Modelling Power Plant Investment Behaviour

Three modular investment algorithms including hard and soft factors for investments in large scale power generation in a liberalized North-West European electricity market simulation model.

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Abstract

Simulation models become increasingly important in energy policy analysis. A literature review showed that there is demand for analysing the effect of multiple more realistic investment algorithms on the outcomes of energy policy analysis. The reason is that energy policy analysis could be incomplete without insight in the implications of the assumed investment behaviour in simulation models. The research question is: *How is the effectiveness of the EU-ETS mechanism affected by diverse investment algorithms in an electricity market simulation model?*. In EMlab-generation, three modular empirical data based algorithms are designed including behaviour with technology-preferences, credit-risk considerations and risk-averse behaviour. The results showed that more realistic investment behaviour culminates in all experiments in at least one or more technologies with substantially different investment patterns. Different investment patterns caused a lowered CO_2 price volatility in most experiments in relation to homogeneous profit only behaviour indicating that the CO_2 price might be a more stable investment signal than earlier assumed. The effectiveness of the EU-ETS mechanism remains for all experiments however doubtful due to the substantial CO_2 price volatility of more than 100%. The necessity of stabilizing measures such as a price floor and/or ceiling proposed by previous studies is reinforced by the results. This research shows the importance of being aware of the implications of the assumed investment behaviour in simulation models used for energy policy analysis. Two recommendations to deal with the implications of the assumed investment behaviour in models is to design more flexible and modular investment algorithms. Flexibility and modularity in investment algorithms enable and support exploring the effect of different behavioural configurations on outcomes of energy policy analysis.

Keywords: Modelling, Power plant investment, EU-ETS mechanism, CO_2 emission right price volatility.

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Ruben Verweij

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Chapter 1

Introduction

This introduction chapter reveals the general context of this research. The primary objective is to present reasons for performing the research. The secondary objective is to provide a first insight in the research content: the modelling of power plant investment in simulation models. This will be done for the purpose of analysing the effect of different investment algorithms on investments and the effectiveness of the EU-ETS mechanism in a existing simulation model of a liberalized electricity market.

1.1 Research context

The reason wherefore this research was initiated can only be answered on a higher abstraction level. This abstraction level requires to observe the European electricity system as a whole. The important notion is that this European electricity system changed[1] considerably in the last decades [9, 10]. It is possible to observe these changes using different "glasses" also named as perspectives. Two ways to look at these system changes are the social-institutional and the technical-physical perspective. The visible changes from a more social-institutional point of view are related to the shifting role of the regulator and the increasing fraction of private companies. Two changes from the technical-physical point of view are the increasing degree of network integration and the diffusion of more renewable electricity generation capacity. An observation is that changes are visible from both perspectives.

A significant role within the changing system was reserved by the introduction of competition and new energy policies [11]. Due to the entrance of private investors, the introduction of new energy policies and the increasing decentralization of power generation, the complexity in the energy system increased [12]. The ongoing changes and increased complexity in the power sector brings along the need for policy intervention and analysis since the present complex liberalized energy markets are not considered to solve public issues like the increasing amount of CO_2 emissions and security of supply alone [11, 13]. The generation adequacy and emission issues explain the need for insight in the consequences of policy interventions and possibility to measure their effect (e.g. feed in tariffs and implementing capacity mechanisms) on the development of electricity markets [14]. The negative market externalities caused by liberalization also raise new questions for the design and development of effective policies among researchers and authorities.

There are multiple paradigms to explore and analyse the long-term electricity system development. One of these paradigms is simulation containing various applicable approaches like agent-based modelling (ABM) and system dynamics (SD) [15]. From a literature review (see

[1] or evolved

chapter A.1) is known that simulation is used extensively for analysing the long-term electricity market dynamics.

The main reason for performing this research is to support the endeavour to understand the complex electricity system dynamics. This research is positioned in the field of simulating and analysing the long-term dynamics of the European restructured electricity market. The research focus is on modelling large scale power plant investment behaviour based upon empirical data. This research attempts to design more realistic investment algorithms and analyse their effects on investment and the EU-ETS mechanism. This research intends to give insight in the implications of the assumed investment behaviour. The literature analysis in chapter A.1 showed that there is a need for this type of research. In the next chapter the delineation and further project details will be discussed and explained.

1.2 Research definition

This chapter contains the research definition. This definition includes the problem formulation, research questions and research methods. Also the structure of this research is discussed in this chapter. The first paragraph starts with a problem formulation.

