

The Investment Decisions of Firms in the Electricity Sector:

Case Studies of Germany, the Netherlands, and the United Kingdom

A thesis submitted for the degree of Doctor of Philosophy

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Declaration of originality

The thesis author, Rembrandt H.E.M. Koppelaar, confirms that this manuscript is fully my own work. All the data collection and analyses as described and presented in the thesis were carried out independently to fulfill the requirements of the PhD thesis research. All potential errors are also the responsibility of the thesis author.

Rembrandt Koppelaar, December 2017

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Abstract

The research investigates whether financial evaluations in electricity system models can adequately represent investment decisions and analyse power generation technology change. A screening of 51 existing models found that 31 utilised cost minimisation, 16 profit maximisation, and 3 growth rate approaches. A statistical analysis of investment metric values from 1980-2013 for the UK, NL, and DE found that positive threshold financial evaluations coincide with 70%+ of historic capacity investments. A separate empirical model validation of this period, where 64 model variants were tested using the TEMOA optimization model, established that profit seeking gives the best matching result to historical outcomes. Divergence of modelled results and history does occur in two ways due to non-financial factors. First, the impact of political-economy support or exclusion of technologies. Second, constraints to technology scaling limiting the speed of build-out, due to factors including public perception, land availability, and manufacturing/installation scale limitations. Interviews with electricity sector experts established that financial evaluation is the primary means for narrowing down of technology options, after which non-financial factors are considered. If electricity system models are to be employed for testing policy decision impacts on technology selection, investment, and scaling, the incorporation of non-financial factors is essential.

Papers arising from this work

- Koppelaar, R.H.E.M., Keirstead, J., Shah, H., Woods, J., 2016. A review of policy analysis purposes and capabilities of electricity system models. *Renewable and Sustainable Energy Reviews*. Vol. 59. pp. 1531-1544.

Papers in preparation from thesis chapters

Two additional papers are in process of being drafted from the PhD. thesis:

- Koppelaar, R.H.E.M., Shah, H., Woods, J., 2017. A review of investment decisions in electricity system models. (*In Preparation*)
- Koppelaar, R.H.E.M., Shah, H., Woods, J., 2017. How model structure affects technology selection in electricity system models (*In Preparation*)

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Abbreviations and acronyms

Table 1: List of Abbreviations used in the thesis.

Acronym	Full Description
A/E	Architectural and Engineering services
CAPEX	Capital Expenditure
CCS	Carbon Capture and Storage
CCGT	Combined-Cycle Gas Turbine
CEO	Chief Executive Officer
CEGB	Central Electricity Generating Board
CfD	Contracts for Differences
CFO	Chief Financial Officer
EU-ETS	EU Emissions Trading Scheme
EEG	Erneuerbare Energie Gesetz
EPC	Engineered, Procured and Constructed
EPR	European Pressurized Reactor
FiT	Feed-in-Tariff
GAMS	General Algebraic Modelling Systems
GDP	Gross Domestic Product
CHP	Co-Heat Power
GIGO	Garbage In equals Garbage Out
GJ	GigaJoule
IEA	International Energy Agency
IRR	Internal Rate of Return
kW	kilo watt
kWh	kilowatt hour
LCOE	Levelised Cost of Electricity
LHV	Lower Heating Value
MC	Marginal Cost
MCA	Multi Criteria Analysis
MW	Megawatt
MWh	Megawatt hour
NEMS	National Energy Modelling Systems
NFFO	Non-Fossil Fuel Obligation
NPV	Net Present Value
O&M	Operations & Maintenance
OPEX	Operational Expenditure
PVaR	Portfolio Value at Risk
PBT	Payback Time
PVRR	Present value of Revenue Requirements
PWR	Pressurized Water Reactor
RO	Renewables Obligation
ROC	Renewables Obligation Certificate
ROE	Real Options Evaluation
R&D	Research and Development
TIC	Total Installed Cost
TPC	Total Plant Costs
TWh	Terawatt hour
VaR	Value at Risk
WWER	Water-Water Energetic Reactor
WACC	Weighted Average Cost of Capital

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1 Introduction (Aim and Objectives)

1.1 Societal Context

A key driver of economic wealth are countless material conversions into consumable goods by the use and development of technologies. Since the second half of the 19th century material conversions have spurred economic activity to an unprecedented scale due to the emergence of many technological innovations Vaclav (2005). Production and consumption activities grew by a factor fifty globally as measured in Gross Domestic Product (GDP). In contrast from 0 to 1870 AD a factor ten expansion in GDP occurred at the global scale Bolt and van Zanden (2013).

The actors behind the global growth process are companies which operate as a conduit of human knowledge, labour, and energy. These shape and drive the use of technologies at facilities to convert materials into goods. It is their decision making, or more specifically, decisions made by company owners and investors, which have contributed substantially to shaping our technological world. Their investment decisions have led to the creation of new physical capacity in the form of factories to convert materials into goods, and also have helped to make research in new resource conversion technologies possible. As a consequence of the investment process, among other factors, the technological capital of an economy changes, and in relation not only its output capacity, costs and benefits, but also the environmental extractive and pollutive impacts of production, and the social dimensions of employment and wages.

The understanding of how technological infrastructure and production affects environmental and social dimensions has become more poignant in recent times, with the onset of mega-challenges that relate to unprecedented scale of economic activity spanning across the globe. These include issues of climate change, preservation of ecosystems, job shifts and losses from increasing automation, air, soil and ocean pollution, and depletion of cheap to access mineral reserves. To minimize their current impact and future risks a transformation is needed of our technological systems into systems that can function on a carbon neutral basis, with high material recycling rates, low dependence on uncommon to rare materials, in line with labour market adjustment possibilities. Governments, companies, institutes, and broader civil society all play key roles in such transformations via technological development, regulatory steering, planning adjustment, and technology take-off, as these do not come about automatically.

Today an increasingly used tool to support company led technology transformation is computer based modelling for planning support, as part of the toolbox of large companies and governments. The usefulness of this tool follows from the ability of computer models to provide a tangible representation of mentally difficult to grasp interactions and thereby function as decision support tools Wild (1996), Strachan et al. (2009). Policy makers face the complex task of selecting and making adjustment to policy instruments which serve to alter the institutional fabric of markets and thereby company investments. Market adjustments serve to steer investments into a particular technological or socio-economic direction. Computer models can greatly assist in providing insights in policy instrument selection as they can form a test-bed for policy instrument implementation and impact assessment. They can also be used to provide refined scenarios which capture a large number of relevant factors across economic, environmental, and social dimensions, such as for purposes of budget planning and 'what-if' technology selection scenarios. It is therefore not surprising that the use of macro-economic computer models has become an essential service in economic governance, and that, at an increasing scale, a direct influence of modelled results on policy processes is observable Henriksen (2013).

In the management and evolution of electricity systems, computer models can be utilised in several ways among which four uses being prominent today. First, to assess the evolution and timing needs to replace old power plant capacity and meet future demands based on varying scenarios for future electricity demands. Second, to gauge the mix of technologies needed to achieve low carbon emission targets within a set timeframe. Third, to assess the costs of introducing new low carbon technologies at a total investment level and per produced Megawatt hour (MWh), for purposes of budget planning and economic feasibility. The required cost reduction of novel technologies can then be inferred that is needed to be cost competitive relative to today's electricity system cost structures. And finally, to assess the impacts of policy instruments on the cost balance of technologies and impacts on electricity prices, in relation to their take-off and growth in the energy mix.

The thesis contributes at the societal level primarily to the last aspect of model use to evaluate the impact of policy instruments on company investments and technology transformations. The focus lies on the representation of investment decisions of companies and how these affect technological changes in the electricity mix. By more accurately representing investment decisions this could lead to a more accurate evaluation of the impacts of policy instruments on investments, and thus result in more effective government energy policy design.

1.2 Research Context

Infrastructure investment is in economic models usually simplified into a 'central planner' perspective, at an aggregate sector level (e.g. electricity), or aggregate technology capacity (e.g. gigawatts of coal power in a region/country), as opposed to individual facilities with technological characteristics (e.g. a coal power plant). The investment process is, as a consequence, not incorporated at the power plant level, which in the real world economy involves a multiple stage financial contracting process for each individual facility, but instead it is represented as a generation capacity accounting change at the sector-technology level. This macro level approach is also incorporated in the majority of electricity system models, so as to provide insights on how total technological capacity evolves over time as a consequence of demand changes and variations in costs or prices of electricity.

The macro level model implementation of investment in infrastructure used in electricity system modelling originated from economic theory in the 1970s (Hoffmann and Wood 1976). The definition of investment in economics is the creation of capital goods that enable the production of goods or services, in the form of infrastructure which includes machinery, equipment, and inventories Brian (2009). Capital goods evolve in this definition by companies carrying out investment spending from savings accounts or loans. In macro-economics this process has been simplified into an accounting scheme where monetary flows are instantaneously exchanged for capital goods (e.g. power plants) as a result of market mechanisms. The approach was motivated by the need for parsimonious macro-economic models to inform central government budgetary policy decisions, in particular to forecast economic growth as a change in GDP (Solow 1956, Swan 1956, Lucas 1988, Romer 1986, 1990, Acemoglu 2009).

The common implementation of the 'market mechanism' in computer models is a profit maximizing or cost minimizing approach which clears markets instantaneously in each time period, by adjusting prices such that demand and supply functions match each other and form an equilibrium. Growth in supply is associated with new capital goods that are instantaneously introduced through investment spending, in this market clearance representation of the economy, with capital accumulation (infrastructure build out) as a result Sorensen and Whitta-Jacobsen (2004). In electricity system models a simplification to this design is usually made, since demand is usually incorporated as an exogenous variable. In contrast, in micro-economics multiple "individuals" which interact within the objective of maximisation or minimisation are recognised, but in macro-economics a single such entity is taken for simplification purposes. Micro effects such as company interactions, delays or feedback, are thereby ignored in macro-economic based computer models Bewley (2007).

The macro-economics based general equilibrium model implementation - the de-facto standard in most electricity system models - is grounded in five restrictive assumptions:

- Infrastructure (e.g. power plants) can be treated as a general 'capital good'. There typically is no differentiation between underlying components such as machinery, infrastructure types, and input/output flows of construction and operational energy and material resources. Electricity system models differ in this respect as variation is acknowledged between technologies, mainly from a capital and operational cost and operational perspective. However, differences are usually not taken into account for investment risks, technology preferences, and market policies.
- All companies behave similarly as they are represented by a single entity (e.g. a central planner).
- Investment occurs as a lump-sum at individual sector level or at the level of total capacity per technology as the lowest level of disaggregation, as opposed to the level of individual facilities like power plants.
- Additional capital goods (e.g. power plants) can be flexibly and instantaneously purchased as long as the investments generate monetary benefits or they are lowest in cost.
- There is no restriction on information availability on market parameters in the present or the future in how the calculation of 'market clearance' (and thereby investments) takes place.

This modelling framework reduces firm investment decisions into an automated single mechanism process driven by macro-economic conditions of costs and prices. The real world process of infrastructure investment is in contrast complex in that it involves decisions under the uncertainty of how economic factors will develop in the future due to changes in markets and technologies, and the decisions of actors that influence and shape these developments. It involves many parties from financiers to engineering companies to regulatory institutions. Investment decisions take place across several stages from pre-feasibility to engineering to final investment decision, construction, and commissioning. Financial decisions and technology selection involve calculations of future demands and sales, technology costs changes, and market price evolution. And the outcome can be affected by changes in input costs or market pricing, political decisions that alter market regulation, and fiscal instruments. Under this complexity it is not uncommon for power plant investments to be delayed or called off, deliver less than optimal returns, or to be superseded before the end of their life by newer technologies. Substantial future risks are thereby involved that only to an extent can be factored in when planning investments in new power plants.

The many factors and future uncertainties that are involved also make it difficult to establish well working energy policies. It is thereby questionable whether electricity system models results that are based on primarily cost and price driven macro-economic modelling are suitable for designing market policies. If the company perspective of future developments and uncertainties is ignored, it could easily result in policy setting that is not aligned well with the company requirements to invest, and as a consequence more costly outcomes or a failure to reach specific policy targets relating to energy security or environmental performance. If models are able to take into account the impact of policy changes to market regulation and fiscal instruments on company investments, as well as potential non-financial factors that play a role in the investment of technologies, electricity system models plausibly would be much more suitable to evaluate energy policies successfully, thereby allowing for better policy creation.

Some of the more overarching limitations of the macro-economic approach in this respect from a policy perspective were substantiated by Gerrit Zalm, the former Dutch Minister of Finance from 1994 to 2002, in a paper on the relevance of economic modelling for policy decisions from 1998 (Zalm 1998). He suggests to enrich economic models with more micro-economic elements, market imperfections, and aspects of technological change:

“For model builders there are still many avenues to explore. First, the modelling of market behaviour is still rudimentary. More emphasis should be put on imperfections in financial and goods markets. Hereby, one could perhaps rely more on the appealing results of the industrial organisation literature. In order to assess behavioural responses to government policies the focus should be changed from a macro-economic orientation towards a micro-economic orientation. Second, many current policies and policy proposals are aimed at improving the basic technological and ecological infrastructure of the economy. Therefore it seems challenging to model the driving forces behind the process of economic development as infrastructure and technology, and I encourage the current efforts. For these issues the insights from the endogenous growth literature can be useful Zalm (1998, p. 315).”

The discussed incorporation of regulatory policy changes and non-financial factors on investments, as opposed to pure cost or profit based approaches, may not necessitate to ‘throw the baby out with the bathwater’, and use an entirely different modelling approach, since macro-economic simplifications may be sufficient to explain the investment process to a considerable degree Krugman and Wells (2008). To the awareness of the author, little effort has been carried out hitherto to validate the macro-economic based approach (based on an analysis of previous studies in **section 1.4** below). As a starting point such an investigation needs to be carried out. The PhD. research thereby relates to the question: Can the process of investment in electricity generation technologies be sufficiently approximated in the computer model world by a simplification as a vector of profit maximisation or cost minimisation? And if not, can the approach be enhanced in a meaningful way to be better tailored to energy policy instrument testing needs, or are entirely different approaches to structuring electricity system models required?

1.3 Research Concern

This thesis is concerned with the validity of approaches to model infrastructure investment decisions in electricity system models. An empirical approach is taken to ascertain if models (in hindsight) can reproduce historical power generation capacity evolution using a small number of key investment decision variables. The intended benefit of this investigation is that a better representation of company investment decisions will plausibly result in models that perform better when evaluating future outcomes, given particular financial and non-financial market conditions. Thereby, the explanatory power as to why infrastructure investments occurs increases, which allows for providing better feedback on whether market regulatory changes set by governments will be successful or not. As such an evaluation of policies with an a-priori desired outcome on technology investments becomes possible, such as greater security of supply, or decarbonisation of the electricity sector.

The electricity sector was chosen to have an applied focus on how investments change the electricity technology mix and power generation capacity infrastructure. The rationale for choosing the electricity industry is data availability, considerable prior analyses yielding theory and data to build upon, the relative simplicity of investments (e.g. mostly single large facilities) yet complexity of markets, and prior familiarity of the researcher with the sector.

The research is based on the examination of variations in the structure of electricity system optimisation models that minimise costs or optimise profits, which have similar characteristics similar to macro-economic equilibrium models, as described in **section 1.2**. This involves variations as implemented in existing models in the form of investment evaluation metrics, such as variations on cost minimisation or profit maximisation, that provide for financial comparisons between technologies within the model architecture. In addition the effect of the assumption on loosening the full information availability assumption is tested as part of a possible adjustment from the intertemporal full information approach. By examining possible model arrangements around investment metrics, and comparing these with historical developments, observations can be drawn on how appropriate the current approach is to model technology selection and power generation evolution, if the goal is to make forecasts that approximate reality. This is of importance since the evaluation of policy instruments requires modelling of their effect on company investments, in order to know whether policy instruments are adequate to reach required policy goals.

A key distinction in carrying out the research is made between i) the extent to which models provide accurate outcomes, and ii) the extent to which the structure of models resembles reality in an approximate fashion. Since models always simplify reality, and often to a large extent, they typically no longer can be interpreted in analog to a process as they occur in real life. The simplification often can still provides accurate results, however, and on that basis models do not necessarily need to resemble reality from a philosophy of science perspective Friedman (1966). However, the more a real-world process as represented in models omit characteristics of reality, the more difficult their interpretation may become, since a technical understanding of the 'model world' is needed for an accurate interpretation. The research thus does look at the investment process in reality, and its simplification, in addition to the extent to which accurate outcomes in comparison to historic real-life changes are provided.

1.4 Previous Studies

A substantial number of electricity system models and related frameworks have been constructed which are discussed in **chapter 3** in detail. Previous reviews of electricity system models include studies focusing on model to model comparisons (Foley et al. 2010, Bhattacharyya and Govinda 2010), methodologies for particular sub-system purposes such as demand forecasting (Suganthi and Samuel 2012, Torriti 2014), and overall model characteristics and capabilities (Ventosa et al. 2005, Pfenninger et al. 2014). An overview of review studies to date can be found in (Pfenninger et al. 2014), who discusses energy system modelling and treatment of spatial and temporal scales, uncertainty, model transparency, and human interactions. The overview study by (Ventosa et al. 2005) focuses on comparing short-term electricity market structure, electricity dispatch and power buyer purchasing decision algorithms, and grid representation.

A few studies have looked at investment processes in electricity system models. These include the implementation of investment decisions in an oligopolistic market with multiple companies (Sánchez Dominguez 2008, Botterud et al. 2007). Similarly, a multiple company profit maximisation investment decision model of retail electricity markets with micro-generation technologies was developed in the PhD thesis of Wittman (Wittmann 2008). The impact of wind energy introduction and capacity markets on investment decisions in a centralised market using a simulation model was assessed in the PhD thesis of Eager (Eager 2012). The impact of uncertainty on investments was investigated by (Botterud 2003) who looked at real options theory to augment the profit maximisation approach. The effects of perceived strategies of competitors in power capacity investment was explored for competitive markets with many buyers and sellers and oligopolies by Nofri Dahlan Dahlan (2011). The linkage of carbon markets and price floors to electricity market capacity investment, based on company decisions using a Multi-Criteria-Analysis (MCA) approach, was analysed in an agent-based model for the Netherlands in the PhD. Thesis by Emilé Chappin Chappin (2011).

Also a number of studies have looked at specific factors in the investment process. The influence on investments of having the choice to invest in new power plants or modernize existing power plant capacity was evaluated by Schwarz (2005) (Schwarz 2005). The effect of capacity markets and mechanisms was investigated by Hasani and Hosseini (Hasani and Hosseini 2011). The effect of learning and adaptation in an agent-based framework on electricity sector outcomes was evaluated by Anke Weidlich Weidlich (2008).

Out of the studies above the only one which compares outcomes of generation capacity change - as a consequence of investment decisions - with historical developments was for the simulation model of (Eager 2012, p. 148-149). A comparison was made for the UK between the years 2004 and 2009 which found that CCGT and wind power expansion was quite accurately reproduced. The time frame of this study is too short, however, to draw substantive conclusions.

1.5 Aims, objectives, and scope of Study

1.5.1 Research boundaries

The thesis research seeks to understand how electricity system models can be improved in terms of power plant technology selection and capacity change, so as to be more close to actual changes in power plant capacity that emerges. The reason for investigating this is to allow better evaluation of market design, government policy instruments and regulation, to assess their effectiveness on adjusting power plant investments by companies to reach particular policy goals. If company investments can be realistically approximated in electricity system models, it will lead to a better ability to examine how market regulation and fiscal instruments like feed-in tariffs or renewable obligations can be adjusted, so as to reach policy objectives like security of supply or decarbonisation. The focus of this evaluation is on historic power plant capacity and technology change in Germany, the UK, and the Netherlands in the analytical part of the thesis. A three country approach was chosen to improve the validity of the statistical and model analysis carried out in this thesis, in terms of the likelihood of applicability to multiple market contexts (or examined lack thereof).

The three particular countries were selected for their data availability on historical power plant generation change plus investment costs, differences in political settings, diversity in electricity market policies influencing historical investments, and knowledge familiarity of the thesis author. All three countries have a market price driven electricity system yet there are significant nuances between them. Germany has the most Coordinated Market Economy (CME) of the three countries in its substantial reliance on negotiation, bargaining and coordination, with a significant role for the federal and regional governments Judit Kapás (2013). This expresses itself in greater industry support mechanisms for long-term government targets. Germany has provided far greater direct financial support for renewable energy since the 1990s than the Netherlands or the United Kingdom. as elaborated upon in **Chapter 6** in the historic development description since the 1980s for each country. It is also the only one of the three countries that still financially supported hard-coal mining in the 2010s. In contrast the United Kingdom and the Netherlands can be characterised as Liberal Market Economies (LME), in that they seek to provide technological and investment change as much as possible through market mechanisms that rely on competitive costs. The United Kingdom phased out support for coal two decades earlier than Germany because it was not competitive without government support. Financial support mechanisms for renewable energy in the Netherlands and the United Kingdom are substantially more market oriented by focusing on technology neutrality, where the government 'does not pick winners', as opposed to direct specific wind and solar industry support in Germany to foster jobs and revenues of a new industry. The key difference between the Netherlands and the United Kingdom is the framework under which electricity market policies are developed. In the Netherlands energy policies used to be defined from a government centralised approach in the 1980s. Since it is defined more through stakeholder exercises, which results in compromise based policies. For example in the 'Energy Accord' set in 2013 was that was based on a consultation between 40 key entities including energy suppliers, large energy consumers, NGO's, and the government Sociaal-Economische Raad (SER) (2013). The United Kingdom policies in addition to market competitive approaches increasingly rely more on frameworks that are informed by energy system modelling approaches, both within the Department for Energy and Climate Change (DECC now BEIS), and by an externally setup institution the Committee on Climate Change (CCC) Committee on Climate Change (2015). The CCC is mandated as an independent research body to advise the government on how it can meet its future carbon targets. In contrast, in the Netherlands energy modelling exercises for policy evaluation are not carried out internally by the government, but commissioned to external institutes such as Energy Research Centre of the Netherlands PBL and ECN (2017). Such institutes only evaluate policies as requested by the government, whereas the CCC provides independent advice and can also suggest policies that are not proposed by the government itself.

Another research boundary is the use of exogenous historical data, instead of modelling many relationships within electricity markets that influence investment decisions. The electricity sector itself is highly complex, in that it is composed of multiple dynamic markets including day-to-day supply and demand trading, reserve capacity auctions, off the counter supply and demand agreements, retail long-term agreements with households, and long-term investments in new power

generation capacity. Also involved is a technical system of minute to minute technical grid balancing efforts, to manage supply-demand changes over time. A significant number of investment aspects therefore come together in its operation from power plants, to grid connections, to grid load balancing technologies. And the financial justification of these investments needs to come from the various markets as summed above. Since firms accrue investment capital due to successful sales of electricity by market supply bids or the closing of contracts, there is a relevant relationships between the functioning of short-term electricity trading markets, and the long-term evolution of power generation capacity and supply. The interrelation between these two markets is in this thesis not dynamically captured, but set as fixed by taking a historical approach using datasets between 1980 and 2013. The approach thus circumvents the need to elaborate on the dynamics of electricity trading to power generation change and technology choice.

1.5.2 Aim and Objectives of the Study

The aim of the thesis is to understand: “*What quantitative and qualitative factors provide a valid approach to the modelling of power plant investment decisions in electricity system models?*” To make the scope of the research tangible four research questions were formulated which this thesis seeks to answer. Each question has one or more related research objectives that defines the approach used to answer the question (see listing below and Figure 1.5.2). The research questions and objectives are framed from the perspective of electricity system models as tools to understand investment decision outcomes in relation to power plant capacity change. Later on in the thesis, in section 4.2, five hypotheses are formulated, which are formed from research observations on which specific ‘structures’ or ‘settings’ in optimisation based electricity system models are expected to be better at reproducing historic power generation change as a proxy for investments. These five hypotheses form a formalised line of inquiry to provide an answer to research question 3 and the related research objective 4 (see Figure 1.5.2). The following five research questions were established:

1. What financial and non-financial factors of importance are potentially used to inform electricity generation firm decisions to expand production capacity?
2. What power plant investment evaluation metrics are used in existing electricity system models?
3. Which power plant investment evaluation metrics provide robust results from a ‘central planner’ optimisation modelling approach, driven by cost minimisation or profit maximisation, in reproducing historical generation capacity change?
4. How can non-financial factors be captured in the modelling of project investment decisions?

To answer the research questions five research objectives were set to be achieved in the thesis based on the range of methodologies and approaches taken to deliver new insights in the thesis aim. These are formulated as follows:

1. To evaluate a set of key financial and non-financial factors which are potentially usable to inform electricity company decisions in the selection of technologies and investments in power plant capacity, based on a review of the literature and deductive reasoning.
2. To research the functions used in existing electricity system models to represent the investment decision process and particular investment evaluation metrics therein, based on a methodology review and literature screening.
3. To assess whether standard financial investment evaluation metrics in the electricity sector, the Net Present Value (NPV), PayBack Time (PBT), Levelized Cost of Electricity (LCOE), and the Internal Rate of Return (IRR), provide a significant means to establish whether an investment should take place or not, based on a statistical analysis of historical power plant capacity data from 1980 to 2013 as a proxy for investments for the Netherlands, the UK, and Germany.
4. To assess using statistical which investment decision variants in an optimisation model yield outcomes that are close to historical installation of power plant capacity and technology as a proxy for investment, based on running an optimisation model from 1980 to 2013 for the Netherlands, the UK, and Germany, and assessing the correlation of model run results with historical power plant capacity data as a proxy for investments. By variation of investment decision strategies (specified in **section 4.2**), whilst maintaining market and technology characteristics as occurred in this time period, different model settings and their influence on the correlation are evaluated.
5. To evaluate based on a set of expert interviews with electricity market experts what in their view the relevant non-financial and financial factors are that are involved in power plant investment decisions.

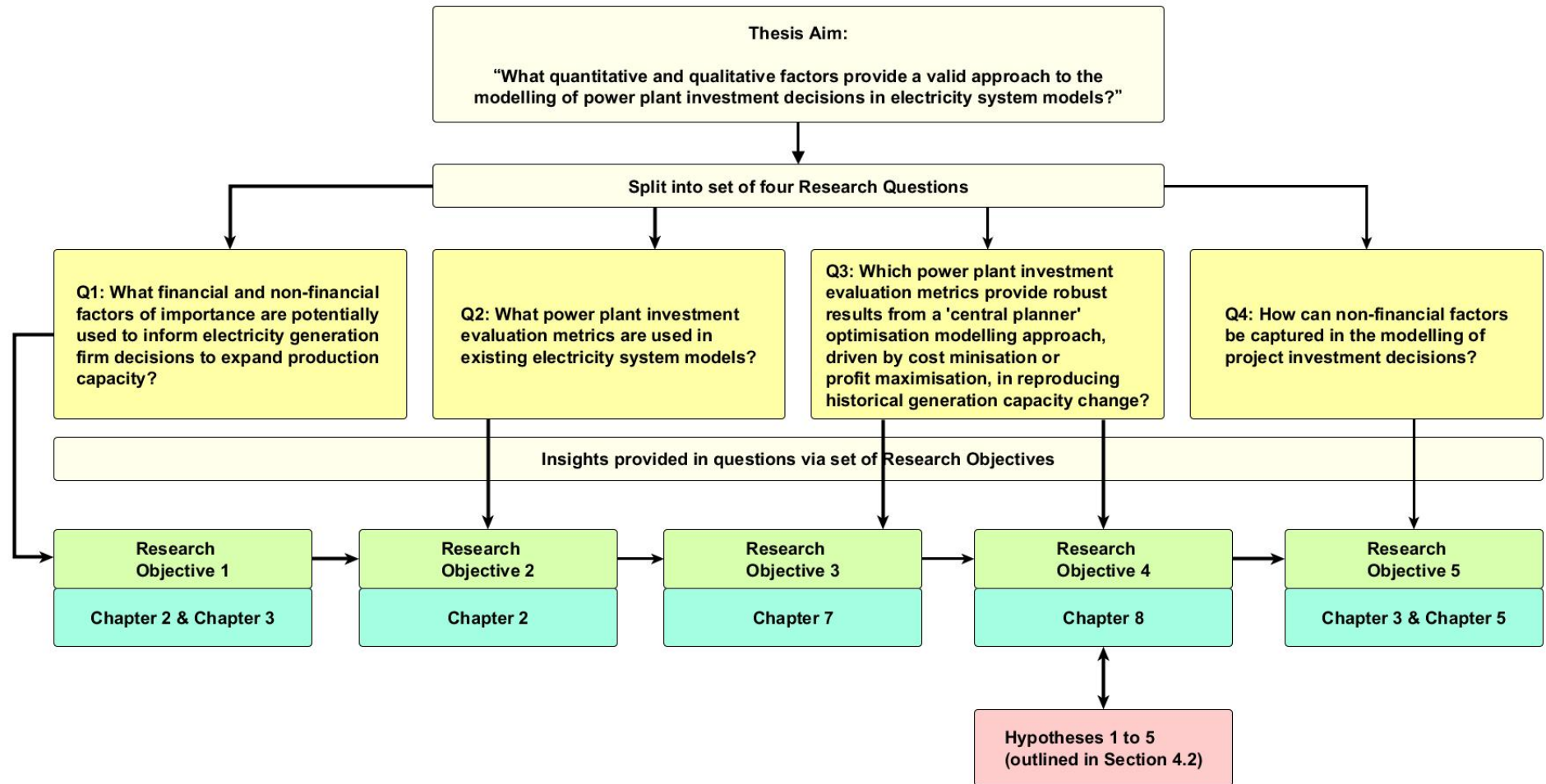


Figure 1: Relationship between Research Questions, Research Objectives, Hypothesis and Thesis Chapters

1.5.3 Thesis Structure

The thesis follows a deductive-inductive structure. In the first half up to and including **chapter 4** existing literature and theoretical approaches are discussed and the used methodologies are elaborated upon. The second half from **chapter 5** subsequently describes the insights and results of the thesis, where in an inductive approach based on a number of computer experiments the objectives are implemented, as well as via a deductive approach in a series of expert interviews. The data used for the use cases is described in **chapter 6**. The structure is summarised in figure 2 on the following page.

In **chapter 2** the literature foundation of the thesis is described. The chapter is separated into **section 2.1**, which looks at the factors of importance in the creation of investment decisions from the literature, and **section 2.2**, where an analysis is made of the structure of existing electricity system models with respect to investment decision. The examination leads to a set of common approaches which can be contrasted with the theoretical and descriptive literature. In the subsequent **chapter 3** a framework is built on how investment decisions can be formulated in electricity system models from a set of conjectures on decision making. These are grounded in the literature on decision processes and investment decisions. The treatise is used to provide theoretical grounding for the interpretation of results and the discussion of analytical outcomes. They form the basis for forming a series hypothesis on decision algorithms to be analysed as described in **chapter 4** on methodologies, to provide the reader with the underlying rationale of each analysis and the steps taken to apply it.

After the methodological description the interview insights, collected data, and statistical and model reproduction results are described in subsequent chapters. First, a selected number of insights from expert interviews are discussed in **chapter 5** which serve to further contextualise the statistical and model reproduction analyses. Second, the collected electricity market data for Germany, the UK, and the Netherlands are set out in **chapter 6**, data anomalies are examined, and general data trends are described. Third, a series of statistical data analyses are carried out in **chapter 7**. These provide for the ability to establish the existence of a correlation between the outcome of occurrence of investments, and the size of capacity invested in, relative to the value of various investment valuation metrics. Fourth, in **chapter 8** each of the project investment valuation metrics is tested for its ability to reproduce historical capacity change outcomes in the electricity markets of Germany, the UK, and the Netherlands, using the TEMOA electricity systems model.

The results of the analyses are interpreted at the end of each chapter, and discussed for their validity and findings in **chapter 9**. In the discussion the results of the analyses are contrasted with outcomes of the literature analysis plus the theoretical treatise on decision making and investment decisions of **chapter 3**. The thesis ends with a set of conclusions from the analyses and discussion, and a number of recommendations for the establishment of endogenous investment modelling in general and in electricity system models in particular.

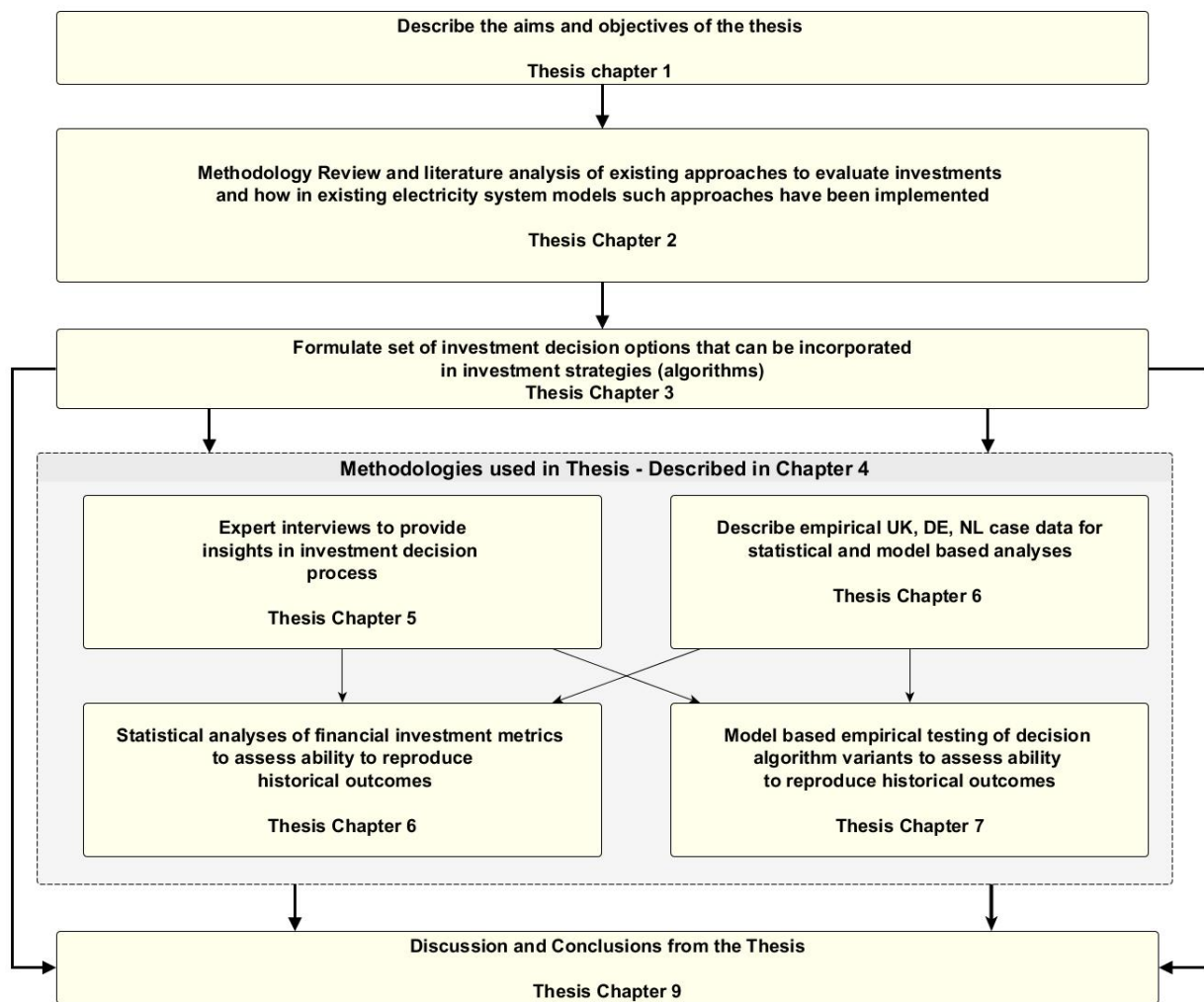


Figure 2: Structure of PhD. Thesis

2 Methodology Review and Literature analysis

The thesis brings together two complementary parts of literature, describing financial metrics to evaluate investments (described in **sections 2.1 to 2.3**), and how investment decisions are implemented in existing electricity system models (**section 2.4**). In doing so the chapter seeks to provide an answer to the sub-research question of **section 1.5.2**: “*What power plant investment evaluation metrics are used in existing electricity system models?*”.

The study of investment focuses on the evaluation of factors that determine whether it is worthwhile to invest - or not - in a particular prospect, and how this affects economic output. Investments generally have been analysed from three perspectives, as individual investments based on their own merits and drawbacks (Nickell 1978), as investments within a market framework with multiple players with uncertainty (Thijssen 2004), and as investment flows at the scale of entire economies (Acemoglu 2009).

The focus in this first literature analysis section is to summarise the investment literature primarily in relation to the first perspective, so as to gain an understanding of evaluating individual investments and the factors related to making the decision to invest, wherein the market environment is treated exogenously. The aspect of aggregate macro-level investment and interactions between market players is not studied as it lies outside of the chosen scope of analyses in this PhD. thesis as defined in **chapter 1**.

The first part of this chapter that summaries financial metrics described in the literature to evaluate investments is organised in three sections:

- **Section 2.1**, the study of individual investments in financial economics based on metrics to assess their merits and drawbacks.
- **Section 2.2**, the approaches used for the analysis of investment risks and uncertainty.
- **Section 2.3**, the use of metrics particular to large infrastructure investments in electricity markets.

2.1 Financial investment theories and metrics

The use of various financial metrics to evaluate investments is a widespread practice today for firms of all sizes since they improve investment efficacy and gained profits. This development is relatively new with the use of most metrics only becoming common after the 1970s in several development waves to the present day. Prior to the 1970s only financial payback time evaluations were used (Rosenblatt and Jucker 1979). The application of new metrics by companies has always come after their theoretical development by researchers in the field of business studies and financial economics. The framework is laid down in theory, gets translated into a practically usable format to calculate the financial valuation, and diffuses over many years across businesses usually starting with large firms who pioneer the new approach (Schwartz and Trigeorgis 2004).

In this evolutionary structure many valuations have been developed, but within the context of infrastructure investment in practice three key decision criteria are used. These include: i) the financial payback period of investment, ii) net present value evaluation (NPV) and related Internal Rate of Return (IRR) valuation, and iii) the real options approach, which is an extension of the NPV evaluation intended to take future uncertainties into account (Jackson 2008). The extent to which these metrics were used was assessed in a 1999 survey among 382 CFOs of small and large firms in the US which found that 75% of firms nearly always used NPV and IRR evaluations, in 55% of cases the payback period was used as a criterion, and 25% of firms also utilised Real Options valuations (Graham and Harvey 2001). Financial metrics are thereby often used in complement to each other since they provide different information sets.

In the next sub-sections all three metrics and their variants are discussed in sequence. Further augmentation of these financial metrics with risk evaluation measures is discussed in **section 2.1.2**.

2.1.1 Payback Time (PBT)

The simplest method to rapidly create a heuristic for an investment decision is the time it takes to recover the costs of an investment, referred to as the payback time, payback period, or payback rule (Jackson 2008, Wittmann 2008, Bhandari 1986). The metric can be calculated as the time period, t , at which investment cost, I , minus the discounted cash flow after taxes, C , is equal to zero. In company surveys spanning from the 1930s to 1980s in the United States, it was found that the payback period was initially used without discounting, since the concept of time value of money was not taken into account. Only since the 1960s did the use of discounting in payback time evaluations become more prominent, and during the 1970s it turned into a common standard used in the majority of firms (Rosenblatt and Jucker 1979). The use of a discounted payback period took place first for larger firms after which smaller firms followed (Bhandari 1986).

The discounted cash flow formulation of payback time (PBT) can be formulated as:

$$\text{Find } T \text{ where } \sum_{t=1}^T \frac{C_t}{(1+r)^t} = I_{t=0} \quad (1)$$

2.1.2 Net Present Value (NPV) and Internal Rate of Return (IRR)

The use of payback time lost its dominance and became a secondary metric for investment analysis when NPV and IRR metrics were added to the investment evaluation toolbox (Kee and Bublitz 1988). In Net Present Value (NPV) evaluation the worth of an investment project is established on the basis of estimated benefits and costs from initial investment to the end life of a project. The value that flows from a NPV calculation is the expected net profit, and is primarily used to establish whether costs do not exceed the discounted total revenue of the project, such that it will have a positive return (Aid 2014). The general rule is that a project should not be undertaken if the NPV is below zero. In the calculation aggregate project life time costs are subtracted from revenues, the total value is discounted, and subsequently

total investment costs in the initial period are subtracted. In practice, instead of revenue and cost accounting the estimated discounted value of cash flows are used to estimate NPV (Myers 1984).

The calculation can be mathematically expressed as a summation of incremental cash flow after yearly taxes, C_t , discounted by a constant interest rate, r , of capital over the project lifetime, T , minus the initial investment $I_{t=0}$:

$$NPV = \sum_{t=1}^T \frac{C_t}{(1+r)^t} - I_{t=0} \quad (2)$$

The interest rate of capital r in the NPV calculation is set equal to a standard market rate, such as the interest rate gained by putting the investment sum on a bank in a country with favourable interest rates, instead of investing it, or a commonly used minimum standardized value such as 5% or 10% (IEA and NEA 2015). Another approach used to calculate a standard value for the interest rate is through a Weighted Average Cost of Capital (WACC) equation. The discount rate is calculated in WACC in two parts. First, by weighting a standard market interest rate by the equity portion of the investment (e.g. the money the firm puts into the investment from its own financial assets). Second, by weighting the interest rate of the loan sum the firm needs to secure to carry out the investment based on the loan portion of the investment. Firms take loans because it allows them to grow more quickly as their existing equity can be leveraged, or because they do not have sufficient equity for the investment available in the first place. The first part of the calculation is based on the relative estimated standard market interest rates, r_e , weighted by the firms equity, E , as a proportion of the investment. Subsequently, added to this is the loan interest rate of incurred debts, r_d , weighted by the quantity of loan(s), D , taken by the firm as a proportion of the investments.

The WACC calculation is thereby formulated as per (Aid 2014) as:

$$r = \frac{D}{D+E} r_d + \frac{E}{D+E} r_e \quad (3)$$

Another commonly used investment metric stems from adjusting the NPV calculation to express it in a form where costs are equal to benefits by adjustment of the interest rate value. The resulting estimated interest rate value is referred to as the Internal Rate of Return (IRR) which can be interpreted as the expected annual percentage return on the investment in project by any investor. The IRR can be calculated by finding the value of the interest rate, r , such that the outcome of the NPV calculation is zero, described as:

$$\text{Find } r \text{ where } \sum_{t=1}^T \frac{C_t}{(1+r)^t} - I_t = 0 \quad (4)$$

The IRR is used across the board by companies as a minimum benchmark because it provides a direct means to compare across projects and forms an easy to interpret value for company shareholders. A company may thereby set rules that any project with an IRR below 5%, 10%, 15% or any other value will not be undertaken, or may strive for a particular IRR, based on a typical value of returns in the market in which it operates. For example, the former CEO of EDF in a communication about the Hinkley Point C Nuclear power plant under development in the UK stated that an anticipated IRR of 10% was the target within the investment criteria of EDF (Proglia et al. 2013). Similarly, the UK Renewable Infrastructure Group Fund, an investment fund setup in 2013 with a starting capital of 300 million pounds to invest in wind and solar generation projects, targets an IRR of 8% to 9% for its projects on UK soil (Mahy 2014).

NPV and IRR calculations can be further augmented to incorporate parameters such as longer construction times or further details of individual cost types. Whilst these metrics provide for larger flexibility and greater realism, they have not fully replaced the more simple payback time, which is still in use as a secondary measure of investment evaluation. The advantage of payback time is its unique information on the occurrence of the investment break-even point (Bhandari 1986). The toolbox of financial evaluation thereby has seen expansion instead of replacement, which also is the case for real options theory that emerged in the 1990s, discussed in the next section.

2.1.3 Real Options Evaluation (ROE)

The core concept of real options is to perceive an investment decision as part of a set of mutually exclusive and/or sequential options the firm can undertake. The mutual exclusivity comes from the execution of an investment, which can only be done once, since a purchased asset such as a power plant cannot be sold at a later stage for a similar price, resulting in irreversibility of execution (Dixit and Pindyck 1994). Real option theory was initially designed to evaluate the value of investing today versus the value of postponing investment to future time periods. The future development of prices and input cost evolution can result in a higher value of postponement, in terms of potentially mitigated losses and/or alternative gains of using the investment money, than if the investment is executed immediately. Since the initial work by Dixit and Pindyck (Dixit and Pindyck 1994) the real options concept has been extended to view every firm investment decision as an “option” including, postponing investment, splicing investments into multiple stages over time each as an option, choosing among various sizes of infrastructure expansion, the option of contraction or shutting down plants, technology switching, R&D, and interactions between these (Trigeorgis 1996).

Several methods have emerged to calculate the real options value of postponing investments. One of the first standardized approaches takes as the base of comparison the discounted present value of the investment over infinite time (Schwartz and Trigeorgis 2004). This cash flow discounted investment value is compared with the cost of investing today, $I_{t=0}$, plus an opportunity cost value, ϕ , calculated as the value that is potentially lost by the investment based on future price developments of the good or service to be sold and their probabilities of occurrence. If the present value is higher, as per formula (2) above, the investment should take place today; if it is lower a re-evaluation should take place in a future period if the price goes up, or the option should be abandoned if the price goes down.

$$\sum_{t=1}^T \frac{C_t}{(1+r)^t} > I_{t=0} + \phi \quad (5)$$

The opportunity cost, ϕ , is calculated either as i) the expected NPV of a future time period minus the present NPV, assuming the NPV is zero if the present value drops below investment cost due to a price decrease, or ii) as the investment value today including hedging for future price changes, often based on a stock market asset portfolio calculated by the replicating portfolio technique (Koursaris 2011). The hedging approach assumes a ‘complete market’, defined as having access to a wide spectrum of financial assets such as bonds, futures, or options, which fluctuate in line with the output value of the good or company produced, so that they can capture price risk of the investment (Brandão et al. 2005). Since the initial development several methodologies have been established to calculate the future price, cost, and interest outcomes for the evaluation, including finite differences such as Black-Scholes formulations (Schwartz and Brennan 1978), Monte Carlo simulation (Gamba 2002), binomial trees (Brandão et al. 2005), fuzzy logic (Collan et al. 2009), and binomial lattice calculations (Copeland and Tufano 2004).

The most common of these approaches due to its transparency is the binomial lattice method, where for each future period the probability of an increase or decrease in cash flow and the size thereof is calculated, such that a binomial tree with two options at each node emerges. The calculation of the option cash-flow C^0 for a single time-step as shown in formula (6) below is based on taking the value of an anticipated upward, C^u , and downward, C^d , movement in cash-flow multiplied by their prior probabilities, p , and discounted by a market interest rate r . The interest rate is assumed to be set equal to a ‘risk-free’ rate such as a government bond or average market stock index return. In real options text-books typically an 8% interest rate value is used (Copeland and Antikarov 2001).

$$\phi = \frac{pC^u + (1-p)C^d}{1+r} \quad (6)$$

The probabilities can be calculated by using the anticipated proportional ratio of the downward and upward movements of the investment value as, d , and, u , respectively, as per formula (7). The upward and downward movements can be derived from the historical cash-flow volatility, or from a financial product that has similar financial characteristics to the

price of the good or service produced. The upward and downward proportion of these movements can be calculated by assuming a log-normal distribution (Copeland and Tufano 2004).

$$p = \frac{(1+r) - d}{u - d} \quad (7)$$

To calculate the option value in an integrated manner also a binomial equation can be used. In the calculation all possible combinations of upward and downward movements from the proportional steps are taken into account, so as to incorporate all possible investments value developments within the chosen time period. The resulting investment value outcomes are summed based on their probability of occurrence, which can be derived from a binomial distribution as per formula (8). Negative outcomes can be ignored, because since they are equal to zero the option will be dropped in those cases.

The binomial equation approach can be carried out by using the formula:

$$\phi_{t=0} = \frac{1}{(1+r)^T} \sum_{n=1}^T \frac{T!}{(T-n)!n!} p^n (1-p)^{T-n} (u^n d^{T-n} C_0 - I_0) \quad (8)$$

The option opportunity cost is here defined as the sum of positive outcomes calculated from a binomial probability. The final value of the investment as an option is based on holding on to the option in all periods, following the set of upward and downward movements minus the investment cost. The summed value is discounted by the market rate under, T , the respective time horizon. A complementary approach to the discrete binomial equation is the continuous formulation based on the Black-Scholes formula. This is equivalent to the binomial calculation under an assumption of an infinite number of time steps (Copeland and Antikarov 2001). The Black-Scholes continuous approach can be carried out using the formulas (9) to (11) as follows:

$$\phi_0 = C_0 N(d_1) - I_0 e^{-rT} N(d_2) \quad (9)$$

$$d_1 = \frac{\ln(C_0/I_0) + rT}{\sigma\sqrt{T}} + \frac{1}{2}\sigma\sqrt{T} \quad (10)$$

$$d_2 = d_1 - \sigma\sqrt{T} \quad (11)$$

In the calculation the value of, $I_0 e^{-rT}$, represents the investment value at the final period which is discounted over the chosen time horizon. This is multiplied by the calculated cumulative normal probability, $N(d_2)$, of the investment value, C , being above the investment cost, I , in the final period. Thereby based on a normal distribution. The term, $C_0 N(d_1)$, provides for the present value of the investment in the final period for all developments where the investment value is above the cost of the investment.

The complexity of real options theory lies in its more difficult calculation and the challenge of how to interpret the results. Even though efforts of simplification using spreadsheet approaches have been made (Copeland and Tufano 2004), this complexity has plausibly contributed to its low popularity in financial practice (Teach 2003). In a survey among CFOs of mid- to large size firms in the UK, Netherlands, Germany, and France with 313 respondents it was found that respectively per country 29%, 36%, 44%, and 56% of firms utilise the real options approach in project investment evaluation (Brounen et al. 2004). The survey held by Andor et al. (2015) with responses from 400 executives in 10 eastern European countries showed that 17% of firms use real options approaches (Andor et al. 2015).

2.2 Risk evaluation in financial investment

The field of financial risk assessment has evolved to establish the potential effects of future developments and events on the financial metrics used to assess investments. In risk assessment the aim is to ascertain the relative probabilities of particular developments, and to capture the combined probability and loss of value into quantitative metrics. Since the future is uncertain different perspectives on how key future conditions could play out are formed. Risks are thereby encapsulated in either probability distributions or scenarios to which probabilities are applied. Probabilities are typically estimated using frequency of occurrence data for discrete events, or time-series data for continuous developments, which are related to losses to obtain a risk probability of loss (Kaplan and Garrick 1981).

The assessment of a power plant's profitability is inherently accompanied by risks since it is a long-term investment involving a large number of assumptions about the future, such as the expected fuel price and electricity price. The understanding that future uncertainty and its assessment is essential has gained prominence in financial evaluations since the 1980s, driven by insights that more complex evaluations, such as NPV and IRR relative to the simpler PBT metric, did not yield better results in case of substantial uncertainty (Kee and Bublitz 1988).

There are two common approaches in existence today in investment evaluation to include risks which are discussed in this section. The first described in **section 2.2.1** assesses risk by means of adjusting the discount rate using the exposure to a risk related time-series to take into account expected risk exposure. The second described in **section 2.2.2** looks at the overall implications of volatility based on a complete risk approach that includes probability distributions and confidence intervals.

2.2.1 Discount Rate adjusted Risk analysis

A common approach in energy markets to include risks is the adjustment of the discount rate to be 'risk-matched' or 'risk-adjusted', by which the evaluation is adjusted for possible costs of risk losses (Brounen et al. 2004, Ringer 2008). The matched-risk rate is commonly calculated using the capital asset pricing model (CAPM) developed by Sharpe (1964), Litner (1965) and Black (1972) (Sharpe 1964, Black 1972, Lintner 1965). In a survey of CFOs of mid- to large size firms with 313 respondents it was found that the CAPM model is used by 47%, 56%, 34%, and 45% of CFO's in the UK, Netherlands, Germany, and France, respectively (Brounen et al. 2004).

The CAPM utilises the difference between a 'risk-free' rate of return of investments, r_z , typically the return on long-term government bonds, and a market premium, F , of the investment. The market premium is calculated by finding an estimated return, r_m , from a standard investment option in the market, which is related to the investment at hand, such as the purchase of stocks in electricity generation companies. The market premium is then found by subtracting from this investment option, r_m , the 'risk-free' rate from the premium, r_z , and multiplying it with, β , an investment risk exposure weight. The calculation as per (Fama et al. 2004) is formulated as:

$$E(r_i) = r_z + \beta(r_m - r_z), \quad (12)$$

The exposure weight, β , falls between 0 and 1 and can be calculated from the correlation between the expected return of the investment r_i , such as the IRR, and the market premium, r_m , through the covariance divided by the variance of the market return, as per formula (13):

$$\beta = \frac{\text{cov}(r_i, r_m)}{\sigma^2(r_m)} \quad (13)$$

The CAPM method has also been applied to calculate specific discount rates for parts of the investment calculation such as tailored discount rates for fuel costs. When plotting historical fuel outlays instead of market return together with

firm revenues using formula (14) for electric utilities in the US between 1982-1991, the analysis by Awerbuch (1993) found a negative, β , for coal of -0.20 and a value for natural gas and heavy fuel oil of -1.25 (Awerbuch 1993). If applied to the fuel cost component, the evaluation metrics for such fossil fuels would receive a much lower discount rate and thereby express a higher cost due to the risk of volatility, at least in the analysed period. The specificity provides for a technology specific risk assessment, because it is not using the risk variation from a single discount rate for all types of technology investments or calculation components (Krohn et al. 2009).

In addition to using discount rates for each part of the investment calculation, the approach can also be extended as per (Gebhardt et al. 2001) to introduce multiple risk, F_j , factors $j = 1, \dots, N$, by which the formulation becomes:

$$E(r_i) = \alpha_i + \sum_{j=1}^N \beta_{ij} F_j \quad (14)$$

The limitation of the model is the underlying assumption that in the calculation of, β , the investment (e.g. a power plant) and the financial investment option need to be correlated, otherwise they do not express exposure to risk. In case of selecting the chosen market return and company rate of return, such as from company stocks, only a weak relationship has been found in many cases, due to which the validity of the measure has been put into doubt. The lack of empirical proof of the correlation at market levels has led to the conclusion that in most applications the model is not valid (Fama and French 1997, Fama et al. 2004).

2.2.2 Value at Risk (VaR)

A method used in insurance and finance for risk evaluation that utilises probability distributions is Value at Risk (VaR). The method was initially developed in the 1980s by Till Guldemann of the US bank J.P. Morgan. It is a consistent statistical measure of potential losses in relation to fluctuations in stock market bonds, and has emerged as a standard tool in the financial sector (Jorion 2007). An implementation example of VaR in relation to energy markets can be found in (Ehrenmann and Smeers 2011) for generation capacity expansion, and in (Jackson 2008) for energy efficiency investments and the implications of fuel price fluctuations.

In its standard form VaR is established using a historical or scenario generated data-set of the returns of an asset, such as a power plant, and from this dataset the returns or losses relative to the mean value are calculated, up to a chosen level of time periods to represent the probability of deviation from the mean, expressed as a confidence interval. In essence it is an empirical test of sensitivity to past market conditions and possible losses under those conditions. The calculation can be made by taking the expected mean return, $C(E)$, and subtracting from it the initial investment cash flow, C_0 , which is multiplied by a lower confidence boundary level rate of return, R , such that VaR is expressed as:

$$VaR = C(E) - C_0(1 + R) \quad (15)$$

In practice a distribution from a time-series is taken to express the boundary level, R , often based on the normal distribution, so as to obtain a statistical measure that is more robust. The lower boundary level is transformed into a standardised value as shown in formula (16):

$$R = -\alpha\sigma + \mu \quad (16)$$

$$VaR = C(E) - C_0(1 - \alpha\sigma + \mu) \quad (17)$$

The VaR formula in this calculation uses a multiplication of the initial cash flow level by its standard deviation, σ , and a chosen multiplier, α , to yield the distance to a desired confidence level, as shown in the example of figure 3 below. For

example, a 5% cut-off which in case of a normal distribution represents a 1.96 standard deviation multiplier, α , from the mean, which yields a 95% confidence interval. The metric can be interpreted that in 95% of cases the annual return will not be lower than the calculated VaR.

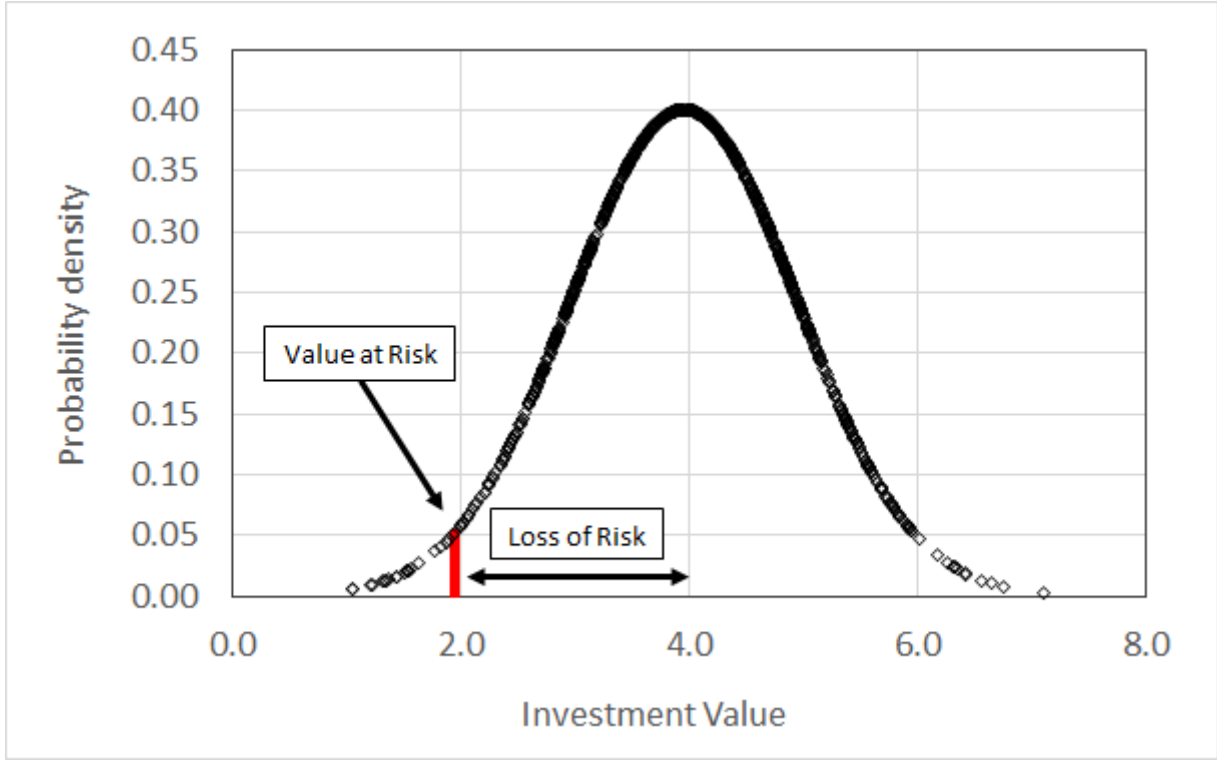


Figure 3: Visual example of VaR calculation under a normal distribution

Whilst the VaR can generate a risk measure for an existing or new investment using a scenario driven approach, so as to establish whether a projects risks are not too significant, it is not useable to gain insights in mitigation of overall risks for large players in markets. For example, in case of anticipated changes in electricity market regulation which have distributed effects on different power technologies. The metrics related to Portfolio VaR (PVaR) have been developed for this purpose as discussed in the next section.

2.2.3 Portfolio Value at Risk (PVaR)

Several more complicated calculations of VaR have been establish to generate an aggregate measure at the level of entire stock portfolio's, a multiple of investment projects, or complete enterprises. In the case of a power plant investor the Portfolio VaR (PVaR) is of use to provide for a relative weighting of how individual power plant with their technologies in a companies portfolio compare based on their contribution to risk of the rate of return for the owner or investors (Jorion 2007). The metric also can be used to establish how changes in a power plant portfolio provides for lower or higher risk exposure. As such it gives a quantitative metric to evaluate whether diversification of power generation technologies creates greater cash flow stability.

The calculation of Portfolio VaR (PVaR) as established in (Jorion 2007) is here adjusted to express its calculation particular to a portfolio of power plants, N , which starts by a complete cash flow calculation as expressed by:

$$C^p = \sum_{t=1}^T \sum_{i=1}^N w_{i,t} C_{i,t} \quad (18)$$

Where, C^p , is the portfolio accumulated net cash flow, $i = 1, 2, 3, \dots, n$, an index for individual power plants, and w the relative weight of a power plant in the portfolio, $i = 1, 2, 3, \dots, n$, as the percentage contribution to the total produced electricity in MWh. The PVaR can be expressed by establishing a portfolio variance as the sum of the variance of individual power plants cash flow values, σ^p , and multiplying this with a confidence interval, α , and the accumulated cash flow value, C^p , for all power plants in the portfolio, similar to formula (19) above, such as:

$$PVaR = \alpha \sigma^p C^p \quad (19)$$

The VaR of individual power plants can also be established in this approach by taking the respective variance for a power plant, $i = 1, 2, 3, \dots, n$, and multiplying it with the cash-flow share of the total portfolio cash flow, C^p , using a proportional weight, w_i , of the power plants contribution to cash-flow. As mentioned the PVaR can be used to establish how diversification of adding a new power plant in the portfolio, i , will lead to lower or higher or lower risk profile, by calculating the difference between two portfolio's, one with and one without the new power plant. This approach has been referred to as the Incremental VaR of the portfolio, defined as:

$$Incremental\ VaR = PVaR_{i+1} - PVaR_i \quad (20)$$

The PVaR measure is especially useful when assessing a new technology type within an existing portfolio. For example, the influence on expected cash flows by adding wind electricity plants with intermittent load as opposed to adding more base-load coal power.

2.3 Power Plant Investment Specifics

The methods described in **section 2.1** and **2.2** are used to evaluate investments across a wide range of sectors. In case of electricity markets specific values have been developed to evaluate power plant investments costs and benefits (Aid 2014, Zammerilli 2010, Kaplan 2008) which are described in this section. In the first part in **section 2.3.1** a listing is made of cost and fiscal mechanisms in the electricity sector. Subsequently, specific electricity technology comparison metrics including levelised costs are discussed in **section 2.3.2**. Finally, particular power plant investment and operational risks that can be taken into account are discussed in **section 2.3.3**.

2.3.1 An overview of power market costs and fiscal mechanisms

Investment cost values are established in the electricity sector as the Engineered, Procured, and Constructed (EPC) costs of hiring a contractor to build the plant. The EPC value includes the costs of the power plant infrastructure, machinery and equipment and the contractor fees incurred for the establishment of the power plant, but excludes operational costs, site specific costs, and expenditures of the contractee or power plant owner (Zammerilli 2010). The site specific costs that are excluded can include land value, architectural and engineering services (A/E), electricity network interconnection, and site permits. The power plant owner or contractee costs covers overhead, public relations investments, and the owner's labour.

The EPC is used to settle a fixed contract price between the investor plus owner and the construction contractor, such that the contractor for the project bears the risk for increases in the project schedule and budget. The EPC forms the main component for Total Installed Cost (TIC), which also includes the cost of loan interest and equity, as well as Total Plant Costs (TPC), which incorporates land specific and plant owner overhead costs (Zammerilli 2010). Another metric that is frequently used is overnight costs, which is equivalent to TPC except that the cost of interest on loans and equity is excluded (Kaplan 2008). A comparison of the different investment cost metrics and what they include can be found in table 2 below.

Table 2: *Sets of investments costs included in the different cost metrics used in the electricity investment sector.*

Cost Component / Cost Metric	EPC	Overnight Cost	TIC	TPC
Power plant machinery and equipment cost	X	X	X	X
Machinery and equipment transport cost	X	X	X	X
Power plant installation cost	X	X	X	X
Installation contractor fees/costs	X	X	X	X
Land acquisition cost		X		X
Design architectural and engineering service		X		X
Feasibility studies and power plant engineering design		X		X
Electricity network interconnection costs		X		X
Site Permits costs		X		X
Owners overhead and labour costs		X		X
Loan interest costs			X	X
Cost of equity from shareholders			X	X
Power plant operational costs				
Power plant decommissioning costs				

The operational cost of a power plant is usually divided into a fixed portion per year per capacity unit, and a variable portion which is dependent on the operational use rate (see table 3). The fixed portion can include minimum labour costs for plant operation and regular maintenance costs which occur on a periodic monthly and/or annual basis. Variable operational costs can include fuel inputs for conversion into electricity and heat, marginal labour inputs to increase the power output of a power plant per unit time, and irregular maintenance costs. In electricity modelling operational cost

values are often simplified into two sets, fuel input costs, and total operational and maintenance costs excluding fuel inputs. The volatile component of fuel cost is thereby separated from the relatively stable labour operation and maintenance cost.

Table 3: *Sets of operational costs included in the different cost metrics used in the electricity investment sector.*

Cost Component / Cost Metric	Fixed cost	Variable cost	Total operational cost	O&M cost	Fuel cost
Labour costs for baseline operation	X		X	X	
Fuel costs for operation		X	X		X
Maintenance costs (regular)*	X			X	
Maintenance costs (irregular)		X		X	
Marginal labour input costs		X	X	X	

*Includes maintenance that takes place periodically such as weekly, monthly, or annually.

The profit from a power plant in addition to the costs discussed above is often also influenced by taxation, subsidies or other fiscal mechanisms. In case of electricity markets specific transfers can include direct subsidies for particular technologies, or market fee or payment transfers. Four prominent mechanisms include feed-in tariffs, contracts for differences, carbon emission transfers, and capacity remuneration. The feed-in tariff (FiT) consist of a payment per kWh of electricity generated at a fixed or depreciating rate for an arranged duration of time prior to installation of the power plant. The first feed-in-tariffs were first introduced in Germany in the 1990s for renewable power sources and provide a substantial financial incentive and de-risk renewable electricity price volatility (Sijm 2002).

The first Contracts for Differences (CfD) were recently introduced in the UK in 2014 to provide power plant owners a fee equivalent to the difference between an agreed 'strike price' including all costs of establishing and operating the plant, expressed in costs per unit of electricity output, and the actual price in the market as it evolves during the lifetime of the power plant. The financial agreement for CfD is between the UK government and the power plant owner. The financial transfer of the difference is executed by a specific publicly owned company designated by the UK government (Internal Company Team 2014).

Carbon emission transfers are either fixed charges for the amount of carbon emitted from electricity production, or financial fees provided for low-emission sources based on their carbon emissions profile. The largest transfer mechanism of this kind is the EU-Emissions Trading Scheme (ETS) which covers 11,000 power generation and manufacturing plants as of 2015. Power plant owners under the scheme need to purchase emission allowances based on EU-ETS market prices, which from 2013 onwards are auctioned instead of freely provided via EU governments (European Commission Publications Office 2013). In the US renewable electricity production tax credits in the form of direct subsidies for technologies with a low carbon emission profile were introduced in 2009. Each kWh produced from renewable sources benefits from a corporate tax reduction for a 10 year period after commissioning (US Department of Energy n.d.).

The capacity remuneration mechanisms is a market based or direct payment mechanism to provide a fee per MW of capacity held in reserve to be brought online in an agreed time-period. The time duration can be a spinning reserve (10 seconds), supplemental reserve (10 minutes), or backup reserve (one hour) (Finon and Pignon 2008). The instatement of capacity remuneration is a growing part of electricity markets in the EU and US because of the increasing need to have backup for intermittent power sources such as solar and wind energy.

2.3.2 Electricity Market Specific Investment Metrics

A method that is used to create an inclusive cost calculation over a power plant's lifetime for purposes of accurate comparison between technologies is the Levelised Cost of Electricity calculations (LCOE) [Bemis and DeAngelis \(1990\)](#). In the method the total plant costs, TPC , anticipated lifetime operational and maintenance costs, $O\&M$, fuel costs, F , and decommissioning costs, D , are taken together and discounted by a rate, r , which are jointly divided by the anticipated discounted sum of electricity produced over the power plants lifetime, E , so as to provide for the total costs per unit of electricity produced. The calculation can be formulated as adapted from (Salvadores and Keppler 2010) as:

$$LCOE = \sum_t \left(\frac{TPC + O\&M_t + F_t + D_t}{E} (1 + r)^{-t} \right) \quad (21)$$

In case of other applicable costs these can be incorporated in the numerator. The LCOE metric is mainly used by policy makers and in research institutions due to its ease of interpretation, because it can be directly compared to market prices to gain an understanding of commerciality and the potential need for fiscal support mechanisms. It can also provide for a minimum contractual price level to recuperate costs and can thereby be used in long-term contract negotiations with governments (Aid 2014). The metric has come under increasing critique, however, because it does not represent the service value of power plant technologies to balance electricity grid outputs (Boston 2016), which can include up and downward regulation, frequency response, and voltage and power factor control.

2.3.3 Power plant investment risks

The sets of risk associated with power plant investments can be categorised on the basis of pre- and post-commissioning periods (see table 4) (Stephen 1995). The pre-commissioning risks include development period costs, construction cost increases, delay in completion, defective performance on completion, and/or non-completion. These costs are usually borne by the firms which are contracted by the investor and/or power plant operator to construct the power plant under a Engineered, Production, and Constructed (EPC) fixed cost sum contractual framework. Post-commissioning risks can include inadequate fuel supply, fuel price increases, operation and maintenance cost increases, disaster costs not covered by insurance, transmission grid system failure, changes in fiscal support and transfer mechanisms, changes in interest rates of loans, and higher decommissioning costs (Zammerilli 2010). The post-commissioning risks are usually examined relative to a mean anticipated value used in the investment calculations. The mean value is often derived from the contractual arrangement in a bank loan and for establishing the cost of equity.

Table 4: Overview of power plant investments risks split out by the pre- and post-commissioning period.

Specific risk	Category of risk	Pre-commissioning	Post-commissioning
Higher outlays for development costs in feasibility and engineering studies	Development	X	
Construction period completion delays	Construction	X	
Power plant infrastructure, machinery, equipment cost increases during construction	Construction	X	
Non-completion of power plant construction due to financing problems or severe technical problems	Construction	X	
Reduced technical performance of power plant on completion versus anticipated efficiency for expected nameplate capacity	Construction / Operation	X	
Lower sales of electricity due to lower than anticipated demand for power resulting in lower revenues	Operation		X
Inadequate fuel supply provisioning during operation resulting in reduced production	Operation		X
Fuel price increases during operational life above pre-commissioning expectations	Operation		X
Higher operational & maintenance costs above pre-commissioning expectations	Operation		X
Disaster costs not covered by insurance contracts	Operation		X
System failure of transmission systems resulting in loss of electricity sales	Operation		X
Changes in regulatory or political market transfer mechanisms causing loss of expected revenues	Financial		X
Increases in debt interest rates changes during financial lifetime of loan	Financial		X
Higher decommissioning costs than expected values at pre-commissioning	decommissioning		X

2.4 Electricity Sector Models with Power Plant Capacity Expansion

Over 90 electricity system models have been constructed to date with substantial variation in model structure Pina (2012). A key variation is the scope of the represented electricity system in its incorporation of three sub-systems:

- **Electricity supply and demand markets**, which are arranged by market participant price bidding or contracting and exchange over short-term periods such as days, weeks and years. A common implementation is a day-ahead spot market model but also forward, bilateral off the counter, and reserve or capacity market models have been constructed Just and Weber (2008).
- **Generation capacity expansion**, which is the change in physical infrastructure and technology choice over time taking place over the long term of multiple years to decades. The model representation is either at individual firm or sector level and either at individual power plant or aggregate capacity level per technology.
- **Grid flows**, whose representation serves to spatially match electricity supply and demand. The use of grid simulations is growing due to the increasing need to understand how growing intermittent technology shares in electricity systems can be balanced Swider and Weber (2007).

Historically, the three sub-systems were treated as separate models due to computational constraints, with an early exception being the MARKAL model that combines electricity markets with generation expansion, although limited to annual time-steps (Fishbone and Abilock 1981). The MARKAL model, now superseded by TIMES, is an energy systems model that covers electricity, transport and heat use. Such computational constraints are increasingly irrelevant since software and hardware improvements have enabled model operation using time-slices across a year or continuous hourly to sub-hourly blocks. An accurate implementation of high resolution grid flows and renewable stochastics which previously limited coupling of the three electricity sub-systems has become feasible Pfenninger et al. (2014). Hard-linked models have emerged with an expansive and exceedingly granular temporal scope such as E2M2 Spiecker and Weber (2014). Also efforts are becoming increasingly common to soft-link existing models, such as MARKAL for electricity markets and capacity expansion with PLEXOS for grid flow modelling Deane et al. (2012).

In this section models which harbour a long-term generation capacity expansion component are examined from their literature description, so as to examine how power generation capacity investment is handled in existing models. To create a systematic overview the listing of 90 electricity system models from Pina (2012) was screened by assessing the literature describing particulars for each of these models. The listing by Pina (2012) was chosen because it was found to be the most comprehensive in listing all models built to date. In addition a literature search was carried out to find any additional relevant models with a power generation capacity expansion component. The literature search was carried out using Scopus and Web of Science by means of the keywords “Electricity” AND “Investment” AND “Power” AND “Model” AND “Capacity” OR “Expansion” for the period 2006 to 2015. Also a similar search was carried out using Google Scholar with the restriction of keywords occurring in titles only. A summary of the literature search can be found in table 5 below. Finally, the listing of models at the openmod open energy modelling initiative webpage was scrutinized for any models available under open-source or open-access conditions (Richstein 2015).

The combined literature search and screenings resulted in a total of 51 unique models which contain a long-term power generation capacity expansion component.

Table 5: Overview of literature search for electricity system models.

Literature Database	Search Keywords	Period	No. Results / Abstracts screened	Articles Screened
Scopus	Electricity, Investment, Power, Model, Capacity	2006-2015	562	33
Scopus	Electricity, Investment, Power, Model, Expansion	2006-2015	287	61
Web of Science	Electricity, Investment, Power, Model, Capacity	2006-2015	337	32
Web of Science	Electricity, Investment, Power, Model, Expansion	2006-2015	261	27
Google Scholar*	Electricity, Investment, Model	2006-2015	34	14
Google Scholar*	Electricity, Investment, Expansion	2006-2015	11	3
Google Scholar*	Electricity, Investment, Capacity	2006-2015	49	12

*Search based on keywords in title only

The variation in approaches among the 51 models is influenced by the overarching model structure which can be classified as either an optimization or a simulation approach. These structural model paradigms and sub-classes are described in the next **section 2.4.1**. Afterward differences in model characteristics in relation to how power plant investment is effectuated in the 51 models is highlighted in **section 2.4.2**. A synthesis is subsequently made in **section 2.4.3** of the different ways in which investment has been structured in electricity system models. Finally, a summary is made in **section 2.4.4** of existing and missing capabilities of investment decision representation in existing electricity system models.

2.4.1 Electricity Sector Modelling Paradigms

Electricity system models can be classified into three modelling paradigms: optimization, simulation, and equilibrium (Ventosa et al. (2005)). The first energy system models developed in the 1970s used optimization methods to study the energy system from a “central planner” perspective, as if there is one investor, which implements the lowest cost combination of energy technologies and their capacity (Bhattacharyya and Govinda (2010)). The architecture is designed to find this ‘optimal’ system configuration by means of an objective such as minimizing the cost of the energy system, or the maximisation of total sector profit, over a chosen time period. The implementation was borrowed from the macro-economic models as discussed in **section 1.2**, where demand and supply match instantaneously in each time period either by adjusting prices, or more commonly by using an exogenous demand time-series. The typical setup includes a ‘central planner’ approach, instantaneous realisation of power plants, lump-sum investments per technology, and no restriction on information availability.

