisation intensity variable, under specific conditions (see section 8.4 for the details about those conditions). The capability of the system for creating an arbitrary number of simulations, using samples of the decarbonisation intensity variable, played an important role in the analysis stage of this dissertation. Due to the large number of scenarios under analysis, only the extreme cases of the decarbonisation intensity variable (0 or 1) are shown in most of the simulations presented in this thesis, with a few exceptions, such as the aforementioned case of chapter 8.

the relative impacts of the different policy instruments are analysed. This issue, with a particular focus on the abatement contribution of the different policy instruments (and their combinations), is discussed below in sections 5.3 and 5.6.

The price of carbon in FTT:Power is defined exogenously, with an annual price between 2005 and 2050 (in 2008 USD). In the case of EU (regions 1-27), carbon price is taken from E3ME[2] between 2005 and 2015, while all the other regions are assumed to have no carbon price before 2015. From 2016 onwards, the carbon price varies according to the scenario analysed.

From 2016 until 2050, a **base curve** for the carbon price is defined exogenously. The curve rises gradually from 35 to 184 euros per ton of carbon (€/tC) between 2016 and 2050, respectively (red solid line in figure 5.2). This curve corresponds to the carbon price for the FTT:Power regions within the EU (regions 1-27), and it is assumed to remain constant between the BAU and the MID scenarios (decarbonisation intensity in the interval [0 0.5]). The other FTT:Power regions (28-53) increase their carbon price from zero (in the BAU scenario) up to a fraction of the base curve (in the MID scenario): the fraction is 1 for European countries outside the EU (regions 28-33, red solid line in figure 5.2), 0.75 for advanced economies outside Europe[3] (regions 34-38, blue solid line), and 0.5 for the rest of the world (regions 39-53, green solid line).

The changes in carbon price between the MID and DEC scenarios (decarbonisation intensities in the range [0.5 1]) follow a very simple pattern. The carbon price increases from one to four times the value in the MID scenario, proportionally to the decarbonisation intensity. So, European countries reach a maximum price of carbon of 736 [€/tC] (red dashed line in figure 5.2), advanced economies reach 552 [€/tC] (blue dashed line) and developing economies reach 368 [€/tC] (green dashed line).

It is important to emphasize that BAU and DEC are feasible limits within the borders of what FTT:Power can analyse. While in the BAU scenario only Europe has a carbon price, in reality there are already several countries outside Europe which have implemented carbon pricing policies. For instance, the Regional Greenhouse Gas Initiative (RGGI) in the Northeast

[2]E3ME (www.e3me.com) is a well established global non-equilibrium macroeconometric model developed and maintained at Cambridge Econometrics. It is frequently used by the European Commission for impact assessment of environmental policy, including the assessment of the 2030 climate and energy targets and other policy analyses (Barker et al., 2012; Pollitt et al., 2015a,b).

[3]The group of advanced economies outside Europe includes USA, Japan, Canada, Australia and New Zealand.

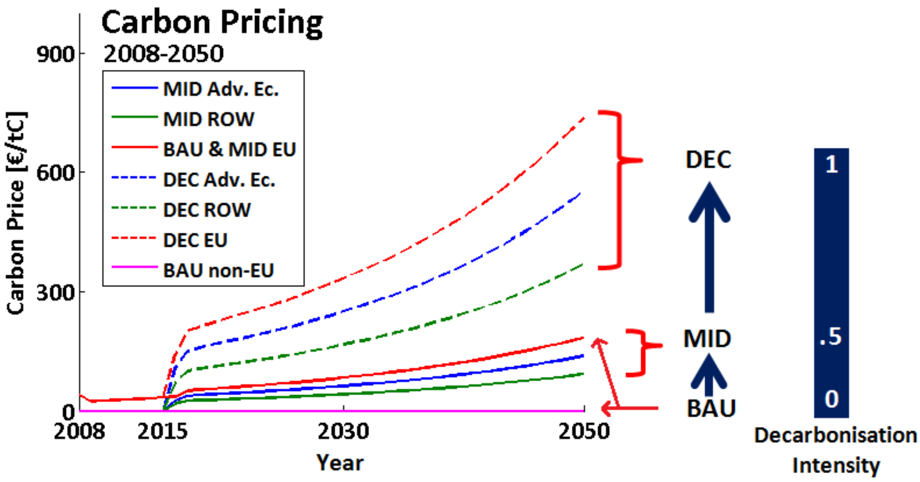


Figure 5.2 Carbon pricing for the BAU, MID and DEC scenarios between 2008 and 2050. For the BAU scenario, EU has a carbon price defined by the solid red curve, while the rest of the regions have no carbon price (purple line, at the bottom of the chart). Between the BAU and MID scenarios, carbon price in EU remains the same, while in the other regions it rises, proportionally with the increase of the decarbonisation intensity. In the MID scenario (decarbonisation intensity = 0.5), all European countries have the same carbon price (solid red curve), while the advanced economies outside EU and the rest of the world follow the carbon price described by the solid blue and green lines, respectively. Between MID and DEC scenarios, carbon price in all regions increase proportionally to the increase of the decarbonisation intensity. The carbon price in the DEC scenario (dashed lines, decarbonisation intensity = 1), is 4 times the price in the MID scenario. The carbon price for the scenarios between the MID and DEC limits in 2050 are within the ranges presented in IPCC (2014b, p. 59), for the scenarios between 430 and 580 ppm CO_2eq.

and Mid-Atlantic U.S. states;[4] the California's Cap-and-Trade Program;[5] the New Zealand Emissions Trading Scheme (NZ-ETS);[6] the Quebec Cap-and-Trade System[7] and the Chinese pilot ETS,[8] are some examples of carbon markets outside Europe. The small size of some of these markets (such as New Zealand), or the fact that some of them are still sub-national and

[4]The RGGI is the first mandatory emissions trading scheme in the United States, operating since January 1, 2009. The programme initially covered CO_2 emissions from power plants in the states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont (Ecofys, 2013)

[5]The California's Cap-and-Trade Program started in 2012, and entered into its first compliance period as of January 1, 2013 (ICAP, 2016b)

[6]The NZ-ETS started in 2008, and is now under its second statutory review (ICAP, 2016a)

[7]The Quebec Cap-and-Trade System was officially launched in 2013, and one year later it was linked with California's scheme, as part of the Western Climate Initiative (Ecofys, 2013)

[8]China's National Development and Reform Commission (NDRC) approved in October 2011 seven pilot carbon trading schemes for Beijing, Shanghai, Tianjin, Chongqing, Guangdong, Hubei, and Shenzhen (Ecofys, 2013)

do not cover the whole country (such as the cases of USA, China and Canada), are part of the reasons why they are not yet incorporated in FTT:Power. It is expected that for the next versions, some non-European carbon markets will be included.

5.2.2 Subsidies and Feed-in-Tariffs

Subsidies and feed-in-tariffs are defined exogenously in FTT:Power, per technology per region per year. Each scenario requires to define 24 x 53 x 43 = 54,696 values for subsidies, and other 54,696 values for feed-in-tariffs. If the decarbonisation intensity range was sampled 100 times, then 10,939,200 exogenous points would be required. In order to keep tractability, some simple rules to automatically create subsidies and feed-in-tariffs scenarios were implemented.

Subsidies

Subsidies in FTT:Power are defined as a percentage of the investment cost,[9] granted by the regulator to investors, to decrease the LCOE of favoured technologies. So, a subsidy of 10% for technology i in year t, means that the investment cost of technology i in year t is 10% cheaper. The corresponding impact on the LCOE can be calculated using the equation 4.7.

A maximum nominal rate of 30% subsidy is defined for the following technologies:[10]

- Biogas in all regions
- Geothermal energy in all regions
- Technologies using carbon capture and storage (CCS) in all regions
- Tidal energy in Spain, France, Ireland, Portugal and UK
- Nuclear energy in China, India, Korea and Taiwan

The nominal rates change proportionally to the decarbonisation intensity value, between zero (BAU) and the maximum nominal rate (DEC). So, in the BAU scenario, all subsidies are zero, while in DEC scenario, all subsidies are at the maximum nominal rate, changing proportionally to the decarbonisation intensity in the intermediate scenarios. In all the

[9]Total investment costs include owner's cost, EPC (engineering, procurement and construction), contingency and interests during construction (IDC), and exclude refurbishment or decommissioning (IEA et al., 2010).

[10]Tehcnologies that are not on the list do not have any subsidy, or equivalently, a nominal rate of 0%.

scenarios, subsidies are maintained at the nominal rate between 2015 and 2025. From 2026 until 2044, subsidies decline linearly to zero.

Similarly to the carbon price, subsidies in FTT:Power are not required to be defined at the policy instrument level. In the model, the effectiveness of these policies is fully determined by the corresponding impact on the Levelised Cost of Electricity (LCOE). In reality, however, the impact of subsidies on investment decisions changes depending on the specific policy instrument being applied. For instance, subsidies can be implemented in the form of grants, favourable loans or fiscal incentives (such as reduced taxes, accelerated depreciation, tax credits and tax deductions), all of which have different levels of acceptance among investors on specific sectors (IPCC, 2007, p. 481). In the context of the stylised scenarios analysed in this thesis, a detailed specification of the subsidy instrument is not required. However, it is important to keep this aspect in mind when analysing the relative impact of policy instruments in the decarbonisation scenarios. The differences between the FTT:Power representation of subsidies and the real instruments is discussed below in section 5.3.

Feed-in-tariffs (FiTs)

FiTs are the most popular form of renewable energy regulatory support policy worldwide (REN21, 2015, p. 88). Consequently, it is not surprising that FiT instruments are analysed separately from traditional subsidy instruments, although they are equivalent from a theoretical perspective. In the case of FTT:Power, FiTs are defined as a percentage of the retail price of electricity, and granted to investors as the difference between the LCOE of a specific technology, and the retail price of electricity, times a premium. Therefore, FiTs can be considered as a subsidy proportional to the amount of electricity generated. In contrast, traditional subsidies in FTT:Power are assumed to be proportional to investment costs (see previous section). Given these differences, it makes sense to study their effects separately.

In reality, FiTs instruments are more complex than their stylised representation on FTT:Power. Real feed-in-tariff instruments can be divided into two main groups: *fixed tariff* and *premium tariff*. In the former, generators receive a fixed remuneration per unit of energy produced, independently of the market price of electricity. In the latter, generators receive a premium per unit of energy produced proportional to the price of electricity, which can be either fixed or variable. On the one hand, the fixed tariff scheme represents lower investment risk for investors. On the other hand, the premium tariff scheme shows higher compatibility with liberalised electricity markets (Couture et al., 2010; Held et al., 2014). For the sake of simplicity, all the regions using FiTs in FTT:Power are assumed to have the same instrument:

a premium tariff scheme, with a variable premium proportional to the difference between the price and the levelised cost of electricity. The premium varies proportionally to the decarbonisation intensity value: in the BAU scenario, the premium is zero (equivalent to not having FiT), and it increases gradually from 0 to 1 between the BAU and MID scenarios (decarbonisation intensity between 0 and 0.5). Premium values between zero and one work, effectively, as a subsidy: the producer of electricity receives a grant, proportional to the difference between the LCOE and the market price of electricity. From the MID to the DEC scenario (decarbonisation intensity between 0.5 and 1), the premium increases gradually from 1 to 1.1, making the LCOE less expensive than the market price of electricity.[11] The technologies that are subjected to FiT are solar PV, concentrated solar power (CSP), wind onshore and wind offshore, in all regions.

5.2.3 Regulation: limits on new installed capacity for specific electricity generation technologies

The 2°C target proposed by the IPCC requires the decarbonisation of a large part of the global power sector in a time scale of decades (Mercure et al., 2014). The scenario becomes even more stringent if the 1.5°C target agreed in Paris is pursued (UNFCCC, 2015). The strong dominance of fossil fuels in the global electricity sector makes it difficult for low carbon technologies to achieve the degree of market penetration required by these scenarios. For that reason, limitations in the construction of new power plants for specific electricity generation technologies are imposed in FTT:Power, to accelerate the decarbonisation of the global power sector.

In this dissertation, the policy mechanism implemented in FTT:Power to limit the construction of new power plants is denominated *direct regulation* (or simply *regulation*), following the terminology used in the FTT literature (see for instance Mercure et al. (2014)). The term *regulation*, however, may arguably lead to some confusion, given that IPCC (2014b, p. 1158) associates *regulatory approaches* to energy standards, equitable access to grid and legal status of long-term CO_2 storage. Therefore, it is important to clarify the nature of the 'regulation policy instrument' analysed in this dissertation (see section 5.3 for more details).

In FTT:Power, regulation policies control the construction of new units of specific technologies, an can be used to phase out particular types of systems (Mercure et al., 2014). In

[11] In FTT:Power, a FiT rate of 1.1 means that the price of the technology, from the investor's perspective, is less expensive than the price of electricity by 10% of the difference between the price of electricity and the cost of the technology (LCOE).

the context of this dissertation, regulation policies are used for limiting the construction of new coal and gas power stations on specific regions. Similar to the case of the other policy instruments, FTT:Power does not require a specific definition of the legal instrument behind the limitation on constructing new power stations. Consequently, regulation is assumed to be effective in the model, and the limitations on the use of specific technologies are assumed to hold. The stylised policy representation in FTT:Power has, however, a more complex counterpart in reality. For instance, a partial limitation or a complete ban in the use of a specific technology usually requires the coordination of several institutional agents, and faces strong opposition from the affected industry. While these considerations are not part of the model representation of regulations, it is important to have them in mind when the effectiveness and the efficiency of the policy instruments are analysed. The differences between direct regulation in FTT:Power and reality are further discussed in section 5.3.

In FTT:Power, installed capacity is defined endogenously, based on the evolution of the market shares, modelled through coupled logistic differential equations (see section 4.6). As a way to impose limits in the adoption of specific technologies, installed capacity can also be defined exogenously. These limits are defined per technology per region per year (similarly to subsidies and FiT), and can switch between exogenous and endogenous definition at any time. Regulation can, therefore, be imposed as exogenous installed capacity in the model.

There are two sets of regulation that are maintained in all the scenarios:

Nuclear phase out in Germany. After Fukushima's disaster in 2011, Germany decided to phase out nuclear energy by 2022 (Knopf et al., 2014). Therefore, no nuclear reactors are allowed to be built in Germany in any scenario after 2012.

Coal regulation in Europe. Due to the Large Combustion Plant Directive, that was superseded by the Industrial Emissions Directive in 2016, the emissions from combustion plant having thermal capacity of 50 MW or greater have been limited in Europe since 2007 (European Union, 2010). Several coal power plants have already opted out, and the total production of electricity from coal sources has declined in Europe since then (IEA, 2015). Therefore, coal-based electricity in Europe is capped in FTT:Power by its value in 2007.

As in the case of subsidies and FiT, regulation in FTT:Power can be applied to any specific technology in any region at any point in time. In order to simplify the analysis, the portfolio of technologies that are regulated in this work include only three alternatives: coal, integrated gasification combined cycle (IGCC) and combined cycle gas turbine (CCGT) power stations. All of these technologies are fossil fuel based, and they are assumed to be banned at a

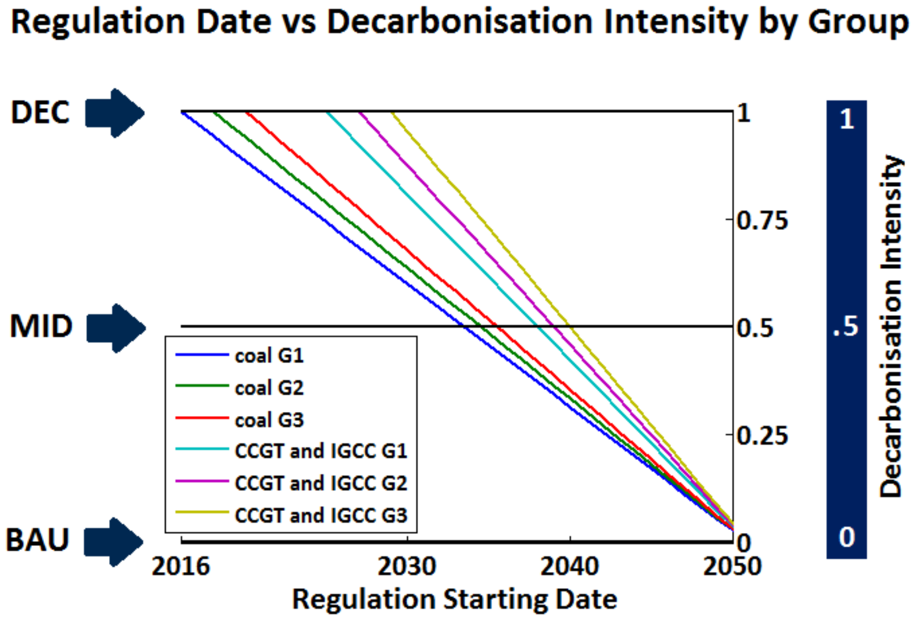


Figure 5.3 Relation between decarbonisation intensity (ordinate) and the starting date of regulation (abscissa) for coal (blue, green and red lines) and CCGT-IGCC (cyan, purple and yellow lines). In the case of the BAU scenario (decarbonisation intensity equal zero), there is no regulation. In the MID scenario (decarbonisation intensity equal 0.5), coal is banned in 2033, 2034 and 2035 in the regions of group 1, 2 and 3, respectively, while CCGT and IGCC are banned in 2038, 2039 and 2040 in the same regions. For the DEC scenario (decarbonisation intensity equal one), the ban for using coal in regions of groups 1, 2 and 3 starts on 2016, 2018 and 2020, respectively, while the ban for using CCGT and IGCC in the same groups starts on 2025, 2027 and 2029, respectively.

time that depends on the decarbonisation intensity value, and the region where the policy is applied. Three sets of regions are defined for the application of regulation:

Group 1 : Europe, USA, Japan, Canada, Australia and New Zealand (regions 1-38)

Group 2 : China, Brazil, Korea and Taiwan (regions 41, 44, 48, 49)

Group 3 : The rest of the world (regions 39-40, 42-43, 45-47, 50-53)

For the first group, coal is assumed to be banned at some point between 2016 and 2051 (the latter is one year after the end of the simulation, so in practice, it means no regulation). The year when the regulation takes place, changes inversely proportional to the decarbonisation intensity. If the decarbonisation intensity is 0 (BAU scenario), then coal is banned in 2051 (in practice, no regulation). If the decarbonisation intensity is 1 (DEC scenario), then coal is banned in 2016. Any value of the decarbonisation intensity in between these two, implies a linear interpolation of the ban date between 2016 and 2051 (including a decarbonisation intensity equal to 0.5 in the MID scenario, which corresponds to 2033). The starting date of the regulation can be calculated as:

$$\text{Starting date of regulation} = 2051 - \text{round}\left(35 * \left(\text{decarbonisation intensity}\right)\right) \tag{5.1}$$

For the second and third groups, the same mechanism is applied, but the time intervals are different: 2018-2051 for group 2, and 2020-2051 for group 3 (in contrast with 2016-2051 for group 1). So, before 2018, there is no regulation for coal in the regions of the group 2, and before 2020 there is no regulation in the regions of the group 3.

In the case of IGCC and CCGT, the starting year of the regulation in the BAU scenario is 2025 for group 1, 2027 for group 2 and 2029 for group 3. The date increases inversely proportional to the decarbonisation intensity, until 2051 in the BAU scenario (same as coal). Figure 5.3 presents a graphical representation of the relation between regulation starting date and decarbonisation intensity for coal, IGCC and CCGT in groups 1, 2 and 3.

5.2.4 Electricity Demand

Through efficiency enhancement and behavioural change, there exists large potential for electricity demand reductions, and they could decrease mitigation costs significantly (IPCC, 2014b). To analyse the potential effects that the reduction in the demand for electricity might have in the technological evolution of the power sector, different scenarios for energy demand are implemented. In reality, electricity demand reductions can be driven by both supply and demand side policies. From the supply side, regulatory instruments in the form of efficiency standards for electricity power plants improve efficiency and drive electricity consumption down (IPCC, 2014b, p. 567). From the demand side, combinations of policy instruments aiming to decrease electricity demand include standards on appliances and market-based mechanisms such as taxes and information policies (Linares and Labandeira, 2010). In FTT:Power, electricity demand is defined exogenously, therefore, there is no policy instrument associated to it. However, it is important to understand what type of instrument could potentially be driving the reductions in electricity demand.

Following the decarbonisation intensity approach explained in the previous sections, electricity demand is assumed to gradually decrease between the BAU and DEC scenarios. The extent of reduction increases proportionally with decarbonisation intensity, up to a maximum value that varies for different world regions. World regions are grouped in three categories, same as in the case of regulation: Group 1 (regions 1-38), with a maximum reduction of 50%; group 2 (regions 41, 44, 48 and 49), with a maximum reduction of 45%; and group 3 (all the other regions), with a maximum reduction of 40%, in comparison with BAU. The electricity demand reductions are assumed to start in 2016 (0% reduction in 2015), and increase linearly until 2050. Figure 5.4 shows how electricity demand changes between BAU and DEC scenarios.

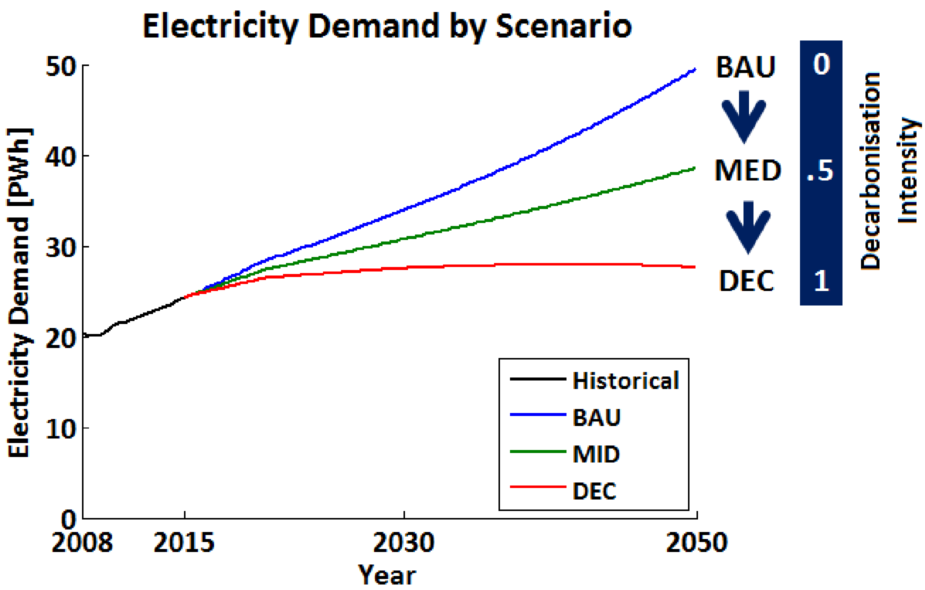


Figure 5.4 Global electricity demand by scenario. The blue, green and red lines represent the global electricity demand for BAU, MID and DEC scenarios, respectively. Electricity demand is assumed to gradually decrease in comparison with the BAU scenario, proportionally to the decarbonisation intensity. The extent of reduction in 2050 in comparison with BAU changes among regions: 50%, 45% and 40% for groups 1, 2 and 3, respectively. The reduction increases linearly with time, starting in 2016.

5.3 Policy instruments beyond modelling

The global character of the FTT:Power modelling approach requires a high level of aggregation. While some regions represent countries, other regions represent large set of countries, such as Rest of Latin America (region 47), Asean (region 51) and Rest of the World (region 53).[12] Consequently, it is impractical to define policies at the instrument level in the model. Instead, a stylised approach is used, in which policies are defined in terms of their impact on

[12]See appendix section A.4 for the regional definition of FTT:Power.

the LCOE. As explained in section 5.2, the only policy instrument that is partially defined in the model is the feed-in-tariff, which is assumed to be a premium tariff scheme, with a variable premium proportional to the difference between the price and the levelised cost of electricity. In the case of carbon pricing, subsidies, regulation and electricity demand, no specification of the policy instrument is required.

In reality, however, the type of instrument used for limiting or promoting the deployment of particular types of technology matters. On the one hand, regulatory instruments such as energy efficiency standards and renewable portfolio standards, directly limit GHG emissions by specifying technologies or their performance, as well as promoting diffusion and innovation of emerging technologies (IPCC, 2014b, p. 1168). On the other hand, market based mechanisms rely on prices to encourage investment on low-carbon technologies (such as in the case of subsidies and feed-in-tariffs) or discourage investment on carbon intensive technologies (such as in the case of carbon taxes and cap-and-trade systems) (IPCC, 2014b, p. 1155). In all these cases, the specific regional requirements, as well as the local politico-legal landscape, play an important role in the choice as well as the implementation of the policy instruments. A very good example is the case of nuclear energy regulation in Germany. In 2002, the Nuclear Phase-Out Act[13] was amended to include a ban on new nuclear power plants. Due to the politico-legal nature of the policy instrument (legislation proposed by an SPD/Green coalition), it is not surprising that in 2010 the policy was subject to further changes by the "Energy concept 2050" (German Federal Government, 2010), presented by the Conservative/Liberal coalition, granting life extensions to several nuclear power plants. Only a few months after the changes were approved, and due to the Fukushima Daiichi nuclear disaster, a new amendment to the Atomic Energy Act was passed in parliament, setting a date for the final shutdown of all the remaining nuclear power plants in Germany (Mann, 2014).

Modelling policy instruments in FTT:Power requires to balance a global representation of the power sector with regionally relevant policy scenarios. On the one hand, the large variability among politico-legal regimes in different regions renders impractical the creation of realistic representations of policy instruments in the model. On the other hand, the use of stylised policies in the model may hinder the relevance of the instruments in the policy analysis. Therefore, in order to provide a clearer picture of what the policy portfolio analysed in this thesis represents in the real world, a translation table is presented below.

[13] Act on the Peaceful Utilisation of Atomic Energy and the Protection Against its Hazards (Atomic Energy Act), of 23 December 1959 (BGBl. I, p. 814), as amended and promulgated on 15 July 1985 (BGBl. I, p. 1565), and amended by the Act of 22 April 2002 (BGBl. I, p. 1351) https://goo.gl/xFOigV

Policy name	FTT:Power implementation	Examples of policy instruments in reality
Carbon Price.	The price of carbon is accounted in the model as the carbon cost component of the Levelised Cost of Electricity (see equation 4.6).	Carbon pricing can include international, national or supranational cap-and-trade systems, carbon taxation or any hybrid combination of those. In order to match the type of instrument used in FTT:Power, the equivalent instrument in reality would have to be applied to the entire electricity sector, with the value of the allowances (or the tax) being proportional to the carbon content of the electricity being generated.
Subsidies.	Subsidies are defined as a percentage of the investment cost, granted by the regulator to investors, to decrease the LCOE of specific technologies.	Subsidies can be implemented in several ways, including grants, favourable loans or fiscal incentives such as reduced taxes, accelerated depreciation, tax credits and tax deductions for investors. In order to be equivalent to the FTT:Power case, the subsidy instrument in reality would have to be granted at the early stage of construction of the power plant (investment phase), for an amount proportional to the total investment cost.
Energy Demand.	Energy demand is defined exogenously in the model, as the amount of energy per year consumed at every region.	In reality, electricity demand reduction policies can be implemented through several mechanisms, including the adoption of energy efficiency standards and direct regulation on energy use. One possible case of real policy instrument could be the use of obligatory efficiency standards for appliances installed in houses, offices and commercial building.

Table 5.1 Carbon price, subsidies and energy demand policies in FTT:Power, and the equivalent policy instruments in reality.

Policy name	FTT:Power implementation	Examples of policy instruments in reality
Feed-in-Tariffs.	FiTs are defined as a percentage of the retail price of electricity, and granted to investors as the difference between the LCOE of a specific technology, and the retail price of electricity, times a premium	Real feed-in-tariff instruments can be divided in two main groups: *fixed tariff* and *premium tariff*. In the former, generators receive a fixed remuneration per unit of energy produced, independently of the market price of electricity. In the latter, generators receive a premium per unit of energy produced proportional to the price of electricity, which can be either fixed or variable. In the case of FTT:Power, it is assumed that the FiT instrument corresponds to a *premium tariff* with a variable premium.
Regulation.	In FTT:Power regulation policies control the construction of new units of particular technologies, an can be used to phase out particular types of systems.	In reality, the limitation in the construction of new coal and gas power stations can be accomplished with different types of regulatory instruments. For instance, it could be through emission standards, portfolio standards, authorisation requirements, direct legislation specifying limits and bans, and liability for environmental harm, among others.

Table 5.2 Feed-in-tariffs and regulation policies in FTT:Power, and the equivalent policy instruments in reality.

5.4 Business as Usual or BAU

Based on the aforementioned assumptions, a whole range of scenarios are implemented. They are a combination of two extreme visions of the world, represented by the BAU and DEC scenarios. The BAU scenario represents a future of growing emissions, based in the intensive use of fossil fuels. It represents a future were almost no effort is made to decarbonise the economy, and technology adoption is completely driven by the market price of the different alternatives. Support mechanisms for renewable energies are completely absent in this scenario, with no subsidies or feed-in-tariffs for any technology. The only regions that incorporate a minimum set of policies in this scenario is Europe. An European carbon price, which rises slowly from 35 [€/tC] in 2016 to 184 [€/tC] in 2050 is assumed in the region. In the context of the Large Combustion Plant Directive, it is assumed that coal is not expanded in Europe after 2007. For all the other regions, there is no limitation in the use of any technology after 2015, including coal. A summary of the main assumptions of this scenario are presented below.

- No subsidies are implemented, neither for renewable energies nor for fossil fuels.
- No feed-in-tariffs are implemented, neither for renewable energies nor for fossil fuels.
- Carbon is not priced/taxed,[14] except in Europe.
- The price of carbon rises slowly in Europe from 35 [€/tC] in 2016 to 184 [€/tC] in 2050.
- Coal is limited in Europe after 2007 (in line with the Large Combustion Plant Directive).
- The demand for electricity is expected to be high, aligned with the baseline scenario of the macroeconomic model E3ME.[15]

5.5 Decarbonisation or DEC

The Decarbonisation scenario represents a future where strong efforts are made to decarbonise the global power sector. In this scenario, policy mechanisms to support the deployment of

[14] Carbon pricing or taxing is not conceptually different in FTT:Power, since the price/rate is determined exogenously.

[15] The electricity demand for the BAU scenario is taken from the E3ME-BAU scenario presented in Mercure et al. (2014).

low carbon technologies are implemented in all regions, in the form of specific subsidies for biogas, geothermal, nuclear and tidal energy, and in the form of feed-in-tariffs for solar (photovoltaic and concentrated solar power) and wind (onshore and offshore) energy. Carbon capture and storage (CCS) technologies also receive strong support in the form of subsidies, in all regions. In addition, limitations to build new coal power plants are in place after 2016 in all regions, and no new combined cycle gas turbine (CCGT) and integrated gasification combined cycle (IGCC) power stations are allowed to be built after 2025. A summary of the main assumptions of this scenario are presented below.

- Technologies using Carbon Capture and Storage (CCS) are subsidised in all regions at rates of 30% between 2015 and 2025. From 2026 until 2044, subsidies decline linearly to zero.

- Technologies such as biogas, geothermal, nuclear and tidal are subsidised in specific regions, using the same mechanism (constant until 2025, and linearly decaying until 2044).

- Feed-in-tariffs for solar technologies (photovoltaic and concentrated solar power) and wind technologies (onshore and offshore) are implemented in all regions between 2015 and 2050.

- Coal is limited in Europe after 2007 (in line with the Large Combustion Plant Directive).

- Limitation for new coal power stations are in place, after 2016 (group 1), 2018 (group 2) and 2020 (group 3).

- Limitation for new combined cycle gas turbine and integrated gasification combined cycle power stations are in place, after 2025 (group 1), 2027 (group 2) and 2029 (group 3).

- Unless stated otherwise,[16] the demand for electricity in DEC decreases linearly in comparison with the demand in BAU, up to a maximum difference of 50%, 45% and 40% in groups 1, 2 and 3, respectively, by 2050 (starting in 2016).

Similar to the case of the BAU scenario, DEC scenario is not expected to be representative of a likely future. On the contrary, it presents a limit scenario under the feasibility spectrum of

[16]In some scenarios, such as those presented in chapter 8, DEC is simulated using the maximum demand for electricity. This happens when the impact of market based policies is being studied, in isolation from the effect of changes in energy demand. The assumptions regarding energy demand are clearly stated in each scenario presented in this thesis.

FTT:Power. It may be argued that some of the policies implemented in DEC are politically and/or legally unfeasible, such as the ban on construction of new power stations using coal, IGCC or CCGT. Without delving on the political and legal aspects of such policies, which is out of the scope of this thesis, it is important to clarify that the goal behind DEC is to explore the theoretical limits of a decarbonisation scenario, under the constraints presented by FTT:Power. On that sense, the scenario presents an upper limit of the potential levels of decarbonisation that can be achieved within the power sector.

One decarbonisation policy that might potentially be implemented in reality, but cannot be analysed in FTT:Power, is the early scrapping of carbon intensive power stations. In FTT:Power, power stations have a lifetime, which defines the rate at which infrastructure can be replaced. If units of capital are decommissioned or scrapped earlier than the date up to which they were expected to operate, then the forgone planned income would have to be accounted for. This can be understood by thinking of a loan that an investor may have taken to purchase a power plant, who uses the income generated by the operation of the power plant to repay the loan. If the investor is required by climate policy to scrap this unit, but he is still required to provide the same service with a unit of cleaner technology, then he might have to take a second loan, and thus have to repay two loans, with the income of a single unit of producing technology. The outstanding loan of the first unit corresponds to the early scrapping loss. The early scrapping loss can only be defined with respect to a difference between income and income planned at the time when the business plan was made and a loan may have been taken (Salas et al., 2015). This phenomenon is not possible to be analysed in the current version of FTT:Power, because the model does not include an explicit representation of the underlying economic interactions. Given the large decarbonisation potential behind early scrapping policies, is expected that future versions of FTT:Power will incorporate these interactions. This may become particularly relevant in the analysis of scenarios of 1.5°C increase in global temperature, as aimed at the COP21 meeting in Paris (UNFCCC, 2015).

5.6 Relative impact of energy policies

Four types of policies (carbon pricing, subsidies, feed-in-tariffs and regulation), combined with scenarios of electricity demand, provide a wide range of decarbonisation potentials. Naturally, each one of them has different abatement mechanism, which interact with one another. For instance, the decarbonisation potential of electricity demand scenarios is directly proportional to the carbon intensity of the grid. I.e., the decarbonisation potential of electricity demand reductions is proportional to the adoption of low carbon technologies, which in turn depends on the implementation of energy policies. In the case of market based mechanisms, such as carbon pricing, subsidies and feed-in-tariffs, the abatement potential depends strongly on the investment response to market incentives. The non-linear and path dependent investment model of FTT:Power provides hysteretic responses to investment incentives.[17] Therefore, the marginal abatement of a specific energy policy will depend on the policy itself, as well as on the concurrent policies. In other words, the marginal abatement of a group of policies is not necessarily equal to the sum of the marginal abatement of each specific policy (Mercure et al., 2014).

Figure 5.5 shows marginal emission reductions for different policy sets and electricity demand scenarios. BAU and DEC are the upper and lower boundaries of emissions, respectively. The top left chart shows the BAU, MID and DEC emission trajectories, as a reference. The colored areas in figure 5.5 represent the marginal abatement of each policy or electricity demand reduction, within the policy set. So, for instance, in the top right chart, the lower boundary of the light brown area represents the emission's trajectory of a scenario with electricity demand reductions in place (with respect to BAU). No policies are included in that trajectory, therefore, the light brown area can be considered as the marginal abatement associated with electricity demand reductions. If in parallel to electricity demand reductions, regulation policies are in place, then the emissions follow the trajectory plotted as the lower boundary of the light blue area. Therefore, the sum of the light blue and light brown areas corresponds to the marginal abatement associated with electricity demand reductions and regulation policies, combined. If we subtract the marginal abatement of electricity demand reductions, we obtained the light blue area, which corresponds to the marginal abatement of regulation. Using the same procedure, the marginal abatement of each policy can be obtained.

Notice that when the policies order is changed, the marginal abatement changes, because only the upper area represents single policies. The areas below the top represent the marginal abatement of single policies under different combinations of coexisting policies. Consequently, given the non-linear behaviour of FTT:Power, it is reasonable to expect that the marginal abatement of each policy changes under different policy combinations. For instance, the marginal abatement of carbon pricing is shown in figure 5.5 as a dark blue area. Clearly, the abatement potential changes on each scenario, although the policy operation (the price of carbon and time of implementation) is exactly the same. In the case of the upper right chart, the marginal impact of carbon pricing, on top of electricity demand and regulation

[17] See chapter 10 for more details of the FTT:Power investment model

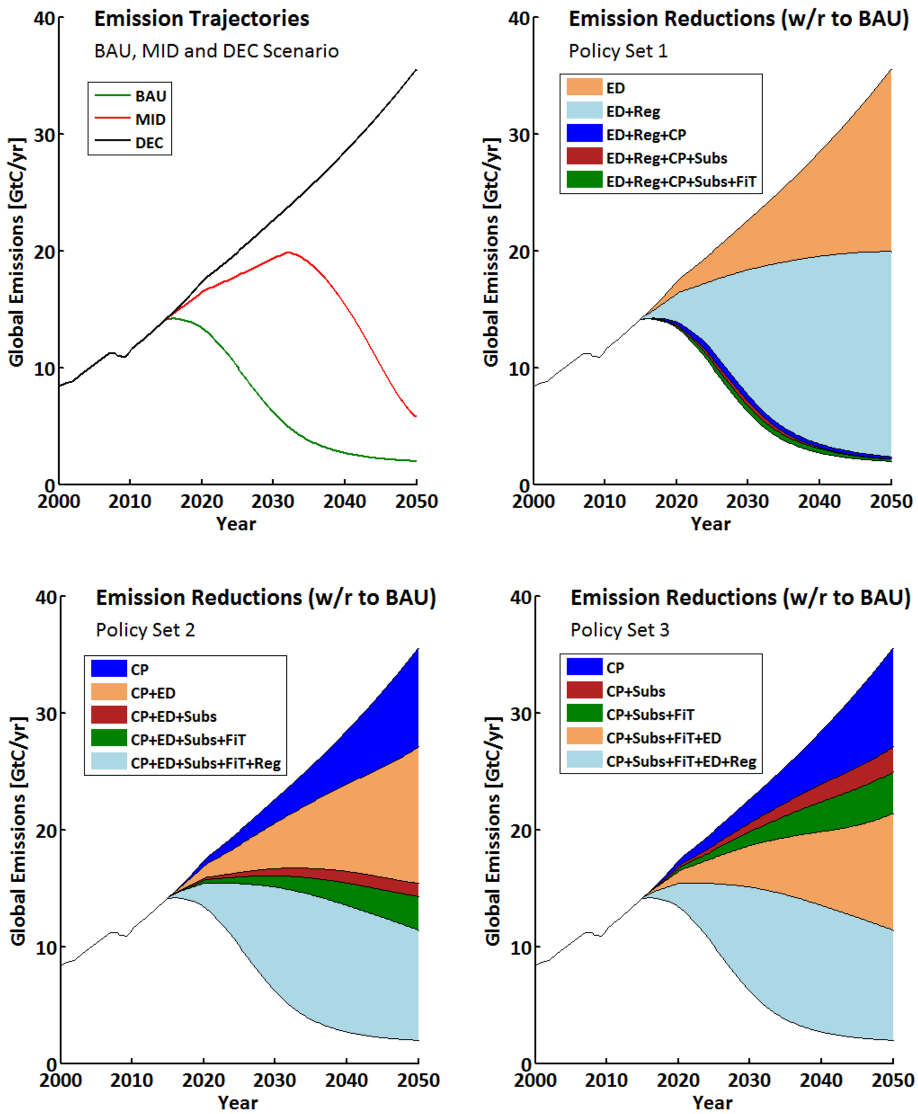


Figure 5.5 Emission trajectories (top left) and emission reductions with respect to BAU (top right and bottom) for different combination of policy sets and electricity demand reductions. The top left chart shows the combined effect, for decarbonisation intensity values of 0 (BAU, black line), 0.5 (MID, red line) and 1 (DEC, green line). The top right and bottom charts show the reduction in emissions (with respect to BAU), associated with different sets of policies and electricity demand reductions in the DEC scenario. The acronyms are CP = carbon pricing, ED = electricity demand reduction, Subs = subsidies, FiT = feed in tariffs and Reg = regulation. For the top right and bottom charts, policies and demand reductions are assumed to be implemented at the maximum intensity (i.e. DEC).

policies, is smaller than in the other scenarios (bottom charts). I.e., the marginal abatement potential of carbon pricing depends on the concurrent policies being implemented. The same happens with the other policies, especially those based on market mechanisms (subsidies and feed-in-tariffs).

The interactions between the policies and the demand reduction is context dependent, and a reflexion of the complexity of the system. The fact that policies interact, also means that each emission trajectory (equivalent to a decarbonisation intensity between 0 and 1) can be reached by different combinations of policies. Therefore, the mapping of the FTT:Power policy domain in the interval [0 1] only includes a subset of the domain. Indeed, it only includes policies moving in the same “decarbonisation direction”: higher the decarbonisation intensity, higher the carbon pricing, subsidies and feed-in-tariffs. The choice of sampling a subset of the FTT:Power policy domain (only policies moving in the same decarbonisation direction), necessary due to the large amount of data and complexity of the model, constraints the analysis of decarbonisation scenarios.

Energy systems are deeply enmeshed in broad social, economic and political regimes (Miller et al., 2015). Agents and institutions involved in the process of policy design and implementation may have different interests, limiting any potential coordination between them. Therefore, the assumption of policies being implemented in the same decarbonisation direction is arguably a strong assumption. Even the implementation of single policies, such as a carbon tax, can become a very difficult challenge in reality. For instance, the European Union has been unable to implement an European-wide carbon tax, despite the efforts made since the early 90s (Grubb, 2014, p. 227). Different policy instruments can have different degrees of political acceptability within specific historical context, making even more difficult any potential coordination. Continuing the example of Europe, while the implementation of a continent-wide carbon tax has not been possible, a cap-and-trade system has been successfully running since 2005 (Ellerman and Buchner, 2007). Similarly, feed-in-tariffs and subsidies have been successful implemented across Europe, as well as in many other regions of the planet (REN21, 2015). Given the various levels of political acceptability of the different policy mechanisms, a gradual implementation of policy instruments is more likely to happen in reality than a simultaneous implementation. However, given the large number of regions and the large ensemble of scenarios analysed in this dissertation, I decided to have a synchronous policy portfolio, in order to limit the degrees of freedom of the simulations. Otherwise, the implementation of policy sequences at different times in different regions would have rendered the analysis impractical.

According to the results presented in figure 5.5, regulation has the largest potential for reducing emissions. These results, however, have to be interpreted with caution, because they are connected with some of the main assumptions of the model. On the one hand, FTT:Power assumes that regulation policies are completely feasible. In other words, the emission reductions by regulation policies presented in figure 5.5 happen because *regulation is implemented at the corresponding regions and times*. In reality, however, partial limitation or a complete ban in the use of specific technologies (coal and gas in this case) are likely to face strong opposition by the incumbent industries. Indeed, the energy system displays strong inertia, and tends to perpetuate the established interests (Grubb, 2014, p. 312). Therefore, the possibility of achieving a complete ban on coal in the short term, as well as a complete ban on gas at the medium term, seems highly unlikely. Consequently, the decarbonisation potential of regulation policies presented in this dissertation is probably higher than the decarbonisation potential of regulation policies in reality. On the other hand, the relative dominance of incumbent technologies in FTT:Power, driven by the assumption of investment being proportional to existing shares (see the shares equation 4.5) produces the opposite effect on non-regulation policies: incumbent technologies dominate investment preferences, and therefore the entrance of low carbon technologies is limited by their relatively small initial shares. Consequently, the process of phasing out fossil fuels without regulatory policies might be underrated in the model. In summary, the abatement potential of regulatory policies is influenced by the assumption of complete feasibility of regulation, while the abatement potential of non-regulatory policies might be underrated in the model due to the strong inertia produced by the shares equation formulation. As a consequence of this, the relative performance of market over non-market based policies needs to be further analysed at the light of the local context of the specific regions under analysis. Therefore, the results presented in figure 5.5 must be interpreted cautiously.

5.6.1 Preliminary conclusions

Energy policies have a direct influence in investment decisions, which drive technology adoption. The allocation of investment in specific technologies, influences future investment allocation, due to self-reinforcing mechanisms. Phenomena such as learning-by-doing or energy resource use and depletion, which are the base for this path-dependent behaviour, are analysed in detail in the following chapters. The specific role of policy in investment allocation is studied in chapter 10.

The analyses developed in the following chapters, provide the elements required to understand the complex dynamics behind figure 5.5. However, there are some relevant aspects that can be highlighted in this section:

- Regulation in the use of fossil fuels has, as it might be expected, the largest abatement potential. Banned power plants are replaced at the end of their lifetime (no early scrapping). Therefore, markets are assumed to adjust to them gradually. The cost of technology replacement is, at the end, paid by consumers through the price of electricity. While the politico-legal implications of implementing such policies are out of the scope of this thesis, the results must be interpreted with caution, as theoretical boundaries in the policy spectrum of FTT:Power (see previous section above).

- The peaks in emissions observed in the MID and DEC trajectories of the top left chart of figure 5.5, are closely connected with the fossil fuel regulation in place in those scenarios, especially coal regulation in China.

- Electricity demand reductions have the second largest impact in emissions. Demand reductions are the result of the implementation of policies in the demand side of the energy sector. According to the data presented by Wilson and Grubler (2011), the market size of the end-use sector and the volume of applications, is at least one order of magnitude larger than the supply-side counterpart. Consequently, it is not surprising that electricity demand reductions play a relevant role in the decarbonisation of the power sector.

- Carbon pricing is the market based mechanism with the largest influence in emission reductions. The marginal abatement potential associated with subsidies and feed-in-tariffs is less significant in these scenarios, especially if compared against regulation.

- The marginal impact of market based mechanisms decreases with the implementation of non-market based policies, as shown in the top right chart of figure 5.5. I.e., there is a decreasing marginal productivity of decarbonisation policies, for stringent decarbonisation scenarios. The relative importance of market versus non-market based mechanisms is, however, strongly influenced by the inertia of the incumbent technologies, and the complete feasibility of regulation policy in the model. Consequently, policy implications based on these scenarios must be further analysed at the light of the local context of the specific region under analysis.

5.7 Variations beyond energy policy

The BAU and DEC scenarios, introduced in the previous sections, are the cornerstone of the analysis presented in the next chapters. Following the decarbonisation intensity approach, future scenarios for the power sector are analysed, under different combinations of policy sets and intensities. The decarbonisation intensity approach is also used in the next chapters for sampling other variables from the FTT:Power domain, such as energy resources and learning rates. There is, though, a subtle difference: scenarios with different energy resources are alternate possible 'worlds', while scenarios with different energy policies are variations of strategy in the same 'world'. Consequently, the amount of natural energy resources is not 'defined', but 'estimated' as a constraint for the entire system in a particular scenario.

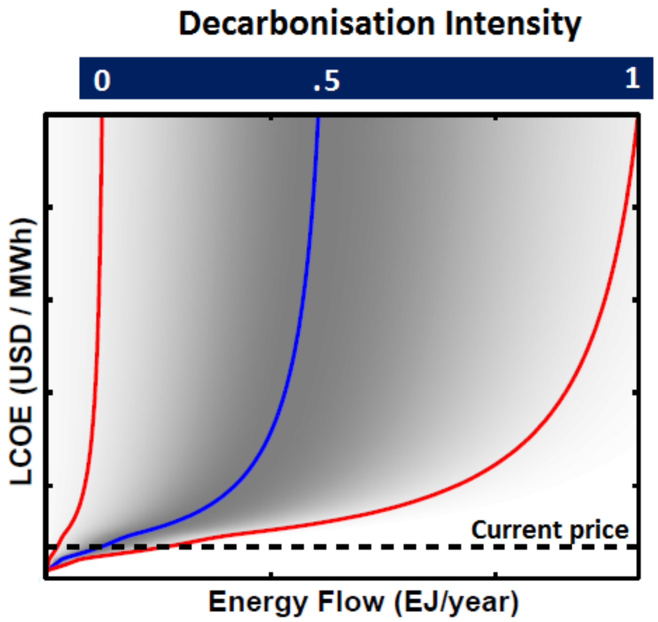


Figure 5.6 Cost supply curves, such as the one shown in this figure, are sampled using the carbon intensity methodology explained in section 5.2. The minimum (zero) and maximum (one) decarbonisation intensities correspond to the lower and upper limits of the cost supply curve, respectively, shown in red. Any intensity between zero and one, represents a curve within the aforementioned limits. The particular case of intensity equal 0.5 corresponds to the most likely cost supply curve, plotted in blue. The shading area corresponds to the uncertainty interval of the cost supply curve. For more information about the cost supply curves framework, please refer to chapter 6 and to Mercure and Salas (2012, 2013b).

5.7.1 Variation of Natural Resources

As explained briefly in section 4.4, FTT:Power has a database of energy resources, which is based on an extensive review of energy assessments, combined with a novel mathematical representation of resource distributions (Mercure and Salas, 2012). This database is part of the Natural Energy Resources (NER) module, and is presented in detail in chapter 6. Economic potentials of energy resources are stored in the NER module as cost supply curves, with uncertainty intervals defined by the upper and lower limits of the technical potential of the underlying primary energy resources.[18] Using the decarbonisation intensity approach, cost supply curves are sampled, to create scenarios for the power sector under different availability of energy resources. Figure 5.6 shows the relation between the decarbonisation potential and the cost supply curve sampling. To see a practical use of this approach, please refer to chapter 8, where the cost supply curve for hydroelectricity in Brazil is sampled, to create 120 emission trajectories for the Brazilian power sector.

5.7.2 Learning

As explained in section 4.5, FTT:Power incorporates learning curves as part of the technology evolution process, using a power relation between cumulative investment and the unit cost of the respective technology. The extent at which the production cost decreases with cumulative investment is defined by the learning rate. Technologies with high learning rates have a large potential for cost reductions, therefore, they represent an important factor to analyse in the technological evolution of the power sector.

Learning rate estimations found in the literature show very large variations (Rubin et al., 2015; Weiss et al., 2010). If uncertainty ranges are used, they can be sampled, using the decarbonisation intensity variable (same approach as the one used with the cost supply curve). For instance, in chapter 9, the extreme of the learning rate intervals, corresponding to decarbonisation intensity values equal 0 and 1, are used for the study of scenarios of the power sector under extreme learning conditions. The technologies used in those scenarios are presented in table 5.3

[18]The theoretical framework behind the cost supply curves is explained in detail in chapter 6.

Scenario	Technology	Range Min Int=0	Range Max Int=1
FF	Oil	0.5	1.5
FF	Coal	3.0	14.0
FF	IGCC	2.5	16.0
FF	CCGT	4.0	34.0
BWS	Biomass	0.0	38.0
BWS	BIGCC	5.0	10.0
BWS	Biogas	0.0	15.0
BWS	Wind On.	4.0	32.0
BWS	Wind Off.	5.0	19.0
BWS	Solar PV	10.0	35.0
BWS	CSP	8.0	16.0

Table 5.3 Learning rate ranges used in the Fossil Fuel (FF) and Bio-Wind-Solar (BWS) scenarios of chapter 9. In the FF scenario, the technologies involved are oil, coal, IGCC and CCGT. In the BWS scenario, the technologies involved are biomass, BIGCC, biogas, wind onshore, wind offshore, solar PV and CSP. For the technologies not involved in the scenarios, the default FTT:Power learning rate coefficient is used (fifth column of table 9.1 in chapter 9). In the scenario with decarbonisation intensities equal 0, the minimum learning rate value is chosen, while in the scenario with decarbonisation intensity equal 1, the maximum learning rate is adopted.

5.8 Conclusions

This chapter presented the framework used in this thesis for the creation of the scenarios of the power sector analysed in chapters 7, 8, 9 and 11. The proposed framework maps a subset of the FTT:Power domain into the range [0 1], using a *decarbonisation intensity* variable. This methodology facilitates the creation and analysis of a large number of scenarios using a single variable. The limits of the decarbonisation intensity (0 and 1) correspond to extreme scenarios of the power sector, based on pessimistic (lower limit) and optimistic (upper limit) assumptions about future decarbonisation efforts, scenarios BAU and DEC, respectively.

The decarbonisation intensity approach is mainly used for sampling the energy policy domain of FTT:Power. However, for some specific scenarios, the methodology is also used for sampling cost supply curves of natural energy resources and learning rates. Ranges of emission trajectories were presented in section 5.2 (figure 5.1) and section 5.6 (figure 5.5), for different decarbonisation intensities and policy sets. The scenarios presented here are the basis for the analysis presented in the next chapters.

The unification of the sampling process through the decarbonisation intensity variable, has a limitation: all the sampled domain variables move in the same direction for increasing values of decarbonisation intensity. So, higher decarbonisation intensity implies more stringent decarbonisation policies, including higher carbon price, subsidies and feed-in-tariffs, as well as more restrictive regulation. In some cases, it might be relevant to analyse policies moving in opposite direction, to reflect issues such as the potential lack of coordination between policy agencies. That type of analysis requires a multidimensional sampling method for the FTT:Power domain, something that would increase the resolution but also the difficulty of processing the data from the scenarios, rising concerns about tractability. In this context, the approach chosen represents a good trade-off between tractability and resolution, sampling a subset of the policy space.

Chapter 6

Model of Natural Resources Use and Depletion

6.1 Chapter summary

This chapter introduces the Natural Energy Resources (NER) module of FTT:Power. The NER module includes a database of energy resources, created with the intention of providing a tool for FTT:Power to study the diffusion of energy technologies, addressing the corresponding feedbacks with the natural world in terms of primary energy use and depletion. The database relies on a novel mathematical representation of energy resources using distributions based on statistical trends. Energy resources are divided in two main groups: resources that have similar productivity (nearly identical resources or NI) and resources that can be easily ranked in terms of their productivity, and follow a hierarchical distribution (hierarchical resources or HI). Functional forms in the cost-quantity space are provided by the two types of resources, which is the basis for the creation of a database of cost supply curves for 17 types of energy resources in 190 countries.

The NER module includes a dynamic model of gradual resource depletion, to represent the evolution of stock resources under exogenous scenarios of energy cost. The dynamic model can also be used in the reverse direction, to analyse the impact on cost of exogenous scenarios of energy demand. The dynamic model, published in *Energy Policy* as "On the global economic potentials and marginal costs of non-renewable resources and the price dynamics of energy commodities" (Mercure and Salas, 2013b), uses the database of energy resources described above, which was published in *Energy* as "An Assessement of Global Energy Resource Economic Potentials" (Mercure and Salas, 2012).[1]

This chapter is structured as follows: Section 6.2 introduces the NER module, including some key concepts. Section 6.3 describes the mathematical representation of energy resources using distributions based on statistical trends. HI and NI distributions are presented in sections 6.3.1 and 6.3.2, respectively. Section 6.4 shows how the HI and NI distributions fit very closely some of the cost supply curves calculated by Hoogwijk et al. using the IMAGE model. The aggregation of information from a large amount of energy assessments is incorporated in the cost supply curve database, in the form of uncertainty intervals. The methodology behind this aggregation is presented in section 6.5. A summary of the information stored in the NER module is presented in section 6.6, as global cost supply curves for renewable and stock resources (figures 6.6 and 6.7, respectively). This section also introduces the "Cost Supply Curves GUI", a software that I developed in MATLAB to visualise the database. Section 6.7 presents the dynamic model of energy resources use and depletion, and includes some results from a modelling exercise presented in Mercure and Salas (2013b). Finally, a critical overview of the NER module is presented in section 6.7.2, where its most important strengths and weaknesses are discussed. The chapter finishes with the Conclusion and further work in section 6.9.

6.2 Introduction

The decarbonisation of the economy requires a significant transfer of energy supply from traditional fossil fuel based technologies to renewable or nuclear alternatives. This transformation is expected to be driven by coordinated policies, that create strong incentives for investment in low carbon energy technologies. Policies, in order to be successful, have to be based on well founded expectation about the future availability of resources. Meanwhile, realistic scenarios of the future are constrained by physical limits imposed by nature, such as maximum resources productivity or extraction limitations. Assessments of the potential availability of natural energy resources are, therefore, essential for planning and policy making.

[1] As explained in section 1.5, the NER module was created as part of a collaborative work between Dr. Jean-Francois Mercure and myself. The development of the NER module was a joint effort, for which each of us claim a 50% authorship. All the information presented in this chapter, which is based on Mercure and Salas (2012, 2013b), is part of that work. The scenarios presented in chapters 5, 7, 8, 9 and 11, all of which use the NER module, are entirely my own work.

The literature on global energy potentials is prolific. Among the recent energy assessment compilations, stand the Energy Study 2015 by the Federal Institute for Geosciences and Natural Resources (BGR, 2015), the World Energy Resources Survey, by the World Energy Council (WEC, 2013), the Global Energy Assessment by IIASA (GEA, 2012), the Special Report on Renewable Energy Sources by the IPCC (IPCC, 2011), the 100% Renewable Energy by 2050 Report by WWF (WWF et al., 2011) and the 2010 Survey of Energy Resources by the World Energy Council (WEC, 2010). Unfortunately, most of the assessments (and therefore the compilations) do not include economic structures associated with the energy potentials. The presentation of total amounts of energy available as an upper limit for use and depletion, without any underlying economic structure, is not particularly useful in terms of policy-making and planning. Energy cost structures are, indeed, absolutely relevant for modelling the energy sector, especially if the focus is to understand the technology transitions from one energy source to another.

Based on a thorough analysis of the available literature, an updated assessment of global energy resources was published by Dr. Mercure and I (Mercure and Salas, 2012). This assessment reflects the latest knowledge about the potential of all the energy resources analysed (seventeen), and it includes a theoretical model of resource distribution according to observed statistical trends. The assessment includes all the major natural energy resources (with a potential larger than 10 EJ/y) and their costs, presented in the form of cost supply curves, for 190 countries. Eleven types of renewable energy resources were studied, four types of fossil fuels, and two types of nuclear resources.[2] The assessment was created with the intention of providing a tool for FTT:Power to study the diffusion of energy technologies, addressing the corresponding feedbacks with the natural world in terms of primary energy use and depletion. Moreover, the creation of the assessment aimed to contribute to the literature and help other groups to parameterise their models. The assessment, and the model of primary energy use and depletion, was incorporated in FTT:Power under the name of **Natural Energy Resources** module (NER).

The next sections describe the theoretical foundations behind the NER module, including a novel mathematical representation of energy resources using distributions based on statistical trends. But first, some key concepts are presented below.

[2]Nine types of renewable sources are listed in the published paper (hydro, onshore wind, solar, geothermal, primary biomass, electricity from biomass, biofuels, wave and tydal), and two more were added later (offshore wind and biogas). The fossil fuel resources listed are soft and hard coal, oil (conventional and unconventional) and gas, and the nuclear resources are uranium and thorium.

6.2.1 Potentials

In a human time scale, energy resources are limited, either in terms of the maximum flow that can be harnessed (for renewable sources), or their remaining stock (for fossil fuels and fissile material). The limits can be physical (amount of resources), technical (technology available to harness the resources) or economic (cost of the resources). Following the approach of Mercure and Salas (2012), these limits can be defined as:

Theoretical potential : Total quantity of energy stock or flow estimated to exist or stem from a particular natural process, disregarding its technical recoverability.

Technical potential : Total quantity of energy stock or flow estimated to exist or stem from a particular natural process, recoverable using a specific technique, disregarding its level of technical difficulty and the associated costs.

Economic potential : Quantity of energy stock or flow estimated to exist or stem from a particular natural process, recoverable at exploitation costs that are competitive compared to all other alternative ways of producing the same energy carrier.

While the theoretical potential is typically constant,[3] the technical and economic potential change with the evolution of technologies and markets. Moreover, what is considered competitive changes continuously, so the economic potential is better expressed as quantities of stock or flow of energy as a function of cost. This can be done through cost supply curves.

6.2.2 Cost supply curves

Cost supply curves are functions of the cost of energy flow or stock from a particular resource, given that a certain quantity is already in exploitation or has already been consumed. Energy resources are harnessed gradually, and as consumptions progresses to higher levels of exploitation, the marginal cost of additional units tends to increase. This dynamic is captured by the cost supply curves, which are a representation of the economic potential of specific resources as a function of cost.

The construction of cost supply curves requires a ranking of the resources in the cost space. Figure 6.1a shows a typical cost distribution of energy resources, which can be created from productivity distributions, or directly from data. If it is created from data, then a smoother

[3] The theoretical potential changes when new knowledge about the availability of the resource on the planet is obtained.

distribution is fitted to the data (figure 6.1b). The integral of the cost distribution (figure 6.1c) represents the amount of resources available as a function of cost. Therefore, if the axes are inverted (figure 6.1d), the relation between the marginal cost of the resources as a function of its cumulative consumption is obtained, i.e., the cost supply curve. It is important to notice the underlying assumption of resources being used in order of cost. While this might seem restrictive from a global perspective, at the regional level resources tend to be exploited in order of their cost of extraction, because investors aim for the most profitable resources to be harnessed first. The upper limit of a cost supply curve is the maximum amount of resources available, independently of cost, which corresponds to the technical potential. The next section explains how the cost supply curves can be described using functional forms, derived from statistical trends.

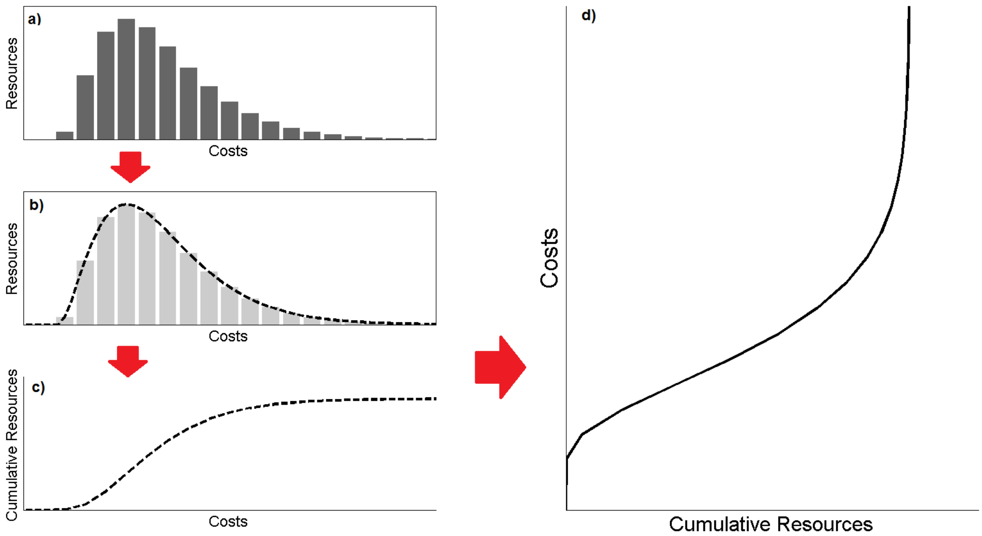


Figure 6.1 Representation of the process of calculating a cost supply curve: a) Hypothetical discrete distribution of resources (pdf) at various cost ranges. b) Smoothered distribution of energy resources, based on a). c) Cumulative distribution of energy resources (cdf). It represents the amount of resources available at a given cost. d) Inverse function of c), known as **cost supply curve**. It represents the cost of extracting an additional unit of energy given that a certain quantity has already been exploited.

6.3 Distribution of resources based on statistical trends

Some statistical trends and pattern can be found when analysing the availability of energy resources in nature, even though the underlying processes of production of energy resources are diverse and complex. From the efficiency perspective, when the productivity of the resources producing units (wells, land plots, energy flows) tend to be similar, then efficiency distributions are narrow. A clear example of this is solar energy: solar panels can be installed on large geographical areas under very similar radiation conditions, with small differences on the infrastructure requirements. In the productivity space, this corresponds to a narrow distribution, limited by the technical efficiency of the photovoltaic technology. Following the nomenclature of Mercure and Salas (2012), the energy resources that follow this type of productivity distribution are called **nearly identical** resources (NI). The opposite case are the resources with productivity values depending on a large number of converging factors. The best example is wind energy: quality of wind sites vary enormously within a small geographical area, because several concurrent conditions have a direct impact on the productivity of the site. These resources can, therefore, easily be ranked in terms of their productivity, and follow a **hierarchical distribution** (HI). Figure 6.2a and 6.2e show examples of a hierarchical distribution (blue) and a nearly identical resources distribution (green), respectively.