Problem formulation

The role of simulation models as tool for energy policy analysis becomes increasingly important for researchers of the electricity sector. The speed and processing time of computers increased excessively in the last decades resulting in new opportunities to explore more complex systems. Various studies regarding electricity market dynamics are performed using simulation as supporting tool to analyse long-term dynamics[2]. One example is [16] where nuclear power investment is modelled using a simulation based upon a real options approach. Another example is [12] where simulation is used to analyse plausible development trajectories of the Dutch electricity system. These examples are only a small selection of studies who are using simulation models. [17] did research on the present trends of electricity market modelling and concluded that simulation[3] has become more and more important.

These examples and further literature presented in Appendix A.1 showed an extensive use of simulation models for energy policy analysis. The literature analysis in Appendix A.1 focussed on how researchers present and discuss their model descriptions and outcomes related to investment behaviour. In the reviewed publications was limited discussion on the shortcomings and limitations of the investment models. Meanwhile some publications notice the importance of modelling investment behaviour for the development path of the simulated electricity market [19, 20].

Among the reviewed publications only some authors elaborated on the possible implications of general modelling assumptions. In these discussions there was even less reflection on the assumptions underlying investment behaviour in the model. For some approaches the absence of this reflection could be explained by the uniformity or logicalness of the assumptions, but still a discussion on modelling assumptions could strengthen the argumentation. One example is the paper of [21] where investments are performed within a perfect competitive and uniform market on the basis of profit maximization. In this article is mentioned that these assumptions are used as foundation, but no further notion is made on the potential sensitivity of model outcomes. This is considered a missed chance. An additional analysis in this article on investment behavioural model sensitivity could have been an additional indicator for energy policy robustness. Models that are able to simulate long-term electricity market dynamics are in some cases assuming that market development is based on perfect competitive rules like complete information and perfect

[2] In the Appendix a literature review is presented including various reviewed articles (see chapter A.1)
[3] Simulation is defined here as the imitation of a real world process over time [18]

resource allocation [14, 20, 21, 24, 25]. An example is presented in the paper of [14] where firms act like homogeneous inter-temporal optimizers with perfect predictions on fuel prices. Another example is presented in the paper of [26] where investment is based upon equilibrium models. In practice it will be very unlikely that a market is in equilibrium [27]. This is not problematic since the model represents an abstraction of reality, but makes additional analysis of investment behavioural model sensitivity more evident. Moreover, due to the commercialization of power production conventional optimization techniques are no longer adequate to explore the dynamic evolution of electricity markets because the behaviour of agents is unknown [20]. The assumption of heterogeneity in project evaluation among investors is also not frequent taken into account. For simulations of the Dutch electricity market this could be problematic since there are all kinds of investors who evaluate investment opportunities in a very different way [8]. There are papers which take heterogeneity into account. One example is the publication of [15] where investing agents are modelled with a "management style" determining for example the attitude towards certain technologies.

Thereby must be said that it is not always possible to analyse the consequences of modelling assumptions on results because the simulation paradigm is not appropriate to do this properly. An example is System Dynamics (SD) modelling where it could be problematic (or time consuming) to include different heterogeneous modes of investment behaviour among various investors. There are also studies where investment behaviour is of minor interest due to the scope and purpose of the model. However, there are various papers where additional analysis on the implications of the assumed investment behaviour would have been beneficial. These benefits of analysing the model outcomes for different assumptions on investment behaviour is also recognized by some authors of the selected papers [19, 20, 22, 23].

The complication of the observations mentioned in the previous paragraphs is that energy policy analysis on the basis of simulations without insight in investment behavioural model sensitivity could be incomplete.

There are however reasons for using one single investment model for policy analysis. In the first place is this easier since there is little information available on how investors make investment decisions in reality. Besides the absence of good data, the complexity and enourmous collection of factors which influence an investment decision makes designing more realistic investment models often not feasible. It is not argued that single simplified investment models are inappropriate, but investment behavioural model sensitivity is expected. Policies that have pretty satisfying outcomes on their analysed criteria could have different outcomes when other assumptions on investment behaviour would have been taken into account. An additional argument for this complication is that empirical and theoretical descriptions of investment behaviour are not very aligned [28]. Meanwhile investment behaviour models are often based upon theoretical assumptions. Since the complication is case-specific[4] and not in all cases extremely problematic, the problem statement could not be simply generalized.

Problem statement

The central problem statement within this research that follows from the problem formulation above:

Energy related policy analysis is incomplete without insight in the implications of the assumed investment behaviour

The problem statement is written in a generic way because it is applicable for energy policy analysis in general, but does not imply that it is problematic for all previous research in the field.