Complete information availability is implemented by finding an ‘intertemporal’ solution by letting the model simultaneously taking into account all time-periods, which allows ‘decisions’ to be made as if all exogenous parameter data is known in advance for future years, for instance for fuel and electricity prices. As a consequence a (local) non optimal solution for individual years or short periods can be included in the results, if it leads to a better aggregate solution for all time-periods. An alternative design is to split the time-periods up in clusters, and to optimise over each cluster in sequence, such that the objective equation is solved in a time-stepped fashion (Ventosa et al. n.d.). In both designs a set of constraint equations ensures that the solution takes into account chosen system qualities (Sarker and Newton (2008)), such as technological characteristics like efficiency, and boundaries on the speed of power plant construction.

Alternative to a cost or profit approach such models can also be setup based on minimizing or maximizing non-financial objectives or multiple weighted objectives, such as solving for a specified greenhouse gas emissions level, so as to identify technology choice and investment cost of meeting low-carbon emission targets. Optimization models can be further classified by the type of algorithmic solver needed due to numerical problem complexity. A standard choice is to constrain variables to pure integer values instead of including real values in the events possibility space, forming either Linear or Mixed Integer Linear Programming (MILP) models (Chong and Zak 2013). The integer formulation allows for modelling of separable units of generation such as for start-up and shut-down of power plants, as opposed to lumping units with the same technology (Traber and Kemfert 2011).

After the formational years of electricity modelling using optimization models, the shift to electricity market liberalization in the 1990s led to a new focus on short-term electricity supply-demand trading (Borenstein et al. 1995) (Bushnell and Ishii (2007)). The equilibrium model class that arose shifted from the ‘central planner’ perspective to an individual firm perspective as a decision maker in model structures. In the latter formulation electricity trading firms effectuate optimization based supply bids with price and capacity allocation solved for by an in-built market clearing equilibrium procedure. Demand is formed either exogenously, using price-elastic demand curves, or by a separate module that generates market participant demand bids (Philpott and Pettersen 2006). Supply bids are placed assuming full or partial knowledge of market demand and responses to perceived behaviour of competing firms. Three bidding strategies are commonly incorporated. In Cournot models firms optimize by production quantity variation, in Bertrand models price variation is used, and supply function equilibrium models let each firm produce a supply curve that integrates both price and quantity variation (Rudkevich (1999)). Since the process of investments is not based on bidding structures within a supply-demand frame, except in case of tenders, this model class is not used to model long term generation capacity expansion. However, the component is increasingly soft-linked to models that optimise investments in power generation.

In the simulation paradigm changes in the state of an entity or variable are modelled based on behavioural type algorithms or differential equations (Pfenninger et al. (2014)). The common differential equation approach to simulation was first developed in the 1970s for electricity systems. The method utilises difference equations to keep track of changes between states, and continuous differential equations are solved numerically to calculate changes between states (Ford (1997)). The approach enables a flexible incorporation of interactive behaviour between variables due to addition, subtraction, multiplication, division, or other mathematical relations, as they happen in time, and potentially space, by virtue of

a modular mathematical implementation. It is referred to as a state-space model in engineering and a stock-flow model in system dynamics literature (Cellier and Kofman 2006). The series of equations can be setup to calculate changes in capacity per technology, and even per technology per firm, although the latter can lead to an intractable implementation due to the number of required equations that need to be parametrized and subsequently computed.

A second simulation approach uses entities as software building blocks referred to as ‘agents’, such as firms, factories, or households, to which behavioural algorithms are ascribed. The first such Agent-Based Models (ABM) for electricity systems were introduced in the 2000s (Weidlich and Veit 2008). A change in an agent’s state between periods occurs by virtue of agent interactions combined with higher system level components influence. The implementation uses a discretised algorithm formulation around a time-clock, typically in the form of conditional logic that defines how agents change. Algorithms are triggered continuously or on an event-response basis and can be varied between sets of agents or even individual agents, moving to a fully bottom up approach North and Macal (2007). The disaggregated architecture is useful for tracking ‘agent’ information across states to include learning from past behaviour, agent spatial data, and network type behaviour of information exchange. ABM’s for electricity systems are often differentiated between types of agent learning algorithms including reinforcement learning, genetic algorithms, and learning classifiers (Weidlich and Veit 2008)(SensfuB et al. 2007).

In some cases the modular structure of simulation models has been exploited to incorporate optimization thereby blurring the paradigm distinction, either by soft-linking simulation with optimization sub-models, or by using meta-heuristic optimisation algorithms Fu (2002)Barton and Meckesheimer (2006). For example, an agent based simulation approach for power supply and demand resolution was soft-linked with a power dispatch optimization model Sarica et al. (2012).

2.4.2 Electricity sector models with long-term capacity change

To provide an overview of how long-term power generation capacity change has been implemented, the structure of the 51 unique models identified in the literature was screened. A total of ten key characteristics were examined:

- **First**, the modelling paradigm including intertemporal optimization, time-stepped optimization, or simulation approaches.
- **Second**, models were analysed on the basis of their time horizon in years modelled and minimum to maximum number of time steps taken within each year.
- **Third**, whether the ability to introduce individual power plants into the power mix is included, or if the implementation is based on fulfilling demand (and thereby capacity needs) as a lumped capacity sum for each technology.
- **Fourth**, the approach by which investment mechanics were included, such as the minimisation or maximisation objective and included variables.
- **Fifth**, whether a financial discount rates is used in the investment decision algorithm.
- **Sixth**, if the investment value is incorporated as a lump-sum one-off investment or if it is amortized over the financial or technical lifetime of the power plant. The amortized value can be calculated either by using a annuity formula or as a linear division over time.
- **Seventh**, if the discount rate is calculated using a Weighted Average Cost of Capital (WACC) rate or not.
- **Eight**, whether investment cost, demand, and fuel price data inputs were taken into account exogenously or via endogenous learning dynamics.
- **Nine**, if investments were resolved immediately or if time-lags were included.
- And **tenth**, if the technical lifetime of the power plant was taken for the investment sum or the financial loan lifetime.

The detailed listed of variant characteristics of these models can be found in table 42 in Appendix A. In this listing in a number of cases insufficient detail was available in the literature on particular details regarding the model's structure as indicated.

2.4.3 Main formulations of long-term capacity expansion

The majority at 31 out of 51 surveyed models are based on an optimization modelling structure with a cost minimisation objective to fulfill electricity demand. The common approach is to minimize total costs, TC , which can be decomposed into operational, O , and fuel input, F , multiplied by electricity production from existing capacity, x , and investment costs per unit of power generation capacity, I , which is multiplied by the total newly introduced capacity, y , as per formula (22).

$$\text{Min}_t TC = \sum_{t=1}^T (O_t + F_t)x_t + I_t y_t \quad (22)$$

The objective is set to be solved under a set of constraints including supply provided by capacity should be at least equal to the set of demands in all periods. In some models also other costs are included such as start-up electricity use and costs to hold power plants in a spinning reserve mode. The basic cost minimisation approach and variants thereof are used in both intertemporal and time-stepped versions found in the literature, as per table 42 in **Appendix A**. Although models can be reconfigured into both variants, in the documentation 24 out of 31 cost optimization models are described with an intertemporal formulation and 7 with a time-stepped formulation.

Two variants of the cost minimisation approach of formula 22 above were located in the literature. These introduce financial market aspects into the objective to represent lending and the time value of money. In the first approach the total set of costs is discounted at a chosen market interest rate, r , to incorporate the opportunity cost time value of money, as summarised in formula (23). This formulation represents an equity investment from the electricity company itself without any bank loans.

$$\text{Min}_t TC = \frac{1}{1+r} \sum_{t=1}^T ((O_t + F_t)x_t + I_t y_t) \quad (23)$$

The other variant takes the structure of formula (24) and replaces the investment value, I , with an annuity value, AI , which is the value of investment as if it would be paid in equal installments over a chosen time period as per formula (24) below. In this formulation the investment value is included as if it is a loan from the bank by accounting for loan interest. The annuitisation period, T , is in financial accounting normally chosen to represent the contractual time to pay off the loan including interest payments, typically less than 20 years. However, out of 10 cost minimisation models that used an annuity value, there were 7 that documented usage of the technical lifetime of the power plant for the annuitisation period. After calculating the annuity value it is inserted in the objective formula, as per formula (25), so as to calculate the minimum cost power generation capacity combination.

$$AI_t = \frac{r I_t y_t}{1 - (1+r)^{-T}} \quad (24)$$

$$\text{Min}_t TC = \sum_{t=1}^T \frac{1}{1+r} ((O_t + F_t)x_t + AI_t) \quad (25)$$

The market interest rate parameter can be based on standard chosen rate or on a Weighted Average Cost of Capital (WACC) basis, as described in **section 2.2.1**. In 6 out of 51 models the WACC calculation method was used to estimate interest rate values (Eager et al. 2012, Held 2010, E3Mlab 2010, US EIA 2013) of which 2 used cost minimisation and 4 profit maximisation.

A special indirect cost minimisation formulation, from which change in installed capacity per individual electricity generating technology is calculated, can be found in the WITCH sector macro-energy model Bosetti et al. (2009). In the WITCH time-stepped optimization the output objective is set to maximize consumption in the economy by means of a

consumptive utility function. The size of consumption, C , is determined by the production output of the economy, Y , in financial value, minus expenditures on financial investment in non-electricity technological capacity, E^n , operational inputs in electricity production, E^o , expenditures in construction of power plants, E^e on research and development, $E^{r\&d}$, of electricity generation options, $j = 1, 2, \dots, N$, as per formula (26) below.

$$C_t = Y_t - E_t^n - \sum_j (E_{j,t}^o - E_{j,t}^e - E_{j,t}^{r\&d}) \quad (26)$$

The allocation of technologies is dependent on their capital costs since the consumption maximisation seeks the minimal necessary investments in power plants to increase consumption. The selection of the lowest cost option is executed by a function that delivers the rate of power plant capacity change as reproduced in formula (27). The function starts with an initial number of power plants, K , and a depreciation rate of the existing stock, δ , which represents shut-downs of power plant capacity per unit time. New power plants are added via investment expenditures, E^e , which also feed into formula (26) above, which are divided by the cost of a unit of capacity, I , for each technology.

$$K_{j,t+1} = K_j(1 - \delta_j) + \frac{E_{j,t}^e}{I_{j,t}} \quad (27)$$

The adjustment in power generation capacity provides a modelled feedback on consumption, since the amount expended is subtracted from the output in the economy, Y , and what is left can be consumed.

The second type of formulation in 16 out of 51 models utilises profit maximisation as the main structure of the investment problem, within either optimization or simulation modelling paradigms. Out of 10 simulation based models 7 were based on a profit maximisation structure, and out of 41 optimization based models 9 used profit maximisation as their objective. A standard formulation in optimisation models revolves around a lumped capacity per technology and its evolution (Pereira and Saraiva 2013, 2011). The amount of electricity produced is calculated based on the total capacity, C , of a technology, a , and its operational use, Q , per unit time, to gain a MWh production value. This amount is multiplied by the price of electricity, P , minus the operational costs, O , and fuel costs, F , to gain net income from power plant operation. Investment costs are included using new capacity of a technology, N , multiplied by investment costs, I , which is added to total capacity, C , as per formula (28) below.

$$Max_t \pi = \sum_{t=1}^T \left(\sum_{a=1}^A (C_{a,t} Q_{a,t} \Delta t (P_t - O_{a,t} + F_{a,t}) - I_{a,t} N_{a,t}) \right) \quad (28)$$

The formulation includes discounting in Botterud (2007) (Botterud and Korpas 2007) as well as Schroder (2012) (Schroder 2012), so as to incorporate the time value of money.

A second formulation revolves around structuring the problem for individual power plants. The objective function is split into two parts, income and the investment cost specified per individual power plants, $b \in B$, and their evolution. The income stream is calculated by means of the amount of electricity generated, E , multiplied by the price of electricity, P , minus the operational cost, O^v , and fuel costs, F , and in a separate term minus fixed operational costs, O^f , per year. In case of new power plants, N , a term is added for the investment costs, which in formula (29) is based on the annuitized investment cost value, AI , as per (Vespucchi et al. 2014). Non-annuitized investment capital cost formulations have also been utilised such as in (Abeygunawardana et al. 2013). Finally, the entire sum of profits or loss from existing and new power plants is discounted at a rate of, r , to incorporate the time value of money.

$$Max_t \pi = \sum_{t=1}^T \frac{1}{(1+r)^t} \left(\sum_{b=1}^B (E_{b,t} (P_t - (O_{b,t}^v + F_{b,t}) - AI_{b,t} N_{b,t} - O_{b,t}^f)) \right) \quad (29)$$

Models using a simulation paradigm with profit maximisation are arranged on the basis of a set of iterative algorithms with a *profit ranking* or an *investment threshold* setting. In the *profit ranking* algorithm a three step procedure is used. First, the expected future value of input variables like electricity demand and prices are estimated, such as modelled using an embedded electricity market model, or as a fully exogenous time-series. Second, from these variables the existence and degree of profitable investment are calculated, such as based on a NPV rule (Eager 2012), as per **section 2.1.2**. The set of profitable investments are ranked by their profitability as indicated by the investment metric. Third, the most profitable investment is selected and added to the expected capacity mix for future time periods. Subsequently, another iteration is carried out of the investment assessment starting with re-calculating input variables to find if any more profitable investments remain. The algorithms are iterated over until no more investments can be made which are profitable. In case that several options are equal in profitability a second selection rule can be introduced, such as the relative ratio of NPV to investment cost (Eager 2012).

In the *investment threshold* comparison variant the algorithm also starts with the calculation of expected future input variables. Subsequently, for each technology, $a \in A$, the calculated investment costs, I , times installed capacity, K , is estimated and compared with anticipated profits, π , in the decision period. In case profits outweigh investment costs, as per formula (30) below, an investment is pursued (Held 2010). In certain formulations an additional threshold requirement, β , is added as a multiplier for investment costs. The algorithm is operated iteratively based on new capacity requirements, with a price feedback between iterations, which continues until the algorithm returns no profitable investments. In this formulation the selection of particular technologies is not orchestrated but each technology is assessed on its own profitability merit (Jaehnert et al. 2013).

$$\text{If } I_a K_a \beta \leq \pi_a \text{ then invest in technology} \quad (30)$$

In the investment threshold comparison the profit level for a technology is usually calculated as per formula (31) below. The marginal cost of production, MC , is subtracted from the price of electricity, P , times the utilization rate, U , of the technology. In the variant in (de Vries and Heijnen 2008) instead of marginal costs the variable costs of operation are used. A key underlying assumption in this formulation is that if a power plant is not utilised no variable additional costs are involved, thereby ignoring shutdown and start up costs. The calculations can be tailored to include profits and investment costs, such as carried out using an annuity formulation (Jaehnert et al. 2013), or without discounting (de Vries and Heijnen 2008).

$$\pi_a = \sum_{t=1}^T (P_{a,t} - MC_{a,t}) U_{a,t} \quad (31)$$

Several expansions within this framework have been made. For example, the algorithm in the PowerAceInvest model uses an investment threshold comparison with a planning authorisation procedure (Held 2010). The outcome of the investment algorithms in this case does not lead to direct investments. Only those that are subsequently authorised through a planning authorisation ruleset are added to a set of power generation capacity to be constructed.

A small number at 3 out of 51 models use growth rate and allocation based formulations to indirectly generate investments, of which two within a simulation paradigm and one within an optimization paradigm. The formulation introduced by Olsina (2006) (Olsina et al. 2006) and adopted in (Assili et al. 2008) (Hasani-Marzooni and Hosseini 2011) utilises a rate based structure per technology, a , as a simplification of investment. The rate of capacity change, and thus indirectly investment, is equal to a logistics rate function, $m(PI_a)$, which is multiplied by the anticipated rate of decommissioning of existing capacity, R , plus the necessary rate of additional capacity, C , to cover demand growth, which is calculated from scenarios or a power load model. The rate of investment change is thereby expressed as:

$$\frac{dI}{dt} = m_t(PI_{a,t}) \left(\frac{dR}{dt} + \frac{dC}{dt} \right) \quad (32)$$

The logistics function for technology profitability includes in the numerator a technology saturation parameter, m^{max} , for the function maximum, and in the denominator a growth function with a slope parameter, β , a profitability index value, PI , and an offset parameter, γ , to shift the initial x-axis index value.

$$m_t(PI_{a,t}) = \frac{m_a^{max}}{1 + \exp^{-(\beta_a PI_{a,t} + \gamma_a)}} \quad (33)$$

The profitability index can be calculated from a financial metric value. The Internal Rate of Return (IRR), as described in **section 2.1.2**, was selected by Olsina (2006) (Olsina et al. 2006), and adopted by Assili (2008) (Assili et al. 2008) and Hasani-Marzooni (2011) (Hasani-Marzooni and Hosseini 2011). The IRR is divided by the required rate of return, or more simply the discount rate, r , to obtain the index value, as per formula (34):

$$PI_{a,t} = \frac{IRR_{a,t}}{r} \quad (34)$$

A second type of formulation is a rate and allocation mechanism is the TIMER simulation model which solves investments using an indirect financial approach (Vries et al. 2001). The amount of required capacity is set equal to an anticipated demand growth function, and the choice of technology is derived from a relative comparison of generation costs of different technologies. The comparison is made using a conditional logit formulation which is borrowed from decision choice models in economics. Logit formulations are based on a probabilistic approach used for situations where no strict causal relationship can be found between observed event and decision. In the conditional logit formulation as per formula (35) a set of options, $j = 1, 2, \dots, N$, are weighted. The probability of a choice, j , is calculated based on a utility value, x , for a choice, multiplied by a scaling factor, λ , and divided by the scaled utilities of all other choice options with the summation of one, such that all probabilities jointly sum to one on the left hand side.

$$P\{y = j\} = \frac{\exp(x'_j \lambda)}{1 + \sum_{j=2}^N \exp(x'_j \lambda)} \quad (35)$$

The conditional logit function has been adopted and adjusted in (Vries et al. 2001) to express the change in market share, IMS , per technology, $j = 1, 2, \dots, N$. The change is based on a cost rate expression, c , for a technology, which in TIMER is based on the total fuel cost, divided by the sum of costs of all other options, both multiplied by the scaling factor that represents the cross-price elasticity. In this case the scaling factor is negative such that an increase in costs results in a decrease in market share.

$$IMS_j = \frac{c_j^{-\lambda}}{\sum_{j=1}^N c_j^{-\lambda}} \quad (36)$$

A third type of formulation based on technology allocation has been implemented in the linked FTT:Power-E3MG simulation model (Dagoumas and Barker 2010, Pollitt et al. 2013, Mercure et al. 2014). Electricity demand is described as a relationship of output per sector in the wider E3MG economy model, and electricity prices, inclusive of model feedback for prices between the FTT:Power and E3MG sub-models. The fulfillment of demand from a technology allocation is derived from the change in a technology market share, ΔS , as per formula (37) below. The change is based on the existing market share, S , of the specific technology which is adjusted using a decommissioning rate, τ , to include only power plants in existence in the next period. Subsequently, the value is multiplied by a series of matrix elements indicating the diffusion rate away from, A_{aj} , and the diffusion rate towards, A_{aj} , the specific technology, a set of investor technology preferences

away from, F_{aj} , and towards, F_{ja} , each technology, and a technical weight, G , that limits how fast a technology switch can be made.

$$\Delta S_a = \Delta t \cdot S_{j=a} \sum_{j=1}^J \frac{S_j}{\tau_j} (A_{aj} F_{aj} G_{aj} - A_{ja} F_{ja} G_{ja}) \quad (37)$$

The set of investor preferences in the model are based on a cumulative cost distribution function, which changes over time as costs are endogenously modelled in FTT:Power from learning curves. The diffusion rate is based on a logistics function using cumulative capacity (Stoneman 2001).

2.4.4 Summary of approaches and capabilities of present models

In the chapter the main metrics used to evaluate investments were evaluated in the first part, and subsequently the results were provided of an investigation on how such metrics have been implemented in existing electricity system models. The first aspect of implementation in current models is the objective set in the model to provide a solution to generate power generation capacity investments. The main objective choice of model developers in 31 out of 51 evaluated models has been the use of an optimization structure with cost minimisation. Less common is optimization with a profit maximisation objective in 9 out of 51 models, or a simulation structure with a profit maximisation decision rule in 7 out of 51 models. The least common, with 3 out of 51 models, is use of an allocation and growth rate based structure which indirectly uses financial values. Finally, one optimisation model uses a non-financial approach by using utility instead of cost or profits as the maximisation objective.

Another aspect is the treatment of time in what the model knows about the future in its calculations. The implementation of optimization models was based on an intertemporal approach in 29 out of 41 models, meaning that the optimization takes into account information over all years in the optimization. The alternative situation, where only a limited number of future years are visible to the model algorithm in a time-stepped fashion, was implemented in the 12 remaining models. Although optimization models can easily be adjusted into a time-stepped or intertemporal version, in only few cases such as in (US EIA 2013, Hunter et al. 2013) the possible difference in outcomes between these approaches are mentioned.

The treatment of time can also be related to the valuation of the future by discounting it relative to the present. A small number of model developers has chosen not to incorporate a discount rate based formulation, as 7 out of 40 optimization and 3 out of 7 simulation models use a financial formulation excluding discounting. Of the 37 models where discount rates are used in 19 cases they also utilise an amortization approach (of which 13 are based on optimisation and 6 simulation), such that investment is spread across either the technical or loan lifetime of the project. The majority utilise an annuitisation formula, but in two cases a linear approach was taken by dividing the investment by the number of operational years before discounting. Of models with an amortization approach a total of 5 utilised a WACC metric to calculate the discount rate, by dividing the investment into an equity and loan fraction (of which 3 based on optimization and 2 simulation). In models with either an annuity value or a WACC implementation 6 were based on the bank loan lifetime of the power plant, as opposed to the technical lifetime, to implement a discount rate estimate or annuitisation parameter. In practice the duration of a typical power plant investment loan is 15-25 years which affects its loan and discount investment value (Schwabe et al. 2011).

A third aspect of model implementation is the physical implementation of technology as actual individual facilities or abstract capacities. In 32 out of 51 models power plant investments are lumped as an abstract aggregate power generation capacity in MW per energy technology, whilst in 19 models the calculations evolve based on individual power plants. A key consequence of lumping is that the exact amount of capacity can be found to generate the supply to fulfill demand, whereas in the opposite case under- or overcapacity can arise as the discrete minimum values for individual power plants are needed. Also incorporating single discrete power plants allows for modelling effects of differences in firm power plant ownership, and greater precision in simulating technological change over time, especially to model technology 'add-ons' to existing power plants like Carbon Capture and Storage (CCS). The construction time of power plants was structured to be immediate (e.g. operational in the year of investment) in 40 out of 51 models.

Finally, financial evaluations for risk were also covered and applied in 3 out of 51 models. These included Value at Risk (VaR) adjustments based on historical parameter fluctuations to investment evaluation, as described in **section 2.2.2**, and real option based multiple scenario evaluations as outlined in **section 2.1.3** (Vespucci et al. 2014, Botterud and Korpas 2007, Eager 2012). In five models scenarios were included based on a 'node' approach where stochastic variations in key parameter time-series across model runs could lead to different 'branch' outcomes (Loulou et al. 2004, Schroder 2012, Powell et al. 2012, Barreto 2001, Hunter et al. 2013). The approach can introduce structural breaks in parameter values or

one-off variable adjustments as discontinuous events. The risk of change in market regulation as events can then be tested for robustness of outcomes under uncertainty Loulou et al. (2004).

In brief, existing approaches are heavily tilted towards using a 'central planner' based approach as if a central government places all the investments. The common approach is to execute the central planner using a financial cost minimisation and less commonly by a profit maximisation criterion, with various additional complexities such as discount rates, risk evaluations, or power plant specific investments instead of lumped technology capacity. That approach can provide for an answer to questions related to lowest cost outcomes in an idealised setting, but are plausibly less suitable to evaluate how policies actually affect company investments in the electricity market. Companies are diverse in their size, market power, cost competitiveness, technology choice, and strategies. What is missing in the methodological approach of electricity systems modelling in general is an investigation in the applicability of centralised approaches to provide answers to what impact specific policy interventions, such as fiscal instruments, could have on power generation change. And in specific how the firm perspective could be represented and structured in models to enable better testing of policies and their investment impacts. In the next chapter a synthesis is provided of key aspects that can play a role in power plant investments from a firm perspective within the scope of electricity systems modelling.

3 Investment Decision Algorithm Assessment Framework

In this chapter a conceptual framework is formulated on the process of firm investment decisions and aspects involved therein. The purpose is to create an overview on the factors which potentially play a role in the decision to invest in new power plant infrastructure, and provide ideas on the operationalisation of these factors in energy system models. Such factors are considered at the level of financial, economic, technology, political, and risk elements which play a role in investment decisions. Thereby a contribution is made to answer the following sub-research questions defined in **section 1.5.2**: “*What financial and non-financial factors of importance are potentially used to inform electricity generation firm decisions to expand production capacity?*” and “*How can non-financial factors be captured in the modelling of project investment decisions?*” The chosen approach is to identify an expansive listing of potentially relevant factors from the literature, and secondly a formulation of ideas on their operationalisation for testing in electricity system models.

The base of the framework is the concept of an investment decision which is outlined in **section 3.1** below. In the subsequent **section 3.2** the investment process is broken down in a series of stages utilising concepts from project management literature. An overview of the factors which can relate to an investment decision are subsequently listed in **section 3.3**. The factors themselves are subsequently discussed in **section 3.4** in how they can potentially be implemented in electricity system models, also taking into account the potential formulations already described in **chapter 2**. The chapter continues in **section 3.5** with a discussion on running models without information availability restrictions, or with restrictions on data to remain ‘hidden’ during the model calculation. Finally, in **section 3.6** a set of investment decision factors is defined and their combinations is summarised.

3.1 The mental process of investment decisions

A real life decision process can be thought of as a person's internal mental evaluation of available information on the impacts of a decision. The process is based on forming a representation of a current 'state' of the outside world as is, plus a representation of one or more envisioned 'states' of the world once the decision is implemented Wild (1996). The mentally constructed states can be compared to evaluate possible decision outcomes to think what the best course of action may be. The forming of these world 'states' in a mental evaluation is in case of a complex decision, such as for investment decisions, supported by a number of analyses to make available information tractable for the human mind. Investment decisions can thereby be split at a high-level into analytical and decision stages Aid (2014), Carter (1971).

In the case of power plant investments three analytical stages can be distinguished. First, the *demand and investment opportunity analysis* signals either if there is a growing demand for electricity that additional power plants are needed, if a replacement of existing to be closed power plants is in order, or whether there is an opportunity to complete with existing plants that are more expensive relate to newer improved technologies. Second, the analysis to collect *available information* for the evaluation of the size and technology of the power plants to invest in. For example, electricity and fuel prices, power plant construction, operation, maintenance, and decommissioning costs, loan information including interest rates, and technical characteristics of power plant technology such as thermal efficiency. Third, the analysis to structure information in a coherent evaluated form as *evaluated information*. This usually takes the form of structured financial and technical metrics to compare alternative outcomes as possible future 'states' of the world which depend on the chosen power plant technology. After these three analyses the actual decision is made as a *decision procedure* on the basis of the evaluated information Kelly and Brown (2011), March (1994). In reality these stages are typically iterative as opposed to a single sequential process Aid (2014).

The distinction between available and evaluated information explicates that different methods are used in the collection of data, and subsequently to structure data and for its evaluation. The collection can include data points for both the past and present, as well as the creation of data on future expectations of variable properties of power plants Zammerilli (2010). There can be differences in the *available information* to market players because of restricted information access or different collection and structuring procedures. For example, smaller firms may be able to exert less effort in the collection process, or new firms may not have the historical sets of data that a long-standing company in the electricity markets may possess. Similarly, a company specialized in a particular technology will likely have more data available to feed into the decision analysis for this technology. There can also be differences in *evaluated information*. Companies may have different evaluations methods or priorities such as in the evaluation of risk, or information necessary for specific risk evaluations may simply not be available to some companies whilst it is available to others Andor et al. (2015).

The notion of a limit to available information is relevant since there is a tendency in energy systems modelling whose framework emerged from economic and financial theories, to assume a situation of 'perfect information' Held (2010). This concept comes from the economic interpretation of 'rationality' wherein it is assumed that a decision maker is able to utilise all available information and screen all available options, so as to maximize a preferred outcome. In economics the outcome is often defined as maximizing utility, and in case of investments the largest degree of profits (Weirich 2004). A large share of electricity generation decision models follow the 'perfect information' approach with 29 out of 51 using intertemporal optimization, as shown in the previous chapter. Alternative theories in economics to describe the more realistic absence of 'perfect information' include bounded rationality and transaction costs.

In the evaluation stage the collected data is taken and one or several analyses are carried out to generate technology, engineering, market, and financial summary metrics to assess available investment options. Financial analyses can include cost and benefit type metrics, risk evaluations, environmental impact and cost analyses, and market evolution assessments, among others. The process to produce *evaluated information* is fluid in that it differs per firm and can change over time. To reiterate an example from **section 2.1.2**, Value at Risk (VaR) metrics developed during the 1980s only became commonly used for a portion of firms in the information structuring and evaluation process in the late 1990s (Jorion 2007). The use of different financial metrics over time has been documented in business survey studies as outlined in **section 2.1.1** (Graham

and Harvey 2001, Rosenblatt and Jucker 1979). A challenge in the stage of evaluated information is how non-financial information is taken into account, since this is difficult to capture in evaluation metrics.

The outcomes from the *evaluated information* stage are used to make the investment decision based on a *decision procedure*. The procedure can be interpreted as an economic interpretation of 'rationality', where the decision making process takes in all available *evaluated information*. The alternative is to assume that in the decision not all alternatives nor all consequences are considered Gigerenzer (2007). Cognitive and/or economic capabilities are limited, such that actions may be intended to be 'rational' in attempting to maximize, but are bounded by not taking all *evaluated information* into account (March 1994). A prominent concept in economic theory to this effect are transaction costs, which poses that there is a cost involved to obtain information that may be too costly relative to the benefits that may be gained from it. However, that also implies that beforehand there is some understanding of what the benefits are of different pieces of information, which in many cases is not realistic.

An assumption much further away from the assumption of 'rationality' is that the cognitive limitations result in a heuristic approach to evaluation based on rules of thumb. A heuristic as a set of if-then decision actions often involves tacit knowledge that can be evaluated quickly with only limited information. A possible power generation capacity example is the simple payback time metric, as outlined in **section 2.1**, by which technologies for an investment with the lowest payback are selected (or ruled out). Even though sophisticated and theoretically much better metrics have evolved payback time is still used in practice. The main defense for its continued use, apart from the cognitive limitations of humans, is that if in an analysis significant uncertainty is involved, it has been found that simple decision rules can often lead to better outcomes than more complex ones (Gigerenzer 2007). For example, in a competition to evaluate forecasting models across 3000 time series a set of 24 models were assessed, and it was found that simpler models typically perform equally as good or better than more complicated and sophisticated ones (Makridakis and Hibon 2000).

In the remainder of this chapter the focus lies on the *evaluated information* stage and the *decision procedure*. The analysis focuses on what information is potentially taken into account and available in the decision process, how is the information evaluated into a set of metrics, and how does the actual decision making process take shape. The arrangement of and combinations between the stages provide a variety of possible *decision strategies*, as described in the final **section 3.6**, which define an investment decision algorithm that can be implemented in an electricity system model. Each of these strategies can be evaluated to find out which is most accurate, relative to historical developments, so as to find out what strategy provides for a modelled outcome that is as close as possible to the historical outcome of the investment decision making process.

3.2 Stages in the information collection, evaluation, and decision process

Investment decisions in the real world are not a one-of process, unlike their simplified implementation in the modelling world, but can be perceived as a series of sequential stages, each with an information collection, evaluation, and decision procedure. These are undertaken by people that are employees of the legal entity of a firm or company. In case of power generation capacity investments it is a series of decisions to come to the establishment of a new power plant and its operation. The decision process can be split up from a project management perspective into five sequential stages (Zammerilli 2010, Oberlender 1993), as per figure 4 below, which includes:

- **The initial project proposal**, which provides for a rudimentary outline of the investment, technologies, and potential location.
- **The feasibility study**, an analysis of the infrastructure, technological, and economic aspects for the chosen power plant facility including the construction schedule and a risk evaluation.
- **The engineering design**, the detailed technical design for the selected power plant facility as a material and engineering blueprint for its construction and operation. The design includes a specification of all the components of the power plant, on the basis of which the economic analysis of the feasibility study can be refined.
- **The procurement and construction phase**, the period in which the infrastructure is erected following a positive evaluation of the engineering design.
- **The final point of commissioning and operation**, the period of start of operation of a power plant after its construction is complete.

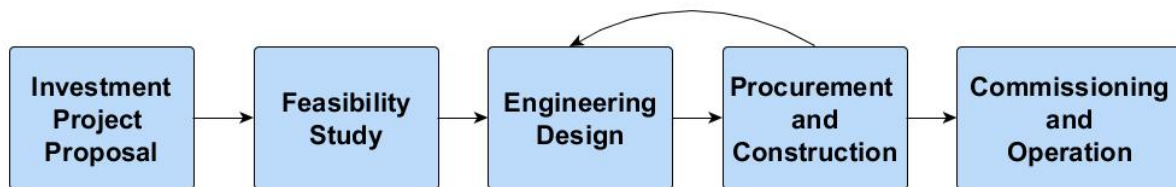


Figure 4: Stages in the project cycle of a power plant from investment to operation

At each of these five stages information is obtained with an increasing level of detail and accuracy as the project advances. The overall procedure is an information collection, evaluation, and decision process, as outlined in the previous section, which is jointly referred to as an appraisal process. There are three possible decision outcomes at each of the five stages: the continuation into the next step, a re-evaluation based on additional information or other assumptions, or the abortion of the entire process. Potential sets of analyses and their information outputs include assessments of costs and benefits, risk analyses, environmental impact assessments, and an overall financial viability assessment in relation to project finance availability and conditions Smith (2002). A large number of participants are involved in shaping an appraisal process including financial managers, engineers, consultants, directors or company owners, and shareholders. The final decision of procurement and construction, as well as intermediary continuation decisions, are normally taken by executive directors of the power plant company (Oberlender 1993).

3.3 Decision factors in the collection and evaluation process

The process of *data collection* and *information evaluation* can be formally structured by a set of information factors, which represent the type of data that is collected and structured in an investment evaluation analysis. A comprehensive set of 24 factors is outlined in table 6 below. The factors can be clustered in a hierarchy of six groups as types of decision components which influence the investment decision. The six groups include:

- **Financial value**, the factors which describe known market values that directly influence profits or losses made from the investment, including standard financial risk measurements. These are used to construct financial metrics such as PBT, NPV, and Real Options estimates.
- **Market strategy**, the factors that identify whether a firm pursues a particular strategy on how it operates in a market in relation to its competitors. Three common strategies include targeting a particular market share, usually effectuated by inducing a lower price, seeking a specialisation market niche, or product and technology diversification. In many cases market strategies do not have immediate financial benefits but are part of a long term process of firm survival to outgrow or stay ahead of competitors.
- **Discontinuous risks**, the factors that relate to trying to measure the occurrence of unforeseen future changes, beyond continuous fluctuations that are captured in standard financial risk approaches, which affect financial value and their probability. For example, political or regulatory changes, fundamental changes in market conditions, or significant technological disruptions. These influence the financial evaluation but lie outside of the standard market financial factors and their underlying determinants, because they cannot be adequately measured or known in advance.
- **Technological preferences**, the non-financial factors which directly influence the choice for a particular technology. These can include long term innovation strategies, non-financial preferences due to environmental impacts, positive experiences in the past in constructing and operating a particular technology, or technological lock-ins because of market regulatory and existing infrastructure.¹
- **Political support**, the factors of a pure political nature which influence the selection of particular technologies in power plant investments. For example, the construction of nuclear or solar power plants as part of an overall bilateral economic package between a technology providing country and the country wherein the power plant investment takes place.
- **Input availability**, the factors that determine availability and security of inputs necessary to construction or operate a power plant. For instance, the availability of a local skilled workforce or research community, availability of fuel inputs for fossil fuel power plants, or the availability of suitable sites such as in case of hydro, onshore wind, or nuclear power.

The six groupings above are often interrelated since they influence each other, such as technological preferences which influences assumptions of future expectations of power plant performance which affects financial factors. The groupings are made because it allows to separately define them on a conceptual level, despite overlaps in individual factors. For example, the aspect of product diversification relates directly to a market strategy, but it could also be placed under market risks in that it can lower risk, and thus overlaps between these two groupings.

¹ A technological lock-in in this context relates to already built physical infrastructure which benefits particular technologies over others. For example, the existence of a natural gas pipeline network creates a large indirect benefit for natural gas power plants. They can also relate to financial lock-in due to past investments in manufacturing infrastructure for a particular technology that still need to be recuperated. Because of this a particular technology can be preferential even though independently on its own it would not be the preferred technology.

Table 6: Overview of possible firm investment decision aspects.

Factor group	Factor	Description
Financial	Price of product	Sales price of the product.
	Investment cost	Total cost of investment to construct infrastructure.
	Operational cost	Fixed and variable costs necessary to keep the production location running, including labour costs, fuel costs, material input costs.
	Maintenance cost	The costs to replace equipment and machinery due to degradation.
	Decommissioning cost	The cost of removing infrastructure on a production site after its end of life or after its premature closure.
	Discount rate	The parameter used to discount future values.
	Subsidies / market transfer payments	Subsidies to firms in the market by governments to support particular technologies, or via market transfer mechanisms.
	Environmental output costs	Additional costs following from outputs into the environment. Particular to electricity investments is an emissions surcharge.
	Standard Insurance cost	The cost to cover risks of future events such as accidents.
Market strategy	Product diversification	Number of product types sold by the firm and their share in provided revenues.
	Market share	The percentage share of the product type sold by the firm in the market.
	Market niche	The utilisation of a market niche by means of specialization in a technology, product type, or production input stream, unique to a firm.
	Acquisition and mergers	The spending of investment capital on the acquisition of a (failing) competitors infrastructure or on a merger with competitive companies.
Discontinuous Risks	Discontinuous jumps in financial fundamentals	Large scale discontinuous jumps to a substantially higher or lower level in a financial factor, such as the price or interest rate.
	Technical breakdowns and accidents	Unforeseen failures in the operation of a power plant due to mechanical or electrical breakdowns or accidents, causing a significant loss in operational time.
	Large scale accidents with societal impacts	Large scale accidents which not only result in loss of operation, but also have wider societal impacts, such as nuclear accidents and hydro-power dam failures, which have their own failure category given the special nature and large impact.
Technological preference	Innovation preference	The preference to invest in a particular technology, despite its higher cost, to gain research and development knowledge.
	Past-experience preference	The preference to invest in a particular technology because of past experience estimated by the number of operation hours.
	Lock-in preference	Technology preference because of the need to write-off past investments associated with said technology, or technical lock-ins such as existing electricity grids favouring particular technologies.
	Environmental preference	The preference for a technology due to its lower output of waste and/or pollution in the environment.
	Diversification preference	The preference to have a diversified portfolio of technologies for purposes of risk reduction.
Political support	Political influence	Factors of investments caused or influenced by political decisions, such as interest rate support and coverage of risks.
	Political continuity	The switch of political parties in government that have different perspectives on energy technologies and market regulation.
	Market continuity	The approach of governments to adjust and iteratively improve markets or to make discontinuous jumps in regulation.
Input availability	Skilled worker availability	The local availability in the area of suitable skilled workers to be employed at the infrastructure site of the investment.
	Market location	The location where infrastructure will be setup by the investment, and how it affects proximity to markets and available production inputs such as skilled workers or production materials in nearby geographies.
	Land availability	The availability of land for placing power generation infrastructure due to physical factors, regulatory constraints, and public opposition.
	Fuel disruption risk	The finiteness of fuel supply and potential of supply disruptions for fuel based technologies.
	Capacity expansion maximum	The maximum power generation capacity that can be expanded in a particular year given manufacturing capacity.

3.4 The formalization of stages, components and their factors into computer algorithms

In the computer the decision maker is represented as a set of algorithms with as an explicit outcome the realisation of new power generation capacity, and thus the implicit decision to invest or not and how much, and which technology to invest in. The outcome can be triggered by a set of values as a maximum or minimum value, or in comparison to a threshold, range, or inter-comparison to other outcome values, or a combination thereof. An algorithm can be structured flexibly to try to approach reality in the best possible manner, or in a simplified approach. For example, it can be structured as a simple rule to find the highest set of profits, or structured with variability to accommodate for reactions to uncertainties in prices and sudden changes in market regulations, with different outcomes across model runs.

The key to structuring a decision process is by breaking it down in multiple interrelated formalised rules using variables and parameters. Each rule forms a transparent representation of sub-evaluations within the decision process with their factors. The *data collection* phase can be represented formally by varying the amount of information available, and their degree of uncertainty in setting parameters and calculating variables. The *information evaluation* phase is represented via metrics that are calculated within the algorithm, such as financial values as described in **section 2.1**, and non-financial components as described in the previous section. The scope in the majority of existing models is to rely solely on financial metrics, sometimes inclusive of standard investment risks, as presented in **chapter 2**. The *decision process* phase can be represented by a set of decision rules that yields an explicit or implicit yes/no or postponement of the investment decision and the selected technology.

To move from the conceptual to the formal construction of algorithms, the *information evaluation* stage is formalized by defining a new set of qualitative and quantitative metrics. In **sections 3.4.1 to 3.4.5** these are built for five of the six respective components as per table 6 and their factors. Subsequently, in **section 3.6**, the incorporation of these metrics into a modelled decision process is treated. The component of political support is not considered in its entirety in this thesis, because it depends on unknown dealings between companies and governments, and in case of bilateral deals also trade between countries, which is a subject of its own necessitating the incorporation of government decisions in electricity generation models. Since the focus of this thesis is on firm investment decision it is considered outside of the thesis' scope.

3.4.1 Financial Component

The *financial component* and their factors and metrics has been the focus of existing models. Since these are already discussed at length prior in **chapter 2** the reader is referred to this chapter.

3.4.2 Market Strategy Component

The *market strategy component* can be divided into four different factors: product diversification, aiming for a higher market share, occupying a market niche through specialization, and an acquisition and mergers strategy. The occupation of a **market niche** can take the form of having the monopoly on constructing specific technologies, on particular inputs to operate a technology which are indivisible and limited in nature, or on being the only company that is allowed to sell a product. Since electricity is a uniform good a specific product market niche does not apply. The monopoly on fuel inputs market niche is potentially applicable to electricity markets for biomass power plants, since the available sourcing and contracting is at present limited to a small number of suppliers which can provide for the large quantities needed to operate a large scale biomass power plant. It can also be argued that there is also a technology niche, such as for advanced nuclear reactors that are sold only by a single to a handful of players. However, these are not owned in terms of intellectual property by power generating firms but by engineering companies which sell and construct power plants. Only in the rare case of exclusive licenses to power generation firms would this type of market niche apply.

A monopoly fuel input access market niche can be operationalised by introducing a variable that denotes the maximum amount of available inputs, I_t^* , available for purchase. For example, the amount of biomass that can be produced and sold in the United Kingdom from waste and residue biomass sourced from non-farmed lands. The niche strategy seeks to capture by investment and contracting in a particular year in the future the majority of this input stream, thereby securing an input market niche. Once captured in contracts other companies cannot capture the biomass stream. A possible algorithmic implementation is to set the required availability of inputs to a power plant, k , of technology type, q , to be higher than half of the maximum available inputs on the market, I_t^* , which can be represented as:

$$\sum_k^K I_{k,t}^q \geq 0.5 I_t^* \quad (38)$$

It is assumed in this strategy that the secured inputs are not fungible but contractually secure, and cannot easily be sold to competitors at higher prices. Since biomass markets do not yet incorporate short-term or spot markets this matches well with the current situation.

A targeted **market share** strategy focuses on out-competing competitors in number of sales based on market pricing strategies. In case of energy system models the simplification is typically made that all purchases of electricity happen instantaneously, analogous to spot markets with electricity supply and demand clearance. In reality electricity is sold in wholesale markets between companies, which can include spot-markets but also bilateral off the counter trades, and in contractual sales on retail markets to household customers. The incorporation of market share requires a representation in the model of multiple firms with variation in capacity ownership. A firm which pursues a market share strategy carries out two potential decisions that can be encased in algorithms: of overbuilding capacity and out-pricing competitors. First, it will overbuild capacity relative to anticipated demand and sales. The degree of overbuilding capacity can be set by a parameter, η , which represent a capacity cushion that forms a multiplier to, S , the existing anticipated amount of electricity sales from current power generation capacity into the future of the firm, $i = 1$, that pursues the market share strategy. This sum in addition to expected supply of other firms should be higher than anticipated demand, as per the formula:

$$D_t^* < \sum_{i \neq 1}^I S_{i,t}^* + \eta S_{1,t}^* \quad (39)$$

The capacity cushion factor can be set based on a targeted market share increase of the company, by setting the desired increase in share, Δs , equivalent to the difference in supply with and without the capacity cushion. This can be represented mathematically as:

$$\Delta s = \frac{S_{1,t}^*(\eta - 1)}{D_t^*} \quad (40)$$

Second, a firm needs to set a sales price which undercuts its competitors to ensure that the additional capacity is utilised to sell more power whilst that of the competitors stands idle. The offered price by the firm, P_t , will thereby need to be adjusted by an undercutting margin, μ_t , which is estimated to form a price that results in capacity utilisation versus a competitors higher sales price. The effect of undercutting the price is that the market clearance will be set at a lower price point, because of which the producers with higher price offers are out-competed.

$$P_t^* = P_t - \mu_t \quad (41)$$

The undercutting margin thereby reduces at minimum the firms profit, that is typically used for more investments or paid out as dividend to external investors, or results in a cash-flow loss in case the firm sells its electricity at a price below marginal operating costs. The strategy may not always result in capacity utilisation by the firm, however, since it may cost more for its competitors to stand idle by not operating their power generation capacity, than to sell it at a loss, due to shut-down and start-up costs of capacity. Thereby a competitor may adjust their sales price downwards as well. The strategy thus could come down to a game of the extent to which a firm has the “deepest pockets” to maintain its strategy, versus the ability of competing firms to continue operating at a loss, up to the point that a competitor needs to write off any excess capacity, sell their capacity, goes bankrupt, or a combination thereof.

After a competitor has had to sell or write-off their capacity the strategy initiating firm can increase the price level to operate at a profitable level within the increased market share. To make the strategy work a boundary condition is required, where the degree of incurred loss, L , by pursuing the strategy, should be equivalent or lower than the gained profits, π , from the excess capacity after the competitor has written off their capacity, and prices can be increased to a profitable level.

$$\sum_t^T L_k < \sum_t^T \pi_k \quad (42)$$

In case of a capacity sell-off the firm may be faced with another competitor purchasing the generation capacity, however, and if this firm can produce at a cheaper price, given a low cost sell-off, the strategy may backfire, as it will result in a loss of market share instead of a gain.

3.4.3 Discontinuous Risk Component

Disruptive future developments that cannot easily be estimated within standard financial market risk metrics, as described in **section 2.2**, are referred to here as discontinuous risks. First, these can be risks that relate to an unexpected sudden breakdown or accident, which results in costly down-time of capacity often paired with repair costs. Such incidents are to an extent covered by insurance, based on the calculations of insurance companies of these costs, plus the residual uninsured value which the firm has to bear. And second, these can be risks related to discontinuous changes in market regulation resulting in outages (e.g. sudden required upgrades of nuclear power plants following a severe accident in a different nuclear power plant) or a sudden change in market rules which heavily affects the financial outcome. The probability of these occurrences is often too low or unpredictable because of which they are ignored in standard risk sensitivity analyses. The sets of discontinuous risks can be split into two types of risks:

- Any events that relate to **insurable technical failures** of power plants for their breakdown and loss of operation hours. These relate to smaller accidents which only affect the power plant itself, such as a breakdown in a natural gas power plant turbine components that cause outages of weeks to several months.
- Any **sudden events that are rarely if ever insured for**, also referred to as tail risks. These relate to rare breakdowns such as a hydro-power dam failure or nuclear power accidents with direct power outages plus societal impacts in flooding or radiation exposure. As well as financial changes in key variables such as prices, regulatory imposed costs, reductions or increases in subsidies, or slumps in demand and sales, which fall outside of the usual market expectations when looking at empirically expected fluctuations (e.g. falling outside of a 95% confidence interval).

The financial calculation of **insurable technical failures** is established within the domains of event risk management and catastrophe modelling in the field of insurance (Garrick 2008). The insurance framework uses the probability of occurrence of a particular 'risk scenario' as an event, which is derived from historical physical incident data where available, such as the number of accidents at a specified severity per number of past operational hours. The identified probability is multiplied by the estimated cost of the event to obtain a loss measure as an insurance value. A risk, R , is thereby defined after Garrick (2008) (Garrick 2008) as having three components, an event risk scenario, S , a set of probabilities of event occurrence, P , and the loss impacts of the scenario, L , denoted for multiple scenarios, $i = 1, 2, \dots, n$, as:

$$R = \{(S_i, P_i, L_i)\} \quad (43)$$

The estimation of the loss impact can be carried out on the basis of empirical data for past losses, when available, and applied to the particular power plant case. In case of technical breakdowns the risk can be applied directly as a stochastic loss of operation within a minimum and maximum range in hours for each power plants per time period of a particular technology type. Another approach is to build a frequency-probability curve, where the probability of occurrence per year or another time period, as a frequency value, ϕ , is established by drawing from a distribution (Garrick 2008). The calculation can be expressed if we assume a normal distribution as:

$$P(\phi) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\phi)^2}{2\sigma^2}} \quad (44)$$

The probability from each draw can be multiplied with the estimated loss to gain an estimate for the annual loss value which needs to be insured for. This can include the loss of operating hours, the cost of repairing the power plant, and the loss of sold electricity and cost of start-up of the power plant. For example, a loss of 3 million euro, with an annual probability of 2%, would translate into a risk loss of 60,000 euro. In case of multiple scenarios for breakdowns joint estimates of probabilities can be built, using a concept called the exceedance probability, $EP(L_i)$, of a given level of loss (Grossi et al. 2005). The value is used in the insurance industry to calculate the probability of a maximum loss for which

the insurer is willing to issue insurance, as per formula (45). The concept is based on ranking sets of losses from highest to lowest, and calculating the joint probability that any of the events above a certain loss value, $i = j$, occurs.

$$EP(L_i) = 1 - \prod_{j=1}^i (1 - p_j) \quad (45)$$

The set of exceedance probabilities can be used to create an exceedance probability curve, which sets out the probability of a particular loss value on the y-axis, taking all possible loss scenarios into account, versus the actual losses themselves on the x-axis, as illustrated in figure 5 below. This curve can then be used to set the loss value for which the insurer will issue insurance, based on the probability to loss ratio that is favourable for the insurer. The curve can be used to set the likely risk loss by multiplying the exceedance probability with the loss value. For example in figure 5 a risk probability of 2% at a loss of 10 million USD results in a risk loss of 200,000 euro. It is in this measure assumed that the events are independent and their probabilities can therefore be multiplied.

A less sophisticated approach is to combine the sum of expected losses on the exceedance probability curve, also referred to as the average loss, AL , which can be established by multiplying the probability, p , with the loss, L , of each event, i , at the chosen frequency of occurrence (such as once per year). The average loss calculation can be formulated as:

$$AL = \sum_i^I p_i L_i \quad (46)$$

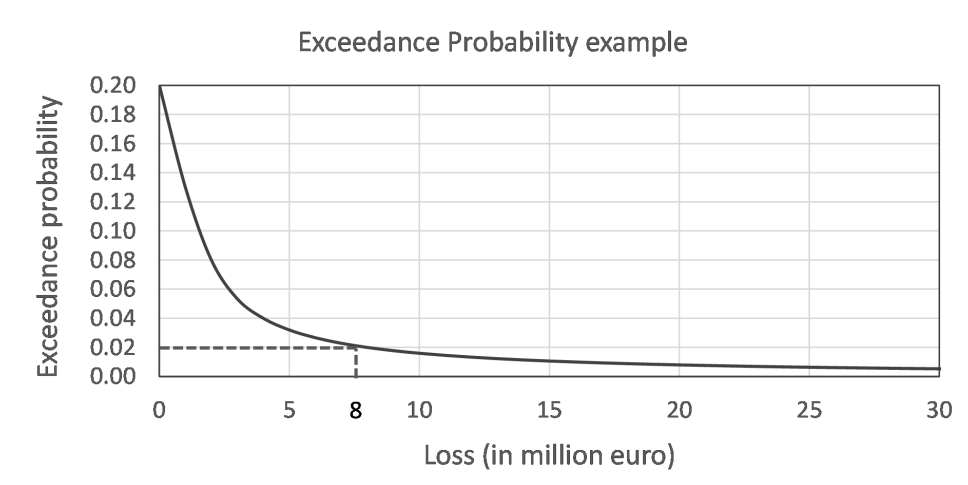


Figure 5: Example of an exceedance probability curve of a power plant accident indicating loss values

In case of **sudden events that are rarely if ever insured for**, the losses themselves are not easily comparable with historical precedents. This is because the nature of these events vary significantly because they are fairly unique, and/or because the environment in which they occur is unique. For example, every hydro-power dammed lake and their lowlands is different in shape and population occupation, due to which a dam break is a unique risk event with unique losses for each hydro-power dam.

In case of such unique events a new approach is being developed called catastrophe modelling that seeks to build a **tailored event-risk model**. In the event-risk model four components are established: the physical event footprint, the exposure of the affected population or infrastructure, the vulnerability of the affected, and the loss consequence thereof (Hochrainer 2006, Oasis 2014). For instance, the spatially distributed flow of water associated with a dam break into the lower lying areas. This enables a theoretical estimate of such rare 'tail-risks' that cannot be empirically evaluated as there is too limited historical data to establish any reasonable assertion. The calculation involves establishing an "exposure" dataset which contains the infrastructure and people in the lower lying area and how it is affected by the event footprint. And subsequently, an assessment of the vulnerability of people and infrastructure given the severity of the event, such as

the flow-speed and size of the dam break. The combined calculations can be used to assess what infrastructure is damaged and what loss of life occurs. The intermediary outcome is a vulnerability function which yields damage for particular infrastructure items, such as wooden frames, in relation to wind speed as established from numerous events. Finally, the insurance cost of estimated damage is calculated from instituted existing insurance policies (Oasis 2014, Grossi et al. 2005). The set of calculations for these unique incidents carried out by the insurance industry is highly complicated and requires intensive modelling, and therefore nearly always falls outside of the scope of any electricity market model.

The more common heuristic approach that is taken for such events, as well as for unexpected financial market changes, is the **construction of a set of scenarios**. A scenario depicts a range of possible sudden changes to calculate their plausible impact. For example, a several fold increase in fuel input prices, or the political decision to phase out a technology such as happened in Germany after the Fukushima nuclear power accident in Japan in 2011.

3.4.4 Technology Preference Component

The aspect of choosing a particular technology to invest in can also be motivated by a series of non-financial considerations. A set of five preference based influences are discussed here, which include considerations of innovation, past-experience, lock-ins, environmental outputs, and technological diversification to reduce risks. The issue of **innovation preference** is relevant for the case where a power generation firm is also involved in the research and development of technologies. An innovation trajectory takes place in an iterative manner and includes the establishment of demonstration plants and the first near commercial to commercial utility scale power plants. In case a company is at the brink of establishing a commercial version it may decide to build such a power plant to further its commercialization even though it is initially at a higher cost. The incorporation of this dynamic requires the incorporation of an R&D component in electricity system models with distinct firms each with their own technology learning curve based on R&D investments.

The aspect of **past-experience** is based on a preference towards technologies that are known by the firm to be reliable, as opposed to technologies of lesser familiarity about which the firm has no knowledge of its inner workings. The aspect can be explained by a number of sub-factors, such as lower costs of fuel supply due to having existing supplier networks for the technology, perceived lower probability of failures and breakdowns whether real or not, and human psychological biases in preferring familiar technologies over unknown ones. The underlying cause and the concept of past-experience are not elaborated upon, since the level of detail is difficult to measure and capture in causal relations and would not necessarily add any investment decision accuracy.

As a simple approach an operational experience based weight measure of past-experience can be established based on the number of operation hours, U , a firm has for a particular technology, $i = j$. In addition it is assumed that above a certain threshold number of operation hours, X , there is no additional benefit for that particular technology because the aspect of familiarity is fully exploited. The degree of favourability due to past-experience can be expressed by normalizing the range from 0 hours to the threshold number of hours, X , into a value between 0 and 1 using a logistics function. The chosen function is utilised since it is assumed that the favourability for a particular technology has a sigmoid shape that grows exponentially up to an inflection point, after which the increase in gains decreases up to the maximum threshold at which full familiarity is established. The past-experience preference weight estimate, We , for a technology then becomes:

$$We(u) = \frac{1}{1 + \exp^{-\tau(u - \frac{1}{2}x)}} \quad (47)$$

In the function the threshold value is multiplied by half to obtain the sigmoid midpoint, and the parameter, τ , serves to set the steepness of the curve to represent the speed of preference increase relative to the number of operational hours for a technology.

The issue of technology **lock-in** can be split into financial and technical lock-ins. The financial lock-in relates to past investments in a particular technology which still need to be recuperated. The standard case is one where a manufacturing company has established a production plant, and before it can move to a different product type, it first needs to produce and sell a certain number of products that allows it to write off the capital infrastructure. In case of power plant investments this situation is not applicable except for the case where manufacturers of particular power plants are also directly or indirectly related to the operational business. A notable example is the French nuclear power plant manufacturing company Areva whose shares are 83% owned by the French state (Vey and Clercq n.d.). For a large number of years the company has operated at a loss, because of heavy R&D investments and limited new construction of new nuclear power plants. Areva's new reactor the EPR-III has only been sold three times including to Finland and China. As a consequence of the lack of sales and cost overruns debts net of available cash on Areva's balance sheet at the end of 2014 accrued to 5.8 billion euro (Areva 2015). Since the cost of writing off this debt by abandoning nuclear would be significant, the French state has been in a position where it "can not afford to let Areva die" (Rose and Clercq n.d.). The French government is therefore preparing a plan to direct funds from the profitable electricity generation company EDF which runs the French nuclear power plants, which is possible because their shares are also 85% owned by the French government (company team 2012). This would be carried out via a power plant renewal and upgrade program of the existing French fleet of nuclear power plants that is

anticipated to require a sum of 300 billion euro of investment over two decades (Matlack 2015, Rose and Clercq n.d.). The French state, due to the existing financial lock-in of nuclear power, thus steers electricity companies like EDF to continue large scale nuclear power usage, even though this may not be the best choice from a cost competitive perspective.

Technology lock-in can also be caused by the environment in which power plants operate, such as the structure of electricity grids which have already been built. These can because of their geographic or technical structure favour certain technologies over others. A common case is the lack of favourability for wind energy technology, because existing grids spatially often do not provide access to sites with a high wind-speed range. In contrast coal and natural gas power plants can be located in places where grid infrastructure is already in place, such as near ports for easy access to fuel inputs. Both financial and technical aspects of lock-in are situation specific, and as such need to be dealt with on a case by case basis. For the aspect of grid structure it would be necessary to include an electricity grid model. To evaluate financial lock-in an analysis of company budgets and investment recuperation needs to be assessed to evaluate the occurrence and impact of this factor.

The preference factor of **environmental outputs** that emerge from operating power plants relates to existing criteria or long term goals to reduce such outputs. The preference can be due to a variety of factors, including compliance with existing emissions regulation, genuine concerns from investors over environmental impacts, or pre-emptive action in the anticipation of future emission targets. The aspect of concern can be found in the strategic choice of electricity companies which opt to provide for only low carbon emissions technologies in their generation mix. For example, the Dutch energy firm Eneco, which in 2014 operated 3 GW of capacity of which 1.68 GW renewable technologies, included as part of its key performance indicators the reduction in carbon emissions relative to the year 2012 (Eneco Energy n.d.b), as part of realising its mission statement to “*produce, transport, and supply energy in a sustainable manner*” (Eneco Energy n.d.a).

The type of emissions can be split for this purposes into direct substance particle emissions, including NO_x, SO₂, and mercury, and gaseous emissions of CO₂. Particle emissions are usually dealt with on a national regulatory basis and as such play less of a role in company firm investment decisions in terms of optional choices, unless there are different regulations across borders and the possibility to transport electricity. The focus here are CO₂ emissions, which have been demonstrated to result in different firm technology preferences and investment strategies. In case of ‘central planner’ models a constraint can be added that forces reductions in emissions based on the estimated aggregate preferences or regulatory changes in the market. If the aspect is perceived from an individual firms perspective, a ranking procedure is proposed which compares the amount of CO₂ emissions per technology. The calculated emissions values are organised in a technology emissions set, $v_i \in V$. The ranking for each technology, i , is normalized on a scale of 0 to 1, Er_i , where the technology with the highest emissions receives a value of 0, and that with the lowest emissions a value of 1. The ranked values can be introduced in a decision weighting procedure, such as a variable in an objective function or a threshold minimum investment requirement. The allocation of normalized values can be expressed as:

$$\begin{cases} \text{if } v_i = \max V \text{ set } Er_i = 0 \\ \text{if } v_i \neq \min \vee \max V \text{ set } Er_i = 1 - \left(\frac{v_i - \min V}{\max V - \min V} \right) \\ \text{if } v_i = \min V \text{ set } Er_i = 1 \end{cases} \quad (48)$$

The preference of **technological diversification** relates to a business strategy to diversify the portfolio of technologies, so as to minimize market exposure to risk due to input cost fluctuations, environmental output cost changes, or market technology perception. A firm which holds such a strategy will try to keep a balanced portfolio of different technologies, as opposed to relying on one or two technologies for the generation of power. The strategy can be expressed in that no technology should dominate the power generation portfolio of a firm or the entire electricity mix. The degree of dominance can be differentiated at a set level, such that any technology, i , cannot exceed a share parameter, x , of the power generation supply, S . The rule for when new capacity, S_n , of that technology, j , is allowed to be invested in can be tested via a model rule as:

$$if \frac{S_{i=j} + S_{n_j}}{\sum S_i} > x \text{ set } investment_{i=j} = false \quad (49)$$

3.4.5 Input Availability Component

The perceived investment case for an electricity generation technology can be impacted by either perceptions of future absolute availability or disruptions in fuel supply. In case of absolute availability the concern can be due to the spatial distribution and intensity of flows such as solar radiation or wind flow, the finiteness of fossil fuels and the affordability of resources to be producible as reserves, and the availability of sites for construction such as in case of hydro-power dams, offshore-wind, and nuclear power licensed sites. Another component relates to the availability of a suitably skilled workforce for construction or operation of a technology which can form a barrier, or the financing means in case of costs, such as for nuclear power plants in low income developing countries with poorly developed capital markets. The expansion of capacity is dependent on the manufacturing capabilities for each technology. This can be represented in a simple manner by restricting the total capacity expansion per year that is possible as an **annual capacity expansion constraint**, either on a maximum basis or a growth rate basis.

The aspect of flow intensity for wind and solar is already taken into account in the financial component, as it is part of the production to revenue calculation. An example is input availability issues due to the finiteness of fossil fuels, their affordability, and the security of input is the perception on the precarious nature over Russian gas imports in Europe (Pirani and Yafimava 2016, Mitrova 2015), and the decline in natural gas production in the UK, in relation to the thesis case countries of Germany, the Netherlands, and the UK.

A **fuel disruption risk** algorithm is proposed that takes into account the perceived risk of companies to future fuel supplies. A two step procedure is proposed starting with an estimate of the technical availability of inputs within the geography of the country where the company's power plant is established. The degree of imports is determined based on the lifetime of present company available reserves within the country wherein its power plant is operational, R , for a particular fuel input, $f = 1, 2, \dots, n$, which is defined as the technically and economically extractable portion of underground resources. The estimated reserves are divided by the total produced electricity supply, S , over the lifetime of the power plants, both from the power plant under consideration of investment, $k = l$, and existing power plants sharing the same fuel inputs. The anticipated generated electricity supply is multiplied by the inverse of an input conversion coefficient, ϵ , so as to obtain the amount of fuel needed to produce the supplied electricity. The formula outputs the remaining lifetime of reserves, RI , in years for the set of power plant(s) as:

$$RI_f = \left(\frac{R_f}{\frac{1}{\epsilon} (\sum_t S_{k=l,t} + \sum_{k \neq l} \sum_t S_{k,t})} \right) \quad (50)$$

The second stage establishes the share of imported supply which defines the fuel disruption risk, based on the amount of fuel imports over the chosen period, Imp , divided by the total amount of input needs of the plant, and multiplied by the inverse of the number of countries, $c \in C$, from which over 10% of imports are drawn from. The diversity of countries is of relevance to minimize the disruption risk if one provider falls away. Thereby the more countries that a company sources from the lower its fuel disruption risk. The share of perceived insecure supply, Is_f , for a fuel can then be established as per formula (51), based on a comparison between the lifetime of reserves, RI , and the operational life of the power plant, Y . The value is already normalized by this calculation procedure and can as such be directly utilised in the decision process for technology comparison purposes. Any technologies that do not rely on fuel inputs automatically receive a ranking value of 0 as the highest level of security.

$$\begin{cases} if \ RI_f > Y \text{ set } Is_f = 0 \\ if \ RI_f < Y \text{ set } Is_f = \frac{Imp_f}{\frac{1}{\epsilon} S_{k,t}} \frac{1}{c} \end{cases} \quad (51)$$

The aspect of land availability can be tackled using a **location permit rule** based on the maximum sites available for each technology, and a permitting process with a limit to the number of sites that can be occupied (permits granted) per year. As a technology advances expansion possibilities become more limited which results in reduced expansions.

3.5 Firm observability of information in the implementation of computer algorithms

The modelled investment decision process can be implemented based on various levels of visibility of *evaluated information* as the values of parameters and variables in future time periods that are modelled. The degrees of visibility is categorised here as varieties of opsis, after the Greek word for the ability to see, which determines the decision maker perspective on what information is visible and is hidden. A distinction can be made between five variants of opsis:

- **Amblyopia** or “reduced vision” as partial past and present knowledge and no future knowledge.
- **Myopia** or “short sightedness” as complete past plus present knowledge but no or very limited future knowledge.
- **Hyperopia** or “farsightedness” as complete past plus present knowledge and using an expectation of the future to shape decisions. However, knowledge of future outcomes produced by the model remains hidden.
- **Diplopia**, or “double sightedness” as partial past, present, and future knowledge. The firm is able to see a number of future pathways but not all pathways.
- **Omniopia** or “all sightedness” as complete past, present, and future knowledge. The usual mode in inter-temporal optimization models where all states are simultaneously known.

The structure of opsis in models is usually limited by the type of modelling paradigm and programming language. In optimization models usually the objective problem is solved in an omniopic manner, but time-stepped variants that have been developed include myopic or hyperopic approaches. An example is the National Energy Modelling System (NEMS) of the US Energy Information Administration used to produce their Annual Energy Outlook. The model solves a set of market equilibria in each time-period and can incorporate expected price or consumption levels using extrapolation (US EIA 2013). Simulation models on the other hand rely in their common implementation only on past and present knowledge, as knowledge of the future is by its structure unknown at the solution time, such that diplopia and omniopia settings are only feasible by looping outputs of runs into inputs. A hyperopic formulation is common in agent-based models using forward-looking extrapolation algorithms such as in ENGAGE (Gerst et al. 2013). In differential equation simulation myopic formulations are typical, although amblyopic ones are also feasible.

The degree of available past and present knowledge in an electricity market and investment context typically relates to hidden information about a competitor’s financial variables. These include operational costs and contractual prices in off the counter contracts and trades. In addition also the competitors strategies that influence technology selection and the size of investments are hidden. In non competitive markets variables in the form of interest rates, power plant CAPEX and OPEX values for new power plants, spot market prices, operating capacity etc. can all be assumed to be visible, as this information is either readily available in the public domain, or should logically be available from institutes or power plant infrastructure supplying companies without any difficulty. The relevance of varying the degree of past to present available decision information is in such a case of less importance, unless the competitive aspect of the market is built into a model that represents multiple firms, then the degree of hidden information about competitors can become relevant.

The degree of future knowledge is highly relevant in the information structure of all models, as it allows for the removal in the modelled world of erroneous decisions that result in investments in power plants that cease to operate long before the end of their lifetime. These do happen in the real world since all outcomes remain hidden at the time of the decision. For example, in Germany in recent years a series of closures have been announced of peak-load fossil fuel plants, caused by market competition of wind and solar which has priority grid access and therefore its electricity will always be sold. The four large German utility companies asked closure approval to the regulator BNetzA for 7.7 GW capacity between 2014-2018 (PennEnergy 2013). Submissions for closure are primarily natural gas peaker plants at 6.8 GW including four boiler units with 2.2 GW capacity built in the 2006-2010 period. In case the German companies would have known in advance that wind and solar would grow in their share so quickly, they may not have invested in gas peaker plants only 10 years earlier. The contra argument is that they did anticipate such a scenario. Decision makers at the helm

of these companies were confident that if it would happen, that a political deal could be struck in time that would bail them out, or provide for alternative capacity payments (Morris 2015).

3.6 Summary: model aspect combinations and decision structure

What the analysis in this chapter shows is that a series of mechanisms that influence investment decision process can be combined to form a model based implementation of an *investment strategy* as a means for decision making. Each strategy consists of one or more *investment strategy decision options*, as summarised in table 7 below arranged as per the investment components described in **sections 3.4**. For instance, a quite commonly implemented strategy in existing electricity system models is to use the strategy option cost minimisation, sometimes with the option of emission variation ranking for technologies, as a single strategy. Since an *investment strategy* can consist of multiple *decision options*, a meta-structure is needed to weigh these options, which in a computer model is structured in an algorithm. Four possible approaches are possible for a meta-structure to implement decision strategies in electricity system models:

- **The single decision rule approach**, where a single decision criteria is used based on which an investment should or should not take place, such as a lowest cost approach. This is the approach typically used in current electricity system models as analysed in **chapter 2**.
- **The sequential rule approach**, where a number of sequential rules for each decision component or factors are used, which represents a decision maker passing through a simplified number of evaluation stages. At a conceptual level the stages can be depicted using a node and arrow diagram. Decision nodes represent one or multiple sets of evaluated information which are held against a decision rule, and the arrows flowing from a node the possible decision outcomes from the rule, that may lead to a next decision node or a final outcome. In the case of investments the decision outcomes can be limited to the set: *{next node, invest, abort, postpone}*.
- **The weighted decision approach**, where every decision component is normalized between 0 and 1 to make them comparable, such that they can all be taken into account at once in one joint metric to compare across technologies. The resulting 'scorecard' approach can also include an expert weighting of the importance of each input component in the 'scorecard'. The weighting could be setup using a questionnaire method of least relevant to most relevant equivalent to a Likert scale with subsequent translation into numerical values.
- **The combined rule approach**, which combines both sequential rule and scorecard type weighting, by having multiple decision nodes, of which one is a 'scorecard' for technology selection using a subset of decision components. The split can be organised by for example first setting a decision rule of financial evaluation, by which only technologies are incorporated in a subsequent scorecard that meet a minimum level of financial benefits.

The meta-structure and investment strategies can be incorporated in both simulation and optimization models. At present optimization is typically utilised using a single decision metric basis (such as cost minimisation) and simulation is used for sequential decision rules, as these meta-structures are easier to utilise within the respective modelling paradigms. Notwithstanding, optimization models can be designed in a sequential structure by employing pre-processing algorithms prior to the optimization, and in a weighted decision manner by using multi-objective optimization.

The investment strategy framework, as eluded in this chapter and summarised above, is a first step to enable a more comprehensive assessment to examine how investments can be better represented in electricity systems models. This in the context of evaluating energy market policy impacts on investments and power generation capacity change in mind. The framework is used to select a number of *investment strategies* in the next chapter together with the selection of a series of methodologies so as to provide insights in the thesis research questions. The focus lies on the evaluation of *investment strategies* with *decision options* that are most common in existing electricity system models as discussed in **chapter 2**.

Table 7: Overview of model investment algorithm strategy decision options.

Aspect	Possible options	Described in Sections
Financial evaluation	minimisation: Cost, Payback Time, LCOE maximisation: IRR, NPV	2.1.1, 2.1.2, 2.3.2
Financial parameters	Discount rates (% range), WACC (equity/debt), lump-sum or amortized investment accounting, loan lifetime (technical/financial)	2.2
Financial extensions	Real options value of postponing investments	2.1.3
Risk evaluation	CAPM discount rate risk adjustment, Value at Risk (VaR) Investment Cost Adjustment. Portfolio Value at Risk (PVaR) adjustment	2.2.1 to 2.2.3
Discontinuous risks (normal-risks)	Loss Risk Insurance Cost (market)	3.4.3
Discontinuous risks (tail-risks)	Event-risk modelling, Scenario evaluation, Market hedging (fuel prices)	3.4.3
Financial lock-in	Power plant manufacturing investment/technology development recuperation	3.4.4
Technical lock-in	Existing electricity grid technology favourability	3.4.4
Environmental outputs	Technology emission variation ranking	3.4.4
Technology diversification	Maximum technology share in generation mix or portfolio	3.4.4
Fuel disruption risk	Potential disruption of fuel due to availability issues	3.4.5
Investment location	Maximum available sites and permit granting	3.4.5
Capacity expansion limit	Annual capacity constraint	3.4.5
Information availability	Time-stepped (Myopia), Scenarios (Hyperopia), Model-runs with output-input iterations (Diplopia), Inter-temporal (omniopia),	3.5
Market Niche Strategy	Monopoly access to technology	3.4.2
Market Share Strategy	Intentional capacity oversupply and price undercutting	3.4.2
Innovation Preference	R&D Investment and Firm Technology Cost Differentiation	3.4.4
Past Experience	Operational experience based weighting	3.4.4

4 Methodologies for Decision Algorithm Assessment

In this chapter methodologies used in this thesis are described. The methodological approach can be placed in the broader art of computer modelling. In its full development cycle computer modelling is a combination of deductive and inductive methods of science. Computer models are built up of algorithms which are composed of computer language based causal statements about objects and their property relationships which take place in time, and if depicted in the model also in space. Property relationships in models are, when designed using scientific principles, built based on causal statements that have been uncovered by means of inductive principles of observation, and can be extended with new causal statements using theoretical logic, that is derived from deductive reasoning. New model outcomes that incorporate statements from deductive logic can be tested by comparison with observational data, thereby again introducing an inductive element. The testing of logical statements provides the means to falsify statements derived by deduction, and uncover new relationships from observational data as well, that can be parsed into new observational statements.

The previous chapter outlined a component framework of factors that could be of influence in a power plant investment decision. In this chapter the selected aspects of the framework that are analysed in this thesis are outlined inclusive of the methodology of the assessment. The first part of this chapter, **section 4.1 and 4.2**, focuses on the scientific grounding of the thesis, in explaining why the methods were chosen, and develops a series of hypotheses to be tested. Subsequently, in **sections 4.3 to 4.5** each of the used methodologies are discussed that have provided the interview insights in **chapter 5** and the statistical and model reproduction results presented in **chapters 7 and 8**. A separate section is reserved for data management as **section 4.6**, that underpins the collected data presented in **chapter 6** even though it is not a methodology per se, but because it is of key importance in improving the accuracy of the analyses performed.

4.1 The testing of hypotheses and scientific evidence

The purpose of science at a fundamental level is to uncover how the world operates and express this into language based descriptions.² The process is to capture the operational workings of the phenomena of interest in language based objects which are discerned in reality or expressed in theory, and their known and asserted properties. The belief of existence of a property in science is tested by encapsulating the property in a statement, such that it can be held up to a set of observations, and can be evaluated in its relation to be false or true. The statement '*electricity is a form of energy with as a necessary property the sub-atomic charge of particles*' can be tested by measurement of the electric charge at a sub-atomic level. Such properties can be classified into intrinsic properties, such as mass, which exist in isolation of other objects, and extrinsic properties, such as weight, which are dependent on other objects. For example, in case of weight the property varies depending on the size of the gravitational field which varies by spatial location in the universe. Another classification can be made into non-relational and relational properties to ascertain whether properties of objects are or are not dependent on other objects and their properties Lewis (1983)(Weatherson and Marshall 2012).³

The discovery of objects and properties and their language encapsulations is conducted in all sciences through four common methodological features. These have been formulated in the contemporary philosophy of science treatise of Schurz (2014) (Schurz 2014, p. 26), which is here fully re-iterated given the clarity of formulation:

- “M1: Science searches for hypotheses which are as general and as content-rich as possible, and recorded in a scientific language. In all disciplines, these hypotheses include *laws* and *theories*, and in some (e.g. the historical sciences) they also include *hypothetical singular sentences*.”
- “M2: Science searches for actual observation sentences, as many as possible (and as relevant as possible), which reflect the results of observations, experiments and measurements.”
- “M3: Science attempts, with the help of general and hypothetical sentences, to *explain* the currently known actual observation sentences, and to *predict* new, and as yet unknown potential observation sentences.”
- “M4: Science attempts to test empirically its general and hypothetical sentences by comparing the predicted (potential) observation sentences with the currently known (actual) observation sentences. If the latter are in agreement with the former, the prediction was successful (it then becomes a successful explanation) and the hypothetical sentence (law or theory) is *confirmed* or *corroborated*. If there is a contradiction between the latter and the former, the prediction was without success and the law or theory is *falsified*, or in the case of a merely statistical prediction, *weakened*.”