Energy resources following a NI distribution are sharply defined in a narrow range of productivity, cutting off at a maximum value, which corresponds to the best possible condition for energy production. This is represented by μ_2 in figure 6.2e. Meanwhile, energy resources following a HI distribution are more spread in the efficiency space, with very few sites with a large productivity, and a large number of sites with very poor productivity. Below certain minimum productivity μ_1, resources are not usable in practice, because they require too much effort to harness the energy (in the case of wind energy, for instance, these would be sites with wind speed below the cut-in speed of the wind turbines). This is represented by μ_1 in figure 6.2a.

The next sections provide functional forms in the cost-quantity space, for the HI and the NI distribution of resources. These functional forms are the basis for creating the cost supply curves, following the procedure described by figure 6.1.

6.3.1 Hierarchical resources

Hierarchical resources require a large number of positively contributing factors occurring simultaneously. Consequently, the number of sites decrease exponentially with productivity. Based on this description, the resource distribution for hierarchical resources in the productivity space can be represented by the following function:

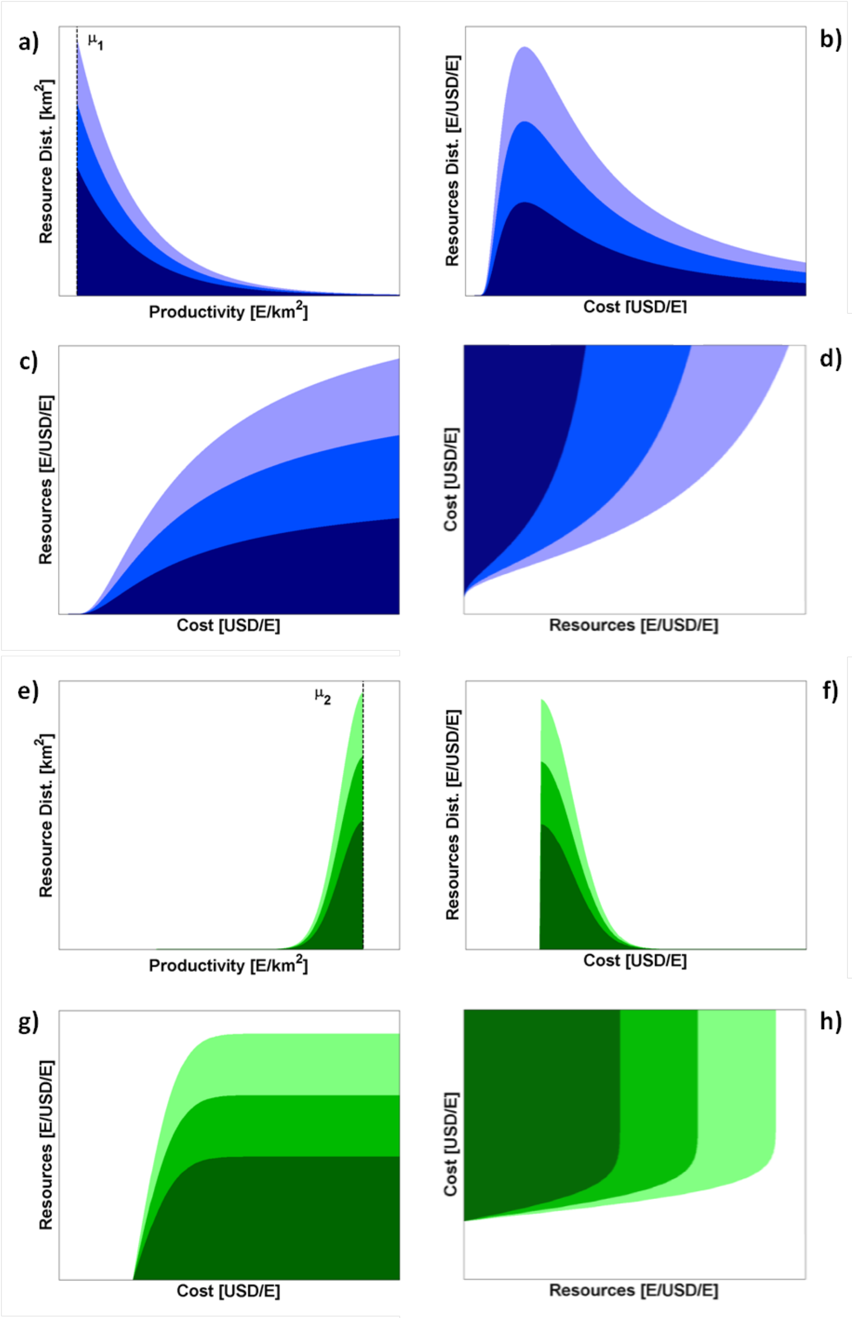


Figure 6.2 Set of curves showing the transformation from the productivity distributions (a) and e)), to cost distributions (b) and f)), to cumulative costs (c) and g)), to the cost supply curves (d) and h)). Blue curves represent Hierarchical (HI) type of resources, while green curves represent Nearly Identical (NI) type of resources. Different shades represent the uncertainty regarding resource distributions, which propagates from the distribution space to the cost supply curves. The percentiles assigned to the uncertainty ranges are explained in section 6.5 (see figure 6.4).

$$f(\nu)d\nu = \begin{cases} \frac{A}{\sigma} \cdot e^{-\frac{\nu}{\sigma}} d\nu & \nu > \mu \\ 0 & \nu \leq \mu \end{cases} \tag{6.1}$$

where ν is the productivity, A is the technical potential, σ^2 is the variance of the distribution and μ is the minimum productivity limit. This is the functional form presented in figure 6.2a. The shading represents different levels of uncertainty regarding the resource distribution. In order to calculate the cost supply curve (in the cost space), the following change of variable can be applied:

$$C = \frac{C_{var}}{\nu} + C_0 \quad \Rightarrow \quad d\nu = -\frac{C_{var}}{(C - C_0)^2} dC \tag{6.2}$$

where C is the cost per unit of energy (inversely proportional to productivity), C_0 is the cost which is independent of productivity, and C_{var} represents a scaling factor with units of cost per production unit (for instance, cost per unit of land in the case of wind energy). The cost distribution is defined in dollars per unit of energy, and given the previous change of variable, it can be written using the following functional form:

$$f(C)dC = \begin{cases} \frac{AB}{(C-C_0)^2} \cdot e^{-\frac{B}{C-C_0}} dC & C > C_0 \\ 0 & C \leq C_0 \end{cases} \tag{6.3}$$

The cost distribution in equation 6.3 is presented in figure 6.2b, including the uncertainty ranges. The integral of the resource distribution in the cost space, as shown in figure 6.1, corresponds to the inverse function of the cost supply curve. Given the functional form presented in equation 6.3, the cumulative cost distribution is:

$$F(C) = \begin{cases} A \cdot e^{-\frac{B}{C-C_0}} & C > C_0 \\ 0 & C \leq C_0 \end{cases} \tag{6.4}$$

The function $F(C)$ and its inverse are plotted in figure 6.2c and 6.2d, respectively. The latter corresponds to the cost supply curve: cost of the resources as a function of the cumulative consumption of energy.

6.3.2 Nearly identical resources

The mathematical derivation of the nearly identical type of resources distribution is slightly more complicated, so it is explained in detail in the appendix section B.1. The NI distribution in the efficiency and cost space are shown in figures 6.2e and 6.2f, respectively, while the functional form in the cost space can be described as follows:

$$g(C)dC = \begin{cases} \frac{A}{B\sqrt{2\pi}} \cdot e^{-\frac{(C-C_0)^2}{2B^2}} dC & C > C_0 \\ 0 & C \leq C_0 \end{cases} \tag{6.5}$$

Similar to the previous case, the integral of the NI resource distribution in the cost space corresponds to the inverse function of the cost supply curve, presented in figure 6.2g. Given the functional form presented in equation 6.5, we obtain:

$$G(C) = \begin{cases} \frac{1}{2}\left[1 + erf\left(\frac{(C-C_0)}{B\sqrt{2}}\right)\right] & C > C_0 \\ 0 & C \leq C_0 \end{cases} \tag{6.6}$$

where *erf* indicates the error function. And this is the inverse function of the cost supply for NI resources. The cost supply curve is presented in figure 6.2h.

6.4 Comparison with IMAGE data

The functional forms described by equations 6.4 and 6.6 have been found to reproduce very closely the cost-supply curves calculated by Hoogwijk et al. using the land use model IMAGE, whose work does not assume any functional dependence on cost for its distributions (de Vries et al., 2007; Hoogwijk, 2004; Hoogwijk et al., 2009; van Vuuren et al., 2009). The distributions from IMAGE were calculated by producing cost ranked histograms of potential renewable energy flows (wind, solar and biomass) using a 0.5° by 0.5° grid of the Earth's onshore land. Thus, their form originates purely from statistical properties of the aggregation and ranking of the resources modelled. The cost-supply curves in their work were found to agree very well with HI or NI distributions given above, depending on the nature of the resources: solar energy and agricultural land are well represented by the distribution for nearly identical resources, while wind power and rest land are well represented by the hierarchical distribution. Additionally, the HI distribution was found to agree well with observed cost distributions of uranium as reported by the International Atomic Energy Agency (NEA and IAEA, 2009). Examples of non-linear fits of these functions to IMAGE data are given in figure 6.3, and more detailed information can be found in the Supplementary Information of Mercure and Salas (2012).

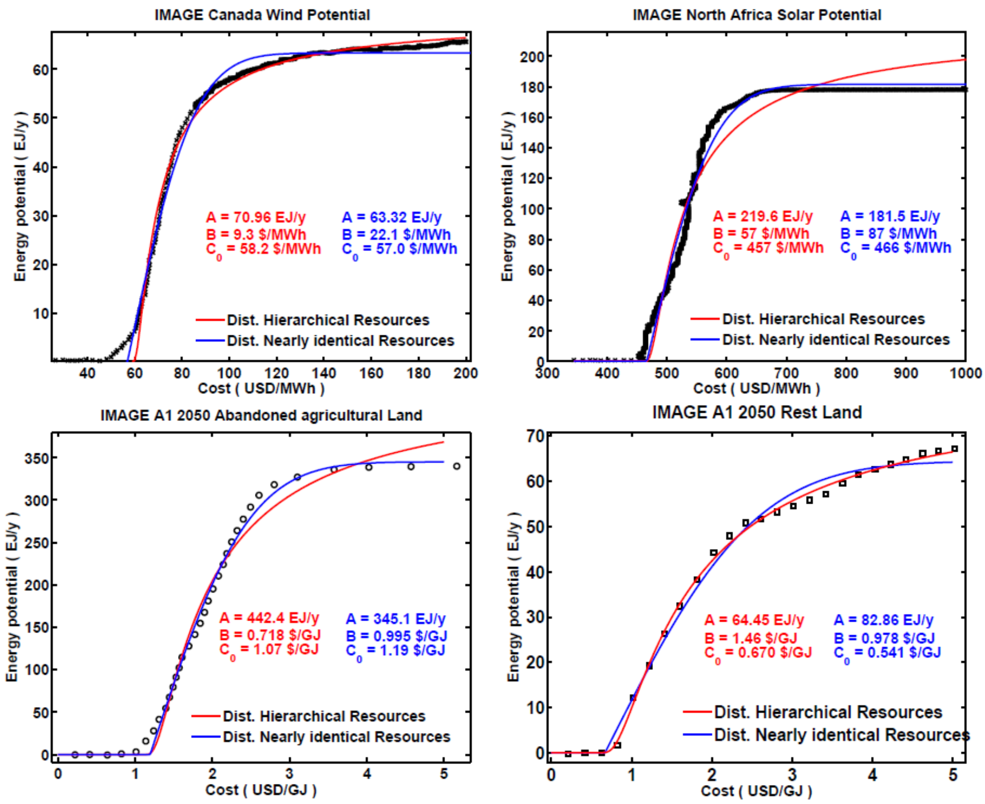


Figure 6.3 Curve fits of HI and NI distributions with data from various studies of renewable energy potentials, calculated using the model IMAGE (reproduced from (de Vries et al., 2007; Hoogwijk, 2004; Hoogwijk et al., 2009)). The goodness of these fits are a good indication for which type of distribution represents best each type of resource. It can be observed that data for wind energy (top left) and low quality agricultural land or rest land (bottom right) are well described by the HI distribution (red curve), while the data for solar energy (top right) and abandoned agricultural land (bottom left) is well described by the NI distribution (blue curve). Only one of the two distribution fits the data correctly each time, and the type of distribution changes depending on the kind of resource. Figure from Supplementary Information of (Mercure and Salas, 2012).

6.5 Uncertainty ranges

Understanding the economic availability of natural energy resources is key for the creation of plausible future energy scenarios. Assessments of natural energy resources, however, possess high levels of uncertainty, which must be taken into account when generating model outputs. For instance, the global bioenergy potential has been estimated to lie between 310 to 660 EJ/y by Hoogwijk et al. (2005), between 0 and 650 EJ/y by Wolf et al. (2003) and between 370 and 1550 EJ/y by Smeets et al. (2007). The differences arise from specific assumptions about the future, which have an embedded degree of uncertainty. These types of uncertainties are present in all assessments of energy resources, including renewable energies, fossil fuels and fissile material. In the case of stock resources, for instance, uncertainty about the oil reserves has led to a prolific production of speculative economic theories (Deffeyes, 2006). Modellers, relying on energy assessments to create future scenarios of energy use, are expected to incorporate, or at least to acknowledge, these uncertainties as part of their analysis. A review of literature is, therefore, not only advisable, but necessary to define ranges of energy potentials. In the absence of justified criteria onto which to base a choice of particular studies over all others, resource assessments must be considered equally, the collection of which can be used to generate uncertainty ranges. This allows to decouple the work from specific assumptions used in specific studies (Mercure and Salas, 2012).

Uncertainty ranges, in this work, are based on variations on the estimation of **technical** potentials, from the review of the literature. Within the uncertainty range, **economic** potentials are estimated through cost-supply curves, combining energy cost and energy quantity data, using the functional forms described in section 6.3. The uncertainty ranges define areas in the cost-quantity/flow plane for where the actual cost-supply curves have a 96% probability of lying. This would correspond to two standard deviations, 2σ, if the distributions were normal, but they are in general skewed. Real values have a 2% probability of occurring below the range, and a 2% probability of lying above.[4] Figure 6.4 shows a typical example of cost supply curve, including the uncertainty ranges.

6.6 The NER database of energy resources

Using the cost supply curve approach described in the previous sections, a global database of energy resources was compiled. The database is part of FTT:Power, and is used for

[4]The actual probabilities are 95.4% and 2.3%. The values 96% and 2% are used instead for convenience.

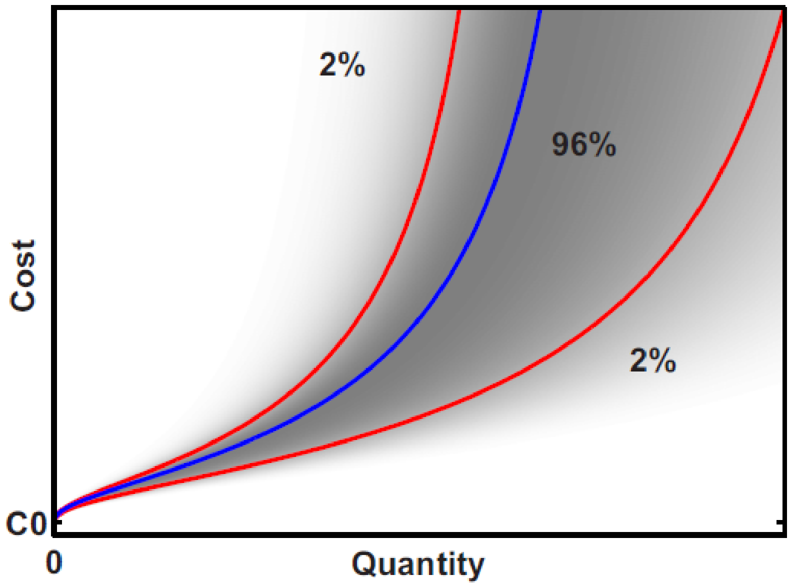


Figure 6.4 Cost supply curve, including the uncertainty ranges. The red curves indicate the limits of a 96% confidence level region in the cost-quantity plane, while the blue curve corresponds to the most probable cost-supply curve. The assumption is therefore taken that there is a 2% chance that the cost-supply curve lies above the upper boundary, and a 2% chance that it lies below the lower boundary. Figure adapted from (Mercure and Salas, 2012).

modelling the dynamics associated with the process of energy use and depletion. Data from 190 countries was collected, regarding the theoretical, technical and economic potential of 17 types of energy resources: 11 types of renewable energies, 4 types of fossil fuels and 2 types of fissile material. Using the resource distributions described in section 6.3, cost supply curves and uncertainty ranges were estimated for each energy resource. In the case of stock resources (fossil fuels and fissile material), global cost supply curves were estimated. In the case of renewable energies, the cost supply curves were created for each country, and then aggregated regionally. In order to analyse the enormous amount of information of the database carefully, in a user friendly way, I built an interactive tool in MATLAB[5]. This tool is called "Cost Supply Curves GUI" and it allows to plot every cost supply curve for every region. Figure 6.5 shows how it looks in its third version.

The work previously described from the PBL group was the main motivation for the theoretical foundations of the NER. However, many other sources of information were required to populate a database with energy resources from 190 countries, necessary to calculate the cost supply curves. The most important sources used to populate the database are the following:

[5]MATLAB (**MAT**rix **LAB**oratory) is a numerical computing software developed by MathWorks (MathWorks, 2012).

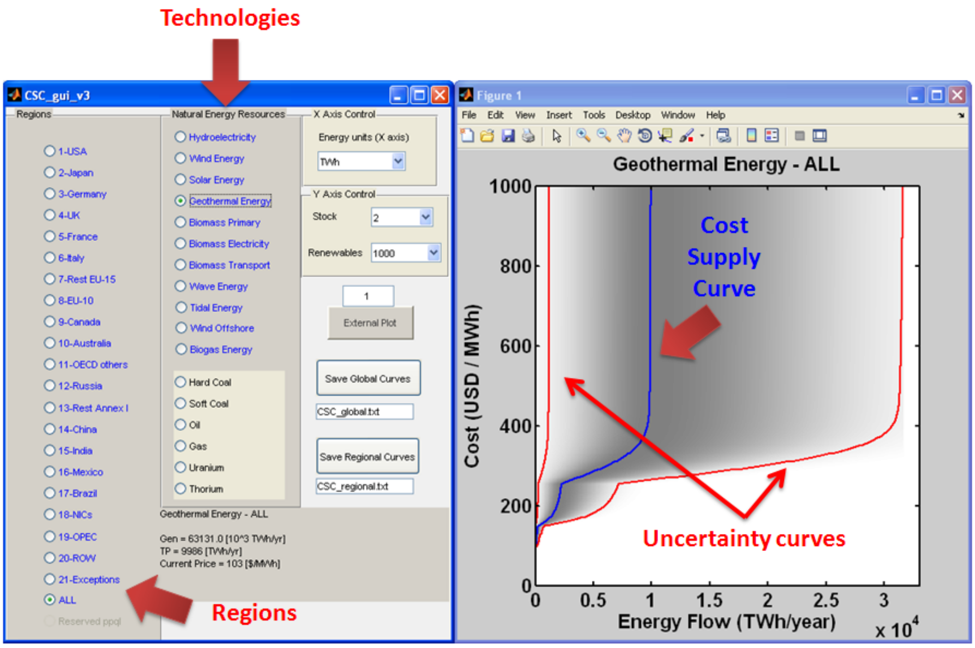


Figure 6.5 The Cost Supply Curves GUI, a tool to analyse the NER database in a friendly way. It was developed in MATLAB.

- **Public Data:**
  Several public sources of information were used to populate the database of the model, such as UN, IPCC, World Bank, World Energy Council, DECC, ETSAP, EIA and several academic institutions.

- **Private Data:**
  Some information necessary to build the model, which can not be found in public sources, was obtained from private institution, in some cases paying a fee (according to the contracts hold by the university, or given the price of a specific publication). These sources are:

  - International Energy Agency: World Energy Outlook (IEA and OECD, 2010, 2011), Energy Technology Perspectives 2012 (IEA and OECD, 2012a), Projected Cost of Generating Electricity 2010 (IEA et al., 2010) and Extended World Energy Balances 2012 (IEA, 2012).

  - Economic and Social Data Service (ESDS): Several databases from ESDS are used in the model, particularly those related to energy and emissions (mostly IEA data), but also some economic data from the World Bank.

- Nuclear Energy Agency: Nuclear Energy Data 2010 (NEA, 2010) and Uranium 2009: Resources, Production and Demand (NEA and IAEA, 2009).

- The International Journal of Hydropower and Dams: 2011 World Atlas and Industry Guide (Hydropower and Dams, 2011).

The figures 6.6 and 6.7 present a selected set of global cost supply curves: six types of renewable energies, four types of fossil fuels and two types of nuclear energy resources. The global curves for renewable energies do not follow necessarily a specific type of distribution, because they are the aggregation of all the curves created at the country level (190 curves per energy technology). Meanwhile, stock resources are considered a global commodity, therefore, cost supply curves are global, following either a HI or a NI distribution. All the details regarding how the curves for each type of technology were calculated, can be found in Mercure and Salas (2012).

6.7 Depletion of stock resources

Each point of the cost supply curve of a renewable resource represents the marginal cost (ordinate) associated with a **specific flow or volume of energy production** (abscissa). Because renewable resources are constantly replenished, the dynamics between the use of renewable energy and the change in its marginal cost fits perfectly the cost supply curves framework, *ceteris paribus*. The case of non-renewable resources, however, is completely different. The production of energy from non-renewable resources is irreversible, with a stock decreasing proportionally to the rate of production.[6] As explained in figure 6.2, the cost supply curve can be built from the histogram of resources. In the case of stock resources, part of the histogram disappears every time the resource is consumed. Therefore, the functional relation between marginal cost and the **amount of stock resources used**, represented by the cost supply curve, is always changing.

In this section, a novel theoretical framework is introduced, to analyse the impact of the exploitation of non-renewable resources in the marginal cost of the associated energy commodities. The model estimates long term base price values below which the production

[6] In this work, the replenishment rate of stock resources is considered negligible, from a human time scale perspective. In a geological scale, however, stock resources can be considered renewable. The case of fissile material is different: nuclear resources cannot be replenished, unless they are harvested from other planets. For the sake of simplicity, fossil fuels and fissile material are not assumed to be replenished in this work. Moreover, the amount of resources is assumed to be constant, while reserves are constantly being updated.

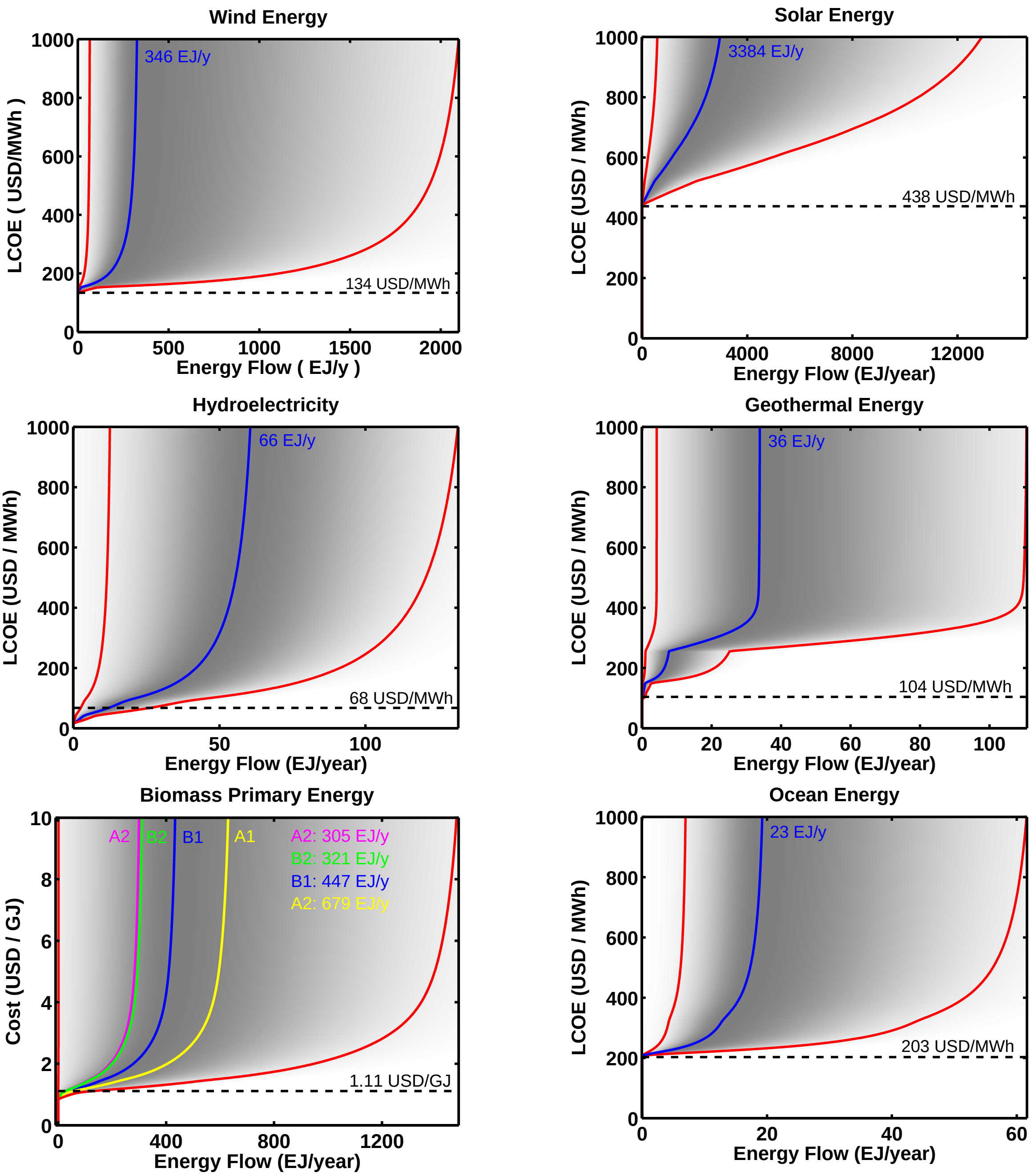


Figure 6.6 Global cost-supply curves for renewable resources: wind power, solar energy, hydroelectricity, geothermal power, biomass and ocean energy (from Mercure and Salas (2012)). These curves are the global aggregation of the regional curves used by FTT:Power.

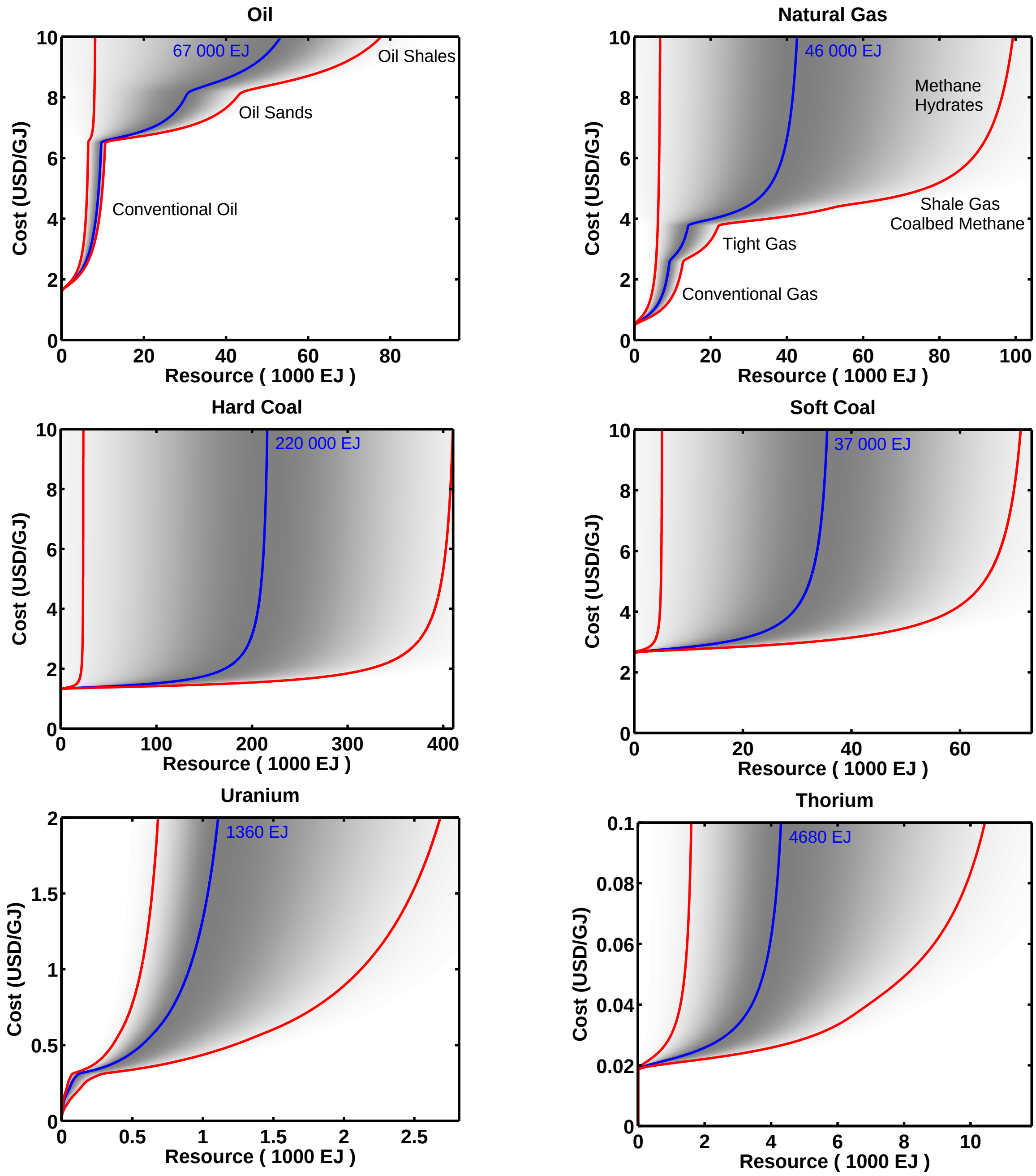


Figure 6.7 Global cost-supply curves for fossil and nuclear resources, including oil, gas, hard coal, soft coal, uranium and thorium (from Mercure and Salas (2012)).

sector cannot supply the demand, and therefore provides a lower bound for the commodity price, equal to the marginal cost of production. The proposed framework is designed to be used with the database of cost supply curves described in the previous section, and it was incorporated in FTT:Power as part of the NER module. A detailed description of the theoretical framework, and some examples of how it can be used, can be found in Mercure and Salas (2013b).[7]

6.7.1 Resources and reserves

Using the nomenclature proposed by McKelvey (1972), and followed by Rogner (1997) and GEA (2012), endowments of exhaustible energy occurrences, that can potentially be used for productive purposes, can be classified in two categories:

Resources: concentrations of naturally occurring solid, liquid or gaseous material in or on the Earth's crust in such form that economic extraction is potentially feasible.

Reserves: economic resources, with known location, grade, quality and quantity.

The limit between reserves and resources is defined by what is *economic*, and therefore, is connected to the marginal cost and price of energy. If resources were to be ordered by cost in a histogram, then there exists a vertical line that defines the upper limit of what is considered reserves. Beyond that limit, resources are no longer considered economic. This is shown in the left chart of figure 6.8. Rise in energy prices, and/or production cost reductions, expand reserves by moving resources into the reserve category and vice versa.

The demand for energy leads to a gradual depletion of the stock resources. The interactions between supply and demand produce changes in the price of the energy carriers, moving the frontier of what is considered economic. As part of the reserves are consumed, part of the resources are re-classified as reserves, driven by the change in price. In the model, this dynamic is represented by the gradual depletion of the resources distribution of figure 6.8b (black curve), as price rises (red curve moving to the right). In order to create a mathematical representation of these interactions, a few definitions are required:

[7] The model proposed in this section does not address the effect on price of speculation and hoarding, or of supply problems related to geopolitical events. Therefore, the model cannot forecast short term price fluctuation of stock resources (such as oil or gas), that commonly occur in global markets. While the model could be used to predict medium term price fluctuations, it cannot predict price hikes associated with very short term supply problems.

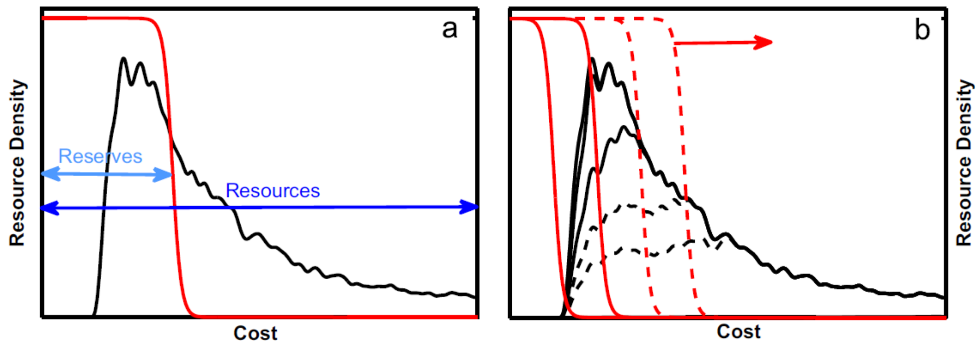


Figure 6.8 Process of the gradual non-renewable resource consumption and related cost changes. The chart at the left (a), shows an arbitrary distribution of resources by cost (black curve). The probability of resource extraction, given the current limit between economic and non-economic resources, is presented in red (its maximum being equal to 1). The right chart (b), describes the dynamic process of resource depletion, as the limit of resources and reserves change. When the price and the marginal cost of energy production increases, the limit between resources and reserves change, and the red curve moves to the left. The black curves correspond to the distribution of resources left after increasing amounts of time have passed and increasing amounts of resources have been consumed. Adapted from Mercure and Salas (2013b).

- The time dependent cost distribution of a particular type of stock resource (e.g. oil, coal, gas or uranium) is represented by the variable $n(C,t)$, C being the cost of the resource, t is time, and n is the amount of resources per unit of cost and time. Each black line in figure 6.8b corresponds to a distribution $n(C)$ evaluated at a specific time. In figure 6.8a, the black curve represents the initial distribution of resources $n(C,t_0)$.

- Let $P(t)$ be the time dependent threshold price, below which resources are considered economic (reserves). Then, the probability function for resource extraction $f(P(t)-C)$, given the price of the resource commodity that delimits reserves out of resources, can be written as:

$$f(P(t)-C) = \begin{cases} 1 & C \leq P(t) \\ 0 & C > P(t) \end{cases}$$

  $f(P(t)-C)$ is the step-like function plotted in red in figure 6.8. With the rise of the price $P(t)$, the economic threshold moves. Consequently, the limit between resources and reserves change, and more expensive resources are used at a higher price of energy, as shown in the right chart of figure 6.8.

Based on the previous definitions, then resources and reserves can be written as:

$$\begin{aligned} \text{Resources} &= n(C,t) \\ \text{Reserves} &= n(C,t)\cdot f(P(t)-C) \\ \text{Production} &= -\tfrac{dn(C,t)}{dt} \end{aligned}$$

If a fraction ν_0 of reserves is extracted for production at time t, the relation between reserves and production becomes:

$$\frac{dn(C,t)}{dt} = -\nu_0 \cdot n(C,t)\cdot f(P(t)-C) \tag{6.7}$$

Equation 6.7 can be rewritten as a first order differential equation:

$$\frac{dn}{n(C,t)} = -\nu_0 \cdot f(P(t)-C)\,dt \tag{6.8}$$

Equation 6.8 has two unknowns functions: the distribution of resources $n(C,t)$, and the energy carrier price $P(t)$. Depending on what the assumptions are, two different approaches can be taken to solve the differential equation:

- For an exogenous energy carrier price, equation 6.8 provides the evolution of the resource distribution.
- For an exogenous demand of resources, the associated energy carrier price can be calculated.

Despite not having an analytical solution, equation 6.8 can be easily solved numerically, for any step function $f(P(t)-C)$, using a mathematical software such as MATLAB. In the context of the FTT:Power scenarios analysed in this work, the second approach is the one to be used: given the exogenous demand for electricity, the associated impact on the price of the energy carrier is calculated using equation 6.8. For instance, if there is a constant or increasing commodity demand, as the size of reserves decreases following consumption, the production flow decreases and generates an upward movement of $P(t)$. This is shown in figure 6.8b. The distribution of resources decreases in the low cost range and the boundary $f(P(t)-C)$ moves to the right. This produces a time dependent supply (or flow) $F(t)$ which is the sum of the production in all the cost ranges:

$$F(t) = -\int_0^{\infty} \frac{dn(C,t)}{dt} dC \tag{6.9}$$

There is an important underlying assumption behind equation 6.7: the ratio between production and reserves is equal to ν_0:

$$\frac{\text{Production}}{\text{Reserves}} = \frac{-\frac{dn(C,t)}{dt}}{n(C,t) \cdot f(P(t)-C)} = \nu_0 \tag{6.10}$$

ν_0 represents the rate at which global reserves are consumed, or alternatively, the proportionality factor between increases in the size of reserves given increases in production. ν_0 can be estimated from data using the ratio of global historical production to global reserves. The inverse of ν_0 is shown in figure 6.9 for oil and gas, calculated from data from the BP Statistical Review of World Energy Workbook (British Petroleum Company, 2009, 2013).

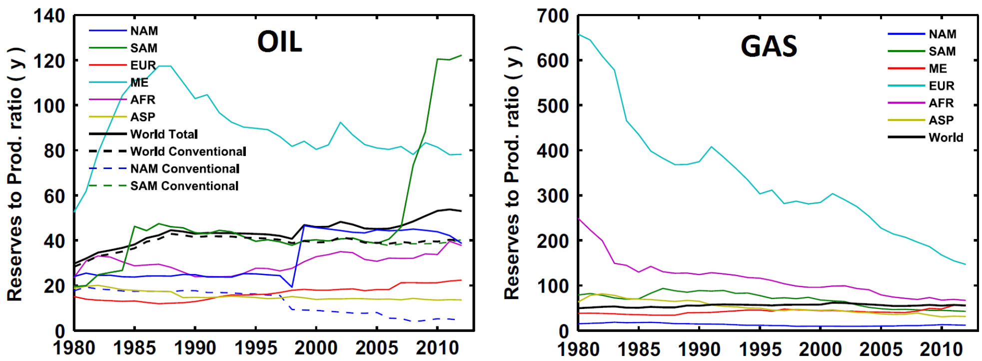


Figure 6.9 Reserves to production ratios for oil (left) and gas (right). The legend abbreviations correspond to North America (NAM), South America (SAM), Europe (EUR), Middle East (ME), Africa (AFR) and Asia-Pacific (ASP). The data originates from British Petroleum Company (2013). Adapted from Mercure and Salas (2013b).

In the case of oil, the global reserves to production ratio (black line in the left chart of figure 6.9) converges towards 44 ± 10 years, stabilising between 1987 and 2006. The variations before 1987, are due to the the oil shocks of the late 1970s, where OPEC was formed and Middle Eastern production decreased faster than reserves due to the oil cartel. The fluctuations after 2006 are related to the inclusion of North and South American unconventional resources into reserves, after reaching extraction costs just below the economic threshold.[8] In the case of gas, the global reserves to production ratio (black line in the right chart of figure 6.9)

[8]Note that the 2009 and 2013 BP statistical workbooks differ in the historical reserves of oil. Historical data have been reclassified, and unconventional oil resources were added to historical reserves retrospectively in the 2013 version (tar sands and heavy oil in North and South America). Thus, BP data is not entirely reliable but only indicative. When one removes unconventional oil from the Americas, the reserves to production ratio becomes constant at 41 years in the 2013 version. For more details, please refer to the Supplementary Material of Mercure and Salas (2013b).

converges towards 56 ± 6 years. In the case of coal, BP's historical reserves to production ratio has a a declining trend, ending in 109 years in 2011. However, reserve data between sources do not agree and the economics of many coal resources appears poorly reported, while very large amounts are known to be in place (BGR, 2010; Mercure and Salas, 2012; WEC, 2010). Thus, the value ν_0^{-1} of 125 ± 50 years was assumed. In the case of uranium, no reliable historical reserves data was found, but a similar process is assumed to take place. The value used for ν_0^{-1} in the case of uranium is 16 ± 1 years, calculated from British Petroleum Company (2013).[9]

The assumption of a constant reserves to production ratio (equal to ν_0^{-1}) might appear restrictive. However, a sensitivity analysis presented in the Supplementary Material of Mercure and Salas (2013b) shows that the ± 10 and ± 6 years margin for oil and gas, respectively, have a minor impact on the results. A much larger source of uncertainty is the one related to the resources endowment, embedded in the uncertain cost supply curves presented in figure 6.7. In the case of coal, the large availability of resources renders the process of depletion implausible within the near future. Therefore, the impact of ν_0^{-1} in scenarios of energy use is negligible. For uranium, while conservative estimations for the underlying resources are presented in figure 6.7, many authors stress that deposits of thorium worldwide are three times larger than those of uranium, and thorium can be used in the $^{232}Th/^{233}U$ fuel cycle (Abu-Khader, 2009; Raj et al., 2011; Urey, 1952; Van Gosen and Tulsidas, 2016). Thorium is also less expensive per unit of energy, due to the higher burnup rate of the thorium systems. Moreover, uranium resources could, in principle, be used with much higher burnup rates, were fast reactors to be deployed globally (Mercure and Salas, 2012). Based on this information, the impact of uncertainty in reserves to production ratio on the availability of nuclear resources in the future is small, in comparison with the technological uncertainty regarding which type of reactors will be adopted in the near future.

6.7.2 Scenarios of stock resources use and depletion

The NER module is not only a theoretical contribution for the modelling of energy resources, but also a practical tool for creating scenarios of energy use and depletion. Figure 6.10 shows an example of how the NER module can be used (independently of FTT:power) to analyse future pathways of energy consumption. Using a linear extrapolation of energy prices

[9] Since our work was published, the value of ν_0 for oil has been changing with a new oil market regime, which has led to an unexpectedly low oil price (Baffes et al., 2015). While in Mercure and Salas (2013b) ν_0 is assumed to be constant, ν_0 could potentially be used conveniently as an exogenous parameter instead, and the assumptions of the model still hold.

(bottom right chart), scenarios of flows of stock resources were produced, for gas, oil and coal.[10]

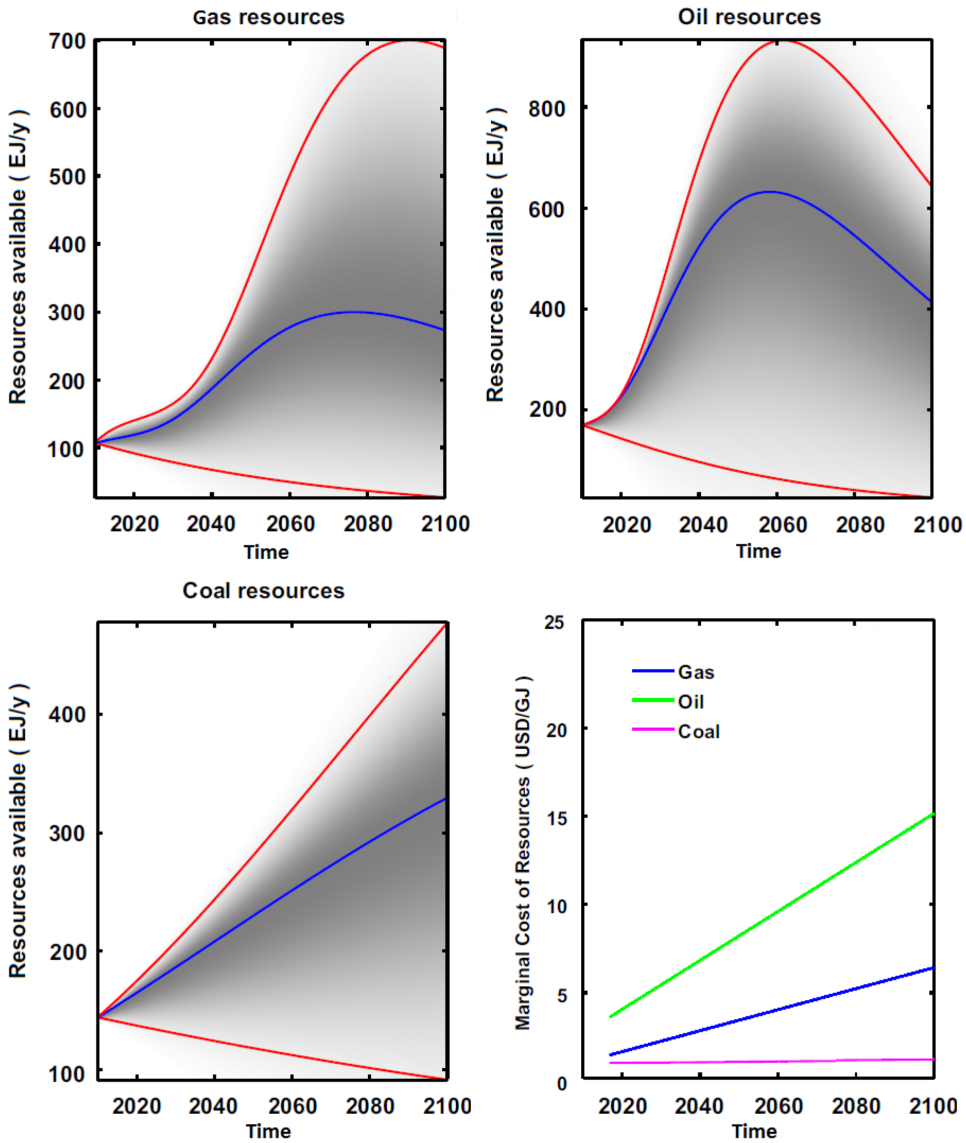


Figure 6.10 Flows of gas, oil and coal resources, calculated using the NER module. Time is represented in the horizontal axis (abscissa), while the flow of resources is represented in the vertical axis (ordinate). Equation 6.8 was used in combination with the cost supply curves of figure 6.7, assuming a linear extrapolation of marginal costs of production for energy carriers (bottom right chart). The curves start in 2008 at current energy consumption values, given by the IEA. Figure adapted from Mercure and Salas (2013b).

[10] For a detailed description of the scenarios presented in figure 6.10, please refer to Mercure and Salas (2013b).

Equation 6.8 defines the dynamic behaviour of the resource extraction process (dn/dt), given exogenous assumptions on price($P(t)$). The initial resource distributions ($n(C,t_0)$) are obtained from the cost supply curves presented in figure 6.7, using the process described in figure 6.1 in reverse. Over time, different consumption patterns are obtained, depending on the size of the various stocks. In the case of oil and gas, a peak in production occurs at around 2060 and 2080, respectively. After that, a depletion process begins. In the case of coal resources, however, no depletion occurs within a foreseeable future, due to the large amount of resources available.

In terms of the calculations behind the scenarios presented in figure 6.10, the price of the energy carriers is defined exogenously, and then the flow of resources is calculated. However, it is important to notice that from a theoretical perspective, the causality goes in the other direction. The increase in the price is driven by the increasing depletion of the stock resources. If the production stops ($dn/dt = 0$), then the price and the stock remain constant. Naturally, the price of stock resources in reality follows a different pattern, governed by the law of supply and demand. It is for that reason, that the proposed model *provides a lower bound for the commodity price, equal to the marginal cost of production* (see beginning of section 6.7). In consequence, the scenarios presented in figure 6.10 are not expected to be realistic, but only indicative of the type of analysis that can be done through the NER module. For more realistic scenarios, the NER module has to be used in combination with an economic model, that provides feedback between prices and demand. This and other limitations are discussed in the next section, where a critical view of the NER module is presented.

6.8 A critical overview to the NER module

The Natural Energy Resources (NER) module of FTT:Power was developed as a tool to support the modelling of technological transitions of the power sector, based on realistic scenarios of natural energy resources use and depletion. Some of the most relevant characteristics of the model, from a theoretical and practical perspective, including its main limitations, are listed below:

- In terms of theoretical contributions, the NER module presents a novel representation of the energy resource distributions, using stylised functional forms that match closely the empirical results of Hoogwijk et al. (see section 6.4).
- In terms of practical contributions, the NER module includes a database of cost supply curves, based on the functional forms presented in section 6.3. The database of global

energy resources addresses an important gap in the resources potential's literature, where abundant information exists about resource estimations, but very little attention is given to the underlying costs.

- The methodology used here for treating uncertainty is fundamental to the analysis of economic potentials, as it allows the incorporation of all available information, even when sources are inconsistent or conflicting (Mercure and Salas, 2012). The uncertainty regarding the availability of natural resources is propagated through the mathematical analysis, providing as a result uncertainty intervals for the outputs (see, for instance figure 6.10 in section 6.7.2).

- The usefulness of the database of economic potentials is, unfortunately, undermined by its increasingly outdated information. Most of the cost data embedded in the cost supply curves come from the *IEA Projected Costs of Generating Electricity - 2010 Edition* (IEA et al., 2010). There are large differences between the costs published in 2010 (with data from 2008) with the current values, especially for renewable technologies such as solar power (IEA et al., 2015). As a result, FTT:Power predicts lower values for capacity investment in solar technologies than the actual investment records, between the beginning of the simulation (2008) and the present date (2016). To compensate for this problem, exogenous values for electricity generation capacity are used in most of the world regions in FTT:Power between 2008 and 2016. However, the question remains about the impact of higher prices on the uptake of solar energy in the future scenarios of the power sector.

- Another important theoretical contribution of the NER module is the novel mathematical model proposed for the study of depletion of stock resources. The model, presented in section 6.7, is not based on mainstream approaches for the study of stock resources, but on the historical trends of the global reserves to production ratio of oil and gas.[11] The model proposes an original contribution, without assumptions about the underlying economic structures of the system or optimality in the use of resources.

- The stylised assumption of a constant reserves to production ratio made in the model of stock resources, is only valid if resources are considered globally. This is one of the reasons why the fossil fuels and fissile material are considered global resources in

[11] Models describing the dynamics of stock resources are mostly classified in two groups, based on whether they use the Hotelling Principle or the Hubbert Peak approach (Mercure and Salas, 2013b; Reynolds and Baek, 2012). The Hotelling Principle provides the optimal rate of resource extraction given a certain resource base and a rate of increase in price (Hotelling, 1931). Peak theory, in contrast, is an empirical model made by Hubbert Peak, based on historical US oil production data from 1900 to 1962, using logistic trends (Deffeyes, 2006; Hubbert, 1962).

FTT:Power, in contrast with a local approach used for renewables. While a constant v_0 is used for the sake of simplicity, the underlaying theoretical model does not require such assumption. A more accurate version of the model, with a regional separation of stock resources, could potentially be implemented.

- Section 6.7.2 shows how the NER module works in practice, using arbitrary linear projections for the price of energy carriers. If instead of these arbitrary projections, an economic model is used, then more sensible results can be obtained, regarding the feedbacks between energy prices and energy demand. If in addition to that, the NER module is used within FTT:Power, to analyse scenarios of technology diffusion, then plausible scenarios for the power sector can be created. In 2014, a group of researchers, including myself, created 10 scenarios for the global power sector using FTT:Power in combination with the macroeconomic model E3ME/E3MG (Barker et al., 2012). The details of that modelling exercise can be found in Mercure et al. (2014) and Foley et al. (2016).

6.9 Conclusion

In this chapter, the Natural Energy Resources (NER) module of FTT:Power was introduced. The NER module uses a novel mathematical representation of energy resources, based on distributions created from statistical trends. This particular mathematical representation facilitated the creation of a large database of 17 types of energy resources in 190 countries. Economic potentials for all the major natural energy resources are presented in the form of cost-supply curves. In the case of renewable energy sources, they represent energy flows; in the case of fossil fuel and fissile material, the cost supply curves represent stocks.

In the context of FTT:Power, the NER module provides the feedbacks between the power sector and the natural world, in terms of primary energy use and depletion. The database of energy resources constrains the diffusion of energy technologies, based on the availability of renewable resources. In the case of stock resources, a more complex feedback mechanism is provided, based on an innovative dynamic model of gradual resource depletion.

The database of cost supply curves incorporates uncertainty intervals, based on an extensive review of the literature of energy potentials. The treatment of uncertainty within the NER module is fundamental to the analysis, because it addresses the different approaches and assumptions underlying the studies on energy assessments. Details on the specific calculation of the uncertainty intervals for each type of energy resource, can be found in the Supplementary Material of Mercure and Salas (2012).

The NER module does not only provide a theoretical contribution in the area of energy resources modelling, but also provides a practical tool that can be used by modellers to study energy transitions in the power sector. The next chapter shows, from a very practical perspective, how the NER module can be used within FTT:Power, to analyse the decarbonisation of the power sector.

As discussed in section 6.8, the NER module has some limitations. On this regard, some future work is proposed below.

6.9.1 Further work

- The update of the cost information in the cost supply curves database is the most critical aspect to address in the NER module. The recently published *IEA Projected Costs of Generating Electricity - 2015 Edition* (IEA et al., 2015), is expected to play an important role as source of updated information on the cost of renewable energies.
- The assumption of a constant reserves to production ratio in the model of energy use and depletion introduced in section 6.7 is expected to be relaxed. Using the same dynamics, but with a regionally differentiated variable v_0, the model can provide a better representation of the energy depletion process.
- The missing feedback between energy demand and prices, limits the capabilities of the NER module to provide sensible scenarios of energy use. Following the work done by Mercure et al. (2014), FTT:Power (and consequently the NER module) was incorporated into the newest version of the macroeconomic model E3ME/E3MG. As part of the work to be done, the NER module of the combined platform E3ME/E3MG-FTT has been updated, especially with the newest cost information from IEA et al. (2015).

Chapter 7

Energy Resources and Policy Performance

7.1 Chapter Summary

This chapter analyses the impact of energy resources availability in the performance of energy policy. *Policy efficiency*, measured by the ratio between *emission reductions* and *energy expenditure*, is compared for different policy sets under high and low availability of natural energy resources. The resource scenarios are created using the uncertainty ranges of the NER module's database, presented in chapter 6.

The chapter is structured as follows: section 7.2.1 identifies the most relevant energy resources used in the power sector in the DEC scenario. Based on that analysis, section 7.4 presents decarbonisation scenarios under extreme resource availability, using the limits of the uncertainty ranges of the most relevant energy resources, extracted from the NER module's database. The scenarios presented in section 7.4 compare 15 policy sets, with all the possible combinations of carbon pricing, subsidies, feed-in-tariffs and direct regulation. Each policy set is evaluated in terms of the emission reductions (with respect to BAU) and energy expenditure. The ratio between these two measures, defined as policy efficiency, is compared in section 7.4.3 for all the policy scenarios under low and high availability of energy resources. The results presented in section 7.4.3 show that the availability of energy resources produces significant differences in policy efficiency, for all the policy sets. The policy implications associated with the results analysed in this chapter, are discussed in section 7.4.4.

7.2 Introduction

Future energy systems have to evolve towards their gradual decarbonisation, if the risks of anthropogenic GHG emissions are to be minimised (IPCC, 2014c, p. 20). In terms of resources, this implies profound changes in the consumption patterns of primary energy (GEA, 2012, p. 1209). Therefore, an understanding of the energy resources available and their cost, is essential for designing the appropriate policies that will facilitate the decarbonisation of the energy sector.

Many models exist that support policy makers in the creation of future scenarios for the global energy systems (for a list of models and recent cross-model comparison exercises, please refer to section 3.2). Such models, in order to produce feasible scenarios, must take into account the limits of each type of natural resource. However, some energy models do not take explicit account of limits to resource flows, and most of them do not consider their associated uncertainty (Mercure and Salas, 2012). In order to address that gap, the NER module presented in chapter 6, provides an extensive database of energy resources, which properly constrain the model scenarios for the future, providing an adequate treatment of the underlying uncertainty.

The database of energy resources includes the economic potentials of 17 types of resources and 190 countries, in the form of cost supply curves. The uncertainty intervals embedded in those curves, enable the exploration of a large part of the resources spectrum. The use of the entire resource domain for the analysis of energy policies using FTT:Power is, however, not an optimal choice. The large amount of potential scenarios available would require an enormous amount of simulations, many of which would explore unlikely pathways for the future. A better option is to focus the analysis in the most relevant scenarios, identifying first the technologies that are expected to play an important role in the evolution of the power sector. The identification of the most relevant technologies, and the appropriate use of the underlying cost supply curves, is analysed below.

7.2.1 Relevant energy technologies

Figure 7.1 shows the global cumulative electricity generation by source in the DEC scenario, between 1970 and 2050, sorted by quantity.[1] At the right-hand of figure 7.1 are the technologies that lead in terms of cumulative electricity generation: coal, hydro, wind onshore,

[1]For details about the DEC scenario, please refer to section 5.5.

nuclear, gas and oil. Based on this information, these technologies are relevant for the study of the effect that availability of energy resources has on future decarbonisation scenarios of the power sector.

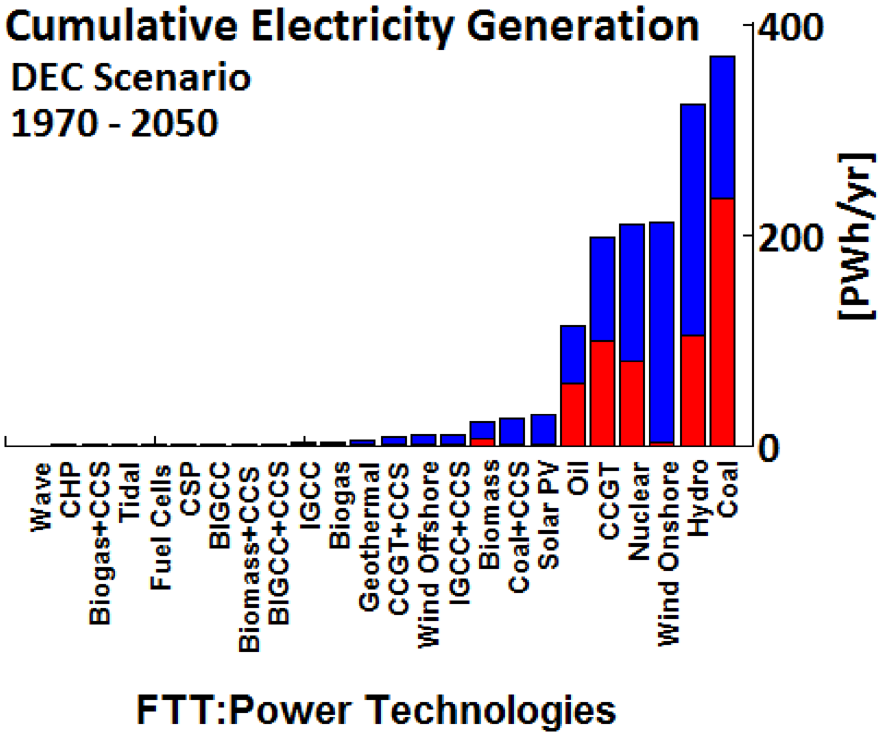


Figure 7.1 Global cumulative electricity generation by technology for the DEC scenario, between 1970 and 2050. In red, the electricity produced between 1970 and 2015. In blue, the electricity expected to be produced between 2016 and 2050. Historical data from IEA (2015).

Coal and gas

Coal and gas are abundant energy resources globally. Even the lower limits of the cost supply curves are orders of magnitude higher than the global primary energy demand (GEA, 2012, p. 453 & 462). Limitations in the use of these technologies are not likely to be rooted in the lack of resources but other considerations, such as pollution control, climate change policies or market competition. No significant differences were found on scenarios of the power sector, when the cost supply curve distributions of these resources were sampled, because even the lower limit of the cost supply curves are far larger than the expected demand. Therefore, in order to optimise the use of computational resources and to simplify the analysis, in the scenarios analysed in this chapter, coal and gas are assumed to follow the most likely cost supply curve.

Oil

Oil is less abundant than coal and gas. However, most of it is used in the transport sector (around 70% in 2013)(IEA, 2015). The power sector only represents a small fraction of the total oil demand (less than 6% in 2014)(IEA and OECD, 2015, p. 121). Availability of oil resources is, therefore, more appropriate for the analysis of other types of energy scenario, such as the adoption of electric cars, or biofuel markets evolution. Only partially connected to the scenarios of the power sector, scenarios of oil availability are out of the scope of this thesis. Therefore, oil availability is assumed to be defined by the most likely cost supply curve.

Nuclear power

Nuclear power is a low carbon technology that currently accounts for 13% of the global electricity generation (IEA and OECD, 2015, p. 584). As figure 7.1 shows, nuclear energy is among the top four technologies producing electricity between 2016 and 2050 in the DEC scenario. Despite some concerns regarding the availability of uranium resources for the next decades (GEA, 2012, p. 469), investment in exploration increased one order of magnitude between 2002 (US$100 million) and 2008 (US$1 billion) (ibid.) Depending on the assumptions on the type of technology to be used in the future (nuclear reactors), the availability of fissile material to produce electricity increases radically (Grimes and Nuttall, 2010). For instance, deposits of thorium worldwide are three times larger than those of uranium, and the nuclear fuel cycle for thorium is more efficient than the cycle of thermal reactors based on uranium (Abu-Khader, 2009; Mercure and Salas, 2012). Therefore, scenarios with strong development of the nuclear industry should have embedded a parallel development of the reactor's technology and the development of the fissile material extraction industry (Grimes and Nuttall, 2010). Under those considerations, for the scenarios analysed in this chapter, no shortages of nuclear primary resources are expected, so the most likely cost supply curve for nuclear energy is used.

Renewables

Based on figure 7.1, the FTT:Power scenarios analysed in this chapter have hydro in a leading position among the renewable electricity generation technologies, just behind coal. In the renewable niche, from figure 7.1 it is also clear that hydro is followed by wind onshore, solar PV, biomass, and far behind by wind offshore, geothermal and the rest of the renewable technologies. In order to analyse the potential impact that the availability of primary renewable resources could have in the decarbonisation of the power sector, the lower and higher limits of the distributions of the cost supply curves for hydro, wind onshore, solar PV and biomass are used in the scenarios of this chapter.

From figure 7.1, it is clear that the rest of the renewable energy technologies have a very small impact in the production of electricity, so the most likely cost supply curves are used for those resources (wind offshore, geothermal, biogas, biogas+CCS, BIGCC, BIGCC+CCS, Biomas+CCS, CSP, tidal and wave). The same approach was taken for the rest of the FTT:Power technologies (IGCC, IGCC+CCS, coal+CCS, CCGT+CCS, fuel cells, CHP).

7.3 Beyond carbon pricing

The process of technological change takes time (decades in the case of the energy sector), with rates of change inversely proportional to the size of the system affected (Grubler, 1996). In the case of the power sector, the long time scales for technological change are exacerbated by the longevity of energy capital stock (Grubler, 2013, p. 51). As a consequence of this path dependency, near-term choices define long-term outcomes, with divergent pathways emerging gradually as existing capital stock is replaced (ibid.) The long time scales of the power sector create a natural barrier for the diffusion of innovation, and consequently, hinder a rapid decarbonisation (Mercure et al., 2014). In this context, the search for policies that facilitate the diffusion of low carbon innovations, and break the lock-in imposed by the incumbent technologies, is paramount to reach the targets stated in the Paris Agreement (IPCC, 2014c; UNFCCC, 2016).

Traditional modelling approaches usually suggest carbon pricing as the foremost solution to spur low-carbon investment (Campiglio, 2016). However, aspects associated with the imperfect nature of energy markets, such as the aforementioned lock-in effects, make difficult to correct for externalities (IPCC, 2014b, p. 233). In that context, carbon pricing represents a necessary, but not a sufficient condition to stimulate low carbon investment (Campiglio, 2016). The evidence suggests that combination of policies improve cost-effectiveness (IEA and OECD, 2012a, p. 119 & 121). Indeed, complementary policies such as feed-in-tariffs, have been crucial for the deployment of renewable energy technologies worldwide (REN21, 2015, p. 88).

In order to implement stringent decarbonisation policies, to accomplish the goals of the Paris Agreement (UN, 2015b), policy makers require information about the energy resources landscape (Mercure and Salas, 2012). This is specially relevant for decarbonisation policies based on the exploitation of resources that might be adversely affected by climate change, such as hydropower resources and biomass (IPCC, 2011, ch. 2 & 5). Policy makers require mechanisms that help them understand the potential risks associated with decarbonisation policies, and look for alternatives to mitigate those risks.