[4] Models can be simplified, but fit for purpose etcetera

In relation to the problem statement, this research studies the EU-ETS mechanism because it is on of the most important subjects among the reviewed articles and considered as an important recently introduced European policy measure.

Research questions

To get insight in the implications of the assumed investment behaviour in a electricity market model diverse modular investment algorithms will be designed. These algorithms will include more realistic behaviour[5] and give the opportunity to analyse investments in the first place and the effectiveness of the EU-ETS mechanism in the second place. It is the main purpose to use the investment models to answer a policy oriented question focussing on the EU-ETS mechanism. This demarcation choice is made because it is considered most relevant and also in line with TPM education where this thesis is initiated from. The main research question is:

> *How is the effectiveness of the EU-ETS mechanism affected by diverse investment algorithms in an electricity market simulation model?*

The question suits the problem statement because answering this question supports knowledge about "how" incomplete energy policy analysis could be without analysing different investment algorithms. Answering this question also might provide and confirm improvement signals or directions for the EU-ETS mechanism. The question here is not how the EU-ETS mechanism affects investment behaviour, but how investment behaviour affects the effectiveness of a policy. This is considered relevant because this research claims that it is able to model more realistic investment algorithms to analyse the effectiveness of the EU-ETS mechanism. The main research question is answered by the following sub-questions.

1. How are investors in North-West European power generation evaluating investment opportunities based upon empirical data, and how to operationalize these evaluations? (answered in chapter 2.2).
2. How are the conceptual models of investment behaviour translated into a modular set of investment algorithms within EMLab-generation? (answered in chapter 3.4).
3. What is the influence of different investment algorithms on investments in an EU-ETS governed electricity market simulation? (answered in chapter 4).
4. How is the effectiveness of the EU-ETS mechanism affected by diverse investment algorithms in an electricity market simulation model .

The data requirements are described in section 1.2. This research design includes scalability which made it possible to extend it in the future. The scalability in the design is defined by the choice for the number of investment algorithms that are analysed and the size of the experimental space. The scalability enabled to increase and decrease the intended amount of work during the research process.

Research objective

The objective of the research is to *1. explore the influence of different investment algorithms on investments in an EU-ETS governed market simulation 2. Research the consequences of different investment algorithms for the effectiveness of the EU-ETS mechanism in the electricity market simulation. 3. Contribute to existing and further research.* One investment algorithm on the

[5] More realistic for investors in the North-West European market whose empirical data on investment processes is used

basis of homogeneous assumptions could give other outcomes than investment algorithms on the basis of heterogeneous assumptions. The deliverables are three modular universal investment algorithms for the North-West European electricity market. Furthermore this research intends to deliver a comprehensive overview on how different investment algorithms are influencing investments in an EU-ETS governed market simulation.

Social and scientific relevance

The social relevance is defined by the intended attempt to contribute to an enhanced quality of energy policy analysis by modelling more realistic investment algorithms. A better understanding of energy policy effects will support policy makers to design more efficient and suitable policies. More insight in the effects of the chosen modelling assumptions could contribute to the quality of the decisions that are taken after a policy evaluation. This could enhance the societal function of the energy system. The scientific relevance is defined by the potential insights of analysing the effects of divergent investment behavioural models on the development of the electricity sector. Another scientific attempt is to open new research possibilities with this research for future student projects.

Research methods

The research methods used in this project are a literature review, interviews and agent-based modelling (ABM). For sub-question one is made use of a literature review combined with interviews with modelling specialists. According to [29] literature reviews are suitable for the these kind of research questions. Drawbacks are that literature reviews will be time consuming and that the answers on the questions are totally dependent on the availability of existing specialists literature. Con-straining factors are the potential to contact the intended specialists, the amount of time and available previous research within this domain.

For sub-question two, three and four agent-based modelling (ABM) is used as research method. In the ABM paradigm agents with states interact with each other and the environment which results in a certain emergent behaviour. ABM is a bottom-up modelling approach which is suitable for modelling different stakeholders, states and interactions [30]. In [15] is concluded that ABM scores positive as paradigm on simulating transitions in energy systems. ABM is able to reveal and model social components, physical components and their interactions. As a modelling environment Springsource toolsuite is chosen which works with the Java language together with AgentSpring as the ABM-framework [6]. The modelling will be performed by using an existing model named EMLab-generation[6]. This model is explained later in chapter 3.1. This model is based upon the Java language and developed by using the AgentSpring framework. This object-oriented approach is very useful to model heterogeneous investment algorithms and explore multiple experiments. A drawback is that the ABM paradigm is time consuming, data intense and hard to validate.