The scientific aim in this thesis is to test a number of hypotheses following the fourth methodological feature of science outlined above, by comparing outcomes of empirical observations with generated hypotheses to assert the presence or absence of their validity. The approach in this thesis is as such primarily inductive. The process of induction entails that based on observations a set of general properties are inferred as a relationship, that can be held up against different sets of observations leading to its confirmation or rejection.⁴

²Including mathematics as a language.

³To illustrate, the object of electricity is defined in relation to several properties including the electric charge of sub-atomic particles, the electric potential, and electric current. The charge of a sub-atomic particle on its own is non-relational and also intrinsic, whilst the behaviour of the sub-atomic particle in being repelled or attracted to another particle is a relation, in that it depends on the other atoms and their positive or negative charges. In other words the extrinsic property of being repelled or attracted exists when a certain relation between atomic particles is satisfied. A crucial addition to the distinction is that it is always the case for an extrinsic property to be relational, whilst an intrinsic property can be both relational and non-relational.

⁴As a counterpart to induction, the second route to discover statements resembling reality is via the process of deduction. The analysis of deduction

The discovery of a congruent statement with empirical observations is normally only a partial explanation of reality however. A large number of validated observational sentences are usually required to provide for a comprehensive understanding of reality. In the context of this thesis, for instance, a large number of statements about both financial metrics as well as non-financial metrics in combination are needed to comprehensively explain the process of investment decisions. In addition, some statements will provide for better explanations than others, in a comparative sense. No absolute generalization can be ascertained, and only the best approximation available to the present moment in time can be made, because not all of reality can be observed creating inherent uncertainty. This cannot be solved since there is an infinite list of possible computable combinations that are necessary to comprehend reality fully, of which a majority are obviously not observable. This issue is more commonly referred to as the problem with induction (Boland 2003). The problem is compounded by the issue that outcomes of decisions remain inherently hidden in the present because they relate to future periods in case of investment decisions, and the past can only explain the future to a limited extent, because the real world is not a deterministic system.⁵

As a consequence of inherently having a limited representation of reality when looking at a phenomenon, only *epistemic induction* principles are sensible when assess observational statements, hypotheses, and theories. Such principles are formulated as “*If a theory T1 has been more successful than T2, so far (explanatory and prognostically), than it is probable, relative to the given state of evidence, that T1 will also be more successful than T2 in the future* (Schurz 2014, page 54)”. The analysis and interpretation in this thesis follow this structure in aiming to find inductive generalizations that can explain past investment decisions as logged in empirical data. These generalizations are found by testing mathematical algorithms which encapsulate a set of to be tested hypotheses. The methodology includes falsification efforts via statistical tests (section 4.4), model reproductions (section 4.5), and corroboration by expert interviews (section 4.3). The outcomes of testing a hypothesis if not falsified is a series of *inductive-statistical generalizations* statements (Schurz 2014), which are for this thesis adapted and expressed in their general form as:

“x% of all modelled outcomes using investment decision algorithms Fs, are congruent with empirical data logged outcomes caused by investment decisions Gs, therefore (probably) approximately x% of investment decisions can be re-sembled by investment decisions algorithms Fs.”

serves to explore using theoretical logic, starting with a set of existing statements that are known to be true for a given set of objects, what other properties and their relationships particular to these objects may be in existence. The starting point is to take existing statements and within the confined space of understanding that these provide, derive new possible or plausible statements about these objects, their properties, and their relationships. The emphasis in deduction lies on utilising logic reasoning to define new statements, and to do so by means of theoretical mental models or computer models.

⁵There is an inherent limitation to observe future outcomes and their probabilities, such as the evolution of the extrinsic property of prices of an object like steel, in a deterministic manner. The reason is that within the structure of the world there are many natural and human driven systems which possess ‘chaotic’ non-linear behaviour. Chaos is expressed in a simplified manner in that a minute change in initial conditions can lead to a significantly different outcome. This is the case for various dynamical systems such as power networks, weather systems, and population dynamics. The reason is that there are three potential types of behaviour which can emerge from variations in small changes in initial conditions:

- As converging to a stable point in the long term, referred to as a point attractor.
- As a continuing oscillation between two points in a regular periodic pattern, referred to as a limit cycle.
- As chaotic or seemingly random behaviour which occurs in a non-periodic manner, yet at an aggregate scale exhibits a steadiness in that it stays within certain bounds, referred to as a strange attractor due to its fractal structure.

Whilst the first two types are predictable in that they are periodic, the steady chaotic behaviour type is not predictable because the state at which the system will be in at a certain moment in time is erratic. The system characteristic that can be inferred is that there is a certain probability for the system to be in a state at a point in time, based on the steadiness of the strange attractor which defines the system, but not at which point in time that will be. The probability of occurrence of an event can thus be ascertained, but not its sequence in time, when looking at the particular system in isolation. Only if both the relationships of the system including all its parameter values, and the exact initial state would be known, can the trajectory within a dynamic chaotic system state in isolation be known. As such to ascertain the future of a price evolution it would be necessary to have complete information of the current state represented as initial conditions to an infinitesimally small level of detail, which is not feasible.

The expression results in the ability to compare across investment decision algorithms, so as to ascertain which decision strategies provide the highest % of explained investment decisions in the empirical data across cases. The approach can also be inversely stated from the general to a particular observation, in an adaptation of (Schurz 2014) as:

“x% of all modelled outcomes using investment decision algorithms F_s , are congruent with empirical data logged outcomes caused by investment decisions G_s , therefore for a particular investment decision G we can be x% sure that the investment decision can be approximated by the investment decision algorithm F .”

4.1.1 Selection of methodologies

The thesis uses three methodologies to create an as robust result as possible by carrying out multiple falsification efforts. The first methodology is a series of interviews of which the outcomes are discussed in **chapter 5**. The interview method discussed further in **section 4.3** serve to corroborate the statistical and model analysis. First, to add to the discussion whether the investment process is to a degree generalizable in the form of computer algorithms. Second, to assess if any particular aspects have been missed in the thesis framework or within the tested components for discussion purposes. The second is a statistical analysis described in **section 4.4** of which the results are contained in **chapter 7**. The analysis provides a structured approach to assert which financial investment decision metrics provide the closest to empirical power plant capacity evolution. The quantitative outcome yields the possibility to express results in inductive-statistical generalization statements. The third is a model based analysis **described in section 4.5** which is discussed in **chapter 8**. The method provides an implementation and test of a series of investment decision strategies in model algorithms, so as to assert the degree to which empirical evolution of power plant capacity can be reproduced using electricity system models. A key part is to isolate the impacts of structural and parameter variations, as changes in entire formulas and model components, and changes in individual parameter values. This is done by using singular and joint combinations of changes within decision strategies.

The algorithms that provide for the largest degree of explanation of outcomes plausibly can also be interpreted to capture real life properties of investment decisions, and thereby provide some explanatory weight as to actual real life investment decisions. However, this need not be the case. The statistical and model empirical falsification effort could have as an outcome a set of algorithms that provide the best empirical fit, but with limited explanatory power to the actual investment decision making process, and thus not be generalisable and externally valid. The best case situation is that the investment process is adequately encapsulated by a limited number of key drivers that yield an explanation of investment decision outcomes, versus the worst case where spurious relationships are captured with no explanatory power at all.

The matter of explanatory power versus capturing reality is a continued debate in the philosophy of science, and to a growing extent in economics due to the poor success of predictive models. The critique has increased on the perspective of the school of instrumentalism, which posits that the representation of reality is of limited importance for a theory or model, what matters is that the model is useful in providing outputs that resemble reality (Boland 2003). No representation of reality would be required, since instrumentalism states as a sufficient condition that the *outcome* of the algorithm needs to be commensurate with the *outcome* of real life investment decisions. As such as long as models provide accurate results no investigation would be necessary to corroborate the realism of the provided algorithms. The discussion is highly relevant to this thesis because the statistical and modelling methodologies as described in **section 4.4 and 4.5** do not look at what happens in reality, but merely whether outcomes of reality match those of particular decision rules, as either statistically described or modelled.

To take a step in the direction of instrumentalism, in the art of modelling it is the case that accurate representations of reality are often unnecessary, nor desirable, as they pose a computational hindrance. In physics an accurate representation of molecular interaction is not required (nor feasible) and instead a simplification is taken at an aggregate level of properties of groups of molecules, as opposed to individuals, which typically have undergone a process of falsification. In the authors perspective the problem of instrumentalism lies in not defining what simplification of reality is warranted. At the extreme interpretation of this view the explanatory power of an algorithm becomes irrelevant, which is problematic from three perspectives:

- First, it works **against falsification and in favour of spurious relationships** by purely focusing on outcome correlations. A set of algorithms can provide for excellent results under particular conditions and thus be seen as sufficient, but those conditions may not be independent and be a result of underlying causal drivers. The relation in the algorithm can thus be spurious and not valid as soon as the underlying driving conditions change. If there is no interest in how the algorithm works and relates to reality, it also does not promote falsification efforts based on both induction and deduction to rule out spurious relationships. As a consequence key algorithm omissions are not

considered and acceptable until the point that the algorithm breaks down in its purpose.

- Second, **improving models is limited due to a black-box treatment** by not seeking an explanation of how outcomes come about. As a consequence the foundational element of science in building knowledge to provide an understanding of phenomena is ignored. Knowledge that can be used to build new better observational sentences that explain reality, as per the methodological foundations M1 and M3 of **section 4.1**. It is important for improving a model to understand why a model's simplification of reality via its algorithms yields good results in explaining outcomes, and for this reason why it does or does not resemble reality. In the absence of such an understanding, it becomes challenging to create a plausible assertion of what algorithmic improvements could constitute.
- Third, it yields **challenges to examine the generalisability** of a set of algorithms so as to understand under what real life conditions the algorithm would be valid. It is plausible that there is no single investment algorithm that is utilised in reality, but that different market players utilise different algorithms. Moreover, in certain countries practices may be different especially in relation to financial evaluation and which metrics are employed. The understanding of which properties as captured in algorithms in relation to properties that are taken into account in reality, aids to ascertain in which cases the algorithm is valid and when it is not, which will result into accurate calculation of outcomes.

The three perspectives aid to hold the results of **chapter 7 and 8** to light in terms of their usability in practice, such as in understanding how changes in policy instruments affect investment decisions. The expert interview insights presented in **chapter 5** also provide a perspective based in experience from reality, so as to ground the analysis with insights from practitioners involved in real life investment decisions, and therefore if the investment decision strategies as tested also resemble to an extent a simplified version of real life investment decisions.

4.2 Selected Investment Algorithms and Hypotheses

A large set of 28 decision factors were outlined in **Chapter 3** that could play a role in investment decisions as part of an investment decision strategy. A decision strategy can thus be formulated based on a single decision factor such as investment cost, or a plethora of decision factors. Now investigation of all the decision factors and combination factors would result in at least 3000 decision strategies that would need to be evaluated. And if individual variants of each factor, such as a discount rate parameter difference is taken, the number of potential combinations rapidly explodes. To make the investigation tractable the scope of decision factors was narrowed by focusing on investment decision factors that are dominant in current electricity system modelling approaches, as identified in **Section 2.4**. The reason is to focus on answering the research questions set out in **section 1.5.2**, and in particular the question: *“Which power plant investment evaluation metrics provide robust results from a ‘central planner’ optimisation modelling approach, driven by cost minimisation or profit maximisation, in reproducing historical generation capacity change?”*

As evaluated in **section 2.4** the majority in 48 out of 51 electricity system models use either a cost minimisation or a profit maximisation approach, with very few utilising non-financial factors, of which 41 are optimisation and 7 are simulation based. The current models also utilise financial discounting parameters in 37 out of 51 screened models, and an amortization approach is used in 19 out of 51 screened models. Similarly, in 29 out of 41 optimisation models an inter-temporal setting with information fully available across all time periods was used, versus 12 that have been implemented with a time-stepped structure. This screening of variability led to the following three aspects that are evaluated in this thesis:

- **Financial Evaluation**, the impacts of using an optimization approach including minimize costs (min-COST), maximize NPV (max-NPV), minimize payback time (min-PBT), and minimize LCOE (min-LCOE).
- **Financial parameters**, the effects of discount rates (at 5% and 10%) and investment accounting as a lump-sum investment or amortized capital costs.
- **Information availability**, the effects between three year time-stepped (myopia) and inter-temporal settings (omniopia) of the optimization.

In addition to these three factors selected because of their prominence in existing electricity system optimisation models, two additional factors were incorporated that define capacity expansion limits and technology diversification by setting a maximum technology share in the generation mix. The reason for their inclusion is that these factors are known to have a significant influence on optimisation model outcomes Price and Keppo (2017), Ostergaard (2009). The reason is that if capacity can expand unfettered the model can select a rapid expansion of particular technologies in years with low capital investment cost values. The effect of capacity restriction is further explored by inclusion of the following two factors:

- **Technology diversification**, the impact of a maximum technology share of the energy mix.
- **Capacity expansion limit**, the effect of an annual capacity expansion limit for each technology.

The aspects that were excluded from the scope of model testing are risk evaluation, scenario based approaches, lock-in aspects, environmental outputs, fuel disruption risk, and investment location. The remaining set of five aspects above leads to 64 combinations or model investment strategy variants. In relation to these aspects a series of hypotheses are formulated here to allow for a structured testing approach. The falsification process aids the formulation of a series of *inductive-statistical generalizations* from these hypotheses as discussed in the previous section.

The **1st hypothesis** to be tested is: *“for all investment decision strategies, the representation of the investment decision process in electricity system models using a fixed financial threshold value, yields a significantly better explanation of*

realised capacity in the past than a random outcome.”. The hypothesis seeks to establish if investors of a power plant project use a threshold value as a necessary condition for any investments, be it a maximum return or a maximum cost threshold. If a project does not meet the threshold level the investment level will not be undertaken, regardless of the technology type. It is plausible that this is not a sufficient condition for an investment to take place, since it is expected that there will be cases where, despite reaching a threshold level, no investments will take place due to other considerations such a demand expectations or financing availability. In a mathematical form the 1st hypothesis can be stated as:

$$\text{if Value} < T \text{ then } x \in X = 0 \quad (52)$$

In the hypothesis, $x \in X$, represents the set of investment decisions, which can have a value of 0 for do not invest, and 1 for go ahead with the investment. The investment value takes shape based on the value of the financial metric being below or above a threshold value, T , such as the interest rate for IRR. To evaluate whether the threshold is also a sufficient condition, an additional binary criterion could be defined as, **if Value > T then $x \in X = 1$** , resulting in a binary decision model.

The **2nd hypothesis** to be tested is: “for all investment decision strategies the representation of the investment decision process in electricity system models with an absolute limit to capacity expansion per technology, as a proxy for technology diversification, is better at explaining realized capacity in the past from investments than assuming no limits to the expansion of individual technologies.” The hypothesis seeks to establish whether aspects of capacity expansion limits and technology diversification play a significant role in investment decisions. The underlying expectation of technology diversification is that companies want to diversify risks and that different energy technologies are complementary to each other in electricity generation systems. The annual capacity limitation stems from the inability to expand in a given year more than the available manufacturing capacity of each technology. The hypothesis can be mathematically expressed as:

$$\forall s \in S: \sum_t^T |C_t^{d,c} - C_t^r| < \sum_t^T |C_t^n - C_t^r| \quad (53)$$

In the hypothesis, $s \in S$, represents the set of investment strategies, and for this set it is anticipated that the distance of realized capacity in GW from investments, C^r , to model inferred capacity investments using technological diversification and capacity expansion, $C^{d,c}$, is **smaller** than those without such constraints C^n .

The **3rd hypothesis** to be tested is: “for all investment decision strategies simulated in electricity systems models, profit based financial metrics yield better results in explaining realized capacity in the past from investment developments than cost based metrics.” The hypothesis serves to assert that financial metrics based on profits such as NPV and IRR yield a better explanation of past investment developments than those that looks at costs such as payback time nad LCOE. In business surveys as discussed earlier in **chapter 2** the financial evaluation is dominated by the use of payback periods, NPV, and IRR, whereas more complex real options approaches are not commonly used (Graham and Harvey 2001). In its equivalent mathematical logic the formulation becomes:

$$\forall s \in S: \sum_t^T \sum_i^I |C_{t,i=j}^m - C_{t,i=j}^r| < \sum_t^T \sum_i^I |C_{t,i=j}^m - C_{t,i=j}^r| \quad (54)$$

In the hypothesis, $s \in S$, represents the set of investment strategies, and for this set it is anticipated that the distance of realized capacity from investments, C^r , to model inferred capacity investments from the set of profit based financial metrics, $i \in I$, for a particular metric, $C_{i=j}^m$, is **smaller** than for cost based financial metrics $C_{i=j}^m$.

The **4th hypothesis** to be tested is: “for all investment decision strategies there is a positive monotonic relation between i) the height of the financial metric that identifies profit or cost of a power plant investments and ii) the capacity size of the power plant technology that is invested in.” The hypothesis brings forward the idea that technologies and time-periods which provide for a better score on a particular investment metric result in larger power generation capacity investments. This implies that beyond a threshold value there is a positive monotonic relation between performance on the financial metric and power plant capacity investment. The hypothesis is mathematically formulated as:

$$\forall i, j \in I: \text{ if } i > j \text{ then } C_i > C_j \quad (55)$$

In the hypothesis, $i, j \in I$, represents the set of values that a financial metric can take. If the value of a metric is higher than that of another instance of that metric, then the expected capacity that is constructed, C_i , as an outcome of that metrics values is expected to be higher than for the value of the other instance, C_j , of the metric.

The **5th hypothesis** to be tested is “*for all investment decision strategies the representation of the investment decision process without prior knowledge of the long-term future using a time-stepped optimization, is better at explaining realized capacity in the past from investment developments than assuming complete prior knowledge of the future using an intertemporal optimization structure*”. The hypothesis serves to investigate whether modelled knowledge of the future has a significant unrealistic effect on outcomes, and is thereby an erroneous approach if the modeller wants to understand what will plausibly happen in terms of electricity market technology developments. This is particularly the case for intertemporal optimization where the underlying structure results in the simultaneous visibility of future market conditions across all time periods from the initialization year. The hypothesis is framed on a language basis as . In its equivalent mathematical logic the formulation becomes:

$$\forall s \in S: \sum_t^T |C_t^{step} - C^r| < \sum_t^T |C_t^{iopt} - C^r| \quad (56)$$

In the hypothesis, $s \in S$, represents the set of investment strategies, and for this set it is anticipated that these strategies will be closer in their inferred capacity for a time-stepped model structure, C_s^{step} , to actual realized capacity C^r , than capacity inferred from an intertemporal optimization based structure, C_s^{iopt} , as the model implementation.

4.3 Expert Interviews

The first analysis that was carried out is the expert interviews to ground the thesis in real life insights, so as to further contextualise the statistical and modelling methodology results. The key reason for carrying out interviews is to add perspectives that support or contradict whether tested investment decision strategies resemble the investment process as experienced by the interviewees. The second reason is to look at whether specific factors of investment have not been missed in the thesis. The risk that the modelled relationships are due to spurious relations or random artificial results is reduced by broadening the evidence base from real life experiences.

The analysis was carried out by means of four expert interviews. The experts were carefully selected based on their experience with project investment evaluation in the electricity sector and the different organisational contributions in which they work to get investments off the ground. The sets of expertises of the interviewees as such are four-fold. Firstly, coverage of financial advisory services to close large scale 100 MW to GW power plant projects between electricity generation companies, lending banks, and governments as a permitting part. Secondly, coverage of financial advisory services of smaller scale community energy projects of a few kW up to a few MW in size. Thirdly, experience within a large corporate electricity company in providing investment decision information to the managerial level using electricity market models and techno-economic project appraisal. And fourthly, expertise as a representative of the UK electricity industry to policy makers on the implications on power generation investments due to regulatory changes. Since the number of interviewees, regardless of their experience, is a small sample of practitioners involved in power plant investment decisions, the results should be treated with caution as partial insights, and not be taken as definitive conclusions on the investment decision process. In the interviews information was elicited under a grouping of four topics:

- **The investment process**, to ascertain the nature of the decision process in terms of decision steps, and the involvement of different players in electricity markets.
- **The use of financial evaluation metrics**, to elicit which evaluation metrics are typically used and how different metrics are used alongside each other.
- **The approach to deal with risks**, the type of risks that are taken into account in the decision process, and the approach on how these are taken into account in relation to future expectations.
- **The incorporation of non-financial aspects**, to ascertain the role which market strategies, technological preferences, political support and the market environment, and input availability play.

The interviews were structured following these topics, where for each topic a set of open ended questions was asked with a particular elicitation purpose in mind. An overview of the questions and elicitation purpose can be found in table 8 below. In **chapter 5** the interview insights are discussed with a division between four sections following the four topic structure outlined above. The interviews were if required by the expert carried out on an anonymous basis, otherwise the interviewee and their background is noted in the chapter. Any quotes from the interviews are not ascribed to particular interviewees.

Table 8: Interview Questions used in thesis.

Topic(s)	Question	Elicitation Purpose
The investment process	How would you describe the key investment decision stages in the investment process of a new power plant?	To obtain the interviewees point of view on how investment decisions are taken
The investment process	What conditions need to be evaluated for an investment decision to go ahead within these stages?	To establish what criteria need to be evaluated before the actual investment decision takes place
The investment process	In what stage(s) does the evaluation of technologies play a role from the perspective of a large utility company which has many technology options?	To elicit where the comparison of technologies versus the further evaluation of particular technologies plays a role in the investment decision process
The investment process	In what way is the investment information structured/brought together for the investment decision(s)?	To evaluate what combination of analyses and simplified indicator are brought together in the decision process
The investment process	Does the investment decision process differ significantly per type of market player (e.g. balance sheet financing, market lending/project finance, given the type of players)?	To examine whether multiple approaches are in co-existence in the decision evaluation in relation to financing routes
Financial factors	What set of financial metrics are commonly used in structuring information on the investment prospects?	To evaluate whether the set of metrics from the literature are corroborated by the interviewees
Financial factors	How are multiple financial metrics taken into account in the investment decision?	To examine if multiple financial metrics are utilised and how they are used alongside each other
Project Risks	What metrics are used to evaluate project risks?	To corroborate what risk specific metrics are incorporated within the financial evaluation
Project Risks	What approaches are used for evaluating operational phase market risks in the decision process? (e.g. fuel and electricity price developments, power demand changes, higher O&M costs)	To gain insights in the use of scenario driven approaches to establish ranges of operational parameters, and if so what assumptions are taken
Project Risks	What requirements are there for risk mitigation by lenders/banks of projects? (e.g. assumptions, contractual structures, commercial terms, risk commitments)	To ascertain what particular assumptions and constraints are set to deal with risks from a debt financing perspective
Project Risks	Do commercial terms which cover risks vary significantly for different technologies?	To understand if for particular technologies additional risks apply which influence the likelihood of investments
Project Risks	What financial costs are commonly incurred to pre-emptively mitigate risks from an investor perspective, and are some of these technology specific?	To examine if risk mitigation bears significant additional investment financing cost, and if it has influence on technology selection
Non-financial factors	What role does strategy play in the investment decision process (e.g. market share, profiling of particular power sources)?	To understand the view of the interviewees if the portfolio of technologies is influenced by specific company strategies
Non-financial factors	How are political/regulatory uncertainties taken into account in the company investment decision process?	To deduce the extent to which political commitment to stability of rules, or anticipation of new regulation, has an influence on taking investment decisions
Non-financial factors	To what extent do environmental emissions form a constraint on investment technology choice, beyond adhering to regulatory standards, in the utility company investment decision process?	To establish if the environmental factors play a key role in the investment decision process, beyond regulatory set costs and anticipation thereof.

4.4 Statistical analysis of investment valuation metrics

The empirical data for each case study of power plant evolution and market financial values are utilised in a series of statistical tests. These serve to assert the extent to which outcomes suggested by investment metrics correlate with datasets of historical investment outcomes, and thus whether an investment metric can be used as a reliable estimate in electricity system models. In all cases the evaluations are carried out using the open source GNU licensed R statistical package, <https://www.r-project.org/>, based on the python programming language. The input values for all analyses are prepared from the datasets described in **chapter 5**, which are available in spreadsheet format in accompaniment to the thesis as described in **section 4.6**. The analysis was carried out with the help of several calculations using scripts constructed in Java.

The first statistical evaluation serves to examine the **1st hypothesis** that a necessary condition of an investment decision is a threshold financial value. The analysis is carried out for the investment metrics PBT, IRR, NPV, and LCOE. The evaluation uses a three step procedure. First, for each technology the financial metric value is established from historical market conditions for all years. Second, the value is compared with a chosen threshold value, which as per the hypothesis, represents a necessary minimum or maximum value for any investment to take place. In all time-periods where the value exceeds the chosen threshold a value of 0 is assigned and vice-versa data-points above or below are assigned a value of 1. Third, the years in the established dataset are compared with the years where an investment decision was taken or not, for each technology. The comparison is carried out by creating a 2 x 2 contingency table that describes the frequencies of combinations between 0 and 1 across both variables as shown in table 9 below.

Table 9: Contingency Table Example.

Variable one \ Variable two	Value 0	Value 1	Total
Value 0	a	b	p_1
Value 1	c	d	q_1
Total	p_2	q_2	1

Subsequently, from the contingency table values two coefficients are established that enable a comparison of similarity of binary variables. First, a phi-coefficient that is constructed by a division with as numerator the mathematical products of corresponding and opposing binary values, and in the denominator the expected value as the square root of the products of all possible combinations (Joost 2008). This phi-coefficient is calculated as:

$$S_{phi} = \frac{ad - bc}{\sqrt{(p_1 q_1 p_2 q_2)}} \quad (57)$$

The range of the phi coefficient lies between -1 and 1, and its interpretation is that of no relationship around a value of 0, a weak positive and negative relationship for values between 0 to 0.5 and 0 to -0.5, respectively, and a moderate to strong relationship for values above 0.5 and -0.5 to 1 and -1. The main advantage is that the phi coefficient is equivalent to a Pearson's product-moment correlation, and can be statistically assessed based on the two variables for which a causal relationship is hypothesised (Zysno 1997).

Second, a matching coefficient is constructed which is a division with in the numerator the number of binary outcomes of 1s and 0s that are commensurate among the expected result from the financial metric and historical investment occurrence. The denominator sums the total number of observations. The results can be interpreted as the percentage of outcomes where the expected outcome matches the historical dataseries. The matching coefficient is expressed as (Joost 2008):

$$S_{sm} = \frac{a + d}{a + b + c + d} \quad (58)$$

A second statistical analysis was carried out to investigate **the 4th hypothesis** on the relation between the size of a financial metric and the size of investment in power generation technologies. The assessment serves to compare the outcome of investment algorithms with the amount of power generation capacity built historically, as opposed to just the yes/no investment in technologies. The statistical test is carried using a Spearman's rank correlation coefficient, which was chosen because it is non-parametric in not assuming any a-priori distribution. In the analysis the value of the two variables for each year, the size of the financial metric, and the historical capacity installed, are each independently ranked from their lowest to highest variables values with an integer value from, 1 to n , by assignment. The test computes the degree of correlation of the ranked variables for each observation by asserting the degree to which the two variables are monotonically related (monotonically increasing), in a sense that if one variable, x , increases in rank, the other one, y , also increases. This can be expressed as:

$$\text{if } \forall x \wedge y : x \leq y \text{ then } f(x) \leq f(y) \quad (59)$$

The degree to which a monotonic relationship exists can then be interpreted from, ρ , the Spearman's correlation coefficient. A value of 1 can be interpreted as a perfectly increasing monotonic set, a value of 0 as a perfect non-monotonic set, a value of -1 as a perfectly decreasing monotonic set, and all ranges in between as lesser and greater (non)-monotonic sets. The coefficient is calculated from the difference between the ranking of the two variables, $d_i = x_i - y_i$, and the number of observations, n , which is mathematically expressed as:

$$\rho = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)} \quad (60)$$

To implement the test in case of financial investment metrics a conversion is made to create a ranked variable, x , with a distinct value for each technology for each year. A ranking from 1 to n is assigned where the value of n depends on the number of technologies. The assignment is made by setting the most favourable technology, in terms of its financial metric outcome equal to the rank value of n , and the least favourable to a rank value of 1. For example, the technology with the assessed lowest payback time would receive a value of 1 for the particular year of calculation, the second lowest a value of 2, and the highest a value of n . In a similar fashion the a ranked variable, y , is created on the basis of established power plants and their capacity. The ranking for capacity is assigned for each year on the basis of empirical investments in installed capacity, where the highest installed capacity in MW in a given year, is ranked with a value of n , and the lowest with a value of 1. If no investment takes place in multiple technologies in the empirical record for a year, the technologies are ranked on the basis of cumulative installations to present. The two variables can then be used to establish a Spearman's correlation coefficient.

4.5 Model based historical reproduction

The second methodology is a model based analysis to compare the outcomes of implemented algorithms in an electricity systems model with datasets of historical power plant capacity evolution for Germany, the UK, and the Netherlands. The analysis serves to evaluate the **2nd, 3rd, and 5th hypotheses** as per **section 4.2**. Since the thesis focuses on testing the approach in the majority of existing models, which are optimisation based approaches, an optimisation model was selected with a single decision metric approach. The existing open-source model, TEMOA, was selected and adapted for each investment algorithm implementation, as outlined in the Appendix C. The adoption of an existing already tested model improves the robustness of the analysis, and it increases the research scope by enabling more time to be devoted to the investment algorithm analysis. In addition, building upon an existing open-source framework model also improves the contribution of this thesis, as it adds to a readily usable electricity systems model.

The TEMOA model was selected based on a screening of fully open-source electricity systems models with a long term capacity evolution component. Five such models were located, EMLab-Generation, Temoa, OSeMOSYS, Calliope, and URBS, which were also included in the review in **chapter 2**. The conditions set for being fully open-source were first, the ability to run the software in a free-of-charge platform, and second, the source code of these models needs to be available and usable directly, as registered under a license that allows free use, distribution, and adaptation, given that the appropriate credit and license conditions are acknowledged in adapted versions. Beyond the five models a few models have provided openly available code, but they are operated within the commercial General Algebraic Modelling Systems (GAMS) environment, such as the BALMOREL model, and thus excluded on the basis of the open-source criteria. An overview of the characteristics of the five located models is provided in table 10 below.

The TEMOA model was chosen because its optimization framework was already sufficiently flexible to incorporate various investment decision algorithms. This includes the flexible Python architecture, and that the code already includes capacity expansion constraints and loan based investment rules. Also an advantage of TEMOA is that it has been benchmarked relative to the long-standing Markal model and found to provide similar results (Hunter et al. 2013).

To run the model a range of input data for variables and parameters was utilised which is described in **chapter 6**. In total 64 model runs were carried out in TEMOA for the period 1980 to 2013, and another 64 for the period 1980 to 2046, with variations in the investment algorithm and in specific parameter values, as described in **section 4.2**. After running the model for all variants a comparative statistical analysis was conducted to assess the ability to reproduce historical changes in power generation capacity. The match between model produced values and the empirical record was evaluated using the Pearsons correlation coefficient. It is calculated based on the covariance of two variables, modelled, m , and empirical, r , which are divided by the product of the standard deviation of the variables. The degree of change is thereby measured as the distance between the variables in a two-axial system, including a weighting by the standard deviations.

The Pearson's correlation coefficient is expressed as:

$$\rho_{m,r} = \frac{Cov(m,r)}{\sigma_m \sigma_r} \quad (61)$$

Model results that were found statistically significant on the pearson' correlation coefficient were screened visually for technology inflection points. These were identified based on two characteristics, the introduction of new technologies that were not previously part of the electricity mix and/or the large scale increase or decrease of technologies in the electricity mix with a generation share shift of 5% or larger. The set of inflection points was subsequently compared with historical developments to analyse their difference to and similarity with historic outcomes, as described in **chapter 8**.

Table 10: Comparison between Temoa, Omeosys, and Calliope open-source frameworks.

Characteristic	EMLabGeneration	Temoa	OSeMOSYS	Calliope	URBS
Model paradigm	Simulation	Optimization with stochastic option	Optimization	Optimization	Optimization
Current problem formulation	Decision algorithm with selection of highest return (Profit Maximization based)	Cost minimisation	Cost minimisation	Cost minimisation	Cost minimisation
Costs in present version	Investment cost (with equity and debt interest), operation and maintenance.	Loan interest, fixed costs, and variable costs.	Capital costs with discount rate, operating costs, emissions penalty, and salvage value.	Capital cost with interest, fixed operation, variable operation, and fuel costs.	Capital in annuity form (with interest), variable operating, and fuel costs.
Loan lifetime	Financial lifetime or technical lifetime	Financial lifetime or technical lifetime	No loans	Technical lifetimes	Technical lifetime
Electricity Network / Spatial Distributions	Yes	No	Yes	Yes	Yes
Existing use case countries	Germany and UK	Synthetic cases	Sweden, Africa river basin countries	UK	1) Indonesia, Malaysia, Singapore, 2) EU-MENA
Architecture	Java using AgentSpring	Python w. Pyomo library	GNU Mathprog / GUSEK	Python w. Pyomo library	Python w. Pyomo library
Solver	Not applicable	GLPK	GLPK	GLPK	GLPK
License	Apache 2.0	AGPL	Apache 2.0	Apache 2.0	GNU GPL
Source code hosting / Adaptability	Github version control	Github version control	Hosted on dedicated website	Github version control	Github version control
Source documentation	(Chappin et al. 2015, Vries et al. 2013)	(DeCarolis et al. 2015, Hunter et al. 2013)	(Howells et al. 2011, <i>OSeMOSYS: an open-source energy modelling system</i> 2015)	(Pfenninger 2015, Pfenninger and Keirstead 2015b)	(Huber et al. 2012, Stich et al. 2014)

4.6 Data management plan

The analyses in this thesis are underpinned by a substantial number of datasets for the studied cases of Germany, the United Kingdom, and the Netherlands. In the perspective of the thesis author the collection, recording, digital treatment, presentation, and interpretation of data necessitates adequate description. These aspects are equally as important as the analysis itself, since the interpretation of results of any analysis is related to whether the input dataset is of sufficient quality and quantity to provide for a meaningful analysis. The principles of transparent data treatment are commonly recognised in sciences that rely on experimentation and measurable observation, in the form of laboratory manuals, as well as computer science, where the notion of input data importance has been popularised as Garbage In equals Garbage out (GIGO). The separation of all aspects of data handling from the analysis also increases transparency, which when done properly adds the advantage of providing the datasets in an open format.

The open publication of data generated in scientific research is gaining increasing traction in overall science. In 2014 Nature publishing group launched the journal Scientific Data for publishing meta-data descriptions alongside research datasets, and in 2012 the open-access journal GigaScience was launched for the publication of large datasets in biology and biomedical science. In line with such contemporary data handling practices a structured data management plan was setup which is described below. The data management plan contains six elements:

- The *data description* outlining which data is collected, attributes of the data, and by what procedure.
- The *formats* in which the data will be contained.
- The *pre-processing* procedures of the data and how it feeds into the undertaken analyses.
- The *storage, backup and versioning* of the data.
- The approach to provide *meta-data and overall documentation*.
- The means of *access and sharing* to other parties of the data.

The elements are described in detail here and summarised in table 11 below. The *data description* includes an outline of data contained in the sets, the unit in which the values are expressed, the source type from which the data is obtained, and its analytical use. Each collected dataset is obtained by means of collection using digital or written literature sources or specific databases. The data is extracted from these sources either by copy pasting data in case of written sources, or direct downloads of datasets when available in .CSV, .XLS, or .XLSX formats. All data is subsequently converted or directly written and maintained into the .XLSX format. In case of model input requirements the data is converted into an appropriate .CSV format. In the .XLSX spreadsheet a master meta-data listing tab is kept for each of the country cases following the outline in table 11 below.

The obtained data is kept in its original raw format in a spreadsheet. In a separate copy of the raw data spreadsheet all *pre-processing* procedures are carried out so as to increase transparency of data changes. Since the majority of data is time-series based an evaluation is done for missing data values for particular years, duplicate values for sequential years, discontinuities in time-series, and outliers. In the pre-processed datasets colour coding is used to outline any adjusted or filled in values. In case of missing data a single imputation is carried out by linear interpolation taking the mean value of the post and prior year(s) as an approximation. The approach is justified by making the assumption that the data is Missing Completely At Random (MCAR) since these are missing 'measurements' (Saunders et al. 2006). In case of a duplicate values for multiple following years the record for the first year is maintained, the values for subsequent years are removed from the dataset, and the removed values are imputed as per missing data values procedure. A similar removal and imputation approach was taken for outliers. The occurrence of outliers is tested using a visual inspection given the limited number of data-points in the time-series (30 years).

Table 11: Datasets collected in the thesis from 1990 to 2014 for each case.

Dataset	Unit	Source Germany	Source UK	Source Netherlands
Investment cost to construct a power plant per technology	euro per MW	(Neij et al. 2003, Expert Group 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppeler 2010, (Schroder et al. 2013, Gielen and Secretariat IRENA 2012, Schwabe et al. 2011, Expert Group 1983, 1989, Bundesverband Solarwirtschaft 2014, Haas 2002, IEA and NEA 2015, Grau et al. 2014)		
The non-fuel operational cost of power plants by type	euro per MWh	(Expert Group 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppeler 2010, Expert Group 1983, 1986, 1989, IEA and NEA 2015)		
The market price of natural gas, coal, and diesel	euro per m^3 /ton/litre	(Kohlenstatistik 2013b, International Energy Agency 2013, C.A.R.M.E.N. 2015)	(International Energy Agency 2013, C.A.R.M.E.N. 2015, Department of Energy & Climate Change 2014)	(International Energy Agency 2013, C.A.R.M.E.N. 2015)
Electricity market price in wholesale markets	euro per MWh	(European Power Exchange 2016, European Energy Exchange AG 2016)	(Energy Solutions Commercial Energy Brokers 2015, Ofgem 2015, APX Power Spot Exchange 2015)	(Boots 2011, APX Power Spot Exchange 2016, Www.nordpoolspot.com 2016)
Electricity market price for industry and households	euro per MWh	(International Energy Agency 2013, Kohlenstatistik 2013b)	(International Energy Agency 2013)	(International Energy Agency 2013)
Electricity generation per year per technology	MWh	(Kohlenstatistik 2013a, BMWi 2016)	(Department of Energy & Climate Change 2015)	(Central Bureau of Statistics 2015)
Evolution of power plant capacity by technology over time	MW per year	(Bundesnetzagentur 2015)	(GOV.UK 2012), this study	(Sandbag 2014, EEX 2015, Enipedia 2015, Oosterheert et al. 1995), this study
Subsidies/feed-in tariffs per technology	euro per MWh	(Mayer and Burger 2014, Lauber and Mez 2004, Sijm 2002, Fulton et al. 2012)	(University of East Anglia 2010, 1999, Renewable Energy Foundation 2013, Ofgem 2014, 2016, Gipe 2009)	(Rijksdienst voor ondernemend Nederland 2015, Rijksoverheid 2009, Rijksdienst voor Ondernemend Nederland 2013, Lensink et al. 2011, SenterNovem 2008)
Generation technology load factor	%	(Expert Group 1983, 1989, 1992, Fraser et al. 2005, Salvadores and Keppeler 2010)		
Generation technology efficiency	%	(Expert Group 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppeler 2010)		
Construction time of power plants	Years	(Salvadores and Keppeler 2010, Fraser et al. 2005, Bertel and Pfaffenbarger 1998)		

After the time-series datasets are checked for quality a final *pre-processing* step is carried out to convert the series in appropriate unit values. All energy units are converted into the international system of units value of joules. The conversion factors for energy are taken from the U.S. National Institute of Standards and Technology guide for the use of the international systems of units (Thompson and Taylor 2008). In case of currency conversions all values are converted into euro's or European Currency Unit equivalents (ECU's). The ECU is a common currency basket unit of account for Western-European countries that preceded the euro and was instituted in 1979. Upon introduction of the euro in 1999 the value of one ecu was equivalent to one euro. Any national currency value data prior to the euro area is as such converted into euro/ecu using the Eurostat exchange rate table, which contains historical national currency exchange rate values into ecu/euro from 1971 onwards (Eurostat 2015).

Also a new dataset was generated based on realisations of power plants in the empirical record. This dataset is based on the records for the first year of operation of power plants, which is transformed to the initial year of the investment decision based on the construction period for each technology. The transformation is carried out because the market conditions that were valid at the time of investment, and thus based on which an investment decision was taken, could have already been changed substantially by the time the power plant becomes operational.

A raw dataset spreadsheet and a pre-processed spreadsheet is maintained for each case. The spreadsheets are maintained in a private Github environment for version control purposes, so as to enable secure *storage, backup and version control* including the possibility to roll-back datasets. The *documentation* of the datasets themselves, in their interpretation of observed trends and presentation, is incorporated in the dedicated **chapter 6**, which aids in strengthening the interpretation of the analyses. The resulting descriptive data analysis describes for each country an overall overview of the time-line of changes and events, and presents all datasets and observed trends found from visual analysis.

Finally, in line with new scientific standards, the final datasets used in the analysis of this thesis are published via the open source Harvard Dataverse Depository (<http://dataverse.harvard.edu>), which is based on a Creative Commons Zero (CC0) public domain dedication waiver. The Dataverse Depository uses a common data referencing standard (*Data Citation Harvard Dataverse* 2015). The repository also includes a database search possibility which aids to improve *accessibility and sharing* of datasets.

Table 12: *Thesis data management plan overview.*

Data management plan aspect	Approach taken
Data description	The data is described using a meta-data listing approach inside the data spreadsheets under a specific tab with the attributes outlined in table x above
Data format	The data is collected and maintained in Microsoft Excel spreadsheet formats .xlsx and where necessary for modelling converted into .CSV formats
Pre-processing	A standardized set of pre-processing steps are carried out for purposes of resolving missing data values, time-series discontinuities, outliers, duplicate values, as well as energy and currency conversions
Storage, backup, and version control	The data is stored on a hard-drive and a private Github version control environment whilst writing the thesis
Meta-data and documentation	In the spreadsheet a meta-data tab is maintained which contains dataset attributes, and sources of data. The data is documented in a specific data description analysis chapter 6 in this thesis
Access and sharing	Dataset spreadsheet are made accessible alongside thesis publication via Harvard Dataverse Depository under open-source conditions of Creative Commons zero (CC0)

5 Insights - Expert Interviews

The interviews summarised in this chapter were initiated to provide a real-life grounding of the thesis. Firstly, to assert

whether the modelling algorithms that were best able to reproduce the historical time-series for power generation capacity development, as presented in **chapter 7 and chapter 8**, are sufficiently grounded in reality. Secondly, to enhance the theoretical framework in **chapter 3** and assess if any specific factors that play a role in electricity sector investment are not missed. The results of the interview methodology within this context contribute to an answer to the following two sub-research questions described in **section 1.5**:

- *“Which power plant investment evaluation metrics provide robust results in reproducing historical generation capacity change in an electricity system model context?”*
- *“How can non-financial factors be captured in the modelling of project investment decisions?”*

The methodology was implemented in four interviews that were guided by the questions outlined in **section 4.3**. Since the number of interviewees, regardless of their experience, is a small sample of practitioners involved in power plant investment decisions, the results should be treated with caution as partial insights, and not be taken as definitive conclusions on the investment decision process. The following four experts were interviewed:

- **David Porter**, author of *Electricity supply: the British experiment* (Mereo Books 2014) and former chief executive of the UK Association of Electricity Producers (today Energy UK) from 1987 to 2012.
- **Andy Boston**, head of the UK Energy Research Partnership, formerly leading the Business Modelling Team at E.ON UK and part of the electricity market modelling team at PowerGen in the UK.
- **Jerome Guillet**, founder and Managing Director of Green Giraffe Energy Bankers, a top ranking global renewable energy project finance firm, formerly energy project finance officer at Dexia and Credit Lyonnais for oil & gas and wind energy.
- **Simon Robinson**, founder and Managing Director of Snell Bridge, a UK based financial advisory firm to the renewable energy sector, a finance associate to Scene Consulting, and formerly an Associate Director at Quayle Munro on renewable energy finance

The interviewees were chosen because of their different complementary expertises in the scope of investment decisions in electricity markets. The sets of expertises include firstly for one interviewee long-standing experience with providing investment decision information to the managerial level in large electricity companies based on electricity market models and project techno-economic financing appraisal. Secondly, extensive experience with the electricity market implications on investments from a company perspective in relation to regulatory change in representation of views to policy makers from the UK electricity industry. Thirdly, experience with the financial requirements to get investments off the ground within the EU from a corporate equity to banking debt perspective for large 50+ MW to GW scale fossil fuel and renewable energy power plants. And the set of expertises for the fourth interviewee is on financial investment requirements for kW scale community energy projects in the UK. All four interviewees thereby cover a different set of experiences and aspects of what factors play a role in power plant investment decisions.

5.1 The Investment Process

The standard power plant project cycle has been characterised as a staged sequential process, where an initial project proposal is followed up with a feasibility study, an engineering design, the procurement and construction phase, and finally commissioning and operation (**section 3.2**). The interviews highlighted a more specific set of steps that involves interrelations between various organisations. As summarised in figure 6 the process can be split into two types of investment decisions:

- The internal electricity company decision to go ahead with an electricity generation project. The decision is made by the company board who selects the project(s) to invest in among a series of competitive projects, based on the companies financial balance and equity evaluation. The set of project analyses presented to the board are prepared by internal company project teams.
- If the project needs to be financed in part or mostly by external loans, which is nearly always the case, the company needs to secure financing from one or more investment banks and/or other financing partners (e.g. pension funds, international finance institutions). The analysis is prepared by financial specialists from the company together with external project finance specialists, which can include a project finance team of the investment bank. The project finance consortium prepares the project's financial analysis, contracting details, and risk assessment, and present a package for deciding upon the loan closure decision to executives within the investment bank and/or external financiers.

The split investment decision also results in a split in responsibilities and risks between the company that will operate a power plant and the external financiers. Whilst the profits for the electricity company from its power plant investment project vary by the power plant's performance, its operational costs, and market prices, a bank has a fixed contract that needs to be adhered to with a fixed rate of interest and a coverage of operational and maintenance risk. As one of the interviewees stated *"For the bank debt coverage is the main aspect they care about. They might have some sort of target for current assets or net current assets or something like that. But really at the end of the day the only thing they are interested in is the Debt Service Coverage."*

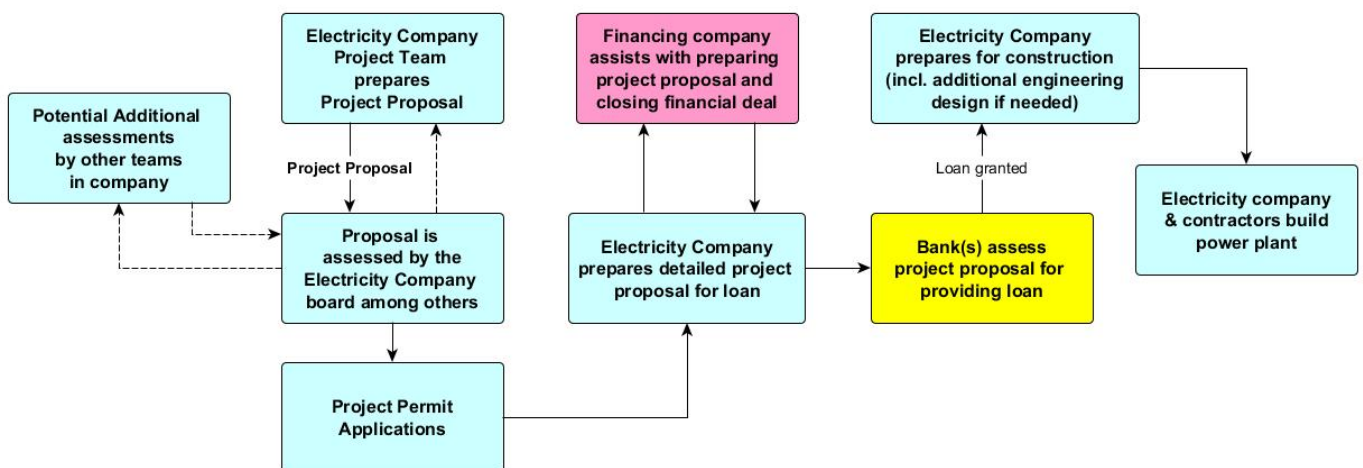


Figure 6: Investment Process within a power plant project cycle

5.2 The use of financial evaluation metrics

The interviewees all stated that the most used metric for company investment decisions in the electricity generating sector is the Internal Rate of Return based on a hurdle rate. As stated by one interviewee: *“The most popular one was the IRR of projects. The threshold value that a new project would get. So that was quite important for internal investment I would say. Payback period wasn’t really a useful concept within the company.”* In the words of another interviewee cost based metrics, such as the LCOE, are also used, but only for comparison purposes: *“In private sector investment it tends to be IRR, that is the main one. Cost of energy is an indirect one to make sure you are competitive to establish your assumptions.”* This was confirmed by another interviewee who stated that the cost based approach came out of regulation: *“When we were looking at American utilities an LCOE was a way that a utility could justify to the authorities that it was the best investment that it could make, but it came out of regulation. Regulation said that you have to find the cheapest sources of your power, so they would compare different power sources on an LCOE basis.”*

The process by which the IRR is assessed relates to a hurdle rate which is taken into account already before a project is forwarded to the company board. As described by an interviewee the rate varies depending on the riskiness of the technology: *“The board have in front of them a number of proposals for spending of capital. To get to the point before you get them to the board you have to pass a hurdle rate in terms of rate of return. It will have to be set higher for more riskier assets. I remember when we were developing wind it was a few percentage point higher than CCGT which we had been doing for 10 years at the time.”*

Another interviewee indicates that the IRR is mainly used by electricity companies to evaluate lending and investment in establishing a power plant: *“The IRR is on the equity side, the level of debt that you manage to reach and the cost of debts are just inputs into the IRR. the more debt you can raise the better your IRR in principle, but also the more risk you are taking because your deliveries are becoming more volatile. If debt takes the first 80% of your revenue than a 20% variation in a given year wipes out all your revenue in that year.”* This was confirmed by another interviewee who indicated that equity is evaluated based on IRR from a company perspective, whilst the party that provides the loan mainly cares about minimizing the risk of repayment of the loan and debt service coverage, measured via a debt service coverage ratio (DSCR). *“It depends on your perspective, if you are an equity investor then ofcourse you are interested in the IRR. If you are a debt investor the only thing you care about is getting paid back, you don’t care about the IRR. For a debt investor you look at down-side scenarios where they can think about the circumstances that enable the project to repay its loans”*

The more complex approaches that focus on probabilistic assessments for inclusion in financial evaluation, such as real options assessments, were explained by one of the interviewees to be too complex for the executive decision makers. They were not fitting well into corporate decision processes: *“We built a series of models that could run together...This took three of us a year to do, four of us a year, it was four man years. We wrote this fantastic model, and what came out of this was probabilistic price distributions. We were pleased with that. The frustrating bid was that when it came to an investment, the financial people had no understanding of this. The accountants were well give me a number, what is the IRR. We would state it is a distribution like this, so that was no good they wanted a single number, and we just gave them a mean. That lost all the value of what we had done with all the clever stuff. Because they, the people involved were not used to that, they could not cope with distributions. Their thinking was does it pass a hurdle rate or not? If you said I will give you three numbers, the quartiles, or the median or whatever. They still came back with what is the number we should use?”*

5.3 The approach to deal with risks

The aspect of uncertainty and risk was from the interviewees perspective different to the type of technology investment, because different market rules apply per technology in todays markets: *"The specifics of renewable energy are quite different than for baseload power generation, because of a fairly simple and straightforward revenue regime. The business model is pretty straightforward, you build it and the power will be produced and you know at what price you are going to sell it. For other power plants you are presumably going to sell at the wholesale market, so you need to make a lot of assumptions about prices and what kind of usage, is it going to be baseload, part-load etcetera, today that is pretty hard given that the market is changing fairly rapidly."*

The difference in rules for renewable electricity was explained as being a reasonably recent development since the 1990s by one of the interviewees, which is in line with the historic country developments as discussed in **chapter 6**. On the new set of financial support rules in electricity markets the interviewees stated: *"Companies that invested in the industry most of their investments were in the safe space, they were always prepared to do a little bit in the more risky space, but what happened was that the risky part seemed to grow. You know building a gas fired combined cycle power station is well understood, its a process that many people have gone through. It is reasonably quick and we have got quite a lot of experience in it. Building an offshore wind farm is different, it seems more normal now, but it is not the same risks. We were being asked as the industry to do more of this higher risk stuff and less and less of the other."*

A key distinction of risks was distinguished between macro-level changes in market regulation and events, and those that relate to individual projects. The main approaches to deal with risks for macro-level changes was discussed from a political discussion and scenario development perspective. One interviewee described the scenario approach as: *"There was a lot of, and there still is, a lot of reliance on scenarios. So companies, or the companies I worked for generally, had four or five scenarios. And investments were tested against those five. So the IRR gave you a simple picture, each scenario had this. And then the criteria used to be it has got to be over the hurdle rate in three of the five scenarios, or four of the five scenarios. That tended to be the way risk was dealt with."* Another interviewee discussed the effort to influence the political arena to provide sufficient financial backing for desired market changes as a means to adjust risks of political changes: *"Even if you the government want us too, you want us to build particular types of power stations. You tell us they got to be low carbon. You tell us that the EU emissions trading scheme is the flagship policy and the carbon price will rise and that will make the sort of investments you want viable, it will make them competitive. But there is no sign of it really rising. And if you the government don't do something, we are just going to sit here and wait. And it was quite a strong argument. I suppose I ought to say as long as you believe that the UK reducing carbon emissions is an important thing, it was a strong argument. And the government said o gosh we need to overcome your fears so we will reform the electricity market."*

One interviewee described that the major policy changes occur so rapidly, however, relative to the timeframe of investment in new power stations, that there is little that can be done by companies to adjust for political risks. As indicated by one interviewee the shift of support for Nuclear power in the UK over time was a consequence of electricity outages, and the shift in perspective over Russian natural gas exports: *"So in 2003 you have this white-paper, then the lights go out, not just in London they went out in Italy and Denmark and on the eastern seaboard of the US. Its panic. By 2006 just three years later, half the time to take a gas fired power station from a board decision to making electricity, it's no time at all in electricity investment. The same government no change of politics, same Blair government, we need new Nuclear power, lots of it. How much off it can you build? If you are relaxed about nuclear power, absolutely fine, but of course it affects everybody else. You are thinking about renewables, about gas, and now you want to favour this new technology what is going to happen to us?"* The blackout mentioned by the interviewee in the UK occurred on 28 August 2003 in London due to two transformer station faults, resulting in a 40 minute blackout starting at 18:10 BST. Large parts of the London underground transport network were not operational during this time period Graham-Rowe (2003).

The key aspect to dealing with project risks at the financial level was brought from the perspective of investment banks that provide the loan and seek to minimize risks. As stated by an interviewee: *"So if you are going to project finance you pretty much have to do what the bank says otherwise you don't get any debt. What banks do is if you are being aware,*

what banks definitely not do is they do not take risk. Banks hate risk. It is pretty well impossible to get anything project financed unless it has an O&M agreement from the OEM. The classic is Enercon, the wind-turbine manufacturer. They are very expensive, you could argue whether they are good or not in terms of performance. The reason that banks like it is because you can get a 15 year O&M agreement from Enercon which is nicely backed up with a decent warranty, decent provenance so the banks love it. “. The comment was corroborated in more moderate form by another interviewee: *“Some want to be operators of their own terms, some are happy to sub-contract this to third parties. The scope of the contract can be extensive, you can have full scope operation and maintenance contracts with the turbine manufacturer, or people who want to do it themselves and they just rely on the manufacturer for spare parts but not for full operations. That depends on the profile of the investor. Some actively want to be operators of their own plants, and some don’t, all is possible. “*

5.4 The incorporation of non-financial aspects

Non-financial aspects were found to play a role at two levels as emerged from the interviews. First, in shaping markets and the playing field of companies by means of government decision making. Government decisions in the energy sphere were characterised as influenced by three priorities which shift over time: *“We want prices as low as possible, we want security of supply, and we want to reduce carbon emissions. They have been the same for years. If you don’t look very hard then you think oh yes they have, so it’s all very stable, you know. Because they change the order of priorities. Sometimes very openly. And sometimes it’s more subtle, it’s just below the surface changes, priority. And that causes difficulties for investors, just as much as a piece of legislation does”*. Electricity market companies thereby follow such policy priorities in how they inform changes in the regulatory framework that needs to be adhered to, and how this affects investment decision rules, in the present and in relation to potential future adjustments in market regulation.

Second, companies take into account non-financial factors within the investment decision process as soon as the financial hurdle rate has been met or the project is close to the hurdle rate. As indicated by one of the interviewees: *“then the board were presented with the different options, a coal power plant that will make you 12%, a wind farm that will make you 17%, or whatever. It won’t necessarily be that we go with wind because that has a higher rate of return, because that already meets the threshold you have set. This is when it gets a little less scientific, because you may really want to move into a certain direction, take a look at the numbers again, see if you can get the numbers stack up a bit better. And there is sometimes an iterative process. The company philosophy counts in certain technologies even when the hurdle rate doesn’t always make it, so it looks good in front of the board when we get that. And that is less scientific because you are then trying to weigh the whole argument towards a particular asset.”*

A part of the aspect of non-financial factors relate to the strategy and image of the company from the customer’s perspective according to one of the interviewees: *“Yes there is, and that is where I said much earlier in our discussion I tried to explain why companies went ahead with certain investments even though they might have known that there were unintended consequences coming from them. There is also the question of what goes in the annual company report and the corporate social responsibility stuff, and they like, just look at the pictures, they like to show that they have got people involved in photovoltaics and wind-power and what have you. So there is a certain amount of satisfying the customer, but they need to be very careful about that because the great majority of customers, in my view, are interested first of all in the lights staying on and second in the price not being too high.”*

One of the non-financial factors that was identified to potentially playing a role in investment decision making, which is missing in the framework in **chapter 3**, was the impact of the personal identities by the main decision makers. *“The CEO’s would start talking to each other, narrowed it down to a target. What was interesting was that at that point the personalities came into play. It was less about the financial stability of the company you are taking over but did the CEO’s actually get on with each other...That was an extreme example, and that took probably six months of evaluation, and then was thrown away as we saw it from our team within a week.”* This type of factor is highly challenging to capture in electricity system models, however, since it is a micro behavioural factor that is difficult to capture in model logic. A possible implementation could be to use a random factor that encompasses such factors, either as part of a direct representation of an investment decision in a simulation approach, or as a slight random adjustment from a solution in an optimisation approach, which could be operationalised through the modelling to generate alternatives (MGA) approach (DeCarolis 2011).

5.5 Summary

The interviewees expressed that a profit driven approach using a minimum Internal Rate of Return is the overriding decision metric used in internal company decisions for investments. Since NPV and IRR are mathematically similar both metrics are a good approximation of real life decision approaches. The interviews also revealed that the maximisation of NPV or IRR is only a partial representation of the financial aspect of investment decisions in the electricity sector. First, the investment decision can be split into an internal company decision based on an internal hurdle rate, and a financing process to obtain loans from banks for a project based on a debt service coverage ratio. And second, there are different financial incentives at these two decision levels, with a minimum IRR used in internal company decision for investments, and debt service coverage for banks. Third, the interviews revealed that the real life approach is not based on a maximisation of investment as such, but on a minimum threshold IRR approach that needs to be met for an investment decision to be approved.

The incorporation of non-financial metrics was explained in the interviews as playing a second decision role in the company decision making process, once a financial hurdle rate is passed. The key non-financial aspects that emerged related primarily to political risks in the form of sudden changes in market regulation, and that investments that at present may be less financially promising, could be more promising under particular market regulatory adjustments, and vice versa.

As the main way to gain insights with such risks at the project level a scenario approach was highlighted, to test potential changes in fuel prices, market regulation, or electricity demand. The key way to minimize the impacts of risks that was mentioned was to encase them in contracting requirements as far as possible, as a part of the lending process, such as for fiscal support mechanisms and operation & maintenance arrangements, which cover risks by the electricity company or other third parties. In case of non-compliance by the counterparty then there is always the option left to pursue judicial means to cover the financial expectations covered in the contract.

6 Use Cases Descriptive Data Overview

In this chapter an overview of the collected electricity system data is presented. The data in the chapter was used to carry out the statistical analysis in **chapter 7** and the model implementation of investment decision strategies in **chapter 8**. The description is split into the different countries starting with Germany in **section 6.1**, followed by the United Kingdom in **section 6.2**, and finally the Netherlands in **section 6.3**. The overview for each country includes a timeline for political decisions shaping electricity markets, and country specific changes in power plant capacity, electricity prices, electricity demand, and power plant costs. Each section ends with a summary of trends in the countries electricity sector. In the next part of the chapter in **section 6.4** statistics used for power plant investment cost and operations and maintenance cost are described, as these were implemented with only slightly differences between the three countries. Subsequently, the data used in a modelling assumption on excess generation capacity on top of what is demand is introduced in **section 6.5**. And finally, the datasets utilised to extend the TEMOA model runs of chapter 7 up to 2046 is presented in **section 6.6**.

6.1 Germany Electricity Sector Statistics 1980 - 2013

6.1.1 Overview of thirty years of German electricity policy, capacity and market changes

The German electricity sector at the start of the 1980s was constituted by a large number of public utility companies, the largest of which VEW, and a few private corporations, of which RWE founded in 1889 was dominant. Private corporations were active in numerous industries, one of which was electricity generation. Typically companies were vertically integrated combining the production of coal with its use in power generation. The continued prominence of coal in the generation mix at the time had its roots in large-scale political support for the German coal industry. Historically, Germany was a large coal producing nation utilising hard and brown coal for heat, steel production, and electricity generation. However, in the 1950s the German coal industry began to be out-competed by lower cost coal exports from the US (Storchmann 2005).

In response to US competition, various regulatory and financial instruments including mandatory purchases of coal by electricity providers, were instituted in the 1950s to support the German coal industry, in agreements between the public and private industry and the federal government. Two decades later in 1973 direct support to electricity generated from coal was instituted, in the form of the *kohlenpfennig*, or “coal penny”. The subsidy measure provided direct coal generated electricity price support between 5% to 8.5% of the total price level. The introduction came on the back of political pressure from the oil crises of 1973 among a wave of energy security concerns. Also long term hard coal use agreements were signed in the late 1970s between VEW as a generation company and RWE’s coal mining arm. This established more stability as several of VEW’s coal mines had closed in the 1950s and 1960s due to US competition (Funding Universe 2015, RWE 2010).

The rapid rise of nuclear power in the 1970s to 1980s resulted in it becoming the second largest source of power generation. Close to 9 GW of capacity was built in the 1970s by public companies, which was fully supported by the federal government based on the expectation that this relatively new form of power supply would provide a cheap and secure form of electricity as a cornerstone of the German economy. Further expansion of nuclear power and hard coal defined the developments in the 1980s in the electricity generation industry. Hard coal use from German coal mines was mandated following the second oil crisis of 1979-1980. In the government’s Third Power Generation Act the prescribed targets for yearly coal inputs in power generation were also increased (Storchmann 2005). The new targets were supported with domestic financial redistribution policies to power generation companies, and paid for by the *kohlepfennig* electricity levy. New natural gas generation capacity played a smaller role, which was fueled by imported gas from the 1970s from Denmark and the Netherlands, after the rise of natural gas production in these countries (Högselius et al. 2010). A total natural gas power generation capacity of 8 GW was built in the 1980s, versus only 0.4 GW built in the previous decade. The remainder of power generation capacity at the time was composed of hydro-power and fuel oil generation.

The public company VIAG which was active in aluminium and electricity production was privatized in several steps leading to fully private ownership in 1988, after the federal government sold its remaining shares. Prior to privatisation the company had largely expanded its nuclear power share which dominated 70% of the companies power generation portfolio by 1988 (Reference for Business 2010). Electricity transmission interconnection from/to neighbouring countries was started with a first direct electricity transmission connection from the German Ruhrgebiet to the Netherlands (Funding Universe 2015).

After the Chernobyl nuclear disaster in Ukraine in 1986 nuclear power expansion came to a standstill, as a consequence of the large increase in nuclear risk perception and opposition in the country. The German public both in East and West Germany was exposed to radiation impacts and several foodstuffs were temporarily banned, such as milk and vegetables, given their radioactive content following the dispersal of radioactive particles by air from the Chernobyl site (Stichting LAKA 2012, The Editors 1986). Already since the advent of nuclear power in the 1960s opposition had grown in Germany including large scale protests in 1977 and early 1980s over concerns of nuclear waste, the risk of accidents, and water temperature impacts, which culminated into a public change of support and the end of nuclear expansion (Flegel 2010). The government, led by the at the time pro-nuclear Christian Democrats which won the 1986 elections, supported

finalization of the three nuclear plants under construction, yet halted licensing of any new power plants, due to which the last nuclear power plant built in Germany started operations in 1989 (Appunn 2015).

The 1990s witnessed an expansion of primarily brown coal and natural gas based power generation, and the introduction of the first wind mill parks of some significance in the country. New natural gas power plants were built based on the technologically advanced Combined-Cycle Gas Turbine design (CCGT) which became the technology of choice, as it made much more purposeful use of hot gas-turbine exhaust thereby increasing fuel to electricity conversion efficiency to 45%+ (IEA ETSAP 2010). In the 1990s also government support for renewable power sources was introduced which significantly increased their financial viability from an investor perspective.

The first Feed-in-tariff (FiT) for renewable electricity sources was introduced in 1990 under a law called the *Stromeinspeisungsgesetz* (StrEG), which resulted in the take-off of wind power as a source of significance, with 1.5 GW of capacity installed by 2000 as a result. A key component of the law was priority access for renewable energy generators to the grid and guaranteed sales. The second component was the fixed nature of the FiT instituted with an undefined duration provided by a % levy on the end-customer electricity price. The introduction of the law was influenced by the Chernobyl disaster in 1986, the increasing concern over climate change starting in the late 1980s, and scrutiny of the viability of state support for coal by the European Union (Laird and Stefes 2009). The *kohlenpfennig* was abolished in January 1996 as a consequence of a European court ruling in 1994 deeming it unconstitutional. However, state subsidies for coal extraction continued directly from the government budget until 2002, after which a new lower cost direct subsidy scheme was introduced after approval by the European Union that lasted until 2010 (Storchmann 2005).

In the development of nuclear energy a key event was the unification of West and East Germany in 1991 after the fall of the Berlin wall and the collapse of the Soviet Union's political structure. As a consequence of the reunification all nuclear power plants in East Germany were closed because they were not outfitted with the safety systems that upheld the former West-German state law standards. The required retrofitting of safety measures for these power plants was deemed impossible by the central authority for the safety of nuclear energy (CEA) (Milhem and Heuser 1993). The closed pressurized water reactors, of the Soviet water-water energetic reactor (WWER / VVER) design, included the Rheinsberg Nuclear Power Plant of 62 MW commissioned in 1966, and the Greifswald plant with a capacity of 2.2 GW commissioned in 1974. Also the Stendal plant under construction at 4 GW of generation capacity was halted and dismantled (Associated Press 1990). Other nuclear power plants deemed safe were kept operational. In 1998 after the Social Democrats (SPD) gained government power together with the green party, which both were opposed to nuclear, a new policy was instituted in collaboration with the large utility companies. The lifetime of existing nuclear power stations would be limited to 32 years due to which the last nuclear plant had to be closed by 2022 (Appunn 2015).

In the 1990s also the process of electricity market liberalization into a fully privately owned market was started at the behest of the 1997 European Union directive on the electricity market. The entire German retail electricity market was opened to liberalization in 1998 with the *Energiewirtschaftsgesetz* (EnWG). At the time a total of 80 regional and 900 municipal utility companies were active, of which eight dominated the market with a 79% production share (CPB Netherlands Bureau for Economic Policy Analysis 1997, Funding Universe 2015). Prior to liberalization these operated based on direct contracting based in supply areas within the region of operation, resulting in many small territorially bounded monopolies, due to which a competitive market was absent (Sioshansi and Pfaffenberger 2004). The new law enabled any firm to enter the electricity production market, any household to choose its own supplier, and it enabled negotiations of third party grid access. The unbundling of networks and generation was part of the law but its implementation was not enforced (Sioshansi and Pfaffenberger 2004).

After the turn of the century a period of consolidation followed that led to today's German electricity giants, and the increasing growth and support of renewable energy as the 'EnergieWende', with the aim to transform Germany's electricity generation mix into a renewable energy based system. In the year 2000 the merger of VEBA and VIAG led to the creation of the electricity giant E.ON (E.ON 2015). In the same year RWE merged with the public utility giant VEW, such that both E.ON and RWE at the time owned over 50% the German power plant capacity. Subsequently, the three municipal utilities HEW, BEWAG and VEAG merged in 2002 into Vattenfall Europe. Today of the large electricity

companies only EnBW AG in South-West Germany is majority state owned. Together RWE, E.ON, EnBW, and Vattenfall owned 67% of German power generation capacity in 2013 (Heddenhausen 2007, Appunn and Russell 2015). The market structure was also significantly altered as a consequence of liberalization, with a shift from negotiated to regulated third party grid access in 2004 together with the institution of a federal regulator (Sioshansi and Pfaffenberger 2004, Yajima 2006).

A policy of a nuclear power phase-out by the year 2022 was institutionalized into law in 2002 by the SPD government under the Atomgesetz (AFP 2002). Two nuclear power plants Stade at 0.64 GW and Obrigheim at 0.34 GW were taken offline in 2003 and 2005. A decision that came under heavy criticism of Angela Merkel, who at the time was chairwoman of the Christian Democrats (CDU) (Appunn 2015). Not surprisingly, given their pro-nuclear stance, the CDU when it came into power in 2009 reversed the prior anti-nuclear position, and adjusted the law by extending the intended operating time of existing nuclear plants by 8 to 14 years, beyond the earlier 2022 phase-out period (Appunn 2015). A position that was itself reversed after the Fukushima nuclear disaster in Japan in 2011. In its wake the German CDU/FDP government decided to revert to the phase-out all nuclear power back to 2022, whereby six older nuclear plants would be shut-down by 2021 at the latest, and the three most recent built plants by 2022 (BBC NEWS 2015). In the industry, Siemens, which had built all seventeen of Germany's nuclear power plants in operation or closed to date, announced stepping out of the nuclear energy industry altogether, from its previous position prior to Fukushima of supplying only non-nuclear parts to nuclear power plant projects (BBC NEWS 2011).

Near the end of the 20th century further changes were made in the renewable energy support structure. The amount of obligatory renewable energy purchase was capped at 10%, new targets were instituted to generate 12.5% of electricity from renewable sources by 2010, and a 100,000 solar roof program was initiated in 1999 following-up from the earlier 1000 roof program (Laird and Stefes 2009). Renewable energy finance support gained a large boost in 2000 where the earlier Stromeinspeisungsgesetz (StrEG) was replaced by the Erneuerbare Energie Gesetz (EEG) law, which introduced a fixed-tariff (FiT) remuneration of 20 years to increase investor security, and a higher FiT which varied by capacity size and location of renewable generation (Laird and Stefes 2009). In addition an in-built FiT decrease for new renewable electricity power plants was introduced based on a four year periodic re-evaluation of new technological developments.

Large-scale companies were also allowed to benefit from the FiT, such that the financial capital pool that could be utilised for renewable expansion was scaled in magnitude. The new policies led to a rapid growth of renewable energy in the electricity mix, especially solar-PV capacity and onshore wind electricity was scaled rapidly. Many additional adjustments on a relatively ad-hoc basis have been made since the new feed-in tariffs were introduced, such as the large-scale increase in solar-FiT in 2003 due to the end of the 100,000 roof program, and recent successive revisions since the 2011s in the wake of unprecedented decreases in solar-PV technology costs (Laird and Stefes 2009). The generous state support and technological advancement have led to an 13.6% share of onshore- wind and 7.5% share of solar-PV electricity in final power consumption in 2015 in Germany (Bundesministerium für Wirtschaft und Energie (BMWi) 2017, Arbeitsgruppe Erneuerbare Energien-Statistik 2017).

In addition to renewable electricity power generation, the second largest expansion since 2000 has been natural gas power generation, at approximately 10 GW capacity built. Few new coal power plants have been built since 2004 as a consequence of large scale public opposition, government climate change policies, and the phasing out of state support for coal extraction and generation.

6.1.2 Power Plant Capacity and Electricity Production

Since 1980 German power plant capacity grew from 94 GW to 184 GW in 2012. Capacity additions in the 1980s were dominated by coal power and nuclear generation, in the 1990s by natural gas and coal, and in the 2000s by natural gas, onshore-wind, and solar-PV, as shown in table 13 and figures 7 and 8 below. These additions did not translate into an equivalent increase in electricity production per source, however, due to significant operational differences between technologies. First, the ability of technologies to only provide baseload (coal, nuclear) versus load at high-demand peaks during the day (natural gas), given the ramp-up and ramp-down speed of power load between these technologies. Second, variation in provided load across technologies due to intermittent energy inputs (wind, solar-PV).

As shown in figure 9, and table 14, coal based power dispatch dropped from a high share of 63.3% in the 1980s to 42.5% in the late 2000s, natural gas first decreased from a 9.7% share in the early 1980s to 6.2% later in the decade, to a subsequent increase to 13.9% in the late 2000s. At the same time Nuclear power increased to a high of 29.9% in the 1990s and dropped to 21.4% in the late 2000s, whilst onshore wind, solar-PV, and biomass all increased from nearly zero in the 1990s to respectively 6.7%, 4.5%, and 1.7% electricity mix shares in the late 2000s. The only source whose share remained stable across the three decades has been hydro-power fluctuating between a 3.7% and 4.5% power share, due to capacity expansions advancing in parallel to electricity consumption increases.