The next section presents an *ex-ante* evaluation of policy efficiency of different policy sets, under uncertain availability of natural resources. This analysis complements the insights provided by section 5.6, in which the relative impacts of energy policies were presented, in terms of abatement potentials. While climate policies aim to reduce GHG emissions, they must take into consideration non-environmental concerns that are relevant for society. From that perspective, in parallel with the reduction in emissions, it is relevant to analyse the amount of economic resources that requires to implement specific policies (Lund, 2007). Under a normative modelling approach, where the goal is to find the minimum-cost pathway, full coordination among agents is typically assumed (Mercure et al., 2016). In that framework, endogenous policies obtain the maximum environmental benefits, using the minimum amount of economic resources. In reality, however, policy implementation works differently. Market failures can inhibit the diffusion of low-carbon technologies, despite their apparent environmental and economic advantages (Unruh, 2000). Phenomena such as technological lock-in, path dependence and inertia, have a strong influence in policy outcomes (Arthur, 1989). In that context, the study of policy efficiency, using a non-optimal dynamic system that do not assume perfect market conditions, and accounts for the use of natural resources, is an extremely valuable contribution to the search of effective decarbonisation policies.

7.4 Policy efficiency and global decarbonisation

This section explores the efficiency of various sets of policy scenarios under extreme conditions of natural resources availability. Policy sets are compared in terms of **abatement**, and **expenditure**. The global power sector scenarios assume the application of different policies to support the adoption of low carbon technologies, including subsidies (*Subs*), feed-in-tariffs (*FiT*), carbon pricing (*CarbP*), regulation (*Reg*), and any possible combination of them.[2] Each of the 15 policy sets are simulated under two different conditions of natural resources availability: the 'High CSC' group corresponds to scenarios with high availability of renewable resources, while the 'Low CSC' group corresponds to scenarios with low availability of renewable resources. In the creation of these scenarios, the following assumptions are made:

- In all the scenarios, the default learning rates for all the technologies are used (see section 4.5).
- In all the scenarios, the maximum electricity demand reductions are assumed, in line with the definition of the DEC scenario (see sections 5.2.4 and 5.5).
- For the 'Low CSC' group of scenarios, the lower limits of the cost supply curves of the most relevant renewable energy resources are used: hydroelectricity, wind onshore, biomass and solar energy. For the 'High CSC' group, the higher limits of the cost supply curves of the same resources are used (see sections 4.4 and 6.2.2). For the other technologies, the most likely cost supply curve are used on each scenario.
- On each scenario, only the policies indicated in the name (labels) are applied, at the maximum intensity (decarbonisation intensity equal 1). The rest are deactivated (policies are deactivated using decarbonisation intensity equal 0, see sections 5.2.1 and 5.2.2 for more details).

7.4.1 Abatement by policy set

Figure 7.2 shows the cumulative emission reductions (with respect to BAU, see section 5.4) between 2016 and 2050 for the 15 policy scenarios, corresponding to all possible combinations of subsidies, feed-in-tariffs, carbon pricing and regulation. As it might be expected, the scenarios with higher availability of renewable energy resources achieve higher emission reductions than their lower availability of renewable resources counterpart. If single policies are ranked by emission reductions, regulation is the most effective by far, followed by carbon pricing, feed-in-tariffs and subsidies. The reason why regulation performs better in terms of emission reductions is simple: the replacement of carbon intensive power stations is forced in the case of regulation, while with the other mechanisms, the low price of fossil fuels (particularly coal), undermines the performance of the market based decarbonisation

[2] For a detailed description of each policy instrument, please refer to section 5.2.

incentives. The relative ranking of the policies based on market mechanisms, i.e. carbon pricing, feed-in-tariffs and subsidies, is not a strong indicator in this case, because it depends on the underlying level of the incentives (rate of the subsidies, feed-in-tariffs, and the price of carbon).

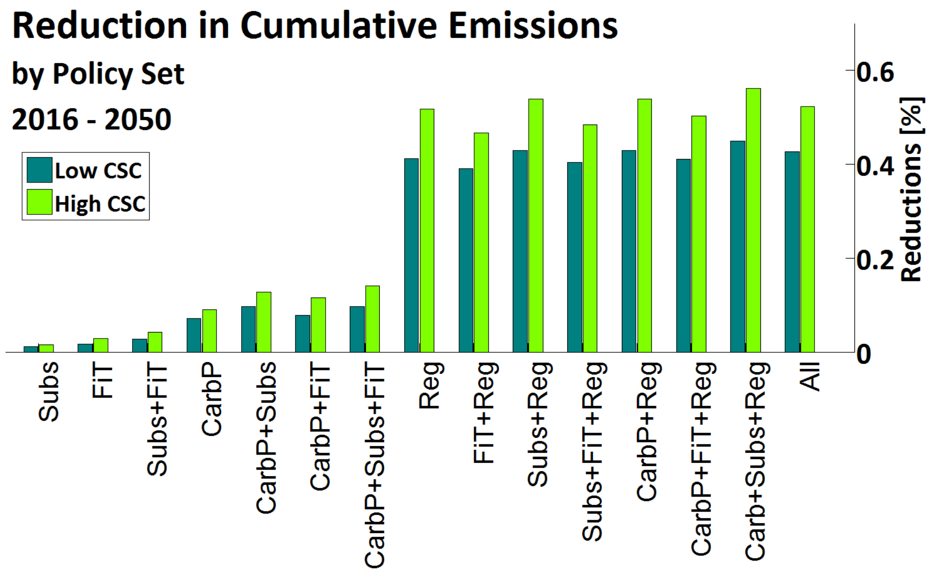


Figure 7.2 Reduction in cumulative emissions for the global power sector between 2016 and 2050, under optimistic (High CSC) and pessimistic (Low CSC) assumptions regarding the availability of hydroelectricity, wind onshore and biomass energy. All the possible combinations of the four policy instruments of FTT:Power are presented: subsidies, feed-in-tariffs, carbon pricing and direct regulation. For a detail description of the the policy instruments, please refer to section 5.2.

As described in section 5.6, the marginal abatement potential of each policy depends on the concurrent policies being implemented. Therefore, the impact of policy instruments is different if used individually or in combination, given their underlying synergies (Mercure et al., 2014). This phenomenon emerges from the complex representation of the power sector embedded in FTT:Power, based on non-linear, hysteretic dynamics (Mercure, 2015). While in general, larger the number of policies being implemented, larger the abatement achieved, there are some particular cases when the opposite happens. For instance, in figure 7.2, the inclusion of feed-in-tariff policies in the scenarios with regulation, produces a decrease (instead of an increase) in abatement. While this might seem contradictory, a detailed analysis of those scenarios shows that the reason for the increase in emissions is the stability constraints of FTT:Power. As explained in section 4.6, the composition of the electricity matrix is constrained by lower and upper limits of baseload, flexible and variable electricity generation technologies. When there is a large increase of variable electricity in the system (due, for instance, to the extensive adoption of wind or solar energy, supported by feed-in-tariffs), FTT:Power activates a control mechanism that hinders the rapid replacement of flexible and baseload electricity sources. When the control mechanism is activated, the regulatory framework that puts a ban in the construction of new coal power stations is superseded, in order to keep the balance between baseload, flexible and variable electricity generation technologies. This phenomenon only happens on extreme decarbonisation scenarios, and is explained in detail in section 4.6.2. Consequently, the policy set with the larger reduction in cumulative emissions in this chapter is the one that combines carbon pricing, subsidies and regulation, without feed-in-tariffs.[3]

Figure 7.3 shows the emission trajectories for all the policy set scenarios presented in this chapter. The trajectories can be divided in two clear groups: those from scenarios without direct regulation policy (top trajectories, excluding BAU), and those from scenarios including regulation policy (bottom trajectories). Highlighted in green, blue, red and magenta are the trajectories associated with scenarios with single carbon pricing, subsidies, feed-in-tariffs and regulation policies, respectively. It is clear, from figure 7.3, the differences in abatement performance of the policy sets with and without regulation.

7.4.2 Electricity expenditure by policy set

The different emission trajectories and abatement performances presented in the previous section, are a representation of the impact of the different decarbonisation policies in the composition of the power sector. To analyse these impacts in more detail, figure 7.4 presents the cumulative electricity generation between 2016 and 2050, for all the 15 policy sets, under low (upper chart) and high (bottom chart) availability of renewable energy resources.

Similar to the charts presented in the previous section, figure 7.4 shows a clear separation between the scenarios that include regulation in the policy mix, with those that do not include it. Without regulation, most of the electricity is generated by fossil fuels, with the associated impacts in emissions presented in figure 7.3. When regulation is incorporated in the policy mix, the electricity matrix becomes more diverse, with a larger participation of renewable energies. Consequently, emissions decrease in scenarios that include regulation, as shown in the previous section.

[3] In chapter 9, the effect of the stability constraints of FTT:Power in extreme decarbonisation scenarios, is analysed in detail. In particular, section 9.8 presents an analysis of the impact of the capability of the grid to balance baseload, flexible and variable electricity on decarbonisation scenarios.

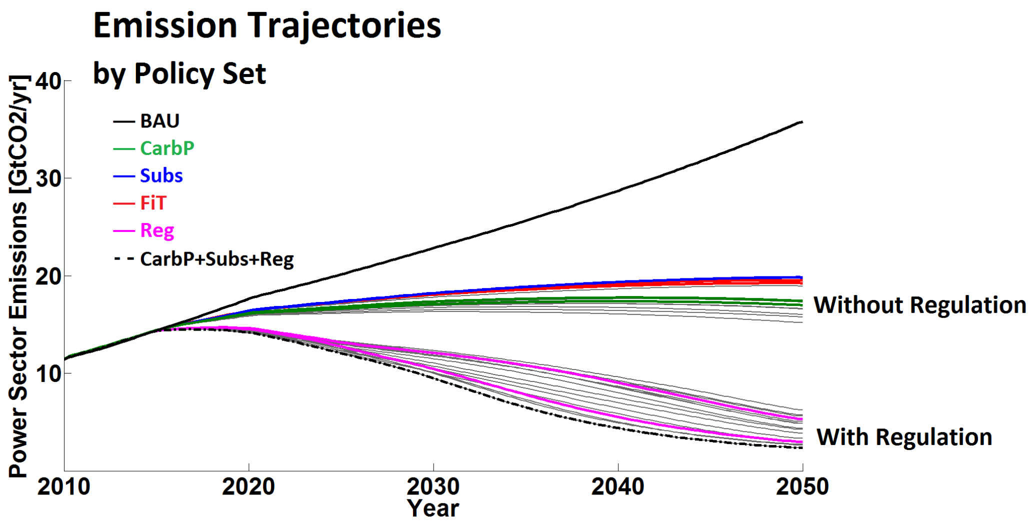


Figure 7.3 Emission trajectories for the 15 policy set scenarios presented in figure 7.2, under low and high availability of renewable energy resources. Green, blue, red and magenta trajectories correspond to single CarbP, Subs, FiT and Reg policies, respectively. The emission trajectories for combined policies, are shown in gray. The top black trajectory corresponds to BAU, and the bottom trajectory corresponds to the one with the highest emission reductions (CarP+Subs+Reg, see figure 7.2).

The lower chart of figure 7.4 shows a larger participation of hydro and wind energy in the electricity matrix than the upper chart. This is consistent with the larger availability of those resources in the HighCSC scenarios. In the case of solar energy, the difference is more subtle between the two groups of scenarios. The reason behind this subtle difference is the large availability of solar resources, even in the LowCSC scenario. As it can be seen in the cost supply curves of figure 6.6, the lower limit of the technical potential of solar energy is larger than the most likely technical potential of wind, and larger than the upper limit of the technical potential of hydro. In the case of biomass, it only participates marginally in all the scenarios, therefore it was not included as a single category in figure 7.4.

Decarbonisation policies require resources to support the deployment of low carbon technologies (such as subsidies and feed-in-tariffs), as well as for pricing the externality (carbon pricing policies). Moreover, the replacement of low-cost carbon intensive power stations with more expensive low-carbon units, has an impact in the price of electricity. In this context, it is relevant to analyse the economic resources required to implement these decarbonisation policies, in the same way that we study their abatement potential. The economic resources associated with each policy scenario, are defined in this context as the **total expenditure on electricity**, corresponding to the sum of the following three quantities:

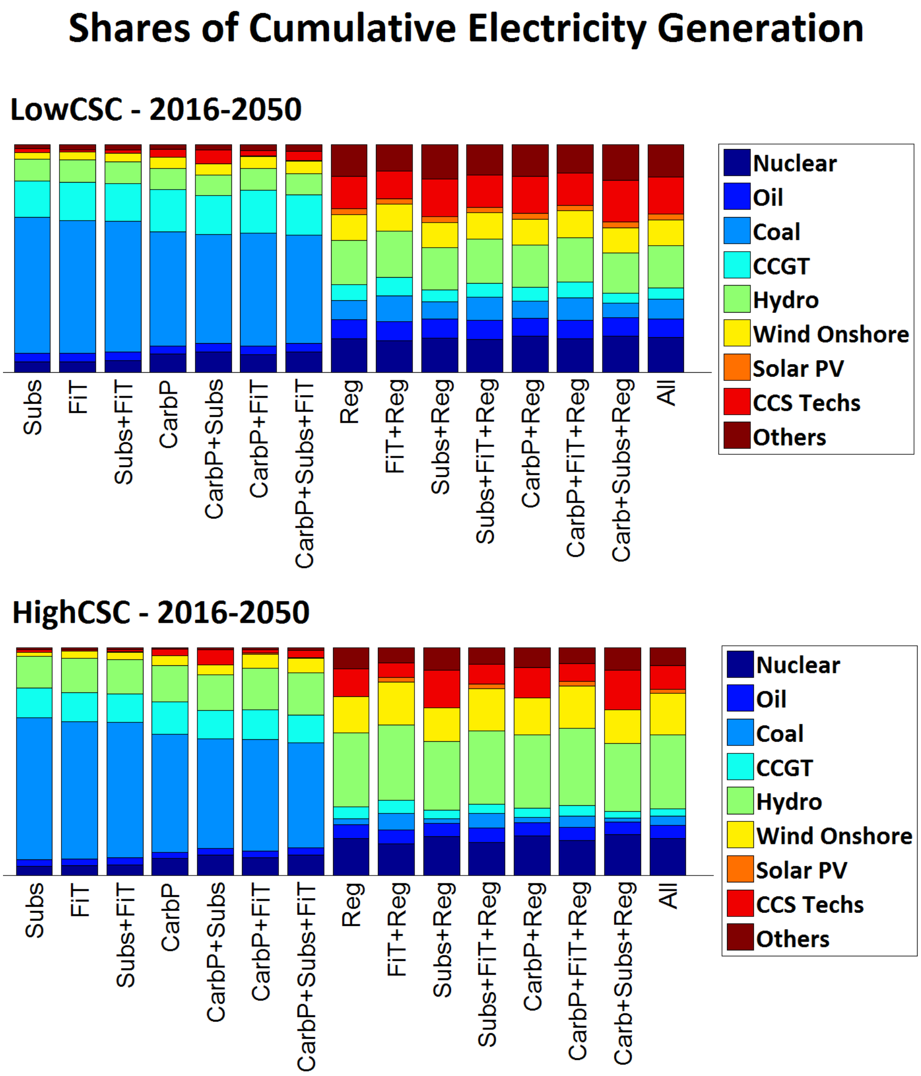
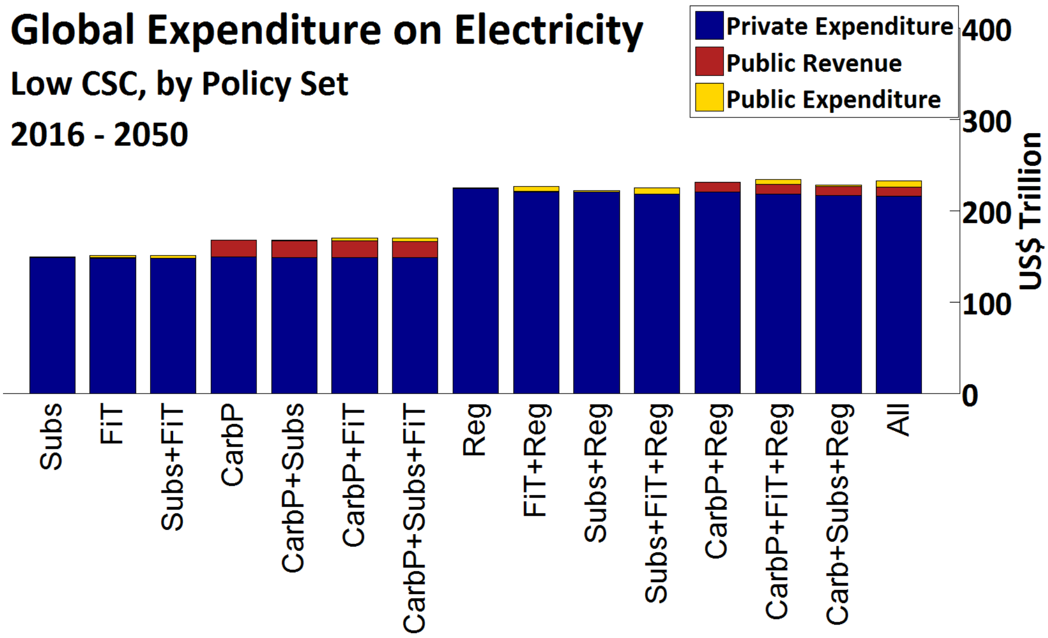


Figure 7.4 Cumulative electricity generation, by policy set, between 2016 and 2050. Top and bottom chart correspond to scenarios of low and high availability of renewable energy resources, respectively.

Public Revenue is the undiscounted sum of the money paid by consumers and collected by the government in the form of carbon taxation or emission allowances, embedded in the price of electricity. In FTT:Power, the price of carbon is included in the calculation of the levelised cost of electricity, as shown in section 4.6.1.

Public Expenditure is the undiscounted sum of the money spent by the governments on subsidies and feed-in-tariffs, to support the deployment of low carbon technologies.

Private Expenditure corresponds to the undiscounted sum of money spent on electricity by final consumers, calculated as the price of electricity times the electricity generated



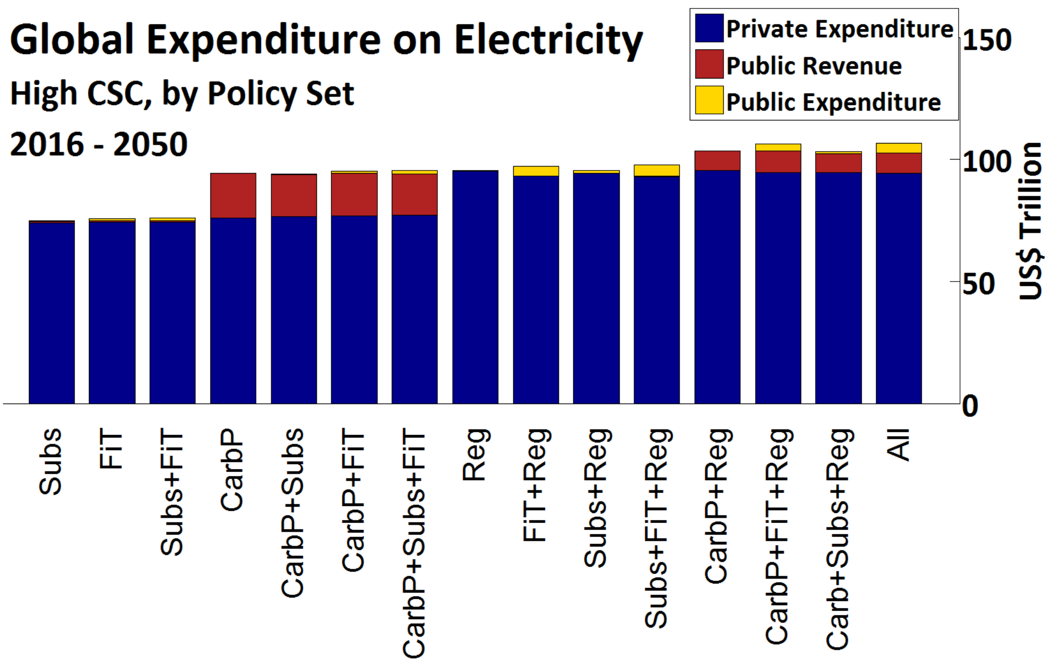


Figure 7.5 Electricity expenditure for the global power sector between 2016 and 2050, under low availability (Low CSC, top) and high availability (High CSC, bottom) assumptions regarding hydroelectricity, wind onshore, biomass and solar energy. All the possible combinations of the four policy instruments of FTT:Power are presented, same as in figure 7.2. Electricity expenditure is divided in private expenditure (blue), public revenues (red) and public expenditure (yellow).

between 2016 and 2050. Private expenditure does not include the carbon price (which is accounted as public revenue), or subsidies and feed-in-tariffs (which are accounted as public expenditure).

The total expenditure on electricity is the sum of private expenditure on electricity, public expenditure on subsidies and feed-in-tariffs and public revenues from carbon pricing. No assumptions are made regarding the use of public revenues, because the economy is not explicitly modelled in FTT:Power. However, its is important to highlight that those revenues could potentially be used to support government spending on technology subsidies, or be redistributed to households in the form of income tax reductions, increasing their disposable income (Mercure et al., 2014). Given that no assumption regarding the use of those revenues are made here, the expenditure on electricity for scenarios with carbon pricing can be taken as an upper limit on expenditure.

The top and bottom charts of figure 7.5 present the (cumulative) total expenditure on electricity, from 2016 and 2050, when there is limited availability (former) and abundant amount (latter) of hydroelectricity, wind onshore biomass and solar energy. The total expenditure on electricity is separated on its three components: the private expenditure on electricity is shown in blue, the money spent on subsidies and feed-in-tariffs is shown as public expenditure in yellow, and the carbon allowances and taxes paid by the consumers are shown as public revenues in red.[4]

Despite the significant differences in emission reductions (shown in figure 7.2), the expenditure on electricity does not change considerably among policy sets, *under the same conditions of availability of natural energy resources*. However, cumulative electricity expenditure between the two groups of policy sets (top versus bottom charts of figure 7.5) presents large differences. In the context of stringent decarbonisation scenarios, such as those analysed in this section, low availability of resources has a negative impact on the price of electricity. Due to the use of the lower limits of the cost supply curves for hydropower, wind, biomass and solar energy, the levelised cost of electricity rises under scenarios of large adoption of these resources. This is particularly relevant in the case of hydroelectricity, which represents by far the largest share among renewables in the electricity mix at present: 16.6% in 2014, compared with 6.2% corresponding to the share of all other renewable energies combined (REN21, 2015).

[4]Notice that the charts of figure 7.5 have different scales, in order to appreciate better the differences within each group.

The long-lasting life of hydropower stations constrains their rate of replacement, producing *technological lock-ins* and *inertia* in the system.[5] This phenomenon is captured by FTT:Power, through the cost supply curves: in scenarios with limited amount of hydrological resources, grids with high levels of hydroelectricity are forced to pay higher prices of electricity when the hydro cost supply curve approaches its technical potential. Even if the technology is replaced, the technology diffusion process occurs at the rate of replacement of existing technology as it ages, which is inversely related to its life span (Mercure et al., 2014). This is the main reason for the large difference in electricity expenditure between the two groups of scenarios of figure 7.5.

7.4.3 Efficiency by policy set

An appropriate measure of policy efficiency, should include both the amount of emission reductions, and the total expenditure on electricity associated with each policy set. If considerations such as energy poverty or fiscal austerity are at stake, then it is relevant to separate the sources of revenues and expenditures: public expenditure in policy support for subsidies and feed-in-tariffs, public revenues from carbon pricing and private expenditure on electricity. However, in the context of this thesis, the aforementioned considerations are out of the scope of the analysis. Therefore, the total expenditure on electricity, defined as the sum of private expenditure on electricity, public revenues and public expenditure, is used. Figure 7.6 shows how **policy efficiency**, measured as **the ratio between reduction in emissions and total expenditure on electricity**, changes between scenarios of low and high availability of renewable energy resources.

The brown bars in figure 7.6 correspond to the differences between scenarios of high and low availability of renewable energy resources, by policy set. Changes in the availability of energy resources have, as the brown bars show, a large impact on the efficiency of policy. Larger the efficiency of the policy set, larger the impact that uncertainty on energy resources has on its efficiency. There are no considerable differences in electricity expenditure between policy sets, therefore the ranking produced by policy efficiency is not significantly different to the one produced by emission reductions (figure 7.2).

In terms of single policy comparisons, regulation is the one with the highest efficiency, despite producing the highest increase in the price of electricity (see figure 7.5). As discussed in section 7.4.1, regulation produces a large reduction in emissions, due to the enforced

[5] Examples of discussions on lock-ins include Arthur (1989), Unruh (2000). For a discussion about inertia in energy systems, please refer to Grubb (2014, p. 20).

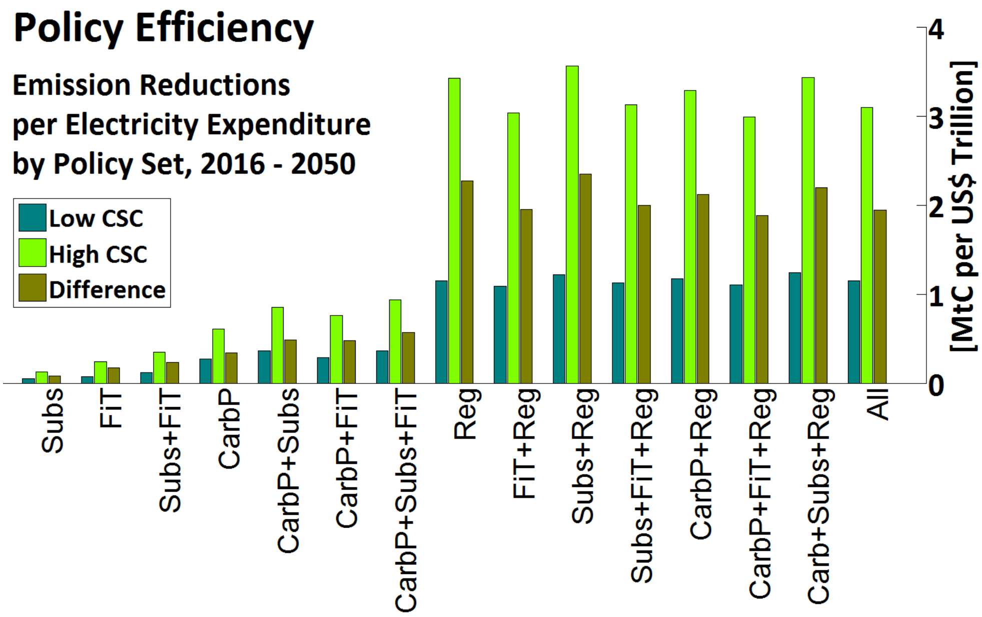


Figure 7.6 Policy efficiency, measured as emission reductions normalised by total expenditure on electricity, by policy set between 2016 and 2050. Scenarios of low and high availability of hydroelectricity, wind onshore, biomass and solar, are presented in dark and light green, respectively. In brown, the differences between the two sets of scenarios, corresponding to the effect that availability on renewable energy resources has on policy efficiency.

replacement of carbon intensive power stations (see figure 7.2). The increase in cost is produced by the same reason: low cost fossil fuel power plants (particularly based on coal) are replaced by more expensive clean alternatives.

The policy efficiency ranking follows closely the emission reductions ranking, because the differences in electricity expenditure are considerably smaller than the differences in abatement. These results suggest that the policy conclusions are robust with respect to changes in electricity demand, even though electricity demand is exogenous in these scenarios.

7.4.4 Policy implications

The first and foremost policy frequently indicated as the solution to the challenge of decarbonise the economy is the introduction of a price on carbon (Campiglio, 2016). There is a vast amount of literature on carbon taxation, and how it can optimally internalise the externalities associated with anthropogenic GHG emissions (see, e.g., Cooper (2008); Hsu (2012); Metcalf and Weisbach (2009); Nordhaus (2015); Weitzman (2013)). While conceptually the need for carbon pricing has long been understood, the difficulty has been in translating concepts into real policies (Ferdi and CEPR, 2015, p. 12). The design and choice of a specific policy instrument (or mix of instruments) depend on many economic, social, cultural, ethical, institutional, and political factors (IPCC, 2014b, p. 235), and countries normally rely on a combination of several instruments with different targets simultaneously (Ferdi and CEPR, 2015, p. 254). In this context, the study presented in this chapter, focuses on different portfolios of policy instruments using regionally differentiated intensities and timings.

The results presented in this chapter, suggest that **direct regulation** (in the form of caps on installed capacity) **can have a larger impact than market-based instruments in the decarbonisation of the power sector**. These results are aligned with the evidence that suggest that when the efficiency of market-based instruments is constrained, regulatory approaches are a more suitable alternative (IPCC, 2014b, p. 240). The superlative performance of regulation policies in the simulations, however, has some caveats. As explained in section 5.6, the relative performance of market versus non-market based mechanisms is influenced by the assumptions of the model. The assumptions of complete feasibility of regulation as well as the strong inertia produced by the shares equation formulation might produce an overestimation of the relative performance of non-market based over market based policies, and consequently the results presented above must be analysed cautiously.

It is important to highlight that technology diffusion in FTT:Power takes place following S-shaped curves (Mercure, 2012). Therefore, the influence of policy instruments is constrained by the rate of replacement of the different technologies, which depends not only on cost considerations, but also on limited access to technology and information, which is embedded in the mathematical dynamics of FTT:Power (Mercure, 2015; Mercure et al., 2014). In this context, the modelling exercise presented above contributes as a positive description of the power sector, capturing some of the limitations associated with the policy diffusion process and decarbonisation. Based on this analysis, some policy recommendations are presented below.

- Scenarios with direct regulation exhibit larger emission reductions than those without regulation. In terms of scenarios with single policy instruments, direct regulation is the one with the largest abatement, followed by carbon pricing, feed-in-tariffs and subsidies. The combination of policies do not follow an additive pattern on emission reductions, due to the complexities of the system. On the one hand, policy instruments have synergies, therefore the marginal abatement of each policy depends on the concurrent policies being implemented (see section 5.6). On the other hand, stability constraints on FTT:Power could hinder, on extreme scenarios, the phase-out of carbon-intensive technologies (see section 4.6.2 for a detailed analysis of this phenomenon). In this context, the abatement of a combination of policy instruments is not straightforwardly the sum of the abatement of each instrument, but a more complex, non-linear emission reduction pattern.

- From a purely environmental perspective, regulation is the most successful policy. However, the relative performance of non-market based over market based policies might be overestimated due to the model assumptions on the feasibility of implementing regulation and the mathematical formulation of inertia. Consequently, while the ordinal performance between market and non-market based policies is clear, the exact difference between them is not necessarily a strong indicator in this case.

- In terms of total electricity expenditure, there are no large differences between the different policy sets (see figure 7.5).

  – Under low availability of hydro, wind, biomass and solar energy, total expenditure can be divided in three big groups (in ascending order of total electricity expenditure): market based policies without carbon pricing, market based policies with carbon pricing, and policy sets with regulation. The first group has the lowest private expenditure, and comparatively small public expenditures and revenues. The second group has the same level of private expenditure as the first group, plus public revenues from carbon pricing. The third group has the highest private expenditure, and comparatively smaller public revenue and public expenditure than market based policies with carbon pricing (varying with the specific policy combination).

  – Under high availability of hydro, wind, biomass and solar energy, private expenditure decreases significantly. The same three groups can be identified in this case, with similar behaviour. In relative terms, public revenues from carbon pricing are a higher fraction of the total expenditure.

  – There are no significant differences on the policy set ranking between the two groups of expenditure scenarios. If “Low CSC” and “High CSC” are considered the extremes, then a more realistic scenario would be expected to be between these two. In that context:

    * Lower the availability of resources, larger the cost of implementing regulation.

        * Higher the availability of resources, larger the public revenues associated with carbon pricing.

    - Revenues from carbon pricing are a net transfer between private and public sector. If those resources were used in the form of subsidies or feed-in-tariffs, then the relative ranking of policy instruments with respect to total electricity expenditure could change.

    - The impact of subsidies and feed-in-tariffs in the total expenditure on electricity is comparatively small with respect to private expenditure on electricity.

- If environmental and economic considerations are combined, using the policy efficiency criterion, then **regulation has the best performance**. This is valid under low and high availability of energy resources. Carbon pricing is the second best, followed by feed-in-tariffs and subsidies.

- The availability of resources has a very strong impact in the level of policy efficiency, due to the differences in the electricity expenditure. Access to affordable energy sources can make a significant difference in the price of electricity, and correspondingly, in private expenditure. Issues such as energy poverty (UN-Energy, 2005) or fiscal austerity (Schaefer and Streeck, 2013) strengthen the importance of considering the availability of resources as part of the policy efficiency analysis.

The analysis presented in this chapter is strongly influenced by phenomena such as inertia and lock-in effects. In FTT:Power, infrastructure has a lifetime, which defines the rate at which power stations can be replaced (see section 4.6). Moreover, investment decisions are taken with no expected coordination, access to limited information and bounded rationality (Simon, 1984), as opposed to classical system level optimisation, where full coordination and foresight is assumed (Mercure, 2012, 2015). This representation allows the emergence of complex, path-dependent dynamics, which are difficult to model, but easier to relate to reality (Mercure et al., 2016). In this context, the analysis presented in this chapter, provides a valuable contribution to the evaluation of policy instruments in scenarios with complex technology diffusion dynamics.

7.5 Conclusions

This chapter analyses the impact of energy resources availability on the performance of decarbonisation policies. Using the database of energy resources of the NER module, introduced in chapter 6, 15 policy sets are analysed under extreme scenarios of hydro, wind, biomass and solar resources availability. *Carbon pricing*, *subsidies*, *feed-in-tariffs*, *direct regulation*, and any possible combination of them, are compared in terms of their abatement performance and their cost, in a global decarbonisation context. From the analysis presented above, the main conclusions obtained are:

- Direct regulation can have a larger impact than market-based instruments in the decarbonisation of the power sector.
- From a purely environmental perspective, direct regulation is the most successful single policy by far, followed by carbon pricing, feed-in-tariffs and subsidies.
- From a cost perspective, market-based policies perform better than regulation, although no significant cost differences among policies are found.
- Environmental and economic criteria are combined in one single indicator, *policy efficiency*, defined as the ratio between *abatement* and *total electricity expenditure*. Due to the considerable differences in abatement, and the less significant differences in cost, the ranking for policy sets under policy efficiency is similar to the ranking from the environmental criterion: in decreasing order of performance, the list of single policies is led by direct regulation, followed by carbon pricing, feed-in-tariffs and subsidies.
- The availability of resources has a very strong impact in the level of policy efficiency. If the scenarios are divided in low and high availability of renewable energy resources, then the efficiency rankings of the policy instruments hold within each group. However, there are significant differences among the two groups (low and high), especially with respect to private expenses on electricity. The main reason behind those differences, is the increase in the price of electricity due to the scarcity of resources.

7.5.1 Future work

The results presented in the previous section and the conclusions presented above depend on the various assumptions underlying the modelling exercise. As discussed in section 5.6, assumptions regarding the feasibility of implementing regulations as well as the inertia of the energy sector might influence the relative abatement performance of the different policy portfolios. Consequently, the policy implications of this analysis have to be understood in the context of the underlying assumptions of FTT:Power. In order to improve the analysis, producing more realistic scenarios, some guidelines for future work are presented below:

- **Foresight and expectations**: In reality, investors have expectations about the future, based on experts judgment and experience. Given the important role that expectations play in the process of allocating investment, they have to be part of the model of decision making. The current version of FTT:Power only includes naive expectations and limited foresight in the investment allocation process. Chapter 10 presents a new methodology to model investment decisions, based on a multi-criteria decision making approach. This new methodology is expected to be used in the future to improve the investment model of FTT:Power in several aspects, including foresight and expectations.

- **Early scrapping**: The decommission of power stations before the end of their lifetime, a process known as early scrapping, is not part of FTT:Power. In scenarios of technological lock-ins (such as those presented in this chapter), early scrapping could represent a valuable policy option. In order to model this process, the costs of shortening the lifetime of power stations needs to be addressed, so a link to the economy is needed. Either if the cost is payed by the private or the public sector, the financial implications of a sudden change in the expected income, and the corresponding impact on investment, have to be part of the analysis. Given the work already done to connect FTT:Power with the macroeconomic model E3ME/E3MG (Mercure et al., 2014), early scrapping scenarios are expected to be analysed in the near future.

- **Endogenous electricity demand**: The use of an exogenous demand of electricity, with no response to price signals, is an important constraint in the analysis of power sector scenarios. To address this issue, the combined platform FTT:Power-E3ME/E3MG is expected to be modified, in order to be able to produce a similar analysis to the one presented in this chapter, but using an endogenous electricity demand.

- **Policies implemented in sequence**: In reality, given the differences in political acceptability, policies are implemented gradually. They do not necessarily start at the same time (see section 5.6). In this dissertation, however, given the large number of regions and policy portfolios analysed, only scenarios with synchronous policies are represented. In order to study more sensible policy landscapes, the Monte Carlo module of FTT:Power is expected to be modified, increasing the number of scenarios that can be analysed simultaneously. This will allow the simulation of more realistic scenarios with policies starting at different times in different world regions.

Chapter 8

Hydropower Resources and Policy Performance in Brazil

8.1 Chapter Summary

This chapter builds on the methodology presented in chapter 7, and applies it to a particular FTT:Power region, in order to analyse in detail the impact that uncertainty in resources availability has on the performance of decarbonisation policy. The region analysed in this chapter is Brazil, which has a power sector extremely dependent on hydroelectricity. The decarbonisation policies are analysed in the context of the Intended Nationally Determined Contribution (INDC) towards achieving the objective of the United Nations Framework Convention on Climate Change (UNFCCC) (Brazilian Government, 2015). *Policy efficiency*, measured as the ratio between *emission reductions* and *total expenditure on electricity*, is compared for different policy sets under high and low availability of hydropower resources.

The chapter is structured as follows: section 8.2 introduces the Brazilian power sector. Then, section 8.3 presents an analysis of decarbonisation policy efficiency in Brazil, under extreme scenarios of hydropower resources. Based on this analysis, section 8.4 discusses the potential policy implications for Brazil, given the commitments made by the country, in the context of the Paris Agreement(UN, 2015b). Finally, some concluding remarks are presented in section 8.5.

8.2 Introduction

Brazil occupies, in many ways, an enviable position in the global energy system (IEA and OECD, 2013, p. 304). While many countries are struggling to decrease the carbon emissions from the power sector, in the year 2012 less than 15% of Brazilian electricity generation came from fossil fuels, around 6% from bioenergy and more than 75% from hydroelectricity, as it is shown in Figure 8.1. In terms of efficiency, Brazil has an energy intensity indicator at the level of the OECD average (0.11-0.12 toe for USD 1,000 GDP), less than two thirds of world average and less than one third of the average of the other BRICS countries (IEA and OECD, 2013, p. 319). Brazil is also rich in terms of fossil fuels: it is the world leader in deep water oil extraction, and the discoveries of offshore fields in the Santos basin open more possibilities for the country regarding oil exports (IEA and OECD, 2013; Marcio Rocha Mello et al., 2013). With a nominal GDP of USD 2.2 trillion, Brazil is the seventh largest economy in the planet, and by far the largest in Latin America (World Bank, 2013).

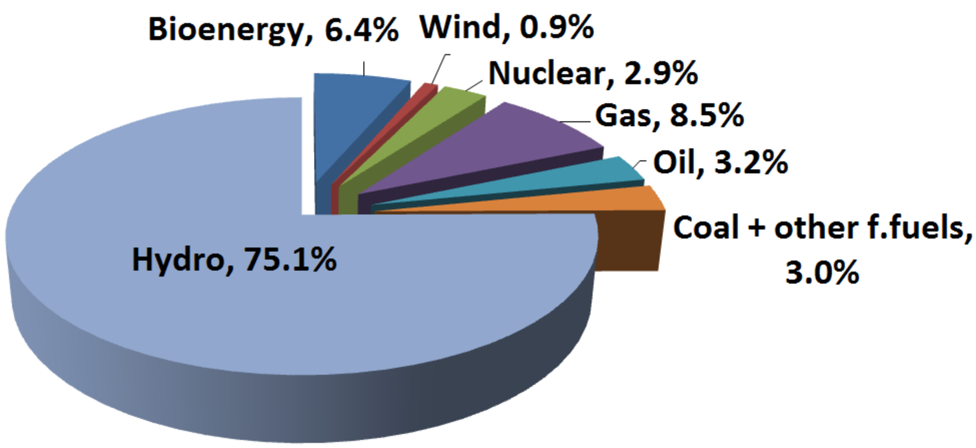


Figure 8.1 Brazilian electricity generation by technology in 2012, based on data from the International Energy Agency Database (IEA, 2015).

Brazil is also rich in terms of bioenergy. The sugarcane plantations harvested in 2012 sum 8.4 million hectares, an area equivalent to the double of the Swiss territory. With a share of more than 20%, Brazil is the second largest biofuel producer globally, after USA (IEA and OECD, 2013). For that reason, it is not surprising that 6% of Brazilian electricity comes from bioenergy, mostly sugarcane-based biomass typically used in sugar-ethanol mills (Khatiwada et al., 2012). Given the large levels of sugarcane production in Brazil, bioelectricity has the potential of playing an important role complementing hydroelectricity during dry seasons.

Despite the minor role of other renewable energies in the Brazilian power sector mix, such as wind and solar energy, their potential is significant. Estimates for the Brazilian wind potential vary from 350 GW up to over 4,000 GW, of which only 2.5 GW are in use (GWEC, 2012; Mercure and Salas, 2012). In the case of solar energy, solar irradiation values in Brazilian territory fluctuate between 4.25 and 6.50 kWh/m^2/day, values comparable to the highest irradiation levels in India, and more than twice the irradiation in Germany (Martins et al., 2007; Pereira et al., 2012). Because the irradiation levels are relatively constant throughout the territory, solar energy is a good candidate for distributed generation in Brazil. Given the challenges associated with the future expansion of the hydropower capacity, wind and solar are good alternatives to increase power supply without increasing carbon intensity and greenhouse gas emissions. Moreover, the capability of hydroelectricity to adjust its output on demand is the perfect complement for variable electricity sources such as wind and solar energy. Therefore, integration costs in the Brazilian power sector are expected to be small (IEA and OECD, 2013, p. 343).

8.2.1 Hydroelectricity in Brazil

The large dominance of hydroelectricity in the Brazilian power sector brings concern regarding the dependence of the country on water availability. During the 90s, Brazil introduced several changes in the regulation of the electricity sector, with the intention to stimulate competition and long term investment. However, the rapid increase in electricity demand, combined with the lack of investment in new generation capacity, left the Brazilian power sector vulnerable to hydrological conditions, given its strong dependence on hydropower (Rosa and Lomardo, 2004). Following a series of dry periods, Brazil entered into an electricity generation crisis in 2001, when the government was forced to implement consumption caps to control electricity demand and to avoid blackouts (IEA and OECD, 2013, p. 311). After years of debate and reforms, finally Brazil improved its regulatory framework, and today the state has a more proactive role in planning as well as financing new power capacity (David Watts and Rafael Ariztía, 2002; IEA and OECD, 2013; Rosa and Lomardo, 2004).

The dependence of the Brazilian power sector to hydroelectricity might have strong implications in the future, given the expected changes in the global climate (Montenegro and Ragab, 2010). Figure 8.1 shows maps of changes in mean temperatures and rainfall (using data from CMIP5[1]) across the Brazilian territory. It is observed that in a scenario of continued high

[1] The figure was created by Dr. Aideen Foley with data from the Coupled Model Intercomparison Project Phase 5 (CMIP5) of the IPCC (Taylor et al., 2012), using an ensemble of General Circulation Models (GCMs).

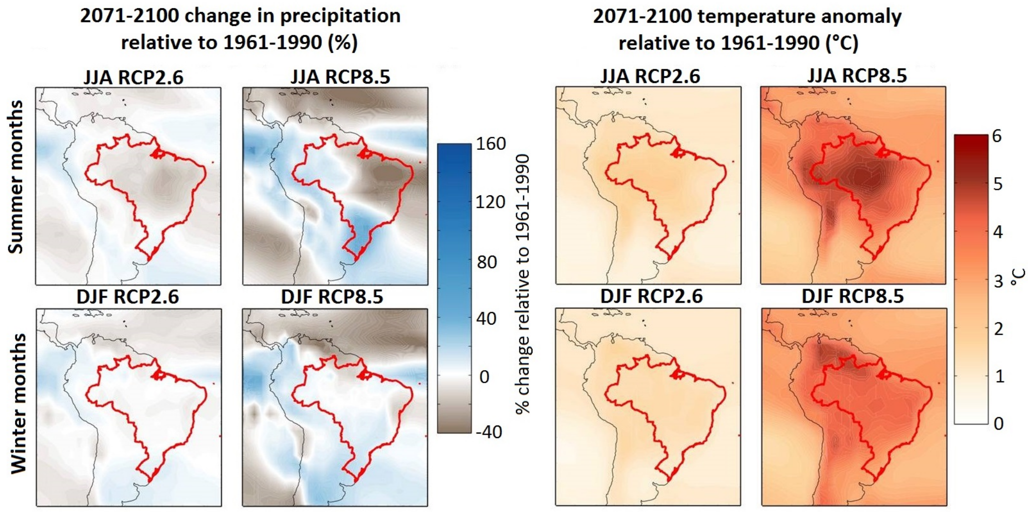


Figure 8.2 Changes in annual average rainfall (as a % change to annual averages) and mean temperature, in the summer (top panels) and the winter (bottom panels), for low cumulative global greenhouse gas emissions (left panels) and high cumulative emissions (right panels). In scenarios of high emissions, temperature changes of up to 6°C are expected over the Amazonian region, and rainfall changes of +60% and -40% are expected in North-Eastern and Southern Brazil, respectively (Mercure et al., 2015).

global emissions, temperature changes of up to 6°C could occur in the Amazonian region. Meanwhile, models project that in such a scenario, rainfall could be significantly disturbed, increasing by 60% in the southern regions while it could decrease by 40% in already arid regions of the north. The estimated technical potential for hydroelectricity in Brazil is in the order of 1.3 PWh/yr, of which around one third is used today (IEA et al., 2012; Mercure and Salas, 2012). Most of the remaining potential sites are predominantly located in the Amazonian region, which as seen in Figure 8.1, could be severely affected by changes in rainfall, and consequently, on water availability for electricity production purposes.

Using the NER module, the next section presents an analysis of the impact of hydropower resource availability in the performance of decarbonisation policies in Brazil, in the context of the INDC submitted for the Paris Agreement (UNFCCC, 2016). Following the methodology presented in chapter 7, the *efficiency* of different policy combinations is analysed, and scenarios of new capacity investment are presented.

8.3 Uncertain Technical Potential for Hydroelectricity in Brazil

In a study of ten scenarios of the global power sector, several decarbonisation policies were analysed for 21 regions of the world (Brazil being one of them) (Mercure et al., 2014). In almost all the regions under study, the technological composition of the power sector was strongly affected by the implementation of decarbonisation policies. The main exception was Brazil: given the already low carbon composition of its electricity sector, both the decarbonisation and the baseline ("business as usual") scenarios maintained a strong dominance of hydroelectricity over all the other technological options. Figure 8.3 presents the electricity generation and emissions data for two of the ten scenarios analysed for Brazil, the one with the highest and the one with the lowest level of emissions, top and bottom respectively.

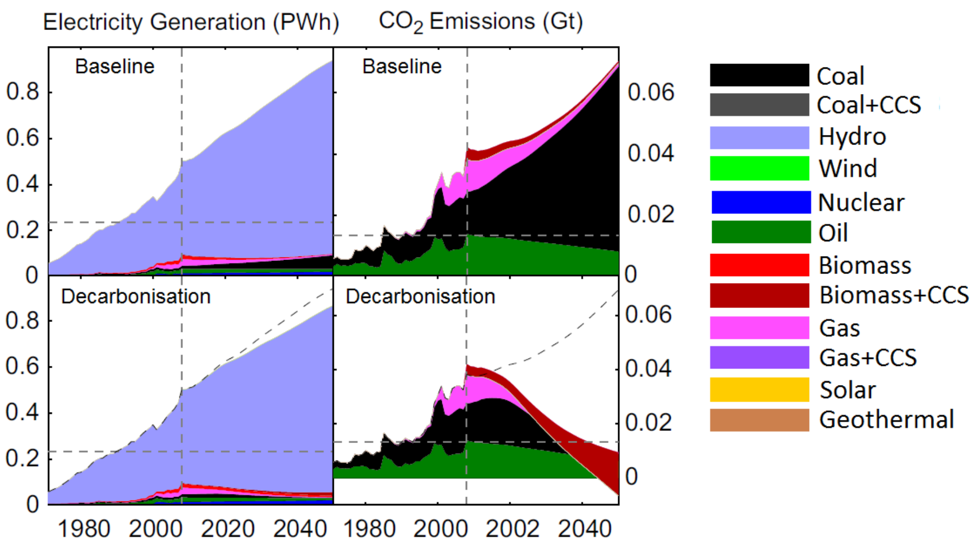


Figure 8.3 Scenarios of electricity production (left) and emissions (right) for Brazil. The top scenario corresponds to "Business as usual", while the bottom corresponds to a 90% reduction in emissions compared with 1990 levels. The vertical dashed lines separate historical IEA data (left) from simulation data (right). Horizontal dashed line indicates 1990 levels of electricity production and emissions. Figure adapted from Mercure et al. (2014).

The small differences in the technological composition of the energy matrix between these two extreme scenarios is a manifestation of the technological lock-in of hydroelectricity in the region (Mercure et al., 2014). Even under different policy landscapes and investment incentives, the long lifetime of the hydropower infrastructure limits the capacity of the system to change. The main risk associated with the strong dependence of Brazil to hydropower is the uncertain amount of hydrological resources the country will have available on the next decades, due to climate change. As figures 8.2 shows, changes in weather patterns could have a big impact on rainfall in Brazil, and therefore on water reservoirs. The effect of water scarcity can directly affect electricity generation (Labriet et al., 2015), and also have an influence on public perception regarding the construction of more hydroelectric dams (Ministry of Mines and Energy of the Federative Republic of Brazil et al., 2010). Most of the remaining potential sites for future development in Brazil are predominantly located in the Amazonian region, far from the demand centres. In order to minimise the social impact associated with future hydropower developments, the government will have to balance appropriate levels of electricity generation with adequate use of the water resources and minimal social and environmental impacts (IEA et al., 2012; Ministry of Mines and Energy of the Federative Republic of Brazil et al., 2010).

For the COP21 meeting in Paris, which was the prelude of the Paris Agreement (UNFCCC, 2016), Brazil committed to a 37% redution of GHG emissions below 2005 levels in 2025. This committment will require a decrease in emissions in several sector, including the power sector. To analyse the effect of different policy instruments in the potential decarbonisation of the power sector in Brazil, scenarios under different availability of hydropower resources are presented below, using FTT:Power. To simulate extreme scenarios of hydropower availability, the lower and upper limits of the cost supply curve for Brazilian hydroelectricity are used. Following the approach of chapter 7, subsidies (*Subs*), feed-in-tariffs (*FiT*), carbon pricing (*CarbP*), regulation (*Reg*), and any possible combination of them are used for the creation of the scenarios.[2] Figure 8.4 shows the efficiency of each policy set, under low and high availability of hydropower resources. In this particular group of simulations, only the availability of hydroelectricity in Brazil is varied, all the other resources are assumed to follow the most likely cost supply curve. In terms of the exogenous electricity demand, the maximum demand trajectory is assumed. The rest of the assumptions are exactly the same as those of section 7.4:

- In all the scenarios, the default learning rates for all the technologies are used (see section 4.5).

- For the 'Low CSC' and the 'High CSC' groups of scenarios, the lower and higher limits of the cost supply curve for hydroelectricity in Brazil are used (see section 4.4). For the other technologies and regions, the most likely cost supply curve is used in each scenario.

[2]For a detailed description of each policy instrument, please refer to section 5.2.

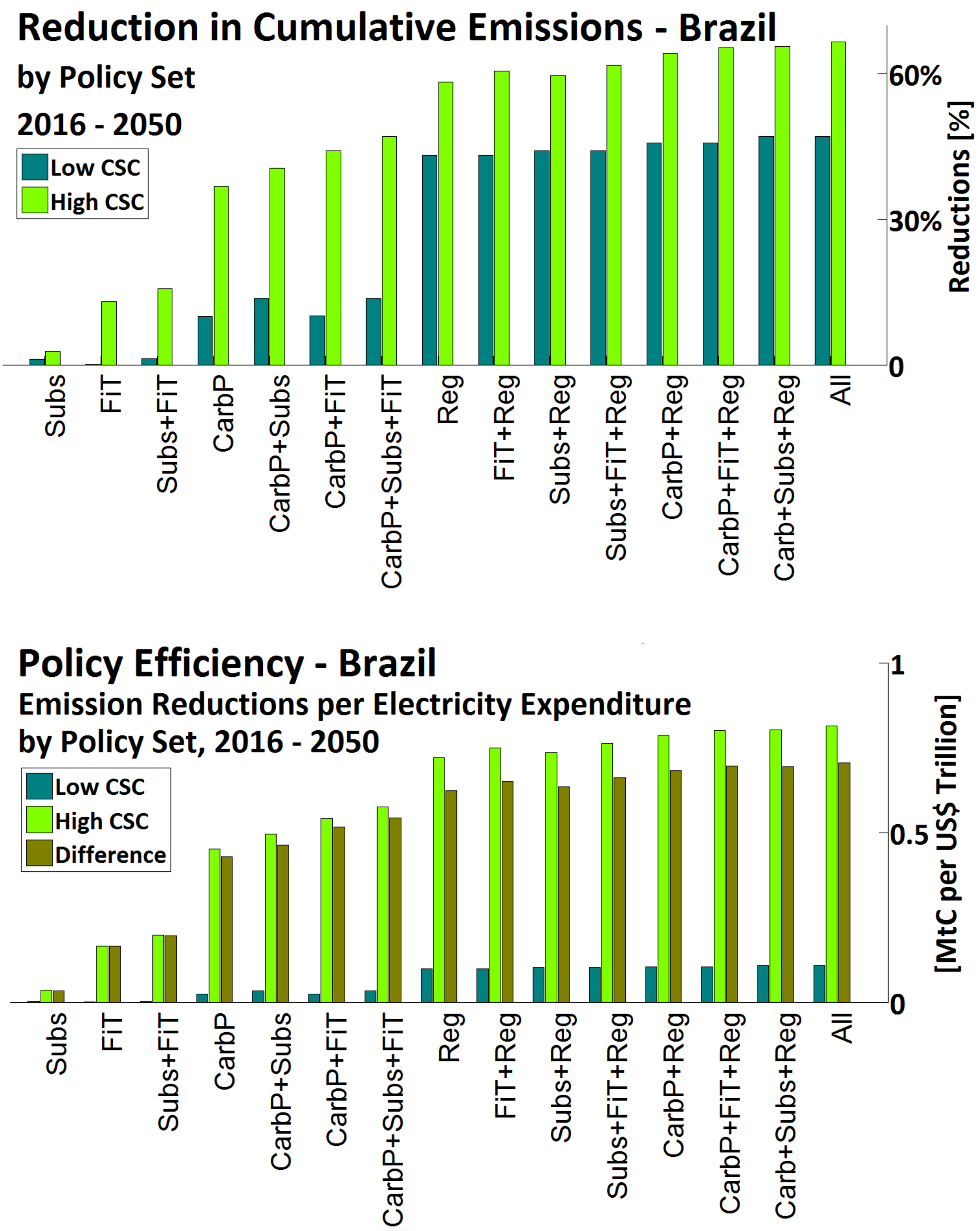


Figure 8.4 Reduction in emissions (top) and policy efficiency (bottom) of different policy sets for the lowest (dark green) and highest (light green) availability scenarios of hydroelectricity in Brazil. The brown bars show the differences between the two sets of scenarios, in the case of policy efficiency.

- On each scenario, only the policies indicated in the name (labels) are applied. The rest are deactivated (policies are deactivated using decarbonisation intensity equal 0, see sections 5.2.1 and 5.2.2 for more details).

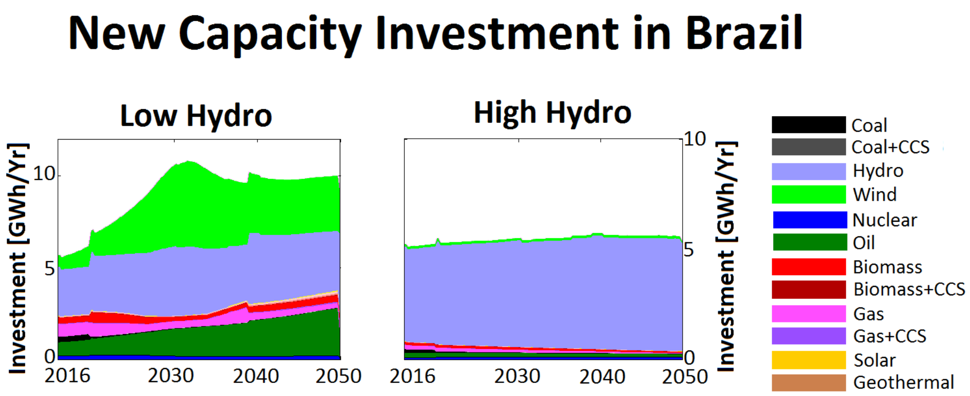
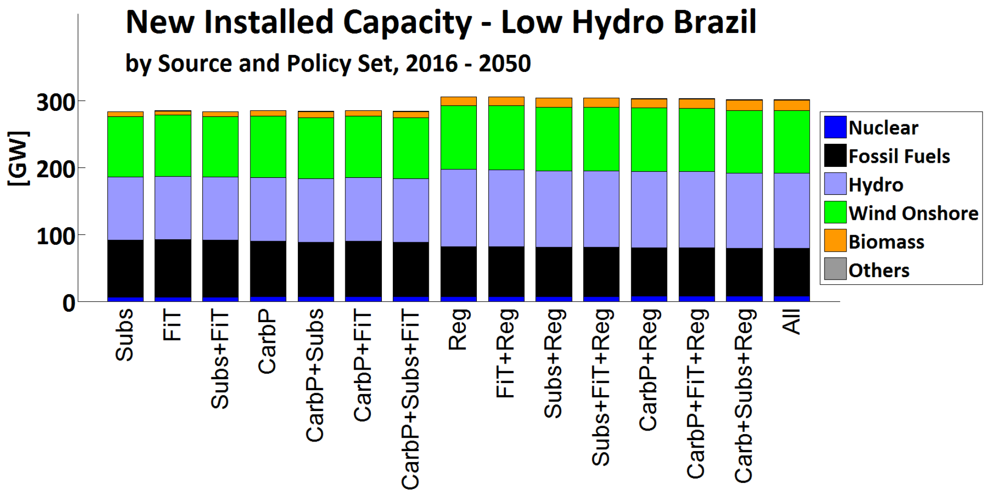


Figure 8.5 Investment in new generation capacity in Brazil, for low (left) and high (right) availability of hydroelectricity, under the policy set "All" (extreme right bar of figure 8.4).

Figure 8.4 shows the reduction in emissions with respect to BAU (top chart) and the policy efficiency (bottom chart) of all the possible policy set combinations for the lowest (dark green) and highest (light green) availability scenarios of hydroelectricity in Brazil. Similar to the results presented in chapter 7, regulation is the single policy instrument that accomplishes the largest reduction in emissions and has the highest policy efficiency, followed by carbon pricing, feed-in-tariffs and subsidies.

According to figure 8.4, large differences in policy efficiency are exhibited between the low and high hydro availability scenarios, for all the policy sets. I.e., **the availability of hydropower resources has a significant effect on the performance of energy policy in Brazil, and therefore it should play a relevant role in the design of decarbonisation policies**.

As mentioned earlier, the Brazilian power sector has a strong hydro-dependency, which works as a self-reinforcing mechanism, producing inertia and technological lock-in. The effect of hydro-dependency in new capacity investment is shown in figure 8.5, for the policy set "All" (extreme right bar of figure 8.4, including all the policy instruments together). On the one hand, under scenarios of large availability of hydro resources, investment in new generation capacity in Brazil is heavily dominated by hydroelectricity, as shown by the the right-hand chart of figure 8.5. Hydroelectricity is a competitive technology, and the strong market position that currently has in Brazil produces a technological lock-in, which is not expected to be broken under scenarios of abundant hydro resources in the future. On the other hand, if hydro resources became scarce, then the situation would be radically different. The marginal price of hydroelectricity rises under scenarios of scarce hydroelectric resources, driving the entire electricity expenditure up. The increase in the price of electricity produces



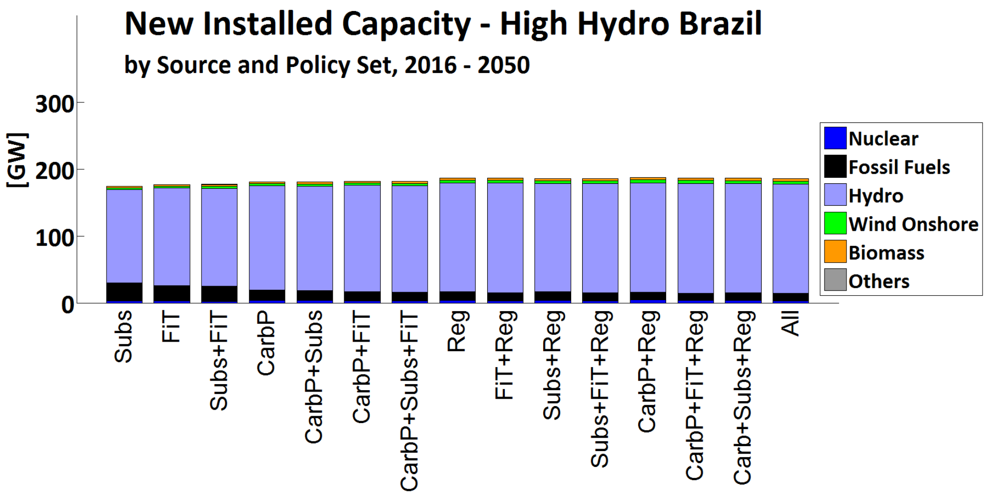


Figure 8.6 New installed capacity in Brazil, between 2016 and 2050, for low (top) and high (bottom) availability of hydroelectricity, for all the policy sets. For a detailed description of the underlying policy sets, please refer to section 5.2.

strong changes in investment patterns, as can be seen in the left-hand chart of figure 8.5. The increase in the price of hydroelectricity (driven by the increase in its marginal cost) creates incentives for the diffusion of other generation technologies, some of which are fossil fuel based. Unsurprisingly, the performance of decarbonisation policies decreases under low availability of hydro resources (as seen in figure 8.4), due to a double effect: the relative carbonisation of the electricity matrix driven by the substitution of hydroelectricity with fossil fuel technologies that are next in the competitive hierarchy, and an increase in the price of electricity.

The situation is very similar for the other policy sets. Figure 8.6 shows the total capacity installed in Brazil between 2016 and 2050, for all the policy sets, under low (top) and high (bottom) availability of hydropower resources. The new investment capacity is aggregated in 6 categories: nuclear, fossil fuels, hydro, wind onshore, biomass and others. As in the case of the policy set “All”, showed in figure 8.5, the new installed capacity in Brazil changes radically under different scenarios of hydrological resources availability (top versus bottom charts of figure 8.6).[3] Due to the large penetration of hydroelectricity in Brazil, part of it is used as baseload, with a high capacity factor. Therefore, it requires less hydropower installed capacity to generate the same electricity than with other electricity generation technologies, such as wind or oil. This is the main reason for the large difference in new capacity investment between scenarios of low and high hydroelectric resources (both having the same electricity demand).

When policies sets are compared within each group (low or high hydropower availability), they do not exhibit large differences on new capacity investment. The largest difference is the increase in new installed capacity for policy sets that include regulation. These policy sets also have less fossil fuel installed capacity than those without regulation (black areas in figure 8.6). Because regulation only affects coal, CCGT and IGCC, oil takes a large part of their share of the market, as can be seen in the left chart of figure 8.4.