Data gathering

This research uses empirical data to develop investment algorithms. Besides these empirical inputs also theoretical assumptions in the model play a role. Two of the theories are neoclassical economics and bounded rationality. The empirical data is obtained from previous research on investment processes performed by [7, 8]. Historic data on investments in Europe and data on CO_2 prices are obtained and used. A short introduction on neoclassical theory and the empirical data is presented below.

[6] `emlab.tudelft.nl`

Neoclassical economics

The neoclassical theory describes in essence that firms intend to maximize their overall present value. This approach is considered to be adequate in static cases, but could be problematic in long-term simulation while it is used in various studies [31]. The neoclassical approach focusses on the determination of prices, inputs and outputs. The theory rest on three main assumptions: agents have rational preferences among outcomes, agents maximize utility or profit and agents act independently and on the basis of complete information. Criticism on this theory is that it has a normative bias and wrong assumptions taken rationality into account [32, 33]. Unless the criticism the theory is widespread and used extensively in various studies. Assumptions described by this theory are of importance in the model that will be used in this research. On this model will be elaborated in section 1.2. Besides neoclassical economics, new institutional economics (including bounded rationality) also play a role.

Empirical data

The empirical data needed in this research is mainly covered by previous research of [8]. This study covered qualitative empirical research on power plant investment processes by interviewing a representative number of investors in the North-West European electricity sector. Some of the non-confidential aggregated empirical outcomes are used as the inputs for the investment algorithms in this research. In general the results of this research provide insight in the way different sorts of investors evaluate energy projects. The aggregated outcomes are translated into design variables for investment processes in table 2.1. The conceptual models are constructed on the basis of this information.

The results of this empirical study are closely related to the theory of bounded rationality. The theory on decision making prescribes that the rationality of agents is limited by the information, cognitive capacity and time there is available [34–38]. The theory was proposed by Herbert Alexander Simon. Although the ideas of the two perspectives of theory and observed reality are conflicting they will together form the theoretical and empirical input of the model.

Further data

The articles collected for the literature review are selected by using the following scientific search engines: Science Direct and Scopus. The keywords used are: investment behaviour, power plant investment, modelling, long term electricity market development, investment processes. The selection of articles is present in the literature list and also in chapter A.1 of the Appendix where the article analysis is presented. The articles and publications will be used for supporting the problem exploration. Further the articles will also be utilized for answering sub-question one.

Another source were the annual reports of the investors describing the general strategy, facts and figures. Also information platforms like "Enipedia[7]" have been utilized to monitor the Dutch electricity sector situation. Concluding dummy data (e.g. evolvement of generation capacity generated by the model) will also play an important role within this research. For data analysis R-studio together with Python will be used. This software is useful for data-analysis. Also the limited time for the research constrained the possibility of collecting the data. For the design of experiments is made use of DECC fuel-price forecast experiments [39]. For the validation various papers of CE-Delft are used to validate observed patterns. Also historic data is used to analyse CO_2 prices. On the next page the research outline is presented. This outline shows how the research was performed.