Table 13: Germany power capacity additions in GW per source from 1980 to 2011

Power Source	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011
Brown Coal	1568	1762	698	241	3443	2676	42	90
Hard Coal	3205	6023	2559	1674	349	123	255	51
Offshore Wind	0	0	0	0	0	0	0	108
Onshore Wind	0	0	0	186	1306	3533	3111	1690
Natural Gas	834	408	448	1518	2642	1810	4129	3901
Oil-fired	248	0	36	302	309	0	80	144
Biomass	0	0	48	0	89	378	369	135
Nuclear	2165	8386	4457	0	0	0	0	0
Hydro run-of-river	83	208	73	87	0	0	0	71
Hydro Pumped	1383	0	153	0	0	0	1052	525
Hydro Dam	500	0	0	0	0	0	0	0
Solar-PV	0	0	2	6	24	403	3735	20869
Waste Incineration	127	123	73	77	294	70	256	365

Source of data: (Bundesnetzagentur 2015), this study

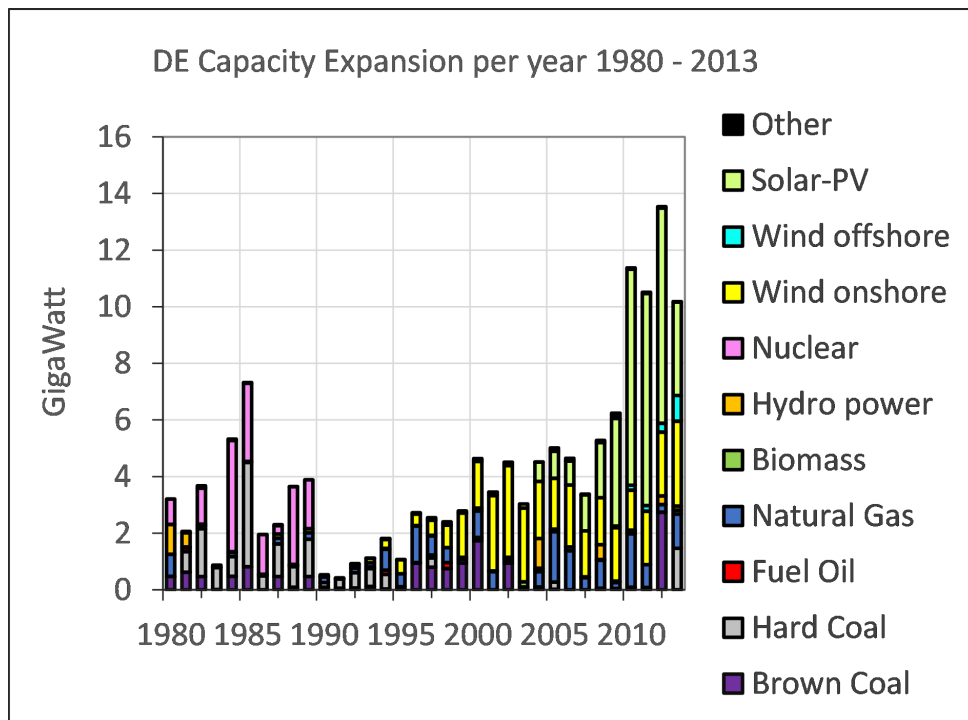


Figure 7: Germany power capacity installation by technology type in MW of capacity per year from 1980 to 2013. Source of data: (BMWi 2016).

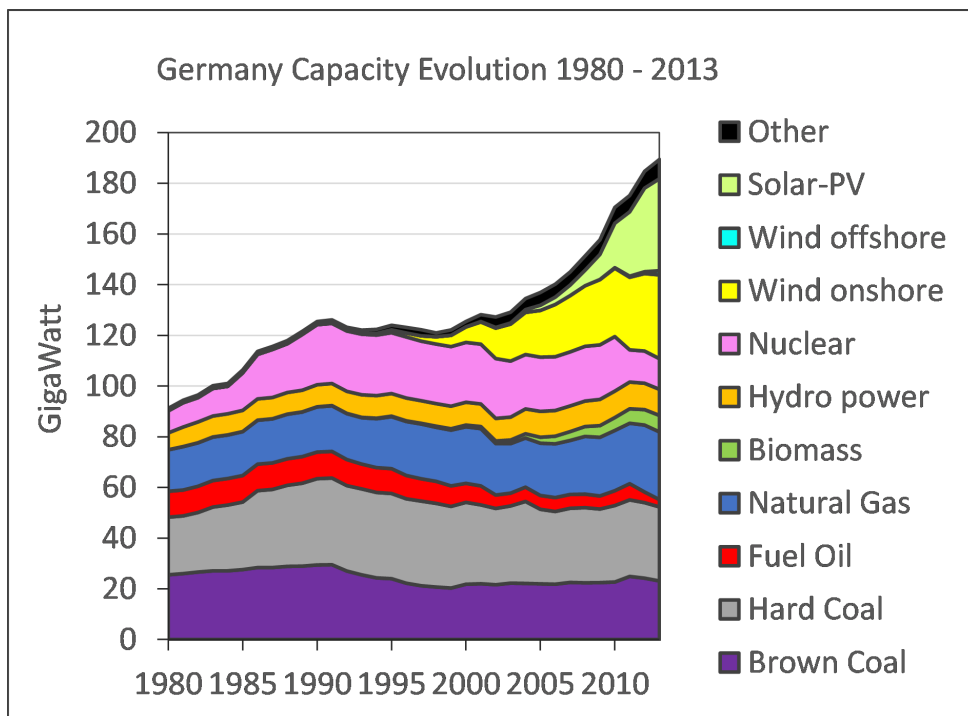


Figure 8: Germany power generation capacity in GW from 1980 to 2013. Source of data: (BMWi 2015, 2016).

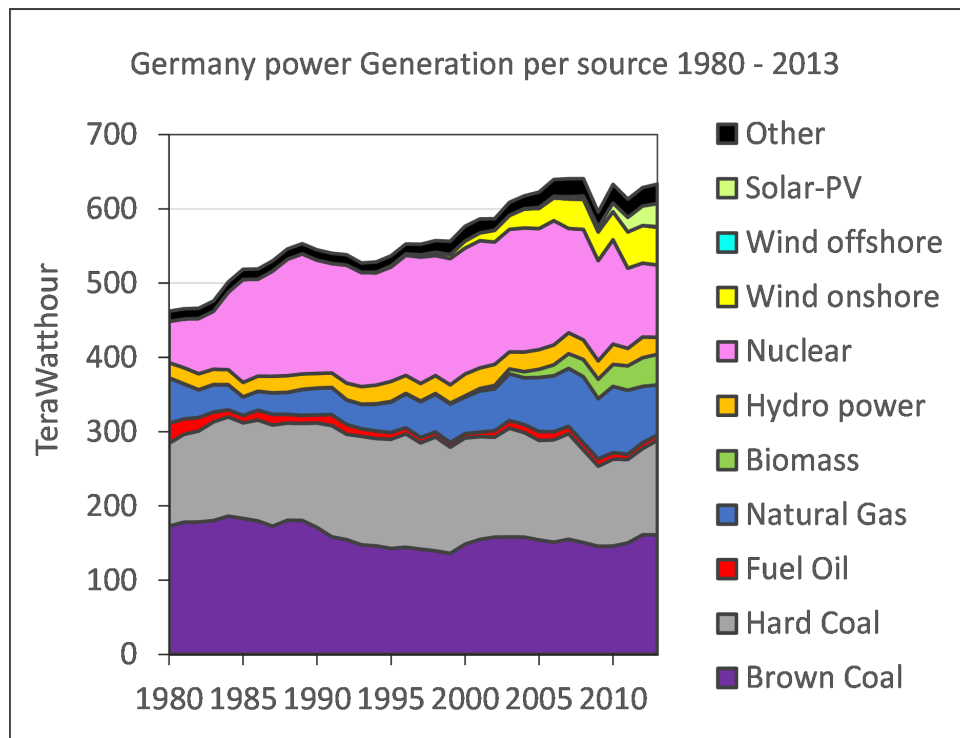


Figure 9: Germany electricity generation in TWh from 1980 to 2013. Source of data: (BMWi 2015, Kohlenstatistik 2013a).

Table 14: Germany power production shares in electricity mix by generation sources from 1980 to 2011.

Power Source	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011
Brown Coal	37.6	34.6	31.4	27.7	25.3	26.3	24.5	23.9
Hard Coal	25.7	25.7	25.1	27.2	26.7	23.9	22.0	18.6
Oil fuels	4.2	2.3	2.2	2.0	1.3	1.3	1.7	1.4
Natural Gas	9.7	5.4	6.2	6.7	8.8	9.5	11.5	13.9
Nuclear	14.5	24.7	28.1	29.0	29.9	28.4	25.3	21.4
Hydro	4.5	4.0	3.7	4.6	4.4	4.6	4.3	4.1
Wind (onshore)	n/a	n/a	n/a	0.2	0.7	2.3	4.9	6.7
Biomass	n/a	n/a	n/a	0.1	0.2	0.7	2.1	4.5
Solar-PV	n/a	n/a	n/a	0.0	0.0	0.0	0.3	1.7
Total other	3.8	3.4	3.3	2.5	2.7	3.0	3.4	3.8

Source of data: (Kohlenstatistik 2013b, BMWi 2015), this study.

6.1.3 Electricity prices, fuel prices, and market support

The German electricity price for **industrial consumers** excluding taxation has since the 1980s ranged between a low of 12.2 to a high of 23.3 euro per GJ of electricity, as shown in table 15 below. The price fluctuated around 19 euro per GJ in the late 1980s to early 1990s, after decreasing slightly in the late 1990s and more significantly in the early 2000s to below 14 euro per GJ. Since then the price has increased again to new highs to a level around 22 euro per GJ. The price for **household consumers** excluding taxation has ranged between lows of 20.9 to highs of 44.8 euro per GJ of electricity. The price rose from its lowest point in the early 1980 to a stable level around 30-33 euro per GJ in the late 1990s to early 2000s, after which it increased significantly towards 40 euro per GJ in the early 2010s.

Electricity price changes excluding taxes are to an extent a consequence of coal and natural gas price changes because of their large share in power production, as shown in table 14 above. The price of coal decreased from 3 euro per GJ in the early 1980s to 1.5 GJ in the mid to end 1990s, after which prices increased steadily to a level between 3 to 4 euro per GJ in the early 2010s. The change in the coal price was largely influenced by government regulation, which led to internal market coal price-setting to be competitive with the import coal price from 1976 to 1996. Natural gas prices initially increased up to the mid 1980s to 3 euro per GJ after which they declined to around 2 euro per GJ up to the late 1990s, rising steadily to 5 euro per GJ in the early 2010s.

Table 15: Electricity and fuel prices for Germany from 1980 to 2013 excluding taxation in euro / GJ of LHV heat or electric content.

euro / GJ	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011	2012-2013
Electricity wholesale	n.a	n.a	n.a	n.a	n.a	n.a	14.3	15.2	12.5
Electricity Industry	16.4	19.1	19.3	19.1	16.9	14.1	19.8	22.4	21.6
Electricity Households	25.4	29.3	30.4	32.3	34.0	34.0	41.6	38.3	40.7
Coal for Power Plants	2.9	2.5	1.8	1.5	1.5	1.8	2.4	3.8	3.4
Natural Gas for Power Plants	2.6	2.9	1.9	2.0	2.1	3.0	4.0	4.7	5.2
Fuel Oil for Power Plants	4.1	3.6	2.1	1.9	2.0	3.1	4.5	7.2	9.7
Biomass - wood chips	n/a	n/a	n/a	n/a	n/a	4.8	6.0	8.5	9.7

Data sources: Electricity wholesale (European Power Exchange 2016, European Energy Exchange AG 2016), Electricity Industry (International Energy Agency 2013), Coal for Power Plants (Kohlenstatistik 2013b), Natural Gas for Power Plants (Kohlenstatistik 2013b), Fuel Oil for Power Plants (Kohlenstatistik 2013b), Biomass - wood chips (C.A.R.M.E.N. 2015)

The impacts of fuel costs on electricity costs, F_c , can be measured as a percentage contribution of fuel cost per energy source, $k = 1, 2, \dots, n$, per MWh electricity produced as per formula (64) below. The contribution is calculated here based on a the fuel price, F_p , multiplied by the share of the studied power generation source in the electricity mix, P_s . The calculated value is divided by the electricity price, E_p , which before division is first converted to a thermal energy equivalent value by a multiplier, ε , that represents the inverse of the average power plant fuel to electricity conversion efficiency. The efficiency value is an approximation as efficiency changes as a consequence of peak balancing, such as for natural gas, is not taken into account. On the basis of this calculation the percentage contribution of fuel costs to electricity prices excluding direct taxes are shown in figure 10 below, for household and industrial consumers.

$$F_{c_k} = \frac{P_{s_k} F_{p_k}}{\varepsilon_k E_p} \quad (62)$$

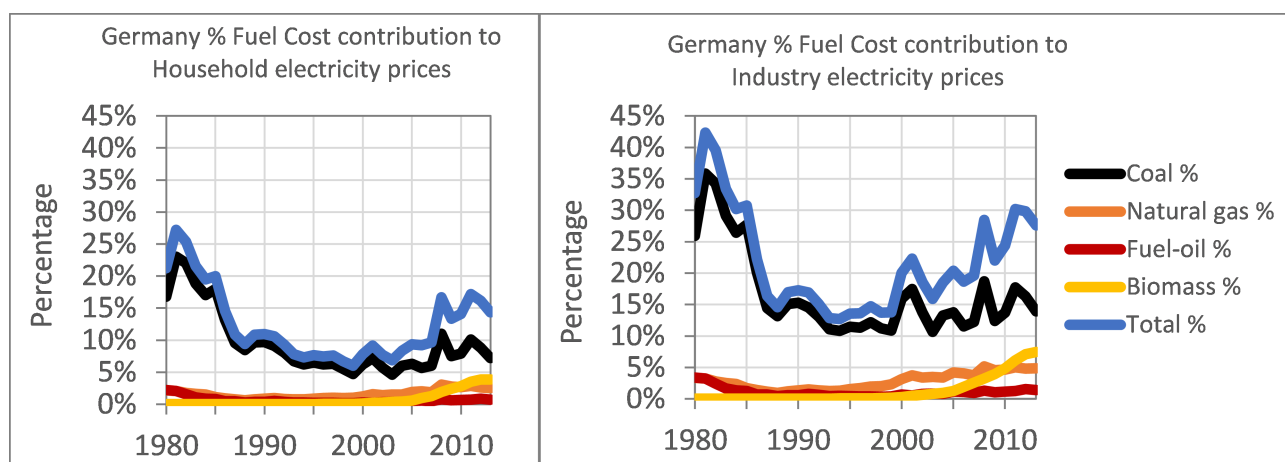


Figure 10: Germany approximate contribution of fuel costs to household and industry electricity prices without taxes for total fuels, natural gas, coal, crude oil, and biomass 1980 to 2013. Source of data: (C.A.R.M.E.N. 2015, Kohlenstatistik 2013b, International Energy Agency 2013), this study.

The value of electricity prices has changed substantially over time due to government taxation on top of producer price levels. Electricity taxation schemes have been instated for various user types, with key differences between industrial and household consumers. Another four sub-taxation categories exist for these two types as classified by usage rate, which are not included in this section for tractability reasons.

Taxation levels for industrial users rose from 0.7 euro per GJ in the early 1980s towards a stable plateau around 1.5 euro per GJ from the late 1980s up to the mid 2000s, after which tax costs rose seven-fold, as shown in table 16 below. Similarly, household electricity taxes fluctuated between 4 and 6 euro per GJ from the 1980s to the mid 2000s until a rapid seven-fold increase towards the early 2010s. The main cause of this rapid increase has been the cost of Feed-in-Tariffs (FiT) for renewable sources in the country due to the rapid absolute uptake of these sources, especially solar-PV and wind energy, as described in **section 6.1.1**. The FiT rates for new renewable installations in euro per GJ of electricity are shown in table 17 below. These were instituted first in the 1990, at levels of 27.6, 24.5, and 9.9 euro per GJ for solar-PV, biomass + hydro-power, and wind, respectively. Whilst Solar-PV feed-in tariffs grew substantially to 103.8 and 150.6 euro per GJ in the late 1990s and early 2000s, the values for wind and biomass remained stable, and hydro-power FiT's decreased to 18.4 euro per GJ. Later in the 2010s solar-PV was heavily reduced to 57.6 euro per GJ, a feed-in tariff for offshore wind was introduced at 15 euro per GJ, whilst onshore wind FiT's remained stable, and hydro-power declined slightly.

In addition to direct electricity taxation also natural gas and heating/fuel oil taxation have contributed to electricity price values and fluctuations, albeit only marginally. The taxation level of both sources has gradually increased since the late 1980s, as shown in table 16 below. In contrast, Germany has never added any taxation to coal fuels due to its large coal mining industry, which instead has been supported with direct and indirect subsidies as described in **section 6.1.1**.

Table 16: Germany direct electricity and fuel taxation levels from 1980 to 2014 in euro / GJ.

euro / GJ	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011	2012-2014
Electricity Industry	0.7	0.7	1.5	1.5	1.6	1.6	1.6	3.6	11.2
Electricity Households	4.3	5.2	6.8	7.5	6.0	4.3	6.4	21.5	34.8
Coal for Power Plants	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Natural Gas for Power Plants	0.0	0.0	0.2	0.5	0.5	0.8	1.1	1.2	1.2
Fuel Oil for Power Plants	4.1	3.6	2.1	1.9	2.0	3.1	4.5	7.2	9.2

Source of data: (International Energy Agency 2013), this study.

Table 17: Germany feed-in price support for new renewable installations from 1991 to 2014 in euro / GJ of electricity.

euro / GJ	1991-1993	1994-1996	1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
Solar-PV	27.6	29.5	103.8	138.3	150.6	150.7	102.7	57.6
Biomass (0 - 20 MW)	24.5	26.2	27.2	26.5	27.7	37.1	48.3	51.1
Hydro-power (0 - 0.5 MW)	24.5	26.2	27.2	21.4	18.4	16.4	15.9	15.1
Hydro-power (0.5 - 5 MW)	19.9	21.3	22.1	18.3	17.4	16.4	15.9	15.1
Geothermal (0 - 20 MW)	0.0	0.0	0.0	24.7	36.0	39.1	56.6	63.4
Wind-onshore	9.9	10.6	11.0	9.1	9.0	8.8	8.9	8.8
Wind-offshore	0.0	0.0	0.0	0.0	0.0	0.0	15.0	15.3
Landfill gas (0 - 0.5 MW)	8.8	9.4	9.8	7.7	7.5	7.0	8.0	8.6
Landfill gas (0.5 - 5 MW)	7.2	7.7	8.0	7.7	7.5	7.0	8.0	8.6

Source of data: (Sijm 2002, Lauber and Mez 2004, Fulton et al. 2012).

6.2 United Kingdom Electricity Sector Statistics 1980 - 2013

6.2.1 Overview of thirty years of UK electricity policy, capacity and market changes

The electricity mix in the UK at the start of the 1980s was dominated by coal power generation at a 71% power generation capacity share, as a consequence of the long history of coal mining and use in the country. The second and third biggest sources of electricity generation were fuel oil and nuclear power stations, at respectively 12% and 10% capacity shares. A small number of natural gas and hydro power plants had also been installed in the country. Power generation and distribution at the time in England and Wales was managed by a public organisation, the Central Electricity Generating Board (CEGB), that was instituted as part of the Electricity Act of 1957. In Scotland power generation and distribution infrastructure was similarly managed by two public bodies, the South of Scotland Electricity Board and the North of Scotland Hydro-Electricity Board. The situation of public management existed since 1947 when electricity generation was nationalised by bringing the 500+ previously established electricity generating organisations under state control by integrating them into twelve regional electricity boards.

In the early 1980s the country via the CEGB initiated steps for a nuclear expansion program as developed by the new Thatcher government in 1979. The aim was to complete the UK designed Advanced Gas Cooled Reactors (AGRs) that were in an advanced planning and construction stage, and to initiate a new program to add 15 GW capacity of Pressurised Water Reactors (PWR) licensed by Westinghouse. The program was a response to anticipated North Sea oil and gas depletion and the 1970s oil crises. The program faltered in the course of the 1980s. Electricity privatisation had revealed that nuclear power costs were far higher than previously considered (Pearson and Watson 2010). The impact of the Chernobyl nuclear power accident compounded the issue by eroding the public support. The only new PWR nuclear power plant that was realised was the 1.2 GW Sizewell B plant commissioned in 1994. In the same period the new Thatcher government restructured the coal industry after it had gained new impetus due to the 1970s oil crises. The electricity industry was allowed to gradually import more coal abroad at cheaper prices, financial support was made conditional on restructuring, and international prices were taken as a benchmark for British coal prices (Turnheim and Geels 2012). Also proposals were made for further closure of British coal pits that were not competitive and were kept open at high cost. The changes led to the unsuccessful 1983/1984 coal miners strike to which the Thatcher government responded by ending all subsidies which resulted in a further down-scaling of the industry (Pearson and Watson 2010). The end of regulated dependence of coal was initiated in parallel to the privatisation of the British electricity industry. The process of privatisation began with the 1988 proposal for restructuring and privatisation, which was solidified into the Electricity Act of 1989. As a consequence the CEGB was split into four companies in 1991, National Power and Powergen who held the majority of fossil fuel power stations, Nuclear Electric which gained ownership of all nuclear power plants, and the National Grid which took care of electricity grid control and expansion. Also the South of Scotland Electricity Board was privatised into Scottish Power, the North of Scotland Hydro-Electricity Board into Scottish Hydro-Electric, and nuclear power plants in Scotland were taken over by Scottish Nuclear (Pearson and Watson 2010).

In the 1990s markets were created to enable private trading between suppliers and demanders of power on a short-term basis, so as to end fixed or long-term contract pricing. The electricity pool of England and Wales was instituted in 1990. It was based on establishing prices in 48 half hourly blocks over a 24 hour period, with bids to be placed 24 hours in advance. The settling of prices was carried out by National grid on the basis of a ranking from lowest to highest prices. One of the main concerns at the time was the large dominance of National Power and Powergen at the time which held the majority of power stations in the country, as such they were forced in 1994 to sell some of their power generation capacity. The second problem was the widespread use that continued after privatisation of bilateral long-term agreements between suppliers and demanders, due to which only a fraction of electricity sales was undertaken via the electricity pool (Pond 2006). In 1997 as the conservative government lost the UK elections and the Tony Blair labour government came to power, the electricity market was again adjusted. First, a one-off “windfall” profits tax was instituted, since the Labour government was of the opinion that the private electricity industry was generating excess profits under the systems in place. The tax transferred a total of 5.2 billion pounds from the private utility companies to the government (Porter 2014). Furthermore, the electricity trading system was restructured in 2001 and replaced with the New Electricity Trading

Arrangements (NETA) system. This also resulted in the inclusion of Scotland into the electricity trading market in 2005. The new system changed, among other aspects, bid pricing where all trades were now valued at the bid price themselves, as opposed to the most expensive traded bid before (e.g. marginal cost pricing), trading continued up to 3.5 hours before the period that was traded, as opposed to 24 hours in advance, and a self-dispatch mechanism was instituted as opposed to national grid scheduling on behalf of all generators (Simmonds 2002).

The main impact of privatisation and freeing up of technology choice was the increased investment in natural gas power plants, in particular new combined cycle gas turbine technologies (CCGTs). In total over the period from 1991 to 2005 over 40 CCGT power plants were built with a combined capacity of 24 GW. The large scale expansion has colloquially become known as the “dash for gas” by the British electricity industry. The expansion of CCGT slowed after 1998 when the government instituted an obligation that the heat from all new gas-fired power station had to be utilised in a Co-Heat Power (CHP) scheme, which made many locations for gas fired power plants less financially attractive (Porter 2014). In the same period the coal industry in the UK was further downsized with the closure of 31 out of 50 coal mines in 1992 by British Coal, which until 1994 was still under UK state ownership. The favour of natural gas over coal in this period of privatisation was further underpinned by the EU Large Combustion Plant Directive (LCPD), which introduced obligatory reductions in emissions of sulphur and nitrogen oxides. As a consequence coal fired power plants had to be equipped in the longer term with gas exhaust scrubbing and desulphurisation equipment (Pearson and Watson 2010). In overall the privatisation was seen as a success from an electricity price perspective, since prices for industrial and commercial users dropped by 30% between 1998 to 2005, and for domestic consumers by up to 17% (Pond 2006). A key cause of the electricity price decline was an over-expansion of capacity due to the large number of CCGT plants built, causing wholesale prices to drop significantly with the bankruptcy of a few power generating companies as a result. Also British Energy faced severe financial difficulties, the nuclear power company that was formed during privatisation that owned all nuclear power stations (previously called Nuclear Electric), which survived thanks to a one-off government loan (Porter 2014, Pearson and Watson 2010).

The introduction of renewable energy in the UK began with the institution of the Non-Fossil Fuel Obligation (NFFO) as a part of the 1989 Electricity Act. The mechanism required the network operators in England and Wales to purchase renewable and nuclear electricity. The obligation came with a subsidy that ranged from 2.7 to 7.5 pounds/MWh during the period of 1990 to 2001, when it was superseded by the Renewables Obligation (RO) in 2001. In total the NFFO had aided in achieving a 1.6% renewable electricity share by 2001, much lower than the anticipated target (Wood and Dow 2011). The funding for the subsidy was obtained by a proportional levy on fossil fuel based electricity collected by Ofgem, the regulating agency that was created in 1990, at initially a 10.6% levy at the start of the scheme, which dropped to 0.3% when it ended in 2001. A large part of the levy went to the nuclear power company British Energy, however, since much more nuclear power was supplied at the time than renewable electricity. The nuclear power company British Energy received up to 6.6 billion pounds from the levy in the period up to March 1995 (Pearson and Watson 2010).

It was not until the introduction of the Renewables Obligation (RO) in 2002 that the adoption of renewable electricity in the UK really started to take off. The aim of this mechanism was to reach a 10% share of renewable electricity for all UK electricity generation by 2010 (Connor 2003). The mechanism is based on a certificate scheme, where power generating companies are awarded with renewable certificates. The number of certificates awarded depends on the size of renewable energy generation capacity as determined by the electricity market regulator Ofgem. Every generator needs to meet a % of supply as set by regulation, which increases over time, and is known in advance. The amount of supply covered by Renewables Obligation Certificates (ROC), and thereby the amount of renewable electricity in the mix, has grown from 3% in 2002 to 9.7% in 2010 and 29% in 2016 (E.ON UK 2013). In the initial setup one Renewable Obligation Certificate (ROC) was awarded per MWh of renewable output, so as to remain technology neutral. The scheme was reformed in 2009, however, in response to falling 2.5% short of the 9.1% target in 2009. A banding system was introduced in the RO where particular technologies were favoured over others, such as offshore wind which received 2 ROCs per MWh or wave technology receiving 5 ROCs per MWh, as of 2010 (Wood and Dow 2011). The reform was underpinned by modelling exercises based on the new technology preference set ROC system, which had shown a 40% increase in renewable electricity generation deployment between 2009-2015 relative to the previous technology neutral system

(Wood and Dow 2011, Internal Company Team 2007). The price setting for ROCs is based on two mechanisms. First, a buy-out market, where if suppliers do not have enough renewable capacity to serve their obligation they need to make a payment per MWh into a fund. The earnings of the fund are paid out to generators in proportion to the ROCs they own, creating an incentive to own more ROCs than strictly needed. The buy-out price is set within the regulation and has grown from 30 pounds/MWh in 2002 to 44.3 pounds/MWh in 2016. Second, a ROCs trading market, where the certificates are sold and purchased between generators. In April 2010 the renewables obligations scheme was extended from 2027 to last ten more years up to 2037.

The support for additional renewable electricity in the mix was further consolidated with the introduction of the Climate Change Act in 2008, which by law institutes a 80% reduction target in carbon emissions equivalent by 2050, relative to the baseline year of 1990. It also instituted intermediary four year periods for which carbon budgets are set, including 2008-2012, and 2013-2017, and so forth. The carbon budget for the period 2017-2022 was set to be equivalent to at least 35% lower than the 1990 baseline, translating into a 3% annual reduction (UK Government 2008). The Climate Change Act has been complemented by the European Emissions Trading Scheme (EU-ETS) that was instituted in 2005, which in its 2008-2012 phase 2 period provided an allowance of 246.2 million metric tonnes of carbon dioxide emissions for the UK across all emitting activities, including those in the electricity sector.

Now that a carbon budget had been set its implementation was the next challenge to solve for the UK government. In light of an estimated 20 GW of power generation capacity that would close between the years 2012-2022, and a limited pipeline of low-carbon capacity investments in the market, the government undertook a major overhaul of electricity markets (Department of Energy & Climate Change 2011). In the proposed and now implemented Electricity Market Reform (EMR) three new instruments were introduced to promote low carbon investments. First, the addition of a Feed-in Tariff based on Contracts for Difference (CfD). The 15 year duration contractual measure provides a price guarantee for renewable and nuclear generation capacity. It is flexibly set using a 'strike price' agreed in the contract that the generator always obtains. The difference between a quarterly market 'reference price' and the 'strike price' is provided for by a charge on the consumer electricity price settled by an independent market agency. As the electricity price changes the additional pay out to meet the strike price thus varies over time. The measure provides for stability of revenues improving the likelihood of market investments, and also puts a price limit for consumers on the support of clean energy (DECC 2012). The CfD is allocated under an auction for renewable power technologies, and in a company negotiation setting for nuclear power plants. The first CfD auction in 2014/15 was successful in allocating 2.1 GW of renewable electricity capacity investments (Baringa Partners 2015). Second, a Carbon Price Floor (CPF) to further reduce long-term uncertainty of the general market direction for phasing out carbon intensive power generation capacity. The carbon price floor has at present been frozen up to 2021 at £18 per ton of CO₂ that is emitted directly at the power plant. Originally the aim was to gradually increase the price step by step towards £30 per ton of CO₂ by 2020, but that target is now under discussion in the UK parliament due to concerns over competitiveness and electricity price stability (Hirst 2017, Energy UK 2017). And thirdly, an Emissions Performance Standard (EPS) which limits the annual allowed emissions from power stations to 450 grams of CO₂ per kWh (DECC 2012). The implication of the EPS is that no new coal fired power stations can be built without Carbon Capture and Storage (CCS).

6.2.2 Power Plant Capacity and Electricity Production

Since 1980 UK power plant capacity grew from 63 GW to 93 GW in 2013. Capacity installations in the 1980s were dominated by nuclear power generation, with smaller contributions by coal, natural gas, fuel oil, and hydro power. In the 1990s almost only natural gas capacity was added, and in the 2000s a combination of natural gas, onshore-wind, and biomass + waste was installed, as shown in table 18 and figure 11. The impact of these additions on the net change in power generation capacity is shown in figure 12 below, including end-of-life closures.

The effect on electricity production per source, which varies due to significant technology and electricity market operational differences, is shown in figure 13, and table 19. Coal based power dispatch dropped from a high share of 67% in the 1980s to 34% in the early 2010s, natural gas grew from a total absence to 16% in the 1990s, 38% in the 2000s, and 36% in the early 2010s. At the same time nuclear power generation increased from 14% in the early 1980s to 25% in the early 1990s which subsequently dropped to 18% in the early 2010s, whilst onshore wind, solar-PV, and biomass all increased from nearly zero in the 1990s to respectively 5%, 0.4%, and 4.1% electricity mix shares in the early 2010s. The only source whose share remained stable across the three decades has been hydro-power, which fluctuated between a 1.9% and 2.3% power share.

Table 18: UK power capacity additions in GW per source from 1980 to 2013

Power Source	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011
Hard Coal	520	1980	0	0	0	393	0	0
Natural Gas	1927	0	229	9299	8663	5400	2096	6105
Nuclear	0	1110	4860	1118	0	0	0	0
Fuel Oil	1370	1000	2	18	0	3	0	0
Biomass + waste	0	0	0	110	662	453	503	1357
Hydro	1728	10	10	0	0	21	17	106
Onshore Wind	0	0	0	155	202	321	1405	2571
Offshore Wind	0	0	0	0	0	64	250	1526
Solar-PV	0	0	0	0	1	5	12	977

Source of data: (Department of Energy & Climate Change 2015), this study

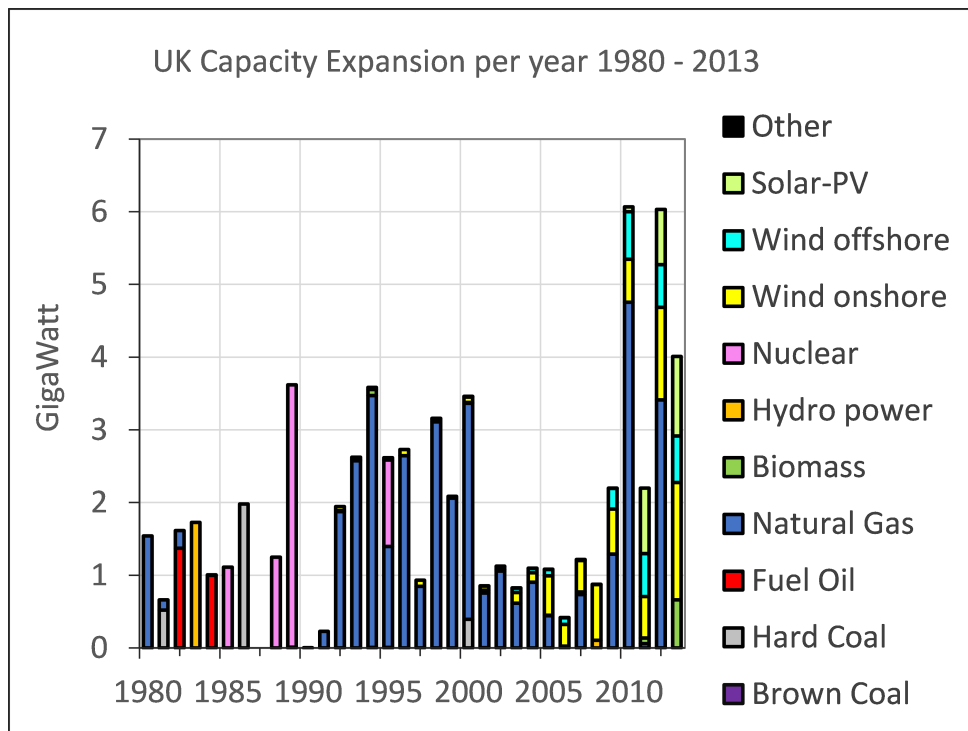


Figure 11: United Kingdom power capacity installation by technology type in MW of capacity per year from 1980 to 2013. Source of data: (Department of Energy & Climate Change 2015), this study .

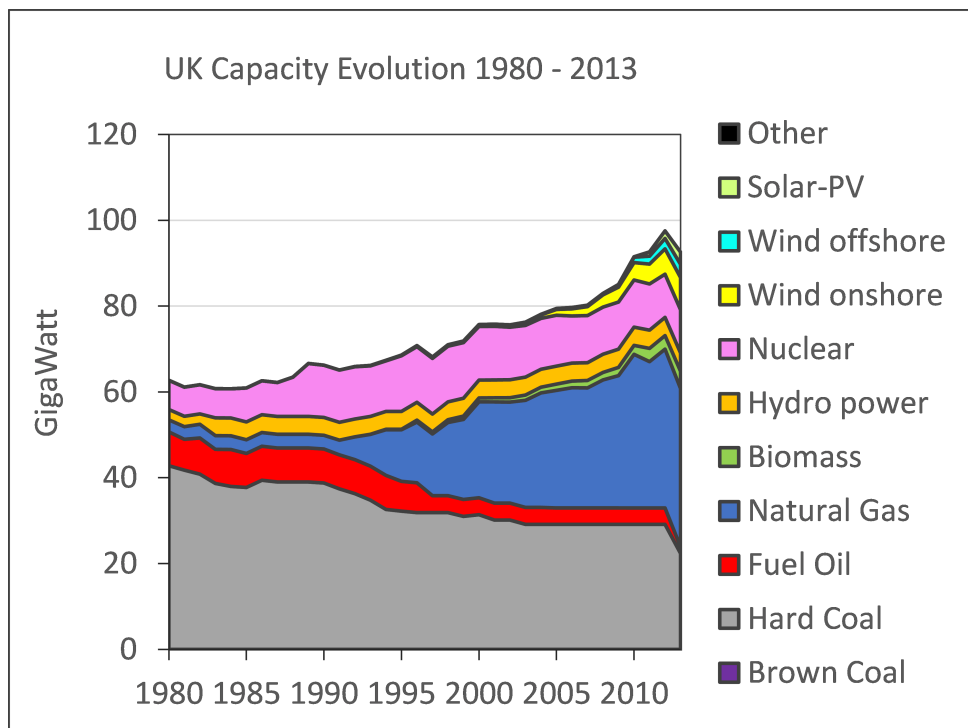


Figure 12: UK installed power generation capacity in GW from 1980 to 2013. Source of data: (Department of Energy & Climate Change 2015), this study.

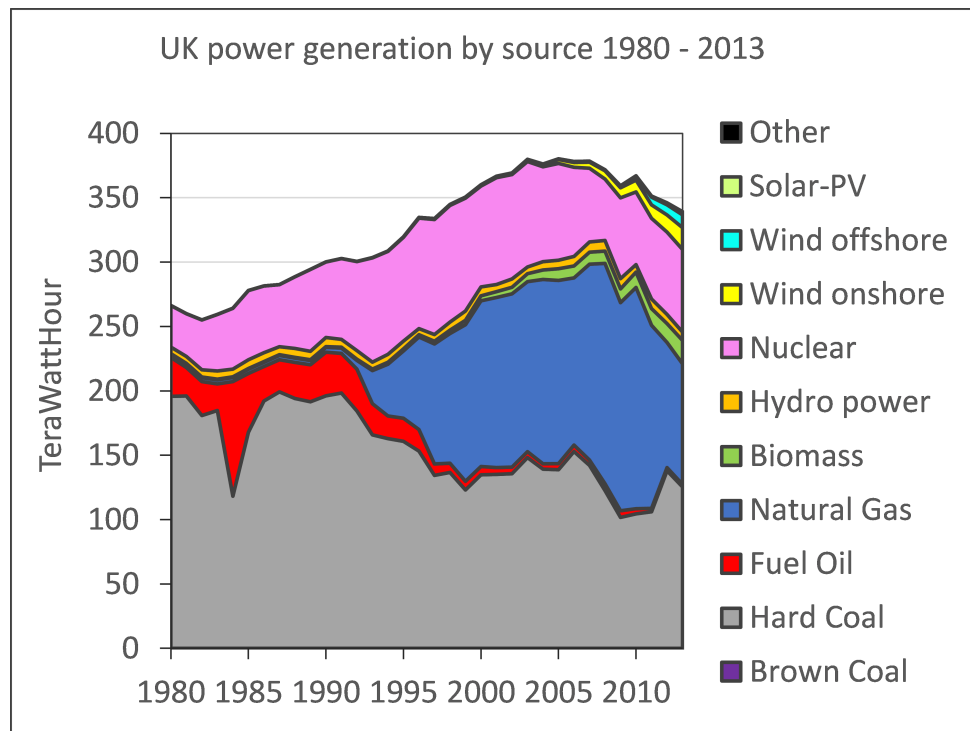


Figure 13: UK electricity generation in TWh from 1980 to 2013. Source of data: (Department of Energy & Climate Change 2015), this study.

Table 19: UK power production shares in electricity mix by generation sources from 1980 to 2011.

Power Source	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011
Hard Coal	72.8	61.2	65.8	54.7	40.1	37.5	37.9	30.0
Natural Gas (CCGT)	0.0	0.0	0.1	9.2	27.7	35.0	36.7	43.9
Gas and oil (OCGT)	1.1	1.2	1.1	0.9	0.7	0.7	0.8	0.7
Nuclear	14.2	18.2	20.3	25.2	25.9	22.0	18.2	15.8
Fuel Oil	9.5	16.9	10.2	7.5	2.9	1.5	1.2	1.2
Biomass + waste	0.2	0.2	0.2	0.4	0.7	1.3	2.3	3.1
Hydro	2.2	2.3	2.2	2.0	1.7	1.6	1.9	2.0
Onshore Wind	0.0	0.0	0.0	0.1	0.2	0.3	0.9	2.3
Offshore Wind	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.8
Solar-PV	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1

Source of data: (Department of Energy & Climate Change 2015), this study.

6.2.3 Electricity Prices, fuel prices, and market support

The UK electricity price for **industrial consumers** excluding taxation was stable around 15.7 euro per GJ prior to privatization. It rose after the market was privatised from 14.6 in the early 2000s to 28.3 euro per GJ in the early 2010s, as shown in table 20 below. The price for **household consumers** excluding taxation rose slowly prior to privatisation from 22.2 to 27.8 euro per GJ from the early 1980s to the late 1990s. In the 2000s it fluctuated around 30 euro per GJ, but started to rise again at the end, and rose to 45.1 euro per GJ in the early 2010s. In comparison, wholesale electricity prices on the market have stabilised around 16 euro per GJ of electricity, after an initial period of low volume trading.

About 20% of electricity prices excluding taxes in the 1980s were caused by coal prices, and after the rise of natural

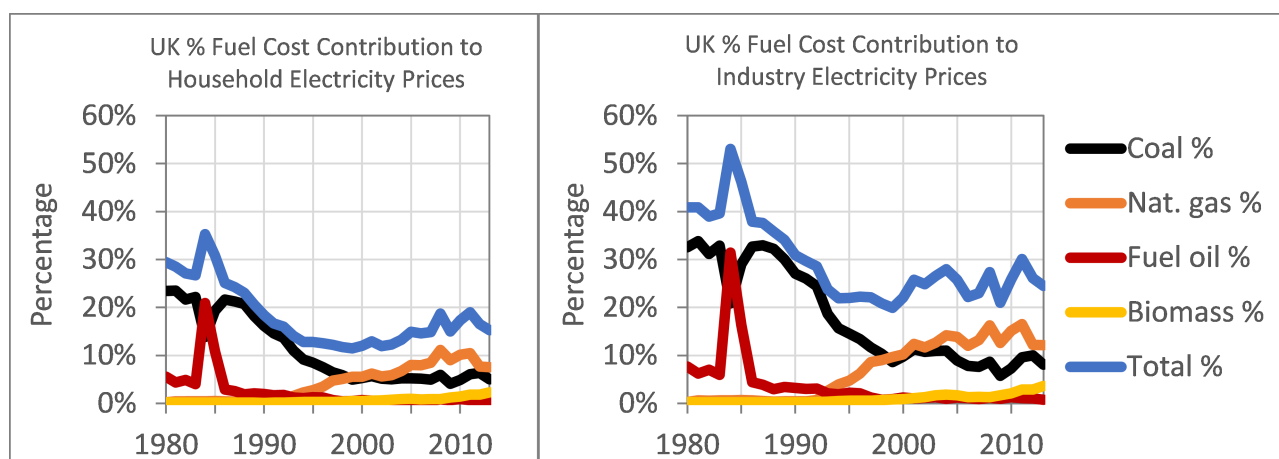


Figure 14: Approximate contribution of fuel costs to UK household and industry electricity prices without taxes for total fuels, natural gas, coal, crude oil, and biomass 1980 to 2013. Source of data: this study .

gas in the 2000s about 10% were caused by natural gas prices, as shown in table 21, and figure 14 below. The price of coal in euro per GJ decreased from 2.6 in the early 1980s to lows of 1.8 in mid to end 1990s, after which prices increased steadily to a level of 3.1 euro per GJ in the early 2010s. A similar trend is visible in natural gas prices with a decline from 3.8 euro per GJ to 2.5 euro per GJ between the mid 1980s to the mid 1990s, after which prices grew again in the 2000s to a high of 7.4 euro per GJ in the 2010s.

Table 20: Electricity and fuel prices for UK from 1980 to 2013 excluding taxation in euro / GJ of LHV heat or electric content.

euro / GJ	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011	2012-2013
Electricity wholesale	n.a	n.a	n.a	n.a	n.a	6.9	12.6	16.0	16.0
Electricity Industry	15.4	15.5	15.7	15.7	15.7	14.6	20.7	25.6	28.3
Electricity Households	22.2	23.5	26.1	27.1	27.8	29.2	34.7	28.1	45.1
Coal for Power Plants	2.6	2.8	2.6	2.0	1.8	1.9	2.2	3.1	3.1
Natural Gas for Power Plants	3.8	3.9	2.6	2.4	2.5	2.8	4.4	5.2	7.4
Fuel Oil for Power Plants	4.3	4.4	1.9	1.9	2.6	4.6	6.9	9.9	14.6
Biomass - wood chips	n/a	n/a	n/a	n/a	n/a	n/a	6.1	7.3	8.9

Data sources: Electricity wholesale (Energy Solutions Commercial Energy Brokers 2015, Ofgem 2015, APX Power Spot Exchange 2015), Electricity Households (International Energy Agency 2013), Coal for Power Plants (International Energy Agency 2013, C.A.R.M.E.N. 2015, Department of Energy & Climate Change 2014), Natural Gas for Power Plants (International Energy Agency 2013, C.A.R.M.E.N. 2015, Department of Energy & Climate Change 2014), Fuel Oil for Power Plants (International Energy Agency 2013, Department of Energy & Climate Change 2014), Biomass - wood chips (International Energy Agency 2013, C.A.R.M.E.N. 2015, Department of Energy & Climate Change 2014).

The value of electricity prices has changed slightly over time due to the introduction of government taxation in the 1990s and 2000s. Taxation levels for **household users** was first set at 0.9 euro per GJ in the early 1990s with increases to 2.3 euro per GJ since. Taxation for **industrial users** was first introduced in the 2000s at a level of 0.7 euro per GJ after which taxes were increased to 0.9 euro per GJ and were held steady at this level, as shown in table 21. In addition to direct electricity taxation also heating/fuel oil taxation was instituted, but given the low share of fuel oil this has only had a marginal influence. The taxation was 0.3 euro per GJ in the 1980s, and has grown ten-fold since, to 3 euro per GJ in the early 2010s.

The impact of the Renewables Obligation (RO) has been substantial since its introduction in 2002, as all renewable energy technologies received a price bonus of around 20 euro per GJ until 2008. After this the RO was differentiated per technology, due to which it rose to 27-33 euro per GJ from 2009 to 2012 for solar-PV, around 20-25 euro per GJ for biomass, 13-16 euro per GJ for onshore wind, and 24-33 euro per GJ for offshore wind, as shown in table 22. The support level declined somewhat in 2013 for solar-PV and onshore wind to levels of 22.4 and 12.6 euro per GJ, respectively.

Table 21: UK direct electricity and fuel taxation levels from 1980 to 2013 in euro / GJ .

euro / GJ	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011	2012-2013
Electricity Industry	0.0	0.0	0.0	0.0	0.0	0.7	0.9	0.9	0.9
Electricity Households	0.0	0.0	0.0	0.9	1.7	1.5	1.7	1.9	2.3
Coal for Power Plants	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Natural Gas for Power Plants	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fuel Oil for Power Plants	0.3	0.3	0.3	0.4	0.7	1.1	2.0	2.8	3.0

Source of data: (International Energy Agency 2013), this study.

Table 22: UK renewable obligations price* support for new renewable installations from 2002 to 2013 in euro / GJ.

euro / GJ	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Solar-PV	20.3	21.4	18.4	17.3	20.1	21.5	19.0	32.7	33.3	37.0	30.4	22.4
Biomass	20.3	21.4	18.4	17.3	20.1	21.5	19.0	24.5	24.9	20.3	22.8	21.0
Wind Onshore	20.3	21.4	18.4	17.3	20.1	21.5	19.0	16.3	16.6	13.5	15.2	12.6
Wind Offshore	20.3	21.4	18.4	17.3	20.1	21.5	19.0	24.5	33.3	27.0	30.4	27.9

*including recycle payments. Source of data: (University of East Anglia 2010, 1999, Renewable Energy Foundation 2013, Ofgem 2014, 2016, Gipe 2009).

6.3 The Netherlands Electricity Sector Statistics 1980 - 2013

6.3.1 Overview of 30 years of Dutch electricity policy, capacity and market changes

The Netherlands in the 1980s produced the majority of its electricity from domestically produced natural gas. After many gas field discoveries in the 1950s and 1960s, including the largest gas field on the European continent in 1959, natural gas consumption for heat and electricity rose rapidly. After 1968 natural gas quickly replaced coal and oil as the previous dominant sources of energy at the start of the 1980s. The speed of introduction was guided by the dominant narrative that natural gas would quickly lose its value due to nuclear power. In 1972 the ministry of economic affairs had drawn up a plan for 35 GigaWatt capacity of nuclear power by the year 2000 (Weijnen et al. 2015). Yet nuclear power never grew substantially beyond two power plants built in 1969 and 1973, as a consequence of large public opposition, and the Three Mile Island and Chernobyl nuclear accidents in 1979 and 1986, respectively, which consolidated the dominant role of natural gas based electricity generation. The second oil crisis in 1979-80 also had a major influence as it led to the phasing out of fuel oil use in electricity generation after a temporary come-back at the end of the 1970s (Verbong and Geels 2007).

Electricity production at the time was arranged under a semi-public system of regulation that began in 1982. Before there had been little steering or control. Generation capacity was directly or indirectly owned and operated by municipalities or provincial governments, who could set their own price levels for different electricity consumers. There was no strict distinction between distribution and generation, and public companies that owned both systems were common. About 16 large companies were in existence with 34 large power generation plants, which cooperated through the sector umbrella organisation SEP that was instituted in 1949 (the N.V. Samenwerkende Elektriciteits Productiebedrijven in Dutch). In addition a substantial number of small decentralised players were active. As of 1982 the SEP took on a price regulatory role as requested by the government. In this system production by the lowest cost generation units was centrally prioritised, and the SEP also gained a commanding role in construction and planning of new electricity power plants (Schenk 1998, Vlijm 2002).

Steps to significantly restructure the electricity market took place in 1986 after several years of negotiations between the government and the electricity sector. The Dutch government held the view that centralisation would substantially reduce the electricity price, which it found too high for industrial users in comparison to West-Germany and France. The government wanted a single electricity generating company, but the SEP disagreed as in their view the cause of higher prices was mainly related to fuel costs and the generating technology, and was not due to the market organisational structure. A final compromise signed by the government, the SEP, and its members led to a new price system that came into effect in January 1987. All power produced by power generating companies above 5 MW would be 'sold' to the SEP based on a standard cost based electricity price. The price level was established from the peak load share of production of individual companies, measured four times per year, and the cost estimate of each producer. To this cost-based price level the costs of the SEP and electricity import costs were added, which resulted in an intermediary price at which the SEP 'sold' the electricity back to the production companies. Finally, a regional price was calculated based on the intermediary price level, which included indirect production and distribution costs. All the price levels had to be agreed within the electricity sector, and approved by the Minister of Economic Affairs, which had the authority to instate a maximum price level. In essence the electricity price became state controlled (Vlijm 2002).

A second part of the agreement was the full separation of generation and transmission/distribution activities, which led to the formation of four large electricity producing firms out of the previously 16 large companies, called UNA, EZH, EPON and EPZ. which jointly had a 75% electricity production share. These changes were formalised by law with the electricity Act of 1989 which also included that only the SEP and large electricity consumers (> 10 million kWh per year) were allowed to import electricity (van Damme 2005). The transmission/distribution market also saw large changes due to the unbundling as many mergers led to a reduction from 80 to 23 companies, of which seven held 90% of the distribution market (Schenk 1998). In 1997 the smallest of the two nuclear power plants in the Netherlands, Dodewaard, was closed prior to the end of its life under the anti-nuclear political climate, but this only had a limited impact given its small capacity at 58 MW.

The centralised pricing system was restructured from 1998 as it conflicted with European Energy Directives, such as the 1996 directive 96/92/EC, that called for the setup of a competitive liberalized electricity market which included third party access (e.g. allowing acquisitions by private parties), unbundling of transmission/distribution and generation, and transparent market trading of electricity. In 1998 an electricity market regulator, DTe, was instated, as well as a grid system operator and manager TenneT. Compulsory pooling of electricity was abandoned and trading agreements were started under wholesale markets, with a day-ahead spot market APX that was initiated in 1999 (van Damme 2005). Also an off the counter market was initiated using a standardised market platform called Endex in 2003, resulting by 2004 in a fully traded market system.

The formerly public electricity giants were privatised. In 1999 the public company EZH was purchased by E.ON, large parts of EPON were taken over by the Belgian company Electrabel, UNA was bought by the US company Reliant (which later was sold to distribution company Nuon), and EPZ's assets were bought by multiple distribution companies, that went forward under the names Delta and Essent (van Damme 2005). Later the EU directive 2003/54/EC called for full unbundling of transmission and distribution networks as well as production, so as to create further separation of roles to reduce market power. In response the unbundling of generation and distribution was carried out in 2006 by sales of assets or division of companies into separate entities, which was completed by 2007 (Tönurist et al. 2015).

Support for renewable electricity sources began in the 1990s, with at first a voluntary target set at 3.2% of electricity sales to come from electricity from wind, solar, or biomass technologies by the year 2000. The second part of the policy was a fiscal tax for every kWh of electricity sold called the REB, starting at a level in 1996 of 3.7 euro per GJ of electricity. Electricity from renewable sources was exempt from this new taxation. The system was managed by a voluntary green labelling system for renewable electricity sources (van Rooijen and van Wees 2006, Kroon 2002). The system made 'green' electricity nearly similar in cost as regular 'grey' electricity, due to which the purchasing of labelled renewable based electricity grew substantially. Domestic renewable electricity generation, however, did not grow quickly enough to meet the demand for labelled renewable electricity as a consequence, and it had to be imported from mainly Germany. The imported electricity also was exempt from taxation as required under EU law. In response the government tried to change its control of the market, starting by placing the renewable electricity labelling system in 2001 under government institutional management (van Rooijen and van Wees 2006).

In the year 2003 the new MEP policy was instated that replaced the REB exemption. This regulation provided a fixed direct subsidy per kWh of electricity produced from solar, wind, and biomass. The level was evaluated and adjusted every year, and ranged from 13 to 27 euro per GJ across its existence until 2006. The money came out of a surcharge on every electricity connection in the country of approximately 100 euro per year. Since there was no fixed limit to the amount of electricity generated that would be subsidised it was an 'open end' regulation. The growing amounts of renewable electricity produced as a consequence led to its sudden termination as of August 2006 and it took 1.5 years before a new capped arrangement was in place, called the SDE (Verhees et al. 2015). The new regulation came into effect on January 2008, and used a similar production subsidy system, but with a capped amount of available subsidy per year combined with a first-serve auction system. Initially the subsidy was paid out of the energy taxation (REB), but later as of 2009 it was coupled to a special surcharge on electricity prices that grows in accordance with the required subsidy value, based on a 50% household and 50% industry payment distribution.

6.3.2 Power Plant Capacity and Electricity Production

Since 1980 Dutch power plant capacity grew from 16 GW to 27 GW in 2013. Capacity additions in the 1980s were dominated by coal power, in the 1990s by natural gas, and in the 2000s by natural gas and onshore-wind, as shown in table 23 and figures 15 and 16 below. These additions did in the 1980s result in increased shares of coal and natural gas generation and the end of fuel oil based electricity generation, in response to the second oil crisis. The share of natural gas due to the expansions grew from 50% in the early 1980s to 64% in the 2010s, as shown in figure 17 and table 24. The share of wind electricity and biomass grew to 4.0% and 5.6% in the 2010s from zero in the 1990s and 1980s, respectively.

Table 23: NL power capacity additions in GW per source from 1980 to 2011.

Power Source	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011
Hard Coal	1203	1546	555	1546	0	0	0	0
Natural Gas	455	1215	530	688	2124	438	1039	1298
Fuel Oil	0	0	0	0	0	0	0	0
Nuclear	0	0	0	0	0	0	0	0
Onshore Wind	0	10	68	167	160	496	842	568
Offshore Wind	0	0	0	0	0	0	108	120
Solar-PV	0	0	0	0	0	20	0	88
Hydro	0	0	36	0	0	0	0	0
Biomass + Waste	0	5	94	80	255	2	85	287

Source of data: (Sandbag 2014, EEX 2015, Enipedia 2015, Oosterheert et al. 1995), This study

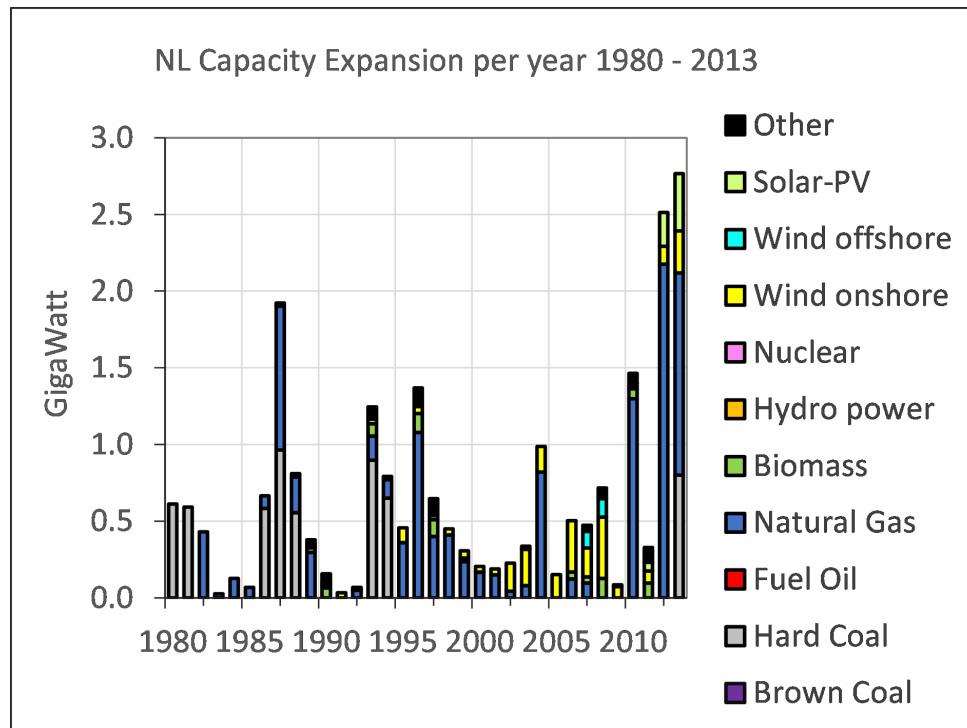


Figure 15: Netherlands power capacity installation by technology type in MW of capacity per year from 1980 to 2013. Source of data: (Sandbag 2014, EEX 2015, Enipedia 2015, Oosterheert et al. 1995), this study.

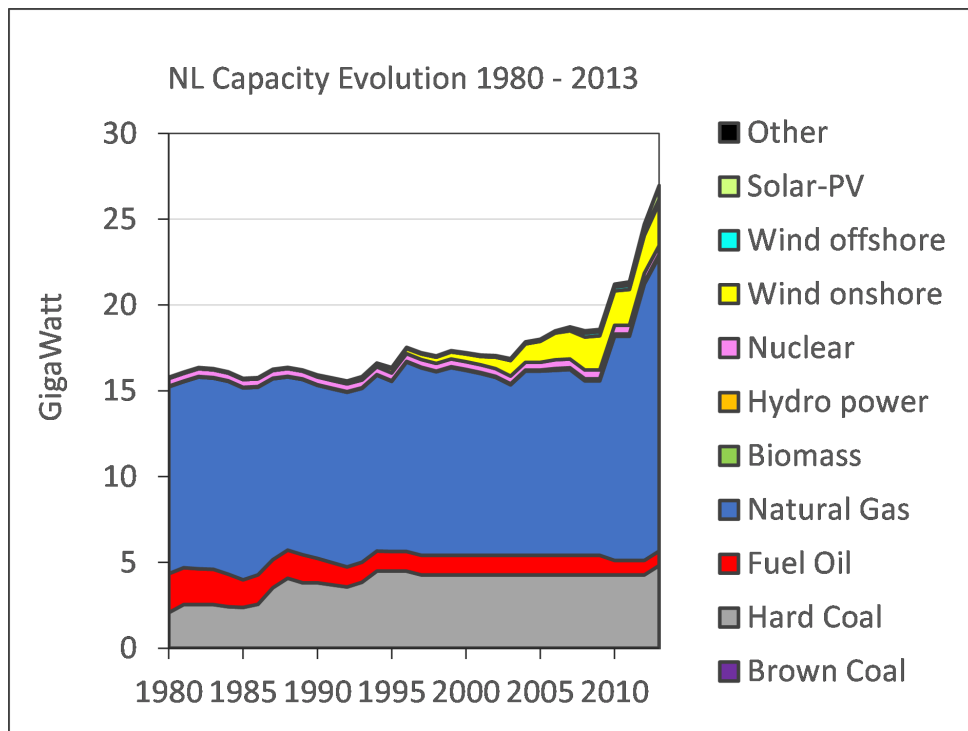


Figure 16: Netherlands installed power generation capacity in GW from 1980 to 2013. Source of data: (Sandbag 2014, EEX 2015, Enipedia 2015, Oosterheert et al. 1995), this study.

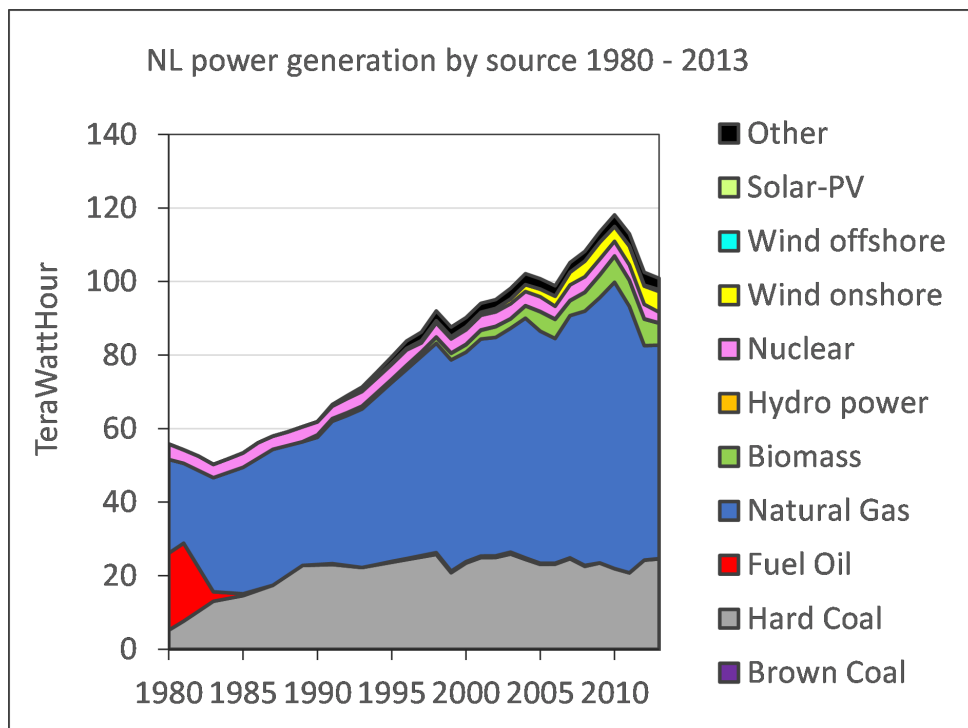


Figure 17: NL electricity generation in TWh from 1980 to 2013. Source of data: (Central Bureau of Statistics 2015), this study.

Table 24: NL power production shares in electricity mix by generation sources from 1980 to 2011.

Power Source	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011
Brown Coal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Hard Coal	17.3	28.1	35.8	31.0	27.5	26.3	23.4	19.6
Fuel Oil	26.1	1.1	0.2	0.2	0.5	0.5	0.3	0.1
Hydro power	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1
Natural Gas	49.4	63.8	57.3	60.4	62.9	62.6	62.7	64.4
Nuclear	7.2	7.0	5.9	5.3	4.1	4.2	3.8	3.7
Wind onshore	0.0	0.0	0.1	0.4	0.7	1.0	2.5	4.0
Wind offshore	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Solar-PV	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Biomass	0.0	0.0	0.5	1.0	1.6	2.6	4.4	5.6
Other	0.0	0.0	0.1	1.6	2.7	2.7	2.8	2.6

Source of data: (Central Bureau of Statistics 2015), This study

6.3.3 Electricity Prices

The electricity price for **industrial consumers** in the Netherlands excluding taxation in the 1980s declined substantially from 17.5 to 11.7 euro per GJ, after which it slowly increased to a high of 22.2 euro per GJ in the late 2000s. A similar trend is apparent for **household electricity** prices, which declined from 28.2 to 22.4 euro per GJ in the 1980s, after which slow increases through the course of the 1990s, and rapid growth in the 2000s to a level of 38.8 euro per GJ is visible. The main reason of the large increase in the 2000s was due to rising natural gas prices, largely driven by the coupling of natural gas to crude oil prices in markets in Western-Europe, including the Netherlands. The total natural gas cost contribution to industry electricity prices grew from 13% in 1999 to 21% in 2011, and for household electricity prices from 21% in 1999 to 40% in 2011, as shown in figure 18. Natural gas prices for power generation increased threefold from 2.6 euro per GJ in the 1990s to a level of 8 euro per GJ at the end of the 2000s.

Table 25: Electricity and fuel prices for NL from 1980 to 2013 excluding taxation in euro / GJ of LHV heat or electric content.

euro / GJ	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011	2012-2013
Electricity Wholesale	n/a	n/a	n/a	n/a	n/a	11.0	12.8	14.3	13.0
Electricity Industry	17.5	15.1	11.7	14.0	15.5	16.6	20.2	22.2	20.6
Electricity Households	28.2	27.0	22.4	22.6	24.3	26.1	32.6	38.8	41.1
Coal for Power Plants	2.9	2.4	1.7	1.7	1.6	1.8	2.5	3.6	3.4
Natural Gas for Power Plants	4.6	4.2	2.5	2.4	2.6	4.5	6.7	8.0	8.5
Fuel Oil for Power Plants	5.8	5.2	3.6	3.6	4.0	5.9	7.6	10.1	13.8
Biomass - wood chips	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Data Sources: Electricity wholesale (Boots 2011, APX Power Spot Exchange 2016, www.nordpoolspot.com 2016), Electricity industry (International Energy Agency 2013), Electricity Households (International Energy Agency 2013), Coal for Power Plants (International Energy Agency 2013), Natural Gas for Power Plants (International Energy Agency 2013), Fuel Oil for Power Plants (International Energy Agency 2013), Biomass - wood chips (International Energy Agency 2013, C.A.R.M.E.N. 2015).

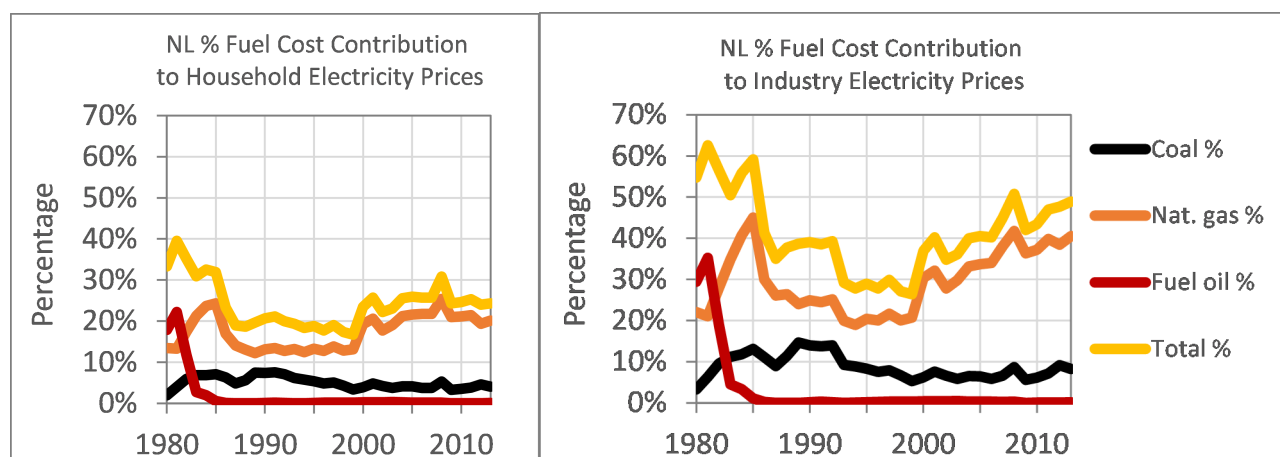


Figure 18: Approximate contribution of fuel costs to NL household and industry electricity prices without taxes for total fuels, natural gas, coal, crude oil, and biomass 1980 to 2013. Source of data: (International Energy Agency 2013, C.A.R.M.E.N. 2015), this study.

The value of electricity prices has also changed substantially over time due to government taxation on top of producer prices. The various taxes included general sales taxes, a general electricity tax instituted in 1996, and the surcharge for renewable electricity instituted in 2009. Taxation for household electricity users fluctuated between 4.0 and 5.2 euro per GJ in the 1980s and early 1990s, and rose to a range of 13 to 20 euro per GJ in the 2000s due to the tax introduction, as shown in table 26. Electricity used by industry was only taxed as of the late 1990s, with levels growing to 3.0 euro per GJ at the end of the 2000s. In addition to direct electricity taxation also natural gas taxation has contributed to the increase in the electricity price, although the influence was minor relative to the market driven natural gas price increase.

The subsidy of renewable energy sources, as shown in 27, has been highly volatile in the Netherlands. In the period 2003 to 2006 with the MEP subsidy the levels grew from 19 to 27 euro per GJ for solar-PV, and for 13.6 to 21.4 for onshore wind power, then there was no subsidy for 1.5 years, after which the new SDE subsidy levels were set at 90 to 100 euro per GJ for solar-PV, which rapidly dropped in subsequent years to levels between 3.6 and 13.8 euro per GJ. Onshore-wind subsidies under the SDE as of 2008 were more stable, with a range between 8.3 to 17.5 euro per GJ.

Table 26: NL direct electricity and fuel taxation levels from 1980 to 2013 in euro / GJ.

euro / GJ	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011	2012-2013
Electricity Industry	0.0	0.0	0.0	0.0	0.1	1.6	2.5	3.0	3.1
Electricity Households	5.1	5.2	4.2	4.0	8.2	18.4	19.9	13.3	15.1
Coal for Power Plants	0.0	0.0	0.1	0.4	0.4	0.4	0.4	0.5	0.5
Natural Gas for Power Plants	0.0	0.0	0.1	0.2	0.2	0.3	0.4	0.6	0.7
Fuel Oil for Power Plants	0.2	0.2	0.5	0.8	0.8	0.8	0.8	0.9	0.9

Source of data: (International Energy Agency 2013), this study.

Table 27: NL MEP and SDE price support for new renewable installations from 2000 to 2013 in euro / GJ of electricity.

euro / GJ	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Solar-PV	18.9	22.8	26.9	26.9	0.0	91.7	80.8	104.4	12.8	3.6	15.0
Biomass	13.3	15.3	19.4	19.4	0.0	18.9	17.5	17.2	16.3	0.0	0.0
Onshore wind	13.6	17.5	21.4	21.4	0.0	15.0	17.5	17.2	16.3	8.3	12.7
Offshore wind	18.9	22.8	26.9	26.9	0.0	0.0	33.9	0.0	18.5	7.8	21.7

Source of data: (Rijksdienst voor ondernemend Nederland 2015, Rijksoverheid 2009, Rijksdienst voor Ondernemend Nederland 2013, Lensink et al. 2011, SenterNovem 2008).

6.4 Power plant investment costs and operational costs

The investment cost values used in the analysis are summarised in table 28 below. Similar values were used for the United Kingdom, Germany, and the Netherlands, with some variations as provided in the literature. Specific large differences include prices for hard coal pulverized plants, which for the Netherlands and the United Kingdom were evaluated to be significantly higher than for Germany in the 2008-2013 time-frame at 1476 to 1764 euro/kW based on the IEA literature values (Schroder et al. 2013, IEA and NEA 2015). In case older values were not available they were backpolated based on the first known value, such as for fuel oil plants in the 1980s. A similar procedure was carried out for operational costs, for which the values used in the analysis for Germany, the United Kingdom, and the Netherlands are summarised in table 29 below.

Investment cost values for fossil fuel generation remained relatively stable for single cycle natural gas and fuel oil power plants, as shown in figure 19. They have increased by a few hundred euro per kW for combined cycle natural gas and hard coal power plants since the early 1990s. A part of this increase will have been caused by the compulsory addition of emissions technology for nitrogen oxides and sulfur particles, and the greater material costs due to the larger material footprint of these facilities. The investment costs for onshore wind declined by 60% from the early 1980s to the mid 1990s, but started to rise again in the course of the 2000s up to 2013, primarily due to increasing steel costs. Even sharper cost changes are visible for offshore-wind values, especially in the 2000s, as documented in literature cost assessments. Solar-PV investment costs as used in this thesis declined sharply for both industrial size and household solar systems by a factor of 15 and 18 since 1980 up to 2013, as shown in figure 20. The investment cost trends show a sharp rise for documented nuclear power costs starting in the early 2000s as shown in figure 20. The plausible cause is the continued update of costs values to higher safety standards and newer nuclear designs, in particular the third generation European Pressurized Water Reactor (EPR-III) . Since large scale construction had not been carried out since the Chernobyl accident in 1986 in the majority of the world, and none in any European Union countries, cost values had become substantially outdated.

Table 28: Power plant investment costs 1980-2014 in euro/kW of capacity.

Year / Technology	1980	1984	1987	1992	1996	2003	2008	2010	2013
Brown Coal	573	829	809	1151	1035	1163	1494	1500	794
Hard Coal Pulverized	573	829	809	1151	1035	829	1294	1286	1273
Fuel Oil / OCGT Natural Gas	352	352	352	426	438	405	353	400	413
CCGT Natural Gas	796	796	796	541	587	445	626	699	733
Nuclear PWR	1085	1600	1665	2002	1659	1567	2789*	3502*	4571*
Wind on-shore	1603	1603	1603	1505	894	1012	1315	1300	1386
Wind off-shore	2754	2754	2754	2586	1536	1669	3326	3373	3765
Solar-PV Industry open-space	16262	13725	11189	6859	4487	2973	2220	1560	1100
Solar-PV Household rooftop	30854	26041	21229	13014	8514	5641	4398	2466	1706
Biomass	1060	1060	1060	1060	1060	1780	2294	2500	2581

Data source: **Brown Coal** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, IHS CERA 2015, Schroder et al. 2013, IEA and NEA 2015), **Hard Coal Pulverized** (Salvadores and Keppler 2010, Fraser et al. 2005, IEA and NEA 2015), **Fuel Oil / OCGT Natural Gas** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, IHS CERA 2015, Schroder et al. 2013, IEA and NEA 2015), **CCGT Natural Gas** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, IHS CERA 2015, Schroder et al. 2013, Pauschert 2009, IEA and NEA 2015), **Nuclear PWR** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Schroder et al. 2013, IHS CERA 2015, Salvadores and Keppler 2010, Fraser et al. 2005, IEA and NEA 2015), **Wind on-shore** (Neij et al. 2003, Expert Group 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, Schroder et al. 2013, Gielen and Secretariat IRENA 2012, Schwabe et al. 2011, IEA and NEA 2015), **Wind off-shore** (Salvadores and Keppler 2010, Schroder et al. 2013, IEA and NEA 2015), **Solar-PV Industry open-space** (Haas 2002, Salvadores and Keppler 2010, Schroder et al. 2013, Bundesverband Solarwirtschaft 2014, Grau et al. 2011, IEA and NEA 2015), **Solar-PV Household rooftop** (Bundesverband Solarwirtschaft 2014, Grau et al. 2011, Haas 2002, IEA and NEA 2015), **Biomass** (IEA and NEA 2015, Schroder et al. 2013, Bertel and Pfaffenbarger 1998).

*Third generation PWR reactor

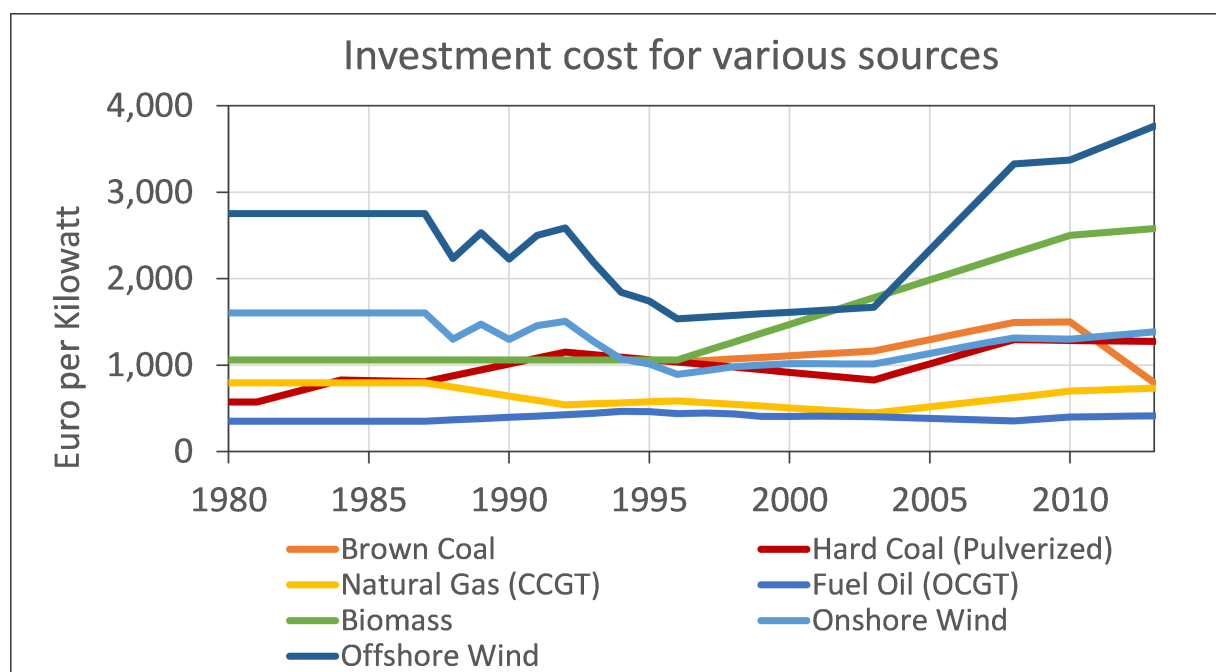


Figure 19: Pulverized coal, CCGT and OCGT (simple cycle), and on-shore wind power investment costs in euro per kW for 1980 to 2012. Source of data: (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Schroder et al. 2013, IHS CERA 2015, Salvadores and Keppler 2010, Fraser et al. 2005), this study.