8.4 Power sector emission in Brazil and the INDC

In September 2015, Brazil submitted the Intended Nationally Determined Contribution (INDC) towards achieving the objective of the United Nations Framework Convention on Climate Change (UNFCCC), for the COP21 meeting in Paris (Brazilian Government, 2015). According to the INDC, Brazil committed to:

- Reduce GHG emissions by 37% below 2005 levels in 2025 (target)
- Reduce GHG emissions by 43% below 2005 levels in 2030 (indicative)

The Brazilian commitment builds on the current low carbon configuration of its energy sector (as explained in the previous section), and an already successful plan for reducing emissions produced by land use changes (IEA and OECD, 2013, p. 318). Figure 8.7 shows how GHG emissions in Brazil decreased by 33% between 2005 and 2014 (29% if is measured between 2000 and 2014). The decrease in emissions, however, is not balanced accross sectors:

[3] Investment capacity in FTT:Power is measured in units of power (GW), not money.

most of the reduction comes from land use changes. In all the other sectors, emissions increase persistently over the same period 2000-2014, with waste and energy having the larger percentage increase, 76% and 61% respectively. If the INDC target is going to be achieved, then other complementary mechanisms will have to be implemented, especially to address the persistent rise in emissions from the agriculture and energy sectors.

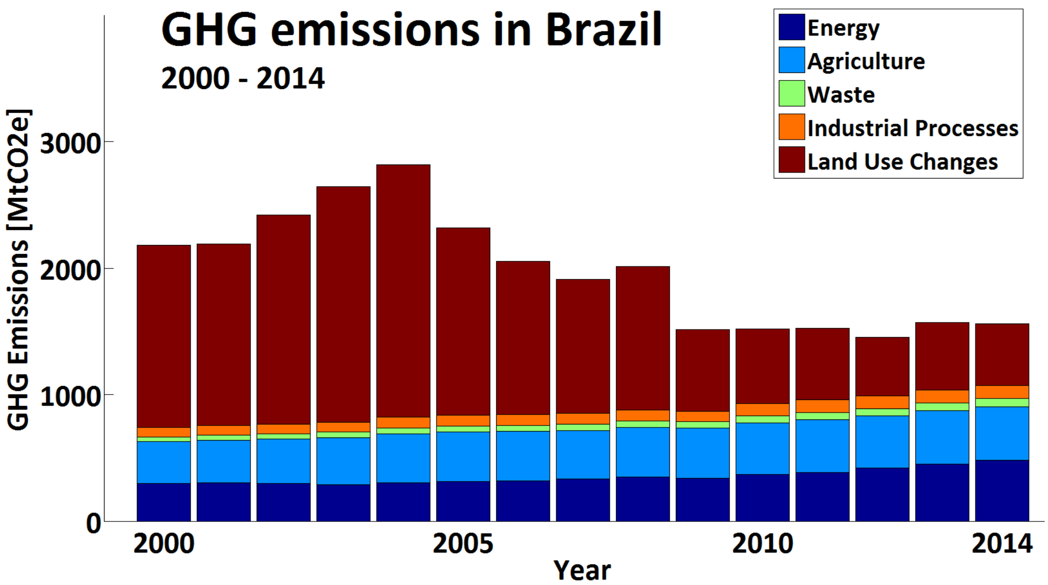


Figure 8.7 Brazilian GHG emissions between years 2000 and 2014, by sector. Data from *Sistema de Estimativa de Emissões de Gases de Efeito Estufa* (SEEG, 2016).

An ensemble with 120 FTT:Power simulations is presented below, to analyse the potential emission pathways of the Brazilian power sector under different scenarios of hydropower availability, in the context of the INDC commitments. Using the resource distributions described in section 6.6 (see figure 6.6), the cost supply curve range of hydroelectricity in Brazil is sampled,[4] so that each scenarios has a different level of hydropower availability. All the policy instruments are applied on the scenarios (which corresponds to the policy set "All"), using he same assumptions described in section 8.3. The emission trajectories of the 120 scenarios are aggregated in figure 8.8. For reference purposes, the BAU trajectory is plotted in black at the top of the chart.

At the extreme left of figure 8.8, are the emissions of the power sector in 2005, which is the base year of Brazil's INDC. If emissions were to be cut proportionally among sectors, then

[4]The sampling method used is latin hypercube sampling (LHS), which guaranties a proportional sampling from the entire distribution range, and therefore is preferred over the traditional Monte Carlo Sampling method (Helton and Davis, 2003)

an emission reduction of 37% would be required by 2025 in the power sector, and that is indicated by the brown dashed horizontal line. In the context of the FTT:Power scenarios analysed in this work, based on the policy sets described in section 5.2, it is not possible to decrease 37% of emission from the power sector, even in the scenarios of high hydro resources availability, let alone the scenarios of low hydropower availability.

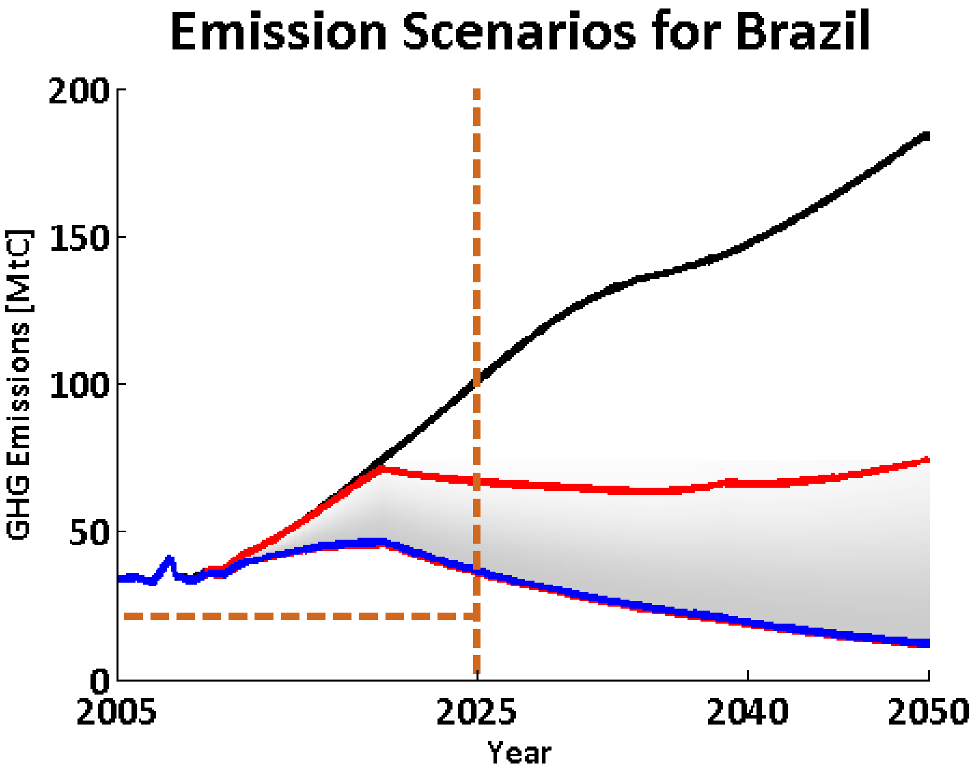


Figure 8.8 The cost supply curve for hydroelectricity in Brazil is sampled, to produce 120 scenarios for the power sector. The shading represents the frequency in the emission trajectories of FTT:Power outputs, based on the distribution of the cost supply curve for hydroelectricity from the NER module. All the scenarios are based on the policy set "All" (except the black line), which assumes that carbon pricing, subsidies, feed-in-tariffs and regulation are in place (for the details about each policy instrument, please refer to section 5.2). The solid red lines represent emission from scenarios produced with the upper and lower limits of the cost supply curve. The solid blue line corresponds to the emissions trajectory from the scenario produced with the most likely cost supply curve. The horizontal dashed brown line indicates a 37% reduction in emissions, in comparison with 2005 level, and the vertical dashed brown line indicates the year 2025, which is the target year for the INDC of Brazil. The black line corresponds to the emissions trajectory from the BAU scenario, inserted for reference purposes only, because is not part of the "All" policy set. In the BAU scenario, no decarbonisation policies are implemented.

The emission trajectories corresponding to the range between the most likely and the upper limit of the cost supply curve of hydroelectricity in Brazil (the upper range of hydropower resource availability), are concentrated between the bottom red and blue lines of figure 8.8, which are overlapping almost entirely. This means that for high availability of hydroelectric resources, there is almost no difference in terms of power sector abatement. This is not surprising: if the total demand for hydroelectricity is matched by the supply, more availability of hydro resources do not provide further decarbonisation potential.

In contrast, the emission trajectories associated with the range between the most likely and the lower limit of the cost supply curve (the lower range of hydropower resource availability), are distributed between the blue and upper red lines of figure 8.8. The large range of emissions associated with the lower range of the hydro cost supply curve, indicates the importance of hydroelectricity in Brazil to maintain its low carbon energy matrix. It is important to notice that, given the exponential distribution of resources, the probability associated with higher emission trajectories are expected to be low. However, despite the low probabilities associated with the high emission scenarios, it is important to understand the underlying risks, which may increase over time due to the effects of climate change in Brazil.

The low carbon intensity of the Brazilian power sector hinder further reductions of GHG emissions, which are required for achieving the international commitments stated by the INDC. As the emission trajectories presented in figure 8.8 show, Brazil has limited decarbonisation possibilities within the power sector, given the large amount of hydroelectricity that is already in place. In order to further reduce power sector emissions, given the current technological lock-in, stringent decarbonisation measures will be required, e.g., regulation on the end-use sector, or early scrapping of carbon intensive power stations (IEA and OECD, 2012a).[5]

Given the existing limitations related to further decarbonise the Brazilian power sector, it is necessary to go beyond traditional sectoral approaches, and look at the system as a whole. In order to look for effective decarbonisation policies, aligned with the INDC commitment, it is absolutely necessary to understand the complex linkages between the food, water and energy sectors in Brazil, usually referred as the *Nexus* (Bazilian et al., 2011). Future changes in the global climate could potentially have detrimental impacts on the land cover and biodiversity in Brazil, with implications on agriculture, cattle and food production, water for electricity production, and consequently on emissions. As can be seen in the data from SEEG, presented in figure 8.7, the land use and agriculture sector can play an important role in further decarbonise the Brazilian economy.

[5] These policies are not included in the current version of FTT:Power.

8.5 Conclusions

This chapter analyses the impact of hydropower resources availability on the performance of decarbonisation policies in Brazil. Using the database of energy resources of the NER module, introduced in chapter 6, 15 policy sets are analysed under extreme scenarios of hydropower availability. *Carbon pricing*, *subsidies*, *feed-in-tariffs*, *direct regulation*, and any possible combination of them, are compared in terms of their policy efficiency. The policy set "All", that includes a combination of all the policy instruments, is analysed in detail. 120 emission scenarios are aggregated and contrasted with the Intended Nationally Determined Contribution submitted by Brazil for the COP21. From this analysis, the main conclusions obtained are:

- The large hydropower-dependence of the Brazilian power sector hinders the efficiency of strong decarbonisation policies, particularly under scenarios of low availability of hydropower resources. As figure 8.4 shows, large differences in policy efficiency are exhibited between the low and high hydro availability scenarios, for all the policy sets. Similar to the results presented in chapter 7, regulation is the single policy instrument with the best decarbonisation performance.

- If Brazil were to apply its emission reduction target of 37% (below 2005 levels in 2025) uniformly across sectors, then the policy sets used in this work are not able to deliver the required emission reductions, even in the scenario with the highest availability of hydropower resources. In the scenario with the lowest availability, the gap between the target and the expected emission trajectories increases (see figure 8.8).

- Over the past 15 years, energy sector emissions have been increasing steadily in Brazil (see figure 8.7). In order to achieve its INDC target, Brazil cannot rely on the decarbonisation of the power sector, which has a limited decarbonisation potential. Therefore, comprehensive decarbonisation policies are required, involving several sectors, especially energy, agriculture, and land use.

Chapter 9

Learning

9.1 Chapter Summary

According to the International Energy Agency, investments in the order of USD 140 trillion are required to achieving a low-carbon energy sector by 2050 (IEA and OECD, 2012a, p. 135). The decarbonisation of the energy sector requires a profound and rapid technological transformation, and governments are required to provide well suited economic and legal frameworks for private and public investment to be allocated in low carbon energy alternatives (IPCC, 2014b). In order to produce effective policies to stimulate low carbon investment, feasible economic and technological scenarios for the future have to be analysed. Such analysis requires a good understanding of the technological landscape, and its potential evolution driven by public and private investment. It is crucial, therefore, to understand how technological change works, and how it can be modelled.

In line with the aforementioned challenges, this chapter provides an introduction to the subject of technological change and learning, how is modelled in FTT:Power (in contrast with some classical approaches), and presents future decarbonisation scenarios under uncertain technological change (in the form of extreme learning rates). The chapter structure is divided as follows:

- First, section 9.2 provides an introduction to the subject of technological change and learning modelling.
- Second, section 9.3 addresses some of the core areas of endogenous technological change modelling, including learning by doing, spillovers and path dependency.

- Third, section 9.4 introduces some of the main sources of uncertainty in the process of learning, and how they are addressed (or not) by the modelling community.
- Fourth, section 9.5 links technology clusters and learning, and show how the link is modelled in FTT:Power.
- Fifth, section 9.6 discusses the difficulties of measuring learning rates, and consequently, the complexities associated with modelling the process of technological change.
- Sixth, section 9.7 explains how learning curves are implemented in FTT:Power, and provides uncertainty intervals for each of the learning coefficients used in the model. These learning intervals were obtained from a thorough literature review, which is presented in the Appendix section C.1.
- Seventh, section 9.8 presents an analysis of the impact that uncertainty in the values of the learning rates has on the emission trajectories of the power sector. Decarbonisation scenarios of the power sector are presented, using extreme learning rates, and different configurations of the system regarding the capability of the grid to incorporate renewable energies. Based on these decarbonisation scenarios, it is concluded that the impact of the grid flexibility on emission reductions is larger than the impact of uncertainty in the learning rates.
- Eighth, section 9.9 concludes with the highlights of the modelling exercise, and some policy recommendations.

9.2 Introduction

Historically, economic models have included technological change and innovation as an important driver of economic growth (Aghion and Howitt, 1992; Romer, 1990; Schumpeter, 1934; Solow, 1956). Early representations of technological change were mostly exogenous and, therefore, unresponsive to drivers such as public policy, R&D investment or regulation. The cornerstone of exogenous technological change in macroeconomic was provided by Solow, who argued that the unexplained difference in productivity coming from its econometrics analysis of US data was due to technological progress (Solow, 1956; Verspagen, 1992). From there, several models focused on human capital formation as the key factor for explaining technological change and economic growth (Phelps, 1966; Shell, 1967; Uzawa, 1965).

The endogenisation of technological change as a factor of economic growth started with the inclusion of ‘externalities’ to explain increasing returns to scale, such as knowledge spillovers (Romer, 1990), international interdependence through trade (Grossman and Helpman, 1994) or entrepreneurial innovation (Audretsch, 1995; Audretsch, David B. and Keilbach, Max C., 2004). Since then, numerous attempts to model technological change as an endogenous factor of economic growth have been produced, many of which can be found on the vast amount of existing literature reviews (Kahouli-Brahmi, 2008; Kohler et al., 2006; Rubin et al., 2015; van der Zwaan and Seebregts, 2004). In many of the existing models, human capital is considered the main input in the innovation process (Verspagen, 1992). Human capital is produced by both private firms in the form of blueprints (Aghion and Howitt, 1992) and from R&D in the form of general knowledge (Grossman and Helpman, 1994; Romer, 1990). In both cases, the link with research and innovations is the key factor for technological progress.

Building on Solow’s exogenous growth model, Kenneth Arrow provided an alternative endogenous theory for explaining the gap between increase in per capita income and the increase in the capital-labour ratio (Arrow, 1962). In its remarkable work about ‘learning by doing’ (or LBD), Arrow provided a simple representation of the complex relation between experience and productivity. The empirical counterpart to Arrows’ theoretical contribution is the ‘learning curve’ or ‘experience curve’, a concept formally introduced by the Boston Consulting Group (BCG) in 1966, but discovered by Wright a few decades earlier.[1] BCG was performing a cost analysis for a major semiconductor manufacturer (Reeves et al., 2013), when they found that the unit production costs felt by a predictable amount (typically 20 to 30 percent in real terms), for each doubling of ‘experience’, or accumulated production volume. That fractional decrease in cost as a function of the production is denominated ‘learning rate’. Three decades earlier, T. P. Wright found a similar pattern followed by the airplane manufacturing industry, something that he described as ‘variation of cost due to production experience’ (Wright, 1936).

The seemingly simple observation made by Wright and the BCG, that cost per unit output declines as production grows, has been observed in several manufacturing industries ever since, including electronics, machine tools, system components for electronic data processing, papermaking, aircraft, steel, apparel, and automobiles (IEA, 2000). The concepts of

[1]In general, the terminology ‘learning curves’, ‘experience curves’ and ‘progress curves’ are used indistinctively. However, some subtle differences can be found in the literature. For instance, Dutton and Thomas differentiate ‘experience curves’ from ‘progress curves’ in their scope. The former represents average production cost of multiple manufacturers, whereas the latter represents production costs at the firm level (Dutton and Thomas, 1984; Weiss et al., 2010). In this work, the three terms are considered equivalent.

learning and experience curves are used indistinctively to represent the empirical log-linear relationship between production cost and cumulative experience (using typically cumulative installed capacity or cumulative sales as a proxy of experience. See section 9.3 below for more details).

Whilst there is vast evidence of the positive influence of knowledge (typically measured using proxies such as R&D expenditure, education or patents) in productivity and economic growth, the magnitude of such influence is still unclear (Griliches, 1994; Hu et al., 2005; Mason et al., 2012; Samaniego, 2007). Despite the lack of consensus in the magnitude, knowledge is considered by many economists as capital stock with a positive influence in productivity and increasing returns to scale. This is valid in both cases, when knowledge is represented by R&D or blueprints from public and private companies (classical growth models), and when knowledge is characterised as experience (LBD perspective). However, the process of acquisition of knowledge (learning) is intrinsically complex and difficult to be measured. For that reason, modelling technological change endogenously presents a series of barriers, especially in the context of optimisation and equilibrium. For instance, learning by doing makes the problem of minimising total energy system costs non-convex, giving rise to multiple equilibria and attendant instability of models' numerical solution (Sue Wing, 2006). Moreover, knowledge has increasing marginal productivity (Romer, 1986), which produces increasing returns to scale and path dependency, leading to technological lock-in (David, 1985). All of these factors hinder the incorporation of endogenous technological change in economic (top-down) and energy (bottom-up) models.

9.3 Learning by Doing, Spillovers and Path Dependence

While the process of knowledge acquisition can be costly, the spread of that knowledge may be almost costless, creating spillovers in other sectors, industries and technologies. This is known as the non-rival public good character of knowledge (Sijm, 2004). Spillovers can be produced at different levels (they may be intrasectoral or intersectoral, as well as local or international), and also at different degrees of embodiment (knowledge having an impact on real goods or in the development of more ideas) (Weyant and Olavson, 1999). The inclusion of these different levels and dimensions varies between different models, going from no correlation between technology prices (no spillovers) up to assuming that all expenditures contribute to cost reduction in all regions and all sectors (Kohler et al., 2006).

In the case of models based on the principle of learning by doing, spillovers are presented as diffusion of cost reductions from one sector, industry or location to another, based on learning curves (Sijm, 2004). While empirical studies show these spillovers exist (Barreto and Klaassen, 2004; Nemet, 2012), it is very difficult to model them as a process, because they depend on knowledge diffusion, and not on tangible data such as investment or sales. The most common form of modelling learning-by-doing in energy models is with learning curves, typically using a power relation between unit cost and cumulative capacity. Progress rates are presented in terms of percentage cost reduction for each doubling of the cumulative generation capacity of production, as it is shown in the equation 9.1, where C is the unit cost, W is the cumulative capacity and b is the learning elasticity (Jamasb, 2007).

$$C_t = C_0 * W_t^b \tag{9.1}$$

Due to the spillovers previously mentioned, the evolution of each energy technology is linked to the evolution of the rest of the industry, and even other industries, like in the case of military R&D and its impact on other sectors (Honig et al., 2006). The effect on markets produced by this complex and highly non-linear interaction is irreversible, and therefore generate path dependence. The dominance of any particular technology through the exploitation of specific competitive advantages creates barriers to entry into the market for new competing technologies, especially if the dominant has increasing returns to scale (phenomenon known as technological lock-in). This process may have the effect of leading toward suboptimal scenarios, where inferior technologies become dominant due to historical factors. Market mechanisms are usually not strong enough to offset technological lock-ins, and in those cases external policies are required to support competition between the different technologies (Arthur, 1989).

In energy system models, in particular those based on optimisation algorithms, path dependence is a phenomenon that hinders the search for a global optimum. The non-convexities created by knowledge spillovers and learning curves normally leads to sub-optimal solutions and multiple equilibria. Although it has been partially solved by limiting the parameter space, limiting the implementation of learning or using Mixed Integer Programming methods (Messner, 1997), the conceptual problem still remains. The introduction of increasing returns to scale also generates instabilities when linear programming methods are used. These difficulties do not only appear in energy system models, but they are also a serious issue in computable general equilibrium models (Kohler et al., 2006). For the reasons previously mentioned, dynamic approaches are better suited to represent complex phenomena like path dependence, technological spillovers and learning in energy system models.

9.4 Uncertainty and Learning

There are several aspects that bring uncertainty about the learning process (van der Zwaan and Seebregts, 2004). Learning curves, for instance, are a representation of cost reduction based on cumulative experience, but time is not explicitly represented in the learning curves, although it plays an important role in the learning process. The analysis of learning over time brings into focus several aspects that are typically ignored by the traditional learning literature. For instance, Kahouli-Brahmi (2008) showed that learning rates are normally measured over long periods, during which the manufacturing technologies and processes evolve, the markets evolve and the technology itself evolves. As a consequence of this, it is not surprising that **learning rates change over time**, a phenomenon that is widely acknowledged but at the same time rarely incorporated into models.

At the core of the learning rate concept is the idea of "doubling cumulative capacity". The increase in cumulative capacity is connected to the size and growth rate of the market as a whole, as well as the market penetration of the specific technology. Therefore, **market penetration constraints** (such as those imposed by regulators to avoid monopolistic markets) limit the capacity of firms to grow, and consequently have an impact in the learning process.

The estimation of learning rates is prone to many different sources of uncertainty. For instance, as can be seen in equation 9.1, the learning curves depend strongly on the initial cost and capacity values. For many technologies, cumulative capacity data is not available. The use of proxies for both experience and costs brings more uncertainty to the estimation of learning rates. For instance, **costs** are difficult to estimate, so they are usually replaced by **prices**. But prices incorporate **profits**, and in some cases **subsidies**, which vary across industries and technologies. Equivalently, **experience** is not measurable, so proxies such as **cumulative installed capacity** or **cumulative sales** are used.

Either if is in the form of R&D or through commercial experience, learning is a process that happens locally. Depending on the nature of the knowledge acquired, spillovers can be produced, and then the new knowledge can be spread over a larger geographical area, even globally. But that is not always the case, particularly if there is intellectual property involved. Therefore, learning rates are bound to several factors, especially **companies**, **geographical**

areas, and **time**. Not knowing this information brings uncertainty about the real scope of a learning rate estimation.

In the case of estimations of future learning scenarios, there are additional factors that bring uncertainty into the calculations. For instance, in the case of energy technologies, future learning scenarios require assumptions about **future energy demand**, **investment**, **energy resources**, **efficiency** levels, energy and environmental **policies**, **emission** reductions and **discount rates**, among others. All of these factors are inherently uncertain, therefore, that uncertainty is transmitted to the learning dynamics.

A type of uncertainty that has been addressed by the learning rates literature is the **methodological uncertainty**. As it is explained in the introduction section, there are two main proxies for knowledge in endogenous learning models: R&D and cumulative production. Multi-factor models typically use both as distinctive proxies of experience, differentiating their contribution to the reduction of cost. The large majority of the models, however, use only one factor as proxy for experience, typically cumulative production, cumulative sales or installed capacity. The disagreement between these two methodologies bring also uncertainty to the estimation of learning rates.

Based on the previous arguments, I decided to use ranges, instead of values, for the learning rates of the 24 energy technologies represented in FTT:Power on this study.[2] Such ranges are based on a literature review of one-factor experience curve models. The values are summarised in Table 9.1.

9.5 Cluster of Technologies

Innovation and technological improvements are heterogeneous processes, with marked differences among industries. In terms of innovation patterns, industries are typically characterised as either Schumpeter Mark I or Schumpeter Mark II industries (Fontana et al., 2012). On the one hand, the Schumpeter Mark I term refers to the early view of innovation that Schumpeter presented in *The Theory of Economic Development* (Schumpeter, 1934). This group of industries are characterized by environments with relatively low entry barriers, where innovations are (mostly) generated and developed by new "entrepreneurial" firms. In this context, there is a high rate of replacement of incumbent industries by new entrants, and technological

[2]The learning rate are assumed to be constant (no variation over time) in the scenarios analysed in this dissertation.

competition can be described as a *creative destruction* process. The Schumpeterian Mark II industries, on the other hand, are characterised by environmnents with high entry barriers, in which large established firms lead the innovation process. Incumbent firms introduce innovations through progressive consolidation of their technological capabilities, following a process of *creative accumulation*. The concept follows the later view of innovation proposed by Schumpeter in *Capitalism, Socialism and Democracy* (Schumpeter, 1942). In both cases, Schumpeter Mark I and II industries, innovation and technology improvements propagate throughout the entrepreneurial ecosystem (horizontally in the former, and vertically in the latter). Developments in one area lead to developments in other areas, especially if they use similar (o the same) technology. When a group of technologies share a common essential component, they define a *cluster* (de Feber et al., 2002). Technological improvements in the shared technological component, generate spillovers in the entire cluster, due to the interdependent learning. Classical examples include the learning on drilling technologies producing benefits on oil, gas and geothermal energy at the same time, or learning on steam turbines producing benefits on coal, gas and solar-thermal power plants.

Technologies can be part of several clusters at the same time, based on the components they share with others. Coal gasification power plants, for instance, belong to several clusters, including the cluster of technologies using gas turbines (IGCC, BIGCC, CCGT and natural gas power plants belong to this cluster) and the cluster of technologies using boilers (concentrated solar power, gas, oil, coal and wood fired power plants belong to this cluster). As a consequence of this, technologies can benefit from the improvements of more than one technology or cluster. Following the previous example, improvements in technologies such as gas or steam turbines, gasifiers and boilers, all add up to a better performance of the coal gasification power plants.

FTT:Power incorporate interdependent learning through a learning spillover matrix B_{ij} (Mercure, 2012). In this way, the cumulative knowledge of technology i is influenced by incremental capacity additions on technology j in the following form:[3]

$$W_i(t) = \sum_j B_{ij} \begin{cases} \int_0^t \left(\frac{dU_j(\tau)}{d\tau} + \delta_j U_j(\tau) \right) d\tau, & \frac{dU_j(\tau)}{d\tau} > 0 \\ \int_0^t \delta_j U_j(\tau) d\tau, & \frac{dU_j(\tau)}{d\tau} \leq 0 \end{cases} \tag{9.2}$$

[3]For more details, please refer to Mercure (2012)

where U_j and W_i are the capacity and cumulative capacity of technologies j and i, respectively, and δ is the depreciation rate. So, in this approach, interdependent learning depends on the 'proximity' of technologies i and j, measured by the weight B_{ij}.

9.6 Modelling technological change under uncertainty

The nature of the technology evolution process, which is path dependent and non-linear, makes it very uncertain. It is not surprise, then, that learning rates estimations found in the literature show very large variations, which can go up to as much as one order of magnitude (Rubin et al., 2015). Although most estimations are positive, there is evidence of nuclear power presenting negative learning rates in particular cases (Grubler, 2010). While positive learning rates confirm the likelihood of declining costs with the increase of production capacity ('experience'), the magnitude of such influence is uncertain.

The reduction of cost as a power law of cumulative capacity is an empirical finding, not necessarily a natural law (Dutton and Thomas, 1984). There are well documented cases of technologies which do not follow this principle (Grubler, 2010; Hultman and Koomey, 2007). Costs reductions are associated with complex multi-level interactions, many of which are exogenous to the manufacturing process. Therefore, even in the cases where technologies seem to follow a 'learning curve' at the aggregate level, there are large variations between and within technological clusters (Weiss et al., 2010).

The complexities associated with modelling the process of technological change, added to the difficulties of measuring learning rates, drives part of the modelling community to avoid the endogenisation of technological change. Nordhaus (2014) postulates that modelling endogenous technological change with such levels of uncertainty is 'dangerous', because it produces a bias optimisation towards the adoption of technologies that are incorrectly specified as having high learning coefficient (Nordhaus, 2014).

Despite the statistical identification problem associated with the quantification of endogenous (versus exogenous) learning, ignoring this process would be somehow equivalent to assume that learning rates are zero (Grubb, 2014, p. 496). Such approach will be in contradiction with a vast amount of evidence that shows the importance of learning as drivers of economic growth and technological transitions (Audretsch, 1995; Grossman and Helpman, 1994; Grubb et al., 2006; IEA, 2000; Kahouli-Brahmi, 2009; Kohler et al., 2006; McDonald and Schrattenholzer, 2001). A more reasonable approach would be to use ranges instead of specific values for the learning rates. Such ranges consolidate the uncertainty surrounding the accuracy of the estimation at a specific point in time.

9.7 Technological Change in FTT:Power

FTT:Power incorporates learning curves as part of the technology evolution process, using a power-law relation between cumulative output and the unit cost of the respective technology. This approach is known as the 'one-factor learning curve', and it's by far the most common model used in the energy literature to forecast changes in technology cost (Rubin et al., 2015).[4] In its simplest form, the logarithm of the cost of production of technology i (C_i) varies linearly with respect to the logarithm of its initial production cost (C_0) and the cumulative sales (W_i):

$$\log C_i(t) = \log C_0 + b * \log W_i(t) \tag{9.4}$$

where C_0 and $C_i(t)$ are the cost of production in time 0 and t respectively, b is the learning index, and $W_i(t)$ is a measured representing the cumulative experience between time 0 and t (typically represented by sales).

The learning rates, which is the fractional reduction in cost associated with a doubling of experience, is represented by:

$$LR = 1 - 2^b \tag{9.5}$$

Learning rate values currently used in FTT:Power are presented in the 5th column of Table 9.1 for each of the 24 electricity generation technologies represented in the model. Due to the inherent uncertainty of the learning process (see section 9.4), a better representation of

[4] There are also 'multi factor' representations of learning, in which the total cost of a technology is represented by the sum of individual components:

$$\log C_i(t) = \log C_0 + \sum_{i+1}^{n} b * \log W_i(t) \tag{9.3}$$

In this case, b_i and W_i represent progress ratio and cumulative experience associated with a particular component of the technology, which can be a sub-component, R&D, or any other element that provides decreases in cost with cumulative experience. The main difficulty associated with multi-factor models of learning by doing is the lack of systematic data for validation and use (Rubin et al., 2015).

learning rates should include distribution of values, or at least ranges. Based on a thorough literature review, table 9.1 presents learning rate ranges for each of the 24 FTT:Power technologies. Appendix C includes a detail explanation of the information sources behind the values on Table 9.1.

9.8 Decarbonisation and Learning Scenarios

As explained in section 9.3, technological learning is a complex phenomenon, in which time and other variables are connected through non-linear relationships and path dependence. Under the classical optimisation approach, the non-convexities created by learning can lead to sub-optimal solutions and multiple equilibria. In those conditions, the search for an optimal intertemporal trajectory, determined by the options available at any specific time, can diverge in multiple different pathways for the technological evolution of the system if endogenous learning is included. Depending upon the initial conditions, the entire system can be driven to the adoption of technologies that first capture sufficient market volume. These phenomena undermines the common assumption of a natural 'least cost' (or optimal) future, determined by the resources and technologies available (Grubb, 2014, p. 322), and has been one of the difficulties to overcome by traditional energy modelling approaches trying to include endogenous technological change (Kohler et al., 2006).

The dynamic approach of FTT:Power, based on interactions of market forces without the assumption of an equilibrium or optimum point, facilitates the study of the learning phenomenon. Even if technologies with high learning rate are 'picked' by investors, and receive support in terms of subsidies and feed-in-tariffs, their market share growth is endogenously constrained by the size of the industry. In that sense, technologies such as wind or solar cannot overtake the global market overnight, due to the market size difference between them and fossil fuels. Technologies with high learning rate are prone to strong reductions in cost under investment intensive scenarios, but if their market size is small (in relative terms), then it takes time to develop the industrial capacity necessary to become the market dominant technology.

FTT Index	Technology	b	PR	FTT Learning	From Literature		Range used	
				Rate Values	L.Rate Min	L.Rate Max	L.Rate Min	L.Rate Max
			[%]	[%]	[%]	[%]	[%]	[%]
1	Nuclear	0.086	94	5.8	0.0	17	0.0	17
2	Oil	0.014	99	1.0	-	-	0.5	1.5
3	Coal	0.044	97	3.0	4.0	14	3.0	14
4	Coal+CCS	0.074	95	5.0	1.1	9.9	1.1	9.9
5	IGCC	0.044	97	3.0	2.5	16	2.5	16
6	IGCC+CCS	0.074	95	5.0	2.1	20	2.1	20
7	CCGT	0.059	96	4.0	4.0	34	4.0	34
8	CCGT+CCS	0.074	95	5.0	0.6	4.8	0.6	5.0
9	Biomass	0.074	95	5.0	0.0	38	0.0	38
10	Biomass+CCS	0.105	93	7.0	-	-	3.5	10.5
11	BIGCC	0.074	95	5.0	10	10	5.0	10
12	BIGCC+CCS	0.105	93	7.0	-	-	3.5	10.5
13	Biogas	0.074	95	5.0	0.0	15	0.0	15
14	Biogas+CCS	0.105	93	7.0	-	-	3.5	10.5
15	Tidal	0.020	99	1.4	8.0	15	1.4	15
16	Hydro	0.020	99	1.4	1.4	1.4	0.7	2.1
17	Wind On.	0.105	93	7.0	4.0	32	4.0	32
18	Wind Off.	0.136	91	9.0	5.0	19	5.0	19
19	Solar PV	0.269	83	17.0	10	35	10	35
20	CSP	0.152	90	10.0	8.0	16	8.0	16
21	Geothermal	0.074	95	5.0	8.0	8.0	5.0	8.0
22	Wave	0.218	86	14.0	9.0	9.0	9.0	14
23	Fuel Cells	0.234	85	15.0	15	25	15	25
24	CHP	0.044	97	3.0	3.0	25	3	25

Table 9.1 List of FTT:Power technologies, their learning rate coefficients and ranges found in the literature review described in Appendix section C. The last two columns (Range used) correspond to the learning rate ranges used in the simulations presented in the following sections.

The large variations among learning rate estimates is an important issue to address if technological learning is treated endogenously. According to Nordhaus (2014), ‘there is a fundamental statistical identification problem in trying to separate learning from exogenous technological change and that the estimated learning coefficient will generally be biased upwards’. If a system is configured to choose the lower cost alternative, then technologies with incorrectly specified high learning rates may drive the system towards a suboptimal solution.

In the case of dynamic models, such as FTT:Power, the upward bias phenomenon described by Nordhaus does not necessarily lead to unrealistic uptake of new technologies with high learning rates. Cost is only one of the drivers of technology diffusion in FTT:Power.[5] As explained above, market size, in combination with the rate of technology turnover (see section 4.6), constrain the diffusion rate of technologies, even if they are cost competitive.

In line with the previous arguments, this chapter provides an analysis of the impact that uncertainty in the values of the learning rates (due to over or underestimation) has on the decarbonisation of the power sector. Using the extreme values of the ranges presented in table 9.1, endogenous emission trajectories are analysed, for different configurations of the system, regarding the capability of the grid to incorporate renewable energies. It is concluded, that the impact of extreme learning rates on the decarbonisation scenarios of the power sector, is less significant than the effect of policy uncertainty and natural resources availability uncertainty (analysed in chapters 5 and 7, respectively). Moreover, when other constraints of the system are taken into account, then the combined effects further reduce the impact of over or underestimation of learning rates in the emission trajectories.

9.8.1 Learning scenarios

Four sets of extreme learning rate scenarios for the power sector are presented below. In all the cases, the power sector is assumed to follow a **decarbonisation** pathway. The main **DEC** assumptions are the following:[6]

[5]Chapter 10 proposes a new methodology to expand the FTT:Power investment model, to analyse the effect of other drivers than cost on the technological evolution of the power sector. Chapter 11 uses the new methodology, to analyse the effect of environmental considerations and policy uncertainty criteria in the uptake of low carbon technology.

[6]For a detailed description of the DEC assumptions, please refer to sections 5.2 and 5.5.

- In all the scenarios, the maximum electricity demand reductions are assumed, in line with the definition of the DEC scenario (for more details about the demand assumptions, see section 5.2.4 and figure 5.4).
- In all the scenarios, the maximum rate for subsidies, feed-in-tariffs and carbon price are in place, as described in sections 5.2.1 and 5.2.2.
- In all the scenarios, direct regulation is in place, that limits the installation of new coal, IGCC and CCGT power plants (see section 5.2.3 for more details).
- The default cost supply curves are used for every technology (see section 6.6 for more details about the default cost supply curves).

In this context, the extreme learning rate scenarios analysed in this chapter are divided in two groups:

Fossil Fuel (**FF**) scenarios, in which extreme learning rates for oil, coal, IGCC and CCGT are used. The rest of the technologies are assumed to have the default learning rate in this scenario.

BioWindSolar (**BWS**) scenarios, in which extreme learning rates for renewable technologies based on biomass (solid biomass, BIGCC and biogas, without CCS), on wind (onshore and offshore) and on solar (solar PV and CSP) are used. Same as the previous case, the rest of the technologies are assumed to have the default learning rate in this scenario.

The learning rate values are taken from the last two columns of table 9.1 (values are summarised in table 9.2). For each of these learning scenarios, two different configurations of the power sector are analysed:

Low Grid Flexibility : The power sector is assumed to have limited capabilities for managing a significant increase of variable electricity during a short period.[7] In practice, this configuration limits the speed at which decarbonisation can happen, based on the peak demand patterns of electricity consumption, on the amount of energy storage available on the system, and the current energy mix.

High Grid Flexibility : The power sector is assumed to have the capability of managing large quantities of renewable energy entering into the grid at each time step. In this

[7] Using the stability constraints (see section 4.6.2), FTT:Power limits the amount of baseload, flexible and variable electricity, to maintain the balance in the system, based on exogenous storage capability and peak-to-average ratios of installed capacity and electricity generation. For details about the stability constraints on the low and high flexibility grid scenarios, please refer to appendix section A.3.

configuration, the grid is assumed to have demand management systems[8] and enough energy storage capacity to compensate for a significant increase or decrease of variable electricity generation.

In the Low Grid Flexibility scenario, it is assumed a storage capacity in the order of 18% of the global installed capacity for electricity generation. In the High Grid Flexibility scenario, the storage capacity increases to 90% (see table A.3 in the Appendix section). Both values are above the current storage capacity, which is in the order of 3% of global installed capacity, around 127GW in 2010 (Beaudin et al., 2010; Dunn et al., 2011). It is important to highlight that FTT:Power requires high level of storage to back up variable electricity, as explained in section 4.6.2. In reality, however, energy storage can be complemented by a variety of mechanism, including supply and reserve sharing, flexible generation, demand flexibility (elasticity to price), variable generation curtailment and controllable loads, all of which increase grid flexibility (Denholm and Hand, 2011). Indeed, according to Denholm et al. (2010), there are substantial diminishing returns for greater amount of storage. The aforementioned mechanisms are not part of the model, and consequently energy storage levels might seem unrealistic. Another limitation associated to the modelling of flexibility in FTT:power is related to the cost of the electricity in an extremely flexible grid. While in reality the cost of increasing flexibility using storage systems or smart grid solutions are still expensive (Denholm and Hand, 2011), in the model those cost are not internalised in the cost of producing electricity, and consequently do not have an effect on investment. For a detail discussion of the role of storage in the stability constraints of FTT:Power, please refer to section 4.6.2.

Figure 9.1 presents the global emissions from the four decarbonisation scenarios using extreme learning rates and low and high flexibility of the power grid. The minimum learning rate scenarios are shown in red, while the maximum learning rate scenarios are shown in blue. The solid and dashed lines correspond to the low and high flexibility configuration of the grid, respectively. The black lines correspond to the Business as Usual (BAU) scenario, plotted for comparison purposes. To facilitate the description of the scenarios, they are classified as:

L-L Low learning rates and low grid flexibility (solid red lines).

L-H Low learning rates and high grid flexibility (dashed red lines).

H-L High learning rates and low grid flexibility (solid blue lines).

H-H High learning rates and high grid flexibility (dashed blue lines).

[8]The existence of demand management systems is modelled in FTT:Power through the peak-to-average demand ratios. See appendix section A.3 for more details.

Following this classification, the scenarios are described using abbreviated names. For instance, the abbreviation *FF L-L* means *fossil fuel, low learning, low grid flexibility* scenario, and *BWS H-H* means *bio-wind-solar, high learning, high grid flexibility* scenario. At the top of figure 9.1, the nomenclature for the names of the scenarios is presented. Each scenario has associated a colour (red or blue) and a type of line (solid or dashed). This nomenclature is followed in all the charts of this chapter.

The scenarios presented in figure 9.1, exhibit several patterns that are worth to highlight:

- All the scenarios presented in figure 9.1 are simulated in a decarbonisation context, under stringent emission reduction policies. Accordingly, emissions decrease significantly, in all cases, with respect to BAU.

- Grid flexibility has a larger impact on emissions, than the variation of the learning rates (the differences between the solid and dotted lines are larger than the differences between the red and blue lines in figure 9.1).

Scenario	Technology	L.Rate Min [%]	Range FTT [%]	L.Rate Max [%]
FF	Oil	0.5	1.0	1.5
FF	Coal	3.0	3.0	14.0
FF	IGCC	2.5	3.0	16.0
FF	CCGT	4.0	4.0	34.0
BWS	Biomass	0.0	7.0	38.0
BWS	BIGCC	5.0	5.0	10.0
BWS	Biogas	0.0	5.0	15.0
BWS	Wind On.	4.0	7.0	32.0
BWS	Wind Off.	5.0	9.0	19.0
BWS	Solar PV	10.0	17.0	35.0
BWS	CSP	8.0	10.0	16.0

Table 9.2 Summary of the learning rates used in the Fossil Fuel (FF) and Bio-Wind-Solar (BWS) scenarios. The third and fifth columns correspond to the minimum and maximum values, respectively, while the default FTT:Power learning rates are presented in the fourth column, as reference. In the FF scenario, the technologies involved are oil, coal, IGCC and CCGT. In the BWS scenario, the technologies involved are biomass, BIGCC, biogas, wind onshore, wind offshore, solar PV and CSP. For the technologies not involved in the scenarios, the default FTT:Power learning rates are used (fifth column of table 9.1).

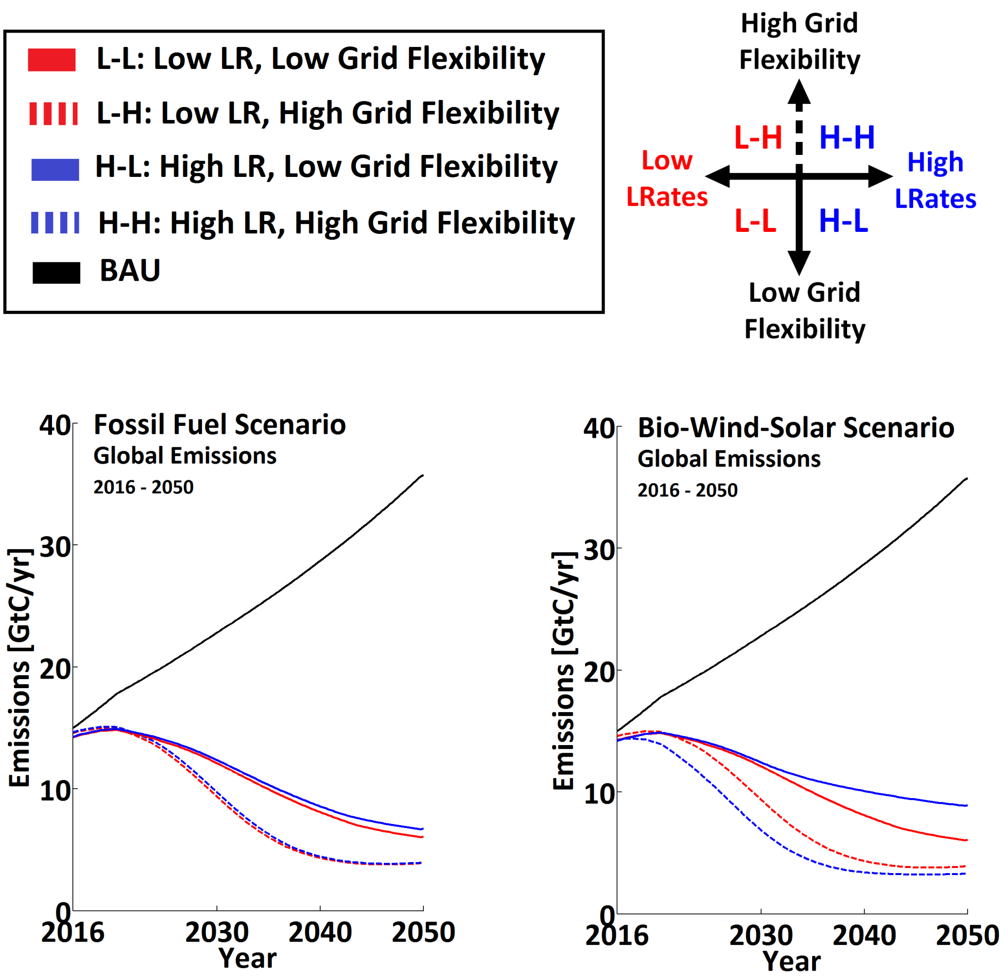


Figure 9.1 Global emissions trajectories for decarbonisation scenarios under extreme assumptions on learning rates: Fossil Fuel (left) and Bio-Wind-Solar (right) scenarios. The blue and red lines correspond to the scenarios with the highest and lower learning rate coefficients, respectively. The scenarios were simulated under two configurations of the power sector: high and low grid flexibility, corresponding to cases with high and low flexibility for adopting renewable technologies (dotted and solid lines, respectively). The black lines are added for reference purposes only, and correspond to the BAU scenario. The scenarios are named, following the nomenclature described above the charts.

- The overall impact of learning rate uncertainty on the emission trajectories is small, if compared with the effect of policy uncertainty and natural resources availability uncertainty, that combined, create most of the differences between the BAU (black lines) and the DEC (blue and red lines) scenarios. See sections 5.6 and 7.4 for more details on the impacts of policy uncertainty and natural resources availability uncertainty on emissions, respectively.

- Scenarios simulated under a high grid flexibility configuration present larger emission reductions than their low grid flexibility counterparts (dotted line trajectories are below the solid lines trajectories in figure 9.1).
- Fossil fuel scenarios, in low and high grid flexibility, follow the same intuitive pattern: higher the learning rates, higher the emissions (in the left-hand chart of figure 9.1, blue curves are above red curves).
- Bio-wind-solar scenarios follow different patterns in high and low grid flexibility configurations.
  - In the high grid flexibility case, emissions follow and intuitive trajectory: higher the learning rates of renewables, lower the emissions (in the right-hand chart of figure 9.1, the blue dotted line is below red dotted line).
  - In the low grid flexibility case, emissions follow a counterintuitive trajectory: emissions increase with higher learning rates of renewables (in the right-hand chart of figure 9.1, the blue solid line is above red solid line).

9.8.2 The importance of a flexible grid

The current level of penetration of variable electricity in global markets is not significant. At the end of 2014, the total amount of electricity generated by wind, biomass, solar, geothermal, and ocean energy combined, added up to 6.2% of the global electricity production (REN21, 2015). Therefore, most of the world regions do not face yet the challenges associated with a large penetration of renewable energies into the electricity mix. Nevertheless, the impact of variable generation into the national network is becoming a subject of increasing relevance, particularly among developed countries. There is an increasing number of studies looking for the optimal integration of intermittent generation systems, particularly in USA and Europe (Hart et al., 2012). The future decarbonisation of the power sector depends on the capacity of national grids to incorporate large quantities of renewable energy. Over the last decade, technologies related to grid stability are showing enormous progress, particularly in the areas of smart grid (Carvallo and Cooper, 2015) and energy storage (Luo et al., 2015). Given the rapidly accelerating rate of technological development and cost reductions in energy storage technologies, several governments are investing in increasing the flexibility of their national networks, to secure the adoption of variable renewable energy (Chen et al., 2009). While nowadays energy storage technologies might seem expensive in terms of cost per unit of energy, the integration of large-scale renewables would be a more difficult challenge without them (Beaudin et al., 2010). Based on this progress, it is reasonable to expect that the current limitations to the adoption of renewable energy will be overcome in the near future.

To analyse in more details the effect of extreme learning rates and grid flexibility in the decarbonisation of the power sector, figure 9.2 shows the cumulative electricity generation between 2016 and 2050 for all the scenarios presented in figure 9.1 (except BAU). Each scenario is labeled according to the nomenclature presented in section 9.8.1. The four bars at the left-hand side correspond to the Fossil-Fuel scenarios, and the four bars at the right-hand side correspond to the Bio-Wind-Solar scenarios. In the case of the high flexibility grid scenarios (those with dashed lines below their names), there is a significant adoption of renewable energies, and a reduction in the use of coal. The case of the *BWS H-H* scenario is particularly interesting: given the relaxation on the constraints associated with the amount of flexible electricity that can enter into the grid, wind energy is able to take a large part of the market. The feed-in-tariffs embedded in DEC provide a strong inventive for investors to adopt wind energy in this scenario, and wind ends-up being the dominant technology, given its fast decrease in cost due to the large learning rate.

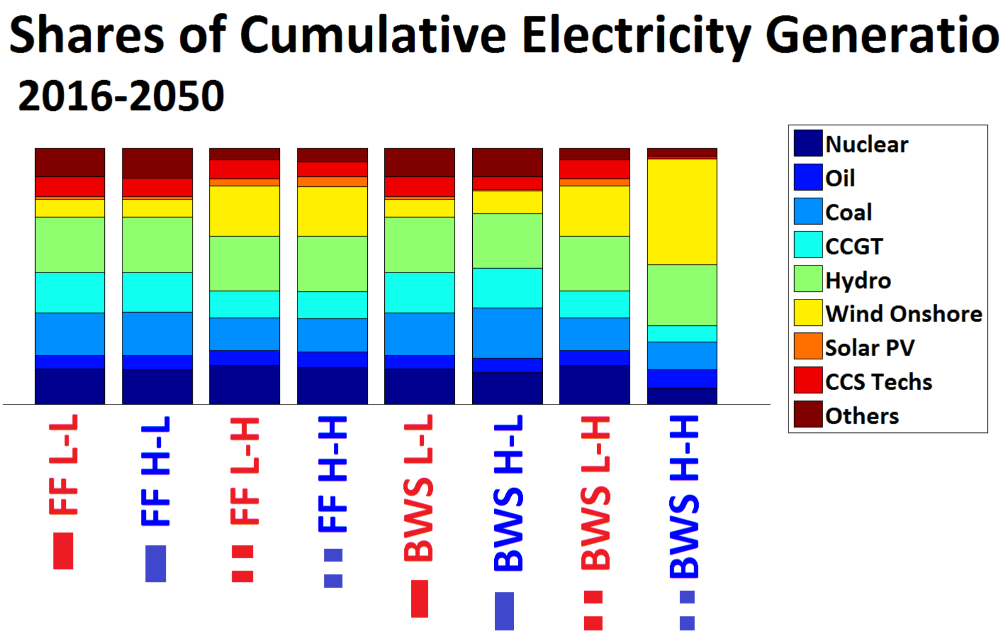


Figure 9.2 Cumulative electricity generation for FF and BWS scenarios under extreme learning rates, for low and high flexibility of the grid. The name of the scenarios follows the convention presented in section 9.8.1. The colored solid and dashed bars are presented at the side of the name, to facilitate the association with figure 9.1.

From the results presented in figures 9.1 and 9.2, it is clear that the flexibility of the grid plays an important role in the decarbonisation scenarios of the power sector. The capacity of the system to deploy variable electricity from renewable energies, determines the speed and extent to which the power sector can be decarbonised. Under a more flexible electricity grid, the differences in learning rates have a larger effect in decarbonisation in both scenarios, FF and BWS, as shown in figure 9.1. This is congruent with the role of flexibility in the potential adoption of renewable technologies in the real power sector. In FTT:Power, as in reality, the adoption of large capacity of variable generation is limited by the flexibility of the grid (Boyle, 2012). This results, however, have to be interpreted with caution, because FTT:power does not internalise the cost of

In FTT:Power, the flexibility of the grid is defined by the capacity of the system to balance baseload, flexible and variable electricity generation technologies (see section 4.6.2 “Stability constraints and storage in FTT:Power”). Technical aspects associated with the composition of the power sector, such as the availability of energy storage systems and peak-demand consumption patterns, define natural limits for the capacity of the system to handle the different types of electricity. Where such limits exceeded, the electrical grid would become unstable, and thus present a risk to investors of either blackouts or seeing their capacity unused. Investors, however, do not necessarily know accurately how much capacity is currently working, and thus may feel inclined to slow down investment even before the limit is reached (Mercure, 2011, p. 21). The uncertainty embedded in the information that investors hold, can be interpreted as a probability distribution, that varies with the flexibility of the grid. In FTT:Power a probability distribution is imposed to the value of the shares of various technologies as seen by investors (ibid.). So, when investment decisions are taken, they are weighted by a *probability of investment* factor that incorporates information about the flexibility of the grid (ibid.). In the case of low-flexibility grid configurations, this investment factor limits the deployment of renewable energies, due to the underlying investors’ concern on the stability constraints of the grid.

An example of how the probability of investment factor works, is presented in figure 9.3 for wind, in the regions of USA (left), China (middle) and India (right) for the BWS scenarios.[9] The three charts of figure 9.3 show the cumulative effect of the investment factor for wind, in the case of high and low grid flexibility (dashed and solid lines), and for high and low learning rates (blue and red lines) for the BWS scenarios. The black dashed line is shown as a reference: it corresponds to the case when the probability of investment factor is zero, due to the extreme concerns of investors regarding the stability of the grid. It can also be

[9]These regions were chosen because they have the largest comparative difference in emissions between the high and low learning rate scenarios, under low grid flexibility. The charts presented in figure 9.3 are focused on the *Bio-Wind-Solar* scenario, to facilitate the discussion and not to saturate the analysis. The extrapolation to the *Fossil Fuel* scenario is straightforward.

interpreted, as the lowest flexibility case scenario. Without delving into the mathematical calculations, that can be found in the appendix section A.5, the differences between the black dotted line and each scenario-line, is a measure of the flexibility of the grid to adopt wind electricity. Equivalently, the area below each-scenario line can be interpreted as the effect of having a low-flexibility grid in the adoption of wind electricity.

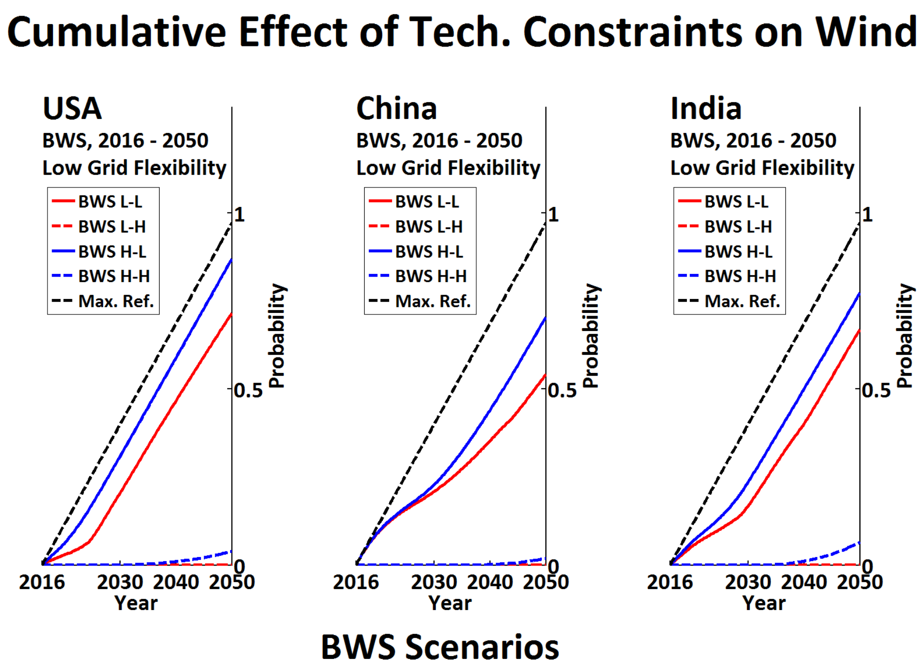


Figure 9.3 Cumulative effect of the technical constraints on wind in USA (left), China (middle) and India (right), for the four learning scenarios: *BWS H-L* (solid blue lines), *BWS L-L* (solid red lines), *BWS H-H* (dashed blue lines), *BWS L-H* (dashed red lines), between 2016 and 2050. The cumulative effect of the technical constraints is calculated as the cumulative difference between the perfect no-limitation case and the limitation factor used on each scenario. Details of the calculations behind these plots can be found in the appendix section A.5.

The differences between the high and low grid flexibility in figure 9.3 are significant, and require a detailed analysis.

- In the low grid flexibility configuration, the effect of investors' concern about the grid flexibility on investment in wind energy is significant, for high and low learning rate scenarios (see solid lines in figure 9.3). Consequently, low grid flexibility scenarios present a lower adoption of wind energy than the high grid flexibility counterparts (see figure 9.2).

- In the low grid flexibility case, the effect of learning and investors' concern lead to opposite effects on decarbonisation.
  - On the one hand, the effect of learning in the price of the BWS technologies drives their price down, fostering the adoption of wind (see figure 9.2, scenario *BWS H-L* versus scenario *BWS L-L*).
  - On the other hand, the extreme concerns of investors regarding the grid flexibility in scenario *BWS H-L* (see figure 9.3), hinders a potentially higher adoption of variable electricity, and limits the phase-out of polluting technologies. As a consequence, emissions decrease less significantly than in the other scenarios. This phenomenon can be appreciated in the right-hand chart of figure 9.1, where the *BWS H-L* scenario (blue solid curve) has the highest emission trajectory.
- In the high grid flexibility configuration, the concern from investors about grid flexibility does not play a relevant role. This is shown in figure 9.3, with dashed lines close to the abscissa. Consequently, a higher adoption of renewables is accomplished in these scenarios (see figure 9.2), and therefore larger emission reductions are achieved, in comparison with the low grid flexibility counterparts (in the right-hand chart of figure 9.1, dashed lines are below solid lines).
- Consistently with the analysis presented in section 9.8.1, figure 9.2 shows that grid flexibility has a larger impact on the adoption of renewable energies, than differences on the learning rates.
- As the scenario *BWS H-H* of figure 9.2 shows, the availability of a flexible power grid, capable of adopting large quantities of renewable energy, in combination with high learning rates for renewable technologies, can have a significant influence in the decarbonisation of the power sector.

9.8.3 Stability constraints versus regulation

As the results from figures 9.1, 9.2 and 9.3 suggest, the flexibility of the grid plays an important role in the adoption of variable electricity generation technologies. In the case of a low grid flexibility configuration, FTT:Power constrains the technology diffusion process, in order to maintain grid stability. In scenarios of extreme decarbonisation (such as those analysed in this chapter), a rapid increase in variable electricity generation in the system activates the stability constraints (see section 4.6.2 for more details). This control mechanism balances the configuration of baseload, flexible and variable electricity in the system. As a consequence of this security measure, if there are policies in place that regulate the amount of installed capacity (such as the regulation that impedes the construction of new coal power stations), these policies can be superseded by the stability constraints. Therefore, the expected replacement of coal power stations can be stopped, as a way of controlling the balance of the system.

In the context of the DEC scenario, countries face stringent regulation for the use of coal: no new coal power stations are allowed to be built after 2016, 2018 and 2020 in USA, China, and India, respectively (see section 5.2.3 for more details). However, as explained above, the process of phasing-out coal can be affected, if the balance of the grid is at stake. Figure 9.4 shows the coal electricity generation in USA, China and India, for the BWS scenarios. While figure 9.3 shows the cumulative effect of the technical constraints on wind, figure 9.4 shows the effect of the technical constraints on coal generation in the same regions.

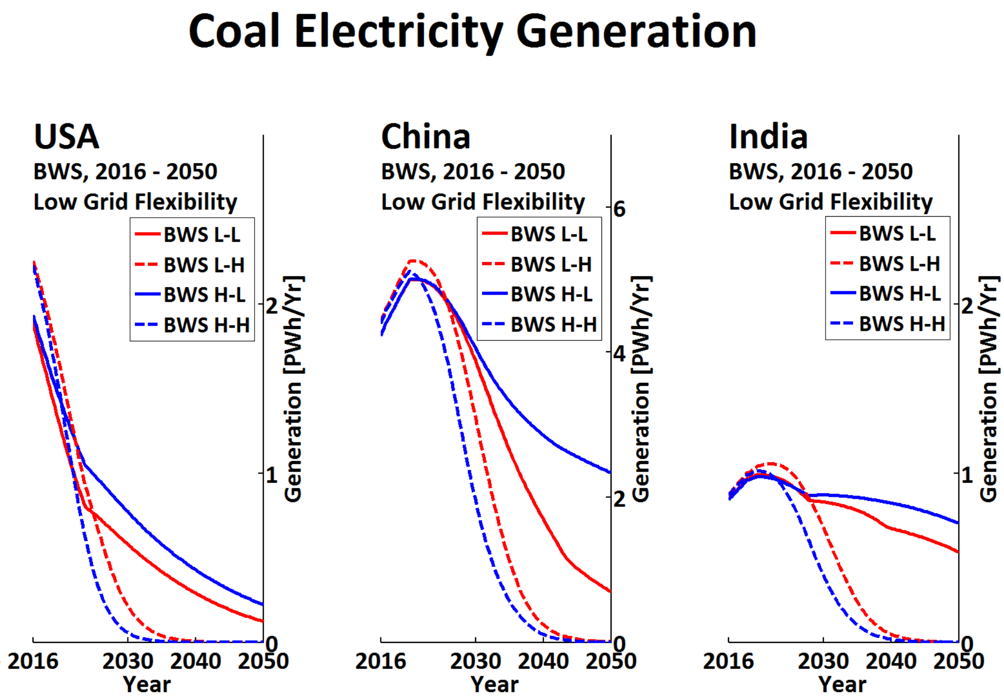


Figure 9.4 Coal electricity generation in USA (left), China (middle) and India (right), for the four learning scenarios: *BWS H-L* (solid blue lines), *BWS L-L* (solid red lines), *BWS H-H* (dashed blue lines), *BWS L-H* (dashed red lines), between 2016 and 2050. Notice that the upper limit for the ordinates axis in the case of China, is larger than the other two cases.

As figure 9.4 shows, in the high grid flexibility configuration, the process of phasing out coal works as expected: coal generation for these scenarios (dotted lines) decrease significantly after the regulation date defined in the DEC scenario. However, the process does not work in the same way in the low grid flexibility configuration (solid lines in figure 9.4). As explained above, security concerns limit the phasing out process for coal, with the intention of maintaining the balance in the system.

The results presented in figure 9.4 are consistent with the cumulative electricity patterns of figure 9.2: the low grid flexibility scenarios have comparatively higher levels of electricity generated by coal than the high grid flexibility counterparts. Similarly, the emission trajectories presented in figure 9.1 are also consistent: low grid flexibility scenarios have higher emissions than high grid flexibility scenarios.

9.9 Conclusion

In this chapter, the subjects of technological change and learning were discussed in general, while the implementation of learning curves in FTT:Power was analysed in particular. Together with an overview of the main challenges associated with modelling technological change, decarbonisation scenarios with extreme learning rate coefficients were presented, using different grid flexibility configurations. Under the assumptions of a decarbonisation pathway (DEC), two learning scenarios were analysed in section 9.8: the **fossil fuel** (**FF**) scenario, with extreme learning rates for oil, coal, IGCC and CCGT; and the **bio-wind-solar** (**BWS**) scenario, with extreme learning rates for technologies based on biomass (solid biomass, BIGCC and biogas, without CCS), on wind (onshore and offshore) and on solar (solar PV and CSP). Each learning scenario was implemented under a high and and low grid flexibility configuration. The main conclusions to be highlighted from that modelling exercise are:

- The overall impact of learning rate uncertainty in the cumulative emissions scenarios created with FTT:Power is comparatively small, as shown in figure 9.1. The impact of policy uncertainty on decarbonisation, presented in chapter 5, and the impact of natural resources availability uncertainty on decarbonisation, presented in chapter 7, are much higher than the impact of learning rate uncertainty.
- Despite the large differences in learning rates, or the different configurations of the grid flexibility, all the decarbonisation scenarios presented in this chapter exhibit significant emission reductions with respect to BAU. Moreover, the scenarios created with FTT:Power, which is a dynamic model, are not significantly affected by the upward bias phenomenon described by Nordhaus (2014). On the contrary, the adoption

of technologies with high learning rates (such as wind in the *BWS H-L* scenario) can be negatively affected by the low flexibility of the grid.