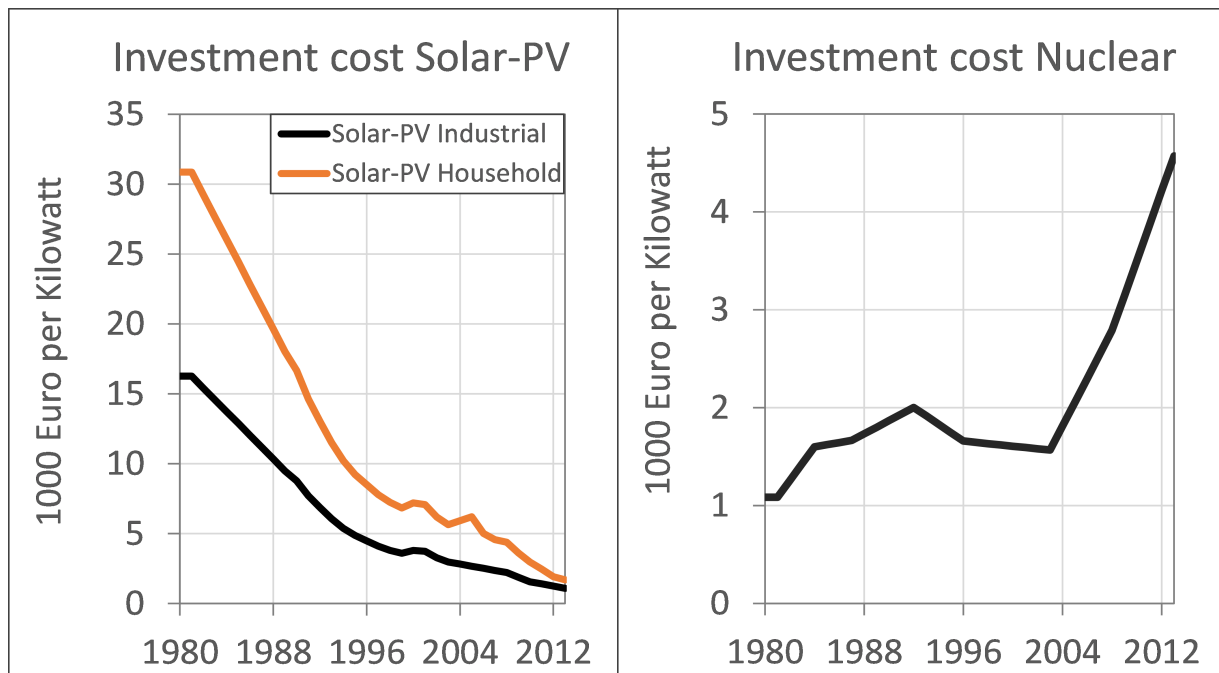


Figure 20: Solar-PV and Nuclear investment costs for industry open-space industrial and household roof-top in 1000 euro per kW for 1990 to 2013. Source of data: (Schroder et al. 2013, Haas 2002, Salvadores and Keppler 2010, Bundesverband Solarwirtschaft 2014, Grau et al. 2011, IEA and NEA 2015), (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Schroder et al. 2013, IHS CERA 2015, Salvadores and Keppler 2010, Fraser et al. 2005, IEA and NEA 2015), this study.

Table 29: Power plant operation & management cost for 1981 to 2010 in euro per kW of capacity per year.

Year / Technology	1981	1984	1987	1992	1996	2003	2008	2010	2013
Brown Coal	15.3	15.3	15.3	15.3	15.3	11.0	9.5	9.1	8.3
Hard Coal Pulverized	6.8	10.0	13.3	14.5	21.5	14.1	8.6	7.9	6.9
Fuel Oil / OCGT Natural Gas	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.5	3.3
CCGT Natural Gas	4.8	4.8	4.8	6.7	7.2	5.8	4.6	5.1	5.8
Nuclear PWR	9.0	9.0	9.5	16.0	13.6	8.9	6.0	9.9	15.8
Wind on-shore	6.3	6.3	6.3	12.1	16.0	22.7	24.9	19.8	26.1
Wind off-shore	23.7	23.7	23.7	23.7	23.7	23.7	31.5	28.3	37.2
Solar-PV Industry open-space	23.5	23.5	23.5	23.5	23.5	23.5	23.9	20.0	14.3
Solar-PV Household rooftop	23.5	23.5	23.5	23.5	23.5	23.5	35.9	35.9	35.9
Biomass	15.3	15.3	15.3	15.3	15.3	11.0	9.5	18.1	30.9

Data source: **Brown Coal** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, IHS CERA 2015, Schroder et al. 2013, IEA and NEA 2015), **Hard Coal Pulverized** (Salvadores and Keppler 2010, Fraser et al. 2005, IEA and NEA 2015), **Fuel Oil / OCGT Natural Gas** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, IHS CERA 2015, Schroder et al. 2013, IEA and NEA 2015), **CCGT Natural Gas** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, IHS CERA 2015, Schroder et al. 2013, Pauschert 2009, IEA and NEA 2015), **Nuclear PWR** (Expert Group 1983, 1986, 1989, 1992, Bertel and Pfaffenbarger 1998, Schroder et al. 2013, IHS CERA 2015, Salvadores and Keppler 2010, Fraser et al. 2005, IEA and NEA 2015), **Wind on-shore** (Neij et al. 2003, Expert Group 1992, Bertel and Pfaffenbarger 1998, Fraser et al. 2005, Salvadores and Keppler 2010, Schroder et al. 2013, Gielen and Secretariat IRENA 2012, Schwabe et al. 2011, IEA and NEA 2015), **Wind off-shore** (Salvadores and Keppler 2010, Schroder et al. 2013, IEA and NEA 2015), **Solar-PV Industry open-space** (Haas 2002, Salvadores and Keppler 2010, Schroder et al. 2013, Bundesverband Solarwirtschaft 2014, Grau et al. 2011, IEA and NEA 2015), **Solar-PV Household rooftop** (Bundesverband Solarwirtschaft 2014, Grau et al. 2011, Haas 2002, IEA and NEA 2015), **Biomass** (IEA and NEA 2015, Schroder et al. 2013, Bertel and Pfaffenbarger 1998).

*Third generation PWR reactor

6.5 Excess Capacity Modelling Assumption and Data

Each power generation system also has a substantial amount of excess capacity to ensure that sufficient supply is available in case of unusual peak demand. The incorporation of only electricity demand data is as such inadequate if the aim is to realistically model the amount of power generation capacity that is built. This also became apparent during the modelling process, whereas the TEMOA optimization model was initially found to lead to a far lower outlay of capacity than realised historically. To this end a new modelling assumption as introduced that required an input dataset to factor in excess power generation capacity over time.

To accommodate for this feature of electricity systems an excess capacity ratio factor was incorporated in the model (see Appendix C for the implemented equation). The factor defines the additional power output on top of electricity demand that needs to be provided by the electricity generation system. The ratio defined from the calculated electricity demand to what the total power system could historically provide, as per table 30, was used in a modelled constraint to set the minimum amount of power that the system must be able to provide. Thereby the model is forced to invest in the amount of extra power generation capacity that was also historically built. In the model runs to 2046 the excess capacity ratio was extrapolated from 2013 forward and kept constant.

Table 30: Excess Capacity Ratio used in the model from 1980 to 2013.

Country	1980-1983	1984-1987	1988-1991	1992-1995	1996-1999	2000-2003	2004-2007	2008-2011	2012-2013
DE	1.30	1.37	1.46	1.50	1.46	1.41	1.41	1.53	1.53
UK	1.24	1.26	1.25	1.28	1.17	1.18	1.13	1.14	1.10
NL	2.04	1.97	1.75	1.47	1.37	1.29	1.29	1.23	1.75

Source of data: this Study.

6.6 Data extrapolation for model runs up to 2046

The set of 64 runs was also carried out with a future looking perspective going from 1980 to 2046. The aim is to evaluate what happens in term of power generation capacity change in the 1980 to 2013 time period when running the model from 1980 to 2013, and when running the model from 1980 to 2046. To make the two sets of model runs as comparable as possible, the exact same model equations were used in the two sets of 64 model runs. As such no additional constraints or model equations were introduced, such as emission constraints equations, since these were also not present in the historic 1980-2013 model runs. Deviations can thereby solely be attributed to the difference in the length of the model run, and the cost evolution effect stemming from the data input for the 2014 to 2046 period. The time-series data inputs for the model runs were selected from reputable external institutions that provided for future cost developments. External exogenous input data was selected because the investigation of learning rates as an endogenous mechanism is not within the scope of this thesis (see **section 1.5** for the thesis scope).

The time-series that were used as data inputs included extrapolated investment costs based on (Schroder et al. 2013), extrapolated fuel costs based on (IEA 2015), and assumptions made by the author for electricity prices, the continuation of fiscal support of renewable electricity, as well as technology efficiency. The operational costs as of 2013 were held constant up to 2046 in the scenarios. The assumptions for investment costs are described in table 31, for electricity prices and fuel costs in table 32, and for fiscal support in table 33.

Table 31: Power plant investment costs 2013-2046 in euro/kW of capacity.

Year / Technology	2013	2017	2021	2025	2029	2033	2037	2041	2045
Brown Coal	794	794	794	794	794	794	794	794	794
Hard Coal Pulverized	1273	1295	1300	1300	1300	1300	1300	1300	1300
Fuel Oil / OCGT Natural Gas	413	355	355	355	355	355	355	355	355
CCGT Natural Gas	733	714	714	714	714	714	714	714	714
Nuclear PWR	4571*	4706	4773	4773	4773	4773	4773	4773	4773
Wind on-shore	1386	1315	1291	1266	1242	1218	1196	1173	1151
Wind off-shore	3765	3425	3044	2946	2876	2779	2684	2588	2496
Solar-PV Industry open-space	1100	1036	960	1266	1242	1218	1196	1173	1151
Biomass	2581	2950	2840	2800	2760	2698	2633	2568	2505

*Third generation PWR reactor. Source of data: (Schroder et al. 2013), this study.

Table 32: Electricity and fuel prices for from 2013 to 2046 excluding taxation in euro / GJ of LHV heat or electric content.

Country	euro / GJ	2013- 2016	2017- 2020	2021- 2024	2025- 2028	2029- 2032	2033- 2036	2037- 2040	2041- 2044	2045- 2046
DE	Electricity Price	43.8	46.1	47.7	48.6	49.2	49.9	50.3	50.5	50.7
UK		60.4	60.8	60.5	59.6	58.3	56.7	54.9	52.9	51.4
NL		52.5	53.1	53.1	52.6	51.8	50.9	49.7	48.5	47.7
D	Coal for Power Plants	2.3	2.3	2.6	2.7	2.7	2.8	2.9	2.9	3.0
UK		2.3	2.3	2.6	2.7	2.7	2.8	2.9	2.9	3.0
NL		2.3	2.3	2.6	2.7	2.7	2.8	2.9	2.9	3.0
DE	Natural Gas for Power Plants	3.4	2.5	3.4	3.9	4.2	4.4	4.5	4.7	4.8
UK		5.1	3.9	5.3	6.1	6.5	6.8	7.0	7.3	7.5
NL		5.6	4.1	5.5	6.3	6.8	7.1	7.3	7.7	8.3
DE	Fuel Oil for Power Plants	5.9	5.2	6.8	7.8	8.4	8.9	9.4	9.8	10.1
UK		10.0	8.8	11.5	13.3	14.4	15.2	15.9	16.7	17.2
NL		9.5	8.3	10.9	12.6	13.6	14.4	15.1	15.5	15.0
DE/UK/NL	Biomass - wood chips	9.9	9.9	9.9	9.9	9.9	9.9	9.9	9.9	9.9

Source of data: (IEA 2015), this study.

Table 33: Financial support for new renewable installations from 2014 to 2046 in euro / GJ of electricity.

Country	euro / GJ	2013-2016	2017-2020	2021-2024	2025-2028	2029-2032	2033-2036	2037-2040	2041-2044	2045-2046
DE	Solar-PV	98	85	80	75	70	47	0	0	0
UK		39	0	0	0	0	0	0	0	0
NL		47	42	38	32	14	0	0	0	0
DE	Biomass	157	129	121	114	106	75	0	0	0
UK		85	0	0	0	0	0	0	0	0
NL		0	0	0	0	0	0	0	0	0
DE	Onshore wind	88	83	78	73	69	49	0	0	0
UK		51	0	0	0	0	0	0	0	0
NL		47	45	41	34	15	0	0	0	0
DE	Offshore wind	151	143	134	126	118	84	0	0	0
UK		112	16	15	15	15	14	14	13	13
NL		44	46	42	35	15	0	0	0	0

Source of data: this Study.

6.7 Summary

The chapter provided an overview of the electricity system data used in the use cases of Germany, the Netherlands and the United Kingdom. Each use case was first separately presented in three **sections 6.1, 6.2 and 6.3**. Starting with a historic time-line that outlines key changes in the electricity market structure since the 1980s up to 2013. The outline served to provide a historic political-economic context to changes in electricity prices and costs and power generation investment. Subsequently, the collected datasets on power generation capacity change and electricity production were presented. And thirdly electricity prices, fuel prices and renewable energy support levies or charges were presented.

In the second part of the chapter an overview was provided on statistics used for power plant investment cost and operations and maintenance cost. Since these were found to have only minor variations between the three case studies similar values were used across all case studies. Subsequently, data used in a modelling assumption used in the TEMOA model of **chapter 8** to incorporate excess generation capacity which historically existed on top of electricity demand was introduced in **section 6.5**. And finally, the datasets utilised to extend the TEMOA model runs of **chapter 8** from 2013 up to 2046 is presented in **section 6.6**. The extension of model runs serves to compare what happens with power generation capacity investments in the 1980 to 2013 time-frame, if the investment time horizon is extended to 2046.

The datasets presented for electricity prices, fuel costs, renewable energy support, capital investments and operational costs, as presented in **sections 6.1 to 6.3** are utilised in the next results **Chapter 7** on the statistical data analysis. Subsequently, all datasets from **sections 6.1 to sections 6.6** are utilised in the TEMOA historic reproduction model runs presented in **Chapter 8**.

7 Use Case Results - Statistical Data Analyses

The results presented in this chapter serve to contribute to an answer to the sub-research question laid out in **section 1.5**: *“Which power plant investment evaluation metrics provide robust results from a ‘central planner’ modelling approach in reproducing historical generation capacity change, within the context of an optimisation based electricity system model setting driven by cost minimisation or profit maximisation?”*. The results of the statistical analysis are presented separately in this chapter for Germany, the Netherlands, and the United Kingdom in **sections 7.1** to **7.3**, respectively. A summary of findings can be found at the end of the chapter in **section 7.4** including a country case comparison. Details on the methodology and data preparation can be found in the methodology chapter **section 4.4**. To briefly recap the analyses as described include:

- The correlation between a binary variable of investment occurrence (yes/no) and a variable for the financial metric result (e.g. profitability or cost) was assessed, so as to assert the status of hypothesis 1 of **section 4.2**, whether there is a threshold condition for investment occurrence.
- A Spearman rank correlation test to evaluate the relation between i) power generation capacity expansion size of a power plant and ii) the size of financial return as based on an investment metric for a power plant technology, so as to assert the status of hypothesis 4 of **section 4.2**, on the existence of a monotonic relation between financial metric scoring and investment capacity size.

Datasets used to analyse the Spearman rank correlation coefficient test were adjusted in all three cases by removing years where no power plant investment took place in the historical record. The removal was necessary because the examination of interest is the size of power generation generation expansion when investment occurs and its relationship to financial metrics.

7.1 Germany

A range of potential threshold values was estimated for each of the financial metrics and compared with the actual binary outcomes of investment occurrence. The threshold values with the highest binary coefficients, which provide the best divisor for assignment of the occurrence of investment (yes/no) relative to actual outcomes, are provided in table 34. Across all financial metrics the Phi-coefficients for the best thresholds for Germany fall between 0.42 and 0.53, which indicates a moderate to strong correlation between the historical record and the expected investment value. The similarity coefficients range between 0.70 and 0.76, which can be interpreted as percentage of binary (yes/no) values correctly classified, demonstrating that when using the threshold values as per table 38 about 70%+ of calculated values were correctly classified. In comparison to a set of two random binary variables, the Phi-Coefficient would yield a value of 0, and the similarity coefficient a value of 0.5, indicating a significant difference of the threshold value results versus random chance. The best performing metrics are PBT and IRR which yield a 76% correct classification of all cases, with LCOE and PBT as slightly lower performing metrics.

Table 34: Results overview of binary coefficient analysis using German electricity sector data from 1980 to 2013.

Investment Metric	Data Variant	Threshold Value	Phi-Coefficient	Similarity Coefficient
PBT	All	11 years	0.560	0.76
PBT	No Renewables	11 years	0.410	0.68
NPV	All	300 million euro	0.491	0.73
NPV	No Renewables	400 million euro	0.302	0.66
IRR	All	13%	0.560	0.76
IRR	No Renewables	13%	0.410	0.68
LCOE	All	62 euro/MWh	0.440	0.71
LCOE	No Renewables	62 euro/MWh	0.428	0.71

The distribution of all-technology dataset statistical results for the phi-coefficient and similarity coefficient can be found in figure 7 for the four financial metrics. The distribution shows that the best thresholds as per table 34 can be interpreted as falling within a relatively 'flat-top', in that slightly higher or lower thresholds, such as an IRR of 12%, 13%, and 14%, exhibits similar explanatory power. The only exception in this is the LCOE, which has a sharp fall off in its ability to explain investments from 62 to 80 euro per MWh.

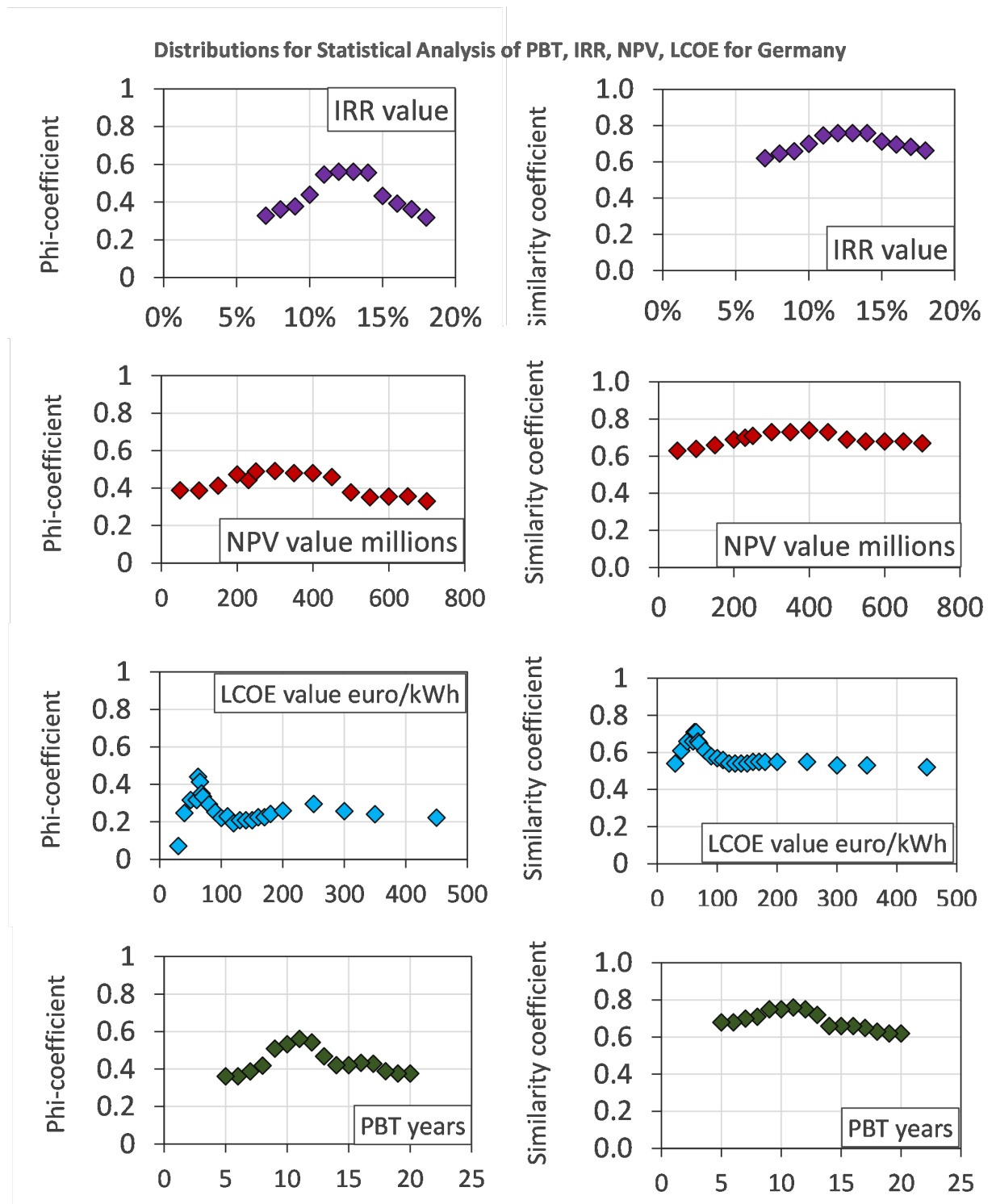


Figure 21: Distribution of results for binary coefficient analysis using German electricity sector data from 1980 to 2013

The estimates for the Spearman correlation for Germany are shown in table 35 for the four investment metrics (PBT, NPV, IRR, and LCOE). The tests were carried out using historical investment occurrence datasets with only renewable electricity sources, no renewable electricity (only thermal generation), and all technologies. The null-hypothesis “*the financial metric variable and the expansion of power generation across all technologies are correlated by rank in magnitude*” is rejected for all four metrics for tested datasets with only thermal generation. The hypothesis is not rejected for datasets with only renewable electricity sources in case of PBT, NPV, and IRR. It is also not rejected when all technology data-points are taken into account for PBT and NPV.

The test shows that the size of invested capacity in terms of MW is related to the profitability of investment for renewable energy technologies. The best correlation is found using the IRR, with a Spearman’s rho of 0.697 and a standard error of only 3478. This relationship can also be shown visually by a plot of the financial metric on the x-axis and the size of expansion on the y-axis, shown for IRR in figure 22 below.

Table 35: Results overview of Spearman correlation for different investment metrics using German electricity sector data from 1980 to 2013

Investment metric	Data Variant	N	Spearman’s rho	p-value	Standard error
PBT	All	118	-0.1589	0.086**	317335
PBT	No renewables	77	0.0351	0.762	73408
PBT	Only renewables	41	-0.6485	0.000*	18924
NPV	All	118	0.3538	0.000*	176916
NPV	No renewables	77	0.0264	0.819	74068
NPV	Only renewables	41	0.3579	0.022*	7371
IRR	All	118	0.1041	0.262	245317
IRR	No renewables	77	-0.0594	0.608	80595
IRR	Only renewables	41	0.6970	0.000*	3478
LCOE	All	118	0.2379	0.009*	208680
LCOE	No renewables	77	0.0266	0.819	74054
LCOE	Only renewables	41	-0.1130	0.482	12777

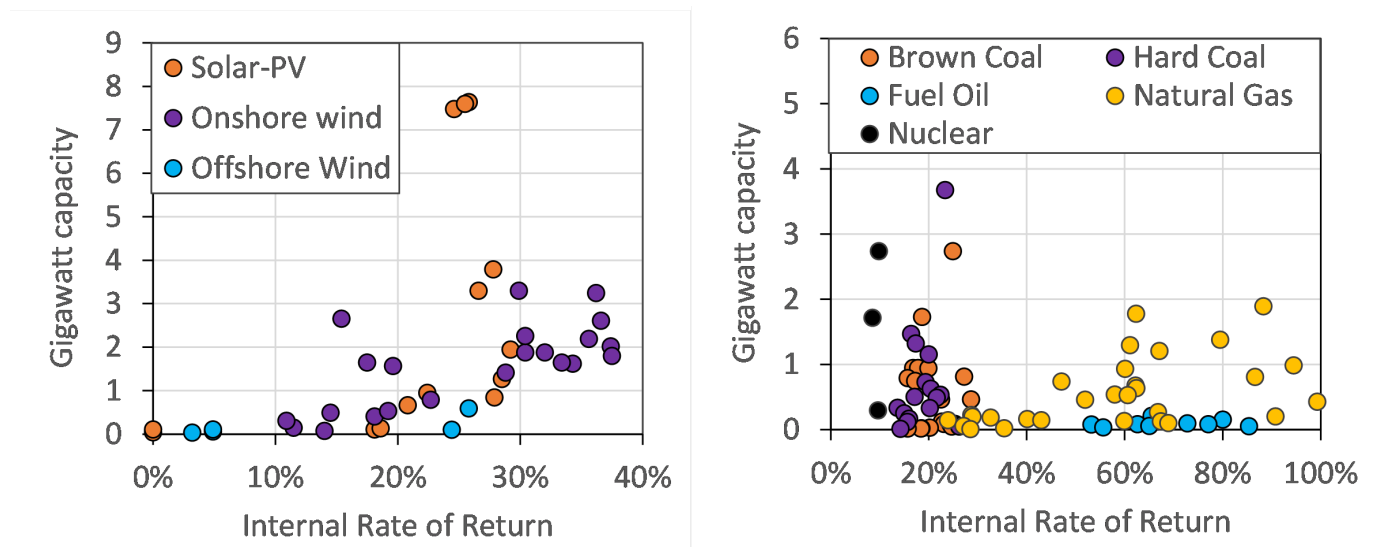


Figure 22: Scatterplot of IRR for renewable energy (left) and fossil fuels (right) in relation to size of technology expansion for Germany 1980-2013 in MW.

7.2 United Kingdom

The threshold value outcomes best able to explain historical outcomes are shown in table enclosed in table 37. The Phi-coefficients for all metrics fall between 0.29 and 0.52 indicating mostly a moderate correlation between the historical record and the expected investment value. The similarity coefficients fall between 0.66 and 0.83 demonstrating that 66%+ of calculated values were correctly classified using the threshold values as per table 36 for the financial investment metrics. The best performing metric out of all four is NPV which enables a correct classification of 80% of cases.

Table 36: Results overview of binary coefficient analysis using UK electricity sector data from 1980 to 2013.

Investment Metric	Data Variant	Threshold Value	Phi-Coefficient	Similarity Coefficient
PBT	All	7 years	0.367	0.73
PBT	No Renewables	7 years	0.393	0.70
NPV	All	560 million euro	0.525	0.80
NPV	No Renewables	800 million euro	0.518	0.83
IRR	All	19%	0.347	0.71
IRR	No Renewables	20%	0.356	0.66
LCOE	All	62 euro/MWh	0.290	0.67
LCOE	No Renewables	55 euro/MWh	0.404	0.71

The distribution of all-technology dataset statistical results for the phi-coefficient and similarity coefficient can be found in figure 7 for the four financial metrics. The distribution shows that similar to Germany and the Netherlands the best thresholds as per table 36 can be interpreted as falling within a relatively 'flat-top', in that slightly higher or lower thresholds, such as an NPV value in the range of 500 to 800 million euro, which exhibit similar explanatory power. Also similar to Germany and the Netherlands the only exception to this is the LCOE, which has a sharp fall off in its ability to explain investments from 62 to 80 euro per MWh.

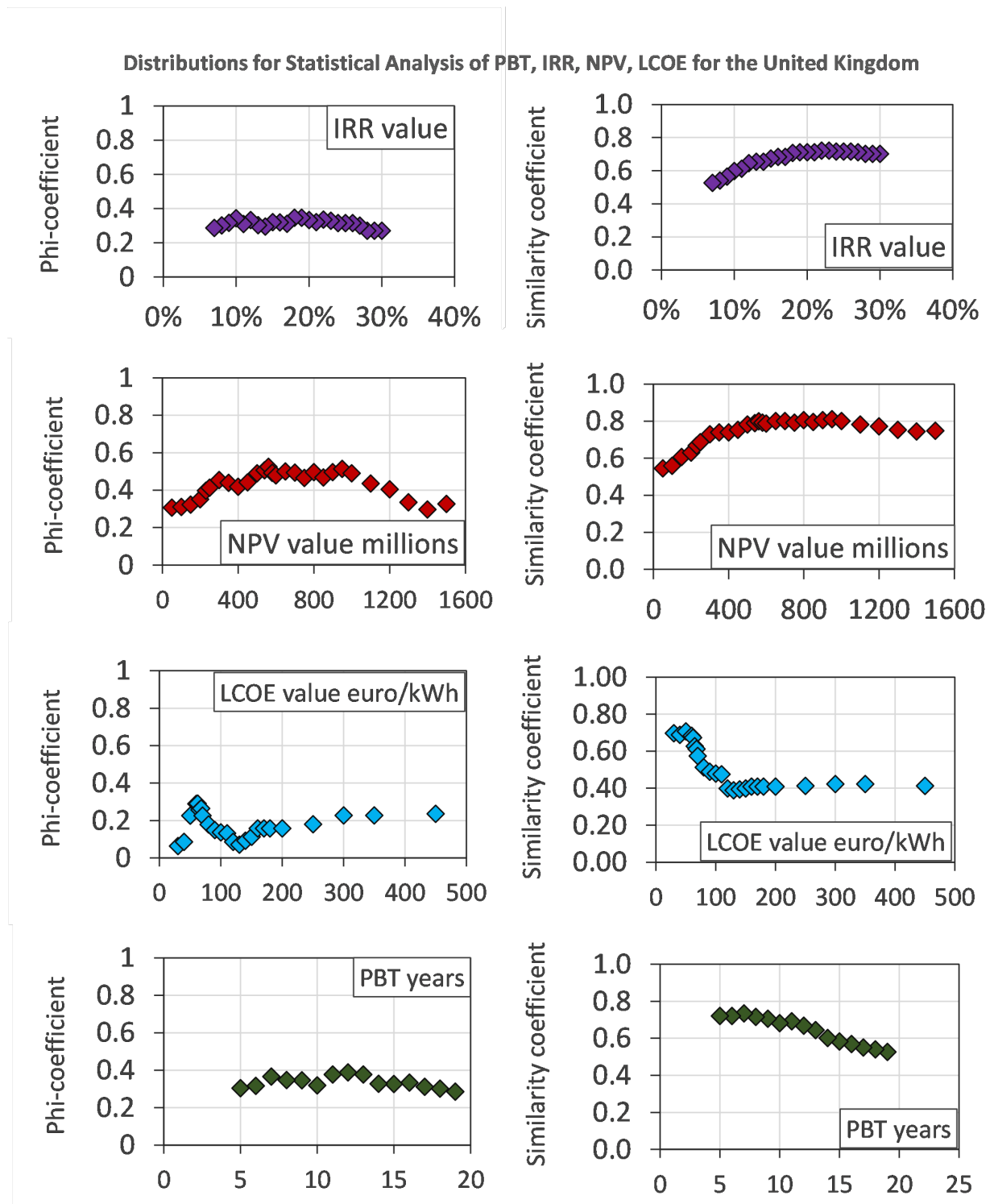


Figure 23: Distribution of results for binary coefficient analysis using United Kingdom electricity sector data from 1980 to 2013

The estimates for the Spearman correlation for the United Kingdom are shown in table 24. The null-hypothesis “the financial metric variable and the expansion of power generation across all technologies are correlated by rank in magnitude” is rejected for tested datasets with only thermal generation for all four financial investment metrics. The hypothesis for the renewable energy only dataset is not rejected for PBT, NPV and LCOE, but is rejected for IRR at an alpha equals 0.05 threshold level of significance. The lack of a relationship for IRR is shown visually by a plot of the financial metric on the x-axis and the size of expansion on the y-axis in figure 24 below.

Table 37: Results overview of Spearman correlation for different investment metrics using UK electricity sector data from 1980 to 2013.

Investment metric	Data Variant	N	Spearman's rho	p-value	Standard error
PBT	All	61	-0.3993	0.001*	52925
PBT	No renewables	27	0.0112	0.953	3237
PBT	Only renewables	34	-0.3400	0.005*	8771
NPV	All	61	0.2777	0.030*	27316
NPV	No renewables	27	-0.0989	0.622	3600
NPV	Only renewables	34	0.6637	0.000*	2201
IRR	All	61	0.4474	0.000*	20898
IRR	No renewables	27	0.0211	0.917	3207
IRR	Only renewables	34	0.2934	0.092**	4625
LCOE	All	61	-0.3666	0.004*	51685
LCOE	No renewables	27	0.0873	0.664	2990
LCOE	Only renewables	34	0.3810	0.026*	4051

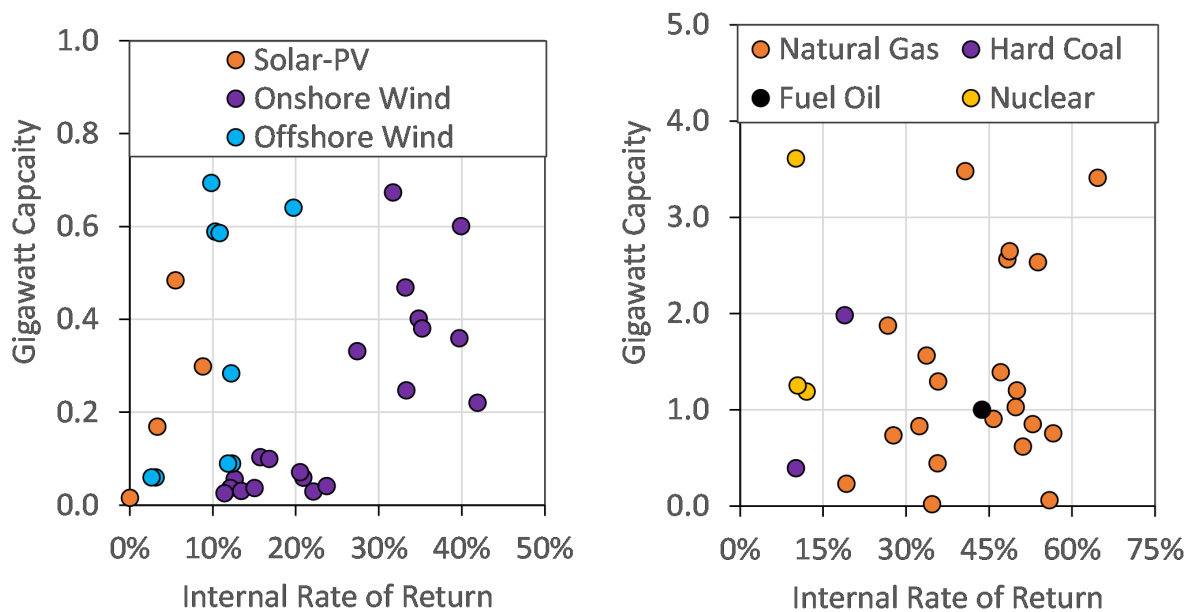


Figure 24: Scatterplot of IRR for renewable energy (left) and fossil fuels (right) in relation to size of technology expansion for the United Kingdom 1980-2013 in MW.

7.3 The Netherlands

The thresholds with the highest coefficients from the statistical test, which indicate the best threshold values that could apply for the investment decision (yes/no) are enclosed in table 38. The Phi-coefficients for all metrics fall between 0.35 and 0.57 indicating a moderate to strong correlation between the historical record and the expected investment value. The similarity coefficients fall between 0.74 and 0.85 demonstrating that 74%+ of calculated values were correctly classified using the threshold values as per table 38 for the financial investment metrics. The best performing metrics are PBT and NPV which provide for a 79% correct classification of all cases, but the thresholds for the other metrics LCOE and PBT fall closely behind.

Table 38: Results overview of binary coefficient analysis using Dutch electricity sector data from 1980 to 2013.

Investment Metric	Data Variant	Threshold Value	Phi-Coefficient	Similarity Coefficient
PBT	All	7 years	0.455	0.79
PBT	No Renewables	7 years	0.537	0.84
NPV	All	350 million euro	0.458	0.79
NPV	No Renewables	350 million euro	0.498	0.83
IRR	All	18%	0.346	0.74
IRR	No Renewables	19%	0.422	0.76
LCOE	All	43 euro/MWh	0.354	0.76
LCOE	No Renewables	43 euro/MWh	0.566	0.85

The distribution of all-technology dataset statistical results for the phi-coefficient and similarity coefficient can be found in figure 7 for the four financial metrics. The distribution shows that similar to Germany and the United Kingdom the best thresholds as per table 38 can be interpreted as falling within a relatively 'flat-top', in that slightly higher or lower thresholds, such as a payback-time of 7 and 8 years, do exhibit similar explanatory power. Also similar to Germany the only exception to this is the LCOE, which has a sharp fall off in its ability to explain investments from 43 to 60 euro per MWh.

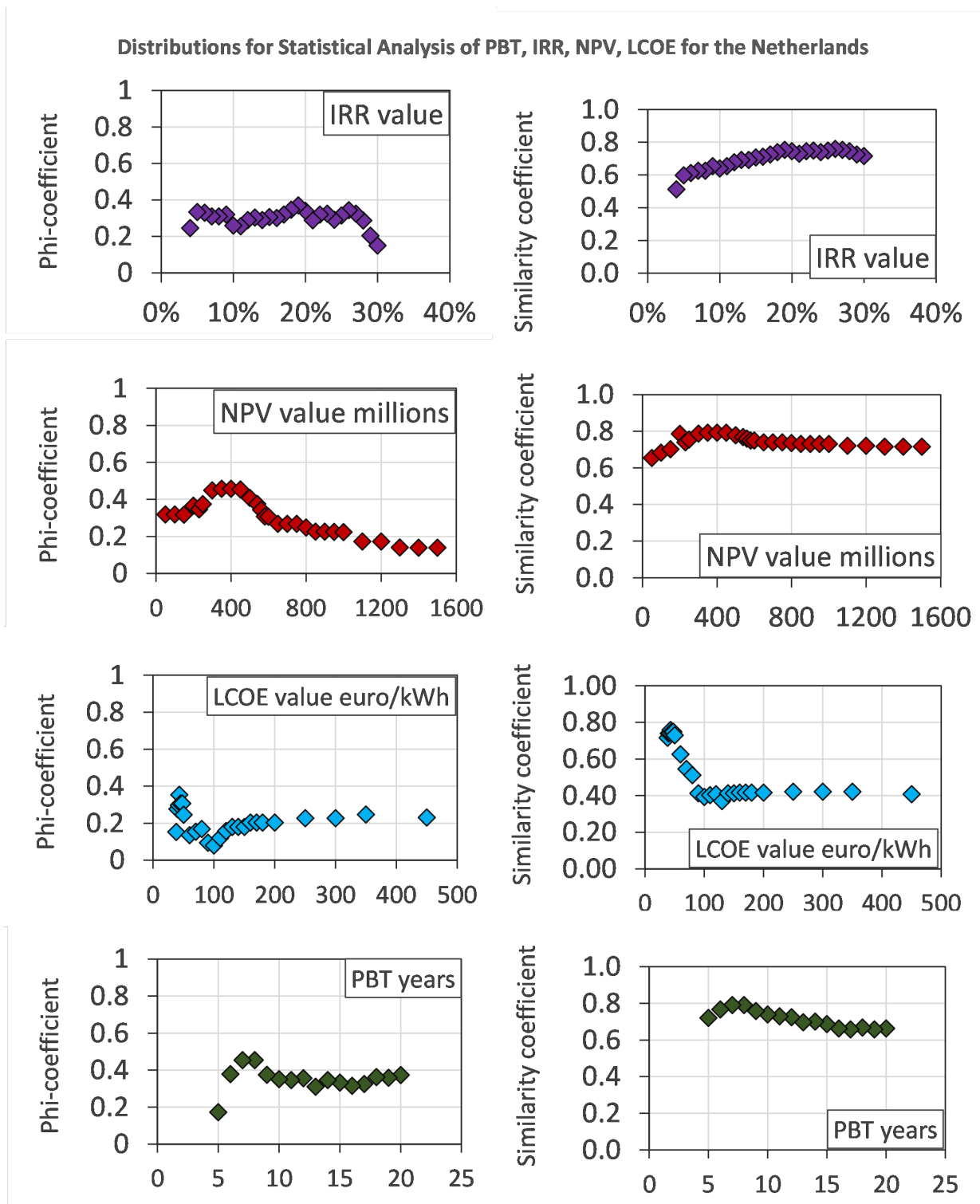


Figure 25: Distribution of results for binary coefficient analysis using Dutch electricity sector data from 1980 to 2013

The estimates for the Spearman correlation for the Netherlands are shown in table 39 to examine if the value of the financial metric impacts the size of power generation capacity investments. The null-hypothesis “*the financial metric variable and the expansion of power generation across all technologies are correlated by rank in magnitude*” is rejected for PBT, NPV and IRR for tested datasets with only thermal generation. The hypothesis is not rejected for thermal generation for LCOE and not rejected for datasets with only renewable electricity sources in case of PBT, NPV, and IRR. The relationship is visually depicted for IRR in figure 26 below by a plot of the financial metric on the x-axis and the size of expansion on the y-axis.

Table 39: Results overview of Spearman correlation for different investment metrics using Dutch electricity sector data from 1980 to 2013.

Investment metric	Data Variant	N	Spearman's rho	p-value	Standard error
PBT	All	65	-0.4762	0.000*	67551
PBT	No renewables	30	-0.0502	0.792	11464
PBT	Only renewables	35	-0.6056	0.000*	4721
NPV	All	65	0.3728	0.000*	28702
NPV	No renewables	30	0.0225	0.907	4394
NPV	Only renewables	35	0.5611	0.000*	3133
IRR	All	65	0.5146	0.000*	22209
IRR	No renewables	30	0.0605	0.751	4223
IRR	Only Renewables	35	0.6209	0.000*	2707
LCOE	All	65	-0.1611	0.200	53130
LCOE	No renewables	30	0.3949	0.032*	2720
LCOE	Only renewables	35	0.1331	0.446	6189

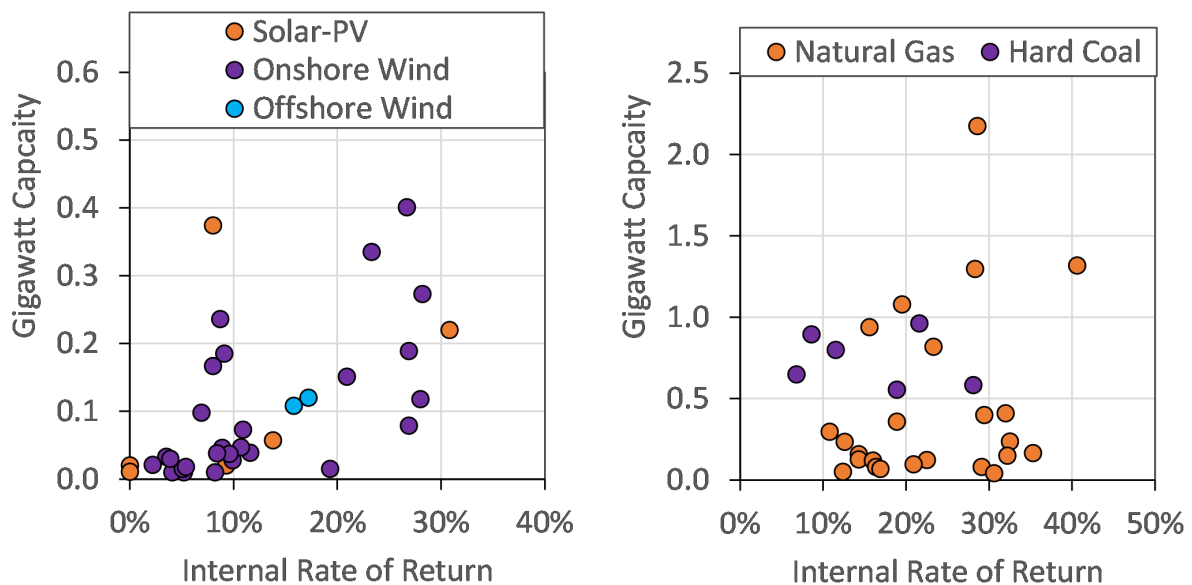


Figure 26: Scatterplot of IRR for renewable energy (left) and fossil fuels (right) in relation to size of technology expansion for the Netherlands 1980-2013 in MW.

7.4 Summary

The chapter evaluated the correlation between historic power generation installation with a time adjustment as a proxy for investments, and a number of financial investment metrics, including Pay-Back Time (PBT), Net Present Value (NPV), Internal Rate of Return (IRR), and Levelized Cost of Electricity (LCOE). The first analysis looked at whether a significant binary (yes/no) threshold value applies that can be interpreted as a threshold that needs to be met before investment occurs. The analysis of Germany yielded 71% to 76% success of investment occurrence based on applying a threshold below which no investment would occur and above which investment always occurs. The variation in classification between the metrics is quite low, with the IRR and PBT yielding a few % better classification. The found thresholds for Germany for these metrics are a 13% IRR and 11 year pay-back time. An analysis of deviations from the threshold show that the number of correct classification drop to around 60% when the IRR is lowered to below 10% or set above 17%, or when the pay-back time threshold is lowered to 5 years or set above 14 years. The thresholds thus fall within a distribution with a 'flat-top' and do not provide a clear binary threshold. The only metric with a less 'flat-top' for Germany is the LCOE, which at a value of 62 euro/kWh has a classification correctness of 71% of investment occurrences, whilst an LCOE below 50 or above 70 yields a 55% or lower correct classification.

The UK statistical analysis of the binary coefficient gave a substantially better result for NPV than the other metrics at 80% correct classifications for a 560 million euro threshold. The best value for LCOE was a 62 euro per MWh threshold which yielded a 67% correct classification, the best value for IRR was a 19% value with a 71% correct classification, and for PBT the best value was 7 years with a 73% correct classification. The percentage correctly classified for the UK changes gradually when using lower IRR or NPV values, and higher PBT values, to 60% or less, but remains at such high levels at higher NPV's, IRR or PBT values. An NPV of 800 million for example, only yields a slightly lower classification. Again the exception is LCOE where classifications drop rapidly to only 40% correctly classified as the LCOE threshold is increased to 100 euro per MWh.

The analysis for the Netherlands of a threshold value yielded a 74% to 79% correct classification of investment occurrence. The best indicators are PBT and NPV with a correct classification of 79% at a threshold value of 7 years and 350 million euro, respectively. The thresholds again fall within a 'flat-top' range where a change in the threshold only changes the classification marginally. An NPV of 600 million or higher still delivers a correct classification of 70%, and below 200 million euro of 65%. Similarly, a PBT of 5 yields a 70% classification and a PBT above 14 a 60% classification. Again the only metric without such a 'flat-top' is an LCOE value which rapidly drops from 76% to below 40% classification when the threshold is set to 100 euro per kWh.

The results for the three countries thus show that a significant binary (yes/no) threshold value applies for investments to take place. The % of correctly classified cases for the three countries, Germany, the Netherlands, and the UK lie within a 66% to 85% range. The metrics can be ranked in terms of their classification power for investment occurrence with first NPV (73% to 80% across the three cases), second PBT (73% to 79%), third IRR (72% to 76%), and fourth LCOE (67% to 76%). Another observation that can be made is that the threshold values that perform best within these 'flat tops' to classify investment occurrence do not diverge substantially between the three cases:

- **Payback time**, at a 10, 7, and 7, years PayBack Time (PBT) or smaller for investment to occur in DE, UK, and NL, respectively.
- **NPV**, at a 300, 560, and 350 million euro or greater Net Present Value (NPV) for investment to occur in DE, UK, and NL, respectively.
- **IRR**, at a 13%, 19%, and 18% or greater Internal Rate of Return (IRR) for investment to occur in DE, UK, and NL, respectively.
- **LCOE**, at a 62, 62, and 43 euro per MWh or lower Levelised Cost Of Electricity (LCOE) for investment to occur in DE, UK, and NL, respectively.

The reason for similar threshold values can plausibly be found in technological similarities, as well as cost and price structures. The only technology variation is Germany where brown or lignite coal is available. Based on that a large number of investment occurrence can be correctly classified, with thresholds that are quite similar across the three cases, the test thereby does not falsify the 1st hypothesis as described in **section 4.2**, as it is shown that there is a threshold level used for investment decisions. We can on this basis make the inductive-statistical generalisation that:

“66% to 85% of all NPV, IRR, payback-time, and LCOE financial metric value threshold expected investment decisions Fs, are correlated with empirical data based outcomes caused by investment decisions Gs, therefore (probably) approximately 70% of investment decisions can be resembled by using financial investment metrics Fs on a threshold value basis.”

What still remains a challenge is that the precision of the threshold is limited given the set of 'flat tops', except for LCOE values, as substantial variation only results in minor reductions in classifications. Only with large changes in the NPV, PBT or IRR threshold value does the number of classified cases drop substantially for all three countries. The key reason is that as the threshold value grows, for instance a higher IRR threshold, the number of correct positive classifications (that investment occurred) decline, but the amount of negative classifications (that investment did not occur) grow. The metrics except for LCOE are not suitable to filter out these effects of increasing correct classification of no investment vs decreasing correct classification of investment occurrence under shifting the threshold value. Why LCOE provides for a sharper threshold may be because this metric fluctuates less over time for thermal power technologies, as can be analysed by looking at the input datasets to compare metric evolution from 1980 to 2013, as a consequence of a balancing out of changes in capital cost, fuel expenditure and improved efficiency of power plants. The PBT, NPV and IRR values are different as they also incorporate fluctuations in the electricity price and feed-in tariffs or other subsidies, and are thereby more volatile. Since metric values that remain relatively stable, like in this case LCOE, suffer less from the shifting threshold effect where mixed improvements in binary classifications occur (a shift means some values are correctly classified but others are not) they have a more precise threshold. However, the stability of LCOE is to an extent arbitrary, and the only non-arbitrary reason that it is more likely to be stable is because it involves less variables in its calculation.

Another observation that can be made is that classifications were at best 80% correct. That the classifications are not higher is because in all three country cases the majority of mis-classifications occur due to cases where no investment occurs, whilst the threshold value indicates that it should have occurred under anticipated favourable economic conditions. There is insufficient demand in many years of demand to warrant expansion for all individual years, which are not filtered out in the statistical analysis. Several other aspects plausibly play a role in the investment mis-match between the analysis and history in certain technologies in these three countries. Political reasons such as a limit to provisioning of construction permits could play a role, as well as additional financial risks which are not factored into the capital and operational cost data used for the analysis. Discontinuous risks include, for example, the risk of low chance yet high impact nuclear accidents, which if not at least partially covered by governments can prove to be a too high cost a risk for investment to make sense for private market players. This is in line with the observation from the interviews that the real life approach is a minimum threshold IRR approach that needs to be met, but that once this is met other factors play a role once a financial hurdle rate is passed. The key role of risk was corroborated in the interview insights which revealed a key method to deal with such risks is to encase them in contractual requirements to minimize these, such as through a power plant investor and operator and the government. Another discontinuous risk are large jumps in fossil fuel prices that are not possible to factor in except for a scenario investment impact testing approach. The range of risk related factors combined with political constraints plausibly always results in a substantial set of misclassifications, and as such it seems that at best a correct number of classifications of 70% to 80% occurs. Another aspect that can be of influence is that, if a threshold is used in reality, it could change over time as profitability of technologies changes or market regulations make all technologies less profitable. Companies may thus expand or shrink their financial threshold level of acceptance. The analysis assumed that the threshold is stable and does not change within the timespan of three decades.

The conclusion that can be drawn from this is that, in order to establish a more precise threshold value, the impact of factors that form prerequisites for a financial investment decision to take place are of importance. First, whether the

expected demand for electricity is there to warrant an investment decisions. If the demand is not met there automatically would be a non-investment occurrence. Second, whether certain technologies are barred from investment, either for non-financial reasons or indirect reasons such as too high risks, such as in case of nuclear power. Even though their direct financial picture might lead to the conclusion that investment would occur if the company had the choice.

The second statistical analysis that was carried out looked at whether the size of investments, in terms of realised power generation capacity, had any relation to the size of the respective financial metric (e.g. if a larger IRR signals a larger financial investment sum). In general no relation was found between the size of investments and the size of the respective financial metric. As such the 4th hypothesis, that beyond a threshold value there is a positive monotonic relation between performance on the financial metric and power plant capacity investment, as described in **section 4.2** was falsified. The exception to this were renewable energy generation technologies for which profitability or lower cost was found to be correlated to investment size in the three countries. A plausible explanation lies in the increasing profitability and cost reductions in renewable electricity sources in general, due to technological change plus government feed-in and subsidy support, which underpins their increasing penetration in these electricity markets. In contrast fossil fuel and nuclear generation electricity technologies exhibit fairly stable capital costs as they are already mature, with fluctuating operational costs due to fuel price volatility over the thirty year period.

8 Use Case Results - Empirical Model Validation

The results presented in this chapter are based on the TEMOA optimization model model run variants, as described in **section 4.5** of this thesis. The technical outline of the TEMOA model implementation can be found in **Appendix C**. The investigation in this chapter aims to contribute to an answer to the sub-research question described in **section 1.5**:

- *Which power plant investment evaluation metrics provide robust results from a 'central planner' optimisation modelling approach, driven by cost minimisation or profit maximisation, in reproducing historical generation capacity change?*

The results are separately discussed for model runs using a time period between 1980 to 2013 for each country in **section 8.2** for Germany, **section 8.3** for the UK, and **section 8.4** for the Netherlands. Prior to the country evaluation a number of general observations are made in **section 8.1** that were similar for the three country studies. Also a large number of elongated model runs with time periods from 1980 to 2046 were assessed, based on similar model settings as the shorter time-period model runs (at least similar for the period 1980 - 2013), as discussed in **section 8.5**. Finally, a summary of the results is presented in **section 8.6**, in relation to the hypotheses as presented in **section 4.2**.

8.1 General Observations

A number of general observations can be established from the 64 model run variants. In a model structure without constraints on the maximum of power generation capacity that can be built, such as in the form of an annual or maximum total constraint, the optimization structure exploits knowledge of all investment costs in all periods, by building substantial double digit power generation capacity for a single technology in a single year. Even in time-stepped variants of the model this is the case, although to a lesser extent. The outcome of the chosen technology and how much power generation capacity is built thereby changes substantially when annual and maximum power generation capacity construction constraints are included.

The adjustment of the discount rate from 5% to 10% was found to have an effect especially in model runs with investment cost amortization in all three country cases. The effect was a change in build-out size between two technologies, where one became larger and the other smaller at a 10% versus a 5% discount rate value. For example, larger hard-coal power generation capacity at a 10% discount rate and smaller nuclear power capacity, versus larger nuclear power capacity at a 5% discount rate and smaller hard coal generation capacity. A key cause for this 'swap' of sizing between two technologies is the higher investment costs of nuclear versus greater fuel costs for hard-coal, whose relative costs are affected by discount rates and amortization.

The variation between the four investment algorithms (max-NPV, min-COST, min-LCOE, and min-PBT) is substantial on the emergence of renewable electricity power generation capacity. In case of maximisation of NPV substantially more investments occur in renewable electricity sources, and even more in the time-stepped variants with max-NPV. In contrast, no to small numbers of renewable electricity generation capacity appears in minimisation based on costs for all the three other financial metric variants. The main cause is the incorporation of financial support mechanisms for renewable electricity generation sources in max-NPV, which since they fall under the profit side (and not the cost side) are only incorporated in the max-NPV maximisation. Without such financial support therefore, renewable electricity power generation is not sufficiently low cost relative to fossil fuel and nuclear power generation technologies, at least not in the time-series datasets utilised.

The effects on amortization of investment cost versus lump-sum investment on the outcome of model runs are mixed. For example, under amortization versus lump-sum investment a reduction in fuel oil power generation capacity is visible (for min-COST in all three countries), an increase in onshore-wind (for max-NPV in all three countries), an increase in natural gas (for max-NPV in the UK), and a decrease of nuclear power generation capacity (for min-PBT for NL).

8.2 Germany model runs

A substantial number at 23 out of 64 model run results were found to yield a statistically significant test result for the Spearman statistic, both for the annual ranking comparison with historical values and for five year interval comparisons. The statistically significant results came mainly from model runs based on max-NPV time-stepped, and min-LCOE intertemporal and time-stepped model settings. Also two intertemporal min-COST runs and three max-NPV intertemporal runs yielded a significant Spearman statistical correlations, as shown in table 40. The best ranking relationship for both the annual and 5-year ranking comparison are found in the max-NPV time-stepped variants as indicated by the higher Spearman rho values at > 0.3 for annual Spearman tests, and > 0.4 for the five year interval comparison. The main difference in the max-NPV time-stepped runs, relative to other model runs, are large increases in renewable electricity generation capacity of solar-PV, onshore-wind, and biomass. In the historical data, solar-PV and onshore wind grow substantially whilst biomass remains fairly low in power generation capacity values. In case of max-NPV intertemporal model runs renewable electricity power generation capacity only appears in amortized variants with maxcap and annual constraints. A second main difference is that the amounts of built brown-coal and nuclear power generation capacity is similar in these model runs to historical values at 12.8 and 14.1 GW, and natural gas build-out is reasonably close to historical values. Not in line with historical developments is the emergence of large multi-digit fuel oil power generation capacity in max-NPV model runs.

A cumulative GW of power generation capacity comparison based on the discrepancy between realised capacity minus model outcomes, in absolute terms, shows substantial differences between no constraints and maxcap + annual constraints. In case of a min-COST intertemporal variant the solution with constraints is on average about 20% closer to the empirical data than the variant without such constraints (e.g. a 145 GW absolute discrepancy with constraints versus a 181 GW discrepancy without versus historical outcomes). In case of a min-COST time-stepped variant the solution is on average about 5% closer to empirical data than without maxcap + annual constraints, for max-NPV intertemporal and time-stepped variants 35% and 20%, for min-PBT-intertemporal and timestepped variants 35% and 28%, and for min-LCOE intertemporal and time-stepped variants 23% and 26% closer. There are no substantial differences on average between lump-sum and amortized model run outcomes for Germany, nor for a 5% and 10% discount rate difference between model runs. When comparing intertemporal with time-stepped variants with maxcap + annual constraints there is a small difference for min-COST, max-NPV, and min-PBT, where time-stepped variants on average yield outcomes that are 5%, 9%, and -4% closer to empirical data values, respectively.

The comparison between historical data and outcomes from model runs for max-NPV and min-LCOE are shown in figure 27 and 28 for intertemporal and time-stepped variants with maxcap and annual constraints, 5% discount rates, and amortized calculations. It can be observed that limited power generation capacity is built at the end of the model run period, as a consequence of reduced benefits from building capacity that will not operate for a substantial number of years. Also power generation capacity expansions are much more substantial in the 1980s relative to historical developments, where substantially lower capacity was constructed per year and built capacity was spread out across years.

8.2.1 German Technology inflection Points and Scaling

Inflection points in the model-runs with the best correlation to historical outcomes for Germany were analysed, namely max-NPV with maximum and annual capacity constraints. Six such technology inflection points were observed. The first is the expansion of nuclear power from 1981 to 1990 in the historical time series. The same magnitude expansion occurs in the model runs with max-NPV with close to the same capacity, but depending on the settings the expansion ranges from 2/3rds to 4/3rds of the historic capacity. Larger expansion occurs under 10% discount rates and lump-sum investment options, and also under the amortized setting for the time-stepped variant. The cause is plausibly due to more favourable economics of this power source in the 1980s until costs rise substantially, in combination with less favourable economics for renewable energy technologies which are either absent (under 10% interest rates) or model runs only develop on a small basis for solar-PV, in the absence of amortization.

The second is the model outcome of an expansion of crude oil power generation capacity starting in 1984 or 1985 and lasting until 1995. This development coincided with a third inflection point in the max-NPV model results, the rapid decline of especially hard coal and to a lesser extent brown coal capacity from 1990 to 1997, with a subsequent decline at a slower pace until 2013. Both developments did not occur historically. Oil capacity never expanded and was slowly phased out historically. And, in contrast, brown coal capacity was in Germany maintained at nearly the same capacity level from the late 1980s until 2013 due to substantial capacity construction in the 1990s. Similarly, hard coal capacity was maintained at the same capacity levels across the 30 year time period as new capacity installations in the 2000s replaced retired capacity.

The fourth inflection point is the introduction starting in 1999 of onshore-wind and biomass generation capacity. In the historic time series onshore wind was already first introduced in 1991 and ramped up slowly in the 1990s, followed by rapid growth from 1998 onwards. Onshore wind reaches about 2/3rd of the capacity in the model runs from 1999 to 2003, as historically built from 1995 to 2013. Biomass was already introduced in the 1980s at small levels and remained at a marginal capacity level until it grew rapidly from 1997 onwards. Biomass historically only reached about 1/5th of the capacity installed in model runs by 2013, however. The fifth is the first installation in the model results of Solar-PV capacity in 2005, and the sixth the first introduction of offshore wind in 2008, in the time-stepped variant only. In the historic time-series solar-PV was introduced first in 1991 but started to ramp up only from 2002 onwards, and offshore wind was first introduced in 2009 after which scaling started immediately. Solar-PV reaches about the same level of capacity in the model runs by the early 2000s as occurred in the historical time-series by 2012. Offshore wind in the intertemporal Max-NPV variants reaches about three times the capacity by 2013 as in the historic time-series, whilst in the intertemporal variant it does not appear at all.

The cause of differences for fossil fuels between the max-NPV model runs and historic outcomes can be found in key political decisions made to support incumbent industrial sectors. The German government instated several support mechanisms which benefitted coal consumption over oil production in order to continue its coal mining industry in the face of international competition and retain coal jobs. As indicated in **chapter 6**, support mechanisms included mandated hard coal mining quantities in the 1980s, and the introduction of a coal levy on electricity prices to support the mining industry. These measures were substantially influenced by the risk perception of importing oil for power production following the 1973 and 1981 oil crises and made the support for domestic coal even more favourable. Even if oil would be cheaper to use than coal on a pure cost basis, as indicated by the max-NPV model runs, these developments made oil unfavourable from a political-economy point of view. Interestingly, the development of nuclear follows a similar trajectory in the historic and the model-run time-series, except for the intertemporal lump-sum investment model-runs. This indicates that, at least for Germany, the political decision to halt nuclear expansion following Chernobyl coincided with unfavourable nuclear power generation economics comparative to other technologies. It is likely that the change in the economics of nuclear and the Chernobyl accident are related, however, as the cost of safety measures and costs of risk management increased following the accident.

The historic adoption speed of solar-PV, onshore and offshore wind, and biomass technologies shows that the introduction of new technologies occurs earlier than price signals may warrant. In the max-NPV model-runs first introduction

occurs about ten to fifteen years later than historically the case. However, the time at which rapid scaling up starts coincides quite well between max-NPV model run results and historic data, indicating that price signals provide a sufficient mechanism for technology scaling. As such early but limited adoption by pioneers and via small government incentives, such as the 1000 roofs solar program, requires the incorporation of non-financial mechanisms in models. Another key difference in technology inflection is the degree of scaling, as seen for biomass and offshore wind in historic data versus model-runs, indicating that several non-financial barriers are in place that restrict technology scaling. In case of biomass and offshore wind this could include availability of feedstock, investment capacity, technology uncertainty and political and regulatory decisions (e.g. number of offshore wind farm sites permitted to developers).

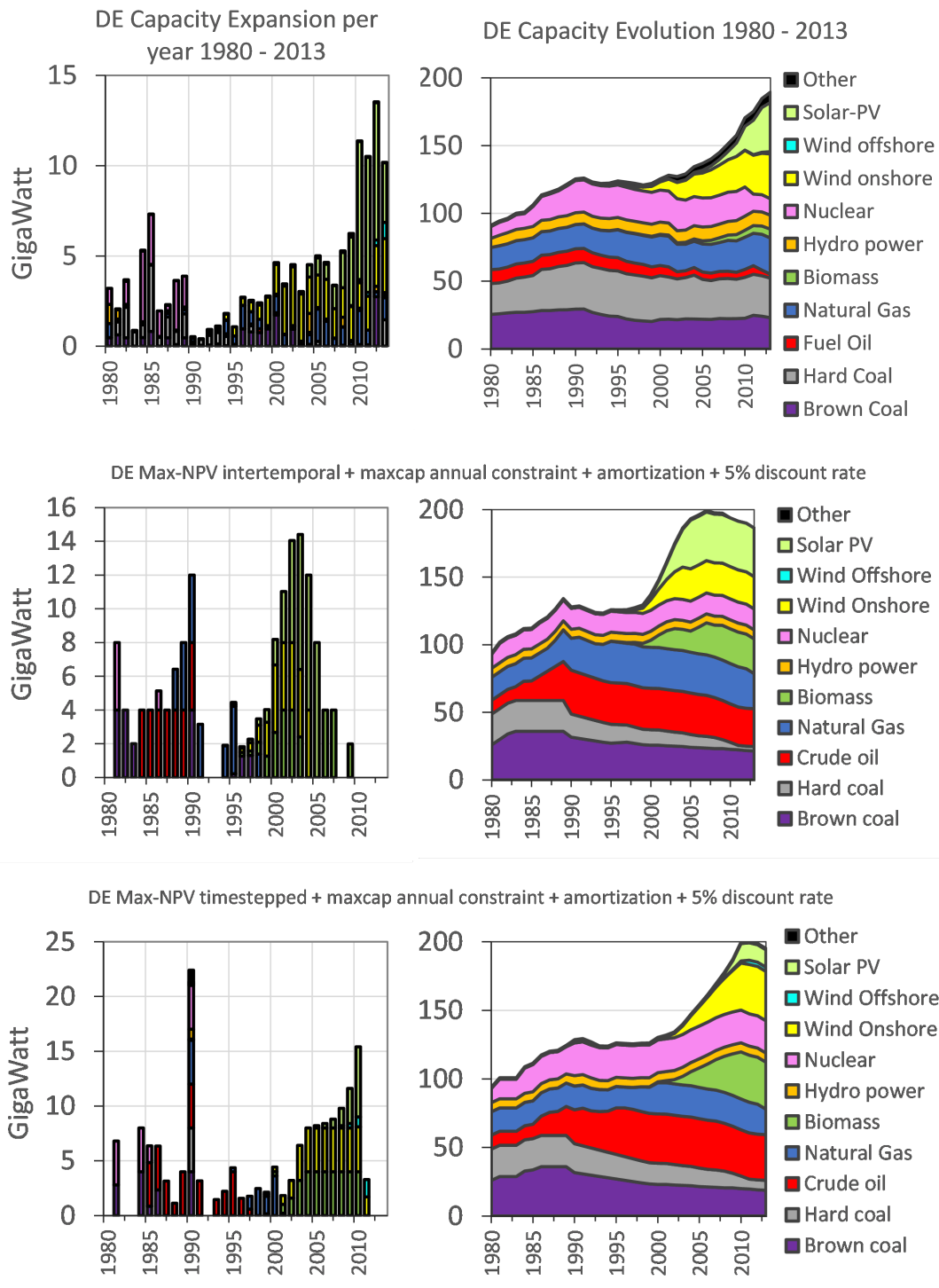


Figure 27: Comparison between historical capacity evolution (top) and model runs with max-NPV (centre and bottom)

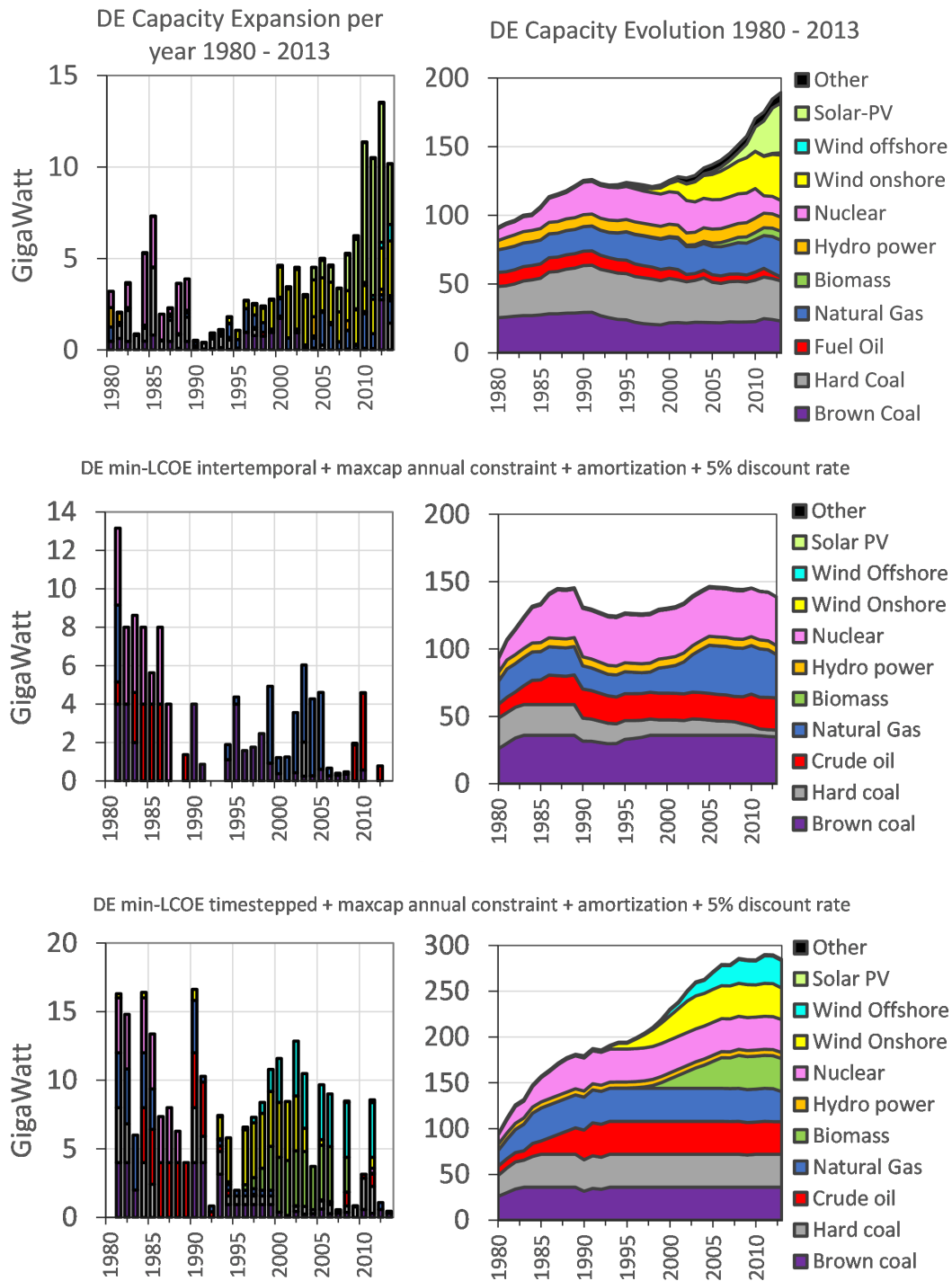


Figure 28: Comparison between historical capacity evolution (top) and model runs with min-LCOE (centre and bottom)

Table 40: Overview of significant results for TEMOA optimization for Germany.

Metric	Time	Structure	Constraints	Disc.	Power generation source* additions 1981 - 2013 (GW)									Δ GW^	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
					BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
n/a	n/a	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
mincost	intertemp	lump-sum	max cap. + annual	5%	26.0	0.0	27.4	35.9	18.9	0.0	0.0	0.0	0.0	148.0	77	260	0.182	0.002*	3573335	0.312	0.013*	28663
mincost	intertemp	lump-sum	max cap. + annual	10%	24.4	16.0	27.4	35.9	4.0	0.0	0.0	0.0	0.0	143.7	64	304	0.126	0.030*	3814904	0.318	0.011*	28404
NPV	intertemp	lump-sum	max cap. + annual	5%	29.2	5.0	27.0	15.7	25.6	15.9	0.0	0.0	0.0	116.4	110	229	0.245	0.000*	3411144	0.396	0.001*	25184
NPV	intertemp	lump-sum	max cap. + annual	10%	29.2	8.0	27.0	17.3	25.6	0.0	0.0	0.0	0.0	130.9	97	229	0.169	0.004*	3716454	0.288	0.022*	29668
NPV	intertemp	amortized	max cap. + annual	5%	16.8	0.0	20.9	28.0	5.1	23.9	0.0	36.0	25.7	92.8	224	387	0.204	0.000*	3474678	0.314	0.012*	28597
NPV	timestep	lump-sum	none	5%	14.7	4.0	6.1	41.3	12.3	42.4	3.2	20.7	34.3	120.4	224	273	0.308	0.000*	3022381	0.490	0.000*	21244
NPV	timestep	lump-sum	none	10%	15.0	4.0	6.1	41.3	12.0	22.3	0.1	3.1	34.3	141.4	212	272	0.214	0.000*	3433300	0.377	0.000*	25942
NPV	timestep	lump-sum	max cap. + annual	5%	12.7	4.0	13.6	33.3	12.0	36.1	3.2	20.7	34.3	97.1	216	261	0.334	0.000*	2910072	0.542	0.000*	19088
NPV	timestep	lump-sum	max cap. + annual	10%	13.6	4.0	15.5	33.3	12.0	36.1	3.2	12.7	34.3	103.9	204	266	0.328	0.000*	2933854	0.489	0.000*	21276
NPV	timestep	amortized	none	5%	14.6	4.0	6.5	41.3	12.0	42.4	3.2	12.7	34.3	128.2	213	273	0.300	0.000*	3056444	0.452	0.000*	22824
NPV	timestep	amortized	none	10%	8.0	4.0	6.6	40.3	20.5	42.4	6.4	28.7	34.3	121.6	225	267	0.334	0.000*	2909885	0.472	0.000*	21998
NPV	timestep	amortized	max cap. + annual	5%	14.2	4.0	13.5	33.3	13.5	36.1	3.2	12.7	34.3	105.0	206	258	0.317	0.000*	2982177	0.480	0.000*	21656
NPV	timestep	amortized	max cap. + annual	10%	8.8	4.0	11.9	33.3	21.6	36.1	6.4	28.7	34.3	103.3	246	253	0.334	0.000*	2906799	0.477	0.000*	21795
LCOE	intertemp	lump-sum	max cap. + annual	5%	26.8	0.0	26.8	29.5	25.6	0.0	0.0	0.0	0.0	148.5	87	344	0.171	0.003*	3621689	0.300	0.017*	29183
LCOE	intertemp	lump-sum	max cap. + annual	10%	21.1	13.0	27.4	26.0	12.0	0.0	0.0	0.0	0.0	119.5	71	404	0.149	0.010*	3714665	0.269	0.033*	30456
LCOE	intertemp	amortized	none	5%	65.5	0.0	36.4	3.6	0.0	0.0	0.0	0.0	0.0	173.5	63	298	0.185	0.001*	3557377	0.248	0.050*	31323
LCOE	intertemp	amortized	none	10%	64.7	0.0	34.5	0.0	0.0	0.0	0.0	0.0	0.0	169.4	94	318	0.233	0.000*	3351122	0.278	0.027*	30083
LCOE	intertemp	amortized	max cap. + annual	5%	30.2	1.8	27.0	23.9	25.6	0.0	0.0	0.0	0.0	144.7	91	309	0.179	0.002*	3583315	0.283	0.025*	29876
LCOE	intertemp	amortized	max cap. + annual	10%	31.0	1.8	27.0	23.3	25.6	0.0	0.0	0.0	0.0	144.9	94	318	0.142	0.014*	374412	0.257	0.042*	30971
LCOE	timestep	lump-sum	max cap. + annual	5%	31.3	32.8	27.8	36.0	26.0	39.1	27.0	0.7	36.0	197.9	306	358	0.246	0.000*	3294340	0.428	0.000*	23847
LCOE	timestep	lump-sum	max cap. + annual	10%	31.3	32.8	15.8	36.0	26.0	39.1	27.0	0.7	36.0	187.1	306	361	0.257	0.000*	3242583	0.435	0.000*	23542
LCOE	timestep	amortized	max cap. + annual	5%	31.3	32.8	27.8	35.6	26.0	37.5	30.1	0.3	36.0	199.4	306	357	0.239	0.000*	3322557	0.387	0.002*	25547
LCOE	timestep	amortized	max cap. + annual	10%	31.3	32.8	28.0	36.0	26.0	42.3	32.1	1.4	36.0	205.7	312	362	0.192	0.001*	3528329	0.358	0.004*	26741

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI). CAPEX and OPEX in billion euro. * value significant at 0.05 threshold. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

8.3 United Kingdom model runs

In the model based assessment for the UK a small number at 9 out of 64 model runs yielded significant results for power generation capacity outcomes in comparison with historical values using the Spearman test, for both the annual and five year interval comparisons. The significant results came from max-NPV variants which were primarily time-stepped, with only 2 intertemporal max-NPV versions, as shown in table 41. The best ranking outcome was found to be a max-NPV variant with a maximum capacity and annual constraint, as well as amortization of investments and a 10% discount rate, as indicated by the higher rho values at > 0.19 for annual Spearman tests, and > 0.34 for five year intervals. The main difference in the max-NPV runs, as well as min-LCOE and min-COST, are large increases in nuclear power generation capacity in model runs versus significant expansions in the historic data of natural gas power generation capacity. In min-PBT model runs a large increase in fuel oil power generation capacity expansion instead of natural gas historically can be observed, mainly as a consequence of lower fuel oil costs prior to the 2000s, and lower investment costs for fuel oil than nuclear and natural gas power. Renewable electricity generation from mainly onshore wind and in a few cases offshore-wind emerged solely in max-NPV model runs, with no investment in renewable electricity power generation in the min-LCOE, min-COST, and min-PBT model run versions.

The comparison of cumulative GW capacity constructed, based on the discrepancy between realised power generation capacity minus model outcomes, in absolute values, mainly yields substantial differences between no constraints and maxcap + annual constraints. In case of min-COST intertemporal variants the solution with constraints is on average about 11% closer to the empirical data (e.g. a 66 GW absolute discrepancy with constraints versus historical outcomes and a 74 GW discrepancy without constraints), in case of min-COST time-stepped variants the solution is on average about 6% closer to empirical data, for max-NPV intertemporal and time-stepped variants 29% and 69%, for min-PBT-intertemporal and timestepped variants 1% and 39% , and for min-LCOE intertemporal and time-stepped variants model run outcomes are 18% and 19% closer to historical data.

In case of lump-sum and amortized model run variants there are only substantial differences on average for max-NPV-intertemporal and min-LCOE-intertemporal and timestepped variants for the UK, with a 26%, 11%, and 9% larger power generation capacity discrepancy for amortized relative to lump-sum investment variants on average, when compared to historical developments. In case of the discount rate, model run comparisons show that the discrepancy value is only substantial for min-LCOE where in a 10% discount rate over 5% discount rate variants, on average, in intertemporal variants a 11% lower capacity discrepancy results, and for the time-stepped variants a 9% higher discrepancy . When comparing intertemporal with time-stepped runs with maxcap + annual constraint there is on average a substantial difference for min-COST, min-PBT and min-LCOE with results that are -13%, 6%, and -53% closer to empirical data for time-stepped variants versus intertemporal ones on average, respectively.

The comparison between historical evolution and model run outcomes for variants with NPV and LCOE are shown in figure 29 and 30, for the variants with intertemporal and time-stepped modes with maxcap and annual constraints, 5% discount rates, and investment amortization. Similar to the analysis for Germany it can be observed that limited power generation capacity is built at the end of model run periods, especially in the intertemporal version. Also power generation capacity expansions in model runs on average are much more substantial in the 1980s than historically the case, whilst expansions in model runs are far lower on average versus historical developments in the 1990s, both in intertemporal and time-stepped versions.

8.3.1 United Kingdom Technology inflection Points and Scaling

The technology inflection points in model-runs with the best correlation to historical outcomes for the UK was analysed, namely max-NPV with maximum and annual capacity constraints. Four technology inflection points were observed. The first is the gradual decline of hard coal generation capacity in the historic time-series starting in the 1980s and continuing until the 2013s due to the closing down of power plants which were not replaced with new builds. The max-NPV Model run results that are based on technology cost comparisons are very similar to historical outcomes, in that they follow the same decisions not to pursue new-build hard coal capacity. As indicated in **chapter 6** UK government policy since the 1980s saw a significant shift from public to private ownership of assets and government set to market price drive investments. Support for the coal industry was under this perspective downsized by the Margeret Thatcher run government after the coal miners' strike of 1983/1984. It took another decade, well into the 1990s, until government support for coal mining was fully phased out.

The second is the rise of nuclear power in the max-NPV model-run results up to the maximum capacity share constraint. In contrast in historic developments nuclear expansions were halted following the Chernobyl nuclear accident in 1986. Both the perception of nuclear safety, and the high cost and liabilities of nuclear power, in a new era of market liberalisation, made it that nuclear power was no longer a viable option. In the historic time-series an entirely different third inflection point emerges, the rise of natural gas combined cycle turbines starting in the 1990s resulting in similar large cumulative capacity installation in the late 2000s as for nuclear in max-NPV model runs. This historic outcome can be predicated upon the combination of technology innovation that led to far more efficient gas turbines, the political exclusion of nuclear technologies, the uncertainty over coal access due to rapid reduction of support and mining activity in the UK, and from the late 1990s onwards, the EU emissions directive which resulted in greater competitiveness for natural gas plants due to the obligation to install scrubbers and desulfurisation units at coal power plants. None of these factors is expressed in the max-NPV model run constraints, except through the influence of the relative cost of technologies.

A fourth set of inflection points in the historic time series is the first introduction of onshore wind, biomass, offshore wind, and solar-PV in 1992, 2000, 2003, and 2010, respectively. The largest growth of these four sources historically is onshore wind with capacity ramping up from 2005 onwards to 7.5 GW in 2013, versus fairly slow yet continuous growth in biomass to 4 GW from 2000 to 2013, and scaling up of offshore wind and solar-PV from 2010 to around 3 GW by 2013. The evolution of onshore wind in the model runs follows a similar timing where capacity ramps up from 2004 onwards to three times larger levels at 25 GW capacity by 2013 than occurred in the historic time series. The results in the model for the introduction of onshore wind coincides with the introduction of the renewables obligation as discussed in **Chapter 6**. In contrast for the model calculations support levels seemed to have been insufficient early on for solar-PV, offshore wind, and biomass. In case of these technologies, results are more fickle as these sources do not appear at all in the intertemporal model runs. Development in the max-NPV time-stepped model runs on the other hand show similar technology developments for offshore wind and biomass as historically the case, up to 3 GW capacities by 2013, whilst solar-PV lags behind. Potentially the lower expansion of solar-PV than occurs in reality is due to its decentralised installation by landowners and households which have limited technology choices and options, and also a different electricity price, resulting in a different economic value and threshold than modelled.

The developments of renewable energy sources in the max-NPV model runs versus the historic outcomes reveal similar mechanisms as was the case for Germany. Price signals provide for a sufficient mechanism to generate technology scaling but are insufficient to include early adoption by pioneers and small scale government incentives or low profitability levels. The degree of scaling varies widely which indicates that on top of price incentives there are non-financial barriers in place, which in this case likely relate to investment capacity, technology uncertainty, continuous risks, and political and regulatory decisions.

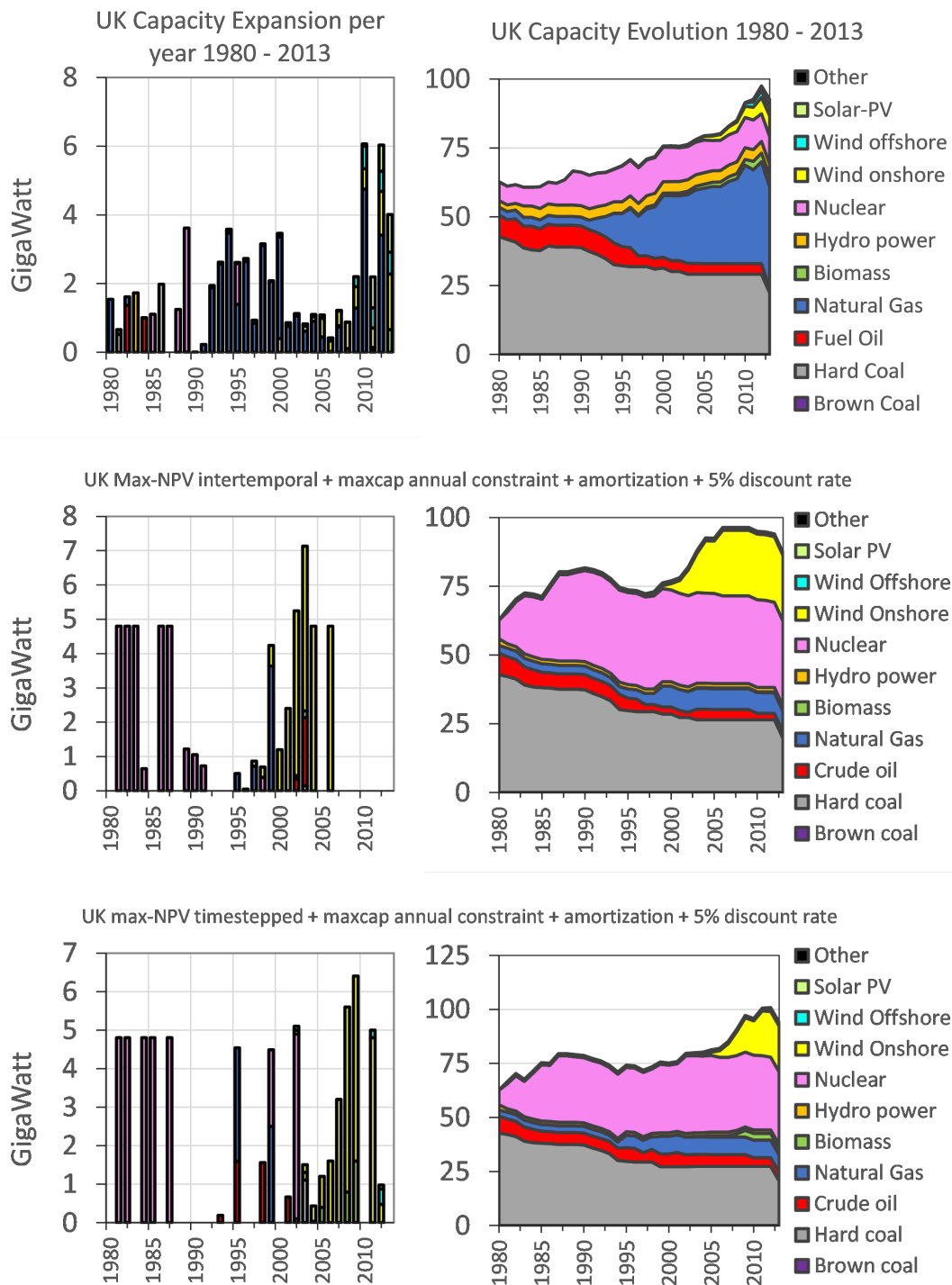


Figure 29: Comparison between historical capacity evolution (top) and model runs with max-NPV (center and bottom)

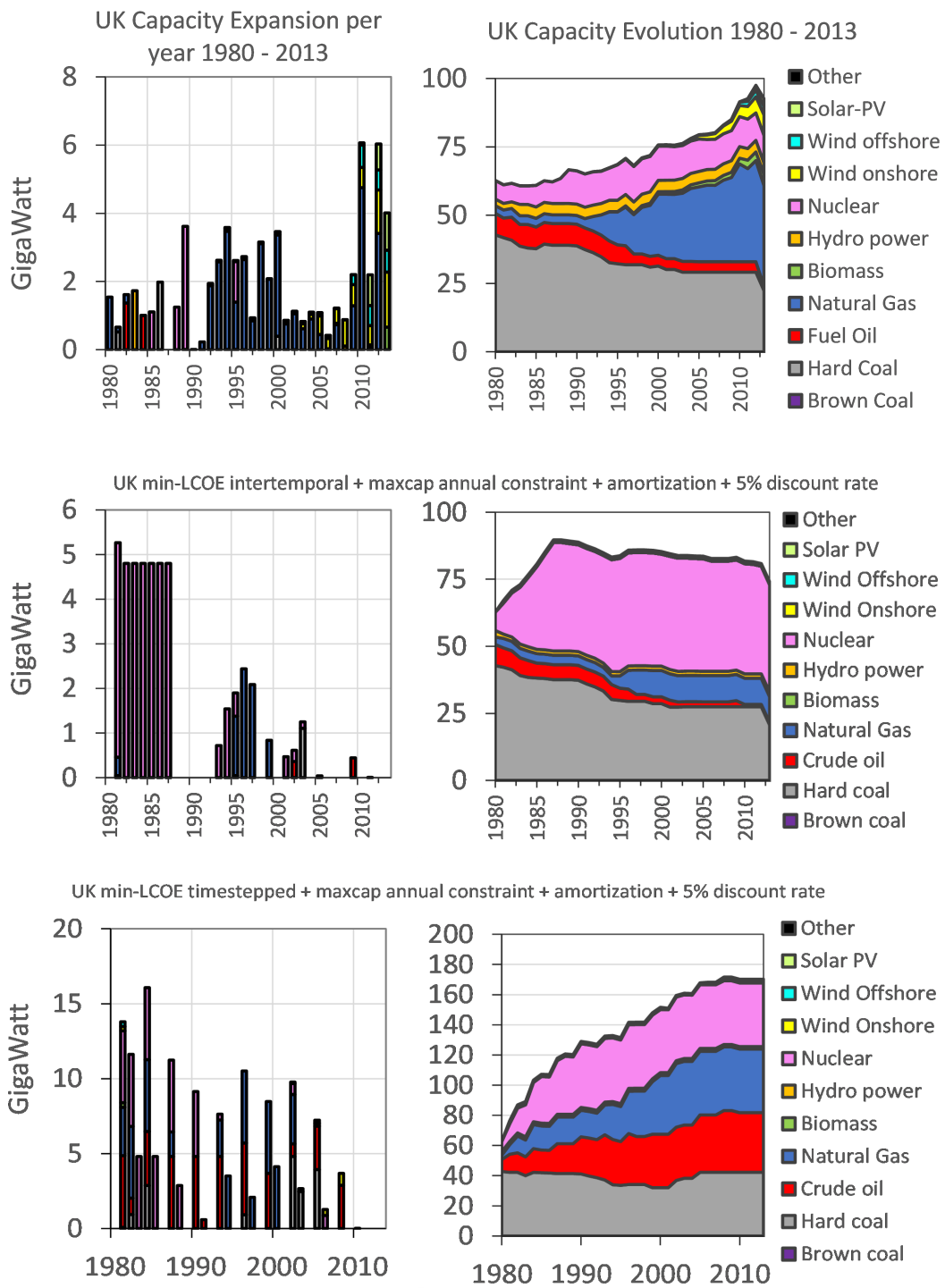


Figure 30: Comparison between historical capacity evolution (top) and model runs with min-LCOE (center and bottom)

Table 41: Overview of significant results for TEMOA optimization for the UK.

Metric	Time	Structure	Constraints	Disc.	Power generation source* additions 1981 - 2013 (GW)									$\Delta GW^{\wedge}$	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
					BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
n/a	n/a	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
NPV	intertemp	amortized	max cap. + annual	5%	-	0.2	4.9	2.3	28.1	23.9	0.0	0.0	0.3	77.4	65	152	0.134	0.029*	2654200	0.332	0.012*	19532
NPV	intertemp	amortized	max cap. + annual	10%	-	2.6	7.0	1.1	24.0	33.5	0.0	0.0	0.3	79.6	75	158	0.232	0.000*	2354234	0.345	0.009*	19173
NPV	timestep	lump-sum	none	10%	-	0.0	6.0	3.2	29.5	201.5	12.6	0.0	0.0	262.9	309	116	0.173	0.005*	2535212	0.313	0.019*	20103
NPV	timestep	lump-sum	max cap. + annual	5%	-	0.0	3.8	4.0	33.5	16.1	0.7	0.1	3.1	78.4	82	105	0.169	0.006*	2549805	0.335	0.012*	19502
NPV	timestep	lump-sum	max cap. + annual	10%	-	0.0	3.8	6.5	30.8	20.8	0.7	0.1	3.1	82.9	85	111	0.193	0.002*	2476076	0.408	0.002*	17320
NPV	timestep	amortized	none	5%	-	0.0	6.1	3.3	29.5	201.5	12.6	0.0	0.0	262.9	309	116	0.187	0.002*	2492793	0.313	0.019*	20103
NPV	timestep	amortized	none	10%	-	0.0	2.6	2.6	33.7	202.2	13.7	0.0	0.0	271.7	317	109	0.174	0.005*	2533464	0.278	0.038*	21125
NPV	timestep	amortized	max cap. + annual	5%	-	1.1	4.1	5.4	30.8	21.2	0.7	0.1	3.1	80.8	86	109	0.179	0.004*	2519046	0.327	0.014*	19706
NPV	timestep	amortized	max cap. + annual	10%	-	0.0	3.2	2.9	35.1	25.5	3.1	0.3	2.7	85.9	103	100	0.198	0.001*	2459863	0.295	0.027*	20619

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI). CAPEX and OPEX in billion euro. * value significant at 0.05 threshold.

8.4 The Netherlands model runs

The model variants that were assessed in all 64 cases did not yield significant results relative to historical developments for the Spearman test, both for a comparison of individual years and five year aggregated segments. All max-NPV variants ran in time-stepped fashion were found to yield a significant result at the $\alpha = 0.05$ threshold for the individual year comparison on the Spearman test, but none for the five year assessment. The significant relationship for individual years is fairly weak, however, as indicated by the Spearman's rho value below 0.2. No other evaluations yielded a significant result at either the individual year or five year comparison on the Spearman test.

In the comparison of historical versus modelled power generation capacity, the closest approximation is found in max-NPV timestepped model runs with annual and maximum capacity expansion constraints, both for lump-sum investment with 5% and 10% discount rates, and for amortized cases with a 5% discount rate. The main difference between reality and modelled outcomes in these max-NPV model runs is that no hard-coal capacity emerges between 1980-2013 (versus 5 GW in reality), about 12 GW of nuclear capacity emerges (versus zero in reality), and that substantially more onshore and offshore wind capacity emerges at around 8 and 3 GW, respectively (versus 2.7 and 0.2 GW in reality). The other power generation capacity build out values are largely in line with historical data, including the emergence of 10.2 GW of natural gas (11.3 GW in reality), 0.7 GW of solar-PV (0.7 GW in reality), and 0.7 to 1.5 GW of biomass (1.2 GW in reality).

The results that do not yield significance on the Spearman test show substantial amounts of fuel oil capacity emerging in intertemporal model variants of min-COST, min-PBT, and min-LCOE based model runs, and in time-stepped versions of min-PBT variants. In the majority of model runs where fuel oil appears in significant proportions, power generation capacity for this type of fuel is built primarily in the 1995 to 2013 period. The difference between intertemporal and time-stepped variants is plausibly due to how fuel costs are treated. The awareness of future price evolutions in intertemporal variants has a significant decision influence, whereas the fuel price level in the time-stepped versions is taken from the limited time horizon and extrapolated into the future. Another key evolution is the emerge of substantial nuclear power generation capacity in all cases except for model runs based on min-PBT, where nuclear expands between 0 and 6.6 GW depending on the other model structures (mainly maxcap and annual constraints, and time-stepped versus intertemporal). Since impacts of political decisions over nuclear power generation capacity are not covered in the model this plausibly explains the discrepancy.

The comparison of cumulative power generation capacity build out, based on the discrepancy between historical power generation capacity minus model outcomes, in absolute values, shows substantial differences between no constraints and maxcap + annual constraints, and between lump-sum and amortized investments. In case of maxcap + annual constraints for the min-COST-intertemporal variants the solution with constraints is on average about 28% closer to the empirical data (e.g. a 25GW absolute discrepancy with constraints and 34 GW discrepancy without constraints versus historical outcomes), and in case of the min-COST time-stepped variants the solution is on average about 7% closer to empirical data, for max-NPV intertemporal and time-stepped variants 33% and 76%, for min-PBT-intertemporal and timestepped variants 3% and 49%, and for min-LCOE intertemporal and time-stepped variants 9% and 16% closer.

Substantial differences emerge on average between lump-sum and amortized model run outcomes of max-NPV-intertemporal, min-PBT-intertemporal, and min-LCOE-intertemporal variants for the Netherlands with a 82%, -14%, and 32% larger power generation capacity discrepancy in amortized than lump-sum investment on average, relative to historical developments. In case of 5% and 10% discount rate model run variants the discrepancy is only substantial in case of max-NPV-intertemporal and min-PBT-intertemporal settings, whereas in the 10% discount case a 45% and 22% larger capacity discrepancy results. When comparing intertemporal with time-stepped model runs with amaxcap + annual constraint there is on average a substantial difference in min-COST, min-PBT and min-LCOE variants at a -12%, 23%, and -18% closer result to empirical data for time-stepped variants versus intertemporal variants on average.

The comparison between historical evolution and outcomes for model runs with max-NPV and min-LCOE are shown in figure 31 and 32 for variants with intertemporal and time-stepped settings with maxcap and annual constraints, 5%

discount rates, and investment amortization. The key difference between historical and model run outcomes is the build-out of nuclear power as opposed to natural gas capacity, which is most pronounced in the 5% discount rate variants than in 10% discount rate variants. It can also be observed, in contrast to the UK and Germany, that power generation capacity is built up to the end of the model run period in both intertemporal and time-stepped variants. Power generation capacity construction as modelled is substantially more spread out over time for the Netherlands, on average, than in model runs for Germany and the UK, which is possibly a consequence of a more strict annual GW construction maximum for the Netherlands, chosen based on the historical maximum capacity that was constructed in a single year between 1980 and 2013.

8.4.1 The Netherlands Technology inflection Points and Scaling

The technology inflection points in model-runs with max-NPV plus maximum and annual capacity constraints was analysed. Three technology inflection points were observed in the historic time series. The first is a small expansion of hard coal generation capacity from 2 to 4.3 GW from the early 1980s to the early 1990s, after which this capacity was maintained. In contrast, in the model-runs nearly no new hard-coal capacity is built. Either existing capacity is phased out, or after a substantial reduction in the 1990s to a low 0.4 GW, new capacity is built in the early 2000s up to 2 GW. The historic expansion of hard coal capacity can potentially be explained by the non-financial factor of technology diversification so as to reduce supply risks, and the proximity of the Netherlands to Germany as a coal producing country and to international coal markets. Coal mines in the Netherlands closed during the 1980s and domestic coal policies did not play a substantive role.

The second is the maintenance of natural gas capacity around 10 GW as the dominant source of power generation, and its expansion starting in 2010 to 17 GW by 2013, further increasing its dominant role in the generation mix. In the max-NPV model runs with annual and maximum capacity constraints instead a substantial expansion of nuclear power can be observed that occurs primarily in the 1980s and/or in the 2000s. Natural gas still plays a substantial role in the model runs but not a dominant one, and capacity gradually declines up to the year 2009. A crucial event similar to the UK and Germany is the influence of the Chernobyl nuclear accident of 1986, which quickly eroded all support for earlier government plans to expand nuclear capacity up to 35 GW as discussed in **Chapter 6**. Another key driver was the availability of large amounts of domestic natural gas. After this expansion the technology was financially locked-in as part of the electricity system for several decades.

The third technology inflection is the first introduction of onshore wind in the historic time series in 1990 which saw a slow but steady rise towards 2.5 GW in 2013. In the max-NPV model runs we see double to quadruple the onshore wind expansions. Historically solar-PV, biomass and offshore wind were first introduced in 1998, 1999 and 2007, respectively. These three renewable electricity generation technologies by 2013, however, still only played a marginal role, except for offshore wind in the max-NPV time-stepped amortized variants, where a large growth of offshore wind to 3 GW from 2006 to 2013 occurs. A key reason for the limited expansion of renewable electricity in general in the historic time-series is plausibly due to the risk of losing financial support, since there were regular substantial changes in subsidy schemes in the Netherlands including the SDE and MEP, and even years where no support was granted, as described in **Chapter 6**. The reason that onshore wind grows most rapidly out of all the four types of renewable sources is the relatively lower cost of onshore-wind versus the other renewable technologies across the 2000s as modelled. As such, the lack of political-economy support and its impact on market risk is plausibly a key factor that, if it would be modelled, could bring results that are closer to historical outcomes.

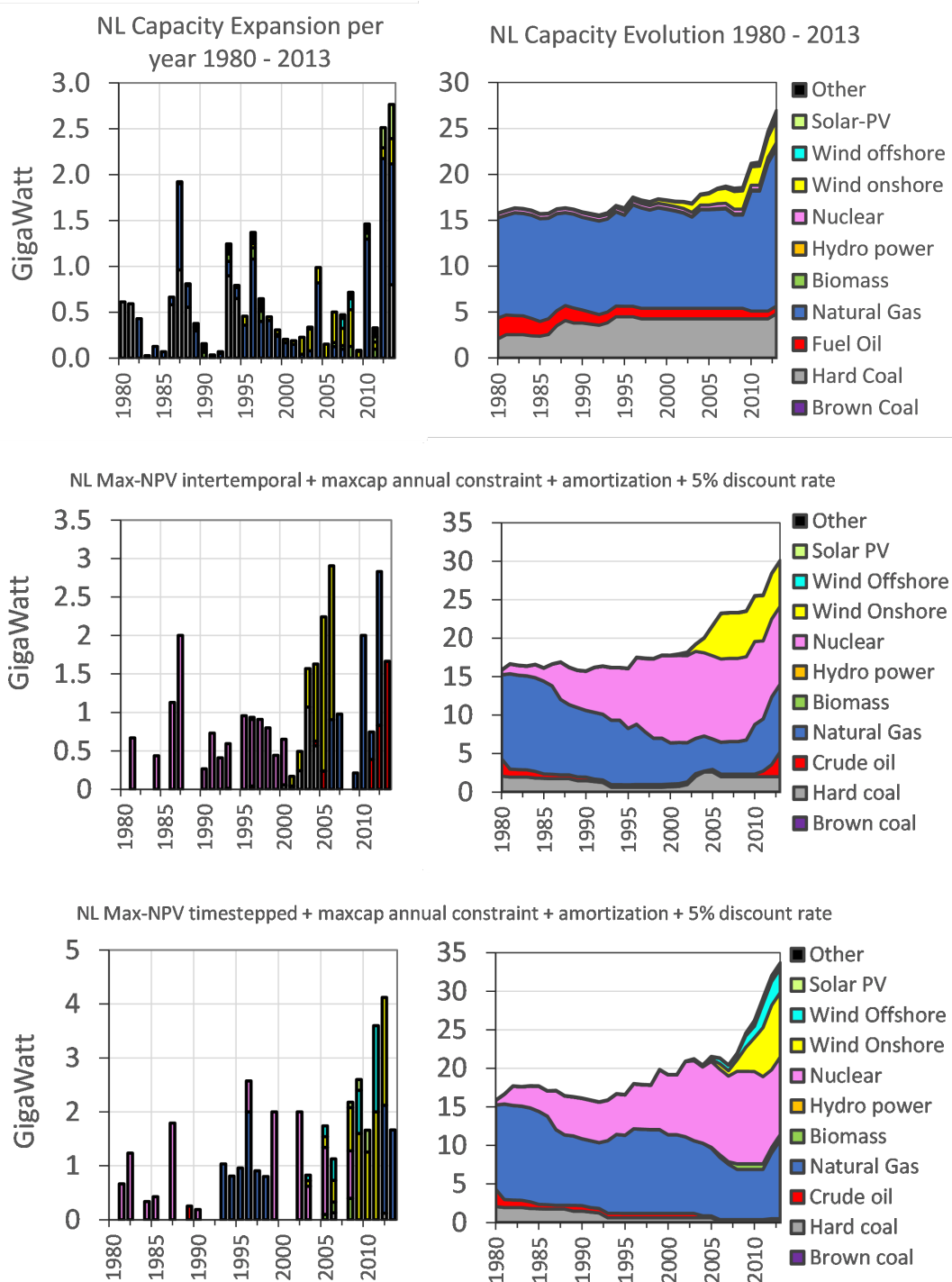


Figure 31: Comparison between historical capacity evolution (top) and model runs with max-NPV (center and bottom)

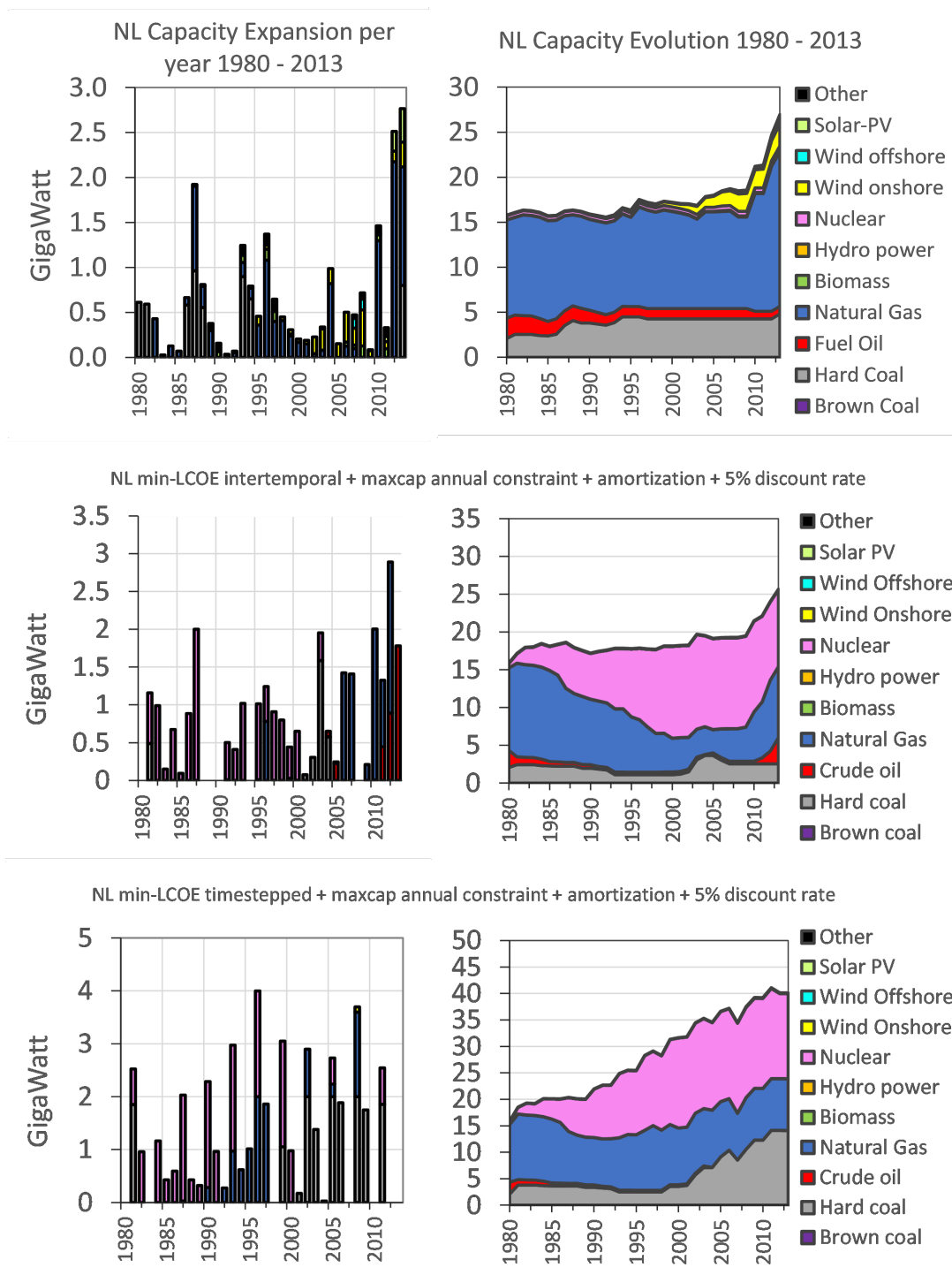


Figure 32: Comparison between historical capacity evolution (top) and model runs with min-LCOE (center and bottom)

8.5 Model runs from 1980 - 2046

The same 64 model run variants were carried out a second time but with the time-period running from 1980 up to the year 2046. The additional parameter values included several time-series for extrapolated investment costs based on (Schroder et al. 2013), extrapolated fuel costs based on (IEA 2015), and assumptions for the continuation of feed-in fiscal stimulation of renewable electricity as described in **section 6.5**. Two effects were analysed by carrying out these elongated model runs. First, if the construction of power plants up to 2013 was different than when just running the model from 1980 - 2013, now that future power demands beyond 2013 were also taken into account. Second, what the effects are on the change in the technology mix over time to 2046 between different model structures, including those that were to an extent able to reproduce the past.

The effects of elongated model runs to 2046 on capacity build-out up to 2013 is a substantially larger construction of solar-PV capacity for DE and NL, and for onshore and offshore wind in DE, UK and NL, in case of max-NPV intertemporal variants, as illustrated in figure 33. Also substantially more natural gas capacity up to 2013 is built in lump-sum investment model runs for the UK in the max-NPV setting with elongated model runs to 2046. There are no significant effects in case of min-COST variants between the two sets of model runs. In case of min-PBT and min-LCOE larger natural gas capacity is built in all three cases in the period to 2013 in elongated model runs to 2046, versus model runs that last only to 2013. Also more nuclear power generation capacity is built for min-PBT model runs in the case of DE and NL in the elongated model runs to 2046.

Power plant capacity built from 2014 to 2046 for **Germany** has the largest variation between time-stepped and intertemporal variants. In the max-NPV case with maxcap and annual constraints, as shown in figure 8.4.1 nearly all fossil fuel capacity is phased out for time-stepped model runs in the 2030s, mainly due to large expansion of solar-PV and offshore wind. In the intertemporal version initially from 2014 a substantial amount of offshore wind capacity is built on top of already substantial renewable electricity generation capacity, but fossil fuels continue to maintain a large share of capacity and increase in their share from the late 2020s onwards, as more brown coal and fuel oil capacity is built to replace the phase-out of earlier onshore-wind, biomass, and solar-PV capacity built in the 2000s and 2010s. The main reason of this reversal is the assumed end to the feed-in tariff subsidies in the 2030s in combination with developments in capital investment costs (Schroder et al. 2013).

The variation in the min-COST model runs for Germany with maxcap and annual constraints from 2014 to 2046 is a large expansion of brown coal capacity plus the complete phase-out of fuel oil in the timestepped case, versus a continued share of fuel oil and brown-coal in the intertemporal case. In the time-stepped min-LCOE model variants substantial biomass, nuclear, onshore- and offshore wind capacity that is built is slowly phased out and replaced by brown coal. Also as solar-PV costs decline this source is introduced at large scale in the 2030s. In the intertemporal variants in contrast no renewable based capacity emerged in the first place, and in the 2030s nuclear power generation capacity is phased out and replaced with fuel oil. In the min-PBT model runs with maxcap and annual constraints in intertemporal variants nuclear, brown-coal, natural gas and fuel oil power generation capacity remains quite steady, whilst in time-stepped variants large expansions of fuel oil emerge which replaces natural gas and nuclear power generation capacity.

In case of the **United Kingdom** power generation expansion from 2014 to 2046 varies substantially between time-stepped and inter-temporal variants. In the max-NPV case with annual and maxcap constraints the initial 2014 share is composed for time-stepped variants out of a combination of onshore-wind and nuclear power generation capacity, and to a lesser extent offshore wind, natural gas, fuel oil, biomass, hard coal, and offshore wind. The capacity mix changes over time as nuclear power is phased out and offshore and onshore-wind is substantially reduced as a consequence of reduced fiscal support for renewable electricity sources in the scenario. Natural gas power generation capacity grows instead, and from the 2030s onwards also hard coal and solar-PV, as the costs of solar-PV declines sufficiently to be commercially viable within the boundaries of the scenario. By 2046 the generation capacity share is largest for natural gas, second hard coal, and third solar-PV. In contrast in the max-NPV intertemporal version the amortized variants show similar starting points where capacity is composed primarily of onshore-wind, nuclear and offshore-wind which is phased out, but hard-coal, natural gas and to a lesser extent fuel oil replace these sources with no introduction of solar-PV.

The UK model run outcomes for min-COST and max-NPV with maxcap and annual constraint with an intertemporal setting show a substantial difference between amortized and lump-sum investment variants. In case of min-COST the lump-sum investment leads to a capacity mix in 2014 with equal shares of nuclear/natural gas/fuel oil which transforms to a capacity mix by 2046 with fuel oil at a 2/3rd share and natural gas with a 1/3rd share. In contrast, the amortized version starts off from the earlier 1980 to 2013 model run part with a capacity mix composed of 2/3rds nuclear complemented with natural gas, hard coal, and fuel oil. It then transforms over time into a capacity mix dominated by hard coal at about 50%, complemented mainly by natural gas and to a lesser extent fuel oil, with nuclear fully phased out. This change is not present in min-COST time-stepped variants, where development is similar to the inter-temporal amortized variant, where at the start the capacity mix is composed for about 50% of nuclear power, complemented primarily by natural gas and a small share of fuel oil and hard coal. Over time this is transformed into a 55% natural gas share and a 35% hard coal share, complemented by fuel oil and nuclear power, and by the 2040s solar-PV is introduced as costs drop sufficiently in the scenario.

In case of max-NPV intertemporal variants for lump-sum investment at the starting point in 2014 a capacity mix emerged that primarily consists of nuclear and natural gas power, and to a lesser extent fuel oil, hard coal, and onshore wind. Over time to 2046 there are substantial expansions of natural gas as a dominant source at 2/3rds of power generation capacity complemented with growing capacity of crude oil, with the remainder met by hard coal, whilst nuclear and onshore-wind are phased out during the 2030s. In contrast the starting point for amortized developments, stemming from the 1980 to 2013 portion of the model run, is already substantially different, with a dominance of onshore and offshore wind for 2/3rds of capacity, primarily complemented with nuclear and to a lesser extent natural gas, fuel oil, and hard coal. Here over time also onshore wind, offshore wind, and nuclear power are phased out during the 2030s as in the scenarios financial support for renewable power generation sources falls away, whilst costs do not decline sufficiently. The sources are replaced by mainly hard coal, second natural gas, and third fuel oil power generation capacity. The UK outcome for min-PBT with maxcap and annual constraint mainly varies between time-stepped and inter-temporal settings as well, although not as substantially. In the intertemporal variants fuel oil and natural gas generation dominates the capacity mix at the start in 2014, based on the 1980-2013 portion of the elongated model run, subsequently fuel oil expands over time towards 2046 to about 2/3rds of the capacity mix. In contrast in the time-stepped variant the capacity mix in 2014 was dominated by fuel oil and is complemented by nuclear, natural gas and hard coal. In the development to 2046 a substantially larger share of natural gas is introduced at the expense of fuel oil capacity, whilst hard coal and nuclear power generation capacity remains similar.

The elongated model runs for **the Netherlands** between 2014 to 2046 similarly show a difference between amortized and lump-sum investments for the intertemporal variant. In case of max-NPV the generation capacity mix in 2014 for lump-sum investment, which emerged from the previous 1980 to 2013 portion of the model run, starts with a combination of first nuclear, second natural gas, and third fuel oil power generation capacity, with a very small share of hard coal. The mix changes over time to one dominated by natural gas for 3/5ths complemented with fuel oil, with a minute share of remaining hard coal power generation capacity. Nuclear power is phased out already in the 2010s. In contrast, in the amortized version in 2014 about 2/3rds of the capacity mix is composed of onshore-wind, offshore-wind and solar-PV, and 1/3rd is composed of natural gas, nuclear, and hard coal power generation capacity. Over time the share of natural gas, solar-PV and hard coal power generation capacity grows, and offshore wind and nuclear are phased out, due to which by 2046 the capacity mix is primarily composed of natural gas complemented with onshore-wind, solar-PV, and hard coal power generation capacity. In the time-stepped variants with max-NPV far less differences between amortized and lump-sum investment can be observed. The starting point in 2014 is a 3/5th share of natural gas and nuclear power generation capacity, complemented largely by onshore wind and a small amount of offshore-wind. Over time this is transformed due to a phase out of nuclear power by the 2030s, a reduction in onshore wind capacity, and the introduction of solar-PV and hard-coal in the 2030s to 2040s. Also natural gas power generation capacity nearly doubles.

The changes for min-COST and min-LCOE in maxcap and annual constraint variants for 2014-2046 are similar for the intertemporal versions. In case of lump-sum investment the starting point in 2014 is a generation mix composed for 2/3rds of fuel oil and 1/3rds of natural gas, which over time changes into 3/5ths fuel oil and 2/5ths natural gas power

generation capacity by 2046. The evolution of amortized versions show a different starting point, with 2/3rds natural gas capacity and the remainder composed of nuclear and hard coal. Over time nuclear is phased out in this variant, and hard coal grows substantially, by which the capacity mix in 2046 is composed between 2/3rds of natural gas and 1/3rd of hard coal. The timestepped versions for min-COST and min-LCOE show less similarities. In the min-LCOE version the starting point in 2014 is a combination of first hard coal, second nuclear, and third natural gas power generation capacity, which changes over time into a larger share of hard coal at over half of capacity, complemented with natural gas and solar-PV as introduced in the 2040s and a small share of nuclear. In the 10% discount rate with amortization variant the development is similar, but a larger share of nuclear is established and a smaller share of natural gas power generation capacity. In the min-COST time-stepped variant the starting point in 2014 is first natural gas, and second nuclear with a small share of hard coal. This changes over time into a capacity mix composed 2/3rds of natural gas, with a 1/3rd share of hard coal and a small amount of solar-PV, as nuclear power is phased out. In the 10% discount amortized variant a 2/3rd share of hard coal evolves near the 2040s complemented with 1/3rd natural gas.

Large differences for min-PBT with maxcap and annual constraints are observed mainly between intertemporal and time-stepped variants. In the intertemporal variant the energy mix in 2014 is primarily composed of natural gas and second fuel oil with a small share of hard coal. This small share is phased out in the 2020s, and is replaced by fuel oil, due to which by 2046 the capacity mix is composed half/half of fuel oil and natural gas. In contrast, in the time-stepped scenario runs, the starting composition in 2014 is made up out of crude oil, natural gas, hard coal, onshore-wind, and nuclear, in order of capacity shares. Over time the shares of natural gas, fuel oil, and hard coal grow, whilst nuclear and onshore-wind are phased out, due to reduced government financial support in the underlying parameter vales as used. In the amortized time-stepped min-PBT versions, however, a small share of solar-PV is also introduced in the 2030s, and a small share of onshore-wind and nuclear remains, on top of these changes.

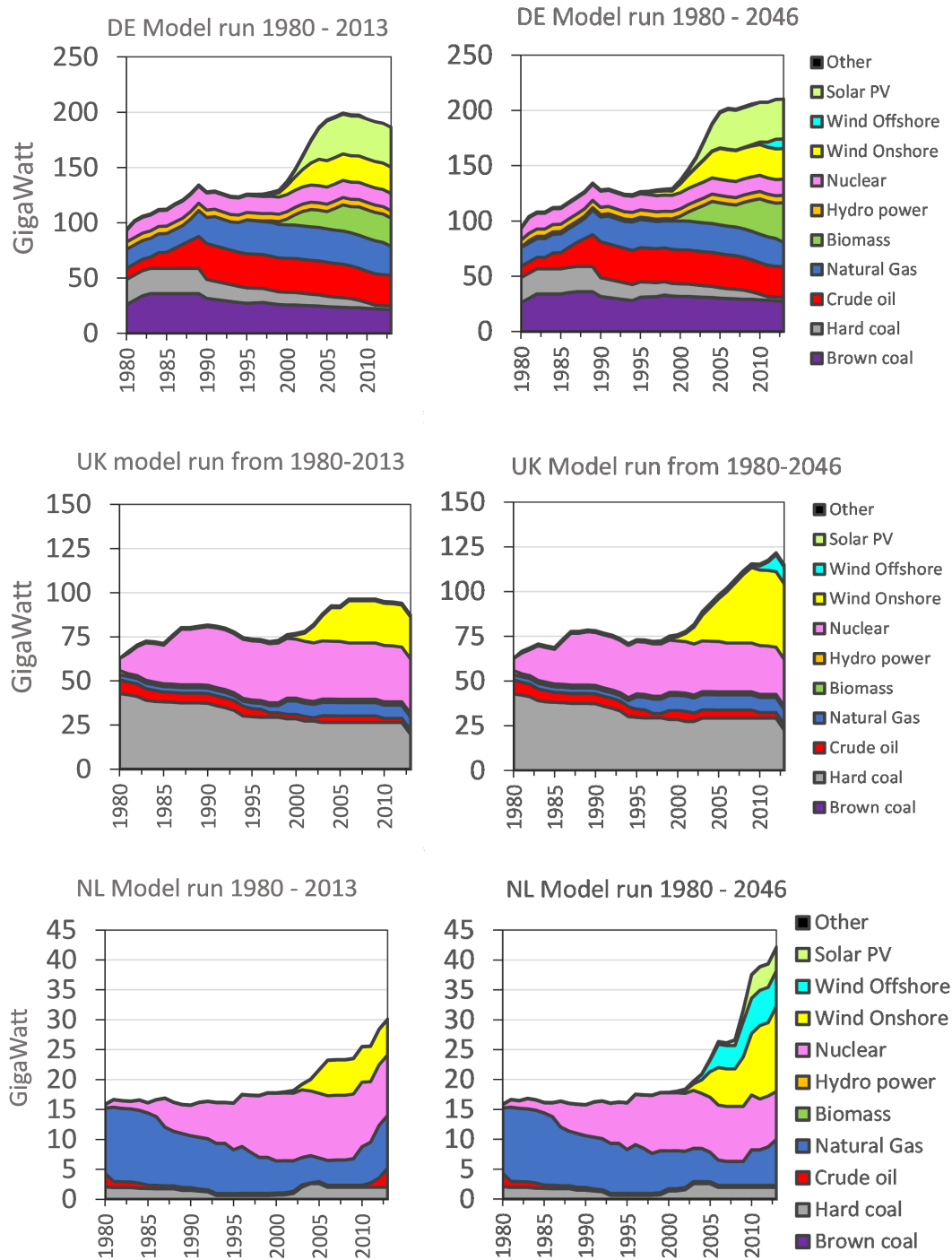


Figure 33: Comparison between model runs from 1980-2013 (left) and from 1980-2046 (right) with the period 1980-2013 shown for DE (top), UK (center), and NL (bottom). Model settings include max-NPV intertemporal, maxcap. annual constraint, 5% discount rate, and amortization.

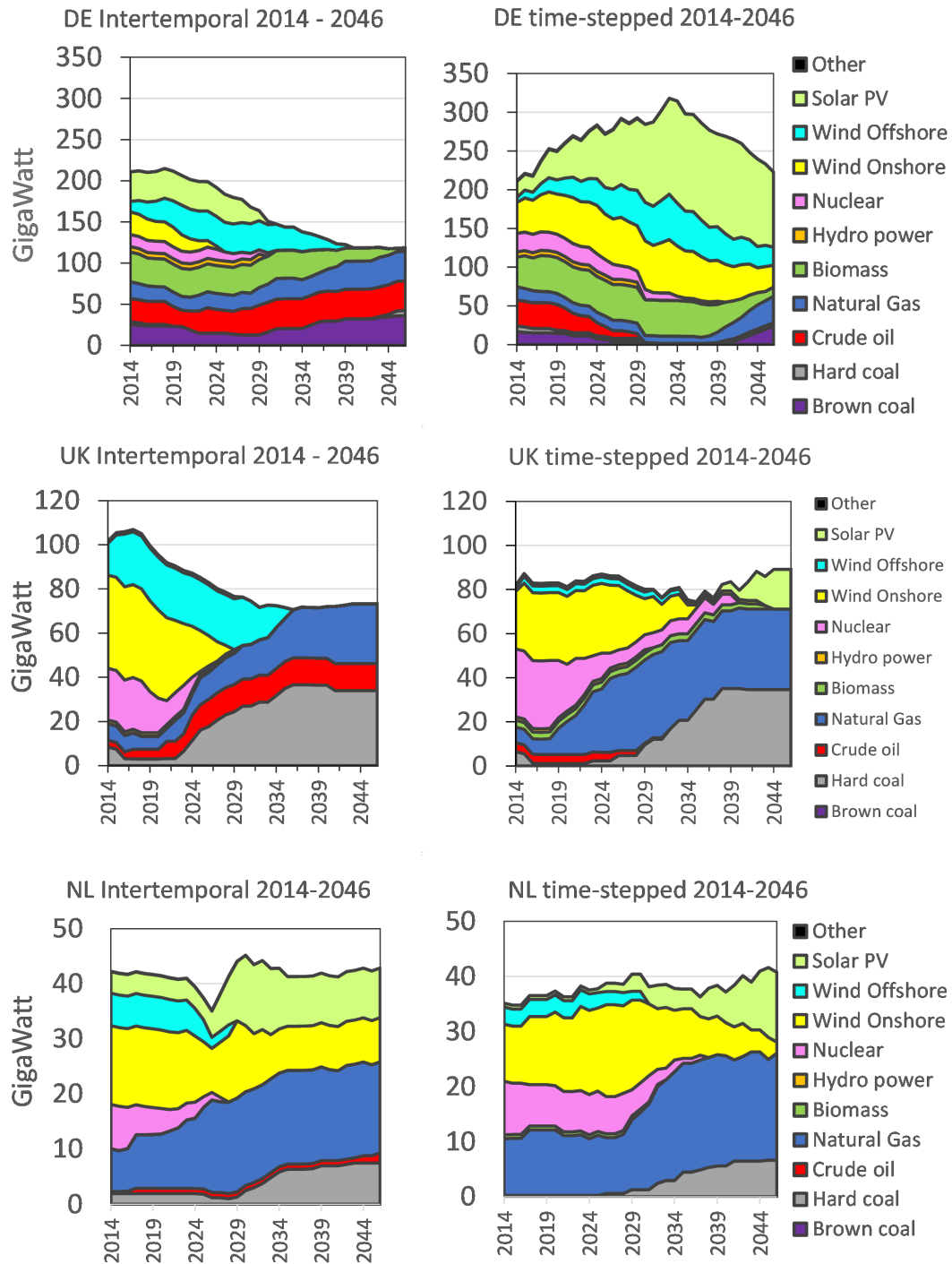


Figure 34: Result for 2014 to 2046 for DE (top), UK (center), and NL (bottom) based on comparison between intertemporal (left) and time-stepped (right) . Model settings include max-NPV, maxcap. annual constraint, 5% discount rate, and amortization.

8.6 Summary

The chapter described the results of a series of analyses of 64 *investment strategies* as applied in the electricity systems model TEMOA to generate power generation change from 1980 to 2013 for three case studies: Germany, the United Kingdom, and the Netherlands. The results were compared with empirical developments in power generation technology and capacity change, using a spearman based ranking correlation. A first aspect of the analysis was to investigate the impact of setting a constraint on capacity expansion. The constraints included capping expansion to a maximum of the historically largest capacity contribution of the dominant technology, capping annual expansion to the largest annual build-out among all technologies. The analysis found that in all three cases model outcomes with maximum capacity construction constraints yielded results closer to historical outcomes than without such constraints. Without such constraints the model exploits the possibility to construct capacity with the lowest investment value in a single year, at a far higher power generation capacity value than historically the case, in inter-temporal and to a lesser extent time-stepped model versions. On the basis of this result it can be concluded that the **2nd hypothesis** from **section 4.2**, that capacity expansion constraints and technology diversification play a role in power generation evolution, was not falsified. On this basis the inductive-statistical generalisation is made that:

“All modelled outcomes using investment decision algorithms F_s including maximum capacity per technology and annual expansion constraints, provide closer results to empirical data logged outcomes caused by investment decisions G_s than without such constraints, therefore for a particular investment decision G we can be sure that the investment decision can be better approximated by an investment decision algorithm F which includes maximum capacity and annual expansion constraints.”

The cause of this sensitivity to annual maximum capacity expansion constraints is plausibly because it represents the real life constraint in constructing large capacities in a single year. Only in exceptional circumstances are multiple power plants of more than a GW scale realised all at the same time for several reasons. There are large logistics and supply chains involved due to which only a few of such projects take place within a country at the same time. If too many projects are taking place at the same time this can lead to substantial cost inflation of raw materials and components. Also the business continuity for power plant construction and component manufacturing companies requires realisation of a portfolio of orders in sequence, instead of many at the same time. The reason for sensitivity to maximum capacity of technologies plausibly relates to a number of *investment decision options* as identified in the framework in **Chapter 3**. These can include the need for technological diversification of portfolio's from a strategic perspective, the importance of lowering the risk of fuel availability disruptions by not relying on a single fuel source, the need for developing market shares by spreading investments in different technologies, and over time increasing importance of environmental outputs which has led to the introduction of new technologies.

The analysis also showed that the closest approximation to historical values was established for model runs with a max-NPV variant in all three country cases. To this end a comparison was made for the historically realised capacity (as a proxy for investments) and the modelled capacity on a year by year basis, and a five year aggregate comparison. The number of correlated values was compared using the spearman ranking correlation. The German case study generated 11 significant out of 16 max-NPV model runs for the Spearman ranking correlation with historical developments, with a moderate ranking relationship expressed by a Spearman's rho-value above 0.3 for year to year comparisons. The UK case study generated 9 significant out of 16 max-NPV model runs for the Spearman ranking correlation with historical developments, with a low ranking relationship expressed by a Spearman rho-value above 0.17 for year to year comparisons. And the Netherlands case study generated 8 significant out of 16 max-NPV model runs for the Spearman ranking correlation with historical developments, with a low ranking relationship expressed by the Spearman's rho-value above 0.13 for year to year comparisons. In contrast the analyses for LCOE only in case of Germany yielded significant results in 10 out of 16 min-LCOE model runs, with a moderate Spearman's rho-value above 0.3 for five year comparisons. In case

of the Netherlands and the UK no significant results were established for LCOE. The other two evaluated metrics, the minimisation of PBT (min-PBT) and costs (min-COST) in all three cases did not yield any significant outcomes, except for 2 out of 16 min-COST runs for Germany.

The **3rd hypothesis** from **section 4.2**, that profit based financial metrics yield a better explanation of past investments than cost based metrics, was on the basis of this result not falsified. On this basis the inductive-statistical generalisation is made that:

“All modelled outcomes using investment decision algorithms F_s based on maximisation of Net Present Value, provide closer results to empirical data logged outcomes caused by investment decisions G_s than those based on minimisation of Costs, LCOE, or payback-time, therefore for a particular investment decision G we can be sure that the investment decision can be better approximated by an investment decision algorithm F based on maximisation of Net Present Value.”

The reason that maximisation of NPV provides a result that is much more close to historical outcomes is plausibly because it is the only metric in the model evaluation that incorporates the impacts of changes in electricity prices and feed-in tariffs and other subsidy systems. As a consequence max-NPV is much better able to explain the rise of wind, solar, and biomass based electricity sources than metrics that include only costs as a relevant factor. A possible way around this from a modelling perspective would be to include subsidies or electricity prices as negative costs under min-COST or min-LCOE metrics, however, that would make it much more difficult to interpret the results, and even more challenging to make them meaningful for interpreting the effects of policy decisions to alter market instruments on company investments.

The comparison between three year time steps and intertemporal model variants showed, especially for the max-NPV evaluations, that results were closer to historical developments for time-stepped variants for Germany, the UK and the Netherlands. The effect also showed a higher degree of significance and Spearman rho-value for Germany and the United Kingdom, especially for the 5 year aggregate comparisons between modelled results and empirical data. The key difference in results comes from the larger growth of solar-PV, onshore wind, offshore wind, and biomass, in the three country cases. Also for Germany nuclear power expansion is far closer to what happened in reality, instead of smaller or larger capacity construction in case of intertemporal model settings. The substantial difference in outcomes between the intertemporal and time-stepped mode can be explained by the difference in relative weights of the market conditions at the time. In case of the time-stepped variant the market conditions as averaged over the three time period intervals were extrapolated in the future. It is plausible that companies also take this strategy in absence of what the future beholds, because of which time-stepped approaches yield better results than intertemporal ones.

The **5th hypothesis** from **section 4.2**, that modelled knowledge of the future has a significant unrealistic effect on model outcomes versus limited knowledge of the future (implemented as a 3 year timestepped variant), was on this basis not falsified. On this basis the inductive-statistical generalisation is made that:

“All modelled outcomes using investment decision algorithms F_s based on three year time stepped horizons with extrapolation, provide closer results to empirical data logged outcomes caused by investment decisions G_s than those based on applying an intertemporal time horizon with full knowledge of the future, therefore for a particular investment decision G we can be sure that the investment decision can be better approximated by an investment decision algorithm F based on a three year time-stepped model structure.”

The analysis of discount rate variation between 5% and 10% did not generally yield model run result differences. In case of min-COST and min-LCOE the increase in discount rates from 5% to 10% yielded almost no difference between outcomes for the three countries. The effects on min-PBT were more substantial for intertemporal amortized variants where a 5% discount rate yielded a better approximation to reality due to lower fuel oil expansions for the UK and the Netherlands, lower natural gas expansions for Germany, and higher natural gas expansions for the UK. And in case of

max-NPV the intertemporal variants yielded a somewhat closer outcome to empirical data for amortized subsets for 5% over 10% discount rates. The cause for Germany are higher expansions of nuclear power and lower biomass and natural Gas expansions. In case of the United Kingdom changes in onshore wind expansion, and for the Netherlands reductions in fuel oil expansion. A potential cause may be due to the relatively limited difference in discount rate over for instance applying a 15% or 20% discount rate variant, or a 2% discount rate value. However, such a high or low discount rate is quite unrealistic for the respective markets in the UK, the Netherlands and Germany in the context of loan conditions for power plant projects, and was thus not investigated.

The impacts of amortized versus lump-sum incorporation of capital investment in the model to have substantial effects only for max-NPV based intertemporal model runs in case of the UK and the Netherlands yielding improved correlations, and to a lesser extent Germany where results changed but correlations did not. The other metrics min-COST, min-LCOE, and min-PBT as evaluated yielded no difference between amortized versus lump-sum investments. The primary impact is a larger investment in capital intensive renewable technologies when amortization is applied. Onshore wind in all three countries, as well as solar and biomass for Germany. The cause can be explained by the lowered temporal profile of costs for intertemporal evaluations when the investments are amortized over time with closer near-term benefits from electricity price and feed-in tariff based revenues. Since the effects were not found to be significant in the few cases that they were applicable, and not generalisable across model variants, the impact of amortization was found to be limited in general.

A key limitation to using only financial factors was found by evaluating the difference in technology inflection points and scaling speed in model results and historical timeseries. The analysis found that across all the three cases both significant historic events such as the Chernobyl nuclear disaster, and technology specific conditions that interrelate to the political-economic structure, in the cases existence of domestic coal resources, can have a substantial impact on market regulatory change and technology outcomes. Financial conditions thereby are insufficient to explain the full spectrum of technology choice, and the existence of public good investments to provide for jobs or anticipate on future technology cost declines was found to also have a substantial influence. The finding is similar to the view that emerged from the interview insights, that a necessary condition for investments to take place is the passing of a financial hurdle rate, but that several other factors provide for a sufficient condition to actually make the investment. Other key non-financial aspects that emerged from the interviews similarly related to political risks in the form of sudden changes in market regulation.

The analysis also found that whilst financial factors can sufficiently explain the onset when scaling of new technologies begins, the rate of scaling is often overestimated based on financial metrics alone. The scaling of new technologies plausibly is constrained by non-financial factors, such as land use availability or public opposition. The incorporation of non-financial factors on technology scaling would be necessary to provide insights in how fast new technologies can be scaled such as to achieve decarbonisation pathways. The incorporation of political-economy factors such as events would allow for testing the robustness to external events in achieving existing policy aims, including cost, emissions and fuel disruption risks, when accounting for potential swift policy and market regulatory shifts.

Also 64 model runs were carried out with an elongated time frame from 1980 to 2046 with similar investment decision strategy combinations as in the shorter 1980 to 2013 model runs. The analysis first looked at whether outcomes in the period 1980 to 2013 were different for the elongated model runs than in the shorter model runs where the final year was 2013. In the elongated runs a substantial increase in capacity build-out to 2013 was established for the expansion of solar-PV, onshore wind, and offshore wind for max-NPV model run variants for all three cases DE, NL, and the UK. The other financial metric optimizations min-PBT and min-LCOE yielded substantially more natural gas capacity in all three country cases up to 2013, and for min-PBT variants for DE and NL less nuclear power capacity. Thereby a substantial effect was found on the evolution in the final years of a model run due to running the model past the intended final year. The effect can be explained by adjusted investment prospects for the latter years of the model run due to the sharp 2013 cut-off, making investments close to that year less financially interesting when no such cut-off is present as in the elongated model runs.

The second aspect that was investigated was how the future capacity evolution differs between model runs from 2014 to 2046. Mixed differences were found between time-stepped and intertemporal model run variants primarily for max-

NPV, with a much more prominent role for solar-PV and onshore wind in time-stepped variants for the UK and DE, but less so in case of the Netherlands. Since in the time-stepped variants three year market conditions are 'locked-in' in the investment assessment, and fiscal support for renewable electricity is phased out in later years under the model run scenarios, this plausibly explains part of the discrepancy. In intertemporal versions the end of renewable energy financial support in the 2030s is known in advance, and expansions starts to drop-off already in the 2020s, whilst in the time-stepped versions expansions continue in the 2030s until financial support is fully phased out.

Another effect was established between lump-sum and amortized model runs. In the UK case for max-NPV and min-COST variants with intertemporal optimization, the amortized variants by 2046 yielded substantially more hard coal and natural gas capacity, versus more fuel oil in lump-sum variants. Similar large differences were established for the NL case for intertemporal max-NPV model runs, where in the lump-sum investment the generation mix by 2046 is primarily composed of natural gas and fuel oil power generation capacity, versus a capacity mix in the amortized case consisting out of natural gas, onshore-wind, solar-PV and hard coal.

In summary, the model based analysis yielded six key relevant results. First, the incorporation of annual and maximum capacity constraints are of significance to yield realistic outcomes in any situation regardless of the application. The specification behind setting the maximum can be investigated from a company investment perspective, in terms of technological diversification, fuel disruption risk reduction, market share diversification, and environmental output requirements. Second, the incorporation of a profit based approach, such as max-NPV was found to yield outcomes that are substantially closer to what happens in reality, indicating that models which take profit based financial approaches are likely to better in their ability to test policy decision effects on power generation investments. Third, the use of a time-stepped structure will likely improve the accuracy of simulating real life company investments, as it was found to provide a model outcome closer to historical results. Fourth, ensuring that all modelled investments take into account the full lifetime revenue of power plants in the decisions made, also those that are closer to the final model run years. This can be done either by extending the model run beyond the final intended year to take this into account, and only evaluating the results up to the intended final year, or by adding relevant revenues that would accrue in years that are not modelled, into the investment evaluation. Fifth, key events and country specific conditions such as domestic resource availability have a substantial influence on technology outcomes in addition to financial factors. And sixth, whilst financial factors do provide for a significant explanation of when capacity scaling off new technologies occurs, the rate of expansion is poorly explained and typically overestimated. The appropriate speed of capacity scaling of new technologies in the electricity mix warrants the inclusion of non-financial factors that impose constraints on how fast capacity can expand. In the next chapter the results from the expert interviews are summarised which bring a real-life perspective to corroborate and deepen the findings so far.

9 Discussion and Conclusions

9.1 Study aims and objectives

The thesis sought to scrutinize electricity system models and their modelling methodology from an investment decision perspective, so as to assess their adequacy to yield insights in real life technology choices and investments, as outlined in **section 1.2**. The expected benefit of the investigation are insights to improve the representation of the investment decisions in electricity system models which plausibly will result in models that are better at testing actual future outcomes under a variety of financial and non-financial market conditions. Such an improvement is key if the purpose of electricity system models is to evaluate the extent to which new government directed market designs and policy regulation will result in desired outcomes, especially when these regulations and market designs seek to alter investments and technology choice by companies. Desired outcomes can, for example, include government objectives of greater security of supply, or decarbonisation.

As identified in **section 1.5** the aim of this thesis within that context was to understand “*What quantitative and qualitative factors provide a valid approach to the modelling of power plant investment decisions in electricity system models?*” The specific objectives related to this aim as formulated were:

1. To evaluate a set of key financial and non-financial factors which are potentially usable to inform electricity company decisions in the selection of technologies and investments in power plant capacity, based on a review of the literature and deductive reasoning.
2. To research the functions used in existing electricity system models to represent the investment decision process and particular investment evaluation metrics therein, based on a methodology review and literature screening.
3. To assess whether standard financial investment evaluation metrics in the electricity sector, the Net Present Value (NPV), PayBack Time (PBT), Levelized Cost of Electricity (LCOE), and the Internal Rate of Return (IRR), provide a significant means to establish whether an investment should take place or not, based on a statistical analysis of historical power plant capacity data from 1980 to 2013 as a proxy for investments for the Netherlands, the UK, and Germany.
4. To assess using statistical which investment decision variants in an optimisation model yield outcomes that are close to historical installation of power plant capacity and technology as a proxy for investment, based on running an optimisation model from 1980 to 2013 for the Netherlands, the UK, and Germany, and assessing the correlation of model run results with historical power plant capacity data as a proxy for investments. By variation of investment decision strategies (specified in **section 4.2**), whilst maintaining market and technology characteristics as occurred in this time period, different model settings and their influence on the correlation are evaluated.
5. To evaluate based on a set of expert interviews with electricity market experts what in their view the relevant non-financial and financial factors are that are involved in power plant investment decisions.

The research, within these objectives, is limited to the approaches taken in existing electricity system models, which simplify investments and technology choice as a vector of profit maximisation or cost minimisation. The analysis was also limited to three countries, Germany, The Netherlands, and the United Kingdom, based on their data availability on historical power plant generation change plus investment costs, their relative diversity in electricity market policies influencing historical investments, and familiarity of the thesis author with these markets (see **section 1.5.1**). The **first objective** to investigate existing electricity system models on their approach to represent the investment decision process was met in **chapter 2**. A total of 51 existing electricity system models were analysed, and it was found that these are heavily tilted towards using a ‘central planner’ based approach as if a central government places all the investments. In the majority of models this central planner has been implemented based on financial cost minimisation, with as a secondary

option a profit maximisation criterion. Specifically, 31 out of 51 evaluated models used an optimisation structure with cost minimisation, 9 out of 51 models used an optimization structure with profit maximisation, 7 out of 51 models used a simulation structure with profit maximisation, 3 out of 51 models used an allocation and growth based structure that is only indirectly based on financial factors, and one optimisation model used an utility based objective approach.

In the existing models various additional complexities have been added such as discount rates, risk evaluations, or power plant specific investments instead of lumped technology capacity. In a total of 37 out of 51 models discount rates were used, of which 19 also incorporated amortization of investment over the power plant lifetime or financial loan lifetime. In 32 out of 51 models power plant investments were lumped at the level of aggregate power generation capacity, and in the other 19 calculations were carried out for individual power plants. And in 3 out of 51 models the impacts of financial risk on power plant investments and change was incorporated, although another 5 out of 51 used a 'node' based approach with multiple 'branch' outcomes which represents some form of risk evaluation.

In answering **the first objective**, it was found that current electricity system models can answer questions related to what the lowest cost technology outcomes will be in an idealised setting, but are plausibly less suitable to evaluate how policies actually affect company investments in the electricity market. An investigation in the applicability of centralised approaches was therefore found warranted to provide answers to what impact specific policy interventions, such as fiscal instruments, could have on power generation change. Specifically, how the firm perspective could be represented and structured in models to enable better testing of policies and their investment impacts. A key consequence is that existing models, because of a narrow range of input assumptions, centralised planner low cost approaches, and no or a limited inclusion of uncertainty, deliver only a limited range of predictive future outcomes. In other words, outcomes when using a purely financial approach, are predicated on the a priori selected technology costs or prices or their development path.

Models structured in this predictive manner have a limited explanatory power from a financial perspective, since the mechanisms that lead to investment decisions are not explicitly incorporated, as they are simplified to only low cost or profit criteria. In contrast, in reality, there is substantial uncertainty in how costs will evolve over time, especially due to the interaction between government policies, technology costs, and prices. For example, the innovation of new technologies over time is enabled by government support, not just in research funding, but also by supporting the scaling and roll-out over longer periods to drive down costs. Government support in the scale-up phase is needed to lower risks for companies to leverage investment in the path to commercialisation. In the UK and Germany, such a roll-out market regulatory support has been implemented over longer periods, so as to create a competitive market for new technology entrants. The idealised long term aim is to enable technologies such as solar and wind to become fully competitive, which based on recent policy adjustments is expected in the course of 2020s. Since there is an interaction between the temporal dynamics of market regulation, the size of company investment, and the cost and prices of technologies, and this interaction is increasingly uncertain the further from the present. The challenge is that running too limited predictive scenarios based on cost and price learning curves will not yield realistic insights, and instead will show a too limited range of technology futures. As such it is imperative to improve the ability of models to more realistically show the emergence and scaling of technologies, both in relation to cost and price developments, but also in relation to how non-financial factors impact technology evolution.

The road to improve electricity system models to become more useful for informing policy decisions is thought by the author to require an answer to three challenges, which all relate to the interaction between government energy policies, market structures, and how they affect investments. First, how to explicitly incorporate in the structure of electricity system models existing market regulatory policies, so that the effects of policy changes become visible. The structure should contain sufficient explanatory power to provide feedback to policy makers, so as to use models as 'test-beds' for policies. The starting point would be further explication of the set of variables that policy makers can influence, beyond the common approach of one subsidy variable in a cost or profit evaluation formula. For example, for the UK representing the renewables obligation certificate ownership in models in a multiple company structure as a system of equations, inclusive of policy levers for the obligation buy-out price and target setting for % of renewables, with its influence on the cost or profit formula. This should provide insights in how changing those two key parameters would potentially affect outcomes.

Second, whether and how to represent the dynamics of change in such regulation as governments change policies due to their perceived successes and failures, and the criteria under which they are examined. Model structures for this reason would need to allow incorporation in a flexible manner various policy regulatory options to select from, including how each interacts with financial and non-financial factors and how these influence investment decisions. For example, the institution of a stricter 1500 meter distance requirement between residential buildings and onshore wind turbines that was recently instituted in Nordrhein-Westfalen in Germany. Once several rulesets are incorporated and can be altered it becomes possible to incorporate either what-if scenarios or even regulatory response functions, by which regulations shift due to intermediate model variable changes, such as cost reductions via learning curves, or a threshold number of already occupied onshore wind sites resulting in stricter policies. This allows for expressing and evaluating step by step changes in regulatory policies to improve policy maker confidence and the ability to evaluate success relative to the required goals. Third, how to represent company investment knowledge of and risk response to potential key changes in regulation. Continuous risks can tangibly be incorporated based on risk measures, such as incorporation of a risk adjusted discount rate, but discontinuous risks are more difficult to meaningfully incorporate. For example, the influence on investment of perceived risks that are envisionable yet unknown, such as due to elections and a potential shift to different government policies, is less certain. Such uncertainties can temporarily affect investment flows despite perfect market conditions, since it can be better to await post-election certainty for a short period of time. A what-if incorporation using a scenario based approach may be the best suitable setting in this case, since such discontinuous risks and their perception are difficult to robustly quantify.

The explication of investments in electricity system model structure related to the **second objective**, which was to evaluate what a potential set of financial and non-financial factors are that potentially used to inform company decisions to select and invest in companies. The literature review and deductive analysis in **chapter 3** presented a framework composed of a series of *decision options* based on which *investment strategies* can be formulated as model algorithms. The analysis focused on six aspects that can play a role in investment decisions, financial, market strategy, discontinuous risks, technological preferences, political support, and input availability. The analysis did not seek out which factors were of particular importance, but sought to find a range of potential influencing factors in investment decisions, to provide input to investigate particular investment decision strategies for application within an electricity system model context. Further analyses, including in this thesis, can lead to a better understanding which factors are of relevance or of only minor or no influence.

The **third objective** was to assess whether the main approaches used today in using financial metric based evaluations as a key criteria in investment decisions is valid. The implementation assumed that financial metrics can be related to a threshold value that needs to be met in order for investments to take place. In **chapter 7** the results of the statistical analysis based on data from 1980 to 2013 for the Netherlands, the UK, and Germany was presented. The analysis found that significant thresholds could be established with a correct classification of 66% to 80% of power plant investments across the three studied countries. Such thresholds, depending on the country studied, included payback-times of 7 to 10 years, NPV values at 300 to 560 million euro, an IRR from 13% to 19%, and an LCOE from 43 to 62 euro per MWh. The found thresholds were thus relatively similar across the countries, which could follow from their similarities in technology, costs, and price structures. However, the analysis also showed that the thresholds were not very precise, except for LCOE, in that changing the threshold value from say an IRR of 13% to 10%, or 16%, would not lead to a large change in classifications. The reason is that as the threshold value grows, the number of correct positive classifications (that investment occurred) decline, but the amount of negative classifications (that investment did not occur) grow. It was also found that this does not occur for LCOE because within the dataset period of 1980 to 2013 the LCOE values for thermal power plants remain relatively stable. Less variables are involved in the establishment of the LCOE metric, and it is also partially an artificial outcome (e.g. not a given and depends on the market and technology). The overall reason for this lack of precision can partially be attributed to not filtering out pre-conditions for investments. This includes the presence of sufficient demand to warrant expansion, and the required preconditions for particular technologies, especially nuclear power, which in the three countries after the 1986 Chernobyl accident was no longer a politically viable investment option, even if cost conditions met a set threshold. The objective to assess the viability of using financial metrics as thresholds

for investments in a modelling context was thus only partially met. A threshold applies, but pinpointing at what level the threshold occurs requires a better methodology that includes pre-conditions for investment, which at minimum includes demand and political-economic government decisions that allow technologies to enter the market in the first place.

The **fourth objective** was to assess investment decision variants in an optimisation model to assert which variants would yield results closest to historical outcomes. The results, presented in **chapter 8**, showed that financial factors alone can only provide an incomplete reproduction of past power generation investment time-series using the optimization framework, as the combinations of technologies and the magnitude of capacity that evolves per technology differ substantially. The best *decision options* as part of an *investment strategy* include the use of profit maximisation, such as the maximisation of NPV, the inclusion of a time-stepped model structure with a three year time-period, and the use of a maximum and annual capacity constraint for the expansion of technologies. Even with these three *decision options* there were still significant differences to historical outcomes, signalling that financial factors alone are insufficient to provide realistic pathways to future electricity generation mixes.

The comparison of time-stepped and intertemporal variants highlights the importance of temporal dynamics and the information that decision makers have available and base themselves on. The empirical model validation found across the case studies that modelled results were closer to historical developments for time-stepped variants for Germany, the UK and the Netherlands. The treatment of time and available information is likely far more important relative to the attention it has received by electricity system modellers, at least when the aim is to represent investment decisions from a close to reality perspective. The aspect interfaces with the element of uncertainty, since it is impossible for decision makers to know future outcomes, and thus plausibly a simple heuristic is used where the present conditions are mostly extrapolated into the future. Exactly based on this idea such an approach was taken in the time-stepped implementation where a three year average value was extrapolated for the financial evaluation. The treatment of time becomes even more important when key events or conditions that result in a political-economic response are incorporated in models. If an intertemporal setting would be utilised in parallel it would mean that investment decisions are made with the a-priori knowledge of such events or change in a condition, and the model could exploit such features by building far more or less of a particular technology before/after the event or condition changes.