- The flexibility of the grid plays an important role in the adoption of variable electricity generation. Moreover, the impact of the grid flexibility on emission reductions is larger than the impact of uncertainty in the learning rates. In stringent decarbonisation scenarios, investors' concern about the stability of the system can hinder the adoption of variable electricity generation technologies, such as wind energy.

It is important to highlight that in the high flexibility scenarios analysed in this chapter, the model assumes that storage capacity increases to 90%, a value that might be considered unrealistic. In reality, energy storage can be complemented by a variety of mechanism that increase grid flexibility, such as supply and reserve sharing, flexible generation, demand flexibility, curtailment and controllable loads. Therefore, the high values of storage used in FTT:Power are a stylised representation of a wider adoption of technologies that increase grid flexibility. However, the stylised representation of grid flexibility in the model does not internalise the costs of adopting technologies such as smart-grid or load-shifting mechanisms. A more flexible grid might increase the price of electricity, and consequently have an impact on electricity demand. While the impact of grid flexibility in the price of electricity cannot be determined from these simulations, the main point of the analysis still holds: the flexibility of the grid plays a significant role in the decarbonisation of the power sector (Denholm and Hand, 2011).

From a policy perspective, it is relevant that the future decarbonisation of the power sector depends on the capacity of the national grids to adapt to the incorporation of large quantities of renewable energy. The differences in the impact of decarbonisation policies between high and low grid flexibility scenarios are significant, in terms of emission reductions and renewable energy adoption. Consequently, policies oriented to facilitate the rapid decarbonisation of the power sector have to address the capacity of the system to absorb significant quantities of renewable energy without jeopardising the stability of the system.

Chapter 10

A New Methodology to Model Investment Decisions in FTT:Power

10.1 Chapter Summary

This chapter introduces a new methodology to model investment decisions in FTT:Power. The new methodology replicates the investment dynamics of the incumbent model, and allows the incorporation of more criteria as part of the investment decision process. The methodology is based on a multicriteria decision-making approach called Analytic Hierarchy Process (AHP). The AHP method allows the combination of an adjustable number of criteria to evaluate alternatives, making the FTT:Power investment model more flexible. As a first step, the incumbent investment model of FTT:Power is replicated, using a combination of AHP with Discrete Choice Theory. This novel approach is able to reproduce the current investment dynamics of FTT:Power, which are based on the Levelised Cost of Electricity (LCOE) as the only investment allocation criterion. Then, a new procedure for expanding the model is presented, in order to incorporate other criteria beyond the LCOE. Chapter 11 uses the methodology presented here, to create a new investment decision model that includes *environmental considerations* and *policy uncertainty* as investment criteria. Using the expanded model, new scenarios of the power sector are analysed.

This chapter is organised as follows. First, section 10.2 presents the bases of the current investment preferences in FTT:Power. Second, section 10.3 presents an explicit representation of the current investment decision model in terms of Discrete Choice Theory. Third, section 10.4 introduces the Analytic Hierarchy Process, a methodology that allows the combination of multiple criteria in the decision making process. Using the concepts introduced in the first three sections, section 10.5 proposes a new methodology to model investment decision in FTT:Power, using a novel combination of Discrete Choice Theory and Analytic Hierarchy Process. Finally, section 10.6 presents a methodology for expanding the investment model, based on a step-by-step procedure to add new investment criteria.

10.2 Investors' Preferences in FTT:Power

Technologies in FTT:Power are compared in a pairwise basis, and the switching process between the two technologies being compared is measured by flows of market shares of electricity generation capacity. This process is driven by the "shares equation" (equation 10.1, explained in detail in section 4.6).[1] The rate at which shares of one type of technology (j) can be replaced by shares of another type (i) is proportional to:

- The rate at which units of technology j come to the end of their lifetime and how many old units require replacement.
- The rate at which the construction capacity for technology i can be expanded.
- The market position of technologies i and j (in terms of installed capacity).
- **Investors' preferences**.
- Technical constraints.[2]

In this chapter, the attention is focused on the **investors' preferences** item, which corresponds to the terms F_{ij} and F_{ji} of equation 10.1. The investor's preference function F_{ij}, compares the LCOE of technologies (i) and (j) and defines the share of investment expected to go to each of them.[3]

$$\Delta S_i = \sum_j S_i S_j \left(A_{ij} G_{ij} F_{ij} \left(\Delta C_{ij} \right) - A_{ji} G_{ji} F_{ji} \left(\Delta C_{ji} \right) \right) \frac{\Delta t}{\bar{\tau}} = \sum_j S_i S_j \alpha_{ij} \tag{10.1}$$

[1] For a detailed explanation of the shares equation, please refer to (Mercure, 2012).

[2] Technical constraints refers to the stability constraints of the grid, regarding the balance between baseload, flexible and variable electricity generation. These are analysed in detail in section 4.6.2.

[3] The role of **A** and **G** in equation 10.1 is analysed in section 4.6. The investment allocation depends on investor's preferences, as well as in the constraints related to the construction and lifetime of the power plants, current market shares, and technical restrictions, such as those studied in chapter 9.

The current implementation of the investor's preferences function in FTT:Power has some limitations, including:

1. Investors do not incorporate uncertainty in their analysis. Perfect foresight is assumed.
2. Investors use naive projections of policy and energy resources availability.
3. Investment decisions are taken solely on the basis of the levelised cost of electricity.

All these issues are addressed by the new investment decision model, using a new methodology to model decision making. The new methodology combines two different theoretical backgrounds: Discrete Choice Theory (DCT) and Analytic Hierarchy Process (AHP). The term F_{ij} in equation 10.1, is replaced by a more complex and flexible multicriteria investment preference function. The mathematical foundations of the new methodology are introduced in this chapter, and complemented with detailed demonstrations in appendix chapter D. The introduction to the new methodology for modelling investment decisions is structured as follows:

- In section 10.3 the pairwise comparison approach used in FTT:Power, represented by F_{ij} in the shares equation, is replicated by a Binary Logit model (BNL). The BNL model, based on Discrete Choice Theory (Ben-Akiva and Lerman, 1985), uses the LCOE as the sole decision criteria to allocate investment.[4]
- The BNL model introduced in section 10.3, is expanded in section 10.3.1, to incorporate the simultaneous comparison of all FTT:Power technologies at the same time. The expansion is done through a Multinomial Logit model (MNL), and a vector of preferences is obtained. The vector of preferences will enable the combination of Discrete Choice Theory with the Analytic Hierarchy Process, a methodology introduced in the next section.
- Section 10.4 introduces the Analytic Hierarchy Process or AHP, a multiobjective multicriteria decision-making approach (Saaty, 1999). This methodology allows the combination of objective and subjective criteria in the decision making process. It is the basis for implementing a multicriteria investor's preference function.
- Section 10.5 combines the vector of preferences obtained in section 10.3.1, with the AHP methodology introduced in section 10.4. From this combination, the incumbent FTT:Power investment model is replicated, using the LCOE as the sole decision criteria to allocate investment.

[4]The theoretical formulation presented in section 10.3 is based on Mercure (2015).

- Section 10.6 shows how to expand the investor's preference function introduced in section 10.5, to include other criteria beyond the LCOE.
- Finally, chapter 11 presents some practical examples of how to expand the model to analyse other investment criteria, beyond market considerations, such as *environmental considerations* and *policy uncertainty*.

It is important to notice that the combination of Discrete Choice Theory with Analytic Hierarchy Process is a novel approach. No literature was found addressing the required mathematical foundations for such combination. Given the potential relevance of the topic, the appendix chapter D provides a formal mathematical formulation for the theoretical model proposed in this chapter.

10.3 A Discrete Choice Model Based on the LCOE

In the case of FTT:Power, investment decisions are assumed to be aggregated at a regional level. Therefore, the decision-maker is an abstract entity, not representing any individual or institution in particular. The unaggregated individual decisions may come from private investors, central planners, a mixed of these two, or even all of the previous alternativces together, depending on how large the region under analysis is. Given this theoretical structure, it is necessary to define some basic characteristics of the abstract "investment decision", which is represented in the model by investment allocation at the regional level. Investment decisions in FTT:Power can be represented by a preference relation $\succeq$, defined over the set of technologies available. If H is the set of power generation alternatives, it is possible to demonstrate that the preference relation $\succeq$ satisfies the following axioms:

Completeness: $a \succeq b$ or $b \succeq a$, $\forall a, b \in H$

Reflexivity: $a \succeq a$, $\forall a \in H$

Transitivity: if $a \succeq b$ and $b \succeq c$, then $a \succeq c$, $\forall a, b, c \in H$

Based on the preference relation $\succeq$, it is always possible to construct a utility function that represents investor's preferences (Anderson et al., 1992). I.e., a function $U(\cdot)$ that satisfies the property:

$$U_i \geq U_j \quad \Leftrightarrow \quad i \succeq j \tag{10.2}$$

That utility function could be, for instance, $U_i = -LCOE_i$, with i being a particular technology.[5] Because investment decisions are based on the preference relation $\succeq$, the technology with the lowest LCOE value is preferred.

The investment allocation in the FTT:Power is neither directly decided by a firm nor by a policy maker. Instead, investment allocation (in the form of installed capacity's share changes) occurs at the regional level, as an aggregation of all the single investment decisions taken within that geographical area. It is reasonable to assume, then, that single investment decisions face slightly different costs, given the large amount of factors that each project has to evaluate, many of which are of very local nature. Therefore, at the aggregate level, the $LCOE_i$ values can be interpreted as a large aggregation of costs around a mean, as shown by the data from IEA et al. (2010, 2015). Under these conditions, the utility function representing investor's preferences, $U_i = -LCOE_i$, can be written as the sum of a constant and a stochastic term:

$$U_i = V_i + \varepsilon_i, \quad i = 1...24 \tag{10.3}$$

Following the pairwise comparison approach taken by FTT:Power, the probability of technology i being preferred over technology j ($i, j \in H, i \neq j$) can be calculated as:

$$\begin{aligned} P_{ij} &= P\left(U_i \geq U_j\right) \\ &= P\left(V_i + \varepsilon_i \geq V_j + \varepsilon_j\right) \\ &= P\left(\varepsilon_j \leq V_i - V_j + \varepsilon_i\right) \end{aligned} \tag{10.4}$$

Calling f and F the density and cumulative distribution functions of the error terms, respectively, the probability P_{ij} can be rewritten as:

[5] To simplify the notation, regional indexes are suppressed. Investment decisions in FTT:Power are aggregated regionally, therefore, it is reasonable to assume that all the variables belong to the same region. The expansion from one region to a multi-regional approach is straightforward, with investment decisions being taken in parallel on each region.

$$\begin{aligned}
P_{ij} &= \int_{-\infty}^{\infty} P\left(\varepsilon_j \leq V_i - V_j + \varepsilon_i \mid \varepsilon_i\right) \cdot f\left(\varepsilon_i\right) d\varepsilon_i \\
&= \int_{-\infty}^{\infty} F_{\varepsilon_j}\left(V_i - V_j + \varepsilon_i\right) \cdot f_{\varepsilon_i}\left(\varepsilon_i\right) d\varepsilon_i \qquad (10.5)
\end{aligned}$$

P_{ij} from expression 10.5 represents the probability of a decision maker choosing alternative i over j within the set H. Following the standard discrete choice theory approach (Anderson et al., 1992; Ben-Akiva and Lerman, 1985), I assume that the error terms follow a Gumbel distribution.[6] The probability and cumulative distribution functions (f and F, respectively) can then be written as follows:

$$f(x) = \frac{1}{\sigma} e^{-\left(\frac{x-\mu}{\sigma} + e^{-\left(\frac{x-\mu}{\sigma}\right)}\right)} \qquad (10.6)$$

$$F(x) = e^{-e^{-\left(\frac{x-\mu}{\sigma}\right)}} \qquad (10.7)$$

Using expressions 10.6 and 10.7, the probability of choosing alternative i over j from 10.5 can be calculated as:[7]

[6]The very large amount of factors that can influence variations around the average cost of the LCOE, suggest the choice of a normal distribution for the error term, based on the central limit theorem. However, given the similarities between the Gumbel and the Normal distributions, it is often the case that the data does not allow to determine the difference between these two (Garrow, 2010). The choice of the former over the latter represents a small trade off in terms of accuracy, with a large gain in terms of tractability, as will be demonstrated later. The Gumbel distribution belongs to the family of the Extreme Value distributions, and it is extensively used as part of the models described in the standard discrete choice theory textbooks, including binary, multinomial and nested models.

[7]The mathematical derivation of P_{ij} presented here follows the approach of the classical discrete choice theory literature, including Anderson et al. (1992); Ben-Akiva and Lerman (1985); Garrow (2010); McFadden (1973); Train (2009).

$$\begin{aligned}
P_{ij} &= \int_{-\infty}^{\infty} F_{\varepsilon_j}\left(V_i - V_j + \varepsilon_i\right) \cdot f_{\varepsilon_i}\left(\varepsilon_i\right) d\varepsilon_i \\
&= \int_{-\infty}^{\infty} e^{-e^{-\left(\frac{V_i - V_j + \varepsilon_i - \mu_j}{\sigma_j}\right)}} \cdot \frac{1}{\sigma_i} e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i} + e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)}\right)} d\varepsilon_i \\
&= \frac{1}{\sigma_i} \int_{-\infty}^{\infty} e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)} \cdot e^{-\left(e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)}\right)} \cdot e^{-\left(e^{-\left(\frac{\varepsilon_i - \mu_j}{\sigma_j}\right)} \cdot e^{-\left(\frac{V_i - V_j}{\sigma_j}\right)}\right)} d\varepsilon_i
\end{aligned} \tag{10.8}$$

The exponential term $e^{-\frac{\varepsilon_i - \mu_j}{\sigma_j}}$ of expression 10.8, can be rewritten, multiplying it by one and adding zero:

$$e^{-\frac{\varepsilon_i - \mu_j}{\sigma_j}} = e^{\left[\frac{-\varepsilon_i}{\sigma_j} + \frac{\mu_j}{\sigma_j}\right] \cdot \frac{\sigma_i}{\sigma_i}} = e^{\left[\frac{-\varepsilon_i}{\sigma_i} \cdot \frac{\sigma_i}{\sigma_j} + \frac{\mu_j}{\sigma_j}\right] + \left[\frac{\mu_i}{\sigma_i} \cdot \frac{\sigma_i}{\sigma_j} - \frac{\mu_i}{\sigma_i} \cdot \frac{\sigma_i}{\sigma_j}\right]} = e^{\left[\frac{-\varepsilon_i + \mu_i}{\sigma_i}\right] \cdot \frac{\sigma_i}{\sigma_j}} \cdot e^{\frac{\mu_j - \mu_i}{\sigma_j}} \tag{10.9}$$

And the following change of variable can be made:

$$x = e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)} \quad \Rightarrow \quad dx = \frac{-1}{\sigma_i} e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)} d\varepsilon_i \quad \Rightarrow \quad d\varepsilon_i = \frac{-\sigma_i}{x} dx \tag{10.10}$$

Replacing 10.10 in expression 10.9:

$$e^{-\frac{\varepsilon_i - \mu_j}{\sigma_j}} = e^{-\frac{\mu_i - \mu_j}{\sigma_j}} \cdot x^{\frac{\sigma_i}{\sigma_j}} \tag{10.11}$$

Expression 10.11 can then be inserted in equation 10.8. Assuming that $\sigma_i \sim \sigma_j \sim \sigma$,[8] the following expression for P_{ij} is obtained:

[8]For the case of the most influential generation technologies, those competing in the market at relatively similar prices, $\sigma_i \sim \sigma_j$ is a reasonable assumption. For the newest and less deployed technologies, larger variations can be found, but their relative impact in the scenarios analysed in this work is limited, mostly due to their very small market share. The appendix section D.3 analyses the impact of $\sigma_i \neq \sigma_j$ in P_{ij}.

$$
\begin{aligned}
P_{ij} &= \int_0^{\infty} e^{-x\cdot\left(1+e^{\left(-\frac{\mu_i-\mu_j}{\sigma}\right)}\cdot e^{-\left(\frac{V_i-V_j}{\sigma}\right)}\right)} dx \\
&= \frac{1}{1+e^{-\left(\frac{V_i+\mu_i-V_j-\mu_j}{\sigma}\right)}} = \frac{e^{\frac{V_i+\mu_i}{\sigma}}}{e^{\frac{V_i+\mu_i}{\sigma}}+e^{\frac{V_j+\mu_j}{\sigma}}}
\end{aligned}
\tag{10.12}
$$

From a modelling perspective, P_{ij} from equation 10.12 corresponds to the **Binary Logit** Model (Anderson et al., 1992; Ben-Akiva and Lerman, 1985; Garrow, 2010; Train, 2009). There are some characteristics of P_{ij} which are worth to highlight:

- The probability of choosing i over j only depends on the normalised differences of utilities: $\frac{V_i+\mu_i-V_j-\mu_j}{\sigma}$. If the utility is defined as -LCOE, then the probability of choosing technology i over j only depends on the LCOE difference.

- For $\mu_i = \mu_j$ and $V_i = V_j$, investors are indifferent between i and j ($P_{ij} = 1/2$). I.e., investors are indifferent between technologies with the same LCOE.

- The framework presented here is completely aligned with the incumbent investment model of FTT:Power. For a complete analysis of the theoretical foundations of the FTT:Power model, and its relation with Discrete Choice Theory, please refer to Mercure (2015).

The binary logit model, represented by P_{ij} from equation 10.12, is based on pairwise comparisons (technologies i and j). So, P_{ij} corresponds to the F_{ij} term in the shares equation, and represents the probability of choosing technology i over j. In other words, P_{ij} corresponds to the binary logit version of the FTT:Power investment model. Using discrete choice theory, the binary logit model (BNL) can be expanded into a multinomial logit model (MNL). In the MNL case, technology i can be compared against the whole technology set H at once. This model is presented in the next section.

10.3.1 From Binary to Multinomial

P_{ij} represents the probability of choosing alternative i over j in a pairwise comparison, given the preference relation $\succeq$ and the utility function U. If instead of doing pairwise comparisons, all the alternatives were to be compared at the same time, the probability of choosing alternative i would be:

$$\begin{aligned}
P_i &= P\left(U_i \geq U_j, \quad \forall j = 1 \cdots 24\right) \\
&= P\left(V_i + \varepsilon_i \geq V_j + \varepsilon_j, \quad \forall j = 1 \cdots 24\right) \\
&= P\left(\varepsilon_j \leq V_i - V_j + \varepsilon_i, \quad \forall j = 1 \cdots 24\right) \\
&= \int_{-\infty}^{\infty} P\left(\varepsilon_1 \leq V_i - V_1 + \varepsilon_i \mid \varepsilon_i\right) \ldots \left(\varepsilon_{24} \leq V_i - V_{24} + \varepsilon_i \mid \varepsilon_i\right) \cdot f_{\varepsilon_i}\left(\varepsilon_i\right) d\varepsilon_i \\
&= \int_{-\infty}^{\infty} F_{\varepsilon_1}\left(V_i - V_1 + \varepsilon_i\right) \ldots F_{\varepsilon_{24}}\left(V_i - V_{24} + \varepsilon_{24}\right) \cdot f_{\varepsilon_i}\left(\varepsilon_i\right) d\varepsilon_i
\end{aligned} \tag{10.13}$$

Under the same conditions of section 10.3, it can be easily demonstrated that P_i follows a **Multinomial Logit**:[9]

$$P_i = \frac{e^{\frac{V_i + \mu_i}{\sigma}}}{\sum_{j=1}^{n} e^{\frac{V_j + \mu_j}{\sigma}}} \tag{10.14}$$

Notice that the binary logit model (BNL) corresponds to a special case of the multinomial logit (MNL), when only two alternatives are compared at the same time. In the case of FTT:Power, the use of a MNL model allows the replacement of the pairwise comparison approach, by a system that compares all the technologies at the same time. From the MNL model, it is possible to re-create a pairwise comparison model:

$$P_{ij} = \frac{P_i}{P_i + P_j} \Longleftrightarrow F_{ij} \tag{10.15}$$

So, the term P_{ij}, either based on the BNL or the MNL model, is the counterpart to the original FTT:Power investment decision model. In the case of the BNL and MNL models, the key element for comparing the technologies is the vector of preferences:

[9] To see the details of the demonstration, please refer to appendix section D.2. The demonstration follows the standard Discrete Choice Theory approach, that can be found in any of the following textbooks: Anderson et al. (1992); Ben-Akiva and Lerman (1985); Garrow (2010); McFadden (1973); Train (2009)

$$\boldsymbol{U} = [U_1, ...U_n], \qquad U_i = \frac{V_i + \mu_i}{\sigma} \qquad i = 1, \cdots, n \quad n = 24 \tag{10.16}$$

The vector of preferences, $\boldsymbol{U}$, has embedded the information that investors require for choosing a specific technology. If the definition suggested above is used, $U_i = -LCOE_i$, then investment allocation follows the traditional FTT:Power approach, based on the LCOE. The terms $P_i/(P_i + P_j)$ (in the MNL case) and P_{ij} (in the BNL case), can work as a direct replacement of the term F_{ij} in the shares equation (using the expression 10.15).

Despite the mathematical compatibility, there is a subtle difference between the traditional FTT:Power investment model and the discrete choice theory approach. The former does not assume rational behaviour of agents, while the latter assumes that agents are utility maximisers. This importance difference is discussed, briefly, in the next section.

10.3.2 Rationality and diversity of agents

As shown in section 4.6.1, investment allocation in FTT:Power represents aggregated decisions at the regional level. The aggregation process conceals large variations related to aspects of local nature, such as the cost of land and labour, and decisional issues which may or may not lead to a rational choice of the option with the lowest LCOE. For that reason, the incumbent investment model in FTT:Power uses a probabilistic approach for representing costs (see figure 4.4). In this approach, aggregated investment allocation going to one technology or another, is proportional to the difference between the median of the cost distributions (comparisons are made pairwise). So, technologies at a lower cost have a higher chance of being chosen, and therefore attract more investment. Under this approach, there is no explicit assumption regarding the rationality of the underlying decision makers. However, at the aggregate level, investment allocation tends to be allocated in the technologies with the lowest LCOE. As such, it is reasonable to assume that individual investors tend to prefer less expensive technologies. If that was not the case, then the aggregate behaviour would follow a different pattern.

Following the discrete choice theory approach, the probabilistic representation of investment decisions in FTT:Power can be described using a different perspective. At the individual level, investment decisions in the supply side of the power sector are taken by firms. Therefore, it is reasonable to assume that individual firms try to maximise their profits. As a consequence, at the firm investment level, the technologies with the lowest LCOE are preferred. Given that LCOE values are different for different investors (due to discrepancy of local or individual nature), rational behaviour at the firm level does not necessarily translate into an optimal investment allocation at the regional level. The aggregation of individual decisions gives place to investment distributions, proportional to the LCOE differences, as well as to the diversity of agents within the region.

In a homogeneous system, with identical rational agents and perfect information, investment allocation is straightforward: the technology with the lowest LCOE absorbs the entire market. When heterogeneity is incorporated, investment patterns become diverse. Even if agents behave rationally at the individual level, the difference in preferences, the limited access to information and the lack of coordination among agents, provide a diversified non-optimum investment allocation. From an aggregate perspective, it is impossible to differentiate the roots of the investment distributions. If distributed patterns of investment are based on irrational behaviour, or based on limited access to information, it is not possible to be inferred from the aggregate. For that reason, if a frequentist approach is used, then the incumbent and the discrete choice theory approach for investment decisions are equivalent, within the current FTT:Power framework.

Under this interpretation, the probability of choosing technology i over technology j, can be calculated as $F_{ij} = P_{ij} = \frac{P_i}{P_i+P_j}$. These probabilities only depend on the preferences vector $\boldsymbol{U}$, which is based on the LCOE values. In order to have investment decisions that incorporate criteria beyond the LCOE, a multicriteria approach is needed. The Analytic Hierarchy Process is a methodology that allows the aggregation of multiple criteria, in one single vector of preferences. If used in combination with the MNL model, then a multicriteria investment decision model for FTT:Power can be implemented.

The AHP methodology is introduced in the next section. Then, in section 10.5, a methodology to combine AHP with MNL is presented. The combination of AHP and Discrete Choice Theory is the basis for the transformation of the FTT:Power investment model into a multicriteria decision making model.

10.4 Analytic Hierarchy Process

The Analytic Hierarchy Process is a *multiobjective multicriteria decision-making approach which employs a pairwise comparison procedure to arrive at a scale of preferences among sets of alternatives* (Saaty and Vargas, 1991). The methodology was introduced by Saaty (1977), who defined it later as a *general theory of measurement* (Saaty, 1987). The AHP method aims to support decision makers when facing a complex problem with multiple conflicting and subjective criteria. It is used in several fields, including healthcare decision making, finance, education, engineering, government, industry, management and manufacturing (Ho, 2008; Liberatore and Nydick, 2008; Steuer and Na, 2003; Vaidya and Kumar, 2006). In the UK, for instance, the Department for the Environment, Transport and the Regions included AHP as part of the official guidance on the application of multi-criteria analysis (UK Government, 2009).

The following sections explain how the AHP method works, framed in the context of FTT:Power and the discrete choice model described above.[10] In AHP, options are ranked, based on pairwise preferences. As a final result, a ranking vector is obtained, with a score for each one of the alternatives analysed. Traditionally, the process is used to choose one option, the one with the highest score. However, in this case, I used the ranking vector as a measure of relative preferences between the alternatives. In other words, the final result of AHP, is a preference vector equivalent to $\boldsymbol{U}$, from MNL.

The distinction between the traditional use of AHP (choosing the best alternative) and the approach used in this chapter (measure of relative preferences) is important. The ranking vector obtained in AHP, is a representation of the investor's preferences. Therefore, if a normative approach is pursued (i.e. looking for optimal strategies), then the preferred option from the ranking should be picked. In other words, the ranking vector should be transformed into a boolean vector, with only zeros except in the position of the preferred option (see figure 10.1). However, the investment model introduced in this chapter, does not follow a normative approach. The aggregation of investment preferences in the AHP ranking vector is not focused on the best alternative, but in the diversity of the preferences. Aligned with the incumbent FTT:Power investment model, the new methodology introduced in this chapter follows a positive/descriptive approach. It does not look for optimum investment allocation, but tries to describe how the power sector might evolve, under specific circumstances. Investors are assumed to have different preferences, and consequently, regional aggregation of investment is not concentrated in the "best alternatives", but in a wide range of options.

In order maintain the positive/descriptive approach of FTT:Power, the AHP ranking vector (which is the final output of the AHP methodology) is interpreted as a measure of relative investment preferences, and not as an optimal alternative indicator. In section 10.5, it is shown how the investment preferences embedded in P_i from equation 10.14, can be transferred to

[10]Depending on the application field and the context, AHP methodology can be described from different perspectives. It can be described using a purely mathematical approach (e.g. Saaty (1977)), using a hands-on almost math-free approach (specially useful for policy-makers, such as in Saaty (2008)), or a mixed approach, as in Saaty (1999). The description style used in this section is based on Saaty (1999), which is compact, mostly mathematical but not particularly complex.

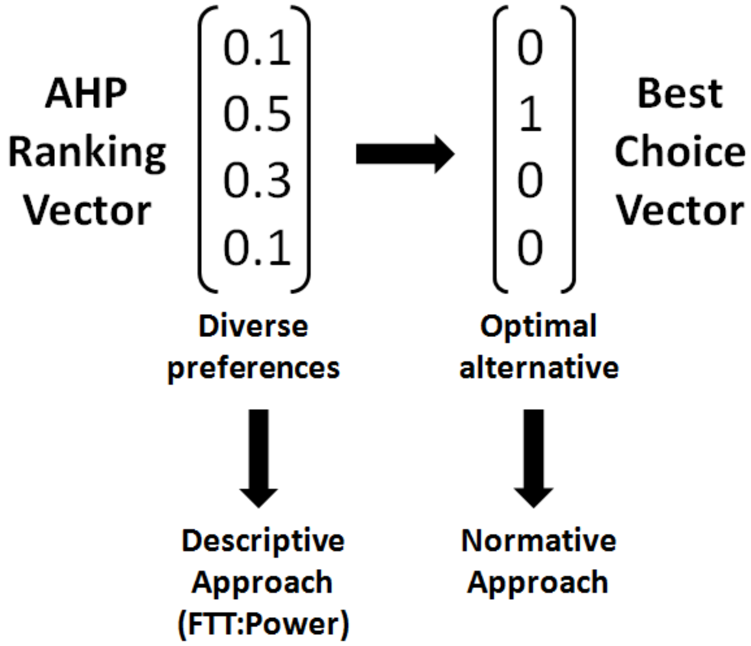


Figure 10.1 The new model introduced in this chapter follows a positive/descriptive approach. Investors are assumed to have different preferences, and consequently, regional aggregation of investment is not concentrated in the “best alternative”, but in a diverse portfolio. The ranking vector obtained in AHP represents a measure of relative investment preferences (left case). When a normative approach is pursued, then the “best option” from the ranking is picked. In that case, the ranking vector is transformed into a boolean vector, with only zeros except in the position of the preferred option (right case).

the AHP ranking vector. In other words, how the incumbent investors’ preferences from FTT:Power, replicated through MNL in equation 10.14, can be replicated using AHP. But first, section 10.4.1 provides a basic introduction to AHP.

10.4.1 Some basic AHP concepts

The aim of the Analytic Hierarchy Process is to help decision makers to evaluate options that may or may not be directly comparable. A representative example would be the use of AHP to decide the purchase of a family car, using a combination of quantitative and qualitative criteria related to specific attributes, such as *purchase price*, *fuel consumption*, *safety* and *style*. Some of these attributes can be easily measured (such as purchase price and fuel consumption); others are subjective to the preferences of the decision-maker (such as style), and others are arguably in between (such as safety). AHP uses a tree-type hierarchical structure to compare alternatives under different criteria, as shown in figure 10.2. The ‘leaves’ of the tree are the alternatives, which are compared under each criterion using a pairwise framework of relative scales (in figure 10.2, the leaves correspond to the car options in green: X, Y and Z, and the criteria are in red: purchase price, fuel consumption, safety and style). Criteria are then aggregated by branch (blue boxes), using a recursive algorithm of pairwise comparison and prioritisation, until the tree trunk is reached. As a result, an overall weight-vector for all the alternatives is obtained. The alternative with the highest weight represents the best alternative for the decision maker, based on the pairwise comparison criteria previously defined.

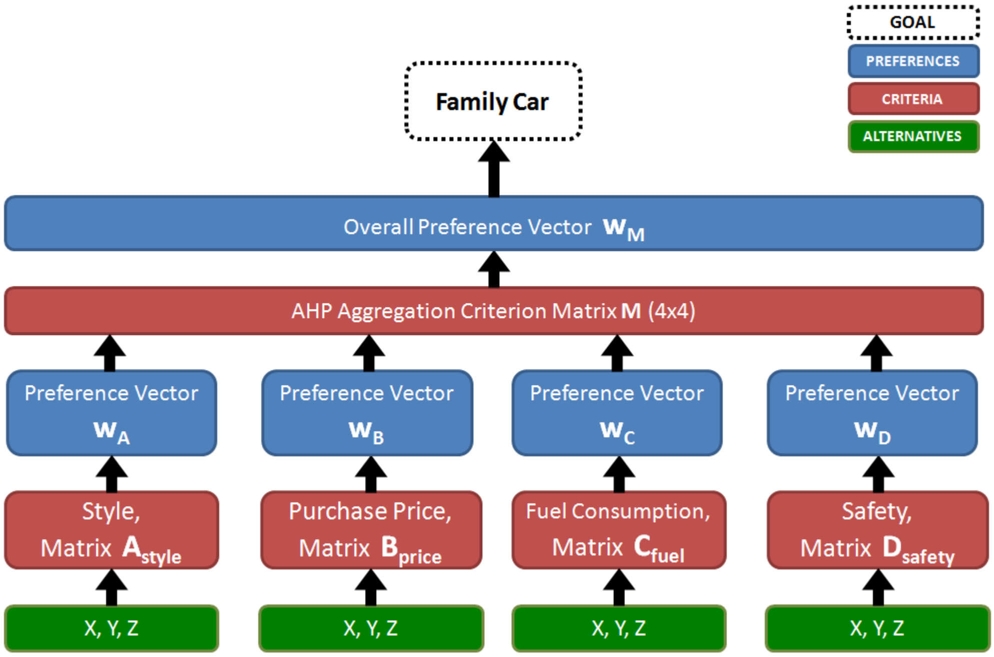


Figure 10.2 AHP tree-type hierarchical structure. In the upper part is the goal (white box). The alternatives (green boxes) are compared using a pairwise comparison matrix (such as $\boldsymbol{A_{style}}$ from equation 10.17). The application of each criterion (small red boxes) generate ranking vectors (w_A to w_D, small blue boxes), that represents the preferences of the decision maker, with respect to each criterion. All the criteria are then compared, using a recursive algorithm. The different branches of the tree are aggregated using an overall comparison matrix with pairwise comparison of the different criteria (in this case, a 4x4 size matrix M, big red box). As a result, a vector w_M with the ranking of the criteria is obtained (big blue box). The final ranking of the entire tree is calculated using equation 10.18, aggregating all the preference information stored in the preference vectors (blue boxes).

Alternatives are weighed in AHP using *judgment of comparison*, a numerical representation of the relationship between two options, based on expert judgment. Because alternatives are compared pairwise, the set of judgments can be represented by a square matrix of $n \times n$ elements, with n being the number of alternatives. In the case of figure 10.2, the set of judgments can be represented by 3×3 matrices, comparing X, Y and Z under a specific criterion. An element in the position (i, j) represents the relative importance of i with respect to j (also known as the *dominance*), while the element (j, i) is the reciprocal of the relative importance. The relative importance is defined over an arbitrary "fundamental scale" of 1 to 9, presented in Table 10.1[11]. If the element (i, j) has a value of k, it means *i is k times more important than j*. From a probabilistic perspective, *importance* means *preference* or *likelihood* of being chosen.

Relative Importance	Reciprocal of Rel. Imp.	Definition	Explanation Explanation
1	1	Equal importance	The decision-maker is indifferent between the alternatives
3	1/3	Moderate importance	Experience and judgment slightly favour one activity over another
5	1/5	Strong importance	Experience and judgment strongly favour one activity over another
7	1/7	Very strong or demonstrated importance	One alternative is favoured very strongly over another; its dominance demonstrated in practice
9	1/9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	1/2, 1/4, 1/6, 1/8	For compromise between the above values	Interpolation of compromise judgment

Table 10.1 Fundamental scale of dominance for the Analytic Hierarchy Process. Adapted from Saaty (1999).

In the example of the family car purchase, with three alternatives, X, Y, and Z, four 3×3 matrices are required, one for each criterion. According to the AHP methodology, in each of these matrices, the decision-maker has to compare the three alternatives in pairs, using the fundamental scale. So, for instance, in the case of the *style* criterion, represented by the $\boldsymbol{A_{style}}$ matrix in equation 10.17, an example of pairwise comparison could be the following:

[11]The exact definition of each category in the fundamental scale varies slightly within the AHP literature. For this work, the main reference is Saaty (1999), with some influences from Saaty (1987, 1977, 2008).

- If the decision-maker is indifferent between two alternatives (for instance, is indifferent between the styles of cars X and Y), then the relative importance is 1 (and is equal to the reciprocal). So, the element (1,2) in the $\boldsymbol{A_{style}}$ 3x3 matrix (corresponding to the preference of X over Y) is one. The reciprocal (the relative importance of Y over X), in the position (2,1), is also one.

- If the decision-maker likes X over Z moderately, then the associated relative importance would be, for instance, 3. The reciprocal would be, therefore, 1/3. So, the elements (1,3) and (3,1) in the $\boldsymbol{A_{style}}$ matrix would be 3 and 1/3, respectively.

- Finally, the relationship between Y and Z has to be defined. If the decision-maker strongly prefers the style of Z over Y, then the relative importance (element (3,2) in $\boldsymbol{A_{style}}$) and the reciprocal (element (2,3) in $\boldsymbol{A_{style}}$) would be 5 and 1/5, respectively.

Therefore, the matrix of preferences $\boldsymbol{A_{style}}$ can be written as:

$$\boldsymbol{A_{style}} = \begin{array}{c} \\ \text{X} \\ \text{Y} \\ \text{Z} \end{array} \begin{array}{c} \begin{array}{ccc} \text{X} & \text{Y} & \text{Z} \end{array} \\ \begin{pmatrix} 1 & 1 & 3 \\ 1 & 1 & 1/5 \\ 1/3 & 5 & 1 \end{pmatrix} \end{array} \tag{10.17}$$

From the comparison matrix, a weight vector (or score vector) is obtained. This vector summarises the preferences of the decision-maker embedded in the comparison matrix. Later in this chapter, I explain how to calculate the weight vector, using the eigenvalues and eigenvector of the comparison matrix. In figure 10.2, the weight vectors are called $\boldsymbol{w_A}$, $\boldsymbol{w_B}$, $\boldsymbol{w_C}$ and $\boldsymbol{w_D}$ (for style, purchase price, fuel consumption and safety, respectively). Each vector has 3 elements, representing the weight (or score) of the alternatives X, Y and Z under each criterion.

In AHP, all the alternatives and criteria are compared using the same algorithm. Each node of the tree requires a comparison matrix such as the one described in 10.17. So, three more 3×3 matrices are needed to compare the alternatives X, Y and Z under the *purchase price*, *fuel consumption* and *safety* criteria. Each comparison matrix gives as a result a weight vector with the "score" of each alternative under the specific criterion.

To combine the branches of the tree, the same recursive algorithm is followed: the criteria *style*, *purchase price*, *fuel consumption* and *safety* are compared, using a 4×4 matrix. As a result, a four-elements vector is obtained, with the score of each criterion: $\boldsymbol{w_M}$. The overall weight vector for the tree would be then a 3×3 vector, with each element of the vector calculated as:

$$\boldsymbol{W}(i) = \sum_{j \in \{A,B,C,D\}} \boldsymbol{w_M}(j) \cdot \boldsymbol{w_j}(i), \quad i = 1, \cdots, 3 \tag{10.18}$$

The goal of the tree-type hierarchical structure of AHP, represented in figure 10.2 (in a white box in the upper part of the diagram), is to rank all the alternatives, according to specific criteria (red boxes). Each criterion can depend on more criteria, using a recursive structure. The alternatives are represented by the leaves of the tree (green boxes).[12]

Figure 10.3 shows the AHP tree for the FTT:Power investment model. The diagram in the left represents the case when only one criterion is used: the LCOE. This is the case of the current FTT:Power investment model. The diagram in the right of figure 10.3 shows how more criteria could be incorporated into the AHP tree. First, the comparison matrices have to be defined, based on the new criteria. Then, an aggregation criterion is needed, to combine all the branches of the tree. Section 10.5 presents the implementation of the AHP tree at the left of figure 10.3, when only the LCOE criterion is used. Then, section 10.6 shows how new criteria can be incorporated in the AHP tree, such as in the right diagram of figure 10.3.

10.4.2 The role of consistency

In general terms, when n alternatives are being compared, the quantitative judgments are stored in a $n \times n$ matrix, calculated using the "fundamental scale" presented in Table 10.1:[13]

$$\boldsymbol{A} = \left(a_{ij}\right), (i, j = 1, ..., n)$$

[12] As explained at the beginning of section 10.4, the traditional objective of the AHP methodology is to obtain the best alternative, given the goal and the corresponding criteria. In this work, the objective is different: we are looking for the ranking, so investment can be allocated proportionally, given the underlying preferences. See figure 10.1.

[13] The scale of 1 to 9 suggested by Saaty is based on the work of Miller (1956) on psychology and information theory. Miller described people's limitations on receiving, processing and remembering information simultaneously. For Miller, seven (plus minus two) was "the magical number" of objects that an individual can compare simultaneously, without being confused. Accordingly, Saaty decided to use a scale of 1 to 9, so the subject can be aware of all graduations at the same time. The scale was tested against other 25 scales, and it gave the best results in terms of consistency. Saaty suggested that these results are a theoretical confirmation of Miller's psychological observations (Saaty, 1977).

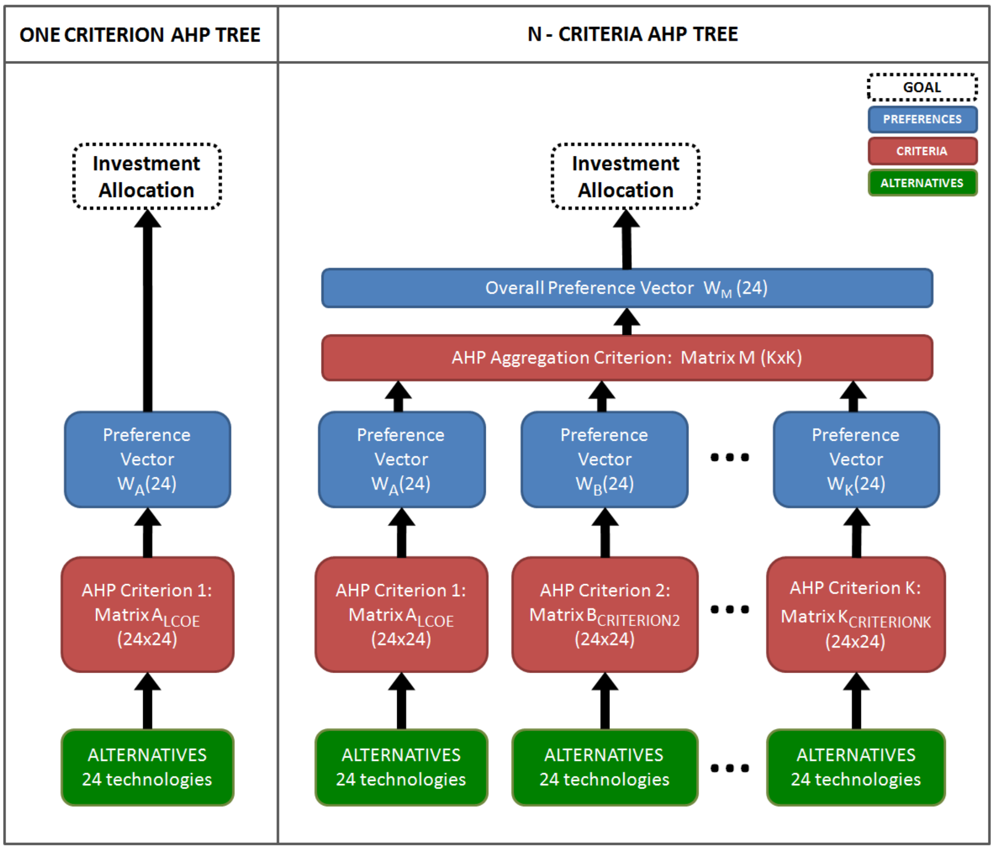


Figure 10.3 AHP tree for the FTT:Power investment model. The alternatives (green boxes), correspond to the 24 technologies available in FTT:Power. The final investment allocation (white box) is defined by a set of criteria (red boxes). The diagram at the left corresponds to the case when only one criterion is used: the LCOE. If that is the case, then the AHP model is the same as the incumbent FTT:Power investment model. This is introduced in section 10.5. The diagram at the right shows an extended model, that incorporates other criteria beyond the LCOE. The methodology to incorporate more criteria to the AHP tree is explained in section 10.6.

From the family car purchase example presented in section 10.4.1, the matrix $\boldsymbol{A_{style}}$ is a particular case of the matrix $\boldsymbol{A}$, with n equal three. Each element of $\boldsymbol{A_{style}}$ (a_{ij}) is a quantitative judgment regarding the style preferences. So, because cars X and Y are equivalent in terms of style, then $a_{12} = a_{21} = 1$; Car X is moderately preferred over car Z, so $a_{13} = 3$ and $a_{31} = 1/3$; finally, car Z is strongly preferred over car Y, so $a_{32} = 5$ and $a_{23} = 1/5$.

The final goal of AHP, is to obtain a vector that represents the preferences of the decision maker. In other words, the idea is to transfer the preferences from the quantitative judgment process, stored in the $\boldsymbol{A}$ matrix, to the final weight vector. In the case of the $\boldsymbol{A_{style}}$ matrix, the goal is to obtain a ranking vector (or weight vector), that represents the style preferences previously described.

Saaty (1999) demonstrated that preferences of the decision maker can be transfered into a vector $\boldsymbol{w_A} = [w_1, ..., w_n]$, if the matrix $\boldsymbol{A}$ is **consistent**. In this context, consistency is defined as:

Consistency: $\boldsymbol{A}$ is consistent if

$$a_{ij} \cdot a_{jk} = a_{ik} \quad \forall i, j, k = 1, ..., n \tag{10.19}$$

When preferences are consistent, Saaty (1999) demonstrated two important properties for the matrix $\boldsymbol{A}$:

Property 1: $\boldsymbol{A}$ is consistent if and only if it can be written as a matrix with the form

$$\boldsymbol{A} \quad = \quad \begin{pmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{pmatrix} \tag{10.20}$$

Property 1 is a direct consequence of the definition of consistency. If the matrix $\boldsymbol{A}$ is consistent, then each element a_{ij} can be written as:

$$a_{ij} = \frac{a_{ik}}{a_{jk}} = \frac{w_i}{w_j} \tag{10.21}$$

The reverse implication is also direct: if each element of the matrix $\boldsymbol{A}$ can be written as $a_{ij} = w_i/w_j$, then we have:

$$a_{ij} \cdot a_{jk} = \frac{w_i}{w_j} \cdot \frac{w_j}{w_k} = \frac{w_i}{w_k} = a_{ik} \tag{10.22}$$

So, $\boldsymbol{A}$ is consistent if and only if it can be written as the ratios of $w_1 ... w_n$. Saaty (1999) demonstrated that the vector $\boldsymbol{w_A} = [w_1, ..., w_n]$ preserves the preferences embedded in $\boldsymbol{A}$. In other words, the vector $\boldsymbol{w_A}$ is the weight vector (or score vector) described previously. This conclusion is based on a second property discovered by Saaty:

Property 2: If we take the ratios defined in equation 10.20 and create a vector $\boldsymbol{w_A} = [w_1, ..., w_n]$, then $\boldsymbol{A}$ is consistent if and only if n is its principal *eigenvalue* and $\boldsymbol{w_A}$ is its principal *eigenvector*, i.e.,

$$\boldsymbol{A} \cdot \boldsymbol{w_A} = n \cdot \boldsymbol{w_A} \tag{10.23}$$

Moreover, $\boldsymbol{w_A} > 0$ is unique to within a multiplicative constant, and defines a ratio scale[14] within A.[15]

According to Property 1, if $\boldsymbol{A}$ is consistent, then it can be written as the combination of weights in 10.20. Then, given the vector $\boldsymbol{w_A}$, the construction of $\boldsymbol{A}$ is straightforward. The reverse implication is a bit more complex: if the matrix $\boldsymbol{A}$ is given, then the vector $\boldsymbol{w_A}$ is the one that solves the equation:

$$(\boldsymbol{A} - n\boldsymbol{I}) \cdot \boldsymbol{w_A} = 0 \tag{10.24}$$

Equation 10.24 is very well known in linear algebra: it has a nonzero solution if and only if $\boldsymbol{w_A}$ is the eigenvector of $\boldsymbol{A}$ (Simon and Blume, 1994). Notice that the rank of the matrix $\boldsymbol{A}$ is 1. According to equation 10.20 from Property 1, all the rows of $\boldsymbol{A}$ are a multiple of each other. Therefore, all the eigenvalues of $\boldsymbol{A}$ are zero, except for the principal eigenvalue, which is n, and $\boldsymbol{w_A}$ is the corresponding eigenvector. In other words, when $\boldsymbol{A}$ is consistent, then n and $\boldsymbol{w_A}$ are its principal eigenvalue and eigenvector, respectively. These are very important results: the ranking vector of the preferences matrix $\boldsymbol{A}$ can be calculated using the standard methodology to calculate eigenvectors. Moreover, given a specific ranking of preferences ($\boldsymbol{w_A}$), the construction of the matrix $\boldsymbol{A}$ is trivial.

The vector $\boldsymbol{w_A}$ from 10.24 corresponds to the weight vector described previously, the one that aggregates a specific branch from the AHP tree. The relation between $\boldsymbol{A}$ and $\boldsymbol{w_A}$ is the cornerstone of the Analytic Hierarchy Process. It shows how from the preferences of the decision-maker (stored in $\boldsymbol{A}$), a weight vector with ranked alternatives can be created. It is expected, therefore, that $\boldsymbol{w_A}$ preserves the preferences defined by the decision-maker, which are embedded in $\boldsymbol{A}$. From equation 10.20 we have:

$$\text{if} \quad a_{ik} \geq a_{jk}, \forall k, \qquad \Rightarrow \qquad w_i \geq w_j \tag{10.25}$$

[14] Saaty (1999) defines a *ratio scale* as a scale invariant under positive multiplicative transformations $a \cdot x, a > 0$.

[15] To see the detailed demonstration of these theorems, which are beyond the scope of this work, please refer to Saaty (1999).

So, if $\boldsymbol{A}$ is consistent, then there is an order relation between $\boldsymbol{A}$ and $\boldsymbol{w_A}$. This is precisely the order relation we are looking for the FTT:Power investment model. If there is a way to store the preferences of the investors in a matrix $\boldsymbol{A}$, then it is possible to calculate a ranking, through the vector $\boldsymbol{w_A}$. This is done in section 10.5.

The calculation of the ranking vector $\boldsymbol{w_A}$, from a consistent matrix $\boldsymbol{A}$, follows the standard eigenvector procedure. For information about how to calculate eigenvectors and eigenvalues, please refer to any linear algebra textbook (for instance, Simon and Blume (1994)).

10.4.3 The inconsistent case

The definition of consistency has embedded the assumption of *transitive preferences*. If a is preferred to b, and b is preferred to c, then a is supposed to be preferred to c. However, preferences are not always transitive. For instance, in the case of the matrix $\boldsymbol{A_{style}}$: while the decision-maker is indifferent between X and Y, and X is preferred to Z, Z is preferred to Y. Using the definition of consistency presented in section 10.4.2, it is clear that the matrix $\boldsymbol{A_{style}}$ is inconsistent:

$$a_{12} = 1 \quad , \quad a_{23} = 1/5 \quad , \quad a_{13} = 3 \neq a_{12} \cdot a_{23} \tag{10.26}$$

The concept of inconsistency (or non-consistency) created by (Saaty, 1977) captures the inherent human judgmental errors, the fact that people's preferences are sometimes intransitive.

The case when $\boldsymbol{A}$ is consistent is straightforward: its eigenvector $\boldsymbol{w_A}$ preserves the order relation of A, and therefore is the perfect option to be the weight vector that aggregates the preferences embedded in $\boldsymbol{A}$.

For a matrix $\hat{\boldsymbol{A}}$ of inconsistent preferences (such as $\boldsymbol{A_{style}}$), Saaty (1999) demonstrated that the order relation described by equation 10.25 is also preserved by its principal eigenvector, if the following conditions are met:

1 - Reciprocity: All the elements of $\hat{\boldsymbol{A}}$ are reciprocal, i.e. $a_{ij} = \frac{1}{a_{ji}} \quad i,j = 1,\cdots,n$.

2 - Near Consistency: The principal eigenvalue of $\hat{\boldsymbol{A}}$, λ_{max}, has to be "close enough" to the number of alternatives n. This is measured by the "Consistency Ratio" (CR):

$$CR = \frac{\lambda_{max} - n}{\lambda_{max}} \tag{10.27}$$

A "rule of thumb" for the consistency ratio is: order of 5% for a 3×3 matrix, 8% for a 4×4 and 10% for larger matrices (Saaty, 1999, 2000).

In the case of the 3×3 matrix $\boldsymbol{A_{style}}$, the main eigenvalue is 3.87, and the normalised eigenvector is $\boldsymbol{w_A} = [.44, .18, .38]$. According to Saaty's methodology, style preferences indicate a ranking in the order X, Z and Y. However, the consistency ratio is 22%, much higher than the recommended 5%. This indicates a relatively high level of intransitivity in the preferences matrix $\boldsymbol{A_{style}}$, as previously discussed.

In the case of FTT:Power, to create the matrix $\boldsymbol{A}$ (or $\boldsymbol{\hat{A}}$), it is necessary to have a scale that defines the investors' preferences. One option is the subjective scale proposed by Saaty (see table 10.1). However, in the case of the LCOE, we already have an absolute scale to rank the different alternatives: the LCOE itself. In the next section, the use of an absolute versus a relative scale to rank the alternatives is discussed, based on the properties of the pairwise comparison matrix.

10.4.4 Beyond the fundamental scale

Comparisons can be made in both, relative and absolute terms. In the former case, alternatives are compared in pairs, according to a common attribute; in the latter, an absolute scale is required, typically from a standard form of measurement. Relative comparisons are very useful for intangible criteria, (such as "style", as in the car comparison example described in section 10.4.1), when no absolute scale exist. For such cases, Saaty has made compelling arguments about the usefulness of the fundamental scale described in Table 10.1 (Saaty, 1987, 1986, 1999, 2000).

When absolute measurements are available, it is possible to apply AHP without using the fundamental scale of Table 10.1. Let exemplify this with the "purchase price" criteria of the car example from section 10.4.1. Let assume the purchase price of the alternatives are the following: $X = £25,000.00$, $Y = £30,000.00$ and $Z = £35,000.00$. On a pairwise comparison basis, the $£5,000.00$ difference between X and Y, and between Y and Z may or may not represent a relevant difference, depending on the buyer. While for some people $£5,000.00$ could represent the difference between purchasing the car or not, other people could potentially be indifferent under the same price gap. Therefore, without having more information about the decision-maker, it is very difficult to create the comparison matrix using the fundamental scale of Table 10.1 in this case. However, there exist an absolute scale already defined intrinsically in the price of the car. Under no more information about the decision-maker, or if a wide range of decision makers are being represented in the model, then the absolute scale defined by the price of the car represents a good candidate for the comparison matrix.

The relative importance of element i over j can be represented, for instance, by the ratio of their prices: $a_{ij} = \frac{P_j}{P_i}, (i, j = 1, ..., n)$. In this case, the pairwise comparison matrix $\boldsymbol{B_{price}}$ can be written as:

$$\boldsymbol{B_{price}} = \begin{array}{c c} & \begin{array}{ccc} \mathrm{X} & \mathrm{Y} & \mathrm{Z} \end{array} \\ \begin{array}{c} \mathrm{X} \\ \mathrm{Y} \\ \mathrm{Z} \end{array} & \begin{pmatrix} 1 & \frac{30}{25} & \frac{35}{25} \\ \frac{25}{30} & 1 & \frac{35}{30} \\ \frac{25}{35} & \frac{30}{35} & 1 \end{pmatrix} \end{array} \tag{10.28}$$

The principal eigenvalue and eigenvector of $\boldsymbol{B_{price}}$ are $\lambda_{price} = 3$ and $\boldsymbol{w_{price}} = [.39, .33, .28]$, respectively, where

$$\boldsymbol{w_{price}} = \frac{\vec{\boldsymbol{w}}_{\boldsymbol{B}}}{||\vec{\boldsymbol{w}}_{\boldsymbol{B}}||}, \qquad \vec{\boldsymbol{w}}_{\boldsymbol{B}} = \left[\frac{\Delta P}{P_1}, \frac{\Delta P}{P_2}, \frac{\Delta P}{P_3}\right]$$

Clearly $\boldsymbol{w_{price}}$ is a good representative weighting vector of the price options presented by X, Y, and Z. Moreover, $\boldsymbol{w_{price}}$ does not only help to find the "best" alternative in terms of price (which in this case would be X), but also provides a relative ranking between the alternatives, with weights that are proportional to the ratio of the price differences and the corresponding price options.

The use of an absolute scale, which comes in this case from the actual price of the cars, is very useful when little or not information about the decision-maker's preferences exist. In the case of FTT:Power, there is also an absolute scale, based on the LCOE. Therefore, a reasonable assumption is to base the investor's preference matrix on that absolute scale, instead of defining an arbitrary transformation to the scale suggested by (Saaty, 1977).

10.4.5 Aggregation of criteria

In the car purchase example, the eigenvector of $\boldsymbol{B_{price}}$, $\boldsymbol{w_{price}}$, defines a ranking of the alternatives regarding their cost. Similarly, using pairwise comparison matrices for the other criteria, rankings can be created using the corresponding eigenvectors $\boldsymbol{w_{style}}$, $\boldsymbol{w_{safety}}$ and

$\boldsymbol{w_{fuel}}$. However, there is still one issue to be addressed: the aggregation of all the different criteria in one single ranking of alternatives. Remember that the AHP methodology is recursive. It means that alternatives, as well as criteria, are compared using a matrix of preferences. In the car example, if the aggregated matrix of preferences is called $\boldsymbol{M}$, it can then be written as follows:

$$\boldsymbol{M} = \begin{array}{c c} & \begin{array}{cccc} \text{price} & \text{fuel} & \text{style} & \text{safety} \end{array} \\ \begin{array}{c} \text{price} \\ \text{fuel} \\ \text{stye} \\ \text{safety} \end{array} & \begin{pmatrix} 1 & \frac{\text{price}}{\text{fuel}} & \frac{\text{price}}{\text{style}} & \frac{\text{price}}{\text{safety}} \\ \frac{\text{fuel}}{\text{price}} & 1 & \frac{\text{fuel}}{\text{style}} & \frac{\text{fuel}}{\text{safety}} \\ \frac{\text{style}}{\text{price}} & \frac{\text{style}}{\text{fuel}} & 1 & \frac{\text{style}}{\text{safety}} \\ \frac{\text{safety}}{\text{price}} & \frac{\text{safety}}{\text{fuel}} & \frac{\text{safety}}{\text{style}} & 1 \end{pmatrix} \end{array} \tag{10.29}$$

where each element $a_{i,j} = i/j, \quad (i, j) \in \{\text{price, fuel, style, safety}\}$ of the matrix $\boldsymbol{M}$ represents the relative importance of the alternative i with respect to j. From the principal eigenvector of $\boldsymbol{M}$, $\boldsymbol{w_M}$, the score of each criterion can be obtained, based on the preferences described in the matrix. If the AHP decision-tree has more branches, then the process is applied recursively until the tree trunk is reached. In this way, criteria based on absolute scales (such as purchase price or fuel consumption) can be combined with more qualitative or subjective criteria (such as style and safety).

As explained in section 10.4.1, the final score for the entire tree is obtained with the linear combination of the ranking vectors:

$$\boldsymbol{W} = \boldsymbol{w_M}(1) \cdot \boldsymbol{w_{style}} + \boldsymbol{w_M}(2) \cdot \boldsymbol{w_{price}} + \boldsymbol{w_M}(3) \cdot \boldsymbol{w_{fuel}} + \boldsymbol{w_M}(4) \cdot \boldsymbol{w_{safety}} \tag{10.30}$$

In the same way that quantitative and qualitative criteria are combined in the car example, AHP can be used in FTT:Power for modelling investment decisions that combine quantitative with qualitative criteria. In the case of the LCOE criterion, there exist already an absolute scale of measurement of the alternatives (the LCOE itself). The pairwise comparison matrix, therefore, can be constructed based on this absolute scale, and be used in combination with other criteria based on different scales.

The next section provides the connection of the AHP methodology, described in this section, with the Discrete Choice Theory investment model introduced in section 10.3. The incumbent investment preference function of FTT:Power is emulated, using AHP. This is the first step towards the expansion of the model, to include other investment decision criteria beyond the LCOE. This is addressed in section 10.6.

10.5 LCOE and the AHP Matrix

In this section, a preference matrix $\boldsymbol{A_{LCOE}}$ is built for the 24 FTT:Power technologies, using the LCOE as comparison criterion (see the left diagram of figure 10.3). From the $\boldsymbol{A_{LCOE}}$ matrix, a weight vector $\boldsymbol{w_A}$ will be obtained, with the respective scores of each technology. If the matrix $\boldsymbol{A_{LCOE}}$ is consistent (or near consistent), then the vector $\boldsymbol{w_A}$ preserves the preferences of the investors (see section 10.4.2). From the elements of $\boldsymbol{w_A}$, a probability to invest on that particular technology can be defined. It will be shown that the probability of investing in technology i is equivalent to the one calculated using the MNL model presented in section 10.3.1. Therefore, the AHP model of investment presented here, is equivalent to the MNL model presented in section 10.3.1, which in turns is equivalent to the incumbent FTT:Power investment preference function F_{ij}.

According to Properties 1 and 2 of section 10.4.2, $\boldsymbol{A_{LCOE}}$ is consistent if and only if a_{ij} can be represented as a ratio from an existing ratio scale, with the form defined in equation 10.20. Therefore, if there is a ratio scale for the LCOE, then a consistent matrix of preferences can be created. Moreover, if the ratios come from an absolute scale, then the preferences can be calculated from that absolute scale, without the necessity to apply the fundamental scale described in Table 10.1, as shown in the previous section.

10.5.1 Scale based on probabilities

The Discrete Choice model presented in section 10.3 defines an absolute scale, based on the probability of each alternative to be chosen by the decision-maker. In a simplified form, the probability of choosing alternative i over alternative j in a pairwise comparison is:

$$P_{ij} = \frac{e^{U_i}}{e^{U_i} + e^{U_j}}, \qquad U_x = \frac{V_x + \mu_x}{\sigma} \tag{10.31}$$

where $V_x + \mu_x$ is a stochastic representation of the LCOE values, with standard deviation σ. If instead of doing pairwise comparisons, all the technologies were to be compared in parallel, the probability P_i of choosing alternative i would be (as presented in section 10.3.1):

$$P_i = \frac{e^{U_i}}{\sum_{j=1}^{n} e^{U_j}} \tag{10.32}$$

The ratio between P_i and P_j is denominated *Odds Ratio*, and provides information on the relative "odds" of alternatives i and j to be chosen (Garrow, 2010):[16]

$$\frac{P_i}{P_j} = \frac{\frac{e^{U_i}}{\sum_{j=1}^{n} e^{U_j}}}{\frac{e^{U_j}}{\sum_{j=1}^{n} e^{U_j}}} = \frac{e^{U_i}}{e^{U_j}} \tag{10.33}$$

From equation 10.31, it can be inferred a relation between P_{ij} and P_{ji} from the Binary Logit, and P_i and P_j from the Multinomial Logit:

$$\frac{P_i}{P_j} = \frac{e^{U_i}}{e^{U_i}} = \frac{\frac{e^{U_i}}{e^{U_i}+e^{U_j}}}{\frac{e^{U_j}}{e^{U_i}+e^{U_j}}} = \frac{P_{ij}}{P_{ji}} \tag{10.34}$$

So, these probabilities define a ratio scale, that reflects the differences in the LCOE values, and consequently provides a ranking for the technologies.

10.5.2 Preference matrix $\boldsymbol{A_{LCOE}}$

With the ratio scale, defined by the probabilities $P_{ij}\,(i, j = 1, 2, ..., n = 24)$, it is possible to formalise an AHP model to compare FTT:Power technologies based on the LCOE criterion. If all the alternative technologies can be ranked relative to each other in terms of preferences, then the resulting ranking criterion can be described using a square matrix:

$$\boldsymbol{A_{LCOE}} = a_{ij} = P_{ij}/P_{ji} \quad (i, j = 1, 2, ..., n) \tag{10.35}$$

where n is the number of alternatives (in this case 24 technologies), a_{ij} represents the relative ranking between alternatives i and j and P_{ij} is the probability of choosing alternative i over alternative j in a pairwise comparison, as defined in 10.31. Then, the matrix $\boldsymbol{A_{LCOE}}$ takes the form:

[16]The odds ratio is usually presented as the log of P_i/P_j, which gives $U_i - U_j$.

$$\boldsymbol{A_{LCOE}} = \begin{pmatrix} 1 & P_{12}/P_{21} & \dots & P_{1n}/P_{n1} \\ P_{21}/P_{12} & 1 & \dots & P_{2n}/P_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1}/P_{1n} & P_{n2}/P_{2n} & \dots & 1 \end{pmatrix} \tag{10.36}$$

By construction, the matrix $\boldsymbol{A_{LCOE}}$ is **reciprocal**, i.e., $a_{ij} = 1/a_{ji}$. Moreover, the matrix is also **consistent**:

$$a_{ij} \cdot a_{jk} = \frac{P_{ij}}{P_{ji}} \cdot \frac{P_{jk}}{P_{kj}} = \frac{\frac{e^{U_i}}{e^{U_i}+e^{U_j}}}{\frac{e^{U_j}}{e^{U_i}+e^{U_j}}} \cdot \frac{\frac{e^{U_j}}{e^{U_j}+e^{U_k}}}{\frac{e^{U_k}}{e^{U_j}+e^{U_k}}} = \frac{\frac{e^{U_i}}{e^{U_i}+e^{U_k}}}{\frac{e^{U_k}}{e^{U_i}+e^{U_k}}} = \frac{P_{ik}}{P_{ki}} = a_{ik} \tag{10.37}$$

Because $\boldsymbol{A_{LCOE}}$ is consistent, the eigenvector $\boldsymbol{w_A}$, associated with the principal eigenvalue n, defines a ratio scale for $\boldsymbol{A_{LCOE}}$. In order to have a unique scale, $\boldsymbol{w_A}$ can be normalised, dividing it by the sum of its entries.

Notice the importance of the ratio scale defined by $\boldsymbol{A_{LCOE}}$. Each couple of elements a_{ij} and a_{ji} define a pairwise comparison between two FTT:Power alternative technologies. Therefore, it is possible to rank the alternatives using the matrix $\boldsymbol{A_{LCOE}}$.

$$\begin{aligned} a_{ik} &> a_{jk} \\ \Leftrightarrow \quad a_{ij} \cdot a_{jk} &> a_{jk} \\ \Leftrightarrow \quad a_{ij} &> 1 \\ \Leftrightarrow \quad \frac{P_{ij}}{P_{ji}} &> 1 \\ \Leftrightarrow \quad P_{ij} &> P_{ji} \end{aligned} \tag{10.38}$$

So, **the preferences embedded in $\boldsymbol{A_{LCOE}}$ preserve the absolute order defined by the Discrete Choice Model from section 10.3**.

10.5.3 The weight vector $\boldsymbol{w_A}$

Following the AHP methodology, the weight vector $\boldsymbol{w_A}$ can be calculated as the principal eigenvector of matrix $\boldsymbol{A_{LCOE}}$, with n being the principal eigenvalue ($n = 24$ in FTT:Power).

The preferences defined by the Discrete Choice Model of section 10.3, which are preserved by the matrix $\boldsymbol{A_{LCOE}}$, correspond precisely to the weight factors inside $\boldsymbol{w_A}$. According to **Property 1** of section 10.4.2 (equation 10.20), the matrix $\boldsymbol{A_{LCOE}}$ has the form:

$$\boldsymbol{A} = \begin{pmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{pmatrix} = \begin{pmatrix} 1 & P_{12}/P_{21} & \dots & P_{1n}/P_{n1} \\ P_{21}/P_{12} & 1 & \dots & P_{2n}/P_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1}/P_{1n} & P_{n2}/P_{2n} & \dots & 1 \end{pmatrix} \tag{10.39}$$

From the element (i, j) of the matrix $\boldsymbol{A_{LCOE}}$, we obtain:

$$a_{ij} = \frac{w_i}{w_j} = \frac{P_{ij}}{P_{ji}} = \frac{P_i}{P_j} \tag{10.40}$$

The last equality comes from equation 10.34. Isolating w_i :

$$w_i = \frac{P_i \cdot w_j}{P_j} \tag{10.41}$$

By definition, the sum of the weighting factors is 1. Therefore:

$$\sum_i w_i = 1 = \sum_i \frac{P_i \cdot w_j}{P_j} = \frac{w_j}{P_j} \quad \Rightarrow \quad w_j = P_j \tag{10.42}$$

This is a very important result. Given the ratio scale defined in section 10.5.1, the weight vector $\boldsymbol{w_A}$, preserves the preferences defined by the probability P_j. These probabilities correspond to the multinomial logit model introduced in sections 10.3 and 10.3.1. Therefore, from the weight vector $\boldsymbol{w_A}$, it is possible to reconstruct the $F_{ij} = P_{ij}$ terms of the FTT:Power shares equation (4.5):

$$P_{ij} = 1 - P_{ji} = 1 - P_{ij} \cdot \left(w_i/w_j\right) \quad \Rightarrow \quad P_{ij} = \frac{w_i}{w_i + w_j} = \frac{P_i}{P_i + P_j} \tag{10.43}$$

While equation 10.42 connects the weight factors of AHP with the MNL distribution, equation 10.43 provides the connection back to the BNL distribution. These results show the theoretical equivalence between the incumbent and the proposed investment decision modelling framework of FTT:Power. While the decision model introduced in section 10.3 is based on a purely discrete choice modelling approach, the model proposed in this section incorporates the AHP methodology. The change in methodology enables the inclusion of a variety of investment criteria, without loosing the FTT:Power main features.

Equation 10.42 is a very important result, that connects two discrete choice models, Binary Logit and Multinomial Logit, with Analytic Hierarchy Process, in an unprecedented level. This is formalised in a theorem, in the appendix chapter D.4.

Sections 10.3 and 10.4 introduce the fundamental elements to create a multicriteria investment model in FTT:Power: Discrete Choice Theory and the Analytic Hierarchy Process. And section 10.5 combines those elements to emulate the original implementation of the FTT:Power's investment model. In the next section, a methodology to expand the investment model is proposed, making use of the flexibility provided by AHP.

10.6 Multicriteria Investment Model

The LCOE is a very good tool to compare the unit costs of different technologies over their economic lifetime (IEA et al., 2010). It combines a large set of information, including expected values of the lifetime of the power stations, energy produced, investment costs, operation costs, fuel use and some environmental costs (see section 4.6.1). However, one of the main limitations of the LCOE to evaluate electricity generation technologies, is the the lack of an explicit representation of risk and uncertainty. All the LCOE components are prone to uncertainty, and the net present value methodology embedded in the LCOE calculation is not fitted to address it, neither in the forecast of costs nor in the forecast of energy production and prices.

The evaluation of technology using the LCOE methodology omits some of the risks faced by investors. Among the main risks listed by IEA et al. (2015), are:

- Regional risks associated with uncertainty on fiscal policy, energy security and exchange rate.
- Technological risks, related to technologies that are capital intensive, first-of-a-kind deployment or that internalise externalities (such as nuclear waste storage and site restoration).

- Project risks at the local level, regarding the availability of natural resources, such as access to water for steam-based power generators.
- Market risks, particularly related to uncertainty in input and output quantities and prices.
- Environmental risks, that can be endogenous (produced by the use of a specific technology), exogenous or mixed.

Many of the aforementioned risks play a relevant role at the investment decision level (IEA et al., 2015). Therefore, it is important to expand the investment decision model of FTT:Power, to incorporate criteria beyond the LCOE. With the inclusion of the Analytic Hierarchy Process methodology presented in the previous sections, the addition of new investment criteria in FTT:Power is straightforward. The next section shows, step by step, how to create new branches of the AHP tree, following the same approach introduced in section 10.5.

10.6.1 New branches in the AHP tree

The flow diagram of figure 10.4 shows the algorithm for incorporating a new branch into the AHP tree of FTT:Power. A generic example of AHP tree is presented in figure 10.5. As mentioned in section 10.4.1, the AHP tree is recursive, so it is the process of adding new branches.

Step 1: Definition of the criterion and the scale

The first step in the addition of a new criterion into the AHP tree, is the definition of the criterion itself, and the corresponding scale of comparison. The alternatives in AHP are compared pairwise, and this pairwise comparison process defines the relative preference of one alternative with respect to another (the *dominance*), under a specific criterion. The qualitative or quantitative nature of the criterion, as well as the subjective or objective type of comparison, constrain the type of scale that can be used for measuring the relative preference of the alternatives. One option for doing the *judgment of comparison* is the **relative scale suggested by Saaty**, presented in table 10.1. This scale is subjective, and works well for comparing alternatives that are difficult to quantify. For instance, in the example of the family car purchase introduced in section 10.4.1, Saaty's scale is used for the *style* criteria (see table

10.17). Another option is to use a **scale constructed from absolute values**. In the same example of the family car purchase, the comparison of the alternatives under the *purchase price* criterion is made on a scale created with the car prices. This scale, based on absolute values (car prices) is presented in section 10.4.5.

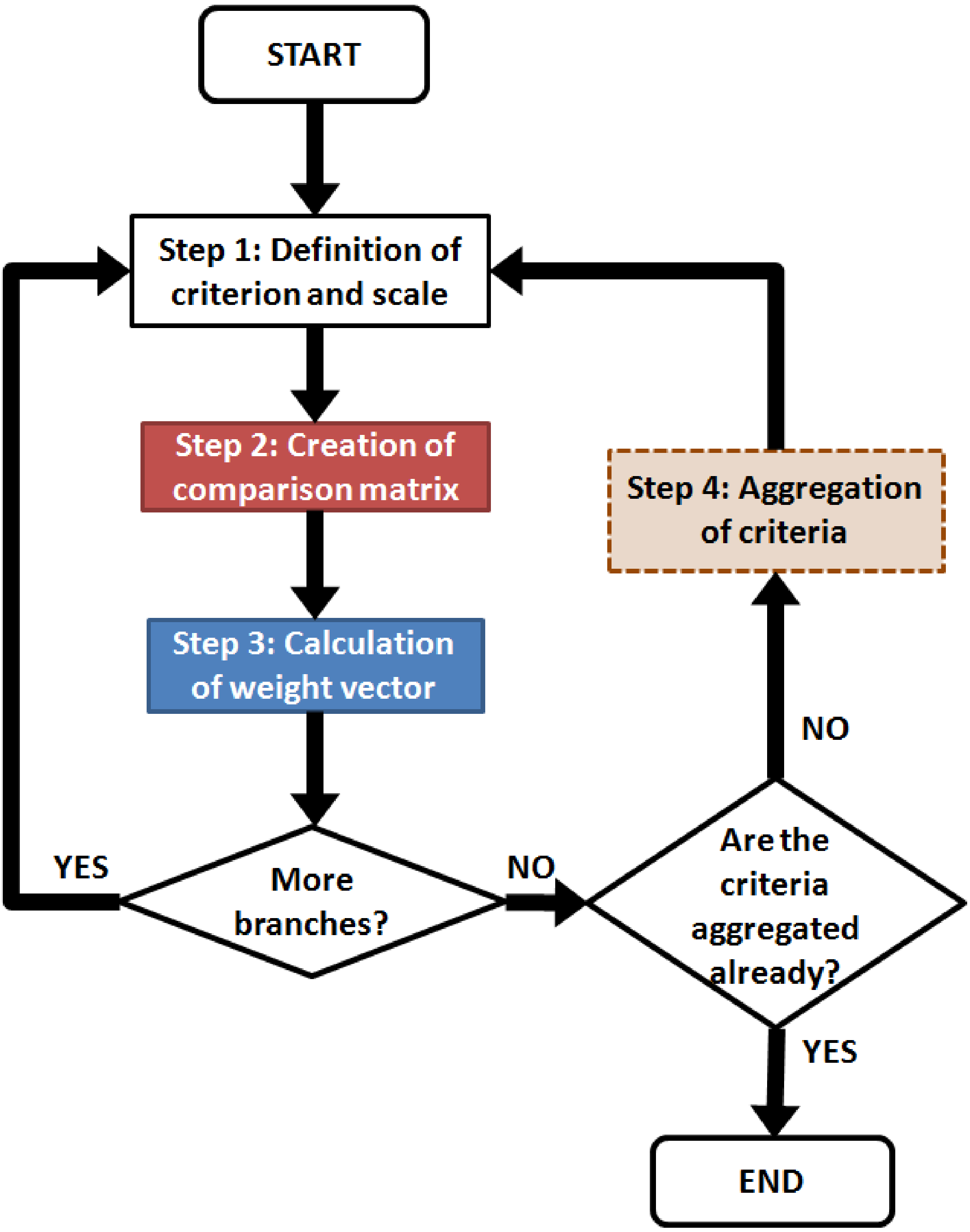


Figure 10.4 Algorithm for the expansion of the AHP tree. The colors in the flow diagram match the corresponding elements of the AHP tree of figure 10.5

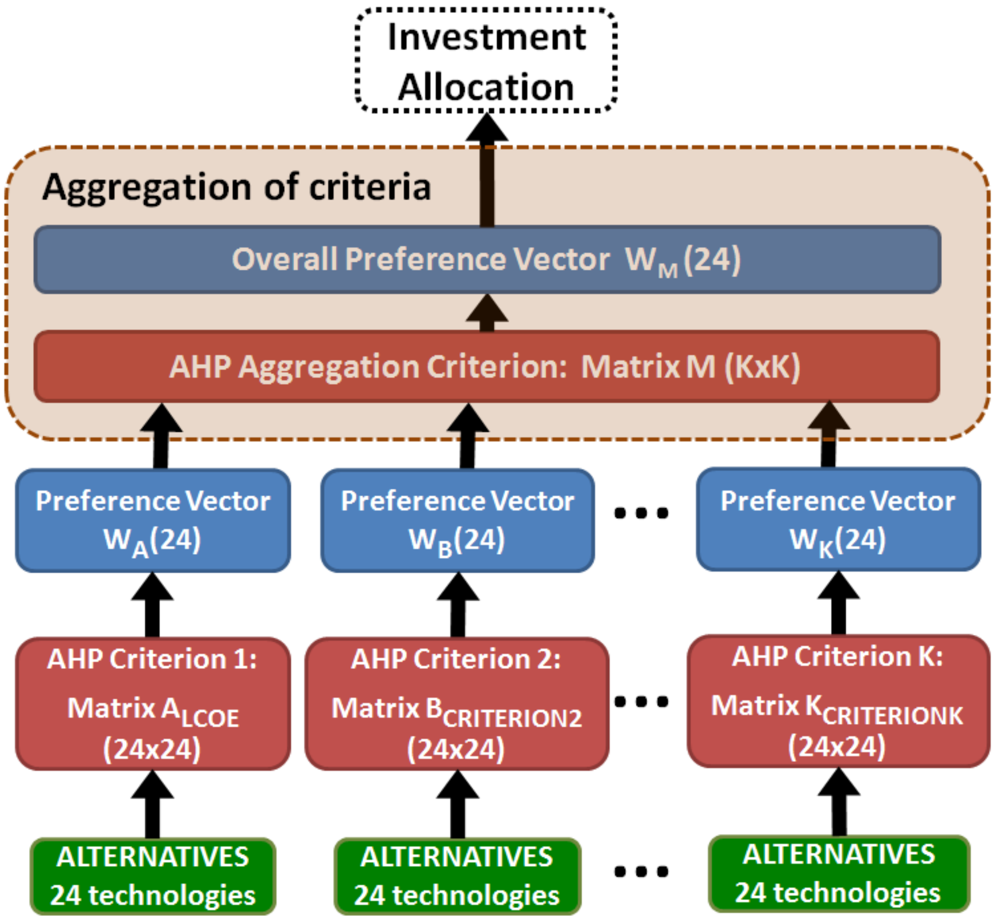


Figure 10.5 Example of a possible AHP tree for the investment model of FTT:Power. It includes the LCOE criterion (extreme left), plus other K-1 criteria. The colors correspond to those used in the expansion algorithm, in figure 10.4.

In the case of the LCOE criterion of the new FTT:Power investment model introduced in section 10.5, and absolute scale is used. This scale is based on the probabilities of choosing a technology, given the multinomial logit model presented in section 10.3.1. The creation of the scale, using the probability values, is shown in detail in section 10.5.1.

Step 2: Comparison matrix

After the definition of the criterion and the scale, the alternatives have to be compared. The pairwise comparison results are stored in a matrix, called *pairwise comparison matrix*. If n alternatives are compared, then the size of the pairwise comparison matrix is $n \times n$. An element in the position (i, j) represents the relative importance of i with respect to j. The diagonal elements of the matrix are equal to 1, that represents indifference between two alternatives (see the example of the $\boldsymbol{A_{style}}$ matrix in equation 10.17).

The pairwise comparison matrix is required to satisfy some conditions, in order to preserve the preferences of the decision maker.

- The pairwise comparison matrix has to be **consistent**: $a_{ij} \cdot a_{jk} = a_{ik} \quad \forall i, j, k = 1, ..., n$
- If there is a degree of *intransitivity* in the decision maker's preferences, then the pairwise comparison matrix might not be consistent. In that case, the matrix has to be:
  - Near consistent: the normalised difference between the principal eigenvalue of the pairwise comparison matrix and the number of alternatives has to be "small". In this context, "small" means 5% for 3 alternatives, 8% for 4 alternatives and 10% for more alternatives.
  - Reciprocal: All the elements of the pairwise comparison matrix have to satisfy $a_{ij} = 1/a_{ji} \quad \forall i, j = 1, ..., n$

If these conditions are met, then the preferences of the decision maker embedded in the pairwise comparison matrix are preserved in the eigenvector of the matrix. The next step is to calculate the eigenvector of the pairwise comparison matrix.

Step 3: Weight (or score) vector

If a consistent (or near consistent) pairwise comparison matrix is created, then its **eigenvector** preserves the order relation embedded in the matrix (Saaty, 1999). The calculation of the eigenvector of a square matrix is a standard procedure, and corresponds to the solution of the equation:

$$(\boldsymbol{A} - n\boldsymbol{I}) \cdot \boldsymbol{w_A} = 0 \tag{10.44}$$

where $\boldsymbol{A}$ is the pairwise comparison matrix, n is the number of alternatives, $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{w_A} = [w_1 ... w_n]$ is the eigenvector of $\boldsymbol{A}$.[17]

Given a criterion, and the associated pairwise comparison matrix, the eigenvector of the matrix represents the top of the corresponding AHP tree branch. These are the small blue

[17] The procedure to calculate eigenvectors can be found in any linear algebra textbook.

boxes in the diagram of figure 10.5. To create each branch, the steps 1, 2 and 3 have to be followed. If an AHP tree has K branches (like the one in figure 10.4), then K vectors of $n = 24$ elements each will be obtained.

After all the branches of the AHP tree have been created, the next step is to aggregate them into one comparison matrix. Because the AHP methodology is recursive, the procedure for aggregating the K branches of the AHP tree is the same procedure used for aggregating the $n = 24$ alternatives in one branch. The only difference is, that instead of having 24 alternative technologies, there are K alternative branches. This is shown by the semi-transparent brown boxes in the diagrams of figures 10.4 and 10.5.

As shown in the flow diagram, after all the AHP branches are created, the aggregation stage requires to go back to Step 1: to define a criterion and a scale to compare the K branches. After the criterion and the scale are defined, the following step (Step 2), is to make a pairwise comparison matrix of size $K \times K$, that stores the preferences of the decision-maker regarding the K alternative criteria. This matrix is represented by the large red box in the upper part of the diagram of figure 10.5. Finally, with the pairwise comparison matrix ready, the next step (Step 3) is to calculate its eigenvector. If the matrix is (at least near) consistent, then the eigenvector preserves the preferences of the decision-maker. This vector is represented by the large blue box at the top of the diagram of figure 10.5.

Step 4: Aggregated preferences vector

At this stage, there are K vectors with $n = 24$ elements each, representing the preferences for the technology alternatives under each specific criterion. And there is another vector, with K elements, with a ranking of the different AHP tree branches. All these vectors are represented by blue boxes in figures 10.2, 10.3, 10.4 and 10.5. This is all the information needed to calculate the overall preferences (alternatives and branches) of the decision maker. The aggregated preferences, is simply the linear combination of the $K+1$ weight vectors:

$$\boldsymbol{W_{final}}(i) = \sum_{j=1}^{K} \boldsymbol{w_M}(j) \cdot \boldsymbol{w_j}(i), \quad i = 1, \cdots, 24 \tag{10.45}$$

where $\boldsymbol{w_M}$ is the ranking of the AHP branches, and $\boldsymbol{w_j}$, $j = 1 \ldots K$ are the K ranking vectors of the K criteria. The vector $\boldsymbol{W_{final}}$ corresponds to the final ranking of the $n = 24$ alternatives, weighted by the respective importance (or dominance) of the criteria included in the AHP tree. In the traditional AHP methodology, the alternative with the highest score (or weight) would be chosen. However, in the case of FTT:Power, the $\boldsymbol{W_{final}}$ is interpreted as a measure of relative investment preferences (the different interpretations are discussed in section 10.4).

10.6.2 Some criticism of the Multicriteria Investment Model

The combination of the discrete choice theory with the analytic hierarchy process methodology provides the mean for the replication of the current investment preference function of FTT:Power, and also for expanding it, so new investment criteria can be incorporated into the decision-making process. The new methodology has some limitations, many of which are connected with the limitations of the underlying theories. In this section, I discuss some of these limitations, from a theoretical perspective. In the next chapter, after introducing a practical example of a new AHP-based investment model for FTT:Power, I retake the discussion from a more practical perspective.

Mutual preference independence and (in)consistency

In the analytic hierarchy process methodology, alternatives are aggregated through linear combination of weights, as shown by equation 10.45. This methodology has the embedded assumption of *mutual preference independence*: trade-offs between two (or more) alternatives do not depend upon the levels of other alternatives (Fischhoff et al., 1984). In the case of the power sector, mutual preference independence would require the options to be perfect substitutes. While the electricity produced by the various technologies is not differentiable, this is not the case for the externalities associated with the process of producing that electricity. Consequently, the electricity produced by two different sources (for instance, coal and wind), are not necessarily seen by investors as the same good.

The assumption of mutual preference independence is also part of the original FTT:Power model. However, the AHP process extends the perfect substitutability requirement from the energy alternatives to the aggregation criteria, if weights are defined independently in the aggregate comparison matrix $\boldsymbol{M}$. In other words, if the elements of the aggregate comparison matrix are independently defined, then trade-offs between two (or more) criteria do not depend upon the levels of other criteria, so perfect substitutability is assumed. If investment criteria are not exchangeable, then a feedback mechanism has to be in place, to reflect the preference relation of one criterion over another. The obvious requirement, on this regard, is the use of a consistent matrix, that imposes a transitive preference relation between the elements of the matrix. This is shown, in practice, in section 11.5.1.

The use of consistent matrices for representing preferences, as it its shown later in chapter 11, has some positive and negative implications. On the one hand, consistent matrices preserve transitivity, and consequently, eigenvectors maintain the preferences embedded in the comparison matrices. On the other hand, there is plenty of evidence that people show persistent patterns of intransitive choice behaviour (Korhonen et al., 1990), that cannot be explicitly represented by consistent matrices. Therefore, there is a clear trade-off between having a "stylised" decision-making model that preserve investor's preferences in the final results, and a more realistic representation of preferences with room for inconsistent behaviour.

Scale of preferences without zero

The ratio scale embedded in the AHP methodology, makes impossible to have values of dominance equal zero. This is clear from the *reciprocity* property (see section 10.4.3).[18] Therefore, if the criterion of the AHP branch is based on a measurement scale that passes through the origin, a transformation must be used. The transformation can, but does not have to have a range equal to the scale presented in table 10.1. The new investment criteria presented in chapter 11 use linear transformations to change from their fundamental scale to the scale of table 10.1, because of this limitation. In the case of the LCOE criterion, the dominance values are calculated as the ratio of probabilities in the form of $exp\left(U_i\right)$, therefore, no transformation is required.

Investors' preferences data

As explained in section 10.4.5, the pairwise comparison matrices can be built using absolute scales, based on standard measurements. In those cases, preferences are based on objective criteria, such as the LCOE (or prices, as in the family car purchase example). There is plenty of evidence, however, that investment decisions are also based on subjective criteria, such as a priori beliefs or technological risk attitudes (Masini and Menichetti, 2012). If those criteria were to be incorporated into the investment decision model, then the process of building the pairwise comparison matrix would require data about the subjective preferences of investors regarding those criteria. Such data is not easy to obtain, or may not even exist at all. Therefore, the theoretical capability of including subjective investment criteria in the decision-making model, is constrained by the practical limitations of investors' preferences data availability.

[18] If the matrix is consistent, then either none or all the elements of the pairwise comparison matrix are zero.

10.7 Conclusions

In this chapter, a new methodology to model investment decisions in FTT:Power is introduced. The new methodology builds on two pillars: Discrete Choice Theory (DCT) and Analytic Hierarchy Process (AHP). Combining these two approaches, the incumbent investment decision model of FTT:Power is reformulated. The new model has a more flexible structure, based on a multicriteria decision making approach.

In the process of reformulating the FTT:Power investment model, a novel link has been established between the AHP methodology, and the Binomial and Multinomial Logit (BNL and MNL) distribution from DCT. The newly proposed methodology transfers the preferences of the decision maker (investor) from the DCT distributions to the pairwise comparison matrix of AHP, bridging the two theories in an unprecedented level. The formalisation of this connection is presented as a theorem in the appendix section D.4.

The replication of the FTT:Power investment model using a multicriteria decision making approach, enables its expansion. Under the new framework, new investment criteria can be incorporated as part of the decision making process. The incumbent approach, based on the LCOE as the solely investment allocation criterion, can now be complemented with considerations that go beyond pure market competition. In order to facilitate the incorporation of new investment criteria in FTT:Power, the methodology to expand the current investment decision model is presented in detail in this chapter, with a step-by-step guidance. This methodology is put into practice in chapter 11, where two new criteria are added to the FTT:Power investment decision model.

Together with the procedure for expanding the model, the chapter presents some fundamental critics to the new multicriteria investment model. They are based on the main limitations of AHP, as well as in the availability of investor's preferences data.

Chapter 11

Energy Scenarios under Different Investment Criteria

11.1 Chapter Summary

This chapter uses the methodology introduced in chapter 10, for the creation of a multicriteria investment model for FTT:Power. As explained in detail in section 10.5, the combination of Discrete Choice Theory (DCT) with the Analytic Hierarchy Process (AHP) provides the basis for the replication of the incumbent FTT:Power investment model. The particular characteristics of AHP, which is a multicriteria decision-making approach, allows the expansion of the model, to incorporate criteria beyond market considerations. Following the step-by-step guidance of how to add a new branch to the AHP tree from section 10.6, sections 11.2 and 11.3 introduce two new criteria into the FTT:Power investment model: *environmental considerations* and *policy uncertainty*.

Chapters 5, 7, 8 and 9 analysed uncertainty from the perspective of variability on the drivers of technological change (policy stringency, availability of energy resources, learning coefficients and flexibility of the grid to incorporate variable electricity), without internalising the uncertainty on investment decisions. In other words, the analyses presented in chapters 7, 8 and 9 correspond to the classical uncertainty propagation analysis using simulation based methods (Lee and Chen, 2008).[1] In this chapter, however, uncertainty about the environmental impacts of climate change, and uncertainty about the effect of energy policy

[1]Uncertainty propagation analysis using simulation based methods is typically based on Monte Carlo simulations (Lee and Chen, 2008). However, the analyses presented in chapters 5, 7, 8 and 9 only use the extreme of the intervals of each uncertainty range, instead of using a representative sample from it. The

on the levelised cost of electricity, are incorporated as part of the investment decision process. In this context, the analysis presented in this chapter can be considered as structural or model structure uncertainty (Walker et al., 2005).

The chapter is structured as follows: sections 11.2 focuses on the effects of environmental considerations in investment decisions. Sections 11.2.1 and 11.2.2 introduce the environmental considerations investment criterion, together with a scale and a pairwise comparison matrix. Then, section 11.2.3 creates an aggregate comparison matrix, to combine the LCOE with the environmental considerations criteria in one single tree. Finally, section 11.2.4 compares power sector scenarios created with the incumbent and the new investment model. As it might be expected, the scenarios based on purely environmental considerations lead to emissions peaking earlier than the scenarios driven by market-based investment decisions. Under stringent decarbonisation policies (DEC scenario), the difference in cumulative emission by 2050 between the investment scenarios based on market versus environmental considerations is approximately 106 $GtCO_2$.

Section 11.3 focuses on the effects of policy uncertainty in investment decisions. Section 11.3.1 introduces the new investment criterion, together with the scale and the pairwise comparison matrix. Then, in sections 11.3.2 - 11.3.4, the steps for the the aggregation of the three criteria, LCOE, environmental considerations and policy uncertainty, is presented in detail. Finally, section 11.3.5 compares scenarios created with the different combinations of the new and old investment criteria. The policy uncertainty investment criterion seems to have a less significant effect on emissions than the environmental considerations criterion. In terms of cumulative emissions by 2050, the scenario based on investment decisions driven by policy uncertainty exhibits approximately 25 $GtCO_2$ less than the decarbonisation scenario based on the incumbent investment model, and around 81 $GtCO_2$ more than the scenario based solely on environmental considerations.

11.2 The Effect of Environmental Uncertainty in Investment Decisions

In the context of a changing global climate, there is growing evidence of the shifts in market sentiment induced by the awareness of future climate risks, and the required changes in asset allocation for hedging against the negative impacts of climate change (CISL, 2015).

only exception is the scenario presented in section 8.4, where the Brazilian cost supply curve range for hydroelectricity is sampled 120 times, using LHS method (Helton and Davis, 2003).

In the case of long term investment, such as sovereign funds as well as some pension funds, stakeholders are putting pressure to allocate the money in sustainable assets, including renewable energies (Mansley and Dlugolecki, 2001; Reiche, 2010). For instance, in 2016 the University of Cambridge joined Oxford and Yale in blacklisting investments in coal and tar sands companies, after facing pressure from students and academics to shun highly polluting fossil fuels (FT, 2016). The gradual change in the relative importance of environmental considerations in energy investment is growing under more uncertain scenarios of climate change, and investment in infrastructure (such as power stations) is increasingly affected by environmental uncertainty (Hallegatte, 2009).

Environmental concerns are addressed in FTT:Power throw policy regulation. The implementation of policies such as carbon pricing, subsidies and feed-in-tariffs have a direct effect on the price of electricity, and correspondingly on investment allocation.[2] However, the influence of market based mechanisms in investment decisions do not take into consideration environmental uncertainty. In order to model explicitly the effect that environmental uncertainty has in energy investment, a new branch for the FTT:Power investment model presented in chapter 10 is proposed, focused on environmental considerations in investment decisions.

The following sections explain how the procedure described in section 10.6 to add new branches to the AHP investment tree is used in practice. In that context, the new FTT:Power investment model proposed in chapter 10, that replicates the incumbent model, is assumed to be already implemented inside FTT:Power. For the details about the new investment model, please refer to chapter 10.

11.2.1 Step 1: environmental criterion

Following the procedure described in section 10.6.1, the first step to create the new AHP tree branch is to define the criterion and the scale. In the context of environmentally driven investment considerations, it is reasonable to assume that preferences are inversely proportional to the environmental impacts of the specific alternatives: technologies with low environmental impacts are preferred over technologies with high environmental impacts.

Atmospheric pollution, land use and water use are among the main environmental impacts associated with the production of electricity (GEA, 2012, ch. 3). The mayor energy-related sources of atmospheric pollution include carbon dioxide, methane, sulphur dioxide and nitrogen oxides, being the former the most important contributor to anthropogenic

[2]See section 4.3 for an explanation of the LCOE framework inside FTT:Power.

climate change (IPCC, 2014d, p. 7). In this context, the environmental impacts of different technologies, in relation to climate change and atmospheric pollution, can be compared using the carbon intensity: higher the amount of carbon emitted, larger the environmental impact, per unit of energy produced using the specific technology. In the case of land use, impacts are associated with the amount of land required (per unit of energy produced), and how the land is used. Biomass, for instance, requires more land than any other type of energy to produce electricity, with a land-use intensity two orders of magnitude higher than coal or nuclear energy (McDonald et al., 2009). And if nutrients demand is taken into account, the different types of biomass resources have different impacts in the land use (Miller, 2010). In the case of water, there are three main areas on which energy production produces relevant impacts: in the production of biomass (plantation stage), in the processing of energy (such as coal washing or cooling of fossil fuel and nuclear power stations), and direct electricity production (such as hydro, wave or tidal power generation) (GEA, 2012, p. 235).

In the context of the new AHP tree branch, only the environmental impacts associated with atmospheric pollution are considered. The impact of electricity production on emissions is quantified through the carbon intensity of the different energy alternatives.[3] Therefore, preferences for technologies are assumed to be inversely proportional to their corresponding carbon intensity, under the environmental criterion. Notice that the environmental criterion does not cancel the effect of policies (such as carbon pricing) on investment decisions, which are embedded in the other AHP tree branch (the LCOE branch).

In parallel with the definition of the criterion, it is necessary to define a scale to compare the alternatives. If c_i is the carbon intensity of technology i, then the set $C = \{c_i, i = 1...24\}$ defines an absolute scale for the FTT:Power technologies. The absolute scale defined by C, however, cannot be directly used in the AHP pairwise comparison matrix, because non-polluting technologies have a value of $c_i = 0$. Therefore, a linear transformation is required (for a discussion about the use of zero in AHP comparison scales, please refer to section 10.6.2). I use a linear transformation $\psi(c_i)$, that coincides with Saaty's fundamental scale[4] (Saaty, 1999):

$$\psi_i = \psi(c_i) = 1 - \frac{8 \cdot (c_i - c_{imax})}{(c_{imax} - c_{imin})} \tag{11.1}$$

[3]Carbon intensity is measured as emissions per unit of energy produced. Values for carbon intensity in FTT:Power are based on the IPCC Guidelines for National GHG Inventories (IPCC, 2006).

[4]For an explanation of Saaty's fundamental scale, and other basic AHP concepts, please refer to section 10.4.1.

where c_{imax} and c_{imin} are the maximum and minimum carbon intensities, respectively. The range of the scale introduced by ψ_i goes from 1 to 9. The lower and upper limits of the interval correspond to technologies with maximum and minimum carbon intensity, respectively.

11.2.2 Steps 2 and 3: comparison matrix and weight vector

Given the criterion and the scale defined in the previous section, the alternatives can now be compared pairwise. Following the example of the LCOE criterion presented in section 10.5, I propose a pairwise comparison matrix $\boldsymbol{A_\psi}$ with the form:

$$a_{ij} = \frac{\psi_i}{\psi_j} \quad \forall i, j = 1, \cdots, 24 \tag{11.2}$$

Then, the matrix $\boldsymbol{A_\psi}$ is consistent (see section 10.4.2), and its eigenvector vector $\boldsymbol{w_\psi}$ defines a ranking for the n alternatives compared by $\boldsymbol{A_\psi}$. The largest and smallest *dominance* values are 9 and 1/9, respectively. They correspond to the cases when technologies with minimum and maximum carbon intensities are compared. According to Saaty's fundamental scale, they represent extreme preference of one technology over another (Saaty, 1999).

11.2.3 Step 4: Aggregated preferences vector

At this stage, we have two AHP branches: the incumbent branch based on the LCOE criterion, and a new branch based on environmental considerations. Each of them have a pairwise comparison matrix and a weight vector: $\boldsymbol{A_{LCOE}}$ and $\boldsymbol{w_A}$ for the former (see section 10.5), $\boldsymbol{A_\psi}$ and $\boldsymbol{w_\psi}$ for the later. The next step is to combine the two AHP branches, using a comparison criterion. The carbon intensity scale introduced in section 11.2.1, is a representation of preferences driven purely by environmental concerns. Similarly, the AHP branch based on the LCOE (presented in section 10.5), only represents preferences driven by economic considerations. The relative importance of both criteria in the final investment decision process is arguably in favour of the latter, especially in competitive markets (IEA and OECD, 2003; Joskow, 2008). However, under increasingly severe scenarios of climate change, the relative importance of these criteria are expected to change (Fayers et al., 2000; Nilsson et al., 2008). Therefore, instead of using a constant comparison criterion for the two AHP branches, **I propose a variable criterion, that depends on the level of environmental uncertainty**.

At the firm level, profit maximisation objectives hinder the inclusion of non-market considerations (such as environmental considerations) as a relevant investment criterion (Haigh and Hazelton, 2004). However, at the aggregate level, environmental considerations have an increasingly influential role in the decision making process. There is clear evidence of the increasing influence of non-governmental organisations (NGOs) in the adoption of corporate social responsibility and responsible business practices (Guay et al., 2004). Companies operating in global markets, are increasingly required by stakeholders and clients to balance economic, social and environmental considerations, while building shareholder value (Morimoto et al., 2005). An increasing number of corporations are adopting initiatives and programs oriented towards the environmental and ethical responsibilities of businesses (for instance, Carroll and Shabana (2010) presents the case of the British paper manufacturer Antalis, while Fowler and Hope (2007) presents the case of the California-based outdoor apparel company Patagonia). In this context, there is a compelling argument to include the environmentally driven considerations, as part of the aggregate investment decision process.

Impacts from recent climate related extreme events, such as heat waves, droughts, floods, cyclones, and wildfires, reveal significant vulnerability to climate variability (IPCC, 2014a, p. 6). The specific relation between global temperature increase and its potential impact on human systems is not yet fully understood, and is subject of heated debate (Grubb, 2014; IPCC, 2014d). Therefore, instead of using an arbitrary function for the uncertainty of the potential damages associated with climate change, I use a proxy of temperature increase as an indicator of environmental uncertainty. According to the Fifth Assessment Report of the IPCC, there is a near-linear relationship between cumulative emissions and global temperature increase (IPCC, 2014c, p. 62). Therefore, cumulative emissions (as a proxy of global temperature increase) can be considered as an indicator of environmental uncertainty.

Based on the previous arguments, an adaptive comparison criterion is proposed for weighing the importance of the LCOE (or market) criterion versus the carbon intensity (or environmental) criterion in the investment decision process. This adaptive comparison criterion uses the cumulative emissions, as a proxy of environmental uncertainty, to weigh both investment criteria. So, larger the environmental uncertainty, lower the relative importance of the LCOE criterion with respect to the carbon intensity criterion. Following the AHP methodology, the environmental criterion has to be compared with the LCOE criterion, in terms of their relative importance (or *dominance*) in the decision process (see section 10.4.1). The dominance of LCOE with respect to environmental considerations, is represented by a function that decreases with environmental uncertainty, captured by cumulative emissions. Assuming an initial *very strong importance* of economic over environmental considerations (IEA and

OECD, 2003; Joskow, 2008), the proposed function follows Saaty's scale presented in table 10.1:

$$f_{LCOE}(t) = \frac{80}{9} \cdot (1 - \tanh(\alpha \cdot (E(t) - E_0))) + \frac{1}{9} \tag{11.3}$$

where E_0 and E are the cumulative emissions at the beginning of the simulation and at time t (in GtC), α is a convergence speed parameter, and *tanh* is the hyperbolic tangent function. The behaviour of the function f_{LCOE} is shown in figure 11.1. The term α in equation 11.3 represents the speed of the convergence of the two criteria. Higher the value of α, faster the two criteria become closer in terms of relevance. In figure 11.1, the curve moves to the left for higher values of α. For a value of $\alpha = 0.0037$ and $E_0 = 400GtC$, investors become indifferent between the LCOE and the environmental considerations, when cumulative emissions rise up to 2 times the initial levels. I.e., in a scenario where cumulative emissions reach the $800GtC$, environmental and economic considerations have an equal degree of importance in the investment decision process.[5]

f_{LCOE} is the dominance of the LCOE criterion over the environmental criterion in the aggregated preferences matrix. I.e., the function f_{LCOE} connects the two AHP tree branches, through the matrix of aggregated preferences. The 2×2 aggregated preferences matrix is presented below, in equation 11.4. If more criteria are incorporated in the AHP tree, then a larger matrix is required, to make the pairwise comparison between all the criteria.

$$\boldsymbol{M} = \begin{array}{c c} & \begin{array}{cc} \text{LCOE} & \text{Env.} \end{array} \\ \begin{array}{c} \text{LCOE} \\ \text{Env.} \end{array} & \begin{pmatrix} 1 & f_{LCOE} \\ 1/f_{LCOE} & 1 \end{pmatrix} \end{array} \tag{11.4}$$

The matrix $\boldsymbol{M}$ is consistent. The eigenvalue of $\boldsymbol{M}$ is 2, and the weight vector (corresponding to the eigenvector of $\boldsymbol{M}$), is:

$$\boldsymbol{w_M} = \left[\frac{f_{LCOE}}{1 + f_{LCOE}}, \frac{1}{1 + f_{LCOE}} \right] \tag{11.5}$$

The upper limit of f_{LCOE} is 9 (for $E = E_0$), and the asymptotic lower limit is $1/9$ (for $E \to \inf$). Therefore, the weight vector varies between:

[5] While the relative importance of environmental considerations is expected to increase under strong scenarios of climate change (Fayers et al., 2000; Nilsson et al., 2008), the speed and final level of such convergence are not possible to predict. Therefore, the use of an uncertainty range is appropriate.

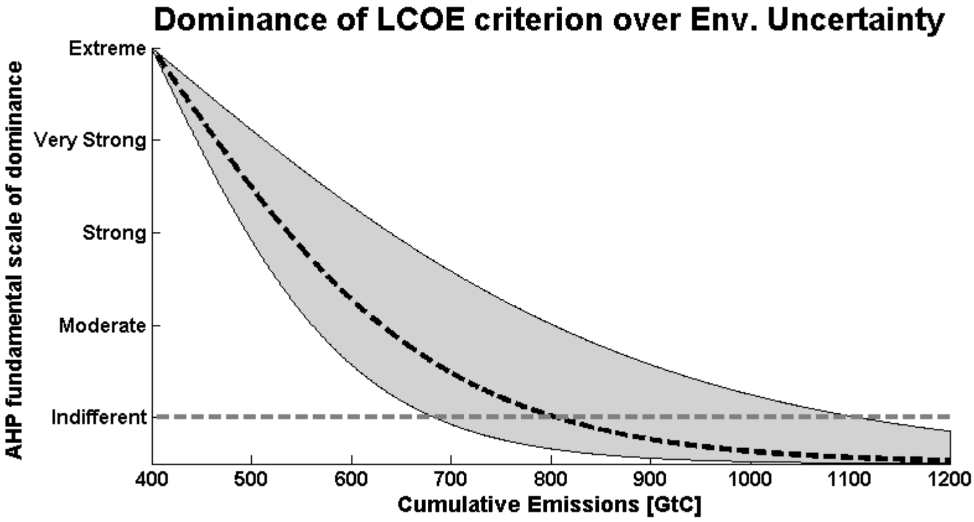


Figure 11.1 Dominance of economic (LCOE) with respect to environmental considerations, as defined by function f_{LCOE} in equation 11.3. The abscissa represents cumulative emissions (in GtC), while the ordinate represents Saaty's fundamental scale of dominance (see table 10.1). The decreasing curve represents the increasing relevance of environmental uncertainty in the investment decision process. The term α in equation 11.3 represents the speed of the convergence of the two criteria. Higher values of α move the curve to the left. The middle curve (black dashed line), represents the case when both criteria, LCOE and environmental considerations, become equally relevant at cumulative emissions approximately equal to $800GtC$ (horizontal dashed line). The minimum, central and maximum values for α are 0.0020 (right curve), 0.0037 (central dashed line) and 0.0070 (left curve), respectively. Values of α were chosen arbitrarily, for illustrative purposes.

- $\boldsymbol{w_M} = \left[\frac{9}{10}, \frac{1}{10}\right]$, for $E = E_0$
- $\boldsymbol{w_M} = \left[\frac{1}{10}, \frac{9}{10}\right]$, for $E \to \inf$.

I.e, under low cumulative emissions, the LCOE criterion has a *very strong importance* in comparison with the environmental criterion.[6] Under increasing cumulative emissions, the importance of the environmental criterion rises, converging to a *very strong importance* for an infinite amount of cumulative emissions. The exact tipping point depends on the uncertain parameter α.

[6]In an environmentally friendly scenario, where cumulative emissions converge to a value smaller than E_0, f_{LCOE} rises over the maximum value of Saaty's scale. In other words, the environmental criterion becomes irrelevant in comparison with the LCOE criterion. Such convergence is reasonable, and indicates that after decarbonising the global economy, environmental uncertainty in not longer relevant in investment decisions.

Finally, combining all the weight vectors, the final ranking of the AHP tree (including the *LCOE* branch and the environmental considerations branch) can be calculated as (see section 10.6.1 for more details):

$$\boldsymbol{W_{final}} = \boldsymbol{w_M}(1) \cdot \boldsymbol{w_A} + \boldsymbol{w_M}(2) \cdot \boldsymbol{w_\psi} \tag{11.6}$$

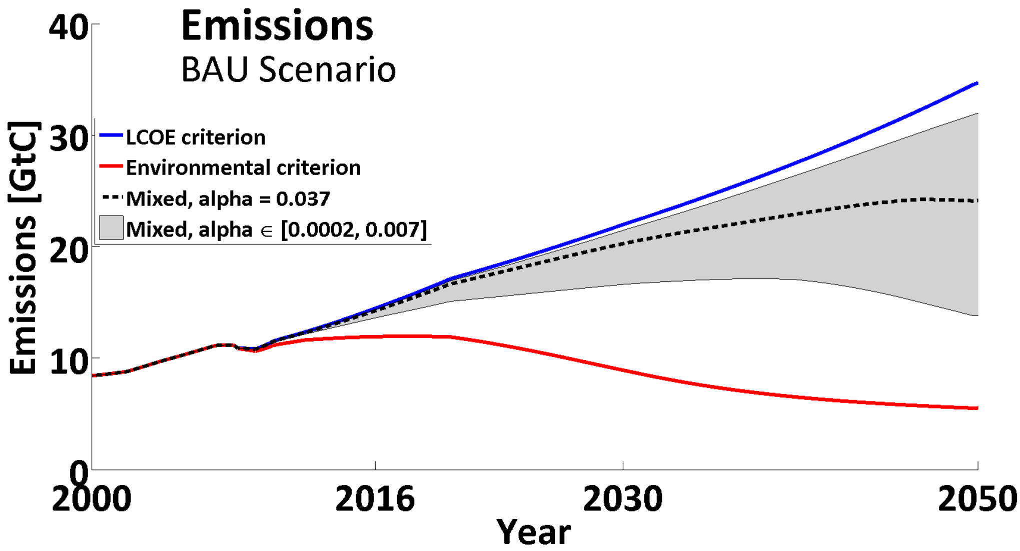
where $\boldsymbol{w_A}$ is the preference vector of the *LCOE* branch, $\boldsymbol{w_\psi}$ is the preference vector of the environmental considerations branch, and $\boldsymbol{w_M}$ is the vector of aggregated preferences.

11.2.4 Comparison of scenarios with different investment criteria

Figure 11.2 shows emission trajectories for the power sector using different investment criteria. The top chart of figure 11.2 corresponds to the business as usual (BAU) scenario, while the bottom chart of the same figure shows the decarbonisation scenario (DEC).[7] The blue lines are the emission trajectories for the incumbent investment decision model, i.e., the LCOE branch of the AHP tree. The red lines are the emission trajectories for the environmental considerations branch of the AHP tree. The gray area corresponds to the combined investment criteria, for different values of α. The upper and lower limits of the gray interval correspond to the values $\alpha = 0.002$ and $\alpha = 0.007$, respectively. The black dashed lines, correspond to $\alpha = 0.0037$, the same value presented in figure 11.1 for the case when both criteria, LCOE and environmental considerations, become equally relevant at cumulative emissions approximately equal to $800GtC$.

The emission pathways presented in figure 11.2, show a range of potential scenarios of the power sector, constrained by two dominant criteria for investment: **market** and **environmental** considerations. As it might be expected, investment decisions driven by environmental considerations produce less emission-intensive pathways. The case of the BAU scenario is particularly clear: despite not having any decarbonisation policy in place, decisions based on purely environmentally driven concerns produce a pathway of decreasing emissions (red line in top chart of figure 11.2). Purely environmentally driven investment is not affected by market based mechanism (such as carbon pricing, feed-in-tariffs or subsidies). Therefore, the decrease in emission between the BAU and DEC scenarios in the case of the environmentally

[7] In order to focus in the effect of the investment criteria, and minimise the effect of other drivers, the default cost supply curves and learning rates are used for the scenarios presented in figure 11.2. Policies and demand reductions are applied, using the decarbonisation intensity approach. For more details, about the decarbonisation intensity approach, and about the BAU and DEC scenarios, please refer to sections 5.2, 5.4 and 5.5, respectively.



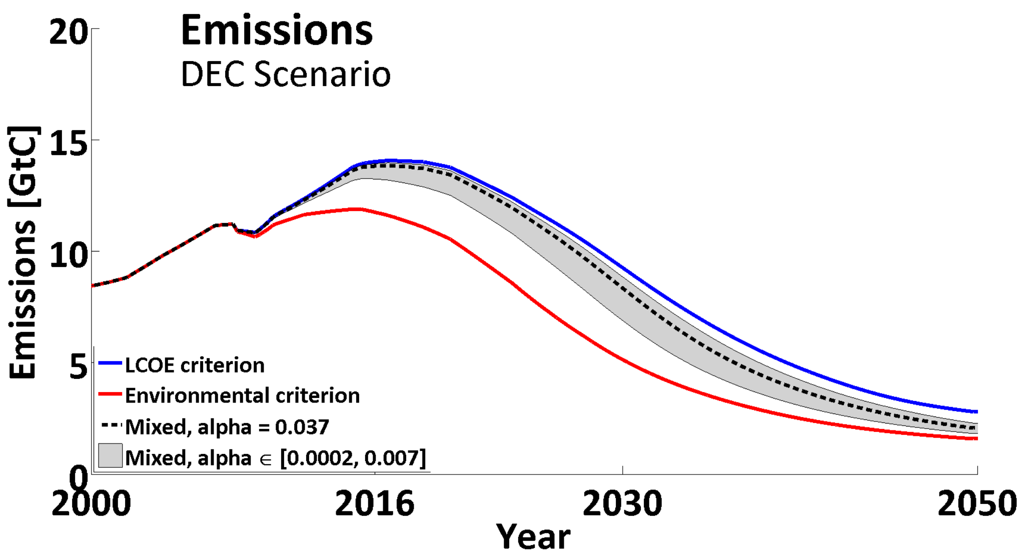


Figure 11.2 Emission pathways for BAU (top chart) and DEC (bottom chart), under different investment criteria. The blue lines in both scenarios correspond to the emission trajectories estimated using the incumbent investment model, based on the LCOE criterion. The red lines are estimated using the environmental criterion, introduced in section 11.2.1. The gray area corresponds to the combined investment criteria, $\alpha = 0.002$ and $\alpha = 0.007$ being the upper and lower limits of the emissions interval, respectively. The dashed black line corresponds to $\alpha = 0.0037$, as in figure 11.1. As it might be expected, when investment preferences are inversely proportional to carbon intensity values, emission trajectories are lower than those estimated using the traditional LCOE approach.

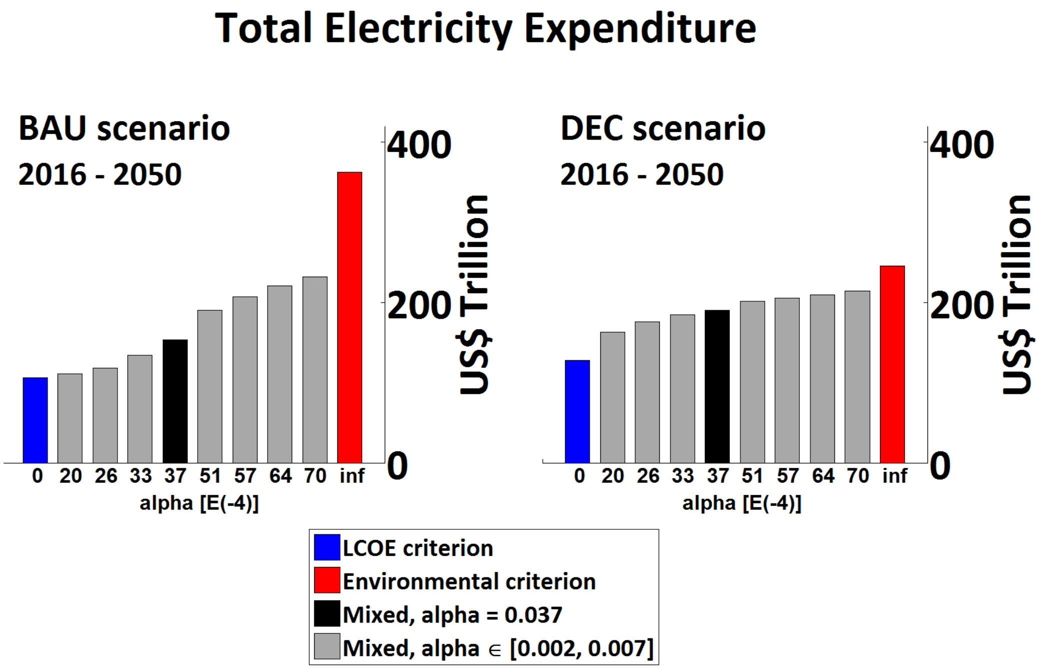


Figure 11.3 Total electricity expenditure in the BAU (left) and DEC (right) scenarios, for different values of α (see figure 11.2). The case $\alpha = 0$ (extreme left, blue bar), corresponds to the case when only the LCOE criterion is used. Equivalently, the scenario $\alpha = \infty$ (extreme right, red bar), corresponds to the scenario when only the environmental criterion is used. The gray bars in between, correspond to different values of α, with $\alpha = 0.0037$ highlighted in black.

driven trajectories (differences between the two red lines in figure 11.2) is due to regulation and reductions in electricity demand.

In the case of the DEC scenario, the main differences between the market driven and the environmentally driven trajectories (red and blue curves of the bottom chart of figure 11.2) are concentrated around the peak on emissions (approximately 2016, the year when the regulation starts), and then a gradual convergence is exhibited. By 2050, the two trajectories lead to a difference in cumulative emissions of approximately 106 $GtCO_2$ between the market driven and the environmentally driven scenarios. These results are aligned with the findings of the cross-model comparison exercises presented in table 3.1 (chapter 3): the political feasibility of keeping the 2°C target within reach, requires strengthening of the abatement efforts before 2030 (Luderer et al., 2016). In a market-driven investment environment, it takes time for strong decarbonisation policies to have a significant impact on emissions. Therefore, unless complementary policies are applied, the delayed response of the system (related to the inertia of the power sector (Kriegler et al., 2015b)) can hinder the accomplishment of the abatement required to reach the target of the Paris Agreement.

In addition to the emission trajectories, the global expenditure in electricity associated with the adoption of the environmentally driven investment criterion is shown in figure 11.3. The BAU and DEC scenarios are presented in the left and right charts, respectively, using the same color code used in figure 11.2. The extreme left bar on each chart represents the case when $\alpha = 0$ (blue bar), which corresponds to the case when the incumbent investment model of FTT:Power is used. In other words, the extreme left bars correspond to the traditional FTT:Power investment model, with the LCOE as the only investment decision criterion. The extreme right bar on each chart corresponds to the case when $\alpha = \infty$ (red bar), i.e., when investment decisions are only driven by the environmental criterion. The rest are cases in between, with different speed of convergence values. The case of $\alpha = 0.0037$ is highlighted in black.

As it might be expected, environmentally driven investment considerations are more "expensive" than market driven considerations. Under the same electricity demand assumptions for the scenarios within each chart, the differences in electricity expenditure come from differences in the price of electricity. The adoption of greener technologies, without considering their cost, is what produces a higher price of electricity in scenarios with higher values of α. This is aligned with the concept of speed of convergence between the market criterion (LCOE) and the environmental criterion, measured by α. More relevant the environmental criterion becomes, less relevant is the price of electricity when new capacity is added to the grid. Because most of the expenditure in electricity comes from the private sector (see a detailed analysis in chapter 7), the charts of figure 11.3 do not separate private and public expenditure.

The total expenditure differences between the scenarios within the DEC group of figure 11.3 is not as significant as the differences in the BAU case. Indeed, the DEC chart of figure 11.3 shows decreasing marginal electricity expenditure per speed of convergence. In other words, the increase in α produces a marginal decrease in the differential of the total electricity expenditure.

Figure 11.2.4 combines the results of figures 11.2 and 11.3, for the DEC scenario. Using the cumulative emissions of BAU as reference, figure 11.2.4 presents the decarbonisation efficiency for different values of α, measured as emission abatement per electricity expenditure (in GtC per US$ trillion). Interestingly, there is an asymptotic convergence in the decarbonisation efficiency, driven by the convergence in the emission trajectories of figure 11.2 (gray

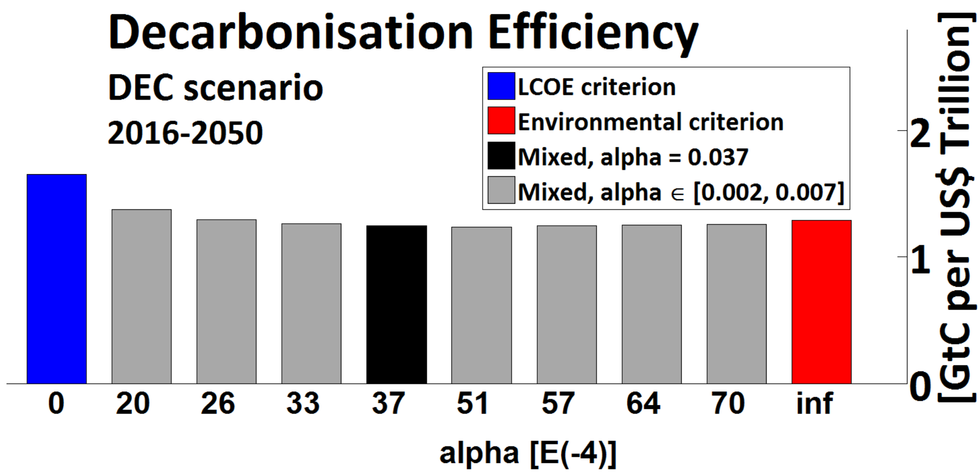


Figure 11.4 Decarbonisation efficiency for different values of α in the DEC scenario. Efficiency is measured as the amount of cumulative emission reductions with respect to BAU scenario, divided by the global electricity expenditure. The case $\alpha = 0$ (extreme left, blue bar), corresponds to the case when only the LCOE criterion is used. Equivalently, the scenario $\alpha = \infty$ (extreme right, red bar), corresponds to the scenario when only the environmental criterion is used. The gray bars in between, correspond to different values of α, with $\alpha = 0.0037$ highlighted in black.

area in the bottom chart) and the convergence on total expenditure on electricity (right-hand side chart of figure 11.3). In other words, because abatement and total expenditure have asymptotic convergence, the ratio between them (decarbonisation efficiency) also converges to the value represented by the red bar at the extreme right-hand side of figure .

From the results presented in this section, based on the scenarios created with the new AHP tree, several points are worth to be highlighted:

- The scenarios presented in figure 11.2 follow the expected pattern: investment decisions based on environmental criteria have higher expenditure in electricity (see figure 11.3), produced by investment in more expensive low carbon technologies, and therefore produce less emissions than investment decisions based on pure market considerations.

- The inertia of the power sector produces a delay in the response of the system to stringent decarbonisation policies, when investment is driven by market-based considerations. The political feasibility of keeping the Paris Agreement target within reach, requires strengthening the abatement efforts before 2030. The effect of direct regulation in the emission trajectories seems to be particularly important, defining the peak in emissions in the DEC scenario. However, as explained in section 5.6, the relative impact of market and non-market based policies in the model might be affected by the shares equation formulation as well as by the assumption of complete feasibility of regulation. Consequently, the policy implications of these results have to be analysed with caution.

- In contrast to the LCOE investment criterion, which does not include any foresight, the environmental investment criterion could be interpreted as an indication of foresight of environmental constraints. For instance, if investors realised that abiding by the Paris Agreement will require a strong reduction in carbon intensity, the gray area in the charts of figure 11.2 would represent different degrees of foresight of environmental constraints. Notice than even in the most extreme case, represented by the red trajectory (pure environmental criterion), there is a gradual decrease in emission, driven by the gradual change of the power fleet as they get to the end of their lifetime. This result is a direct consequence of the shares equation formulation discussed in section 4.6.

- The combined investment criteria has a feedback mechanism proportional to the environmental uncertainty, represented by cumulative emissions (see equation 11.3). Therefore, scenarios with higher cumulative emissions are more sensitive to variations in the relative weight of economic and environmental investment criteria. This can be seen in figure 11.2, with a larger gray area in the BAU scenario than in the DEC scenario. With higher environmental uncertainty (BAU case), more importance is given to the environmental criterion, in detriment of pure market considerations embedded in the LCOE. The response of the system to this feedback mechanism is a representation of the *adaptability* of the power sector, in this case driven by investors' response to environmental uncertainty.

- The emissions trajectories of the purely environmentally driven criterion (red lines of figure 11.2) are very similar in both BAU and DEC scenarios. Under the environmental criterion, market incentives (such as subsidies, feed-in-tariffs or carbon pricing) do not play a role in investment decisions. Therefore, the main driving differences in both trajectories are direct regulation and reduction of electricity demand. The regulation mechanism has a limited effect under the environmental criterion, because low carbon technologies are already preferred in that case. Therefore, the differences between BAU and DEC scenario, under the environmental criterion, are small.

The next section, incorporates yet another criteria into the investment decision process: *policy uncertainty*. The addition of a third investment criterion complements the previous analysis, and also helps to exemplify how the process of extending the AHP tree works in practice.

11.3 The Effect of Policy Uncertainty in Investment Decisions

There is a vast amount of evidence of the detrimental effects of uncertainty on investment, particularly in the energy sector (Barradale, 2010; Kellogg, 2014). In the case of climate policy, for isstance, the evidence suggests that policy stringency and stability are of critical importance to steer the rate and direction of technological change towards the adoption of low carbon technologies (Schmidt et al., 2012).

In the case of FTT:Power, investors have naive expectations about future energy policy, and do not incorporate uncertainty as part of the investment evaluation process. Therefore, FTT:Power scenarios do not show any effect of energy policy uncertainty on investment. In order to analyse the potential impact that policy uncertainty may have in the technological evolution of the power sector, this section proposes a new branch for the AHP investment decision tree. This new branch incorporates, as a matter of practical example, a policy uncertainty criterion to evaluate investment decisions.

11.3.1 Policy dependence

FTT:Power incorporates three types of market based policy mechanisms: carbon pricing, feed-in-tariffs and subsidies. These policies have a direct effect in the LCOE, driving the cost up or down, depending on the type of technology and the underlying policy being applied. In the case of carbon intensive technologies, carbon pricing increases the LCOE, making those technologies less attractive to investors. In the case of subsidies and feed-in-tariffs, low carbon technologies are favoured at the eyes of the investors, with part of the cost being payed by the regulator.

Following the procedure described in section 10.6.1, the first step to create the new AHP tree branch is to define the criterion and the scale. Policy uncertainty, in this context, is defined as the *lack of information regarding potential changes in policy regulation, that may have a detrimental effect on revenues, through changes in the levelised cost of electricity*. The success of decarbonisation policies depends, in no small part, on the psychology of private-sector expectations Rodrik (1991). Consequently, policy uncertainty can act, in practical terms, as a tax on investment (ibid.).[8]

Based on the aforementioned policy uncertainty criterion, technologies can be ranked by their policy dependence. In FTT:Power, the levelised cost of electricity before being affected by policy, is stored in the variable $LCOEs$, while the levelised cost of electricity after policy regulation is stored in the variable $TLCOE$.[9] Therefore, the normalised difference between these two variables corresponds to the effect of policy in the levelised cost of electricity of that technology.

Similarly to the case of the environmental criterion, a linear transformation is necessary to make the pairwise comparison. If Δ_i is the difference between the LCOE with and without policy, then I propose the following linear transformation to create a ratio scale:

$$\Omega_i = 1 - \frac{8 \cdot (\Delta_i - \Delta_{imax})}{(\Delta_{imax} - \Delta_{imin})} \tag{11.7}$$

where $\Delta_i = |LCOEs_i - TLCOE_i|$, and Δ_{imin} and Δ_{imax} are the minimum and maximum values of Δ_i, respectively. Given the scale defined by Ω, the pairwise comparison matrix $\boldsymbol{A_\Omega}$ can be constructed as:

$$a_{ij} = \frac{\Omega_i}{\Omega_j}, \quad \forall i, j = 1, \cdots n \tag{11.8}$$

Using this scale, technologies with policies having the minimum influence in the LCOE, score a maximum value of $\Omega_i = 9$. Similarly, technologies with policies having the maximum effect on the LCOE obtain the minimum value of $\Omega_i = 1$. Therefore, technologies not affected by policies are strongly preferred over technologies affected by policies, under a policy uncertainty scenario. Same as in the previous section, the matrix $\boldsymbol{A_\Omega}$ is consistent, and its eigenvector $\boldsymbol{w_\Omega}$ defines a ranking for the alternatives compared by $\boldsymbol{A_\Omega}$ (see section 10.4.2 for more information about consistency). Notice that the ranking defined by $\boldsymbol{w_\Omega}$ only depends on the absolute value of the net policy dependence of each technology. It means that positive and negative policy influences, driven by subsidies and carbon pricing, respectively,

[8] I use the term policy *uncertainty*, instead of *risk*, because there is no information available for the investors regarding the probability of policy change in the future. However, it can be argued that the scale defined in this section for the ranking of the technologies could be used for defining a risk premium.