A key missing non-financial aspect, based on the analysis of inflection points, at which capacity of particular technologies start to gain or reduce in importance, is the substantial influence of political-economy type events and conditions that result in the alteration of market regulation and technology specific support. A detailed graphical overview for these inflection points can be seen per technology for Germany, the Netherlands, and the UK in 8.4.1, 8.4.1, 8.4.1. The figures compare the historical evolution of power generation change per technology with the change in a model run based on max-NPV with intertemporal, 5% discount rates, and amortization. The inflection point changes as shown in these figures are influenced by responses to one-off key events, such as the Chernobyl accident and decision to halt nuclear power construction, or particular domestic conditions, such as the existence of coal resources that lead to continuous policies to maintain particular economic structures and jobs, in this case coal mining sector and coal power generation support. The case studies also show that the government response to political-economy influencing events and conditions vary. In the UK state support for coal was fully phased out in the 1980s, whilst in Germany it was maintained and still plays a major role today, even though the form of support and regulation has changed over time as influenced by European Union regulation.

As an example, in Germany as per Figure 34 the historical time-series shows substantially more hard coal expansion at 12 GW whilst in the modelled reproductions 15 to 33 GW of fuel oil emerged instead. A key factor not captured in the model runs are fuel disruption risk issues after the 1973 and 1979 oil crises, which despite reduced oil prices in the course of the 1980s and 1990s did not lead to a ramp-up in oil production in reality. As indicated in **chapter 6.1** the German government mandated hard coal usage following the second oil crisis. Also substantially more biomass is built in the modelled time-series at 34 GW versus only 1.2 GW in the historical time-series. The reason for the emergence plausibly lies in a combination of the relative cost levels of biomass, hard-coal, and nuclear in the 2000s, the financial support for biomass in Germany since the 2000s, and the maximum capacity constraint, which limits each source to about 40 GW of

capacity. Since biomass is financially favoured in the 2000s over hard-coal and nuclear, it is the main technology which sees expansion in the model results. In the case of the UK, as per Figure 35, the max-NPV with maximum and annual capacity constraints results in a large expansion of nuclear power in the model reproductions in the 1980s, which never appear in the historical time-series. Instead, in reality, natural gas gained a much more prominent role as of the 1990s and nuclear investment was stopped. The historic cause, as explored in **section 6.2**, was the Chernobyl accident in 1986 which ended government steered plans to build 15 GW of capacity, in combination with the reduced support for domestic coal. Also, in the model results substantially more onshore wind capacity is built than historically the case. In the case of the Netherlands, as per Figure 36, a similar evolution difference as the United Kingdom is established, where in the modelled runs nuclear expands substantially in the 1980s and 2000s, thereby replacing older natural gas power generation capacity, instead of the continued use of natural gas capacity in the historical time-series. In the Netherlands the government prior to market liberalisation also did have a large amount of nuclear power on the drawing table, at no less than 35 GW in the early 1970s, but none of it emerged due to substantial public opposition following the Three Mile Island and Chernobyl accidents.

Second, when inflection points were found to be similar in their development for historic outcomes and model results, such as the introduction and growth of onshore wind, their starting points and the size of technology scaling were still different across all three cases. A common difference was the earlier pre-commercial introduction of technologies in the historic time-series than in model results, albeit in small quantities, indicating early experimentation by companies and individuals, driven largely by non-financial factors. This can include companies with an innovation preference, as part of a longer term innovation strategy to gain early movers advantage for particular technologies, or early pioneers which have an environmental preference. New technologies did however only start to scale up to any significant size once financial conditions merit large-scale investments. The timing at which technologies were scaled to significant capacities at 1% electricity generation and above was thus similar in max-NPV model results as well as historic outcomes. As such financial values do provide a sufficient signal for scaling, and the omission of early experimentation and small scale investment likely does not matter substantially for using electricity system models to test the investment impacts of government market policies. The aspect that did yield a significant difference in outcomes is the degree and speed of scaling. In general in model result the size of investments and related capacity scaling for new technologies like solar-PV and wind energy is far higher than occurred historically. The impact here likely related to non-financial factors that constraint investments, including available locations and permits, preference of companies to use familiar technologies, public acceptance of new technologies, availability to source feedstock for biomass, the absence of sufficiently detailed regulation to address uncertainties and risks, and so forth. Two approaches can help to introduce technology scaling in a more realistic manner. The first is by introducing general growth scaling constraint equations, parameterised based on the timing and speed of historic introductions and scaling speed (Kramer and Haigh 2009). The downside is that this approach does not yield much explanatory power, particularly as to how regulatory policies can affect scaling, since specific non-financial factors are not explicitly considered. The second more meaningful approach, within the context of using models as policy 'test-beds' is to analyse which non-financial factors aid or restrain the scaling of technologies, so as to represent these in the electricity system model structure.

The finding that technologies start to scale up once financial conditions merit large scale investments has another key implication. It implies that if the point can be predicted where technologies reach a particular level of financial competitiveness within existing market structures, that their take-off can be foreseen. The point at which new technologies become competitive, however, is inherently uncertain. So far learning curve based approaches have been utilised to create a plausible trajectory of likely technology costs in the future, which can also express the impact of larger build-outs on faster cost declines as the learning rate increases with capacity expansion of a technology. The key limitation to this approach are potential disruptive step changes that occur which shift the learning rate substantially, typically emerging as a large multitude of innovations occurring in a short-timespan, such as has been the case for solar-PV in recent years. In the empirical model analysis carried out in the thesis, costs and price were known a-posteriori and implemented as such. The importance for electricity system models that are forward looking, such as for purposes to test the potential future effects of new market instruments or changes in existing ones, is that errors on the learning rate and future costs will result in

errors in the take-off point where new technologies start to scale. The point at which market instruments start to become effective may thus be anticipated too soon, or too late, depending on the degree of error in going down the learning curve to reach market competitiveness from a firm investment perspective.

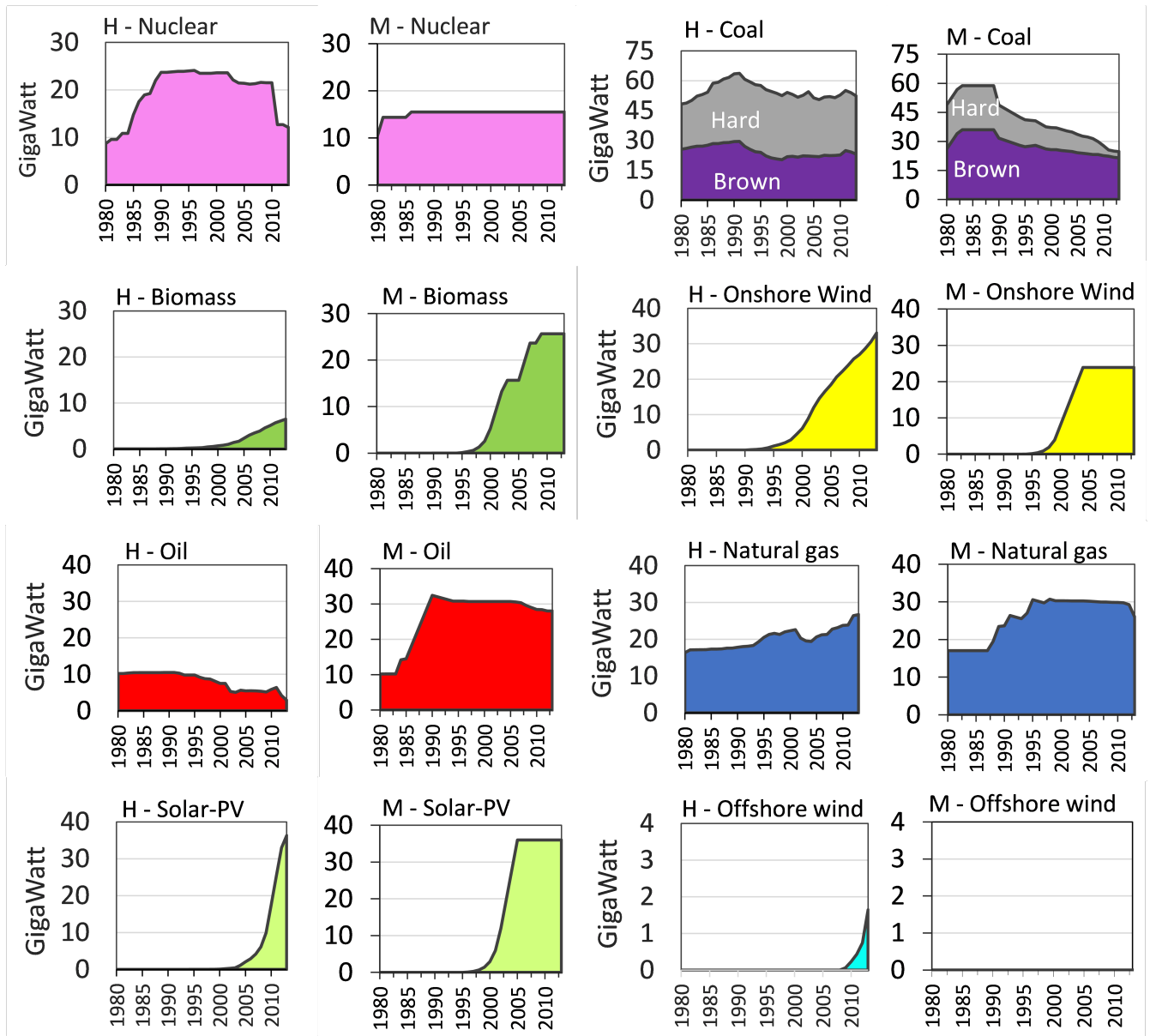


Figure 35: Comparison of German technology inflection points and scaling. In each sub-figure historic data (H) is shown on the left and model results (M) on the right for Max-NPV with 5% discount rate, intertemporal and amortization settings.

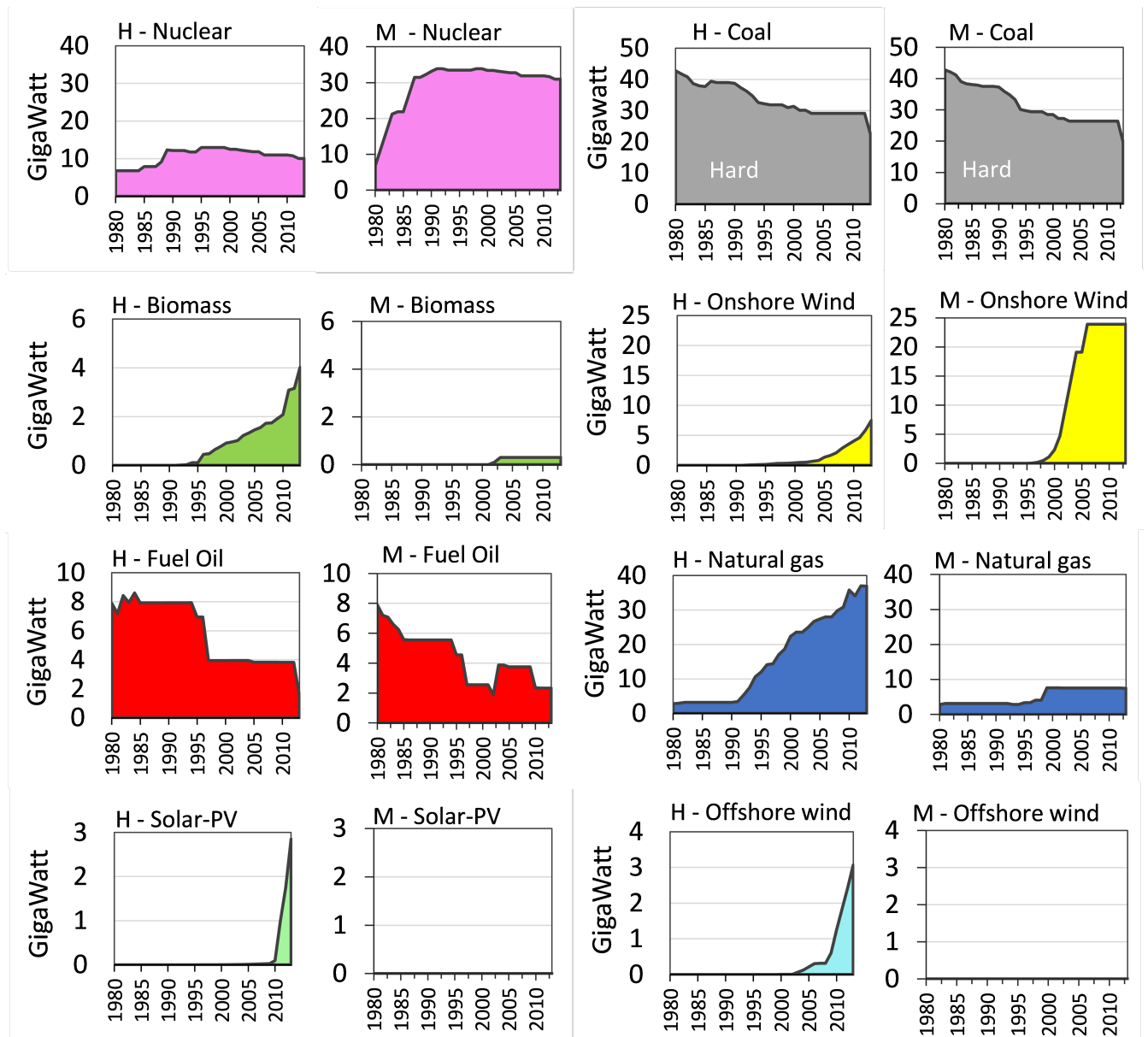


Figure 36: Comparison of UK technology inflection points and scaling. In each sub-figure historic data is shown on the left (H) and model results (M) on the right for Max-NPV with 5% discount rate, intertemporal and amortization settings.

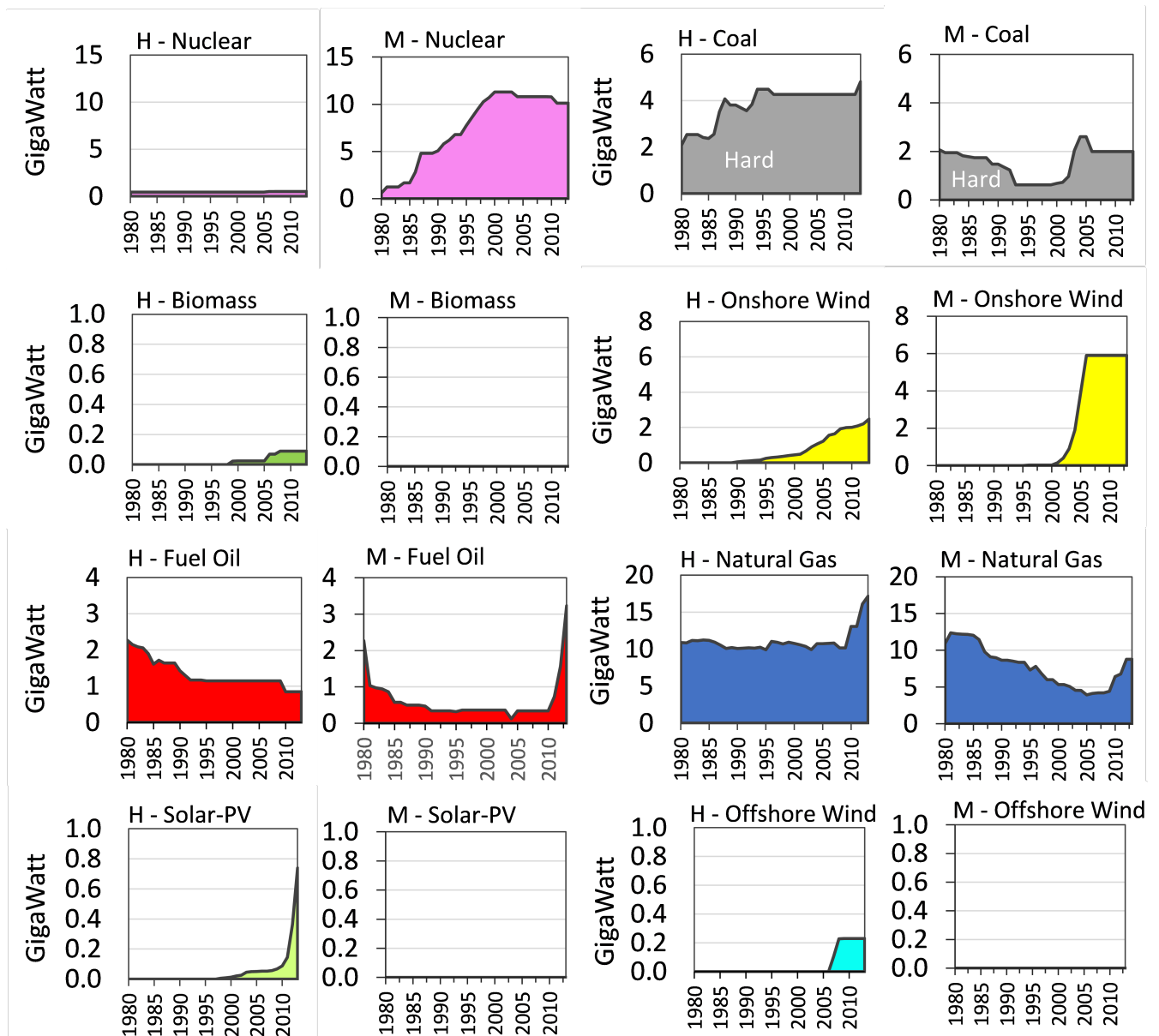


Figure 37: Comparison of NL technology inflection points and scaling. In each sub-figure historic data is shown on the left (H) and model results (M) on the right for Max-NPV with 5% discount rate, intertemporal and amortization settings.

The **fifth objective** was to evaluate what factors in relation to power plant investments were deemed relevant by four electricity market experts. The points made highlighted the importance of difference stages in the investment process and varying financial requirements for investing companies that focus on profit based approaches, especially Internal Rate of Return (IRR), and loan providing banks that focus on a debt service coverage metric. In the interviews it was highlighted that the IRR is used as a hurdle rate and can thus be applied as a threshold value. It was also found that more complex approaches, such as real options assessments or risk evaluations, are potentially too nuanced and complex in their ability to easily compare across investment projects with varying technologies. The complexer approaches may thus not fit well into the decision making process. Risk management was elicited to be of a substantial influence in the decision process from both an individual project risk perspective, such as fuel prices or operation and maintenance, as well as at the level of macro-level risks that relate to changes in market regulation and events. The main approach that came forward was scenario based evaluation, to see how by changing a select number of variables in the future the financial evaluation would change for a particular power plant investment. Non-financial factors were found to play a role, but not as clearly as the financial factors, and these only come in after the financial hurdle rate is met. The expert interviews thus provide a corroboration of the model assessment, in that a hurdle rate at a financial level plays a key role, and add to this that non-financial factors come into play but are likely contingent upon the hurdle rate being met.

In summary, in light of the overall aim to ascertain the quantitative and qualitative factors that provide a valid approach to the modelling of power plant investment decisions, the analysis showed that financial metric evaluations can explain a part of how a decision is formed from a threshold based perspective. However, the accuracy of using just financial metrics, as common in 'central planner' type approaches in electricity system models, is substantially tempered due to other factors that influence technology selection. What at large is missing is that first there are pre-conditions that determine whether an investment will be considered or not from a demand perspective, as well as a pre-determination of which technologies are on the table for financial consideration from a political risk and political-economic perspective. And second, that there are substantial non-financial factors that play a role in choosing between technologies once a financial threshold is met. Substantial different outcomes can evolve depending on what these factors are and how they shape decision making. Furthermore, the effects of events such as the oil crises and nuclear accidents are highly challenging to incorporate a-priori, because both their occurrence and the response to them is unknown. Risk related factors could capture such events based on scenario studies, but that would imply that the user or scenario builder would a-priori introduce such events into the model, regardless of the sophistication of the risk approach, which makes its usefulness limited. For example, a scenario with a risk premium of nuclear power could be introduced that would make it far costlier to expand nuclear power and halt its expansion, which in effect would be an imposition of the modeller itself as an outcome.

A specific aspect where non-financial factors were found to play a substantial role is the more limited expansion in reality of new technologies in the electricity mix, including onshore wind and offshore-wind, solar-PV, and biomass. In model reproductions based on max-NPV, capacity of these technologies were built at a faster pace than historically the case, even in scenarios with an annual, rate, and maximum capacity limitation. A set of plausible factors is that such new technologies are more challenging to introduce due to limited experience, larger risks, and greater land use requirements. To resemble this a stricter ramp-up factor would be required, such as a constraint on the expansion speed of technologies not yet in the infrastructure mix. For example, slow expansion possibilities over a decade before they can be fully expanded like any other technology sources. Another approach would be to incorporate a technology preference constraint based on operational experience, which adds a stronger weight to technologies with greater hours of operating experience in the market, as defined in **section 3.4.4**. This could form part of a sequential decision making procedure in optimization and simulation, or part of a multi-objective optimization approach.

The insights gained with the thesis methodology thus provide a partial answer to fulfilling the thesis aim. It is possible to provide for a valid approach to model power plant investment decisions using a multi-factor approach, with profit maximisation up to a threshold level, in combination with non-financial factors that relate to the speed of introducing new technologies, and political adjustments in market regulation and technology choice. However, changes in boundary conditions of what investments are financially profitable, or even possible, due to political market adjustments, are challenging if not impossible to predict, and thus the approach is only valid with substantial assumptions about the future regulatory

and fiscal changes as set by the government. Since the context of the thesis is to improve the ability to understand the investment decision and technology evolution impacts of exactly such regulatory and fiscal changes, which are exogenous in a testing perspective, making such assumptions would not create an imposition.

The use of electricity system models as a 'test-bed' for the impacts of policy decisions around market instruments and regulation remains relevant in the path to decarbonisation. This will likely be the case until market regulation has sufficiently evolved and settled to incorporate the characteristics of intermittent renewable technologies. There is an expectation that at some point low-carbon technologies can be profitable without market regulatory support such as a 'contract for difference' mechanism, by selling their power on the wholesale market alone. However, the general way that electricity markets function means that the more intermittent resources where the marginal cost of power is zero, and where a large part or all of the financial revenues are based on fixed tariffs, the lower the wholesale power prices will be. As a consequence there is a move away from market based to government driven technology selection and capacity evolution. The recent change to auction systems in the Netherlands, the United Kingdom, and Germany, where specific capacities are tendered with the lowest set of bidders win projects, already signals this change. The tender-auction system is a shift from price based to capacity based steering support, with government control over the set of technologies supported, so far mostly onshore wind, offshore wind, and solar-PV. Although alongside this new approach, smaller market driven projects are possible for solar-PV and onshore wind, these are relatively small in terms of scale. The usefulness of testing market regulation and instruments in electricity system models is at present thus shifting into a split between: i) regulation and instruments in relation to auction driven investments where capacity is pre-determined, and ii) open market driven investment of technologies. In case of auctions several specific applications are relevant: how auctions can best be designed to cost effectively maximize low-carbon technology scaling, how non-financial factors constrain the capacity that can be auctioned over time, and at what point new technologies are mature enough for scaling to start, such as floating offshore wind which is close to a first large scale auction in France.

9.2 Study validity

The internal validity of the thesis results hinge upon the quality of used data and potential errors made in the analyses. The historical time-series datasets were built from literature sources as described in detail in **chapter 6**. Since energy data accounting was less prominent in the 1980s, for this decade there are more gaps for capital and operational cost data that were filled by interpolations, which makes it plausibly the weakest parts in the used datasets. Especially the relative capital costs of power technologies such as nuclear, natural gas and coal could be a substantial factor in technology choice, with 1980s data-points only available for 1981, 1984, and 1987, and for nuclear power generation a part of these costs figures are based on calculations not on real investments (Expert Group 1983, 1986, 1989). The historical time-series for construction of power plants was found in existing databases to extend back to the early 2000s for the UK and NL (GOV.UK 2012)(Sandbag 2014, EEX 2015, Enipedia 2015, Oosterheert et al. 1995). The two decades of missing data was filled through a substantial effort to bring older available literature sources together for these countries, so as to build a comprehensive dataset that included all power plants constructed from 1981 to 2013, including newly built and replacements. The used dataset should given the efforts made, and the absence of any calculations that involve uncertainty, be quite close to the actual construction values for power plant capacity of all technology types.

The choice of case studies of DE, UK, and NL for both the statistical analysis in **chapter 7** and the model historic reproduction in **chapter 8** have a significant influence on the analysis. The countries are similar in that they share the same overarching European Union regulation that led to quite uniform electricity market privatisation and emissions regulation since the mid 1990s. The consequence is a relatively similar historic change from a pre 1970s decentralised to a government centralised from the 1970 to 1990s to a market dominated by a relatively small number of large electricity companies after privatisation during the 1990s, which own and invest in the majority of power plants. This is different than many other high-income economies, such as for example South-Korea where most power plants are still owned and invested in by the state owned electricity giant KEPCO and its subsidiaries, or the United States where far more, at over a hundred large electricity companies, are active in power generation. Also geographically, they have similar wind and solar resources and the three case study countries are quite densely populated. The costs for these technologies are therefore not very far apart, and there are more land restraints for onshore wind and solar-PV, as opposed to a comparison with for example South-Africa. The robustness of the results given the similarities between the case studies is more limited than if countries with far different historic electricity market developments and structures would have been selected.

The main potential measurement error in the statistical analysis of **chapter 7** is the use of a time-lag based on the construction time of power plants to adjust power plant time-series commissioning years into investment time-series years. The logic behind this adjustment was that the market conditions at the start of construction are applicable for the decision, and not those at the time of commissioning when the power plant is already built. The applied time value was based on estimated average construction times from literature sources, and there is always a variation in these values, especially for nuclear power technologies. Furthermore, another error could lie in selecting the start of construction, since investment decisions are taken prior to the start of construction. No reliable data unfortunately exists on how far in advance of the start of construction the decision is made. In addition, in reality investment decisions are typically made in stages, and just before the start of construction the overall decision can still be aborted if unfavourable conditions emerge. As such the start of construction is deemed an as suitable adjustment as possible to approximate market conditions valid for the investment decision.

The internal validity of the model historic reproduction of **chapter 8** hinges largely on the adequacy of the tested model structures in resembling in a simplified manner real-life mechanisms of investment decisions. A key characteristic of the three case study countries and their electricity markets is that all three went through a process of market liberalisation in the 1990s to 2000s. Since privatisation there still is substantial government influence through setting regulatory mechanisms and fiscal support, the latter mainly for renewable energy technologies, yet electricity markets are no longer directly controlled by national governments. Instead electricity markets are organised in a semi-competitive setting with company bidding procedures and long-term contracting within a set of rules that is periodically revisited. The model optimization in this thesis was in contrast carried out as if there is effectively one centralised player that has knowledge of either the

entire time-horizon (intertemporal) or a three year period (timestepped), which leaves out diversification of investment strategies, and market interactions between electricity companies with different technology portfolios. A key consequence of wholesale electricity markets with multiple company bid processes is that companies with renewable electricity sources have increasingly outbid fossil fuel thermal generation electricity providers, due to the low marginal cost of wind and solar power based electricity generation, in combination with substantial fiscal support. The model reproduction does not capture in its structure the effect of diminished or changing electricity sales due to competition, but uses the amount of electricity sold and extra surplus capacity in the past. The results are therefore not valid in terms of being sufficiently adequate to capture substantial technology specific interactions on markets that lead to a change in electricity sales patterns between technologies, as per the identified factor of market share in investment decisions as identified in **section 3.4.2**. Another potential difference of a multi-company modelling approach would be technology competition, in that a few companies have a technology advantage over others. Since the expansion of new technologies (e.g. CCGT, onshore wind, solar-PV) was carried out by many companies in these markets, however, this plausibly did not affect the structural approach and the results.

A structural error that plausibly has been introduced in the model structure is the aspect of risk, since investment risk is no longer borne by the governments since privatisation of electricity markets in the 1990s. Risk was not considered in the model runs in **chapter 8**, but its potential role was explored and discussed in the framework in **chapter 3** and in the interviews in **chapter 5**. Since governments and public companies are less shy of risks because their capacity to resolve the costs of risks is much larger, whereas private companies can go bankrupt due to major risk events, they typically face a higher 'risk premium' for insurance and to obtain investment loans. A comparison of models with different structures for the public and privatised time periods, with different risk effects on technology investment and operational costs, would help to assess the existence and effect of this potential structural error in the ability to reproduce historical investment decisions, and thereby lead to better prediction of future decisions. In the interviews in **chapter 5** it emerged that the difference in risk structure between electricity technologies has been key in the rise of renewable power generation capacity, since due to fiscal support schemes and priority access these have become a low-risk technology, whilst thermal generation is dependent on variable fossil fuel price inputs, where the risk of large fluctuations is usually not covered by government regulation and support.

The external validity of the study depends on whether the results are applicable for other electricity markets than DE, UK, and NL. The key features of the three chosen cases is their limited growth and even stagnation in electricity consumption. The three cases are high income countries with large government budgets which have enabled substantial fiscal support for renewable electricity, and a partially central government led and partially privatised market in the covered time periods. As a consequence, first, the maximum capacity per technology constraint based on historical maxima, as suggested by the thesis, may not be as applicable, or at all, in other electricity markets with considerable electricity consumption growth in the foreseeable future. Instead a flexible maximum approach may be needed that scales in relation to electricity consumption per capita.

Second, the introduction of renewable energy power generation capacity is more and more determined by a target driven by government control in the three countries. This is the case in electricity markets with investments from state owned companies, such as in China and India, but also increasingly so in countries with private markets. The cause is a new instrument of government auctioned markets for large scale renewable power generation capacity that is becoming the common standard in dozens of countries, including the Netherlands and Germany. The effects are twofold, it results in a continuation of the lower risk profile for renewable technologies, and it to an extent cuts-off or slows down community based projects from the market, since participating in auctions is a costlier process than feed-in based regulatory mechanisms. This is even more the case when combined with cutting fiscal support mechanisms for smaller projects. In applying a profit maximisation model structure on a threshold basis, as suggested from the results, the pace as set by the government thus needs to be carefully considered, at least if the modeller wants to test how fiscal support affects plausible technology choices and investment size in a predictive manner within government set regulatory boundaries.

Third, excess power generation capacity in place as shown in **section 6.5** for the Netherlands and the United Kingdom declines substantially when moving from a government to a market oriented system. Excess capacity values are plausibly

substantially higher in pure government based systems, than in private or mixed private/public investment systems, as also seen in China in the last five years with large excess capacity of coal and wind power. The amount of investments that result in excess capacity was tailored to the historical data values for the countries from 1980 to 2013, and extrapolated from the 2013 value to 2046 for the elongated model runs. The chosen excess capacity is specific to each market, and thereby needs to be evaluated on a case by case basis depending on current and historic values to make the proposed algorithm for investment decisions applicable.

9.3 Conclusions

The main conclusion as a synthesis of this thesis, for the studied cases, Germany, the Netherlands, and the United Kingdom, is that the evaluation of technology investment decisions on a financial basis is necessary but not sufficient, especially in the context of electricity system model use as a test-bed for government decisions involving electricity market regulation and financial instruments. In the retrospective case study model runs from 1980 to 2013 using the electricity system optimization model TEMOA, an investment evaluation based on financial factors only was found to provide a valid approach to reproduce a majority of technology outcomes, yet still the model runs missed out on several key technology changes occurring in the 1980 to 2013 period. The missing technology changes were caused by political-economic government led decisions, and by an inability of the TEMOA model to accurately reproduce scaling of new technologies relative to history. The financial evaluation in electricity system models should as such not be implemented as a single selection step, but as part of a larger decision making process, where it is used to narrow down available options once a threshold criteria is met.

The implication is that a better suited investment decision implementation in existing and new electricity system models is needed for purposes of testing the effectiveness of policy decisions around market regulation and financial instrument change. Such a structure, based on the analysis in this thesis, should involve four elements:

- First, the impacts of macro level political-economic decisions need to be captured that do not directly relate to the financial side of technologies, such as disaster events or domestic resource availability. These results in either exclusion of particular technologies (licenses will not be granted) or their promotion and even obligatory continuation (such as support to maintain domestic jobs). The implementation can be based on a 'central planner' perception of risk and an incumbent job bias for each technology. Although the government response that will occur is inherently uncertain, the type of responses can be envisioned and operationalised in scenarios, such as in relation to energy security diversification or domestic supply of resources. The non-financial factors and their influence on technology exclusion or bias can evolve as an electricity system model runs through a selected time-period.
- Second, to narrow down available technologies based on a profit seeking financial evaluation using a financial threshold such as an NPV or IRR, after political-economic adjustments are made at the macro level. The financial evaluation could be implemented as a binary yes/no threshold meeting requirement. In the formulas the financial effects of market instruments such as direct subsidies, renewable obligations, feed-in tariffs, and so forth, should be incorporated. Technologies that do not meet the set financial criteria are discarded as part of the investment decision options.
- Third, to constrain the capacity that can be built for each technology per time period based on a range of non-financial factors. A non exhaustive list of such factors includes public perception and available sites for construction, previous experience with technologies and risk perceptions, available inputs such as skillsets and labour, and company diversification needs. By incorporating non-financial factors and their impacts explicitly, instead of using a general growth rate constraint function with parameter fitting to historic data, the explanatory power of electricity system models improves to give insights in how technology selection and scaling emerges in relation to market regulation and policies. The explicitation is of significance to provide feedback to policy makers on where constraints to technology scaling occur and if they can be influenced. Key in the implementation is therefore to ensure a transparent incorporation of the rules and related variables that governments actually set directly or indirectly, so as to ensure electricity system models can be better used as a 'test-bed' of government policies.
- Finally, a closing selection procedure is needed to carry out the final selection among remaining technologies, inclusive of the established capacity expansion limitations. This procedure could be implemented based on the relative financial ranking of leftover technologies, or a weighted decision procedure which involves both financial and environmental factors such as carbon dioxide emissions, inclusive of any market obligations such as a renewables obligation or quota.

The main conclusion can be contrasted to the approaches in existing electricity system models, as evidenced in the model literature analysis as carried out in **chapter 2**. The screening of 51 models revealed that the majority are structured around financial evaluations to bring about capacity change. It was found that out of 51 models 31 utilise an optimization structure with cost minimisation, a total of 9 incorporate a profit maximization approach within an optimization structure, and that 7 utilise a profit maximization approach within a simulation structure. The least common approach, with 3 out of 51 models, are allocation and growth rate based simulation metrics not linked directly to financial outcomes. Furthermore, in the implementation structure 32 out of 51 models lumped power plants on the basis of aggregate stocks in MW per energy technology, whilst in 19 models they are incorporated per individual power plant. The existing approaches to modelling the investment decision process thus are carry out on an implicit basis using a 'central planner' approach as if a central government places all the investments, with in the majority cases based on lowest cost approaches. That approach can provide for an answer to questions related to lowest cost outcomes in an idealised setting, but is not suitable to evaluate how policy decisions around market instruments affect company investments in the electricity market. It can thus be concluded that existing electricity system models, in general, are not fit for purpose to inform policy decision making from the perspective of using models as a 'test-bed' for policy decisions. The four element perspective above can result in a better representation of the investment decision making process and involved factors, so as to enable better testing of policies and their investment impacts.

The evidence for the first element, to incorporate political-economic decision making by governments that excludes or promotes particular technologies, irrespective of their financial conditions, was established in the empirical model validation of **Chapter 8**, with support from the descriptive analysis of each countries electricity sector history in **Chapter 6**. The model analysis revealed that if financial factors alone are utilised to model change in power generation capacity, that in Germany and the Netherlands no or limited investments would occur for coal power generation, whilst historically substantial investments were made throughout the 1980 to 2013 period (see Fig. 34 and Fig. 36). In the United Kingdom in contrast the modelled development for coal largely followed the historic development for coal (see Fig. 35). The analysis also showed that the modelled nuclear power expansion in both the UK and the Netherlands was far more substantial than the historical outcome, whilst the outcome in Germany was in a similar order of magnitude as the historical development. Since historical technology cost and electricity price data were incorporated in the models as if financial factors were the only factor of importance, such a difference between historic and modelled results would not have emerged. The alternative explanation is thus plausible that the government response at a political-economic level to the Chernobyl nuclear disaster and the coal mining situation triggered a different outcome.

The evidence for the second element, of the need to incorporate financial evaluations based on a profit seeking approach as the means to narrow down technology choice, was established in **Chapters 5, 7 and 8**. The statistical analysis in **Chapter 7** established that the majority of investment decisions are made when a threshold financial factor is met, as tested for Net Present Value (NPV), IRR, Payback Time (PBT) or Levelized Cost of Electricity (LCOE). To be precise a 66% to 85% correlation between meeting the threshold and the occurrence of an actual investment outcome was found, based on the best evaluated threshold levels. The thresholds that resulted in these best correlations included PBT, at a 10, 7, and 7, years payback time or less in DE, NL, and UK, respectively. NPV, at a 300, 350, and 560 million euro or greater value in DE, NL, and UK, respectively. IRR, at a 13%, 18%, and 19% or greater value in DE, NL, and UK, respectively. And LCOE, at a 62, 43, and 62 euro per MWh or lower value in DE, NL, and UK, respectively. The analysis did not filter out years where no investments took place because there is insufficient demand, even though the financial analysis would indicate a favourable investment as the threshold value is met, which when filtered out would plausibly have led to an even greater correlation. The empirical model validation of **Chapter 8**, where 64 variants of the financial evaluation of investments was modelled, corroborated and expanded upon this conclusion. The best significant statistical correlation between historic results and modelled outcomes was found to relate to profit maximization using NPV maximization, among analyses covering Max-NPV, min-LCOE, min-PBT and Cost minimization (min-Cost). Thereby corroborating that financial evaluations can explain a majority of investment outcomes, whilst finding that of the assessed metrics profit maximisation is best suited. The interviews in **Chapter 5** corroborated these conclusions, based on the elicited perspective that companies do base their investment decision on an internal decision using a minimum IRR hurdle rate.

The evidence for the third element, that of a need to introduce non-financial factors to constrain the capacity that can be built for each technology per time period, was established in **Chapters 5 and 8**. The empirical model validation of **Chapter 8** found that financial thresholds are able to explain the start of scaling of new technologies such as solar-PV or onshore wind, but that these by themselves are poor at explaining the rate of expansion, as typically a much faster capacity expansion than historically the case results (see Fig. 34 to 36). Plausibly several non-financial factors play a key role in constraining the expansion speed for technologies, which can include public opposition, regulation such as minimum distance to residential buildings, availability of skilled workers, and several others. In the interviews in **Chapter 5** the perspective was elicited that non-financial aspects are taken into account in the investment decision process as a second decision aspect, after the financial hurdle rate is met, especially in relation to factors related to market and political risk, as well as long term strategic technology investments.

9.4 Recommendations and future work

The study found that the financial part of the investment decision process in electricity markets can in computer models, at least for the UK, Germany, and the Netherlands, best be represented using a profit based approach incorporating a minimum hurdle rate of an NPV or IRR type metric. It is therefore recommended for forward looking electricity system modelling exercises, at least those which seek to investigate the plausible future evolution the energy mix, to use such a profit based approach. A key advantage of the use of profit over cost based approaches lies in the ability to incorporate government financial support systems for energy technologies, such as for wind and solar power technologies in today's markets.

Non-financial metrics were found to play a substantial role, but evaluated to be contingent upon passing a financial hurdle rate. To incorporate non-financial elements in the model implementation of investment decision strategies two elements as part of a model structure were suggested. First, to evaluate technologies in the model rules for their a-priori exclusion or promotion due to political-economic decisions that relate to perceived risks or benefits irrespective of the financial evaluation of technologies. Second, to evaluate how non-financial factors constrain the expansion of new technologies in the electricity mix. For example, land use constraints, technology preference based on past-experience, or environmental preferences which are not financially motivated. The inclusion of non-financial factors was found to be key to improve the scaling rate of new technologies to a more realistic pace. A key area of study for future work is to analyse which non-financial factors are most relevant for particular technologies, geographies and their electricity systems, and how these constrain the expansion of technologies.

The thesis also found that the outcome of investment decisions in electricity system models are more close to real-life decisions with two additional settings. First, when maximum and annual growth rate technology capacity constraints are included. The values can be informed by the historically largest capacity contribution of dominant technologies, and historical growth rates and annual maximum capacity as constructed in the past, so as to implement the capacity expansion constraints. Second, greater proximity to historic outcomes was found when model structures are implemented using a time-stepped approach where present market conditions are extrapolated in the future, as opposed to an intertemporal approach. The tested implementation was a 3 year time horizon for the timestep.

The influence of the political economy structure on electricity technology investment decisions necessitates further consideration. At the core are political support and regulatory changes due to changing conditions in markets and technologies, as well as key historic events known only in hindsight. The first key challenge is how to meaningfully incorporate the influence of events like Chernobyl, or the availability of domestic resources, on how market regulations are shaped and eventually influence outcomes. A key reason for assessing such events and conditions, even though they are uncertain, is to test the robustness of current regulatory policies and their efficacy and coherence under different future event pathways. A recommended approach would be to carry out what-if scenarios where a-priori introduced events or changing domestic conditions, introduced on a fixed or stochastic basis, result in an a-priori determined range of responses in either changing market regulation or parameters. The what-if scenarios can be tied to the three step decision element implementation as above, based on the first step to carry out an a-priori risk evaluation for technology exclusion, and the third step to incorporate non-financial factors such as public goods of jobs as a weight to technologies on the size of investment therein. The second is how to incorporate policy maker feedbacks due to changing market or technology conditions, such as the impact of market regulation and its success or failure within a particular aim. Both will lead to policy adjustment over time and thereby changing market regulation. Such feedbacks would require the inclusion of a sophisticated approach with response functions which adjust parameters or switch between market regulations over time.

The analysis as presented in the thesis still has a number of substantial gaps since the scope was limited to evaluate a number of key *decision options* as part of a set of 64 *investment strategies*. First, based on the established results more work is required to test and evaluate the greater accuracy of using a four element sequential decision ruleset as proposed to explain power plant investment decisions. Such a test can be carried out in a similar approach as this thesis, namely in relation to the ability to reproduce historical outcomes. Future evaluations should compare sequential versus single decision approaches, so as to identify to what extent a sequential decision approach yields different results. Key *decision*

options that are recommended to be evaluated in future work, as came out of this thesis, are a decision step wherein electricity demand expectations and the need for investments are evaluated, a decision step that incorporate the impact of investment risks such as fuel price changes and market regulatory changes, and potential technology preferences that may emerge from the company itself, or due to the market regulatory and political framework under which companies operate. Potential other *decision options* that could be relevant and should be examined in future work are whether past experience with technologies, fuel disruption risks, and environmental outputs, play a significant role within a sequential decision investment decision procedure.

Finally, the conclusions and recommendations are based on the case studies of the Netherlands, the UK, and Germany. Although each of these countries have many unique electricity sector elements they are in many respects politically and economically quite similar. Another future area of study would be to carry out attempts to falsify and enrich the analysis by using similar methods as in this thesis or adaptations thereof on other geographies that have different political and economic structures and histories. These could include diverse economies such as South-Korea which still has a fully nationalised electricity sector even though it is a high income country with many elements of free market capitalism, and Chile which was one of the earliest country that began the process of privatisation of electricity markets in the mid 1980s, with majority ownership by foreign firms of the electricity sector by the late 1990s.

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Appendix A - Characteristics Listing of Electricity System Models

Table 42: Overview of electricity system models with a long-term generation capacity change component.

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
BALMOREL	(Ravn 2005, Karlsson and Meibom 2008, Ravn 2001)	>1 and ≤ 30	>1 and ≤ 8760	Optimization (Time-step)	Lumped per technology	Cost minimisation objective using combined annuity of investment, fuel, operational costs	Yes	Yes	No	Extrapolation of current year exogenous fuel prices & demand	None	Loan lifetime
CALLIOPE	(Pfenninger and Keirstead 2015b,a, Pfenninger 2016)	>30	>1 and ≤ 8760	Optimization (Intertemporal)	Individual power plants	Cost minimisation objective using discounted value of investment, fuel, operational, transmission, and balancing cost.	Yes	No	No	Exogenous fuel price, investment cost & demand scenario for all time periods	None	Technical lifetime
DIME / DIMENSION	Richter (2003)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Intertemporal)	Individual power plants	Cost minimisation objective using existing plant fuel and operational costs, and annuity of new plant investment cost	Yes	Yes	No	Exogenous fuel price, investment cost & demand scenario for all time periods	None	Loan lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
E2M2	(Swider and Weber 2007, Spiecker and Weber 2014, 2011)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using existing plant startup, operational, and reversible fixed costs, and annuity of new plant investment cost	Yes	Yes	No	Exogenous fuel price, investment cost & demand scenario for all time periods	None	Technical lifetime
EMLab-Generation	(Vries et al. 2013)	> 30	>1 and ≤ 100	Simulation (agent decision based time step)	Individual power plants	Profit maximisation selection in bidding rounds based on filling future expected demand and discounted value of investment cost plus anticipated cash flow based on revenues, fuel and operational cost.	Yes	Yes (before discounting)	Yes	Endogenous demand and electricity price, exogenous fuel and investment cost development	Yes	Loan lifetime
EMPS-Invest	(Jaehnert et al. 2013)	>2 and ≤ 30	>1 and ≤ 8760	Simulation (differential equations time-step)	Individual power plants	Profit maximisation using marginal operational profit, and investment costs lower than threshold relative to marginal operational profits	Yes	Yes	No	Exogenous fuel price, investment cost & endogenous demand	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
ESSYMETRY-Invest	(Schroder 2012, Traber and Kemfert 2011)	>30	>1 and ≤ 760	Optimization (Intertemporal)	Lumped per technology	Profit maximisation based on discounted value of investment, fuel, operational, costs and operational income	Yes	No	No	Exogenous fuel price, investment cost & demand scenario for all time periods	None	Technical lifetime
FTT:Power-E3MG	(Dagoumas and Barker 2010, Pollitt et al. 2013, Mercure et al. 2014)	>30	≤ 1	Simulation (differential equations time-step)	Lumped per technology	Growth rate based expansion of capacity influenced by size of existing technology capacity, past sales profits and decommissioning.	No	No	No	Endogenous demand, investment costs, and fuel price developments	Yes	Technical lifetime
EGEAS	Porat et al. (1997)	>1 and ≤ 30	≥ 760	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using discounted value of investment, fuel, operational, unplanned capacity extension cost	Yes	No	No	Exogenous investment, fuel price & demand scenario for all time periods	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
ERIS	Barreto (2001)	>30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using discounted value of investment via learning, fuel, and operational costs	Yes	No	No	Eogenous fuel price and operation and management for all time periods, endogenous investment	None	Technical lifetime
genERIS	Markus Haller (2006)	>30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using discounted value of investment, fuel, and operational costs	Yes	No	No	Exogenous fuel price & demand scenario for all time periods	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
IKARUS	(Martinsen, Krey and Markewitz 2007, Martinsen, Linssen, Markewitz and Vögele 2007, Martinsen, Krey, Markewitz and Vögele 2006, Martinsen, Krey, Markewitz and Vögele 2006)	>30	≤1	Optimization (Time-step)	Lumped per technology	Cost minimisation objective with structure not reported	No	No	No	Exogenous fuel price, investment cost & demand scenarios	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
IMRES	(Sisternes 2013)	>30	>1 and ≤ 8760	Optimization (Intertemporal)	Individual Power Plants & Lumped per technology	Cost minimisation objective based on annuitized value of investment costs, operational costs, fuel costs, power plant start-up costs, and lost load cost.	Not specified	Yes	No	Exogenous fuel price, investment cost & demand scenarios	None	Technical lifetime
MARKAL/ SAGE	Loulou et al. (2004)	>30	>1 and ≤ 8760	Optimization (Time-step)	Individual Power Plants & Lumped per technology	Cost minimisation objective using existing plant fuel and operational costs, and annuity of plant investment cost, plus fuel delivery costs	Yes	Yes	No	Extrapolation of current year exogenous fuel prices & demand	None	Technical lifetime
MELP	Santos and Legey (2010)	>2 and ≤ 30	≤ 1	Optimization (Intertemporal) / stochastic	Lumped per technology	Cost minimisation objective using discounted value of investment, fuel, and operational costs	Yes	No	No	Exogenous investment cost, fuel price & endogenous demand for all time periods	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
MESSAGE	(Messner et al. 1996, Messner and Schratzenholzer 2000)	>30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using discounted value of investment, fuel, and operational costs	Yes	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
MESEDES	(Unsihuay-Vila et al. 2010, 2011)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Time-step)	Individual power plants	Cost minimisation objective of annuity value of investment cost, operation and fuel costs, transmission cost	Yes	Yes	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
MULTIMOD	(Huppmann and Egging 2014)	> 30	>1 and ≤ 8760	Optimization (Intertemporal)	Lumped per technology	Profit maximisation objective using endogenous prices, costs of transmission and exogenous cost of fuel, operation, investment, and storage. The total sum is multiplied by a discount factor	Yes	No	No	Endogenous demand and prices using inverse demand curve and exogenous fuel price, investment, and operational cost.	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
NEMS	(U.S. Energy Information Administration 2014, US EIA 2013)	>2 and ≤ 30	≤ 1	Optimization (Time-step)	Individual power plants	Cost minimisation objective using discounted value from WACC of investment, fuel, operational, transmission, transportation, and carbon market costs	Yes	No	Yes	Endogenous demand and exogenous investment costs and fuel price	None	Loan lifetime
Not named	(Abeygunawardana et al. 2013)	>2 and ≤ 30	≤ 1	Optimization (Intertemporal)	Individual power plants per firm	Profit maximisation of firms from existing operational plants and new capacity using discounted investment costs	Yes	No	No	Exogenous investment cost, fuel price & demand scenario for all time periods	None	Technical lifetime
Not named	(Assili et al. 2008)	>2 and ≤ 30	≤ 1	Simulation (Decision-based time step)	Lumped per technology	Profit maximisation based on expected electricity prices and marginal costs, plus investment costs with technology allocation using a logistics curve with profitability index	No	No	No	Exogenous investment cost & demand scenarios, and endogenous price formation	Yes	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
Not named	(Bakirtzis et al. 2012)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Intertemporal)	Individual power plants	Cost minimisation across all time periods at discounted value including investment capacity cost, operational costs, fuel costs, power interruption load costs, policy penalties, refurbishment costs	Yes	No	No	Exogenous investment cost, fuel price & demand for all time periods	None	Technical lifetime
Not named	(Barforoushi et al. 2010)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Time step)	Lumped technologies per firm	Profit maximisation of firms existing operational plants and new capacity using annuity based investment costs	Yes	Yes	No	Exogenous investment cost, fuel price & demand for all time periods	Yes	Technical lifetime
Not named	(Botterud and Korpas 2007)	>2 and ≤ 30	≤ 1	Optimization (Time step)	Lumped technologies per firm	Profit maximisation of investments based on discounted annuity of investment costs and operational profits, including decision to postpone and risk adjusted discount rate for	Yes	No	No	Exogenous investment costs, fuel price & demand for all time periods	Yes	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
Not named	(Choi and Thomas 2012)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Intertemporal)	Lumped per technology	Cost minimisation for all time periods using risk adjusted discount rate over annuity value for investment capital, operating, and fuel costs	Yes	No	No	Exogenous investment cost, fuel price & demand for all time periods	None	Technical lifetime
Not named	(Dahlan and Kirschen 2010, Dahlan 2011)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Time step)	Individual power plants per firm	Profit maximisation of firms existing operational plants and new capacity using discounted investment costs and anticipated profits using operational price bids	Yes	No	No	Exogenous investment cost, fuel price & demand for all time periods	None	Technical lifetime
Not named	(de Vries and Heijnen 2008)	>2 and ≤ 30	>1 and ≤ 8760	Simulation (decision based time step)	Individual power plants per firm	Profit maximisation of firms using direct value of investment costs, operation costs, fuel costs, and market prices based on marginal cost of generation	No	No	No	Extrapolation of demand using growth rate of past five years, exogenous investment costs and fuel price	Yes	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
Not named	(Eager 2010, Eager et al. 2010, 2012, Eager 2012)	>30	>1 and ≤ 8760	Simulation (differential equation timestep)	Lumped per technology	Profit maximisation of firms using discounted value of income minus operating costs, fuel costs, investment costs, and decommissioning cost. Additional risks evaluated based on Value at Risk (VaR) of profits using Monte-Carlo simulation	Yes	Yes	Yes	Exogenous investment cost, fuel price & demand for all time periods	Yes	Technical or Loan lifetime
Not named	(Giraldo et al. 2012)	>2 and ≤ 30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective of discounted value of investment costs, operational cost, fuel costs, and carbon taxation.	Yes	No	No	Exogenous investment cost, fuel price & demand for all time periods	None	Technical lifetime
Not named	(Hasani-Marzooni and Hosseini 2011, 2012, 2013b,a)	>2 and ≤ 30	≤ 1	Simulation (differential equations time step)	Lumped per technology	Profit maximisation based on the discounted value of investment costs, operation costs, fuel costs, capacity payments, profits,	Yes	No	No	Exogenous investment cost, fuel price, endogenous demand for all time periods	Yes	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
Not named	(Koltsaklis et al. 2014)	>2 and ≤ 30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation of discounted investment costs, operation and fuel costs, electricity storage and transmission costs, import costs	Yes	No	No	Exogenous investment cost, fuel price & demand for all time periods	None	Technical lifetime
Not named	(Li et al. 2014)	>30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation of discounted investment costs, operation cost, fuel cost, and unmet demand penalty cost	Yes	No	No	Exogenous investment cost, fuel price & demand for all time periods	None	Technical lifetime
Not named	(Nagl et al. 2013)	>30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation of annuitized value of investment costs, operation, fuel, and carbon emission costs	Yes	Yes	No	Exogenous investment cost, fuel price & demand for all time periods	None	Technical lifetime
Not named	(Olsina and Garcés 2008, Olsina et al. 2006, 2007)	>2 and ≤ 30	≤ 1	Simulation (differential equations time-step)	Lumped per technology	Growth rate based expansion of capacity influenced by price expectations multiplier formed from power demand and existing generation capacity.	Yes	Yes	No	Endogenous demand, exogenous investment costs, and fuel price developments	Yes	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
Not named	(Pereira and Saraiva 2013, 2011)	>2 and ≤ 20	≤ 1	Optimization (Intertemporal)	Lumped per technology	Profit maximisation objective using electricity price, minus direct cost of investment, cost of operation, and fuel cost.	No	No	No	Endogenous demand, exogenous fuel price and investment cost	None	Technical lifetime
Not named	(Vespucchi et al. 2014)	>2 and ≤ 30	≤ 1	Optimization (Intertemporal)	Individual power plants	Profit maximisation objective based on discounted value of annuity of investment costs as debt repayment, operational costs, fuel costs electricity sale revenue, costs of carbon dioxide permits, and risk assessment using Conditional Value at Risk (CVAR)	Yes	Yes	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
OseMoSYSIS	Howells et al. (2011)	>2 and ≤ 30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using discounted value of investment, fuel, operational, and salvage costs	Yes	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
PERSEUS-CERT	(Heffels et al. 2013, Perlwitz et al. 2005)	>30	>1 and ≤ 8760	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using value of investment, fuel, operational, and carbon market costs	Yes	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
PLEXOS	Deane et al. (2012)	>2 and ≤ 30	≥ 8760	Optimization (Intertemporal)	Lumped per technology	Cost minimisation objective using value of investment, fuel and operational costs	No	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
PowerACE	Pfluger and Wietschel (2012)	>30	>1 and ≤ 8760	Optimization (Intertemporal)	Individual power plants	Cost minimisation objective using discounted value of investment, fuel and operational cost	Yes	Yes	No	Exogenous investment, fuel price & demand scenario for all time periods	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
PowerACE-ResInvest	(Held 2010, Bublitz et al. 2014)	>30	≤ 1	Simulation (Agent decision based time-step)	Individual power plants (renewable only)	Profit maximisation selection based on highest annuity valued investment calculated from endogenous expected income minus electricity generation costs	Yes	Yes	Yes	Exogenous investment costs, fuel price & demand scenario for all time periods	Yes	Technical lifetime
PRIMES	(E3Mlab 2010)	>30	≤ 1	Optimization (Intertemporal or time-step)	Individual power plants	Profit maximisation selection based on highest annuity valued investment calculated by capital costs, operational and fuel costs, annual fixed costs and plant characteristics of supply	Yes	Yes	Yes	Endogenous cost supply curves and demand formation	None	Technical or loan lifetime
REMix-CEM	(Fichter et al. 2014)	>30	>1 and ≤ 8760	Optimization (Time-step)	Individual power plants	Cost minimisation based on capital investment costs, operational costs, and fuel costs	Yes	Yes	Yes	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
SMART	(Powell et al. 2012)	>30	≥ 8760	Optimization (Time-step)	Lumped per technology	Cost minimisation at level of hourly dispatch based on capital costs of all power plant stock, and dispatch costs from operational costs	No	No	No	Endogenous production scenarios, exogenous demand, prices, and capital costs	None	Technical lifetime
SWITCH	Fripp (2012)	>4 and ≤ 30	>1 and ≤ 8760	Optimization (Time-step)	Lumped per technology	Cost minimisation at annual calculated level including investment costs, fixed and variable operations, fuel, and carbon costs	Yes	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
TEMOA	Hunter et al. (2013)	>30	>1 and ≤ 8760	Optimization (Intertemporal)	Lumped per technology	Cost minimisation across all time periods using the annuity of discounted loan costs, fixed and variable operational costs, fuel costs	Yes	Yes	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Loan lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
TIMER	Vries et al. (2001)	>30	>1 and ≤ 8760	Simulation (Multinomial logit Time-step)	Lumped per technology	Share allocation of thermal, nuclear, and renewable energy based on relative shares of generation costs using an annuity factor adjusted investment cost	Yes	Yes	No	Endogenous demand and investment costs for renewables and nuclear, fuel price developments	Yes	Loan or Technical lifetime
UREM	Cai et al. (2009)	>30	≤ 1	Optimization (Intertemporal)	Lumped per technology	Cost minimisation over all time periods using discounted value of investment costs, operational, and fuel costs, emissions, environmental costs	No	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
URBS	(Richter et al. 2015, Dor-fner 2016)	> 30	>1 and ≤ 8760	Optimization (Intertemporal)	Lumped per technology	Cost minimisation over all time periods using the non-discounted investment, fuel, startup, and fixed operational cost	No	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime

Model	References	Time horizon (years)	Time step (number per year)	Model Paradigm	Individual Power Plants/ Lumped per Technology	Investment Mechanics	Discount Rate	Annuity Value	WACC	Data input	Construction timelag	Technical or Loan lifetime
WASP-IV	(Jenkins and Joy 1974, McCalley 2008, Kim et al. 2009)	>2 and ≤ 30	>1 and ≤ 8760	Optimization (Intertemporal)	Individual power plants	Cost minimisation over all time periods using discounted value of investment costs, fuel costs, operational costs,	Yes	No	No	Exogenous investment costs, fuel price & demand scenario for all time periods	None	Technical lifetime
WITCH	(Bosetti et al. 2007, 2009)	>30	≤ 1	Optimization (Time-step)	Lumped per technology	Utility maximisation objective using consumption, which needs to be equal to electricity outputs minus investments, generated from power plant capacity stock	Yes	No	No	Endogenous learning curves for capacity cost based on installed capacity	None	Technical lifetime (depreciation rate)

Appendix B – Overview of TEMOA Model Results

Minimum Cost - Intertemporal - 1981-2013

Table 44: Results overview of TEMOA optimization for 1981-2013 using minimum cost + intertemporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									Δ GW^	CAPEX	OPEX	Spearman Annual			Spearman 5-year periods		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	66.9	0.0	26.1	12.9	0.0	0.0	0.0	0.0	0.0	173.9	56	257	0.055	0.345	4126270	0.115	0.371	36890
DE	lump-sum	none	10%	35.6	0.0	0.0	66.6	0.0	0.0	0.0	0.0	0.0	203.0	46	331	-0.084	0.148	4734185	-0.046	0.723	43560
DE	lump-sum	max cap. + annual	5%	26.0	0.0	27.4	35.9	18.9	0.0	0.0	0.0	0.0	148.0	77	260	0.182	0.002*	3573335	0.312	0.013*	28663
DE	lump-sum	max cap. + annual	10%	24.4	16.0	27.4	35.9	4.0	0.0	0.0	0.0	0.0	143.7	64	304	0.126	0.030*	3814904	0.318	0.011*	28404
DE	amortized	none	5%	54.1	0.0	47.6	0.0	0.0	0.0	0.0	0.0	0.0	171.9	65	256	0.219	0.000*	3411144	0.179	0.160	34199
DE	amortized	none	10%	40.5	0.0	25.9	39.2	0.0	0.0	0.0	0.0	0.0	173.6	68	302	0.149	0.010*	2716454	0.221	0.082	32459
DE	amortized	max cap. + annual	5%	28.9	0.0	27.0	33.5	17.0	0.0	0.0	0.0	0.0	146.2	73	259	0.094	0.105	3955180	0.192	0.132	33666
DE	amortized	max cap. + annual	10%	29.6	4.0	27.6	33.8	11.2	0.0	0.0	0.0	0.0	143.8	82	275	0.047	0.421	4161776	0.091	0.478	37870
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	9.2	2.3	32.1	0.0	0.0	0.0	0.0	68.7	43	145	0.049	0.432	3215657	0.244	0.070	22125
UK	lump-sum	none	10%	-	0.0	5.2	15.9	23.3	0.0	0.0	0.0	0.0	77.3	35	194	0.032	0.606	3164314	-0.002	0.989	29311
UK	lump-sum	max cap. + annual	5%	-	0.0	9.5	2.3	29.2	0.0	0.0	0.0	0.0	65.5	43	154	0.031	0.620	2972534	0.331	0.013*	19589
UK	lump-sum	max cap. + annual	10%	-	0.0	10.5	16.3	14.6	0.0	0.0	0.0	0.0	63.7	29	223	-0.001	0.990	3068842	0.171	0.208	24255
UK	amortized	none	5%	-	3.2	0.0	2.3	32.6	0.0	0.0	0.0	0.0	75.8	46	144	-0.120	0.051#	3435222	0.049	0.719	27821
UK	amortized	none	10%	-	0.0	7.8	1.2	35.0	0.0	0.0	0.0	0.0	74.1	50	143	0.041	0.505	2940337	0.243	0.071#	22138
UK	amortized	max cap. + annual	5%	-	3.4	6.5	2.3	28.8	0.0	0.0	0.0	0.0	65.7	44	154	-0.009	0.880	3095168	0.222	0.098#	22760
UK	amortized	max cap. + annual	10%	-	0.0	7.8	1.2	30.6	0.0	0.0	0.0	0.0	69.7	48	154	-0.056	0.364	2894558	0.249	0.065#	21984
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	1.8	1.9	11.2	1.9	0.0	0.0	0.0	0.0	30.5	19	57	-0.120	0.051	3435602	-0.192	0.157	34865
NL	lump-sum	none	10%	-	0.0	6.3	15.8	4.1	0.0	0.0	0.0	0.0	34.7	15	95	-0.053	0.391	3229208	-0.102	0.453	32253
NL	lump-sum	max cap. + annual	5%	-	2.9	6.6	5.1	11.6	0.0	0.0	0.0	0.0	28.3	21	58	-0.111	0.071#	3408271	-0.117	0.392	32675
NL	lump-sum	max cap. + annual	10%	-	1.8	10.6	2.0	12.4	0.0	0.0	0.0	0.0	23.1	15	95	-0.021	0.737	3130151	-0.071	0.601	31349
NL	amortized	none	5%	-	2.1	2.5	10.7	10.3	0.0	0.0	0.0	0.0	37.5	26	49	-0.102	0.097#	3380077	-0.145	0.287	33495
NL	amortized	none	10%	-	0.7	6.0	15.3	3.7	0.0	0.0	0.0	0.0	33.4	29	47	-0.090	0.145	3342222	-0.131	0.335	33103
NL	amortized	max cap. + annual	5%	-	2.7	8.2	3.2	11.5	0.0	0.0	0.0	0.0	24.9	27	49	-0.075	0.227	3295360	-0.051	0.708	30760
NL	amortized	max cap. + annual	10%	-	2.1	10.9	1.7	12.0	0.0	0.0	0.0	0.0	21.8	29	48	-0.071	0.248	3285337	-0.087	0.524	31806

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Minimum Cost - Time-stepped - 1981-2013

Table 45: Results overview of TEMOA optimization for 1981-2013 using minimum cost + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									Δ GW^	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	24.4	4.0	15.7	42.3	20.4	0.0	0.0	0.0	0.0	140.0	91	211	0.017	0.771	4292377	0.122	0.339	36564
DE	lump-sum	none	10%	24.4	4.0	15.8	42.3	20.3	0.0	0.0	0.0	0.0	139.8	91	211	0.025	0.664	4255786	0.148	0.247	35503
DE	lump-sum	max cap. + annual	5%	25.2	4.0	24.4	33.3	19.9	0.0	0.0	0.0	0.0	138.6	91	199	0.072	0.218	4053205	0.201	0.114	33291
DE	lump-sum	max cap. + annual	10%	23.0	4.0	25.4	33.3	21.1	0.0	0.0	0.0	0.0	138.6	93	204	0.071	0.221	4055150	0.197	0.122	33464
DE	amortized	none	5%	24.5	4.0	16.0	42.3	20.0	0.0	0.0	0.0	0.0	139.4	90	211	0.037	0.529	4206144	0.169	0.186	34633
DE	amortized	none	10%	21.7	4.0	11.2	40.3	30.7	0.0	0.0	0.0	0.0	150.1	104	210	0.006	0.911	4394638	0.081	0.529	38299
DE	amortized	max cap. + annual	5%	26.4	4.0	22.0	33.3	21.2	0.0	0.0	0.0	0.0	138.7	94	194	0.081	0.166	4014653	0.224	0.078#	32310
DE	amortized	max cap. + annual	10%	26.8	4.0	16.2	33.3	25.6	0.0	0.0	0.0	0.0	138.1	100	190	0.035	0.554	4215696	0.159	0.214	35046
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	3.4	3.4	38.5	0.0	0.0	0.0	0.0	81.8	54	94	0.018	0.767	3122888	0.019	0.889	28700
UK	lump-sum	none	10%	-	0.0	6.0	3.4	35.7	0.0	0.0	0.0	0.0	76.4	51	101	0.019	0.759	3008425	0.116	0.395	25868
UK	lump-sum	max cap. + annual	5%	-	0.0	4.5	4.0	33.5	0.0	0.0	0.0	0.0	76.3	52	106	0.001	0.984	3062694	0.107	0.434	26141
UK	lump-sum	max cap. + annual	10%	-	0.0	7.0	4.0	30.8	0.0	0.0	0.0	0.0	71.1	49	113	0.034	0.579	2961287	0.196	0.149	23538
UK	amortized	none	5%	-	0.0	6.1	3.5	35.7	0.0	0.0	0.0	0.0	76.4	51	100	0.031	0.619	2972443	0.116	0.395	25868
UK	amortized	none	10%	-	0.0	2.6	2.6	40.1	0.0	0.0	0.0	0.0	83.4	56	87	0.017	0.781	3013907	0.072	0.599	27158
UK	amortized	max cap. + annual	5%	-	1.6	5.4	4.2	30.8	0.0	0.0	0.0	0.0	71.3	49	112	-0.004	0.944	3080015	0.094	0.489	26497
UK	amortized	max cap. + annual	10%	-	0.0	2.9	3.4	35.6	0.0	0.0	0.0	0.0	79.4	54	100	-0.039	0.523	3187544	0.036	0.793	28212
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0.0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	1.4	12.7	0.3	13.7	0.0	0.0	0.0	0.0	23.8	38	37	0.064	0.298	2869383	0.090	0.509	26622
NL	lump-sum	none	10%	-	1.4	12.7	0.3	13.7	0.0	0.0	0.0	0.0	23.8	38	37	0.064	0.298	2869383	0.090	0.509	26622
NL	lump-sum	max cap. + annual	5%	-	2.5	11.4	0.3	13.5	0.0	0.0	0.0	0.0	21.2	38	37	0.034	0.583	2962475	0.019	0.533	26772
NL	lump-sum	max cap. + annual	10%	-	1.7	12.4	0.3	13.4	0.0	0.0	0.0	0.0	22.9	37	37	0.042	0.500	2938755	0.089	0.513	26649
NL	amortized	none	5%	-	1.4	12.7	0.3	13.7	0.0	0.0	0.0	0.0	23.8	38	37	0.101	0.101	2756499	0.090	0.509	26622
NL	amortized	none	10%	-	2.3	11.2	0.0	14.5	0.0	0.0	0.0	0.0	22.1	37	29	0.058	0.352	2890304	0.085	0.890	28707
NL	amortized	max cap. + annual	5%	-	2.5	11.4	0.3	13.5	0.0	0.0	0.0	0.0	21.2	38	37	0.056	0.365	2894816	0.085	0.533	26772
NL	amortized	max cap. + annual	10%	-	3.7	9.9	0.0	14.0	0.0	0.0	0.0	0.0	21.5	37	29	0.017	0.784	3014657	-0.002	0.987	29325

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Net Present Value - Intertemporal - 1981-2013

Table 46: Results overview of TEMOA optimization for 1981-2013 using NPV + inter-temporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									$\Delta GW^{\wedge}$	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	80.9	0.0	20.9	3.5	1.0	0.0	0.0	0.0	0.0	172.3	62	243	0.107	0.065	3897605	0.191	0.133	33698
DE	lump-sum	none	10%	80.9	0.0	20.9	3.5	1.0	0.0	0.0	0.0	0.0	172.3	62	243	0.107	0.065	3897605	0.191	0.133	33698
DE	lump-sum	max cap. + annual	5%	29.2	5.0	27.0	15.7	25.6	15.9	0.0	0.0	0.0	116.4	110	229	0.245	0.000*	3411144	0.396	0.001*	25184
DE	lump-sum	max cap. + annual	10%	29.2	8.0	27.0	17.3	25.6	0.0	0.0	0.0	0.0	130.9	97	229	0.169	0.004*	3716454	0.288	0.022*	29668
DE	amortized	none	5%	54.1	0.0	47.6	3.8	0.0	0.0	0.0	0.0	0.0	173.5	65	256	0.219	0.000*	3411144	0.179	0.160	34199
DE	amortized	none	10%	40.5	0.0	25.9	39.2	0.0	0.0	0.0	0.0	0.0	173.6	68	302	0.149	0.010	3716454	0.221	0.082#	32458
DE	amortized	max cap. + annual	5%	16.8	0.0	20.9	28.0	5.1	23.9	0.0	36.0	25.7	92.8	224	387	0.204	0.000*	3474678	0.314	0.012*	28597
DE	amortized	max cap. + annual	10%	17.4	0.0	24.2	28.2	0.0	27.9	0.0	36.0	35.7	108.0	247	422	0.219	0.000*	3409105	0.216	0.089#	32652
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	0.0	0.9	38.4	21.6	0.0	0.0	0.0	92.2	66	129	0.026	0.675	3146076	0.174	0.199	24157
UK	lump-sum	none	10%	-	0.0	0.0	0.8	44.3	0.0	0.0	0.0	0.0	91.6	51	123	-0.089	0.150	3339257	0.056	0.683	27630
UK	lump-sum	max cap. + annual	5%	-	0.0	0.1	1.0	36.8	10.0	0.0	0.0	0.0	78.8	57	137	0.138	0.025*	2643401	0.252	0.061#	21895
UK	lump-sum	max cap. + annual	10%	-	0.0	2.7	1.1	37.3	0.0	0.0	0.0	0.0	81.6	50	139	0.018	0.769	3010843	0.211	0.119	23089
UK	amortized	none	5%	-	0.0	7.6	1.6	28.5	86.4	0.0	0.0	0.0	138.8	125	163	0.075	0.227	2837694	0.351	0.081#	18998
UK	amortized	none	10%	-	0.0	9.7	1.2	27.1	88.6	0.0	0.0	0.0	137.9	127	167	0.082	0.182	2813741	0.351	0.008*	18978
UK	amortized	max cap. + annual	5%	-	0.2	4.9	2.3	28.1	23.9	0.0	0.0	0.3	77.4	65	152	0.134	0.029*	2654200	0.332	0.012*	19532
UK	amortized	max cap. + annual	10%	-	2.6	7.0	1.1	24.0	33.5	0.0	0.0	0.3	79.6	75	158	0.232	0.000*	2354234	0.345	0.009*	19173
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0.0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	2.0	8.2	2.0	13.3	0.0	0.0	0.0	0.0	26.2	26	45	0.025	0.684	3143656	-0.077	0.570	31526
NL	lump-sum	none	10%	-	2.0	8.2	2.0	13.3	0.0	0.0	0.0	0.0	26.2	26	45	-0.025	0.684	3143656	-0.077	0.570	31526
NL	lump-sum	max cap. + annual	5%	-	2.2	6.8	3.3	13.6	0.0	0.0	0.0	0.0	29.0	26	46	-0.055	0.373	3235301	-0.056	0.682	30898
NL	lump-sum	max cap. + annual	10%	-	2.2	6.8	3.2	13.6	0.0	0.0	0.0	0.0	28.9	26	46	-0.055	0.373	3235301	-0.056	0.682	30898
NL	amortized	none	5%	-	1.6	5.1	5.1	9.0	21.5	0.0	0.0	0.0	44.6	43	51	-0.068	0.272	2374681	-0.042	0.758	30494
NL	amortized	none	10%	-	0.8	3.7	2.0	9.7	16.6	0.0	52.0	0.0	90.1	117	49	-0.020	0.751	3126684	0.004	0.976	29138
NL	amortized	max cap. + annual	5%	-	2.0	6.5	3.2	10.8	5.9	0.0	0.0	0.0	27.1	31	49	0.021	0.730	3001020	0.022	0.874	28626
NL	amortized	max cap. + annual	10%	-	1.8	1.7	10.5	10.8	5.9	0.3	0.1	0.2	39.0	34	49	0.056	0.366	2895440	0.060	0.662	27514

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. $\wedge$ Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Net Present Value - Time-stepped - 1981-2013