[9] $LCOEs$ is the levelised cost of electricity, without carbon pricing, subsidies or feed-in-tariffs. $TLCOE$ corresponds to the levelised cost of electricity, after adding the cost of carbon, and after including subsidies and feed-in-tariffs. Both variables are time dependent, and are influenced by the availability of natural resources and learning. For more details about the LCOE calculations, please refer to section 4.6.1.

have the same net effect in the ranking. The underlying assumption is that the effect of policy uncertainty on investment is independent of the environmental or financial nature of the policy. The policy dependence criterion does not address the environmental impact or the cost implications of specific policies, it addresses only the impact of policy uncertainty in the investment decision process.

After defining the pairwise comparison matrix for the new criterion (policy uncertainty), the next step is to create the pairwise comparison matrix for the aggregation of criteria: LCOE, environmental considerations and policy uncertainty. Following the guidance of section 10.6.1, a 3×3 matrix is required.

$$\boldsymbol{M} = \begin{array}{c} \\ \text{LCOE} \\ \text{Env.} \\ \text{Policy} \end{array} \begin{array}{c} \begin{array}{ccc} \text{LCOE} & \text{Env.} & \text{Policy} \end{array} \\ \begin{pmatrix} 1 & \frac{\text{LCOE}}{\text{Env.}} & \frac{\text{LCOE}}{\text{Policy}} \\ \frac{\text{Env.}}{\text{LCOE}} & 1 & \frac{\text{Env.}}{\text{Policy}} \\ \frac{\text{Policy}}{\text{LCOE}} & \frac{\text{Policy}}{\text{Env.}} & 1 \end{pmatrix} \end{array} \tag{11.9}$$

11.3.2 LCOE vs Environmental Criterion

In section 11.2.3, the dominance of LCOE over the environmental criterion is described using the function

$$f_{LCOE} = \frac{80}{9} \cdot (1 - \tanh(\alpha \cdot (E - E_0))) + \frac{1}{9} \tag{11.10}$$

The pairwise comparison of these two criteria remains the same in the new AHP tree, therefore, I use the same function. In other words, the 2×2 aggregated preferences matrix defined in section 11.2.3, is a subset of the aggregated preferences matrix defined in this section.

11.3.3 LCOE vs Policy Uncertainty

The evidence indicates that policy uncertainty creates a risk premium for power generation investment (Blyth et al., 2007). Countries with stable financial institutions, are considered safer places for investment, and as such they are awarded with higher credit scores, and consequently smaller risk premia. It is, therefore, reasonable to assume that policy uncertainty varies among regions, in the same way the financial risk premia do. Following the regional aggregation for policy regulation of section 5.2.3, the 53 FTT:Power regions are divided in three groups:[10]

- Developed countries, including Europe, USA, Japan, Canada, Australia and New Zealand (regions 1 to 38), are considered to have a *low* policy uncertainty. In the context of AHP, this implies a strong dominance of the cost criterion (LCOE) over the policy uncertainty criterion. I assume this dominance to be $k = 5$, following Saaty's scale of table 10.1.
- Fast developing economies, including China, Brazil, Korea and Taiwan, are considered to have a *medium* policy uncertainty, equivalent to a dominance of $k = 5/2 = 2.5$.
- For the rest of the world, the policy uncertainty is assumed to be *high*, equivalent to a dominance of $k = 1$ (policy uncertainty is as important as market considerations).

11.3.4 Environmental vs Policy Uncertainty

One of the conditions on the pairwise comparison matrix to preserve the preferences of the decision maker in its eigenvector, is that the matrix has to be **consistent** (or at least near consistent, see section 10.4.3):

$$a_{ij} = a_{ik} \cdot a_{kj} \quad \forall i, j, k \tag{11.11}$$

Given that the aggregate pairwise comparison matrix has size 3×3, only two criteria can be defined freely. If the criteria are listed as 1) LCOE, 2) environmental considerations, and 3) policy uncertainty, then the 9 elements of the matrix are:

- $a_{11} = a_{22} = a_{33} = 1$, diagonals are equal to one.
- $a_{12} = f_{LCOE}$ and $a_{21} = 1/f_{LCOE}$, dominance of LCOE over environmental considerations.
- $a_{13} = k$ and $a_{31} = 1/k$ dominance of LCOE over policy uncertainty.
- $a_{23} = a_{21} \cdot a_{13}$ and $a_{32} = a_{31} \cdot a_{12}$, due to the reciprocity property (see section 10.4.3)

[10] The geographical division used here aims to keep consistency with the regional aggregation of section 5.2.3, and does not follow the credit score ranking defined by institutions such as Moody's, Standard & Poor's (S&P) or Fitch (White, 2010).

Therefore, calling h the dominance of the environmental considerations over policy uncertainty criterion:

$$h = k/f = \frac{k}{\frac{80}{9} \cdot (1 - \tanh(\alpha \cdot (E - E_0))) + \frac{1}{9}} \tag{11.12}$$

Figure 11.5 shows the behaviour of h for different values of cumulative emissions and speed of convergence. The abscissa in figure 11.5 represents cumulative emissions (in GtC), while the ordinate corresponds to the dominance of environmental considerations over the policy criterion, equal to h. The upper and lower limits of the shadow areas correspond to the maximum and minimum values of α, respectively. The gray area represents the case of $k = 5$ (first group of regions), while the yellow area represents the case of $k = 1$ (third group of regions). The area representing fast developing economies, which is a tradeoff between the other two cases, is not plotted in order not to saturate the chart. The black dashed lines correspond to the central value of $\alpha = 0.0037$. The horizontal red dashed line corresponds to the case when both criteria are indifferent ($h = 1$). For small values of cumulative emissions, the dominance is smaller than one, which means that policy uncertainty dominates over environmental considerations. When cumulative emissions rise, the environmental considerations criterion dominates over the policy uncertainty criterion. The exact value of cumulative emissions for which the environmental considerations criterion becomes dominant depends on the values of α and k.

In the cases where the market (LCOE) and the policy uncertainty criteria are indifferent ($k = 1$, yellow area in figure 11.5), the dominance of environmental uncertainty over policy uncertainty follows the dominance scale of Saaty presented in table 10.1. In other words, given that $f \in [1/9, 9]$, when $k = 1$, then $h = k/f \in [1/9, 9]$. In order to preserve transitive preferences in the aggregate pairwise comparison matrix, the environmental criterion is required to show a large dominance for high values of cumulative emissions, when there is a strong dominance of the LCOE over the policy criteria ($k = 5$, gray area in figure 11.5). This is a reasonable assumption: when environmental uncertainty increases, investor's preferences are dominated by environmental considerations more than policy uncertainty considerations. Moreover, both criteria are dominated by the LCOE criterion, unless environmental uncertainty is really large (cumulative emissions rise over $800 GtC$), in which case environmental considerations become the most relevant criteria.

Based on the definitions of f, k and h, the aggregate comparison matrix $\boldsymbol{M}$ is:

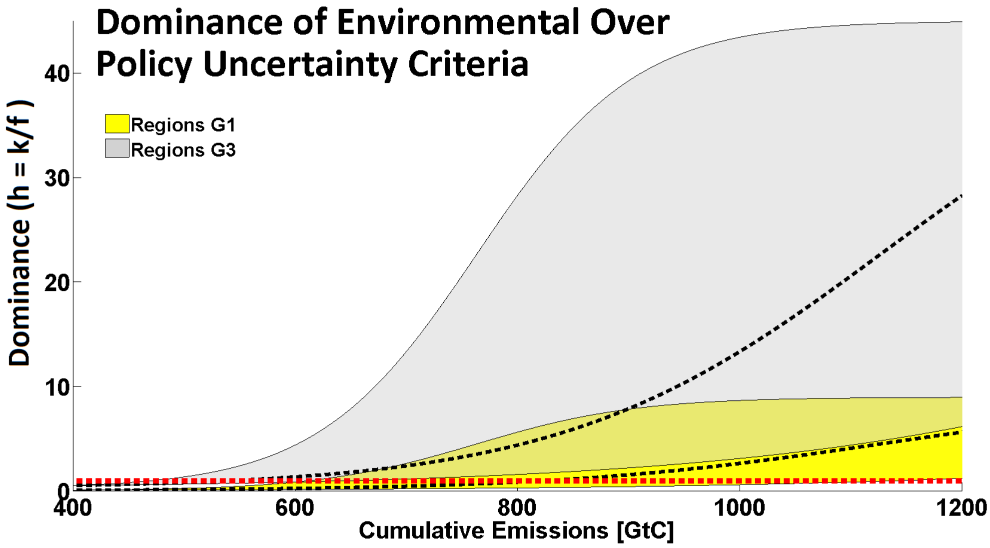


Figure 11.5 Dominance of environmental considerations over the policy uncertainty criteria, as defined by h in equation 11.12. The limits of the shadow ranges correspond to the cases of minimum and maximum values for α (0.002 and 0.007 respectively). The gray area represents the case of $k = 5$ (first group of regions), while the yellow area represents the case of $k = 1$ (third group of regions). The abscissa represents cumulative emissions (in GtC), while the ordinate corresponds to the dominance of environmental over policy criteria. The horizontal red dashed line corresponds to the case when both criteria are indifferent ($h = 1$). The black dashed lines correspond to the central value of $\alpha = 0.0037$. Higher values of α move the curve to the right. The monotonically growing curve represents the increase in relative importance of environmental considerations, under higher level of cumulative emissions. Notice that for small values of cumulative emissions, policy uncertainty dominates ($h \leq 1$), up to a threshold that depends on α and k.

$$\boldsymbol{M} = \begin{array}{c c} & \begin{array}{ccc} \text{LCOE} & \text{Env.} & \text{Policy} \end{array} \\ \begin{array}{c} \text{LCOE} \\ \text{Env.} \\ \text{Policy} \end{array} & \begin{pmatrix} 1 & f & k \\ 1/f & 1 & h = k/f \\ 1/k & 1/h = f/k & 1 \end{pmatrix} \end{array} \tag{11.13}$$

Because the matrix $\boldsymbol{M}$ is consistent, then the eigenvector $\boldsymbol{w_M}$ preserves the preferences embedded in the matrix. Finally, the preference vector of the entire AHP tree can be calculated as:

$$\boldsymbol{W_{final}} = \boldsymbol{w_M}(1) \cdot \boldsymbol{w_A} + \boldsymbol{w_M}(2) \cdot \boldsymbol{w_\psi} + \boldsymbol{w_M}(3) \cdot \boldsymbol{w_\Omega} \tag{11.14}$$

where $\boldsymbol{w_A}$ is the preference vector of the *LCOE* branch, $\boldsymbol{w_\Psi}$ is the preference vector of the environmental considerations branch, $\boldsymbol{w_\Omega}$ is the preference vector of the policy uncertainty branch, and $\boldsymbol{w_M}$ is the vector of aggregated preferences.

11.3.5 Comparison of scenarios with different investment criteria

Figure 11.6 shows the emission trajectories for BAU and DEC, (top and bottom, respectively), for scenarios based on different combinations of the AHP tree branches. Similar to figure 11.2, figure 11.6 shows in blue the trajectories for the LCOE criterion (incumbent investment decision model of FTT:Power); in red, the trajectories for the environmental criterion; and in green, the trajectories for the policy uncertainty criterion. The green area corresponds to the combination of the three criteria, for different values of α (in contrast with the gray area, that only includes two criteria, LCOE and environmental considerations, same gray area of figure 11.2). The black dashed line corresponds to the central value of $\alpha = 0.0037$. The reason why the green and gray areas in figure 11.6 are so similar, is because the influence of the policy uncertainty branch in the entire decision making process (AHP tree), is less significant than the influence of the LCOE and the environmental criterion branches, given the definition of the aggregated preferences matrix $\boldsymbol{M}$ in equation 11.13.

The AHP tree branch associated with policy uncertainty, ranks the technologies according to the level of policy support (in the case of subsidies and feed-in-tariffs) or burden (in the case of carbon pricing) on investors, embedded in the LCOE calculations. In the BAU scenario, there is a low level of policy influence (decarbonisation intensity equal zero), mostly associated with the carbon price in Europe. Therefore, in most of the world in the BAU scenario, the policy uncertainty ranking is indifferent between technologies. Consequently, fossil fuels maintain their dominance in the composition of the energy matrix. As a result, the emission trajectories of the incumbent FTT:Power investment model and the policy uncertainty criterion in the BAU scenario follow a similar pattern. This is shown by the green line, following relatively close the blue line (in comparison with the other trajectories), in the top chart of figure 11.6.

The case of the DEC scenario is different, because there are strong policy influences in several technologies. A high carbon price affects the carbon intensive technologies, while strong subsidies and feed-in-tariffs affect the low carbon technologies. As mentioned in section 11.3.1, positive and negative policy influences have the same net effect in the policy uncertainty ranking. The policy uncertainty criterion does not address the environmental or the cost implications of specific policies, it addresses only the impact of policy uncertainty in

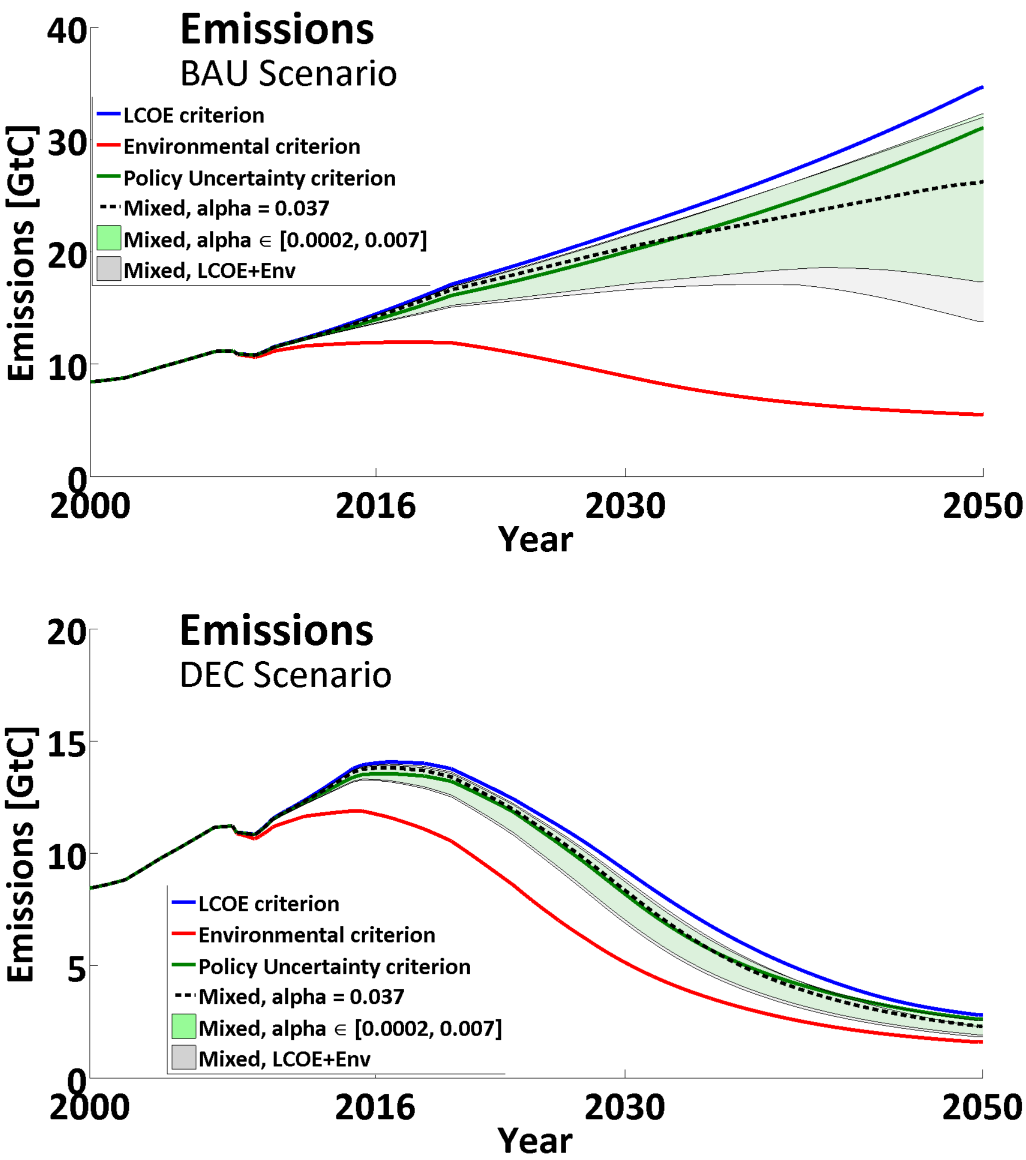


Figure 11.6 Emission pathways for BAU (top chart) and DEC (bottom chart), under different investment criteria. Following the same approach presented in figure 11.2, the blue lines correspond to the LCOE criterion, the red lines are estimated using the environmental criterion, and the green lines correspond to the policy uncertainty criterion. The green areas correspond to the combined investment criteria, with $\alpha = 0.002$, and 0.007 being the upper and lower limits of the emissions interval, respectively. The gray area correspond to the same values of α, but without the policy uncertainty criterion (same as gray area in figure 11.2). The black dashed line correspond to $\alpha = 0.0037$.

the investment decision process. Therefore, technologies at both sides of the environmental spectrum are affected by policy uncertainty. The net effect in emissions, shown in green in the bottom chart of figure 11.6, is a trajectory slightly higher than the middle range of the combined criteria ($\alpha = 0.0037$), lower than the emission trajectories of the incumbent FTT:Power investment model.

The dynamic evolution of the average global AHP ranking, for the policy uncertainty branch, is shown in figure 11.7. The ranking corresponds to the DEC scenario, for a subset of representative FTT:Power technologies.[11] The evolution of the ranking is completely connected to the evolution of the policy landscape of the DEC scenario:

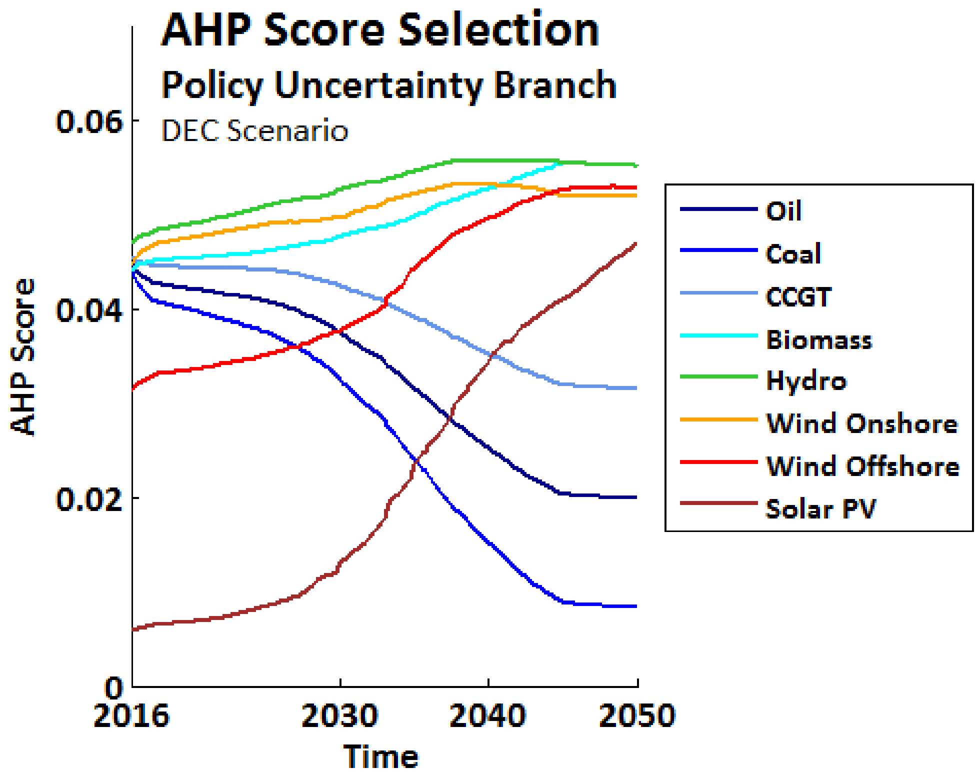


Figure 11.7 Global average ranking of the AHP policy uncertainty branch over time, for a subset of FTT:Power technologies, under the DEC scenario. The scores (or weights) presented here correspond to the green trajectory of the bottom chart of figure 11.6.

- At the top of the ranking is hydro, a technology that is not affected by any policy.
- In 2016, the price of carbon is low, therefore carbon intensive technologies have high scores at the beginning of the simulation. The score is inversely proportional to the level of carbon pricing.

[11] Only a subset of technologies are shown in the diagram, for the sake of simplicity and order.

- The policy uncertainty ranking of the carbon intensive technologies decreases rapidly over time, due to the investors' concern associated with the increasing carbon price. Higher the carbon content, lower the score.
- The ranking of modern renewable technologies, such as solar PV, follows the inverse pattern of the carbon intensive technologies. In 2016, solar PV receives strong policy support, in the form of feed-in-tariffs. Because solar PV is comparatively expensive (in 2016), the feed-in-tariff contribution it receives is large. Consequently, solar PV performs badly at the beginning of the simulation in the policy uncertainty ranking, given its strong dependence on policy support. Over time, however, solar PV becomes less expensive (due to learning-by-doing), and feed-in-tariffs decrease. As a result, the policy uncertainty ranking improves.
- Other renewable technologies, such as biomass and wind onshore, also receive strong policy support. However, by 2016, they are less expensive than solar. Therefore, the policy dependence of wind onshore and biomass is less significant, due to the small amount of money they receive in the form of feed-in-tariffs, and that translates in a higher policy uncertain scores. Wind offshore is somewhere in between solar PV and wind onshore.
- By 2045, biomass does not longer receive any more subsidies, and it reaches the top of the ranking, together with hydro.

11.4 The Effect of Environmental Considerations and Policy Uncertainty in the Technological Evolution of the Power Sector

Focusing on the same subset of FTT:Power technologies as in figure 11.7, figure 11.8 shows the cumulative capacity investment by AHP branch, between 2016 and 2050, measured in units of capacity (TW). The letters **L**, **E** and **P** correspond to the AHP branches **L**COE, **E**nvironmental criterion and **P**olicy uncertainty criterion, respectively. The differences between the scenarios of figure 11.8, correspond to the effect of investment criteria in the adoption of new installed capacity.

Notice that the addition of the policy uncertainty branch to the combined LCOE and environmental considerations tree has little effect in the total investment in new capacity, as well as in the distribution of it. As a consequence, there are no significant differences in electricity prices and policy efficiency between the scenarios L+E, L+P and L+E+P. In other words, the similarities of the scenarios L+E, L+P and L+E+P of figure 11.8, makes unnecessary to analyse electricity expenditure and policy efficiency for L+P and L+E+P, because they are very close to those shown in figures 11.3 and 11.2.4, respectively.

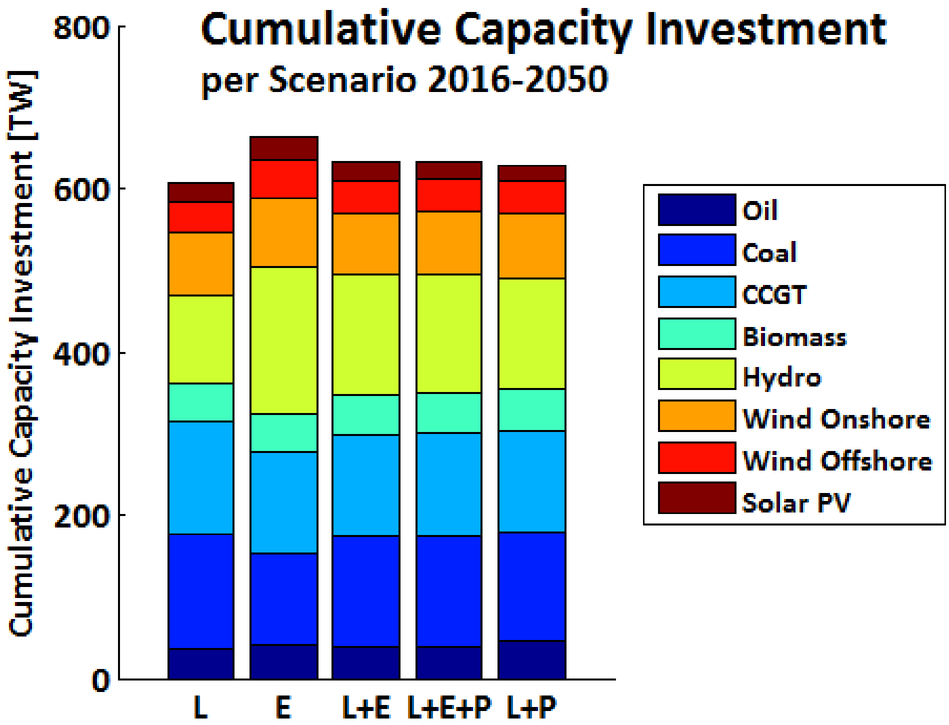


Figure 11.8 Cumulative capacity investment by AHP tree, measured in TW, for a selection of FTT:Power technologies. **L** corresponds to the LCOE criterion, **E** is environmental criterion and **P** is policy uncertainty criterion. **L+E**, **L+P** and **L+E+P** are scenarios with multiple branches in the AHP tree.

The scenario based on pure market considerations (L), presents a lower level of investment than the other scenarios (the extreme left bar is the smallest). This is particularly pronounced in the case of hydroelectricity (green area). This result is in line with the analysis presented in chapters 6, 7 and 8, regarding the role of the Natural Energy Resource module (NER) on FTT:Power. As explained in detail in chapter 6, natural resources in FTT:Power are assumed to be finite. Moreover, the cost of the resources is controlled by the underlying cost-supply curve, which has as a vertical asymptote the technical potential of the primary energy resource. Therefore, under strong decarbonisation policies, with large uptake of renewable energies, hydroelectricity becomes expensive.[12] The increase in the price of hydroelectricity has a strong effect on electricity expenditure, as explainned in detail in chapter 7. In this context, it is reasonable to expect a limitation in the adoption of new hydropower capacity, when the LCOE is part of the investment decision criteria. In the case of the L scenario, LCOE is the only investment decision criterion, therefore is the scenario with the less significant amount of hydroelectricity.

If economic considerations are not longer relevant, then a large adoption of hydroelectricity is expected. This is what happens in the scenario E, in which investment decisions are purely based on environmental considerations. In such scenario, the consumption of coal, which is the most polluting technology (and also the most competitive) follows the exactly opposite pattern than hydroelectricity. And as the extreme right bars of figure 11.3 show, expenditure on electricity rises in the environmentally driven investment scenario (when cumulative emissions $E \to \inf$). The large adoption of hydropower in this scenario, however, has to be analysed with caution. While the Natural Energy Resources module (NER) of FTT:Power accounts for the increasing marginal cost of sites available to install hydroelectric dams, it does not account for other impacts associated to large scale construction of hydropower capacity. For instance, water scarcity in some regions might have a strong influence on public perception regarding the construction of new hydroelectric dams (see section 8.3 for an analysis of the Brazilian case on this regard). Cases such as HydroAysen, a 2.7 GW project approved by the Chilean government in the region of Patagonia, but halted due to social pressure, show the importance of not underestimating the role of public perception on hydroelectric investment (Susskind et al., 2014). Social aspects are not considered in the risk formulation of environmental and policy uncertainty criteria, and that might produce an upward bias on the uptake of hydroelectricity on those scenarios.

As discussed in section 11.2, the scenario based on the LCOE and environmental considerations criteria (L+E), is a trade off between the scenarios of pure market and environmental considerations. Closer to the former, the L+E scenario presents a higher level of hydropower adoption than scenario L, driving up the electricity expenditure (as discussed in section 11.2.4). The differences between the scenarios L+E, L+P and the L+E+P are less significant. The inclusion of the policy uncertainty criterion in the AHP tree does not represent a significant change in the results, due to the strong dominance of the LCOE and environmental criteria over the policy uncertainty criterion. Based in the aggregate comparison matrix

[12] Hydroelectricity is the most developed of all renewable resources, to the extent that around 23% of the global hydroelectric technical potential is currently in use (Mercure and Salas, 2012). As a consequence of this, decarbonisation scenarios in FTT:Power tend to be limited by the amount of hydroelectric resources they can incorporate at reasonable cost, due to the high percentage of the resources already in use.

M, the impact of policy uncertainty is less significant than the impact of environmental uncertainty.

Figure 11.9 shows the differences in cumulative capacity investment between the scenario L (incumbent FTT:Power investment model) and the scenario L+E+P, for the same subset of technologies presented in figure 11.8. Notice the change in the ordinates axis: the differences are between one and two orders of magnitude smaller than the cumulative capacity investment values. The larger difference is in hydropower capacity, driven by the favourable assessment that it receives under the environmental and the policy uncertainty criteria. Coal and CCGT represents the exact opposite: they have a low environmental assessment, and they also score badly under the policy uncertainty criterion. Oil does not show the same pattern as coal and CCGT, due to its classification as flexible technology (see discussion of stability constraints in section 4.6.2), and also because is not part of the group of banned technologies under the direct regulation policies of DEC (see section 5.5).

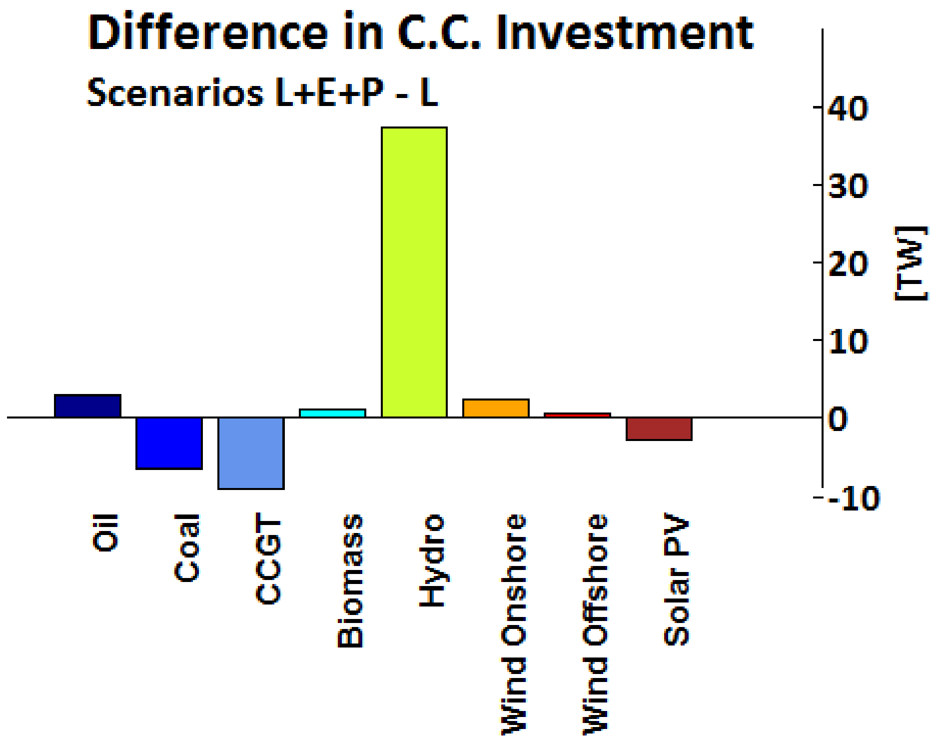


Figure 11.9 Differences in cumulative capacity investment, between the **L+E+P** and the **L** scenarios of figure 11.8, for a selection of FTT:Power technologies. The larger positive difference corresponds to hydroelectricity. All the other technologies present relatively small differences, negative in the case of coal, ccgt and solar pv, and positive in the case of oil, biomass, and wind.

The investment implications for the rest of the renewable technologies in figure 11.9 is different. While they all have a favourable environmental assessment (based on their low carbon content), the policy uncertainty criterion hinders investment in low carbon technologies under strong policy support. The net impact on biomass and wind offshore investment is almost zero (i.e., the positive effect of the environmental criterion on investment is almost completely counterbalanced by the negative impact of policy uncertainty on investment). In the case of wind onshore, the net impact on investment is positive, driven by the environmental considerations outweighing the small dependency on policy support. The opposite happens in the case of solar PV: the negative policy uncertainty evaluation, based on its large dependence on feed-in-tariffs, outweighs the environmental incentives that investors have for choosing this technology.

From the results presented in this section, based on the scenarios created with the combination of the three AHP tree branches (LCOE, environmental and policy uncertainty criteria), several points are worth to be highlighted:

- The overall effect of the policy uncertainty branch of the AHP tree is subtle, as shown by the negligible differences between the cumulative investment scenarios L+E and L+E+P in figure 11.8.
- When comparing DEC scenarios based on the new and the incumbent investment decision model, technologies under strong policy support (such as solar PV) or under pressure by environmental policy (such as coal under the high carbon pricing) exhibit negatives effects on investment, as shown by figure 11.9. For the rest of the technologies, the impact of policy uncertainty is counterbalanced by the environmental criterion (such as in the case of wind and biomass), or by technical constraints of the model (such as in the case of oil).
- Because the composition of the power sector does not suffer large changes between the scenarios L+E and L+E+P (the size of the colored areas in the bars L+E and L+E+P of figure 11.9 are almost the same), the electricity expenditure is also very similar. Moreover, the gray area in the cumulative emission trajectories (figures 11.6 and 11.2) are very similar as well, showing a small impact of adding the policy uncertainty criterion in cumulative emissions. As a consequence, policy efficiency remains more or less the same as in the L+E scenario.
- If compared with the pure marker based criterion, the main difference produced by bringing environmental and policy uncertainty considerations is related to the use of hydropower resources (see figure 11.9). This result is aligned with the findings of

chapters 7 and 8, where scenarios of hydropower availability are analysed. Under higher availability of hydropower resources, FTT:Power increases the consumption of hydroelectricity, driving down emissions. This is shown by figures 7.2 and 8.4: emissions decrease under higher availability of hydropower resources. Therefore, it is clear that the main constraint in the use of hydropower, is the increasing in cost when the cost supply curve is close to the technical potential (see chapter 6 for a detailed description of the NER module). If this limitation is relaxed, either by increasing the technical potential (as in chapter 7), or by using an investment criterion not based on cost (as in this chapter), then hydropower consumption increases.

- Policy uncertainty hinders investment in low carbon technologies that require strong policy support, such as solar PV. As noted by Miranda (2010), if there is uncertainty that a policy will remain in place, loans or grants for project that require large capital investments can be difficult to obtain (and costly), if they depend on that policy. The results presented in this section are aligned with the evidence showing that policy uncertainty discourages investment on new technologies, such as solar PV (White et al., 2013).

11.5 A critical analysis of the new investment model

The possibility of complementing the LCOE criterion with other considerations, is a great step towards a better understanding of the role that different investment drivers have in the technological evolution of the power sector. The particular cases of environmental considerations and policy uncertainty, analysed in this chapter, are only examples of how new criteria, beyond the LCOE, can be incorporated in the investment decision process of FTT:Power. Naturally, the use of the AHP methodology has its limitations. From the constraints associated with the use of the expert judgment scale (see table 10.1), to the requirement of (near) consistency, the main limitations of the new investment model are discussed below.

11.5.1 Mutual preference independence

In the analytic hierarchy process methodology, alternatives are aggregated through linear combination of weights:

$$\boldsymbol{W_{final}} = \sum_{i=1}^{n} \boldsymbol{w_{agg}}(i) \cdot \boldsymbol{w_i} \tag{11.15}$$

As discussed in section 10.6.2, this methodology has the embedded assumption of *mutual preference independence*: trade-offs between two (or more) alternatives do not depend upon the levels of other alternatives (Fischhoff et al., 1984).

In the specific cases analysed in this chapter, I avoid the mutual preference independence of criteria, through the use of feedback mechanisms in the aggregation process. The dominance of LCOE over environmental considerations, for instance, depends on the level of cumulative emissions ($f(E)$). So does the dominance of environmental considerations over the policy uncertainty criterion ($h(E)$). And because the aggregate comparison matrix $\boldsymbol{M}$ is consistent, then the dominance of the LCOE over policy uncertainty criterion is the multiplication of the other two dominances ($k = f \cdot h$). Therefore, given the way that the aggregate comparison matrix $\boldsymbol{M}$ is defined, the investment criteria are not assumed to be independent. In other words, the relative weight of two aggregation criteria depends on the level of the third criterion, and as such, they are not independent.

The case of mutual preference independence of electricity generation technologies, is also indirectly addressed by the expansion of the AHP tree. The inclusion of criteria beyond market considerations allows the explicit incorporation of the externalities into the decision making process. Therefore, the creation of the environmental concerns and policy uncertainty branches of the AHP tree, provides an integration of market and non-market considerations in the investment allocation process. Naturally, there are many externalities that are not explicitly included in the examples provided in this chapter. Issues such as land and water use, described in section 11.2, or health impacts associated with the production of electricity, are not part of the model. However, the methodology introduced in this section, is aimed to provide the means to incorporate those (and other) criteria inside the FTT:Power investment model.

11.5.2 Consistency and intransitive behaviour

As explained in the previous sections, the aggregate comparison matrix $\boldsymbol{M}$, as well as the comparison matrices $\boldsymbol{A}, \boldsymbol{A_\psi}$ and $\boldsymbol{A_\Omega}$,[13] are required to be (near) consistent. Behind the concept

[13] The matrices $\boldsymbol{A}, \boldsymbol{A_\psi}$ and $\boldsymbol{A_\Omega}$ are the pairwise comparison matrices for the LCOE, environment considerations and policy uncertainty criteria, respectively.

of consistency, is the idea of "perfect judgment" (or absolutely consistent judgment), which requires preferences to be perfectly transitive (Alonso and Lamata, 2006). However, there is plenty of evidence that people show persistent patterns of intransitive choice behaviour (Korhonen et al., 1990). Investors do not necessarily have perfectly transitive preferences, and therefore, some degree of inconsistency should be allowed. In that sense, the threshold for near consistency given by Saaty has been criticised as too restrictive, particularly when the 9-point scale is used with large matrices (Lane and Verdini, 1989).

In the model presented in this chapter, all the comparison matrices were required to be consistent, for the following reasons:

- The judgments of comparison, in the three AHP criteria, are based on ratio scales from absolute quantities. In other words, objective criteria are used for compare the different alternatives, using ratios in the form of $a_{ij} = w_i/w_j$. The use of those ratios facilitates enormously the creation of the pairwise comparison matrices, given the *Property 1* (equation 10.20) analysed in section 10.4.2:
  - In the case of the LCOE criterion, the judgment of comparison is calculated using the ratio of the probabilities of the multinomial logit model described in section 10.5:
  $$a_{ij} = \frac{P_i}{P_j} \tag{11.16}$$
  - In the case of the environmental criterion, the judgment of comparison is calculated using a linear function of the carbon intensity, as described in section 11.2.2:
  $$a_{ij} = \frac{\Psi_i}{\Psi_j} \tag{11.17}$$
  - In the case of policy uncertainty criterion, the judgments of comparison is calculated using a linear function of the policy influence in the LCOE, as described in section 11.3.1
  $$a_{ij} = \frac{\Omega_i}{\Omega_j} \tag{11.18}$$

  Therefore, the consistency of the pairwise comparison matrices appears as a natural consequence of the reciprocal property that the aforementioned matrices have:
  $$a_{ij} = a_{ik} \cdot a_{kj} \tag{11.19}$$

- In the case of the criteria aggregation, defined by the aggregated preferences matrix (equation 11.13), the consistency is imposed in order to preserve the preferences of the investors in the eigenvector of the matrix. Although this matrix could, eventually, be only near consistent, the consistency property is imposed due to practical reasons. The AHP decision process is applied at each time step in FTT:Power, on every region, during the entire simulation. This means $53 \times 169 \sim 9,000$ aggregation matrices, that would need to be checked for near consistency if they were to be built differently. This represents an absolutely impractical endeavor, and as such, it is avoided through the use of consistent matrices.

11.5.3 Main sources of uncertainty

There is inherent uncertainty when modelling complex decision-making. In the case of the AHP investment decision model proposed in this chapter, some of the main sources of uncertainty include:

- **Structural** or **modelling uncertainty**, regarding the aggregation of information. The creation of a ranking vector (the ultimate output of the AHP process), using a linear combination of score vectors, is clearly a simplification of a more complex process. In reality, investors aggregate all type of inputs, including incomplete sets of information, personal experiences, non-quantifiable knowledge and well structured data (such as cost, profits, emissions, policies and others), in order to make an informed decision. It is only the last aforementioned group, the well structured data, the one that is included in the investment decision model. Without more knowledge of how exactly these different sources of information are combined, a reasonable assumption is to use the scaling and aggregation methods proposed by Saaty (1977).

  Another source of modelling uncertainty is connected to the use of cumulative emissions as a proxy of environmental uncertainty (see section 11.3). Based on the near-linear relation between cumulative emissions and global temperature increase (IPCC, 2014c, p. 62),[14] I use cumulative emissions as a proxy of environmental uncertainty. The perception of environmental uncertainty, however, is not necessarily proportional to cumulative emissions (or global temperature increase), but most likely to the impact of climate change in the economy. This is traditionally modelled by economists through a *damage function*. There is plenty of evidence that the shape of the damage function

[14]The near-linear relation between cumulative emissions and global temperature increase, based mostly on empirical data, is itself subject to a large parametric uncertainty (IPCC, 2013, p. 102).

can greatly affect the results of the modelling exercise (Ackerman and Stanton, 2011; Peck and Teisberg, 1992). Moreover, damages are typically assumed to be proportional to economic output, and FTT:Power does not explicitly incorporate economic activity in the scenarios. Therefore, any type of damage function that could possibly be used in the model, would be an important source of uncertainty. For that reason, I opted for using cumulative emission as a proxy of environmental uncertainty, a decision that might arguable be considered as a better option in terms of modelling uncertainty, than using a damage function.

- **Parametric uncertainty**, that arises from the imperfect knowledge about specific variables and parameters included in the model, is arguably one of the main sources of uncertainty in the new investment model. The "speed of convergence" parameter α is a very good example. The central value chosen for α comes from expert judgment regarding the trade-off between market and environmental considerations, given the current level of environmental uncertainty. If the α parameter were to be estimated using econometrics, data would need to be gathered (through surveys or other methods), regarding power sector investor's preferences on market versus environmental considerations. As explained in section 11.2.4, the preferences embedded in α may vary among regions and over time, making the task even more difficult. Therefore, a reasonable solution is to define a wide range of values, and use sensitivity analysis.

  The AHP model proposed in this chapter builds on two main sets of comparisons, both of which are subject to parametric uncertainty. Pairwise comparison of *technologies* are represented by the pairwise comparison matrices ($\boldsymbol{A_{LCOE}}$, $\boldsymbol{A_{\psi}}$ and $\boldsymbol{A_{\Omega}}$). Pairwise comparison of *criteria* are represented by the aggregated preferences matrix ($\boldsymbol{M}$). The former group of comparisons is based on absolute quantities, using the ratio scales P_i/P_j, ψ_i/ψ_j and Ω_i/Ω_j. As discussed in section 10.4.5, the use of a scale based on absolute quantities provides an objective comparison of alternatives, in contrast with a more subjective comparison purely based on the scale of 10.1. However, the linear transformations used in the environmental considerations and the policy uncertainty criteria, have embedded assumptions regarding sets of parameters connected to Saaty's scale.[15] Naturally, there is parametric uncertainty surrounding those linear transformations.

  The pairwise comparisons of criteria, is subject to a higher degree of parametric uncertainty. Technologies are compared using absolute scales (LCOE, carbon intensity

[15] The linear transformation is necessary, due to the requirement of not having zero values in the scale. See section 10.6.2 for a discussion about AHP scales that pass through the origin.

and policy support/taxation values), with well defined units (USD/MWh and tC/MWh). However, criteria cannot be objectively measured. The scale to compare the *importance of* market versus environmental versus policy *considerations* is intrinsically subjective. As such, it is prone to be strongly influenced by the modeller (in this case, myself), and therefore is subject to parametric uncertainty. This parametric uncertainty is explicitly represented, up to some extent, by the uncertainty intervals of figures 11.1, 11.2, 11.5 and 11.6, and by the different height of the bars in figures 11.3 and 11.2.4.

11.6 Conclusion

This chapter describes, in practical terms, how the methodology introduced in chapter 10 can be used to incorporate new investment criteria in the FTT:Power investment decision model. *Environmental considerations* and *policy uncertainty* are added to the Analytic Hierarchy Process tree structure, using the step-by-step guidance introduced in section 10.6.1. Power sector scenarios based on the incumbent investment model of FTT:Power, are contrasted with scenarios created using the extended investment decision model.

11.6.1 Environmental considerations

In the first half of the chapter, environmental considerations are incorporated into the investment decision model. The results follow the expected patterns: the adoption of low carbon technologies increases, driving up the price of electricity, and decreasing emissions. Under purely environmentally driven investment considerations, the use of low carbon technologies, particularly hydropower, surges. Given the relationship between the use of resources and their cost, controlled by the Natural Energy Resources module of FTT:Power (NER), the LCOE increases under higher demand of hydro resources. Consequently, the decrease in emissions caused by the replacement of fossil fuels with low carbon alternatives, is accompanied with an increase in expenditure on electricity. Interestingly, abatement and electricity expenditure change almost proportionally, having a small impact on the decarbonisation efficiency, for different degrees of dominance of market and environmental considerations.

The inertia of the power sector produces a delay in the response of the system to stringent decarbonisation policies, especially under market-driven investment (see section 11.2.4). The effect of direct regulation in the emission trajectories seems to be particularly important, defining the peak in emissions in the DEC scenario. In line with the findings of the cross-model comparison exercises presented in chapter 3, in order to maintain the political feasibility of keeping the target of the Paris Agreement within reach, strong abatement efforts before 2030 are required (Kriegler et al., 2013). However, as explained in section 5.6, the relative impact of market and non-market based policies in the model might be affected by the shares equation formulation as well as by the assumption of complete feasibility of regulation. Consequently, the relative importance of regulation against market-based policy instruments has to be analysed with caution.

11.6.2 Policy uncertainty

In the second half of the chapter, the AHP tree is expanded, to incorporate policy uncertainty as an investment criterion. The effect of policy uncertainty in a set of representative technologies is analysed in detail. The environmentally neutral and market neutral character of the policy uncertainty criterion produces a more subtle impact in the adoption of technology than the other two investment drivers (LCOE and environmental considerations). Carbon intensive technologies (such as coal and gas), as well as policy-supported low carbon technologies (such as solar PV and wind) are negatively affected by the policy uncertainty criterion. In the case of coal and gas, the source of policy uncertainty is the rising price of carbon; in the case of the low carbon technologies, the strong dependence on subsidies and feed-in-tariffs drives up the policy uncertainty levels.

While the policy-supported low carbon technologies are negatively affected by policy uncertainty, at the same time they are positively affected by environmental considerations. The net effect, in terms of cumulative installed capacity, is slightly positive for wind onshore and offshore, and negative for solar PV, with a large underlying uncertainty. The case of hydroelectricity is different: because hydropower does not receive any policy support or burden, it is very attractive for investors under the policy uncertainty criterion. If the positive assessment under the environmental considerations is taken into account, then hydroelectricity is by far the technology with the highest increase in cumulative installed capacity in the scenarios with the new investment model.

It is important to highlight that while scenarios with large uptake of hydroelectricity might seem technically feasible, the associated impact on local communities might strongly influence social perception on hydroelectricity (Susskind et al., 2014). Therefore, the general policy implications of these scenarios have to be weighed against the specific local context if any practical policy recommendation is expected to be drawn.

Chapter 12

Conclusions

As discussed in the opening section of this dissertation, the dominant position of fossil fuels in the global energy matrix, creates strong inertia (Grubb, 2014, p. 312), and hinders profound decarbonisation in the short time scale required for meeting the targets of the Paris Agreement (UNFCCC, 2016). The power sector is particularly important in this regard, because low-carbon electricity has system-wide benefits that go beyond the electricity sector, enabling significant reductions of CO_2 emissions in other sectors through electrification (IEA and OECD, 2012a, 10). The long time scales of the capital stock in the power sector, however, constrain the speed at which technology diffusion can occur (Grubler, 2013, p. 51). Therefore, to break the technological lock-in imposed by fossil fuels, it is necessary to apply stringent policies (Campiglio, 2016), that facilitate the adoption of low carbon technologies, and stimulate private-sector investment (IEA and OECD, 2012a, p. 115). In this context, the work presented here provides decarbonisation scenarios of the global power sector, under uncertain drivers of technological change, and in doing so, enables a better understanding of the process of technology diffusion in the power sector.

Figures 12.1 and 12.2 combine the main decarbonisation trajectories analysed in this dissertation into two single charts: emissions (former) and cumulative emissions (latter) between 2010 and 2050 for the DEC scenarios presented in chapters 7, 9 and 11. In gray, are the trajectories associated with the uncertainty surrounding policy and natural resources availability, presented in chapter 7. In magenta, are the decarbonisation trajectories associated with the extreme scenarios of learning and flexibility of the grid with regard to adopting variable electricity, from chapter 9. The blue, orange and green dashed lines correspond to the single investment criteria analysed in chapter 11: LCOE, environmental considerations and policy uncertainty, respectively. The scenario that combines the three investment criteria (using

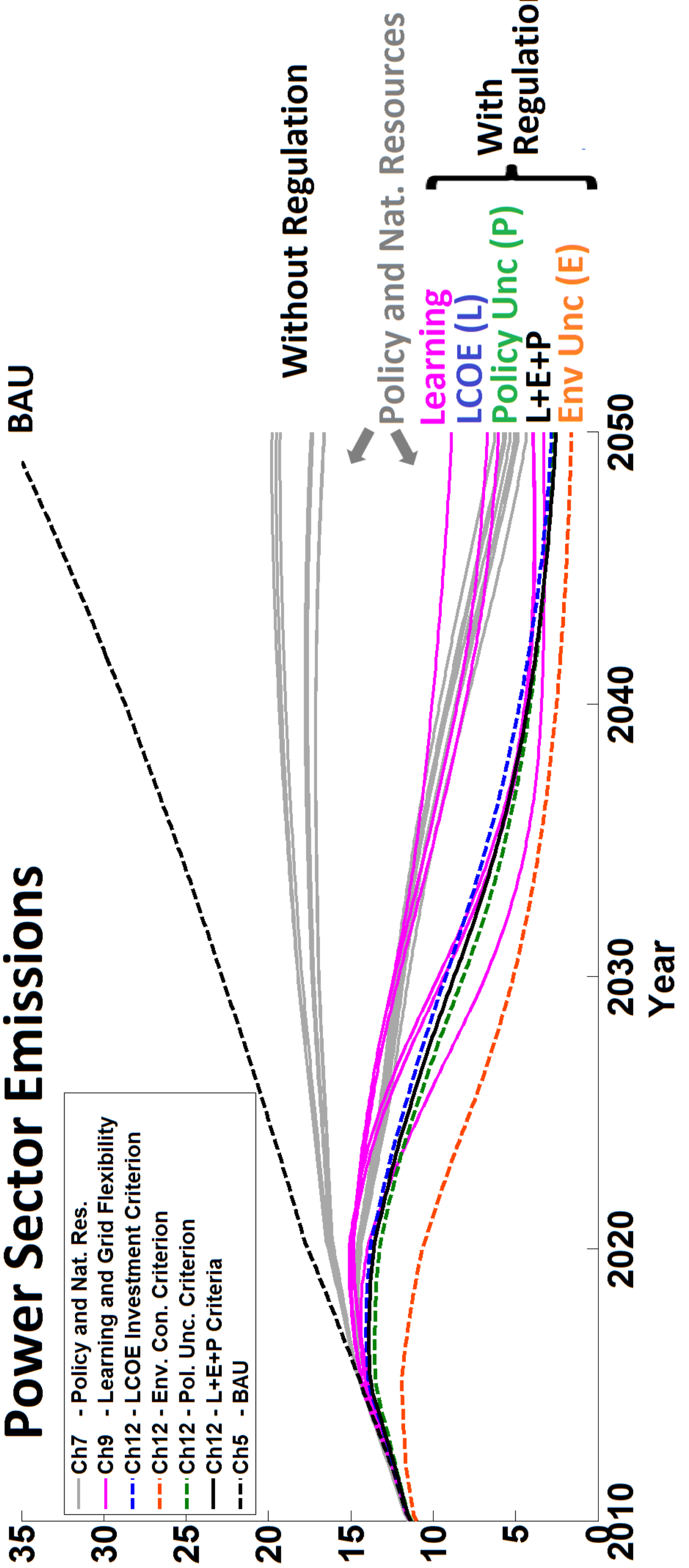


Figure 12.1 Emission trajectories of the main scenarios analysed in this dissertation. All of the trajectories follow the DEC assumptions, with the exception of the top black line, which corresponds to the BAU scenario (plotted as a reference).

$\alpha = 0.0037$) is shown as a black solid line on each chart. The black dashed lines correspond to the BAU scenario, added as a reference.

On the one hand, the trajectories from chapters 7 and 9 are part of an uncertainty propagation analysis (Lee and Chen, 2008), based on the variability of the underlying drivers of technological change (policy and natural resources availability in the former, learning and grid flexibility in the latter). On the other hand, in the scenarios presented in chapter 11, uncertainty is evaluated as part of the investment decision process, providing a structural or model structure uncertainty analysis (Walker et al., 2005). So, while the gray and magenta trajectories of figures 12.1 and 12.2 represent the effect of variability on decarbonisation, the green and orange dashed lines, as well as the black solid lines, show the impact of uncertainty on decarbonisation via investment decisions. All of them have to be compared against the blue dashed lines, that corresponds to the incumbent FTT:Power investment model, under the default assumptions regarding learning rates and natural resource availability (please refer to section 5.2 for more details).

The main conclusions obtained from the analyses of the scenarios summarised in figure 12.1 are presented below.

12.1 The role of the policy portfolio

Four types of policies were analysed in this work: *carbon pricing*, *subsidies*, *feed-in-tariffs* and *direct regulation* (in the form of an exogenous cap on installed capacity). They were combined with exogenous scenarios of electricity demand, learning and natural resources availability.

- In contrast with traditional modelling approaches, which suggest that carbon pricing is the foremost solution to spur low-carbon investment (Campiglio, 2016), the results presented in this work show that **a combination of market-based and regulation policies present greater efficiency and larger abatement than single policy instruments**.
- In terms of single decarbonisation policies, direct regulation exhibits the highest policy efficiency, followed by carbon pricing, feed-in-tariffs and subsidies.
- The abatement of a combination of policy instruments is not simply the sum of the abatement of each instrument, but rather a more complex, non-linear emission reduction pattern.

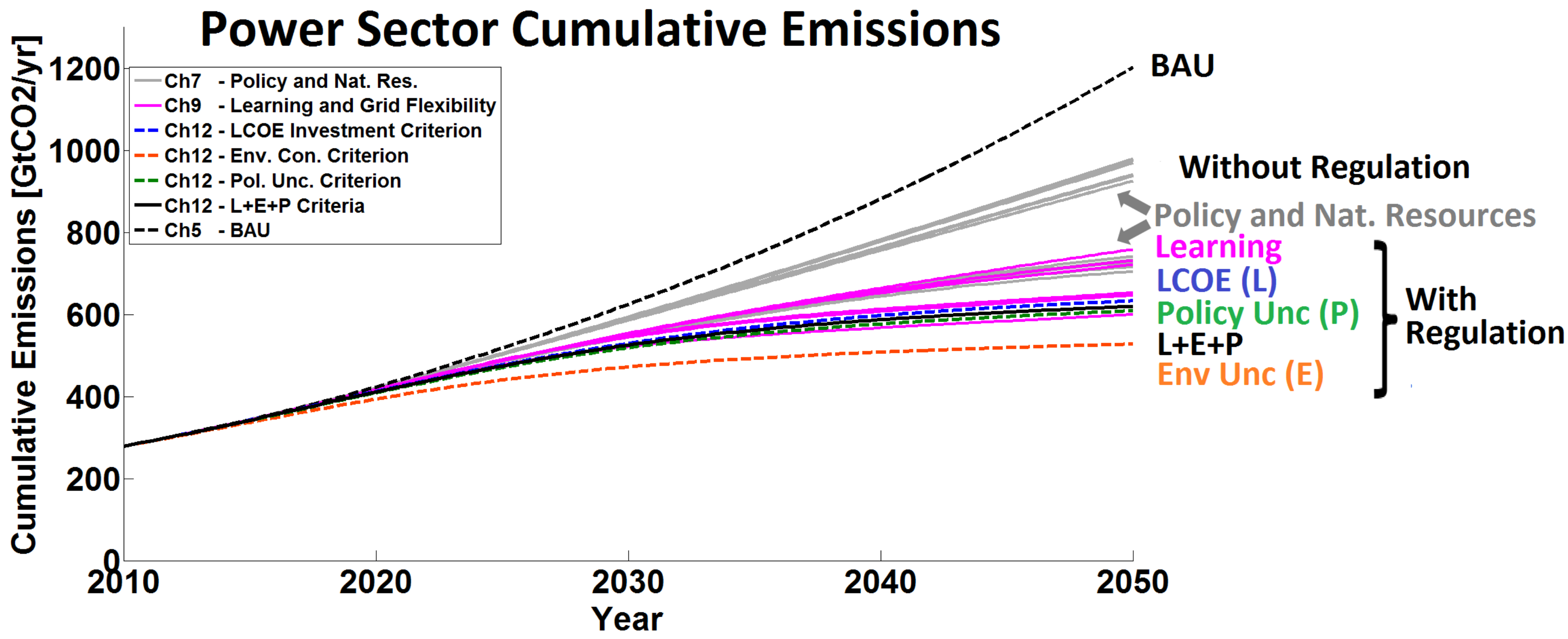


Figure 12.2 Cumulative emission trajectories of the main scenarios analysed in this dissertation. All of the trajectories follow the DEC assumptions, with the exception of the top black line, which corresponds to the BAU scenario (plotted as a reference).

- As explained in section 5.6, the abatement potential of regulatory policies is closely connected to the assumption of complete feasibility of regulation. Similarly, the abatement potential of non-regulatory policies might be influenced by the strong inertia produced by the shares equation formulation. As a consequence of this, policy implications based on the relative performance of market over non-market based policies need to be interpreted with caution, and further analysed at the light of the local context of the specific region under analysis.

12.2 Availability of energy resources

In chapters 7 and 8, the efficiency of policy instruments was analysed under extreme scenarios of renewable energy availability. In that context, the main conclusions obtained are:

- **Policy efficiency is strongly affected by the availability of energy resources**. Access to affordable sources can make a significant difference to the price of electricity, therefore, the assessment of energy resources and costs (such as those provided in chapter 6) is essential to the design of efficient policy portfolios. This is particularly relevant when policies have to address energy poverty issues (UN-Energy, 2005), or fiscal austerity (Schaefer and Streeck, 2013), as well as when policies are based on energy resources that could be adversely affected by climate change, such as hydropower and biomass (IPCC, 2011, ch. 2 & 5).
- Brazil is an excellent example in this regard: its high dependency on hydroelectricity hinders the efficiency of strong decarbonisation policies, particularly under scenarios of low availability of hydropower resources. In order to achieve its INDC target, Brazil will require comprehensive decarbonisation policies, involving several sectors, especially energy, agriculture, and land use.

12.3 Learning uncertainty and grid flexibility

- In the context of the dynamic modelling framework of FTT:Power, **the overall impact of learning rate uncertainty, due to over or under estimation, on scenarios of the power sector, is comparatively small**, with respect to the impact of policy uncertainty on decarbonisation, presented in chapter 5, and the impact of natural resources availability uncertainty on decarbonisation, presented in chapter 7.

- In contrast with the relatively low impact of uncertainty in the learning rates on emission reductions, **the flexibility of the grid to adopt variable electricity plays an important role in the adoption of renewable energies, and therefore in decarbonisation**. This can be seen by the differences between the two groups of magenta trajectories on figures 12.1 and 12.2.
- The capacity of the system to deploy variable electricity from renewable energies, determines the speed and extent to which the power sector can be decarbonised (Boyle, 2012). In stringent decarbonisation scenarios, investors' concern about the stability of the system can hinder the adoption of variable electricity generation technologies, such as wind energy. Therefore, to reach the target stated by the Paris Agreement (UN, 2015b), the capacity of the grid to adopt renewable energies needs to increase accordingly.
- The high values of storage used in FTT:Power are a stylised representation of a wider adoption of technologies that increase grid flexibility, including supply and reserve sharing, flexible generation, demand flexibility, curtailment and controllable loads. While the impact of grid flexibility in the price of electricity cannot be determined from these simulations, the main point of the analysis still holds: the flexibility of the grid plays a significant role in the decarbonisation of the power sector (Denholm and Hand, 2011).

12.4 Investment criteria

Using the investment decision model proposed in chapter 10, decarbonisation scenarios under different investment drivers are analysed in chapter 11, including *market considerations* (part of the incumbent investment model in FTT:Power), *environmental concerns* and *policy uncertainty*. The abatement scenarios analysed with the new investment model, provide a better understanding of the potential effects of uncertainty on decarbonisation, given the underlying policy landscape. This is an important step towards the creation of more comprehensive models of investment decision-making under uncertainty in the power sector. The proposed modelling approach incorporates quantitative and qualitative criteria, and model more realistically the actual decision-making process of energy investors. The most important conclusions obtained from this analysis are:

- **The emission trajectories based on investment decisions driven by environmental concerns, policy uncertainty, or a combination of these with market-based**

considerations, are lower than the emission trajectories from scenarios of investment decisions driven by pure market-based considerations. The orange and green dashed trajectories of figures 12.1 and 12.2, corresponding to the environmental and policy uncertainty criteria, respectively, are below the trajectory based on the incumbent investment model of FTT:Power (blue dashed lines), *ceteris paribus*. The same happens with the black solid lines, representing the three investment criteria combined. Currently, fossil fuels have a dominant position in the power sector, and therefore, the system displays strong inertia, and tends to perpetuate the established interests (Grubb, 2014, p. 312). Under pure market-based investment considerations, the replacement of competitive incumbent technologies with low-carbon alternatives, requires strong external support (Campiglio, 2016). Consequently, the incorporation of investment criteria based on environmental concerns or policy uncertainty, hinders the strong dominance of market-based investment considerations, that perpetuate the dominance of fossil fuels. It is important that we understand the effect of environmental and policy uncertainty criteria on investment decisions. This is the first step towards the design of investment incentives that offset the strong dominance of fossil fuels, and thus help to break the technological lock-in of the power sector.

- The inertia of the power sector creates a delay in the response of the system to stringent decarbonisation policies. This can be seen when market-driven emission trajectories are compared with environmentally driven counterparts (see section 11.2.4). In figure 12.1, the peak in the orange dashed line is produced earlier in the simulation than the peak in the blue dashed line. After 2030, the difference between the orange and blue dashed trajectories diminishes monotonically, showing a convergence in emissions of the two scenarios in the long run. As a consequence of the difference between the two trajectories before 2030, the cumulative emissions by 2050 (represented by the orange and blue dashed lines in figure 12.2) have a difference of approximately 106 $GtCO_2$. These results are in line with the findings of the cross-model comparison exercises presented in chapter 3: in order to maintain the political feasibility of keeping the target of the Paris Agreement within reach, strong abatement efforts before 2030 are required (Kriegler et al., 2013).

- Policy uncertainty hinders investment in low carbon technologies that require strong policy support, such as solar PV. Therefore, in order to encourage investment in low carbon technologies, it is paramount that policy makers maintain a stable policy landscape (White et al., 2013), and minimise investors' concern regarding potential changes in market-based policy instruments.

- If compared with the pure market-based investment criterion, the main difference produced by bringing environmental and policy uncertainty considerations into power sector scenarios is in the use of hydropower resources (a conclusion consistent with the findings of chapters 7 and 8). If the constraints in the use of hydropower resources are relaxed, either by increasing the technical potential of hydroelectricity (as in chapter 7), or by using an investment criterion not based on cost (as in chapter 11), then hydropower consumption increases radically. It is important to highlight that while scenarios with large uptake of hydroelectricity might seem technically feasible, the associated impact on local communities might strongly influence social perception on hydroelectricity (Susskind et al., 2014). Therefore, as part of the study of potential decarbonisation pathways in the power sector, the general policy implications of modelling the process of energy resource use and depletion have to be weighed against the specific local context if any practical policy recommendation is expected to be drawn.

12.5 The effect of uncertainty and the RCP reference levels

Figure 12.3 contrasts the cumulative emission trajectories presented in figure 12.2 with the RCP trajectories of the IPCC (2014d, page 11). The RCP reference levels presented in figure 12.3 correspond with the cumulative emissions up to 2050 of the RCP scenarios, as presented in Table 6.3 in IPCC (2014b, p. 431), scaled down proportionally to the ratio between the total emissions and the emissions from the power sector in the year 2010 (IEA, 2015). i.e., the RCP reference levels of figure 12.3 assume that, with no further information regarding other sectors of the economy, all of them (including the power sector), are decarbonised proportionally.

The chart of figure 12.3 presents the uncertainty intervals associated with the main subjects analysed in this work: policy efficiency under uncertain availability of natural resources, learning rate uncertainty under extreme grid flexibility, and the combination of different investment criteria. Based on figure 12.3, a number of important conclusions can be drawn:

- **The largest effect of uncertainty on the decarbonisation of the power sector is associated with the effect of policy stringency** (green interval): the extremes of the intervals correspond to trajectories with and without direct regulation policy in place (bottom and top, respectively).

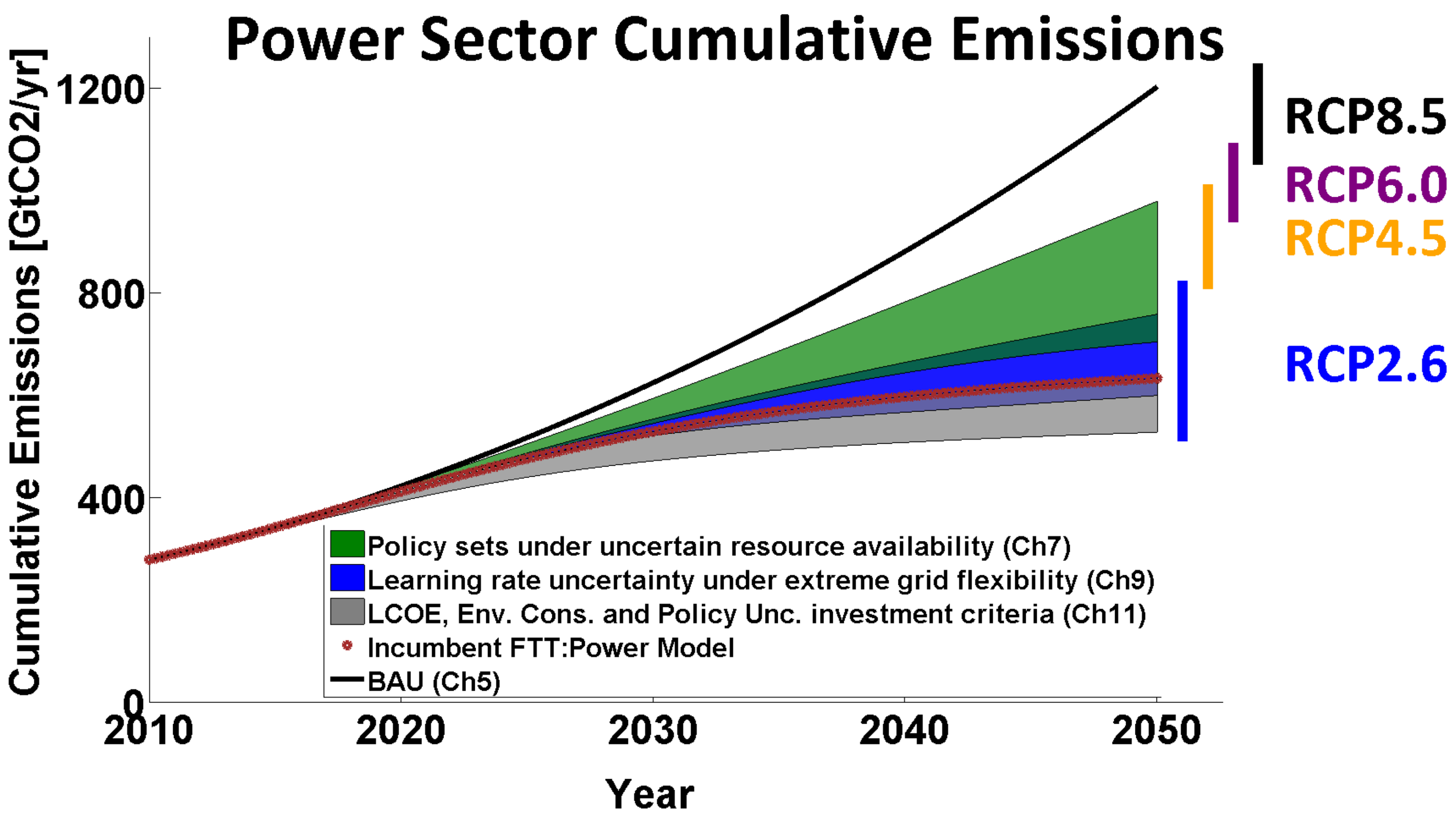


Figure 12.3 Cumulative emission trajectories of the main scenarios analysed in this dissertation. At the extreme right-hand, reference levels from the RCP scenarios are highlighted. Because the emissions in this chart only involve the power sector, RCP levels are scaled down by the ratio between global emissions and power sector emissions in the year 2010. Data regarding the RCP scenarios from Table 6.3 in IPCC (2014b, p. 431), while data about emissions in 2010 from IEA (2015).

- The effect of natural resource availability uncertainty is not as significant as the effect of regulation. In figures 12.1 and 12.2, the variation within each of the gray groups of emissions is associated with extreme availability of natural resources (see figure 7.3 for more details).

- The scenarios of emission reductions based on market-based policies without direct regulation (the top group of gray trajectories in figures 12.1 and 12.2), do not follow the RCP2.6 trajectory. i.e., **market-based decarbonisation policies would not be sufficient to reach the Paris Agreement targets** (IPCC, 2014c, p. 20), even if all of the sectors of the economy are decarbonised proportionally.

- The impact of learning rate uncertainty is less significant than policy uncertainty and resource availability uncertainty. Most of the uncertainty represented by the blue range of figure 12.3 corresponds to variations in the grid flexibility to adopt variable electricity (see figure 9.1 for more details).

- **The incorporation of policy uncertainty and environmental regulation in the investment decision process produces lower emission trajectories** (gray area of figure 12.3). From a policy perspective, these results show the importance of providing incentives to investors that go beyond pure market-based considerations when facing decisions of low-carbon technology adoption. The use of short-term considerations for investment decisions has been identified as one of the key problems hindering long term sustainable investment (Beale and Fernando, 2009; Duruigbo, 2011). Therefore, a better understanding of the investment decision-making process is paramount to the creation of appropriate incentives that foster low-carbon innovation. In this context, the new methodology to model investment decisions presented in chapter 10, represents a significant contribution to the modelling literature.

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Appendix A

FTT:Power Main Equations and Variables

A.1 Chapter Summary

This chapter describes some of the main variables and equations in FTT:Power, that were not described with enough detail in the main text. The chapter also includes a table with the regional definition of the model.

Most of the information presented in this appendix is based on Mercure (2012).

A.2 Supply and Demand

D : Electricity demand (GWh)

G : Electricity generation (GWh)

U : Installed capacity (GW)

CF : Capacity Factor (%)

S : Market share (%)

The electricity demand of a particular region can be described as:

$$D = \sum_i G_i(t) = \sum_i U_i(t)CF_i(t)T_D = U_{tot}T_D \sum_i S_i(t)CF_i(t) \tag{A.1}$$

where i corresponds to a specific technology, and T_D is the amount of hours in a year (8766). Calling $\overline{CF} = \sum_i S_i(t)CF_i(t)$, and replacing $U_i = U_{tot} \cdot S_i$, then we have

$$U_i = \frac{S_i D}{T_D \overline{CF}} \tag{A.2}$$

Therefore, the change of installed capacity of a specific technology over time can be described as:

$$\frac{dU_i}{dt} = \frac{S_i}{T_D \overline{CF}} \frac{dD}{dt} + \frac{D}{T_D \overline{CF}} \frac{dS_i}{dt} - \frac{S_i D}{T_D \overline{CF}^2} \frac{d\overline{CF}}{dt} \tag{A.3}$$

The first term represents changes in installed capacity due to changes in total demand (larger the demand, more capacity is needed). The second term represents changes in installed capacity due to changes in the market share (larger the market share of a technology, more installed capacity of that technology is required). Finally, the third term represents changes in installed capacity due to changes in the overall capacity factor of the system, which is a measure of the efficiency (more efficient the system is, less installed capacity is required).

A.3 Technical Constraints

Figure A.1 shows a hypothetical profile of daily power demand. The variation in daily demand imposes constraints in the amount of electricity that can be generated using different energy sources, if the stability of the system is to be addressed. The unpredictable nature of some renewable energy resources such as wind, have to be complemented with flexible generation sources, such as gas. To analyse this phenomenon in detail, a dispatch model would be required, to match supply and demand at every moment. The level of detail of such modelling approach is beyond the capabilities of the current version of FTT:Power. Instead, a more simple approach is used, based on constraints over the main variables of the system.

The demand for electricity in FTT:Power is satisfied by three types of electricity generation sources: *baseload*, *flexible* and *variable*. Table 4.1 in chapter 4 provides a detailed description of which technology belongs to each group. The case of flexible technologies is special,

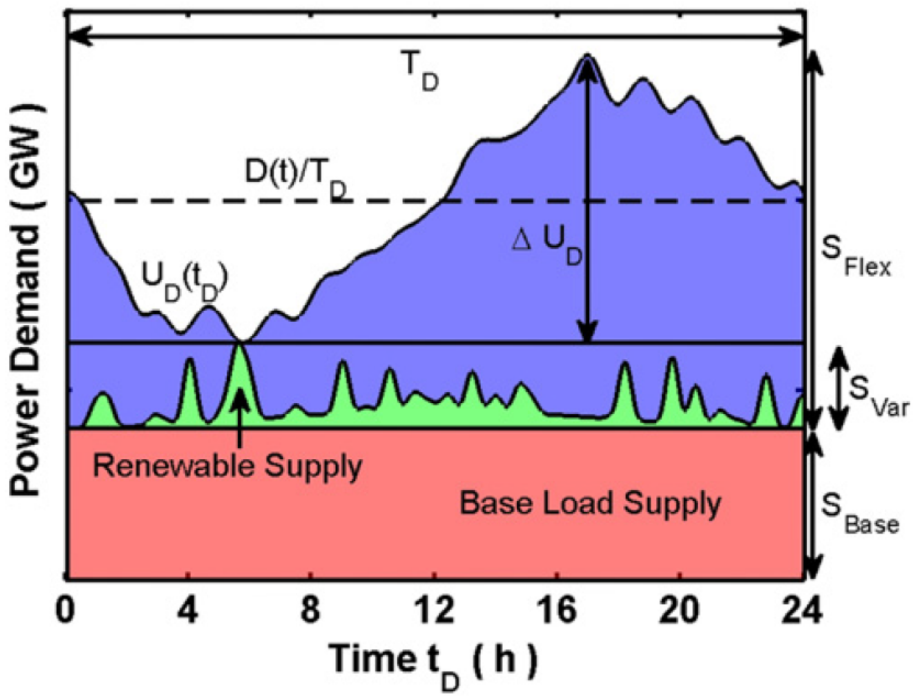

Figure A.1 Sketch of a hypothetical profile of daily power demand $U_D(t_D)$ as a function of the time of day t_D. From Mercure (2012).

beacause they can be used as baseload (continuous operation) or as complement to variable technologies. If the subscripts B, F and V are used for *baseload*, *flexible* and *variable* generation technologies respectively, then the demand equation can be written as:

$$\begin{aligned} D &= G_B + G_V + G_F \\ &= G_B + G_V + G_F^{base} + G_F^{peak} \end{aligned} \tag{A.4}$$

where G_F^{base} and G_F^{peak} correspond to electricity generation from flexible technologies used for baseload and peak demand respectively. Defining ΔD as the energy required in peak demand, and E_S the electricity generated by energy storage systems, then the electricity generated by flexible and variable technologies at peak demand must be:

$$G_V + G_F^{peak} = \Delta D - E_S \tag{A.5}$$

Replacing in equation A.4 and isolating G_F^{base}, we have:

$$G_F^{base} = D - G_B - \Delta D + E_S = U_F^{base} \cdot CF_F^{base} \cdot T_D \tag{A.6}$$

where CF_x^{base}, $x \in \{B, F, V\}$, is the capacity factor averaged over the corresponding category, using rated values:

$$CF_x^{base} = \frac{\sum_x S_i CF_i^{rated}}{\sum_x S_i} \tag{A.7}$$

Part of the flexible installed capacity is directed to cover baseload demand, while the rest of the flexible installed capacity is directed to cover peak load demand:

$$U_F = U_F^{base} + U_F^{peak} \tag{A.8}$$

being U_F^{base} and U_F^{peak} the flexible capacity installed to respond for baseload and peak demand respectively. The installed capacity of peak load flexible sources plus storage generation capacity (U_S) must be at least able to cover for possible variations of power demand (ΔU_D) and variable capacity (U_V from renewable technologies):

$$U_F^{peak} + U_S = \Delta U_D + U_V \tag{A.9}$$

Replacing A.6 and A.9 in A.8, we have:

$$\begin{aligned} U_F &= U_F^{base} + U_F^{peak} \\ U_F &= \frac{G_F^{base}}{CF_F^{base} T_D} + \Delta U_D + U_V - U_S \\ U_F &= \frac{D - G_B - \Delta D + E_S}{CF_F^{base} T_D} + \Delta U_D + U_V - U_S \end{aligned} \tag{A.10}$$

From A.2 we know that $U_i = \frac{S_i D}{CF T_D}$. Replacing in A.10 we obtain:

$$\frac{S_F \cdot D}{\overline{CF} \cdot T_D} = \frac{D - G_B - \Delta D + E_S}{CF_F^{base} T_D} + \Delta U_D + U_V - U_S$$

$$\begin{aligned}
\Rightarrow S_F \cdot CF_F^{base} &= \overline{CF}\left(1 - \frac{G_B}{D} - \frac{\Delta D}{D} + \frac{E_S}{D} + \left(\frac{\Delta U_D}{D} + \frac{U_V}{D} - \frac{U_S}{D}\right) CF_F^{base} T_D\right) \\
&= \overline{CF}\left(1 - \frac{U \cdot S_B \cdot CF_B}{U \cdot \overline{CF}} - \frac{\Delta D}{D} + \frac{E_S}{D}\right) + \left(\frac{\Delta U_D \cdot \overline{CF}}{D} + \frac{U_V \cdot \overline{CF}}{D} - \frac{U_S \cdot \overline{CF}}{D}\right) CF_F^{base} T_D \\
&= \overline{CF}\left(1 - \frac{\Delta D}{D} + \frac{E_S}{D}\right) - S_B \cdot CF_B + \left(\frac{\Delta U_D}{U} + S_V - \frac{U_S}{U}\right) CF_F^{base} \qquad \text{(A.11)}
\end{aligned}$$

Isolating $\overline{CF}$ we obtain:

$$\overline{CF} = \frac{S_F \cdot CF_F^{base} + S_B \cdot CF_B - \left(\frac{\Delta U_D}{U} + S_V - \frac{U_S}{U}\right) CF_F^{base}}{1 - \frac{\Delta D}{D} + \frac{E_S}{D}} \qquad \text{(A.12)}$$

Noting that

$$\overline{CF} = S_B \cdot CF_B + S_F \cdot CF_F + S_V \cdot CF_V \qquad \text{(A.13)}$$

CF_F can be isolated from A.12, obtaining:

$$CF_F = \left(\frac{1}{S_F}\right)\left(\frac{S_F \cdot CF_F^{base} + S_B \cdot CF_B - \left(\frac{\Delta U_D}{U} + S_V - \frac{U_S}{U}\right) CF_F^{base}}{1 - \frac{\Delta D}{D} + \frac{E_S}{D}} - S_B \cdot CF_B - S_V \cdot CF_V\right) \qquad \text{(A.14)}$$

Equation A.14 constrains the use of flexible generation sources to match supply and demand, through the modification of the capacity factor. I.e., flexible technologies can be used more or less intensively, to maintain supply and demand in equilibrium, given the extra requirements during peak-demand ($\frac{\Delta U_D}{U}$), the amount of storage available ($\frac{E_S}{D}$), and the current state of the system (defined by the shares).

In chapter 9, extreme learning rate scenarios for the power sector are analysed under low and high grid flexibility configurations. For these scenarios, the ratios of peak-demand and storage are modified, to allow the system to manage different levels of variable, flexible and baseload technologies. The values used in chapter 9 are presented below, by region and scenario:

A.3.1 Demand profile dD/D

Regions	low grid flexibility	high grid flexibility
1,4,5,7,9-11,13,14,31,36,40,42	0.13	0.0013
2,3	0.03	0.0003
6,8,18,19,22,24,27-30,32,34,37-39,43-47,49-53	0.2	0.002
12,35	0.06	0.0006
15	0.07	0.0007
16,26,41	0.05	0.0005
17	0.02	0.002
20,25	0.1	0.001
21	0.16	0.0016
23	0.03	0.0003
33	0.01	0.0003
48	0.04	0.0004

Table A.1 Demand profile dD/D, low and high grid flexibility configuration.

A.3.2 Storage generation normalised by demand E_S/D

Regions	low grid flexibility	high grid flexibility
1,7,9-11,14	0.03	0.9
2	0.8	0.9
3	0.5	0.9
4,13,35,53	0.1	0.9
5,6,15,20	0.2	0.9
8,31,34,40,49	0.06	0.9
12,25,42	0.13	0.9
16	0.48	0.9
17	0.9	0.9
18,19,21,22,27,30,32	0.046	0.9
23,33	0.6	0.9
24	0.08	0.9
26	0.3	0.9
28,29,36,38,39,43-47,50-52	0.006	0.9
37	0.12	0.9
41,	0.22	0.9
48	0.4	0.9

Table A.2 Storage generation normalised by demand E_S/D, low and high grid flexibility configuration.

A.3.3 Storage capacity normalised by the total capacity

Regions	low grid flexibility	high grid flexibility
1,7,9-11,14	0.05	0.9
2	0.5	0.9
3,16,48	0.4	0.9
4,13,27,35,40	0.15	0.9
5,6,20,26,41	0.3	0.9
8,31,49	0.1	0.9
12,25,42,53	0.2	0.9
15	0.25	0.9
17,33	0.55	0.9
18,19,21,22,30,32	0.07	0.9
23	0.45	0.9
24,34	0.12	0.9
28,29,36,38,39,43-47,50-52	0.01	0.9
37	0.18	0.9

Table A.3 Storage capacity normalised by the total capacity

A.3.4 Demand profile dU/U

Regions	low grid flexibility	high grid flexibility
1,15,20,25,	0.15	0.0015
2,17,33	0.05	0.0005
3,12,16,26,35,48	0.1	0.001
4,5,7,9-11,13,14,31,36,40	0.2	0.002
6,8,18,19,22,24,27-30,32,34,37-39,43-47,49-53	0.3	0.003
21	0.25	0.0025
23	0.07	0.0007
41,42	0.17	0.0017

Table A.4 Demand profile dU/U, low and high grid flexibility configuration.

A.4 Regional Definition

FTT Region	Member Countries
1 - Belgium	Belgium
2 - Denmark	Denmark
3 - Germany	Germany
4 - Greece	Greece
5 - Spain	Spain
6 - France	France
7 - Ireland	Ireland
8 - Italy	Italy
9 - Luxembourg	Luxembourg
10 - Netherlands	Netherlands
11 - Austria	Austria
12 - Portugal	Portugal
13 - Finland	Finland
14 - Sweden	Sweden
15 - UK	UK
16 - Czech Republic	Czech Republic
17 - Estonia	Estonia
18 - Cyprus	Cyprus
19 - Latvia	Latvia
20 - Lithuania	Lithuania
21 - Hungary	Hungary
22 - Malta	Malta
23 - Poland	Poland
24 - Slovenia	Slovenia

Table A.5 FTT:Power regions 1-24 / 53.

FTT Region	Member Countries
25 - Slovakia	Slovakia
26 - Bulgaria	Bulgaria
27 - Romania	Romania
28 - Norway	Norway
29 - Switzerland	Switzerland
30 - Iceland	Iceland
31 - Croatia	Croatia
32 - Turkey	Turkey
33 - Macedonia	Macedonia
34 - USA	USA
35 - Japan	Japan
36 - Canada	Canada
37 - Australia	Australia
38 - New Zealand	New Zealand
39 - Russia	Russia
40 - Rest of Annex I	Belarus, Ukraine
41 - China	China
42 - India	India
43 - Mexico	Mexico
44 - Brazil	Brazil
45 - Argentina	Argentina
46 - Colombia	Colombia

Table A.6 FTT:Power regions 25-46 / 53.

FTT Region	Member Countries
47 - Rest of LatAm	Barbados, Belize, Bolivia, Chile, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Falkland Island, French Guiana, Grenada, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Jamaica, Martinique, Netherlands Antilles, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, St Vincent & the Grenadines, Suriname, Trinidad and Tobago, Uruguay
48 - Korea	Korea
49 - Taiwan	Taiwan
50 - Indonesia	Indonesia
51 - Asean	Buthan, Brunei, Cambodia, Hong Kong, Laos, Malaysia, Myanmar (Burma), Philippines, Singapore, Sri Lanka, Thailand, Vietnam
52 - OPEC	Algeria, Iran, Iraq, Kuwait, Libyia, Nigeria, Qatar, Saudi Arabia, UAE, Venezuela
53 - Rest of the World	All other countries not specified elsewhere

Table A.7 FTT:Power regions 47-53 / 53.

A.5 Cumulative effect of technological constraints on wind

In section 9.8.2, the cumulative effect of the technical constraints on wind in USA, China and India is analysed, for extreme learning rate scenarios under different grid flexibility configurations. In this section, it is explained how figure 9.3, which is part of that section, is created. The mathematical formulation presented here, is based on the theoretical basis of FTT:Power, which can be found in Mercure (2011, 2012, 2015).

Let define the function G_{max} for wind such that

$$G_{max}(t) = tanh(\alpha \cdot (\hat{S}(t) - S(t))) \tag{A.15}$$

where S(t) is the share of wind at time t, α is a scale parameter and $\hat{S}$(t) is the share limit of wind at time t, defined as:

$$\hat{S} = S - \left(S_v - S_f + \left(\frac{\Delta U_D}{U} - \frac{U_S}{U}\right)\right) \tag{A.16}$$

where S_v and S_f are the sum of the shares of variable and flexible technologies, respectively, and $\frac{\Delta U_D}{U}$ and $\frac{U_S}{U}$ are the *demand profile* and the *energy storage capacity normalised by the total capacity*, as defined in section A.3. If $\hat{S}$ is written in expanded form, it looks like the following:

$$\hat{S} = S_{gas} + S_{hydro} + S_{oil} + \cdots + \left(\frac{\Delta U_D}{U} - \frac{U_S}{U}\right) - S_{solar} - S_{wave} - \cdots \tag{A.17}$$

So, the share limit of wind is defined by the amount of flexible electricity available in the grid ($S_{gas} + S_{hydro} + S_{oil} + \cdots$), by the amount of variable electricity that is already in the system ($S_{solar} + S_{wave} + \cdots$), by the peak-demand consumption pattern of the system ($\frac{\Delta U_D}{U}$) and by the energy storage capacity of the system ($\frac{U_S}{U}$).

Given the previous definition, the function G_{max} approaches one for share values of wind that are far from the share limit ($\hat{S} \gg S$), and it approaches 0 for share values of wind that are close to the share limit $\hat{S} \sim S$. Because $\hat{S} >= S$, then the range of G_{max} is defined in the interval [0 1).

As mentioned in section 9.8.2, when investment decisions are taken, they are weighted by a *probability of investment* factor that incorporates information about the flexibility of the grid. G_{max} corresponds to one of those factors, part of the term G_{ij} of the shares equation (see section 4.6 for more details about the shares equation).

G_{max} provides a measure of the investors' concern regarding the stability of the grid:

- If $\hat{S} \gg S$, then G_{max} is close to one, so there is no concern regarding problems with the stability of the grid due to the excess of variable electricity (the shares equation are not affected by G_{max})
- If $\hat{S} \sim S$, then $G_{max} \to 0$, so investors' concern regarding the stability of the grid hinders the adoption of more variable electricity (the shares equation are modified through G_{ij}, such that no more variable electricity is adopted).

If G_{max} is interpreted as the probability of investing in wind, equal to the probability of not having passed the share limit (Mercure, 2011, p. 22), then the probability of passing the limit is defined as $p = 1 - G_{max}$. Because G_{max}, and therefore p, are instantaneous indicators, the cumulative effect can be calculated using integration over time. So, the cumulative effect of the G_{max} on wind is defined as:

$$P = \frac{1}{\beta} \int_{2016}^{2050} p dt = \frac{1}{\beta} \int_{2016}^{2050} (1 - G_{max})\, dt \tag{A.18}$$

where β is a normalisation factor such that $P \in [01]$. The black dashed line of figure 9.3, which corresponds to the theoretical maximum of P, is calculated using $G_{max} = 1$ over the entire period.

For more details about how G_{max} interacts with the shares equation, please refer to Mercure (2011, ch. 3).

Appendix B

NER Complementary Information

B.1 Nearly Identical Resources Distribution

In the case of NI type of resources,[1] the N energy producing units are assumed to be situated narrowly at a productivity value μ. If their productivity is truly identical, a Dirac delta function[2] can be used to describe the distribution:

$$g(\nu)d\nu = N\nu\delta(\nu-\mu)d\nu \quad \Rightarrow \quad A = \int_0^\infty g(\nu)d\nu = N\mu \tag{B.1}$$

So, the total amount of energy available, i.e. the technical potential, is $A = N\mu$. In reality, however, the suitability factor of the land reduces its productivity. If the reductions are normally distributed, then the resource distribution can be calculated as the integral over all the possible reductions in productivity ε:

$$g(\nu)d\nu = \int_0^\infty N\nu\delta\left(\nu-(\mu-\varepsilon)\right)\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{\varepsilon^2}{2\sigma^2}}d\nu d\varepsilon = \frac{N}{\sigma\sqrt{2\pi}}\cdot\nu\cdot e^{-\frac{(\nu-\mu)^2}{2\sigma^2}}d\nu \tag{B.2}$$

[1]The mathematical derivation for this section is adapted from Mercure and Salas (2012).

[2]The Dirac delta function $\delta(\cdot)$ is the one that satisfies $\int_{-\infty}^{\infty} f(x)\delta\left(x-a\right)dx = f(a)$

Therefore, the productivity distribution can be written as:[3]

$$g(\nu)d\nu = \begin{cases} \frac{N}{\sigma\sqrt{2\pi}} \cdot \nu \cdot e^{-\frac{(\nu-\mu)^2}{2\sigma^2}} d\nu & \nu < \mu \\ 0 & \nu \geq \mu \end{cases} \tag{B.3}$$

where σ^2 is the variance of a very narrow normal distribution around μ ($\sigma << \mu$). To move into the cost space, let make the same change of variable as the one made for the HI distribution (equation 6.2 in chapter 6), but taking into consideration that ν can be written as a small variation around μ: $\nu = \mu - \varepsilon$. Therefore,

$$C = \frac{C_{var}}{\nu} + \hat{C}_0 = \frac{C_{var}}{\mu - \varepsilon} + \hat{C}_0 \tag{B.4}$$

Using the approximation $1/(1-x) \approx 1 + x$ for small x:

$$C \approx \frac{C_{var}}{\mu}\left(1 + \frac{\varepsilon}{\mu}\right) + \hat{C}_0 = \frac{C_{var}}{\mu}\left(1 + \frac{\mu - \nu}{\mu}\right) + \hat{C}_0 \tag{B.5}$$

Isolating ν and renaming $C_0 = C_{var}/\mu + \hat{C}_0$:

$$\nu = (C_0 - C)\frac{\mu^2}{C_{var}} + \mu \tag{B.6}$$

Replacing in B.3:

$$g(\nu)d\nu = \begin{cases} \frac{N}{\sigma\sqrt{2\pi}} \cdot \left((C_0 - C)\frac{\mu^2}{C_{var}} + \mu\right) \cdot e^{-\frac{(C_0-C)^2\mu^4}{2\sigma^2 C_{var}^2}} \frac{\mu^2}{C_{var}} dC & \nu < \mu \\ 0 & \nu \geq \mu \end{cases} \tag{B.7}$$

Let rename $B = \frac{\sigma C_{var}}{\mu^2}$. Replacing and re-arranging the previous equation:

$$g(\nu)d\nu = \begin{cases} \frac{N\mu}{B\sqrt{2\pi}} \cdot \left(\frac{(C_0-C)\sigma}{B\mu} + 1\right) \cdot e^{-\frac{(C_0-C)^2}{2B^2}} dC & \nu < \mu \\ 0 & \nu \geq \mu \end{cases} \tag{B.8}$$

[3]The NI productivity distribution is assumed to be zero for $\nu \geq \mu$. This assumption comes from having positive reductions in productivity around μ.

Finally, let notice that C cannot be below C_0 by definition, but also, the factor $exp[-(C-C_0)^2/2B^2]$ decreases rapidly to zero as $C-C_0$ becomes larger than B. Therefore, the value of the term $(C_0-C)/B$ is less than one wherever a significant potential of energy exists. Since σ is much smaller than μ, this results with

$$\frac{\sigma(C-C_0)}{\mu B} << 1 \tag{B.9}$$

and therefore the solutions becomes

$$g(C)dC = \begin{cases} \frac{A}{B\sqrt{2\pi}} \cdot e^{-\frac{(C-C_0)^2}{2B^2}} dC & C > C_0 \\ 0 & C \leq C_0 \end{cases} \tag{B.10}$$

Appendix C

Learning Rates Complementary Information

C.1 Literature Review

C.1.1 Nuclear Energy

The range chosen for the learning rates of nuclear energy is [0% - 17%] while the default value on FTT:power is 5.8%. The upper limit is based on Weiss et al. (2010), that estimates a learning rates range of [1% - 17%]. Rubin et al. (2015) proposes a lower limit of -38%, based on investment cost data from USA and France as a function of cumulative installed capacity, taken from (Grubler, 2010). However, the calculations do not take any of the considerations described in Grubler's paper. Therefore, it is considered only as a reference, not as a learning rate limit. A lower range limit of zero was used for nuclear energy, instead. Other estimates include an upper limit of 5.8%, proposed by Kouvaritakis et al. (2000), based on OECD investment costs as a function of cumulative installed capacity. This upper limit can also be found in several other publications, including EPRI (2013); Kahouli-Brahmi (2008); McDonald and Schrattenholzer (2001) and Rubin et al. (2015).

C.1.2 Oil

The only references to oil learning rates found in the literature are in Blackwood (1997) and in McDonald and Schrattenholzer (2001). They estimate the learning rate in 25%, based on oil extraction costs as a function of labour. This extremely high value was not included in the FTT:Power analysis of chapter 9. Instead, the learning rate range was defined as ±50% of the default value, (1%), i.e., [0.5% - 1.5%].

C.1.3 Coal and Coal+CCS

The default FTT:Power learning rate value for coal is 3%, and the range used in chapter 9 is [3% - 14%]. The lowest learning rate value for coal found in the literature was 4%, higher than the default value in FTT:Power. The 4% value comes from Weiss et al. (2010), that estimates a learning rate range for coal and lignite power plants of [4% - 14%]. This is the source for the upper limit of the range chosen in chapter 9.

There exists many other estimates for coal learning rates. For instance, Kahouli-Brahmi (2008); Kouvaritakis et al. (2000) and McDonald and Schrattenholzer (2001) estimate learning rates of 7.6% and 8.6%, based on OECD coal and lignite power plant investment costs as a function of cumulative installed capacity, respectively. EPRI (2013) and Rubin et al. (2015) estimate a range of [5.6% - 12%]. The lower limit comes from the decomposition of coal-based plants into sub-systems, being 5.6% the overall learning for the construction cost of subcritical boilers (the basic building block of a pulverised coal power plant). The upper limit is derived from the experience curve for plant construction costs, from McNerney et al. (2011). Junginger et al. (2010) calculates a learning rate value for coal of 8%, based on investment price as a function of installed capacity.

In the case of Coal+CCS, Rubin et al. (2007) estimated the learning rate range based on the total plant capital cost, O&M cost and electricity production, excluding CO_2 transport and storage costs, as [1.5% - 5.4%]. The upper limit is later cited by Junginger et al. (2010) as 6%. Eight years later, Rubin et al. (2015) wider the range for coal+CCS, to [1.1% - 9.9%]. The lower limit corresponds to future learning estimations for overall pulverised coal power plants based on USA designs for new supercritical plants, based on Rubin et al. (2007). The upper limit corresponds to a component-based learning curve for pulverised coal power plants with CCS in China, based on Li et al. (2012). The range [1.1% - 9.9%] is the one used in chapter 9, while the default FTT:Power value is 5%.

C.1.4 IGCC and IGCC+CCS

Due to the low number of IGCC plants in operation worldwide, EPRI (2013) and Rubin et al. (2015) present learning rates estimations based in bottom up approaches from Rubin et al. (2007); van den Broek et al. (2009) and Li et al. (2012). The range presented in EPRI (2013) for IGCC is [2.5% - 7.6%], while Rubin et al. (2015) estimated the IGCC range as [2.5% - 16%]. The learnign rate range used in chapter 9 is the comnbination of these two ranges: [2.5% - 16%] (the default value in FTT:power is 3%). Rubin et al. (2007) estimates the learning rate of IGCC+CCS between [2.1% - 7.5%], while in Rubin et al. (2015) the estimated range is [2.5% - 20%]. The learnign rate range used in chapter 9 is the comnbination of these two ranges: [2.1% - 20%] (the default value in FTT:power is 5%).

C.1.5 CCGT and CCGT+CCS

The default FTT:Power learning rate value for CCGT is 4%, and the range used in chapter 9 is [4% - 34%]. The lower limit estimate can be found in IEA (2000); McDonald and Schrattenholzer (2001) and Kahouli-Brahmi (2008). Claeson (1999) provides an upper limit estimation for the learning rate of CCGT of 26%, while Kouvaritakis et al. (2000) estimates the upper limit in 34%, the latter used as the upper limit in chapter 9. Other estimations include Colpier and Cornland (2002), that estimated the range as [6% - 15%], based on the cost of electricity generation as a function of cumulative electricity production. Claeson (1999) provided an estimation for the lowest limit of the learning rate of -11%, a value that was considered unrealistic, and therefore discarded.

Regarding CCGT+CCS, the default learning rate value in FTT:Power is 5%. The range used in chapter 9 is [0.6% - 5%], taken from Rubin et al. (2007), an estimation for total plant capital cost, O&M cost and electricity, excluding CO_2 transport and storage costs.

C.1.6 Biomass

The default FTT:Power learning rate value for Biomass is 5%, and the range used in chapter 9 is [0% - 38%]. The lower limit of the learning rate range is from EPRI (2013), based on data from Junginger et al. (2010) and Koornneef et al. (2007). The same study estimates an upper limit of 24%. The upper limit of the range is taken from Weiss et al. (2010), that provides a range estimate of [10% - 38%]. Another estimation of 15%, based on the EU-ATLAS project, is presented in IEA (2000).

C.1.7 BIGCC

The default FTT:Power learning rate value for BIGCC is 5%, and is also used as the lower limit of the range for chapter 9: [5% - 10%]. The upper limit is taken from de Feber et al. (2002). The value is taken from the SAPIENT database, and corresponds to the gasifier cluster, were BIGCC and IGCC belong.

C.1.8 Biogas

The default FTT:Power learning rate value for Biogas is 5%, and the range used in chapter 9 is [0% - 15%]. This range is estimated by Junginger et al. (2006), based on values for Danish biogas plants that use manure and organic waste, between 1984 and 2002.

C.1.9 Biomass+CCS, BIGCC+CCS and Biogas+CCS

Due to the lack of reliable information about the learning rates of these technologies, the range was defined as $\pm$50% of their default FTT:Power learning rate (7%), i.e., [3.5% - 10.5%].

C.1.10 Tidal

The default FTT:Power learning rate value for Tidal is 1.4%, and is also used as the lower limit of the range for chapter 9: [1.4% - 15%]. The upper limit is taken from the range estimated by SI OCEAN (2013): [8% - 15%]. The values were estimated using expert judgement, and they match data based on bottom up engineering modelling.

C.1.11 Hydroelectricity

The default learning rate value for hydroelectricity in FTT:Power is 1.4%, based on Kouvaritakis et al. (2000), and also published by Kahouli-Brahmi (2008); McDonald and Schrattenholzer (2001) and Rubin et al. (2015). The value is based on capital costs as a function of cumulative installed capacity from OECD countries data. Due to the lack of more reliable studies about learning rates of hydroelectricity, the range for chapter 9 was defined as $\pm$50% of the default FTT:Power value: [.7% - 2.1%].

C.1.12 Wind Onshore

There is a vast amount of literature regarding the learning rates of onshore wind energy. The lowest estimate (used as lower limit of the learning rate range in chapter 9) is 4% (IEA, 2000; Kahouli-Brahmi, 2008; McDonald and Schrattenholzer, 2001; Neij, 1999), based on Danish wind turbine costs as a function of cumulative sales. Neij et al. (2003) estimated learning rate based on the capital cost as a function of cumulative production of wind turbines in Germany between 6% and 12%, and between 8% and 14% for Danish data. Ibenholt (2002) estimated the learning rate based on electricity production cost as a function of cumulative installed capacity in Denmark, Germany and the UK in 7.8%, 8% and 25%, respectively. Based on the capital cost of wind turbines as a function of cumulative installed capacity in USA, Mackay and Probert (1998) and Kahouli-Brahmi (2008) estimates was 14.3%. Other estimates include [5% -19%] (Weiss et al., 2010), 8% (Kahouli-Brahmi, 2008; McDonald and Schrattenholzer, 2001; Neij, 1999), 15% (Junginger et al., 2010), 17% (Kouvaritakis et al., 2000), and 18% (IEA, 2000).

The default FTT:Power learning rate value for Wind Onshore is 7%, and the range used in chapter 9 is [4% - 32%]. The uper limit is taken from IEA (2000); McDonald and Schrattenholzer (2001) and Kahouli-Brahmi (2008). A value of 32% was estimated for the learning of wind energy in USA, based on cost of generating electricity as a function of cumulative electricity production.

C.1.13 Wind Offshore

The amount of estimates for the learning rates of wind offshore are far less than for onshore. Rubin et al. (2015) estimated a range between [5% - 19%], which is the one used in chapter 9. The lower limit is based on projections made by Lemming et al. (2008). The upper limit is based on estimations of wind turbine capital cost as a function of cumulative production, from Jamasb (2007) and Junginger et al. (2010). The default FTT:Power value is 9%.

C.1.14 Solar PV

The default FTT:Power learning rate value for Solar PV is 17%, and the range used in chapter 9 is [10% - 35%]. The lower limit is based on Schaeffer et al. (2004), and the upper limit is based on IEA (2000); McDonald and Schrattenholzer (2001) and Kahouli-Brahmi (2008).

Neij (1997) estimated an extremely low value: 5%, based on electricity generation cost as a function of cumulative installed capacity, assuming capacity factors between 20% and 25%. The upper extreme found in the literature is 47%, from IEA (2000). Both values were discarded. Other estimates include [14% - 30%] (Weiss et al., 2010); 18% (IEA, 2000; McDonald and Schrattenholzer, 2001), 19.9% (Kahouli-Brahmi, 2008; Mackay and Probert, 1998), 20% (Harmon, 2000; Hernández-Moro and Martínez-Duart, 2013; Kahouli-Brahmi, 2008; McDonald and Schrattenholzer, 2001), and 20.6% (Junginger et al., 2010). The latter is based on based on investment price as a function of cumulative installed capacity, while the previous three were based on PV module prices as a function of cumulative sales.

C.1.15 CSP

The default FTT:Power learning rate value for CSP is 10%, and the range used in chapter 9 is [8% - 16%]. The lower limit is taken from Enermodal (1999). This study estimates the learning rate to be in the range [8% - 15%], based on power plant capital costs as a function of cumulative installed capacity. The upper limit of the learning rate range is taken from Viebahn et al. (2011), which estimates values in the range [6% - 16%]. These values are based on electricity generation costs as a function of cumulative installed capacity, using a central estimation of 12%, taken from Neij (2008), that is, in turn, based on Enermodal (1999). Other learning rate estimations include 11% (Hernández-Moro and Martínez-Duart, 2013), based on data from Enermodal (1999); [10% - 20%] (Lilliestam et al., 2012; Williges et al., 2010), based on values from the model MARGE; and 15% (Hinkley et al., 2011), based on cost data from Hayward et al. (2011).

C.1.16 Geothermal

The default FTT:Power learning rate value for Geothermal is 5%, and is also used as the lower limit of the range for chapter 9: [5% - 8%]. The upper limit is taken from Hayward et al. (2011). The value is estimated using data from the Global And Local Learning Model (GALLM), based on learning on drilling as well as other considerations.

C.1.17 Wave

The default FTT:Power learning rate value for Wave is 14%, and is also used as the upper limit of the range for chapter 9: [9% - 14%]. The lower limit is taken from Hayward et al.

(2011). The estimation is based on learning rate values of offshore wind from the GALLM model.

C.1.18 Fuel Cells

The default FTT:Power learning rate value for Fuel Cells is 15%. According to Neij (2008), the learning rate is likely to be in the range [15% - 25%], although experience curves with a learning rate of 30% have been reported for a relatively modest number of technologies. The range proposed by Neij (2008) is used in chapter 9. Enermodal (1999) estimated a value of 16% for the learning rate of fuel cells, based on data from Hosier and Larson (1999).

C.1.19 CHP

The range for the learning rate of CHP used in chapter 9 is [3% - 25%], based on Junginger et al. (2006), were values are calculated using information of biomass fuelled CHP plants from Sweeden. The lower limit corresponds to the FTT:Powe default value.

Appendix D

Investment Model Complementary Information

D.1 Introduction

This appendix chapter includes complementary information to the new investment model presented in chapter 10. The chapter is divided as follows:

- Section D.2 provides the derivation of the multinomial logit. It complements the information presented in section 10.3.1.

- Section D.3 shows the effect of comparing technologies with different standard deviations, in the preference relation P_{ij} (section 10.3). The assumption of similar standard deviations was required for the derivation of a closed form of P_{ij} in chapter 10.

- Section D.4 establishes a link between the pairwise comparison matrix of the AHP methodology, and the Multinomial Logit (MNL) distribution from Discrete Choice Theory, under some specific conditions of the preferences of the decision-maker. The combination of Discrete Choice Theory with Analytic Hierarchy Process is a novel approach. No literature was found addressing the required mathematical foundations for such combination. The information in this section is currently being transferred into a paper, which is expected to be submitted in the following months.

D.2 Derivation of the Muntinomial Logit

P_{ij} represents the probability of choosing alternative i over j in a pairwise comparison, given the preference relation $\succeq$ and the utility function U. If instead of doing pairwise comparisons, all the alternatives were to be compared at the same time, the probability of choosing alternative i would be:

$$
\begin{aligned}
P_i &= P\left(U_i \geq U_j, \quad \forall j = 1 \cdots 24\right) \\
&= P\left(V_i + \varepsilon_i \geq V_j + \varepsilon_j, \quad \forall j = 1 \cdots 24\right) \\
&= P\left(\varepsilon_j \leq V_i - V_j + \varepsilon_i, \quad \forall j = 1 \cdots 24\right) \\
&= \int_{-\infty}^{\infty} P\left(\varepsilon_1 \leq V_i - V_1 + \varepsilon_i \mid \varepsilon_i\right) \ldots \left(\varepsilon_{24} \leq V_i - V_{24} + \varepsilon_i \mid \varepsilon_i\right) \cdot f_{\varepsilon_i}\left(\varepsilon_i\right) d\varepsilon_i \\
&= \int_{-\infty}^{\infty} F_{\varepsilon_1}\left(V_i - V_1 + \varepsilon_i\right) \ldots F_{\varepsilon_{24}}\left(V_i - V_{24} + \varepsilon_{24}\right) \cdot f_{\varepsilon_i}\left(\varepsilon_i\right) d\varepsilon_i \\
&= \int_{-\infty}^{\infty} f_{\varepsilon_i}\left(\varepsilon_i\right) \prod_{j \neq i} F_{\varepsilon_j}\left(V_i - V_j + \varepsilon_i\right) d\varepsilon_i \\
&= \frac{1}{\sigma_i} \int_{-\infty}^{\infty} e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)} \cdot e^{-e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)}} \cdot \prod_{j \neq i} e^{-\left(e^{-\left(\frac{\varepsilon_i - \mu_j}{\sigma_j}\right)} \cdot e^{-\left(\frac{V_i - V_j}{\sigma_j}\right)}\right)} d\varepsilon_i
\end{aligned}
\tag{D.1}
$$

The same change of variable made in section 10.3 is applicable. The exponential term $e^{-\frac{\varepsilon_i - \mu_j}{\sigma_j}}$ can be rewritten, multiplying it by one and adding zero:

$$
e^{-\frac{\varepsilon_i - \mu_j}{\sigma_j}} = e^{\left[\frac{-\varepsilon_i}{\sigma_j} + \frac{\mu_j}{\sigma_j}\right] \cdot \frac{\sigma_i}{\sigma_i}} = e^{\left[\frac{-\varepsilon_i}{\sigma_i} \cdot \frac{\sigma_i}{\sigma_j} + \frac{\mu_j}{\sigma_j}\right] + \left[\frac{\mu_i}{\sigma_i} \cdot \frac{\sigma_i}{\sigma_j} - \frac{\mu_i}{\sigma_i} \cdot \frac{\sigma_i}{\sigma_j}\right]} = e^{\left[\frac{-\varepsilon_i + \mu_i}{\sigma_i}\right] \cdot \frac{\sigma_i}{\sigma_j}} \cdot e^{\frac{\mu_j - \mu_i}{\sigma_j}} \tag{D.2}
$$

And the following change of variable can be made:

$$
x = e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)} \quad \Rightarrow \quad dx = \frac{-1}{\sigma_i} e^{-\left(\frac{\varepsilon_i - \mu_i}{\sigma_i}\right)} d\varepsilon_i \quad \Rightarrow \quad d\varepsilon_i = \frac{-\sigma_i}{x} dx \tag{D.3}
$$

Then, replacing in expression D.2:

$$e^{-\frac{\varepsilon_i-\mu_j}{\sigma_j}} = e^{-\frac{\mu_i-\mu_j}{\sigma_j}} \cdot x^{\frac{\sigma_i}{\sigma_j}} \tag{D.4}$$

Replacing the expression D.4 in equation D.1, and assuming that $\sigma_i \sim \sigma_j \sim \sigma$ (see section D.3).

$$\begin{aligned}
P_i &= \frac{1}{\sigma}\int_{-\infty}^{\infty} e^{-\left(\frac{\varepsilon_i-\mu_i}{\sigma_i}\right)} \cdot e^{-e^{-\left(\frac{\varepsilon_i-\mu_i}{\sigma_i}\right)}} \cdot \prod_{j\neq i} e^{-\left(e^{-\left(\frac{\varepsilon_i-\mu_j}{\sigma_j}\right)} \cdot e^{-\left(\frac{V_i-V_j}{\sigma_j}\right)}\right)} d\varepsilon_i \\
&= \int_0^{\infty} e^{-x\cdot\left(1+\sum_{j\neq i} e^{\left(-\frac{\mu_i-\mu_j}{\sigma}\right)} \cdot e^{-\left(\frac{V_i-V_j}{\sigma}\right)}\right)} dx \\
&= \frac{e^{\frac{V_i+\mu_i}{\sigma}}}{\sum_j e^{\frac{V_j+\mu_j}{\sigma}}}
\end{aligned} \tag{D.5}$$

The term P_i in equation D.5 corresponds to the **Multinomial Logit** Model (Anderson et al., 1992; Ben-Akiva and Lerman, 1985; Garrow, 2010; McFadden, 1973; Train, 2009). It represents the probability of technology i being picked, among the whole set of alternatives. The MNL model is the generalisation of the Binomial Logit model presented in section 10.3.

D.3 The effect of different standard deviations in P_{ij}

In sections 10.3, in order to obtain a closed expression for P_{ij}, it is required to assume similar standard deviations for the technologies involved in the comparison. I.e., it is necessary to assume that $\sigma_i \sim \sigma_j$. In this section, I explore the case where $\sigma_i \neq \sigma_j$ for P_{ij}. For the case of the most influential generation technologies, those that have the largest impact in the power sector, the similarity of σ_i and σ_j is not too far from reality, because they compete in the market at relatively similar prices. For the newest and less deployed technologies, this assumption might not hold, but their relative impact in the scenarios analysed in this work is limited, mostly due to their very small market share.

The derivation of P_{ij}, under similar standard deviations, converges to the following expression (from equation 10.12):

$$
\begin{aligned}
P_{ij}\left(V_i+\mu_i, V_j+\mu_j\right) &= \int_0^{\infty} e^{-x\cdot\left(1+e^{\left(-\frac{\mu_i-\mu_j}{\sigma}\right)}\cdot e^{-\left(\frac{V_i-V_j}{\sigma}\right)}\right)} dx \\
&= \frac{1}{1+e^{-\left(\frac{V_i+\mu_i-V_j-\mu_j}{\sigma}\right)}} = \frac{e^{\frac{V_i+\mu_i}{\sigma}}}{e^{\frac{V_i+\mu_i}{\sigma}}+e^{\frac{V_j+\mu_j}{\sigma}}}
\end{aligned}
\tag{D.6}
$$

If P_{ij} is thought as a function, then it can be written as:

$$
P_{ij}\left(V_i+\mu_i-V_j+\mu_j\right) = f\left(\Delta V\right) = \frac{1}{1+e^{\frac{\Delta v}{\sigma}}}
\tag{D.7}
$$

The function **f** described in D.7, is a logistic function in ΔV. It shows a perfect S-shaped transition, from zero for $\Delta V \rightarrow -\inf$, to one for $\Delta V \rightarrow \inf$. In this context, σ represents the speed of the S-shaped transition: larger the value of σ, faster the convergence from 0 to 1. The black dotted line in figure D.2, shows the S-shaped transition represented by **f**.

From the perspective of FTT:Power, ΔV represents the LCOE difference between the technologies being compared. Remember that the original investment model in FTT:Power uses pairwise comparisons. Larger the difference in LCOE (larger ΔV), larger the exchange of shares between the technologies. And σ, calculated in FTT:Power as $\sigma = \sqrt{\sigma_i.^2+\sigma_j^2}$, defines the speed of that process. Larger the σ, steeper the S-shaped curve.

In reality, the standard deviation in LCOE calculation vary among technologies, as well as time IEA et al. (2015). Technologies such as coal or wind, presents smaller geographical variations than technologies such as solar PV. This translates into different σ values for P_{ij}. So, the question that naturally emerges is: What is the effect on P_{ij} of having different standard deviations?

Figures D.1 and D.2 provide an overview of how the preference relation between i and j changes for different ratios of σ_i/σ_j. Clearly, the S-shaped transition is maintained, with a moderate lost of symmetry. For ratios smaller than one, the indifference point moves slightly below $\Delta V = 0$, while the opposite happens for ratios larger than one. Notice that the large differences in LCOE are unlikely to be counterbalanced by the small change in

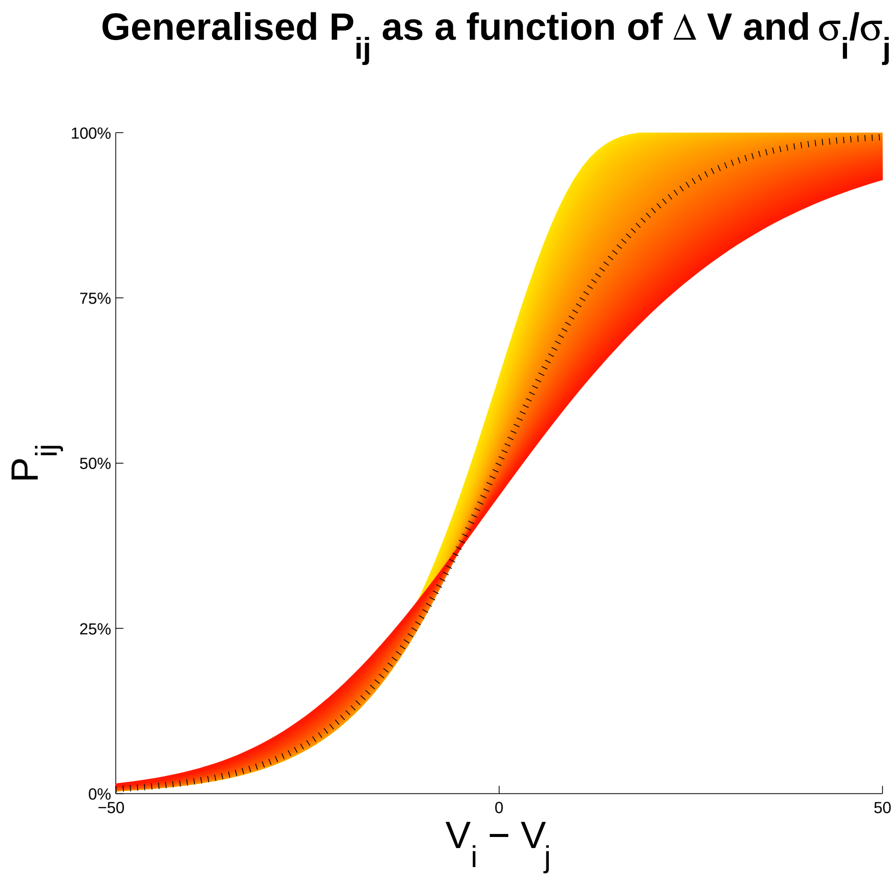

Figure D.1 Probability of choosing i over j as a function of differences of utility. The shading represents different ratios of σ_i/σ_j, going from 0.02 (yellow) to 2 (orange). The dotted black line in the middle represents the case when $\sigma_i = \sigma_j$.

symmetry. Therefore, under the large gain in tractability that provides a functional form for P_{ij}, it is reasonable to accept the small lost in accuracy provided by assuming similar standard deviations.

D.4 Analytic Hierarchy Process and the Multinomial Logit

The Analytic Hierarchy Process (AHP) is methodology introduced by Saaty (1977), that *uses a pairwise comparison procedure to arrive at a scale of preferences among sets of alternatives* (Saaty and Vargas, 1991). The Multinomial Logit (MNL) model from Discrete Choice Theory, *predicts the probability a decision-maker will choose one option among a*

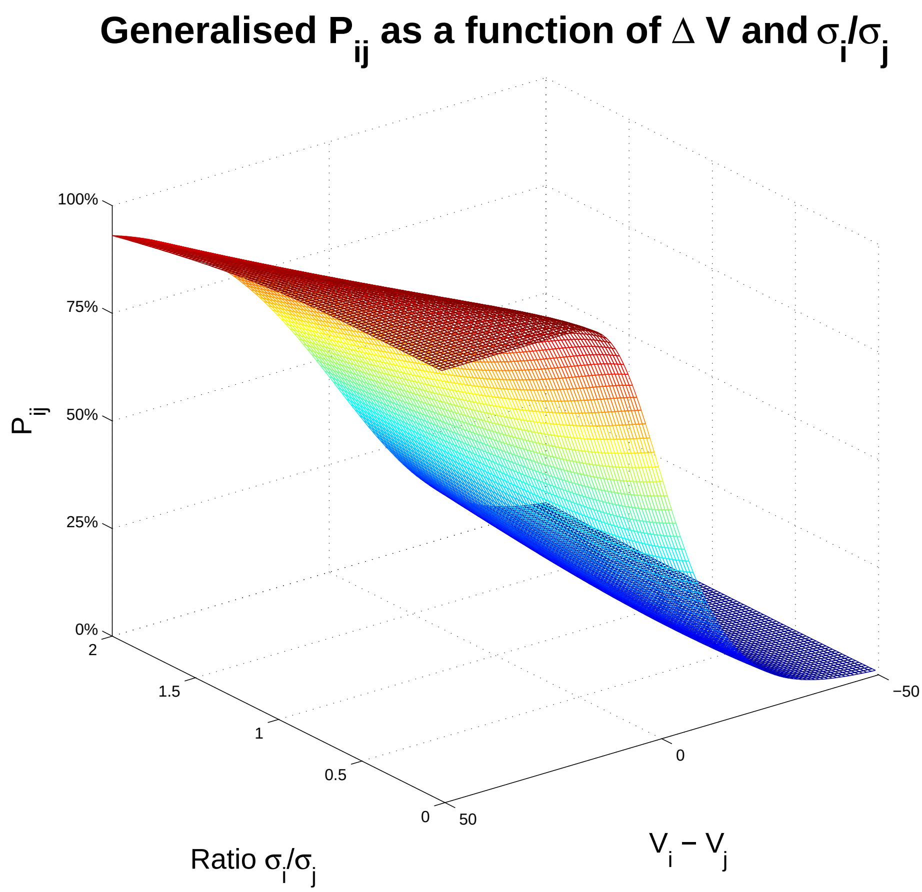

Figure D.2 Probability of choosing i over j (vertical axis) as a function of differences of utility (axis on the right) and the ratio between σ_i and σ_j (axis on the left). The shade changes with z-axis, i.e., the value of P_{ij}.

finite set of mutually exclusive options (Garrow, 2010). Without further information, both theories seem to address the same core issue: selection of alternatives.

This section establishes a link between the pairwise comparison matrix of the AHP methodology, and the Multinomial Logit (MNL) distribution from Discrete Choice Theory, under some specific conditions of the preferences of the decision-maker. In order to provide the appropriate theoretical framework, some theorems from external sources are stated. For the sake of simplicity, those theorems are not proven in this work, and full references are provided.

The description of the basis of AHP and MNL are beyond the scope of this chapter. While some references are provided within the text, the reader is expected to have a basic understanding of the underlying theoretical framework.

D.4.1 The Discrete Choice Model

Let define a decision-maker M and a set $\mathcal{H}$ of N mutually exclusive alternatives, on which the whole mathematical formulation will be based on. Let be $\succeq$ a preference relation of M over the entire set $\mathcal{H}$ that satisfies the following axioms:

Completeness: $p \succeq q$ or $q \succeq p, \forall p,q \in \mathcal{H}$

Reflexivity: $p \succeq p, \forall p \in H$

Transitivity: if $p \succeq q$ and $q \succeq r$, then $p \succeq r, \forall p,q,r \in H$

Let define a utility function $U : \mathcal{H} \times \mathcal{H} \rightarrow \Re$ that represents the preference relation $\succeq$ within $\mathcal{H}$. Therefore, U satisfies the property

$$U(p) \geq U(q) \quad \Leftrightarrow \quad p \succeq q, \quad \forall p,q \in \mathcal{H} \tag{D.8}$$

Let be P_i the probability of alternative i to be chosen by the decision-maker over the entire set, defined as:

$$P_i = P\left(U_i \geq U_j, \quad \forall j \in \mathcal{H}\right) \tag{D.9}$$

and let be P_{ij} the probability of alternative i to be chosen by the decision-maker over alternative j in a pairwise comparison, defined as:

$$P_{ij} = P\left(U_i \geq U_j, \quad i,j \in \mathcal{H}\right) \tag{D.10}$$

According to McFadden (1973)[1], if U_i follows a Gumbel distribution, such that $U_i \sim G\left(\mu_i, \sigma\right), \forall i \in \mathcal{H}$, then P_i and P_{ij} satisfy the following properties:

a) P_i follows a Multinomial Logit distribution

$$P_i = \frac{e^{U_i}}{\sum\limits_{j \in \mathcal{H}} e^{U_j}} \tag{D.11}$$

[1] Detail mathematical proof of the properties mentioned here, can be found on several discrete choice theory books, including Anderson et al. (1992); Ben-Akiva and Lerman (1985) and Garrow (2010)

b) P_{ij} follows a Binary Logit distribution

$$P_{ij} = \frac{e^{U_i}}{e^{U_i} + e^{U_j}} = \frac{P_i}{P_i + P_j} \tag{D.12}$$

Based on the utility function and the probabilities previously described, it is possible to construct an AHP pairwise comparison matrix that satisfies the following properties:

Theorem D.4.1 (AHP and the Logit Preferences)**.** *Let be $\boldsymbol{A}$ an AHP pairwise comparison matrix of all the N alternatives within $\mathcal{H}$. Let assume $\boldsymbol{A}$ is made such that it represents the preferences of the decision-maker M, and each element $a_{ij} \in \boldsymbol{A}$, can be written as:*

$$a_{ij} = \frac{P_{ij}}{P_{ji}} \tag{D.13}$$

Then, the AHP comparison matrix $\boldsymbol{A}$ satisfies the following properties:

- *The matrix $\boldsymbol{A}$ is reciprocal and consistent.*
- *All the eigenvalues of $\boldsymbol{A}$ are zero, except for the principal eigenvalue, which is equal to N*
- *If $\boldsymbol{W}$ is the principal eigenvector of $\boldsymbol{A}$, then the ith element of $\boldsymbol{W}$ is equal to P_i.*

Proof. Following the definition of a_{ij}:

Reciprocal

$$a_{ij} = \frac{P_{ij}}{P_{ji}} = \frac{1}{\frac{P_{ji}}{P_{ij}}} = \frac{1}{a_{ji}}$$

Consistent

$$a_{ij} \cdot a_{jk} = \frac{P_{ij}}{P_{ji}} \cdot \frac{P_{jk}}{P_{kj}} = \frac{\frac{e^{U_i}}{e^{U_i}+e^{U_j}}}{\frac{e^{U_j}}{e^{U_i}+e^{U_j}}} \cdot \frac{\frac{e^{U_j}}{e^{U_j}+e^{U_k}}}{\frac{e^{U_k}}{e^{U_j}+e^{U_k}}} = \frac{\frac{e^{U_i}}{e^{U_i}+e^{U_k}}}{\frac{e^{U_k}}{e^{U_i}+e^{U_k}}} = \frac{P_{ik}}{P_{ki}} = a_{ik}$$

Eigenvalues The proof of this property can be found in Saaty (1999, page 399). Saaty demonstrated that $\boldsymbol{A}$ is consistent if, and only if, it can be written in the form:

$$\boldsymbol{A} = \begin{pmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_N \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_N \\ \vdots & \vdots & \ddots & \vdots \\ w_N/w_1 & w_n/w_2 & \dots & w_N/w_N \end{pmatrix} \tag{D.14}$$

with $\boldsymbol{W} = [w_1, \cdots, w_n]^T$ being the normalised principal eigenvector of $\boldsymbol{A}$ ($\sum_i w_i = 1$).

$$\boldsymbol{A} \cdot \boldsymbol{W} = N \cdot \boldsymbol{W} \tag{D.15}$$

The vector $\boldsymbol{W}$ is the one that solves the equation:

$$(\boldsymbol{A} - N\boldsymbol{I}) \cdot \boldsymbol{W} = 0 \tag{D.16}$$

Equation D.16 is very well known in linear algebra: it has a nonzero solution if and only if $\boldsymbol{W}$ is the eigenvector of $\boldsymbol{A}$ (Simon and Blume, 1994). Notice that the rank of the matrix $\boldsymbol{A}$ is 1. According to equation D.14, all the rows of $\boldsymbol{A}$ are a multiple of each other. Therefore, all the eigenvalues of $\boldsymbol{A}$ are zero, except for the principal eigenvalue, which is N, and $\boldsymbol{W}$ is the corresponding eigenvector. In other words, when $\boldsymbol{A}$ is consistent (demonstrated already), then N and $\boldsymbol{W}$ are its principal eigenvalue and eigenvector, respectively.

Eigenvector Based on the previous point, the element (i, j) of the matrix $\boldsymbol{A}$ can be written as the ratio $a_{ij} = w_i/w_j$. But from the definition of a_{ij}, we have that:

$$a_{ij} = \frac{P_{ij}}{P_{ji}} = \frac{w_i}{w_j} \tag{D.17}$$

Given the properties of P_i and P_{ij} described in D.11 and D.12, the term a_{ij} can be written as:

$$a_{ij} = \frac{P_{ij}}{P_{ji}} = \frac{P_i}{P_j} = \frac{w_i}{w_j} \tag{D.18}$$

Isolating w_j from the last equation:

$$w_j = \frac{P_j \cdot w_i}{P_i} \tag{D.19}$$

Summing over j

$$\sum_j w_j = 1 = \sum_j \frac{P_j \cdot w_i}{P_i} = \frac{w_i}{P_i} \quad \Rightarrow \quad w_i = P_i \tag{D.20}$$

So, if $\boldsymbol{W}$ is the principal eigenvector of $\boldsymbol{A}$, then the ith element of $\boldsymbol{W}$ is equal to P_i.

$\square$

If a multinomial logit distribution can be fitted over a set of stochastic choices, then Theorem D.4.1 shows that a straightforward AHP pairwise comparison matrix exists.