Table 47: Results overview of TEMOA optimization for 1981-2013 using NPV + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									Δ GW^	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	14.7	4.0	6.1	41.3	12.3	42.4	3.2	20.7	34.3	120.4	224	273	0.308	0.000*	3022381	0.490	0.000*	21244
DE	lump-sum	none	10%	15.0	4.0	6.1	41.3	12.0	22.3	0.1	3.1	34.3	141.4	212	272	0.214	0.000*	3433300	0.377	0.000*	25942
DE	lump-sum	max cap. + annual	5%	12.7	4.0	13.6	33.3	12.0	36.1	3.2	20.7	34.3	97.1	216	261	0.334	0.000*	2910072	0.542	0.000*	19088
DE	lump-sum	max cap. + annual	10%	13.6	4.0	15.5	33.3	12.0	36.1	3.2	12.7	34.3	103.9	204	266	0.328	0.000*	2933854	0.489	0.000*	21276
DE	amortized	none	5%	14.6	4.0	6.5	41.3	12.0	42.4	3.2	12.7	34.3	128.2	213	273	0.300	0.000*	3056444	0.452	0.000*	22824
DE	amortized	none	10%	8.0	4.0	6.6	40.3	20.5	42.4	6.4	28.7	34.3	121.6	225	267	0.334	0.000*	2909885	0.472	0.000*	21998
DE	amortized	max cap. + annual	5%	14.2	4.0	13.5	33.3	13.5	36.1	3.2	12.7	34.3	105.0	206	258	0.317	0.000*	2982177	0.480	0.000*	21656
DE	amortized	max cap. + annual	10%	8.8	4.0	11.9	33.3	21.6	36.1	6.4	28.7	34.3	103.3	246	253	0.334	0.000*	2906799	0.477	0.000*	21795
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	3.4	3.2	32.3	201.5	12.6	0.0	0.0	268.3	312	113	0.145	0.019*	2622119	0.231	0.087#	22497
UK	lump-sum	none	10%	-	0.0	6.0	3.2	29.5	201.5	12.6	0.0	0.0	262.9	309	116	0.173	0.005*	2535212	0.313	0.019*	20103
UK	lump-sum	max cap. + annual	5%	-	0.0	3.8	4.0	33.5	16.1	0.7	0.1	3.1	78.4	82	105	0.169	0.006*	2549805	0.335	0.012*	19502
UK	lump-sum	max cap. + annual	10%	-	0.0	3.8	6.5	30.8	20.8	0.7	0.1	3.1	82.9	85	111	0.193	0.002*	2476076	0.408	0.002*	17320
UK	amortized	none	5%	-	0.0	6.1	3.3	29.5	201.5	12.6	0.0	0.0	262.9	309	116	0.187	0.002*	2492793	0.313	0.019*	20103
UK	amortized	none	10%	-	0.0	2.6	2.6	33.7	202.2	13.7	0.0	0.0	271.7	317	109	0.174	0.005*	2533464	0.278	0.038*	21125
UK	amortized	max cap. + annual	5%	-	1.1	4.1	5.4	30.8	21.2	0.7	0.1	3.1	80.8	86	109	0.179	0.004*	2519046	0.327	0.014*	19706
UK	amortized	max cap. + annual	10%	-	0.0	3.2	2.9	35.1	25.5	3.1	0.3	2.7	85.9	103	100	0.198	0.001*	2459863	0.295	0.027*	20619
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0.0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	0.0	7.1	0.3	9.2	43.1	0.0	59.1	0.0	118.9	260	42	0.134	0.029*	2654924	0.127	0.353	25555
NL	lump-sum	none	10%	-	0.0	7.1	0.3	9.2	43.1	0.0	59.1	0.0	118.9	260	42	0.134	0.030*	2656492	0.127	0.353	25555
NL	lump-sum	max cap. + annual	5%	-	0.3	10.2	0.3	12.0	8.4	3.1	0.7	0.7	27.2	53	39	0.175	0.004*	2530845	0.166	0.172	23847
NL	lump-sum	max cap. + annual	10%	-	0.1	10.2	0.3	11.5	8.0	3.1	0.7	1.5	26.3	52	40	0.198	0.001*	2494642	0.108	0.227	24463
NL	amortized	none	5%	-	0.0	7.1	0.3	8.2	46.9	0.0	59.1	0.0	121.7	262	42	0.192	0.002*	2478389	0.185	0.222	24405
NL	amortized	none	10%	-	0.0	3.3	0.0	10.2	51.3	0.0	62.3	0.0	134.8	279	34	0.128	0.038*	2674317	0.164	0.427	26090
NL	amortized	max cap. + annual	5%	-	0.3	10.2	0.3	12.0	8.4	3.1	0.7	0.7	27.2	53	39	0.192	0.002*	2477875	0.185	0.172	23847
NL	amortized	max cap. + annual	10%	-	0.3	6.7	0.0	11.6	15.1	5.1	0.7	1.7	38.7	64	32	0.228	0.000*	2368347	0.205	0.129	23253

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Pay-Back-Time - Intertemporal - 1981-2013

Table 48: Results overview of TEMOA optimization for 1981-2013 using PBT + inter-temporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									$\Delta GW^{\wedge}$	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	0.0	0.0	3.6	102.8	0.0	0.0	0.0	0.0	0.0	252.6	38	474	0.085	0.144	4737581	-0.060	0.639	44173
DE	lump-sum	none	10%	0.0	0.0	0.0	106.3	0.0	0.0	0.0	0.0	0.0	232.7	38	484	-0.101	0.082#	4807388	-0.130	0.311	47069
DE	lump-sum	max cap. + annual	5%	18.0	25.6	27.4	36.0	0.0	0.0	0.0	0.0	0.0	151.0	61	327	0.130	0.025*	3799961	-0.042	0.744	30197
DE	lump-sum	max cap. + annual	10%	17.7	25.9	27.4	36.0	0.0	0.0	0.0	0.0	0.0	151.0	66	304	0.121	0.037*	3837713	-0.060	0.640	30185
DE	amortized	none	5%	0.0	0.0	6.8	98.8	0.0	0.0	0.0	0.0	0.0	218.4	41	461	-0.103	0.077#	4815047	0.275	0.029*	43414
DE	amortized	none	10%	0.0	0.0	3.6	101.9	0.0	0.0	0.0	0.0	0.0	224.7	41	470	-0.144	0.013*	4997090	0.276	0.029*	44168
DE	amortized	max cap. + annual	5%	14.0	29.4	17.4	36.0	0.0	0.0	0.0	0.0	0.0	140.8	66	304	0.089	0.125	3977053	0.212	0.095#	32832
DE	amortized	max cap. + annual	10%	15.9	27.2	27.4	36.0	0.0	0.0	0.0	0.0	0.0	150.5	55	434	0.054	0.355	4130980	0.149	0.243	35451
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	7.3	31.4	0.0	0.0	0.0	0.0	0.0	81.8	16	329	0.000	0.998	3067138	0.099	0.466	26350
UK	lump-sum	none	10%	-	0.0	4.6	35.2	0.0	0.0	0.0	0.0	0.0	88.3	16	341	-0.046	0.453	3208758	0.001	0.999	29256
UK	lump-sum	max cap. + annual	5%	-	0.0	9.6	29.4	0.0	0.0	0.0	0.0	0.0	77.5	17	320	0.052	0.397	2905886	0.099	0.466	26351
UK	lump-sum	max cap. + annual	10%	-	0.0	2.9	36.6	0.0	0.0	0.0	0.0	0.0	91.4	16	348	-0.048	0.438	3213448	0.000	0.999	29256
UK	amortized	none	5%	-	0.0	7.3	31.4	0.0	0.0	0.0	0.0	0.0	81.8	16	329	0.000	0.977	3067138	0.109	0.422	26058
UK	amortized	none	10%	-	0.0	4.5	35.4	0.0	0.0	0.0	0.0	0.0	88.6	16	342	-0.046	0.455	3208167	0.000	0.999	29256
UK	amortized	max cap. + annual	5%	-	0.0	9.6	29.4	0.0	0.0	0.0	0.0	0.0	77.5	17	320	0.052	0.397	2905886	0.109	0.422	26058
UK	amortized	max cap. + annual	10%	-	0.0	2.9	36.6	0.0	0.0	0.0	0.0	0.0	91.4	16	348	-0.048	0.438	3213448	0.000	0.999	29256
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0.0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	0.7	4.3	13.0	6.7	0.0	0.0	0.0	0.0	35.8	16	76	-0.087	0.159	3332943	-0.089	0.516	31856
NL	lump-sum	none	10%	-	0.8	5.3	16.1	3.1	0.0	0.0	0.0	0.0	34.2	14	99	-0.065	0.295	3264875	-0.064	0.639	31133
NL	lump-sum	max cap. + annual	5%	-	2.4	4.5	13.8	4.6	0.0	0.0	0.0	0.0	32.6	15	84	-0.067	0.276	3272778	-0.093	0.495	30142
NL	lump-sum	max cap. + annual	10%	-	0.8	4.7	16.7	3.1	0.0	0.0	0.0	0.0	35.4	14	100	-0.072	0.243	3287758	-0.182	0.179	32217
NL	amortized	none	5%	-	4.8	7.1	12.1	2.1	0.0	0.0	0.0	0.0	23.4	15	88	-0.035	0.576	3172595	-0.030	0.825	31986
NL	amortized	none	10%	-	0.8	5.9	22.5	0.0	0.0	0.0	0.0	0.0	36.9	13	123	-0.096	0.121	3359759	-0.101	0.459	34587
NL	amortized	max cap. + annual	5%	-	4.8	7.1	12.3	2.0	0.0	0.0	0.0	0.0	23.5	15	89	0.009	0.883	3038707	-0.092	0.500	31953
NL	amortized	max cap. + annual	10%	-	0.8	7.2	21.2	0.0	0.0	0.0	0.0	0.0	34.3	13	121	-0.050	0.414	3221315	-0.107	0.431	32402

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Pay-Back-Time- Time-stepped - 1981-2013

Table 49: Results overview of TEMOA optimization for 1981-2013 using PBT + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									Δ GW^	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	4.0	4.0	10.3	83.0	4.0	0.0	0.0	0.0	0.0	187.1	52	354	-0.120	0.039*	4890140	-0.052	0.686	43828
DE	lump-sum	none	10%	4.0	4.0	10.3	83.0	4.0	0.0	0.0	0.0	0.0	187.1	52	354	-0.120	0.039*	4890140	-0.052	0.686	43828
DE	lump-sum	max cap. + annual	5%	6.6	30.8	27.6	36.0	4.0	0.0	0.0	0.0	0.0	153.4	60	285	0.034	0.554	4215865	0.120	0.348	36655
DE	lump-sum	max cap. + annual	10%	6.6	30.8	28.0	36.0	4.0	0.0	0.0	0.0	0.0	153.8	58	285	0.034	0.554	4215865	0.120	0.348	36655
DE	amortized	none	5%	4.3	4.0	10.2	83.0	4.0	0.0	0.0	0.0	0.0	186.9	48	352	-0.137	0.018*	4965065	-0.058	0.654	44062
DE	amortized	none	10%	4.3	4.0	10.2	83.0	4.0	0.0	0.0	0.0	0.0	186.9	48	352	-0.114	0.050*	4863035	-0.058	0.654	44062
DE	amortized	max cap. + annual	5%	6.9	30.5	27.6	36.0	4.0	0.0	0.0	0.0	0.0	152.8	60	285	0.036	0.536	4208996	0.085	0.507	38188
DE	amortized	max cap. + annual	10%	7.0	30.4	27.6	36.0	4.0	0.0	0.0	0.0	0.0	152.6	58	285	0.004	0.942	4347790	0.078	0.543	38411
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	0.0	39.7	48.6	0.0	0.0	0.0	0.0	131.6	80	318	-0.034	0.586	3169888	0.005	0.973	29124
UK	lump-sum	none	10%	-	0.0	0.0	39.7	48.6	0.0	0.0	0.0	0.0	131.6	80	318	-0.034	0.586	3169888	0.005	0.973	29124
UK	lump-sum	max cap. + annual	5%	-	7.4	7.8	36.3	8.5	0.7	0.7	0.7	0.7	79.1	75	312	0.119	0.054#	2702883	0.076	0.579	27042
UK	lump-sum	max cap. + annual	10%	-	7.4	7.8	36.3	8.5	0.7	0.7	0.7	0.7	79.1	75	312	0.119	0.054#	2702883	0.076	0.579	27042
UK	amortized	none	5%	-	0.0	0.0	39.7	48.6	0.0	0.0	0.0	0.0	131.6	80	318	-0.043	0.487	3198271	0.005	0.973	29124
UK	amortized	none	10%	-	0.0	0.0	39.7	48.6	0.0	0.0	0.0	0.0	131.6	80	318	-0.052	0.403	3224978	0.005	0.973	29124
UK	amortized	max cap. + annual	5%	-	7.4	7.8	36.4	8.5	0.7	0.7	0.7	0.7	79.2	75	312	0.119	0.054#	2702914	0.076	0.579	27042
UK	amortized	max cap. + annual	10%	-	9.3	7.8	36.4	8.5	0.7	0.7	0.7	0.7	81.1	79	312	0.109	0.078#	2732996	0.076	0.579	27042
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0.0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	0.0	3.0	16.2	6.6	13.5	0.0	0.0	0.0	49.0	38	87	-0.080	0.196	3311663	-0.122	0.371	32825
NL	lump-sum	none	10%	-	0.0	3.0	16.2	6.6	13.5	0.0	0.0	0.0	49.0	38	87	-0.080	0.196	3311663	-0.122	0.371	32825
NL	lump-sum	max cap. + annual	5%	-	5.7	6.1	11.6	3.8	5.1	0.3	0.1	1.0	24.6	37	91	0.047	0.449	2923216	0.167	0.217	24361
NL	lump-sum	max cap. + annual	10%	-	5.6	6.2	11.6	3.8	5.1	0.3	0.1	1.0	24.4	36	91	0.047	0.449	2923020	0.169	0.213	24309
NL	amortized	none	5%	-	0.0	4.4	14.5	6.6	13.5	0.0	0.0	0.0	45.9	39	86	-0.094	0.143	3343859	-0.087#	0.524	31805
NL	amortized	none	10%	-	0.0	4.4	14.5	6.6	13.5	0.0	0.0	0.0	45.9	39	86	-0.090	0.143	3343859	-0.087#	0.524	31805
NL	amortized	max cap. + annual	5%	-	4.8	6.8	11.6	3.8	5.1	0.3	0.1	1.0	23.4	36	91	0.028	0.652	2981010	0.191	0.158	23659
NL	amortized	max cap. + annual	10%	-	4.4	6.6	11.6	3.8	5.1	0.7	0.1	1.5	24.5	37	92	0.025	0.687	2990172	0.181	0.182	23956

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Levelised Cost of Electricity - Intertemporal - 1981-2013

Table 50: Results overview of TEMOA optimization for 1981-2013 using LCOE + inter-temporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									Δ GW^	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	79.8	0.0	14.0	12.8	0.0	0.0	0.0	0.0	0.0	179.4	57	296	-0.075	0.199	4692944	0.011	0.934	41223
DE	lump-sum	none	10%	60.5	0.0	3.8	41.6	0.0	0.0	0.0	0.0	0.0	199.1	52	336	-0.066	0.255	4655471	0.010	0.939	41252
DE	lump-sum	max cap. + annual	5%	26.8	0.0	26.8	29.5	25.6	0.0	0.0	0.0	0.0	148.5	87	344	0.171	0.003*	3621689	0.300	0.017*	29183
DE	lump-sum	max cap. + annual	10%	21.1	13.0	27.4	26.0	12.0	0.0	0.0	0.0	0.0	119.5	71	404	0.149	0.010*	3714665	0.269	0.033*	30456
DE	amortized	none	5%	65.5	0.0	36.4	3.6	0.0	0.0	0.0	0.0	0.0	173.5	63	298	0.185	0.001*	3557377	0.248	0.050*	31323
DE	amortized	none	10%	64.7	0.0	34.5	0.0	0.0	0.0	0.0	0.0	0.0	169.4	94	318	0.233	0.000*	3351122	0.278	0.027*	30083
DE	amortized	max cap. + annual	5%	30.2	1.8	27.0	23.9	25.6	0.0	0.0	0.0	0.0	144.7	91	309	0.179	0.002*	3583315	0.283	0.025*	29876
DE	amortized	max cap. + annual	10%	31.0	1.8	27.0	23.3	25.6	0.0	0.0	0.0	0.0	144.9	94	318	0.142	0.014*	374412	0.257	0.042*	30971
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	0.0	0.4	46.4	0.0	0.0	0.0	0.0	94.1	54	128	-0.106	0.087#	3390449	0.056	0.683	27630
UK	lump-sum	none	10%	-	0.0	8.8	2.8	35.1	0.0	0.0	0.0	0.0	72.4	45	165	0.071	0.249	2848414	0.239	0.076#	22261
UK	lump-sum	max cap. + annual	5%	-	0.1	4.5	0.4	36.0	0.0	0.0	0.0	0.0	79.1	50	155	0.077	0.212	2830343	0.215	0.111	22956
UK	lump-sum	max cap. + annual	10%	-	0.1	9.8	5.6	27.5	0.0	0.0	0.0	0.0	66.5	43	193	0.082	0.186	2816119	0.326	0.014*	19730
UK	amortized	none	5%	-	0.0	0.0	0.9	49.0	0.0	0.0	0.0	0.0	96.2	61	128	-0.122	0.048*	3440153	0.004	0.979	29157
UK	amortized	none	10%	-	0.0	0.0	0.9	50.1	0.0	0.0	0.0	0.0	97.3	63	129	0.107	0.083#	3394588	-0.035	0.800	30271
UK	amortized	max cap. + annual	5%	-	1.2	7.1	0.9	37.2	0.0	0.0	0.0	0.0	76.1	54	152	0.452	0.464	2927926	0.168	0.217	24354
UK	amortized	max cap. + annual	10%	-	1.1	9.3	0.9	37.3	0.0	0.0	0.0	0.0	74.1	57	158	0.005	0.932	3050478	0.164	0.228	24465
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0.0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	1.6	2.6	11.6	11.4	0.0	0.0	0.0	0.0	39.9	22	57	-0.123	0.046	3444445	-0.085	0.533	31747
NL	lump-sum	none	10%	-	0.3	6.0	15.5	6.3	0.0	0.0	0.0	0.0	36.6	17	90	0.002	0.977	3071947	-0.035	0.795	30297
NL	lump-sum	max cap. + annual	5%	-	3.0	2.3	11.2	10.4	0.0	0.0	0.0	0.0	37.4	22	59	-0.110	0.075#	3402718	-0.109	0.422	32460
NL	lump-sum	max cap. + annual	10%	-	2.7	4.9	15.5	4.3	0.0	0.0	0.0	0.0	33.3	16	59	-0.018	0.766	3122934	-0.025	0.854	29998
NL	amortized	none	5%	-	2.7	7.5	5.1	12.4	0.0	0.0	0.0	0.0	28.4	27	49	-0.092	0.135	3349217	-0.084	0.538	31718
NL	amortized	none	10%	-	1.3	11.3	2.0	13.2	0.0	0.0	0.0	0.0	23.7	30	47	-0.098	0.111	3367987	-0.007	0.959	29466
NL	amortized	max cap. + annual	5%	-	3.0	8.7	3.5	12.0	0.0	0.0	0.0	0.0	24.9	28	49	-0.103	0.094#	3383166	-0.046	0.738	30597
NL	amortized	max cap. + annual	10%	-	2.7	11.0	1.7	12.3	0.0	0.0	0.0	0.0	21.4	29	49	-0.092	0.137	3347873	-0.078	0.570	31530

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Levelised Cost of Electricity - Time-stepped - 1981-2013

Table 51: Results overview of TEMOA optimization for 1981-2013 using LCOE + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									Δ GW^	CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI				rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	0.0	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	35.7	0.0	5.0	50.2	135.1	0.0	0.0	0.0	0.0	288.6	260	219	0.033	0.577	4224300	0.150	0.239	35399
DE	lump-sum	none	10%	44.5	0.0	5.0	50.8	125.4	0.0	0.0	0.0	0.0	288.3	255	222	0.043	0.462	4179213	0.210	0.099#	32912
DE	lump-sum	max cap. + annual	5%	31.3	32.8	27.8	36.0	26.0	39.1	27.0	0.7	36.0	197.9	306	358	0.246	0.000*	3294340	0.428	0.000*	23847
DE	lump-sum	max cap. + annual	10%	31.3	32.8	15.8	36.0	26.0	39.1	27.0	0.7	36.0	187.1	306	361	0.257	0.000*	3242583	0.435	0.000*	23542
DE	amortized	none	5%	43.7	0.0	5.5	50.2	126.7	0.0	0.0	0.0	0.0	287.7	256	220	0.040	0.497	4193651	0.244	0.054#	31507
DE	amortized	none	10%	41.3	0.0	0.0	24.0	160.5	0.0	0.0	0.0	0.0	298.4	295	155	-0.055	0.347	4605362	0.092	0.475	37844
DE	amortized	max cap. + annual	5%	31.3	32.8	27.8	35.6	26.0	37.5	30.1	0.3	36.0	199.4	306	357	0.239	0.000*	3322557	0.387	0.002*	25547
DE	amortized	max cap. + annual	10%	31.3	32.8	28.0	36.0	26.0	42.3	32.1	1.4	36.0	205.7	312	362	0.192	0.001*	3528329	0.358	0.004*	26741
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	0.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	22.7	1.1	109.4	0.0	0.0	0.0	0.0	133.7	173	87	0.088	0.153	2796328	0.337	0.011*	19411
UK	lump-sum	none	10%	-	0.0	23.6	1.1	108.5	0.0	0.0	0.0	0.0	131.9	172	88	0.098	0.114	2767213	0.337	0.011*	19408
UK	lump-sum	max cap. + annual	5%	-	15.6	39.5	39.6	38.4	1.7	0.2	0.0	0.2	97.3	113	206	0.054	0.119	2702761	0.087	0.231	22507
UK	lump-sum	max cap. + annual	10%	-	15.6	39.5	39.6	38.4	1.7	0.2	0.0	0.2	97.3	113	208	0.059	0.116	2709782	0.082	0.235	22382
UK	amortized	none	5%	-	0.0	23.7	1.1	108.4	0.0	0.0	0.0	0.0	131.7	172	88	0.088	0.153	2796122	0.337	0.011*	19411
UK	amortized	none	10%	-	0.0	10.7	0.2	121.6	0.0	0.0	0.0	0.0	158.8	185	75	0.040	0.151	2942605	0.335	0.012*	19469
UK	amortized	max cap. + annual	5%	-	15.6	39.5	39.6	38.4	1.8	0.3	0.0	0.3	97.0	113	208	0.059	0.116	2709408	0.225	0.096#	22677
UK	amortized	max cap. + annual	10%	-	16.0	39.5	33.8	38.4	20.7	0.3	0.0	0.7	98.7	132	198	0.011	0.156	2586823	0.260	0.053#	21666
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	0.0	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	4.6	8.6	0.0	29.5	0.0	0.0	0.0	0.0	37.4	68	39	-0.428	0.489	3197743	-0.128	0.347	33010
NL	lump-sum	none	10%	-	4.6	8.6	0.0	29.5	0.0	0.0	0.0	0.0	37.4	68	39	-0.050	0.417	3220357	-0.128	0.347	33010
NL	lump-sum	max cap. + annual	5%	-	16.0	9.8	0.0	17.7	0.1	0.0	0.0	0.0	34.9	53	51	-0.043	0.483	3199522	0.100	0.463	26332
NL	lump-sum	max cap. + annual	10%	-	15.7	9.8	0.0	17.7	0.1	0.0	0.0	0.0	34.6	52	51	0.037	0.549	3180074	0.097	0.476	26414
NL	amortized	none	5%	-	4.6	8.6	0.0	29.5	0.0	0.0	0.0	0.0	37.4	68	39	-0.058	0.347	3244826	-0.128	0.347	33010
NL	amortized	none	10%	-	0.2	3.9	0.0	36.8	0.0	0.0	0.0	0.0	53.8	75	29	-0.059	0.343	3246427	-0.233	0.084	36071
NL	amortized	max cap. + annual	5%	-	16.0	9.8	0.0	17.7	0.0	0.0	0.0	0.0	35.0	53	51	0.035	0.569	3174695	0.100	0.463	26332
NL	amortized	max cap. + annual	10%	-	16.0	9.6	0.0	17.7	0.7	0.0	0.0	0.0	34.5	53	51	-0.008	0.891	3092610	0.110	0.419	26034

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at $\alpha = 0.05$, # significant at $\alpha = 0.10$. **CAPEX and OPEX values in billion euro. ^Cumulative difference between absolute values of modelled time-series outcome minus historical time series

Minimum Cost - Intertemporal - 1981-2046

Table 52: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using minimum cost + inter-temporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	54.4	0.0	33.0	33.2	0.0	0.0	0.0	0.0	0.0	64	301	0.054	0.355	4131057	0.176	0.168	34329
DE	lump-sum	none	10%	23.6	0.0	27.0	55.3	0.0	0.0	0.0	0.0	0.0	48	343	0.001	0.980	4359859	0.137	0.284	35957
DE	lump-sum	max cap. + annual	5%	22.1	3.3	27.6	33.2	25.6	0.0	0.0	0.0	0.0	89	262	-0.011	0.851	4413943	0.201	0.114	33284
DE	lump-sum	max cap. + annual	10%	18.4	10.2	27.6	33.6	21.7	0.0	0.0	0.0	0.0	85	277	-0.048	0.408	4576866	0.207	0.103	33020
DE	amortized	none	5%	51.4	0.0	42.3	11.8	0.0	0.0	0.0	0.0	0.0	66	265	0.218	0.000*	3412440	0.250	0.048*	31236
DE	amortized	none	10%	43.4	1.6	32.4	37.1	0.0	0.0	0.0	0.0	0.0	71	297	0.128	0.028*	3808869	0.201	0.114	33282
DE	amortized	max cap. + annual	5%	28.3	7.2	27.6	22.3	21.1	0.0	0.0	0.0	0.0	92	246	0.099	0.087#	3932397	0.241	0.057#	21608
DE	amortized	max cap. + annual	10%	29.6	7.4	27.6	28.4	13.2	0.0	0.0	0.0	0.0	87	267	0.055	0.342	4124606	0.140	0.273	35817
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	6.0	23.3	13.7	22.2	0.0	0.0	0.0	0.0	51	208	0.075	0.222	2835198	0.239	0.076#	22269
UK	lump-sum	none	10%	-	0.0	14.5	17.3	21.7	0.0	0.0	0.0	0.0	40	208	0.028	0.655	2981832	0.160	0.238	24566
UK	lump-sum	max cap. + annual	5%	-	6.5	14.1	11.6	21.2	0.0	0.0	0.0	0.0	45	210	0.022	0.719	2998411	0.259	0.054#	21695
UK	lump-sum	max cap. + annual	10%	-	0.0	19.4	17.2	15.9	0.0	0.0	0.0	0.0	38	222	0.059	0.338	2885009	0.341	0.010*	19281
UK	amortized	none	5%	-	6.0	7.3	1.7	37.1	0.0	0.0	0.0	0.0	58	140	-0.027	0.663	3149300	0.170	0.209	24275
UK	amortized	none	10%	-	1.6	3.0	1.2	38.8	0.0	0.0	0.0	0.0	55	136	0.027	0.659	3150359	0.115	0.399	25903
UK	amortized	max cap. + annual	5%	-	5.3	7.5	2.2	32.9	0.0	0.0	0.0	0.0	56	151	-0.011	0.856	3101043	0.170	0.210	24278
UK	amortized	max cap. + annual	10%	-	1.4	3.0	1.2	34.6	0.0	0.0	0.0	0.0	53	147	-0.009	0.884	3094152	0.153	0.260	24776
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	1.6	10.8	6.1	8.9	0.0	0.0	0.0	0.0	22	66	-0.060	0.335	2835198	-0.143	0.294	33433
NL	lump-sum	none	10%	-	0.5	6.9	17.7	3.6	0.0	0.0	0.0	0.0	15	100	-0.038	0.540	2981832	-0.166	0.220	34131
NL	lump-sum	max cap. + annual	5%	-	1.9	9.2	7.3	8.0	0.0	0.0	0.0	0.0	21	69	-0.091	0.141	2998411	-0.153	0.261	29240
NL	lump-sum	max cap. + annual	10%	-	0.7	7.3	14.9	4.2	0.0	0.0	0.0	0.0	16	91	-0.050	0.418	2885009	-0.164	0.227	32310
NL	amortized	none	5%	-	1.8	13.8	0.3	10.9	0.0	0.0	0.0	0.0	27	53	0.033	0.591	3149300	0.001	0.996	33731
NL	amortized	none	10%	-	1.9	12.2	0.3	12.3	0.0	0.0	0.0	0.0	30	48	-0.062	0.312	3150359	-0.104	0.444	34061
NL	amortized	max cap. + annual	5%	-	2.0	12.7	0.5	10.9	0.0	0.0	0.0	0.0	28	52	-0.036	0.562	3101043	-0.026	0.852	30007
NL	amortized	max cap. + annual	10%	-	1.9	12.0	0.4	12.3	0.0	0.0	0.0	0.0	30	48	-0.036	0.562	3094152	-0.026	0.852	30007

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro.

Minimum Cost - Time-stepped - 1981-2046

Table 53: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using minimum cost + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	24.4	4.0	15.7	42.3	20.4	0.0	0.0	0.0	0.0	91	211	0.017	0.771	4292327	0.122	0.339	36564
DE	lump-sum	none	10%	24.4	4.0	15.8	42.3	20.3	0.0	0.0	0.0	0.0	91	211	0.025	0.664	4255786	0.148	0.247	35503
DE	lump-sum	max cap. + annual	5%	25.2	4.0	24.4	33.3	19.9	0.0	0.0	0.0	0.0	91	199	0.072	0.218	4053205	0.201	0.114	33291
DE	lump-sum	max cap. + annual	10%	23.0	4.0	25.4	33.3	21.1	0.0	0.0	0.0	0.0	93	204	0.071	0.221	4055150	0.197	0.122	33464
DE	amortized	none	5%	24.5	4.0	16.0	42.3	20.0	0.0	0.0	0.0	0.0	90	212	0.037	0.529	4206144	0.169	0.186	34633
DE	amortized	none	10%	21.7	4.0	11.2	40.3	30.7	0.0	0.0	0.0	0.0	104	200	-0.006	0.911	4394638	0.081	0.529	38299
DE	amortized	max cap. + annual	5%	26.4	4.0	22.0	33.3	21.2	0.0	0.0	0.0	0.0	94	195	0.081	0.166	4014653	0.224	0.077#	32310
DE	amortized	max cap. + annual	10%	26.8	4.0	18.2	33.3	25.6	0.0	0.0	0.0	0.0	100	190	0.034	0.554	4215696	0.159	0.214	35047
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	3.4	3.4	38.5	0.0	0.0	0.0	0.0	54	94	-0.018	0.767	3122888	0.019	0.888	28700
UK	lump-sum	none	10%	-	0.0	6.0	3.4	35.7	0.0	0.0	0.0	0.0	51	101	0.019	0.759	3008425	0.116	0.395	25868
UK	lump-sum	max cap. + annual	5%	-	0.0	4.5	4.0	33.5	0.0	0.0	0.0	0.0	52	106	0.001	0.984	3062694	0.107	0.434	26142
UK	lump-sum	max cap. + annual	10%	-	0.0	7.0	4.0	30.8	0.0	0.0	0.0	0.0	49	113	0.034	0.579	2961287	0.196	0.149	23538
UK	amortized	none	5%	-	0.0	6.1	3.5	35.7	0.0	0.0	0.0	0.0	51	100	0.031	0.620	2972443	0.116	0.395	25868
UK	amortized	none	10%	-	0.0	2.6	2.6	40.1	0.0	0.0	0.0	0.0	56	87	0.017	0.781	3013907	0.072	0.599	27158
UK	amortized	max cap. + annual	5%	-	1.6	5.4	4.2	30.8	0.0	0.0	0.0	0.0	49	112	-0.004	0.944	3080015	0.094	0.489	26498
UK	amortized	max cap. + annual	10%	-	0.0	2.9	3.4	35.6	0.0	0.0	0.0	0.0	54	100	-0.039	0.523	3187544	0.036	0.793	28212
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	1.4	12.8	0.3	13.7	0.0	0.0	0.0	0.0	38	37	0.064	0.298	2869383	0.090	0.509	26622
NL	lump-sum	none	10%	-	1.4	12.7	0.3	13.7	0.0	0.0	0.0	0.0	38	37	0.064	0.298	3869383	0.090	0.509	26622
NL	lump-sum	max cap. + annual	5%	-	2.5	11.4	0.3	13.5	0.0	0.0	0.0	0.0	38	37	0.034	0.583	3962475	0.085	0.533	26772
NL	lump-sum	max cap. + annual	10%	-	1.7	12.4	0.3	13.4	0.0	0.0	0.0	0.0	37	37	0.042	0.500	2938755	0.089	0.513	26649
NL	amortized	none	5%	-	1.4	12.7	0.3	13.7	0.0	0.0	0.0	0.0	38	37	0.101	0.101	2754699	0.090	0.509	26622
NL	amortized	none	10%	-	2.3	11.2	0.0	14.5	0.0	0.0	0.0	0.0	37	29	0.057	0.352	2890304	0.019	0.890	28707
NL	amortized	max cap. + annual	5%	-	2.5	11.4	0.3	13.5	0.0	0.0	0.0	0.0	38	37	0.056	0.347	2894816	0.085	0.533	26772
NL	amortized	max cap. + annual	10%	-	3.7	9.9	0.0	14.0	0.0	0.0	0.0	0.0	37	29	0.017	0.784	3014567	-0.002	0.987	29325

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro

Net Present Value - Intertemporal - 1981-2046

Table 54: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using NPV + inter-temporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	29.7	3.0	11.5	24.6	43.0	51.6	0.0	0.0	0.0	150	263	-0.055	0.348	4605146	0.167	0.192	34718
DE	lump-sum	none	10%	39.5	3.0	16.9	19.8	51.6	0.0	0.0	0.0	0.0	121	239	-0.038	0.509	4543752	0.141	0.272	35805
DE	lump-sum	max cap. + annual	5%	29.0	5.1	27.4	19.1	25.6	16.1	0.0	0.0	0.0	111	242	0.149	0.010*	3715975	0.364	0.003*	26483
DE	lump-sum	max cap. + annual	10%	30.0	5.2	27.4	22.6	25.6	0.0	0.0	0.0	0.0	97	244	0.473	0.417	4159669	0.240	0.059#	31679
DE	amortized	none	5%	47.7	0.0	16.0	10.2	0.0	0.0	0.0	297.0	4.0	195	305	0.208	0.000*	3459993	0.232	0.068#	32003
DE	amortized	none	10%	19.8	0.0	13.8	40.3	0.0	0.0	0.0	297.0	4.1	191	354	0.203	0.004*	3478898	0.260	0.039*	30812
DE	amortized	max cap. + annual	5%	22.8	0.0	16.8	28.0	11.9	27.9	8.7	36.0	36.0	281	457	0.197	0.000*	3504425	0.204	0.109	33175
DE	amortized	max cap. + annual	10%	19.4	0.0	22.8	28.8	0.0	31.9	7.9	36.0	36.0	285	432	0.238	0.000*	3325681	0.203	0.110	33194
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	16.9	3.5	21.4	53.9	0.0	0.0	0.0	98	191	0.108	0.080#	2735726	0.443	0.000*	16305
UK	lump-sum	none	10%	-	1.8	24.6	2.3	30.9	0.0	0.0	0.0	0.0	58	175	0.072	0.247	2847222	0.264	0.049*	21532
UK	lump-sum	max cap. + annual	5%	-	2.3	17.0	2.6	26.8	15.0	0.0	0.0	0.0	65	182	0.179	0.074#	2518404	0.366	0.005*	18557
UK	lump-sum	max cap. + annual	10%	-	2.3	16.8	2.6	30.4	0.0	0.0	0.0	0.0	54	179	0.075	0.288	2838028	0.261	0.052#	21627
UK	amortized	none	5%	-	0.0	8.1	3.5	26.2	87.7	0.0	0.0	0.0	125	172	0.110	0.004*	2728629	0.288	0.032*	20838
UK	amortized	none	10%	-	0.0	8.6	2.3	27.1	90.8	0.0	0.0	0.0	129	169	0.066	0.228	2865461	0.288	0.031*	20827
UK	amortized	max cap. + annual	5%	-	3.0	5.8	3.1	0.0	42.2	9.5	0.1	0.1	116	163	0.364	0.000*	1951355	0.242	0.073#	22186
UK	amortized	max cap. + annual	10%	-	2.8	7.5	1.5	23.0	42.2	14.2	0.1	0.3	135	162	0.333	0.000*	2044001	0.419	0.001*	17013
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	0.8	12.7	1.0	13.1	0.0	0.0	0.0	0.0	28	55	0.039	0.530	3185741	0.024	0.862	28563
NL	lump-sum	none	10%	-	0.8	12.7	1.0	13.1	0.0	0.0	0.0	0.0	28	55	-0.039	0.530	3185741	0.024	0.862	28563
NL	lump-sum	max cap. + annual	5%	-	1.3	8.9	5.4	10.9	0.0	0.0	0.0	0.0	24	65	-0.105	0.089#	3388324	-0.101	0.459	32216
NL	lump-sum	max cap. + annual	10%	-	1.3	8.9	5.4	10.9	0.0	0.0	0.0	0.0	24	65	-0.105	0.089#	3388324	-0.101	0.459	32216
NL	amortized	none	5%	-	2.0	3.5	0.3	8.9	16.5	0.0	76.9	0.0	154	51	0.044	0.474	3202325	-0.034	0.804	30253
NL	amortized	none	10%	-	0.7	3.5	0.4	9.2	19.6	0.0	72.2	0.0	150	50	-0.061	0.324	3253409	-0.132	0.333	33117
NL	amortized	max cap. + annual	5%	-	2.0	7.0	0.3	9.2	14.3	5.9	3.9	0.0	65	52	0.115	0.062#	2713163	0.190	0.161	23710
NL	amortized	max cap. + annual	10%	-	1.9	7.1	0.3	9.6	14.5	5.9	3.9	0.0	66	50	0.057	0.358	2892502	0.164	0.228	24473

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro

Net Present Value - Time-stepped - 1981-2046

Table 55: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using NPV + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	14.7	4.0	6.1	41.3	12.3	42.4	3.2	20.7	34.3	185	273	0.308	0.000*	3022381	0.490	0.000*	21245
DE	lump-sum	none	10%	15.0	4.0	6.1	41.3	12.0	42.4	3.2	12.7	34.3	173	272	0.300	0.000*	3056634	0.452	0.000*	22824
DE	lump-sum	max cap. + annual	5%	12.7	4.0	13.6	33.3	12.0	36.1	3.2	20.7	34.3	177	261	0.334	0.000*	2910072	0.542	0.000*	19088
DE	lump-sum	max cap. + annual	10%	13.6	4.0	15.5	33.3	12.0	36.1	3.2	12.7	34.3	165	266	0.328	0.000*	2933854	0.489	0.000*	21276
DE	amortized	none	5%	14.6	4.0	6.5	41.3	12.0	42.4	3.2	12.7	34.3	173	273	0.300	0.000*	3056444	0.452	0.000*	22824
DE	amortized	none	10%	8.0	4.0	6.6	40.3	20.5	42.4	6.4	28.7	34.3	212	267	0.334	0.000*	2909885	0.472	0.000*	21999
DE	amortized	max cap. + annual	5%	14.2	4.0	13.5	33.3	13.5	36.1	3.2	12.7	34.3	166	258	0.317	0.000*	2982177	0.480	0.000*	21656
DE	amortized	max cap. + annual	10%	8.8	4.0	11.9	33.3	21.6	36.1	6.4	28.7	34.3	206	253	0.334	0.000*	2906799	0.477	0.000*	21795
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	3.4	3.2	32.3	201.5	12.6	0.0	0.0	312	113	0.145	0.019*	2622119	0.231	0.087#	22497
UK	lump-sum	none	10%	-	0.0	3.2	6.0	29.5	201.5	12.6	0.0	0.0	309	116	0.173	0.005*	2535212	0.313	0.019#	20103
UK	lump-sum	max cap. + annual	5%	-	0.0	4.0	3.8	33.5	16.1	0.7	0.1	3.1	82	105	0.169	0.006*	2549805	0.333	0.012#	19502
UK	lump-sum	max cap. + annual	10%	-	0.0	6.5	3.8	30.8	20.7	0.7	0.1	3.1	85	111	0.193	0.002*	2476076	0.408	0.002#	17320
UK	amortized	none	5%	-	0.0	6.1	3.3	29.5	201.5	12.6	0.0	0.0	309	116	0.187	0.002*	2492793	0.313	0.019#	20103
UK	amortized	none	10%	-	0.0	2.6	2.6	33.7	202.2	13.7	0.0	0.0	317	109	0.174	0.005*	2533464	0.278	0.038#	21125
UK	amortized	max cap. + annual	5%	-	1.1	5.4	4.1	30.8	21.2	0.7	0.1	3.1	86	109	0.179	0.004*	2519046	0.327	0.014#	19706
UK	amortized	max cap. + annual	10%	-	0.0	2.9	3.2	35.1	25.5	3.1	0.3	2.7	103	100	0.198	0.001*	2459863	0.295	0.027#	20619
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	0.0	7.1	0.3	9.2	43.1	0.0	59.1	0.0	260	42	0.134	0.029*	2654924	0.127	0.353	25555
NL	lump-sum	none	10%	-	0.0	7.1	0.3	9.2	43.1	0.0	59.1	0.0	260	42	0.134	0.030*	2656492	0.127	0.353	25555
NL	lump-sum	max cap. + annual	5%	-	0.3	10.2	0.3	12.0	8.4	3.1	0.7	0.7	53	39	0.175	0.004*	2530845	0.185	0.172	23847
NL	lump-sum	max cap. + annual	10%	-	0.1	10.2	0.3	11.5	8.0	3.1	0.7	1.5	52	40	0.198	0.001*	2459464	0.164	0.227	24463
NL	amortized	none	5%	-	0.0	7.1	0.3	8.2	46.9	0.0	59.1	0.0	262	42	0.192	0.002*	2478389	0.166	0.222	24405
NL	amortized	none	10%	-	0.0	3.3	0.0	10.2	51.3	0.0	62.3	0.0	279	34	0.128	0.038*	2674317	0.108	0.427	26090
NL	amortized	max cap. + annual	5%	-	0.3	10.2	0.3	12.0	8.4	3.1	0.7	0.7	53	39	0.192	0.002*	2477875	0.185	0.172	23847
NL	amortized	max cap. + annual	10%	-	0.3	6.7	0.0	11.6	15.1	5.1	0.7	1.7	64	32	0.228	0.000*	2368347	0.205	0.129	23253

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro

Pay-Back-Time- Intertemporal - 1981-2046

Table 56: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using PBT + inter-temporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	6.4	0.0	26.8	72.9	0.0	0.0	0.0	0.0	0.0	44	398	-0.021	0.724	4456026	0.096	0.456	37682
DE	lump-sum	none	10%	0.0	0.0	21.0	85.0	0.0	0.0	0.0	0.0	0.0	42	433	0.084	0.147	4735038	-0.002	0.990	41732
DE	lump-sum	max cap. + annual	5%	14.0	22.1	27.6	33.6	13.0	0.0	0.0	0.0	0.0	78	312	-0.028	0.628	4489423	0.056	0.664	39340
DE	lump-sum	max cap. + annual	10%	14.0	22.4	27.6	33.6	13.0	0.0	0.0	0.0	0.0	78	310	-0.040	0.492	4541101	0.054	0.673	39408
DE	amortized	none	5%	0.0	0.0	19.7	85.9	0.0	0.0	0.0	0.0	0.0	43	435	0.002	0.973	4357824	0.086	0.500	38062
DE	amortized	none	10%	0.0	0.0	10.7	94.8	0.0	0.0	0.0	0.0	0.0	42	452	-0.075	0.200	4692260	0.007	0.958	41383
DE	amortized	max cap. + annual	5%	16.8	28.3	27.6	35.7	0.0	0.0	0.0	0.0	0.0	71	328	0.038	0.513	4199700	0.235	0.063#	31858
DE	amortized	max cap. + annual	10%	16.1	26.9	27.4	35.6	0.0	0.0	0.0	0.0	0.0	75	327	0.054	0.356	4131727	0.149	0.243	35451
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	18.4	29.9	0.0	0.0	0.0	0.0	0.0	26	312	0.052	0.403	2908207	0.336	0.011*	19424
UK	lump-sum	none	10%	-	0.0	7.6	39.8	0.0	0.0	0.0	0.0	0.0	21	329	-0.032	0.603	3165296	0.062	0.652	27460
UK	lump-sum	max cap. + annual	5%	-	0.0	26.5	25.6	0.0	0.0	0.0	0.0	0.0	28	298	0.064	0.298	2869529	0.319	0.017#	19933
UK	lump-sum	max cap. + annual	10%	-	0.0	18.8	30.9	0.0	0.0	0.0	0.0	0.0	26	309	0.003	0.961	3057176	0.106	0.437	26161
UK	amortized	none	5%	-	0.0	10.0	28.7	0.0	0.0	0.0	0.0	0.0	17	326	0.038	0.542	2951106	0.108	0.430	26109
UK	amortized	none	10%	-	0.0	5.1	34.8	0.0	0.0	0.0	0.0	0.0	17	340	-0.019	0.763	3123694	0.092	0.499	26563
UK	amortized	max cap. + annual	5%	-	0.0	12.9	29.0	0.0	0.0	0.0	0.0	0.0	19	311	0.083	0.178	2811546	0.069	0.614	27247
UK	amortized	max cap. + annual	10%	-	0.0	9.9	32.5	0.0	0.0	0.0	0.0	0.0	17	319	0.035	0.575	2960398	0.054	0.691	27670
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	3.5	12.0	13.7	0.0	0.0	0.0	0.0	0.0	16	103	-0.002	0.974	3072774	-0.114	0.403	32495
NL	lump-sum	none	10%	-	1.7	10.5	17.0	0.0	0.0	0.0	0.0	0.0	15	112	-0.029	0.644	3154172	-0.086	0.531	31763
NL	lump-sum	max cap. + annual	5%	-	3.1	12.5	13.6	0.0	0.0	0.0	0.0	0.0	16	104	0.003	0.958	3056480	-0.021	0.881	29861
NL	lump-sum	max cap. + annual	10%	-	1.5	11.1	16.5	0.0	0.0	0.0	0.0	0.0	15	112	0.012	0.841	3028434	-0.007	0.957	29478
NL	amortized	none	5%	-	3.5	12.0	13.7	0.0	0.0	0.0	0.0	0.0	16	103	-0.002	0.974	3072774	-0.114	0.403	32595
NL	amortized	none	10%	-	1.6	10.5	17.0	0.0	0.0	0.0	0.0	0.0	15	112	-0.029	0.643	3154482	-0.086	0.531	31763
NL	amortized	max cap. + annual	5%	-	3.1	12.5	13.6	0.0	0.0	0.0	0.0	0.0	16	104	0.003	0.958	2056480	-0.021	0.881	29861
NL	amortized	max cap. + annual	10%	-	1.5	11.1	16.5	0.0	0.0	0.0	0.0	0.0	15	112	0.012	0.841	3028434	-0.007	0.957	29478

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro

Pay-Back-Time - Time-stepped - 1981-2046

Table 57: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using PBT + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	4.0	4.0	10.3	83.0	4.0	0.0	0.0	0.0	0.0	60	354	-0.120	0.039*	4890140	-0.052	0.686	43828
DE	lump-sum	none	10%	4.0	4.0	10.3	83.0	4.0	0.0	0.0	0.0	0.0	55	354	-0.120	0.039*	4890140	-0.052	0.686	43828
DE	lump-sum	max cap. + annual	5%	6.6	30.8	27.6	36.0	4.0	0.3	0.0	0.0	0.7	81	290	0.034	0.554	4215867	0.120	0.348	36655
DE	lump-sum	max cap. + annual	10%	6.6	30.8	227.6	36.0	4.0	0.3	0.0	0.0	0.7	81	290	0.034	0.554	4215867	0.120	0.348	36655
DE	amortized	none	5%	4.3	4.0	10.2	83.0	4.0	0.0	0.0	0.0	0.0	55	352	-0.137	0.019*	4965065	-0.058	0.654	44062
DE	amortized	none	10%	4.3	4.0	10.2	83.0	4.0	0.0	0.0	0.0	0.0	55	354	-0.114	0.050#	4863035	-0.058	0.654	44062
DE	amortized	max cap. + annual	5%	6.9	30.5	27.6	36.0	4.0	0.0	0.0	0.0	0.7	80	285	0.036	0.536	4208996	0.085	0.507	38118
DE	amortized	max cap. + annual	10%	7.0	30.4	27.6	36.0	4.0	0.0	0.0	0.0	0.7	81	285	0.004	0.942	4347790	0.078	0.543	38411
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	0.0	0.0	39.7	0.0	48.6	0.0	0.0	0.0	80	318	-0.034	0.586	3169888	0.005	0.973	29124
UK	lump-sum	none	10%	-	0.0	0.0	39.7	0.0	48.6	0.0	0.0	0.0	80	318	-0.034	0.586	3169888	0.005	0.973	29124
UK	lump-sum	max cap. + annual	5%	-	7.4	7.8	36.3	8.5	0.7	0.7	0.7	0.7	75	312	0.119	0.054#	2702883	0.076	0.579	27042
UK	lump-sum	max cap. + annual	10%	-	7.4	7.8	36.3	8.5	0.7	0.7	0.7	0.7	75	312	0.119	0.054#	2702883	0.076	0.579	27042
UK	amortized	none	5%	-	0.0	0.0	39.7	0.0	48.6	0.0	0.0	0.0	80	318	-0.043	0.487	3198271	0.005	0.973	29124
UK	amortized	none	10%	-	0.0	0.0	39.7	0.0	48.6	0.0	0.0	0.0	80	318	0.052	0.403	3224978	0.005	0.973	29124
UK	amortized	max cap. + annual	5%	-	7.4	7.8	36.3	8.5	0.7	0.7	0.7	0.7	75	312	0.119	0.054#	2702914	0.076	0.579	27042
UK	amortized	max cap. + annual	10%	-	9.3	7.8	36.4	8.5	0.7	0.7	0.7	0.7	79	312	0.109	0.078#	2732996	0.076	0.579	27042
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	0.0	0.0	14.6	6.6	2.3	0.0	0.0	0.0	38	87	-0.133	0.031*	3474376	-0.250	0.063#	36569
NL	lump-sum	none	10%	-	0.0	0.0	14.6	6.6	2.3	0.0	0.0	0.0	38	87	-0.133	0.031*	3474376	-0.250	0.063#	36569
NL	lump-sum	max cap. + annual	5%	-	5.7	6.1	11.6	3.8	5.1	0.3	0.1	1.0	37	91	0.047	0.449	2923216	0.167	0.217	24361
NL	lump-sum	max cap. + annual	10%	-	5.6	6.2	11.6	3.8	5.1	0.3	0.1	1.0	37	91	0.047	0.449	2923020	0.169	0.213	24309
NL	amortized	none	5%	-	0.0	4.4	14.5	6.6	13.5	0.0	0.0	0.0	39	86	-0.090	0.143	3343859	-0.087	0.524	31806
NL	amortized	none	10%	-	0.0	4.4	14.5	6.6	13.5	0.0	0.0	0.0	39	86	-0.090	0.143	3343859	-0.087	0.524	31806
NL	amortized	max cap. + annual	5%	-	4.8	6.8	11.6	3.8	5.1	0.3	0.1	1.0	36	91	0.028	0.652	2981010	0.191	0.158	23659
NL	amortized	max cap. + annual	10%	-	4.4	6.6	11.6	3.8	5.1	0.7	0.1	1.5	37	92	-0.017	0.787	3117923	0.040	0.769	28085

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro

Levelised Cost of Electricity - Intertemporal - 1981-2046

Table 58: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using LCOE + inter-temporal for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	80.2	1.8	25.6	24.5	0.0	0.0	0.0	0.0	0.0	76	338	-0.017	0.775	4439139	0.137	0.286	35976
DE	lump-sum	none	10%	50.6	0.0	29.4	26.2	0.0	0.0	0.0	0.0	0.0	54	344	0.030	0.608	4235872	0.147	0.250	35541
DE	lump-sum	max cap. + annual	5%	28.8	4.9	27.6	25.9	25.6	0.0	0.0	0.0	0.0	96	336	0.060	0.306	4106293	0.199	0.117	33361
DE	lump-sum	max cap. + annual	10%	14.0	14.2	27.6	33.6	23.7	0.0	0.0	0.0	0.0	85	401	-0.010	0.859	4411436	0.101	0.429	37439
DE	amortized	none	5%	65.7	2.3	27.6	9.9	0.0	0.0	0.0	0.0	0.0	68	303	0.151	0.009*	3708735	0.200	0.116	33337
DE	amortized	none	10%	65.5	2.3	28.4	9.3	0.0	0.0	0.0	0.0	0.0	72	303	0.190	0.001*	3537334	0.221	0.082#	32457
DE	amortized	max cap. + annual	5%	31.3	7.2	27.6	17.6	25.6	0.0	0.0	0.0	0.0	98	291	0.127	0.029*	3811324	0.301	0.017*	29125
DE	amortized	max cap. + annual	10%	31.3	4.6	27.0	20.2	25.6	0.0	0.0	0.0	0.0	96	309	0.152	0.009*	3700670	0.273	0.031*	30300
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	3.7	33.6	3.2	37.1	0.0	0.0	0.0	0.0	69	181	0.023	0.705	2994785	0.316	0.018*	30023
UK	lump-sum	none	10%	-	0.0	15.4	8.2	32.0	0.0	0.0	0.0	0.0	48	212	0.096	0.121	2773402	0.298	0.026*	20550
UK	lump-sum	max cap. + annual	5%	-	4.7	16.5	7.4	30.4	0.0	0.0	0.0	0.0	57	207	0.080	0.194	2820624	0.353	0.008*	18919
UK	lump-sum	max cap. + annual	10%	-	0.0	27.0	9.8	21.0	0.0	0.0	0.0	0.0	48	252	0.150	0.015	2606862	0.445	0.000*	16232
UK	amortized	none	5%	-	3.4	2.1	1.8	48.8	0.0	0.0	0.0	0.0	66	143	-0.057	0.359	3240264	0.143	0.293	25076
UK	amortized	none	10%	-	1.0	0.7	0.9	52.5	0.0	0.0	0.0	0.0	69	133	0.039	0.530	3185700	0.139	0.308	25198
UK	amortized	max cap. + annual	5%	-	7.5	6.8	1.5	37.3	0.0	0.0	0.0	0.0	61	160	-0.013	0.836	3105772	0.183	0.176	23895
UK	amortized	max cap. + annual	10%	-	6.8	7.9	0.9	37.5	0.0	0.0	0.0	0.0	61	160	0.015	0.811	3021244	0.185	0.173	23859
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	0.9	11.3	6.3	9.9	0.0	0.0	0.0	0.0	23	66	-0.029	0.638	3155746	-0.098	0.472	32129
NL	lump-sum	none	10%	-	0.3	7.0	15.3	5.8	0.0	0.0	0.0	0.0	17	92	-0.035	0.573	3173490	-0.127	0.351	32974
NL	lump-sum	max cap. + annual	5%	-	1.2	8.4	8.9	9.1	0.0	0.0	0.0	0.0	22	70	-0.025	0.681	3144423	-0.095	0.486	32043
NL	lump-sum	max cap. + annual	10%	-	2.8	6.7	15.4	3.5	0.0	0.0	0.0	0.0	16	99	-0.035	0.567	3175075	-0.115	0.399	32623
NL	amortized	none	5%	-	1.3	14.1	0.3	12.1	0.0	0.0	0.0	0.0	29	52	0.040	0.519	2944447	0.029	0.831	28408
NL	amortized	none	10%	-	0.8	12.8	0.3	13.9	0.0	0.0	0.0	0.0	31	46	-0.034	0.582	3170926	0.065	0.636	27370
NL	amortized	max cap. + annual	5%	-	2.3	13.5	0.3	11.4	0.0	0.0	0.0	0.0	29	52	-0.004	0.949	3078605	0.043	0.754	28008
NL	amortized	max cap. + annual	10%	-	2.2	12.1	0.3	12.9	0.0	0.0	0.0	0.0	31	48	-0.052	0.401	3225832	-0.036	0.791	30320

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro

Levelised Cost of Electricity - Time-stepped - 1981-2046

Table 59: Results overview of TEMOA optimization for 1981-2013 based on 1981-2046 model run using LCOE + time-stepped for DE, UK, NL.

Case	Structure	Constraints	Discount	Power generation source* additions 1981 - 2013 (GW)									CAPEX	OPEX	Spearman Annual			Spearman 5-year		
				BC	HC	NG	FO	NU	NW	OW	SP	BI			rho	p-value	SE	rho	p-value	SE
DE	n/a	ACTUAL	n/a	12.8	12.0	16.4	1.1	14.1	34.5	0.9	35.6	1.2	-	-	-	-	-	-	-	-
DE	lump-sum	none	5%	68.1	4.8	49.9	42.7	49.4	40.3	0.0	0.0	0.0	272	283	0.080	0.169	4017100	0.148	0.246	25490
DE	lump-sum	none	10%	68.1	4.0	52.9	45.6	44.1	40.3	0.0	0.0	0.0	266	292	0.086	0.139	3990047	0.177	0.165	34279
DE	lump-sum	max cap. + annual	5%	31.3	32.8	27.9	35.9	26.0	72.0	28.7	0.7	36.0	360	360	0.174	0.003*	3605648	0.295	0.019*	29369
DE	lump-sum	max cap. + annual	10%	31.3	28.8	28.9	33.9	26.0	72.0	28.7	0.7	36.0	360	360	0.161	0.006*	3664036	0.290	0.021*	29596
DE	amortized	none	5%	69.9	4.0	48.1	46.1	47.3	28.3	0.0	0.0	0.0	249	292	0.093	0.108	3958620	0.156	0.222	35163
DE	amortized	none	10%	72.7	2.4	41.2	38.7	58.4	68.3	0.0	0.0	0.0	329	255	0.066	0.253	4076044	0.130	0.312	36266
DE	amortized	max cap. + annual	5%	31.3	32.8	27.6	36.0	26.0	72.0	31.1	0.3	36.0	361	364	0.216	0.000*	3422182	0.320	0.011*	28332
DE	amortized	max cap. + annual	10%	32.8	31.3	27.6	35.6	26.0	72.0	34.0	0.7	36.0	368	358	0.153	0.008*	3696714	0.274	0.030*	30260
UK	n/a	ACTUAL		-	2.9	35.6	2.4	7.2	7.5	3.1	2.8	1.0	-	-	-	-	-	-	-	-
UK	lump-sum	none	5%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
UK	lump-sum	none	10%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
UK	lump-sum	max cap. + annual	5%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
UK	lump-sum	max cap. + annual	10%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
UK	amortized	none	5%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
UK	amortized	none	10%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
UK	amortized	max cap. + annual	5%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
UK	amortized	max cap. + annual	10%	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
NL	n/a	ACTUAL		-	5.0	11.3	0.0	0.0	2.7	0.2	0.7	1.2	-	-	-	-	-	-	-	-
NL	lump-sum	none	5%	-	4.6	8.6	0.0	29.5	0.0	0.0	0.0	0.0	68	39	-0.043	0.489	3197743	-0.128	0.347	33010
NL	lump-sum	none	10%	-	4.6	8.6	0.0	29.5	0.0	0.0	0.0	0.0	68	39	-0.050	0.417	3220357	-0.128	0.347	33010
NL	lump-sum	max cap. + annual	5%	-	16.0	9.8	0.0	17.7	0.1	0.0	0.0	0.0	53	51	0.043	0.483	3199522	0.100	0.463	26332
NL	lump-sum	max cap. + annual	10%	-	15.7	9.8	0.0	17.7	0.1	0.0	0.0	0.0	52	51	-0.037	0.549	3180074	0.097	0.476	26414
NL	amortized	none	5%	-	4.6	8.6	0.0	29.5	0.0	0.0	0.0	0.0	68	39	-0.058	0.347	3244826	-0.128	0.347	33010
NL	amortized	none	10%	-	0.2	3.9	0.0	36.8	0.0	0.0	0.0	0.0	75	29	-0.059	0.343	3246427	-0.238	0.084	36072
NL	amortized	max cap. + annual	5%	-	16.0	9.8	0.0	17.7	0.0	0.0	0.0	0.0	53	51	-0.035	0.569	3174695	0.100	0.463	26312
NL	amortized	max cap. + annual	10%	-	16.0	9.6	0.0	17.7	0.0	0.0	0.0	0.0	53	51	-0.008	0.891	3092610	0.110	0.419	26034

*Brown Coal (BC), Hard Coal (HC), Natural Gas (NG), Fuel Oil (FO), Nuclear (NU), Onshore Wind (NW), Offshore Wind (OW), Solar-PV (SP), Biomass (BI), * significant at a = 0.05, # significant at a = 0.10. **CAPEX and OPEX values in billion euro

Appendix C – Overview of TEMOA Model Specification

The model notation follows the nomenclature as described in (Hunter et al. 2013), with the addition of adjustments made by this thesis author. The optimization problem is formulated as a LP, modelled in Python-Pyomo and solved with GLPK.

The model contains the following main features:

- The energy system is designed by selection of technology mix and capacity based on optimization of either minimal costs, levelised costs, payback-time or maximizing net present value.
- The amount of built capacity needs to be sufficient to meet electricity demands plus reserve capacity providing surplus generation in the electricity system based on empirical values.
- Capital costs are based on either a full investment basis (e.g. lump-sum) or a loan value that is amortized over time.
- The operational costs can include variable and fixed operational costs.
- The benefits which are taken into account in net present value calculations include the revenues from electricity generation and fiscal support for technologies as variable benefits.
- The code implementation allows the model to be run on either an intertemporal basis or using time periods of three years across the desired time horizon.

Sets, Parameters, and Variables:

Table 60: TEMOA Energy System Model Unit Descriptions.

Symbol	Unit	Description
Sets		
$c \in C$		All user-defined resources (commodities in TEMOA)
$C^d \subset C$		Subset of set C that includes only the demand and supply resources
$C^e \subset C$		Subset of set C that includes only emissions
$d \in D$		Daily time segments
$i = c$		An alias for representing the resource inputs for a technology
$o = c$		An alias representing the resource output from a technology
$p \in P$		Set of annual periods defined the model
$P^e \in P$		Set of periods before the first period that is modelled to define the technology vintages
$P^f \in P$		Set of periods modelled (future periods)
$v \in V$		Set of technology vintages defined as the time period (p) in which a technology (t) is installed
$s \in S$		Set of all user defined seasons
$t \in T$		Set of all user defined technologies
$T^b \subset T$		Subset of technologies that includes only baseload electric technologies that can provide constant loads on an hour to hour basis
$T^d \subset T$		Subset of technologies that includes only demand technologies that can service an end-use demand (excluding extraction and conversion technologies)
$T^r \subset T$		Subset of technologies that includes only resource extraction technologies such as for fossil fuels
$T^s \subset T$		Subset of technologies that includes only storage technologies which can balance storage and dispatch across daily time segments (D)
Θ		Sparse superset representing allowable combinations of set elements.
Parameters		
$C2A_{t,v}$	proportion	Parameter to convert capacity units into activity units
$CF_{s,d,t,v}$	percentage	Capacity factor for technologies that can vary by season and time of day
$DEM_{p,c}$	unit value	End-use demands that can vary by period and resource (electricity in the model)
$DSD_{s,d,c}$	percentage	Percentage distribution of demand per time slice

Symbol	Unit	Description
$EAC_{e,i,t,v,o}$	unit value	Emissions rate of a process based on a pairing of input/output resources
$ECAP_{t,v}$	unit value	Amount of pre-existing process capacity for technologies prior to period P^f for technology vintages v
$EFF_{i,t,v,o}$	percentage	Conversion efficiency of resources based on a pairing of input/output resources (e.g. fuels to electricity)
$ELM_{p,e}$	unit value	Emissions limit specified per period
$ECR_{p,c}$	ratio	Excess capacity for resource output set as a ratio of demand for a resource (c) varying per unit time
$FC_{p,t,v}$	financial value	Fixed costs for operations and maintenance (OPEX)
GDR	percentage	Global discount rate used to calculate present value of future period costs
$GR_{p,t}$	ratio	Absolute maximum growth rate for a technology varying per year
GM_t	unit value	Absolute maximum increase in technology capacity per year
$IC_{t,v}$	financial value	Investments costs for technologies (CAPEX)
$LA_{t,v}$	unit value	Loan amortization factor to convert future lump sum investment costs into annualized amounts, based on parameter TDR
LEN_p	year value	Calculated number of years in period $P^f \in P$
$LIF_{p,t,v}$	unit value	Lifetime of a technology varying by vintage and period
$LLN_{t,v}$	percentage	Process specific loan terms
$MAX_{p,t}$	unit value	Upper bound on capacity installation by model time period
$MIN_{p,t}$	unit value	Lower bound on capacity installation by model time period
$MLL_{t,v}$	unit value	Minimum value of either number of years until the end of technology loan lifetime or the final year in the P^f horizon of future years
$MTL_{p,t,v}$	unit value	Minimum value of either number of years until the end of technology lifetime or the final year in the P^f horizon of future years
$PRI_{p,c}$	unit value	Price of a resource (electricity, fuels) that can vary by period
$RSC_{p,c}$	unit value	Upper bound on resource production
$SEG_{s,d}$	proportion	Fraction of year represented by each combination of season (s) and time-of-day (d)
$SPL_{i,t,o}$	proportion	Fraction of total input commodity (i) converted to the output commodity (o) of technology (t)
$TDR_{t,v}$	percentage	Technology specific discount rate used to calculate the loan amortization factor. If not specified defaults to GDR parameter.
$TLF_{p,t,v}$	proportion	Fraction of period p that a process is active
$VC_{p,t,v}$	financial value	Variable operation and maintenance costs
$VB_{p,t,v}$	financial value	Variable benefits from financial support for energy technologies such as feed-in-tariffs, renewable obligations, or direct subsidies.
Variables		
$ACT_{p,s,d,t,v}$	unit value	Total resource production of a process
$CAP_{t,v}$	unit value	Total capacity of a technology to support all processes
$CAPAVL_{p,t}$	unit value	Total capacity available for a technology per period
$FI_{p,s,d,i,t,v,o}$	unit value	Resource flow into a process to produce a specific output per time period for a specific vintage of technology
$FO_{p,s,d,i,t,v,o}$	unit value	Resource flow into a process to produce a specific input per time period for a specific vintage of technology
$LC_{p,t,v}$	financial value	Loan costs as the total investment cost made including adjustments for amortization and discount rates where applicable
$LCOE_{p,c}$	financial value	Levelised cost of Electricity based on the costs of production divided by the production level
$LOST_{p,t}$	unit value	Lost capacity of a particular technology in a period due to decommissioning
$PBT_{p,t,v}$	unit value	Payback time for a technology varying by vintage and period of investment
$REV_{p,c}$	financial value	Revenue from sales based on price and output quantity

Objective equations:

Table 62: Objective equations used in the model.

Goal	Type	Objective	Description
Min-COST	lump-sum invest	$MIN\ COST = \sum_{p,t,v} \{VC_{p,t,v} + FC_{p,t,v} + IC_{p,t,v}\}$	Minimum cost of a system based on the investment costs (or loan costs) and fixed and variable O&M costs
Min-COST	Amortized invest	$MIN\ COST = \sum_{p,t,v} \{VC_{p,t,v} + FC_{p,t,v} + LC_{p,t,v}\}$	
Max-NPV	lump-sum invest	$MAX\ NPV = \sum_p (REV_p - \sum_{t,v} \{VC_{p,t,v} + FC_{p,t,v} - VB_{p,t,v}\} - \sum_{t,v} IC_{p,t,v})$	Maximum Net Present Value based on the Electricity Revenue minus fixed and variable O&M costs plus variable benefits from fiscal support, and minus investment (or loan) costs
Max-NPV	Amortized invest	$MAX\ NPV = \sum_p (REV_p - \sum_{t,v} \{VC_{p,t,v} - VB_{p,t,v}\} - \sum_{t,v} LC_{p,t,v})$	
Min-LCOE	lump-sum invest	$MIN\ LCOE = \sum_{p,t,v} \{VC_{p,t,v} + FC_{p,t,v} + IC_{p,t,v}\} - \sum_p \{LCOE_{p,c} \cdot \sum_{s,d,t,v,o=electricity} FO_{p,s,d,i,t,v,o}\}, \forall \{c \in C^d\} \in \Theta_{electricity}$	Minimizing Levelised Cost of Electricity based on the dinklebach adjustment of the LCOE rule using costs including investment costs minus LCOE times production
Min-LCOE	Amortized invest	$MIN\ LCOE = \sum_{p,t,v} \{VC_{p,t,v} + FC_{p,t,v} + LC_{p,t,v}\} - \sum_p \{LCOE_{p,c} \cdot \sum_{s,d,t,v,o=electricity} FO_{p,s,d,i,t,v,o}\}, \forall \{c \in C^d\} \in \Theta_{electricity}$	
Min-PBT	lump-sum invest	$MAX\ NPV = \sum_p (IC_{p,t,v} - \left\{ \sum_{t,v} PBT_{p,t,v} \cdot (REV_p - \sum_{t,v} (C_{p,t,v} + FC_{p,t,v})) \right\})$	Minimizing Payback Time based on the dinklebach adjustment of the PBT rule using investment costs (or loan costs) minus payback time multiplied by revenue from electricity minus O&M costs
Min-PBT	Amortized invest	$MAX\ NPV = \sum_p (LC_{p,t,v} - \left\{ \sum_{t,v} PBT_{p,t,v} \cdot (REV_p - \sum_{t,v} (C_{p,t,v} + FC_{p,t,v})) \right\})$	

Design Constraints:

Table 63: TEMOA Energy System Model Unit Descriptions.

Constraint	Description
Constraints from original TEMOA version	
$ACT_{p,s,d,t,v} = \sum_{i,o} FO_{p,s,d,i,t,v,o} , \forall \{p,s,d,t,v\} \in \Theta_{activity}$	Constraint to set activity of technology processes equal to resource output.
$(CF_{s,d,t,v} \cdot C2A_t \cdot SEG_{s,d} \cdot TLF_{p,t,v}) \cdot CAP_{t,v} \geq ATC_{p,s,d,t,v} , \forall \{p,s,d,t,v\} \in \Theta_{activity}$	Constraint to set a maximum to the activity of technology process based on available capacity (CF), active capacity (C2A), fraction of the year of a season and defined periods (SEG), active periods (TLF).
$\sum_{i,t,v} FO_{p,s,d,i,t,v,c} \geq DEM_{p,c} \cdot DSD_{s,d,c} , \forall \{p,s,d,c \in C^d\} \in \Theta_{demand}$	Constraint to set total end use demands as demands per time slice (DEM) multiplied by percentage distribution of demand per period (DSD) equal to supply calculated from the resource output variable (FO).
$FO_{p,s,d,i,t,v,o} \leq EFF_{i,t,v,o} \cdot FI_{p,s,d,i,t,v,o} , \forall \{p,s,d,i,t \in T - T^s, v, o\} \in \Theta_{flow}$	Constraint to ensure that that output of a process (FO) is smaller or equal than a required input quantity (FI) multiplied by an efficiency factor (EFF).
$\sum_{i,t,v} FO_{p,s,d,i,t,v,c} \geq \sum_{t,v,o} FI_{p,s,d,c,t,v,o} , \forall \{p,s,d,c\} \in \Theta_{balance}$	Constraint to ensure that the sum of all resource inputs are equal to the sum of outputs over all technologies in each period for each vintage.
$DSD_{s,d,c} \cdot \sum_i FO_{p,s',d',i,t,v,c} \geq DSD_{s',d',c} \cdot \sum_i FO_{p,s,d,c,t,v,c} , \forall \{p,s,d,t,v,c \in C^d, s' \in S - \{s\}, d' \in D - \{d\}\} \in \Theta_{DemandActivity}$	Constraint to make sure that if demand distribution (DSD) is used that the same output (FO) as distributed in a specific time-slice cannot be similar to another time slice.
$SEG_{s,d'} \cdot ACT_{p,s,d,t,v} = SEG_{s,d} \cdot ACT_{p,s,d',t,v} , \forall \{p,s,d,t \in T^b, v, d' \in D - \{d\}\} \in \Theta_{baseload}$	Constraint to make sure that the proportion of total outputs of a process (ACT) in a specific fraction of the year (SEG) cannot be equal to the proportion in another part of the year.
$\sum_d (EFF_{i,t,v,o} \cdot FI_{p,s,d,i,t,v,o} - FO_{p,s,d,i,t,v,o}) = 0 , \forall \{p,s,i,t \in T^s, v, o\} \in \Theta_{storage}$	Constraint to make sure that for storage technologies the sum of resource inputs (FI) multiplied by efficiency (EFF) is equal to outputs (FO).
$\sum_{s,d,i,t \in T^r, v} FO_{p,s,d,i,t,v,c} \leq RSC_{p,c} , \forall \{p,c\} \in \Theta_{resource}$	Constraint to set the sum of process outputs (FO) equal or less than an upper bound (RSC) on resource production
$CAPAVL_{p,t} \leq MAX_{p,t} , \forall \{p,t\} \in \Theta_{max}$ $CAPAVL_{p,t} \leq MIN_{p,t} , \forall \{p,t\} \in \Theta_{min}$	Constraint to set the sum of all technology vintages (CAPAVL) equal to a user defined maximum (MAX) and minimum (MIN) capacity
$SPL_{i,t,o} \cdot FO_{p,s,d,i,t,v,o'} = SPL_{i,t,o'} \cdot FO_{p,s,d,i,t,v,o} , \forall \{p,s,d,i,t,v,o,o' \in C - \{o\}\} \in \Theta_{split}$	Constraint for multiple output technologies to set the fraction of outputs equal to the user specified fraction.
$\sum_{s,d,i,t,v,o} (EAC_{e,i,t,v,o} \cdot FO_{p,s,d,i,t,v,o}) \leq ELM_{p,e} , \forall \{p,e \in C^e\} \in \Theta_{emission}$	Constraint to set a maximum to emission outputs (ELM) by setting the emissions output intensity of a technology (EAC) multiplied by the resource output (FO) lower or equal to this maximum.
$LA_{t,v} = \frac{TDR_{t,v}}{1 - (1 + TDR_{t,v})^{LLN_{t,v}}} , \forall \{t,v\}$	Constraint set to calculate loan amortization factor based on discount rates (TDR) and loan term interest rate (LLN)

$LC_{p,t,v} = \sum_{t,v} \left(\left\{ IC_{t,v} \cdot LA_{t,v} \cdot \sum_{y=0}^{MTL_{t,v}} \frac{1}{(1+GDR)^{y+v-P_0}} \right\} \cdot CAP_{t,v} \right)$	Constraint to calculate the cost of investment loans based on the total capacity built multiplied by the investment costs per unit of capacity (IC) multiplied by the loan amortization factor (LA) which is multiplied by a discount rate.
$FC_{p,t,v} = \sum_{p,t,v} \left(\left\{ FC_{p,t,v} \cdot \sum_{y=0}^{MTL_{p,t,v}} \frac{1}{(1+GDR)^{y+p-P_0}} \right\} \cdot CAP_{t,v} \right)$	Constraint to calculate the fixed cost of operation and maintenance based on the fixed costs (FC) per capacity operated multiplied by the amount of capacity in place (CAP) which is multiplied by a discount rate.
$VC_{p,t,v} = \sum_{p,s,d,t,v} \left(\left\{ FC_{p,t,v} \cdot \sum_{y=0}^{LEN_p} \frac{1}{(1+GDR)^{y+p-P_0}} \right\} \cdot ACT_{p,s,d,t,v} \right)$	Constraint to calculate the variable cost of operation and maintenance based on the variable costs (VC) per capacity operated multiplied by the amount of process operation (ACT) which is multiplied by a discount rate.
New TEMOA Constraints made by thesis author	
$REV_p = \sum_c (DEM_{p,c} \cdot PRI_{p,c} \frac{1}{(1+GDR)^{y+p-P_0}})$ $\forall \{c \in C^d\} \in \Theta_{electricity}$	Constraint to set the revenue from electricity equal to the demand multiplied by the price and a discount factor when applicable
$LOST_{p,t} = ECAP_{t,v}, \forall \{t, v\} : v \in V + LIF_{p,t,v} = p \in P$	Constraint to set the decommissioned capacity (LOST) equal to the pre-existing capacity vintage plus the lifetime of the technology
$CAPAVL_{p,t} \leq CAPAVL_{p-1,t} + GM - LOST_{p,t}$	Constraint set to limit annual growth rate of a technology equal to previous period capacity plus a growth maximum minus the decommissioning capacity
$CAPAVL_{p,t} \leq CAPAVL_{p-1,t} \cdot GR_t - LOST_{p,t}$	Constraint set to limit annual growth rate of a technology equal to previous period capacity plus a growth rate minus the decommissioning capacity
$ACT_{p,s,d,t,v} \geq 0.35 \cdot CAP_{t,v} \cdot CF_{s,d,t,v} \cdot C2A_t \cdot SEG_{s,d} \cdot TLF_{p,t,v}$	Constraint set to set minimum activity of a built power plant to 35% of total capacity to ensure operation of available power plants
$CAP_{t,v} \cdot CF_{s,d,t,v} \cdot C2A_t \cdot SEG_{s,d} \cdot TLF_{p,t,v} \geq ECR_{p,c} \cdot DEM_{p,c}$ $\forall \{c \in C^d\} \in \Theta_{electricity}$	Constraint to set activity of all technologies equal or higher to excess demand as historically present in the system