[7] `enipedia.tudelft.nl/wiki/Main$_$Page`

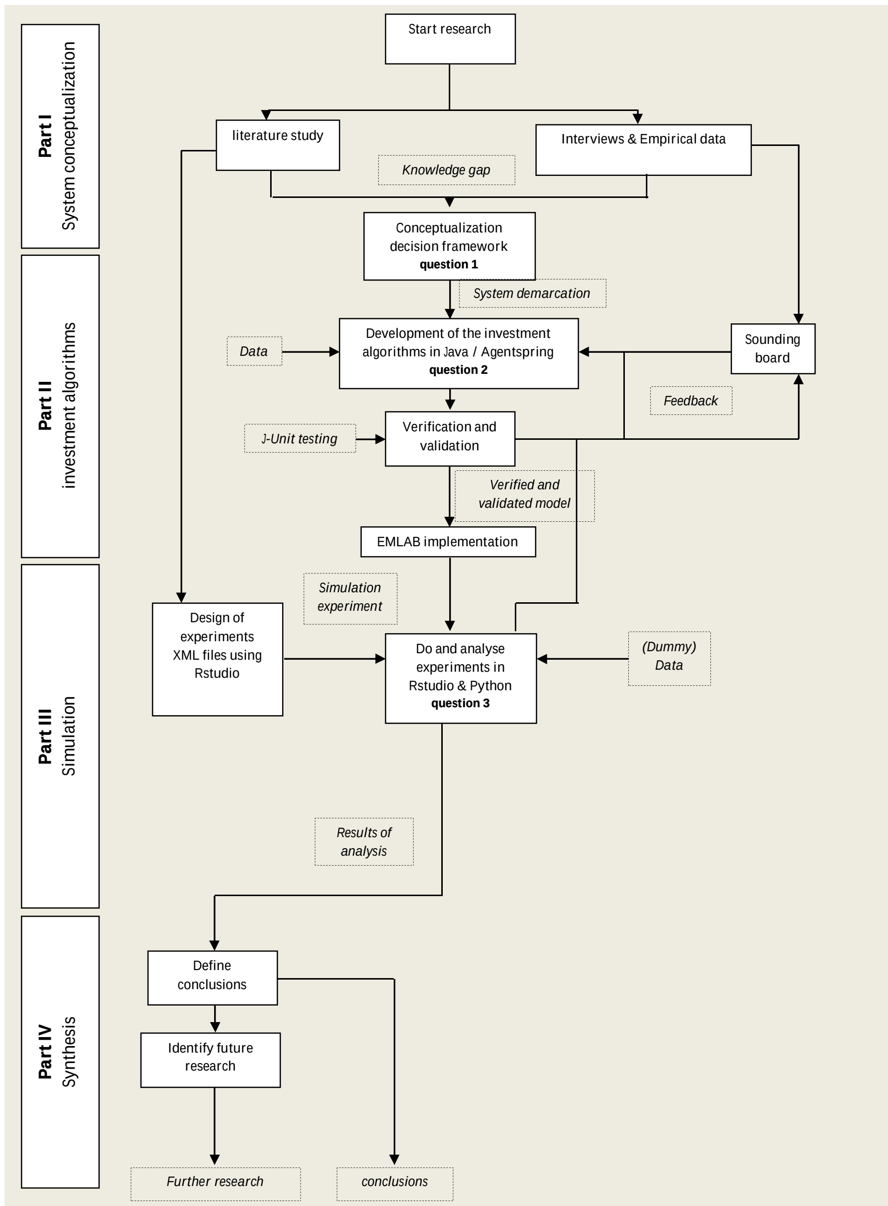


Figure 1.1: Outline of the thesis

Chapter 2

Conceptualisation

This chapter intends to provide a concise overview on the functioning of the Dutch electricity system [1]. The primary goal is to support the reader in understanding the electricity market related concepts in this research. Without any domain related knowledge this chapter will be mandatory reading material to understand the further research content. A second objective is to provide an introduction on investments in the power generation sector. The primary focus of the research is investment processes in the North-West European market, but to limit the scope for the explanation of the market related concepts, the Dutch system is described. The Dutch system is selected because it is part of the North-West European market. Further, data of the Dutch electricity system is transparent and easily accessible. This electricity market overview is related to chapter A.1 in the Appendix.

2.1 Introduction to an electricity market and large-scale investments

Electricity market concepts: the Dutch case

It is possible to observe the electricity system as a social-technical system including technical and social sub-systems. More specific: this system contains technical-physical and social-institutional elements [40–43]. The technical-physical elements of the value chain comprise of generation, transmission, distribution and load of electricity. The generation of electricity is performed by large scale central installations (63 percent in 2010) or medium- small scale de-central installations (37 percent in 2010, see table 2.2). The central production of electricity is generated by large scale power plants with capacities up to more than 1500 MW_e. The de-central produced electricity is performed by smaller energy companies, large industries or even households. Examples of de-central electricity production are the individual solar panel installations on houses or other buildings. In the Netherlands around 11 percent of the production is generated by renewable energy sources (table 2.2). The transmission of electricity is performed by approximately 9.000 kilometres of 110-450 kV lines [44–46]. The 450 kV lines are the inter-connectors between foreign countries like Norway the United Kingdom. An example is the NorNed connection which connects Norway and the Netherlands by a 580 kilometres long HVDC cable with a capacity of around 700 MW [44]. The more regional low and medium voltage cables are called distribution

[1] The Dutch electricity system is part of the primary focus of this research: the North-West European Market

lines which transport electricity to the final consumer. The distribution of electricity is transported trough low and medium voltage lines up to 50 kV [47]. The load of electricity is related to the final user connections and the measurement of the electricity consumption. In figure 2.1 the electricity system is visualised including all physical and institutional elements.

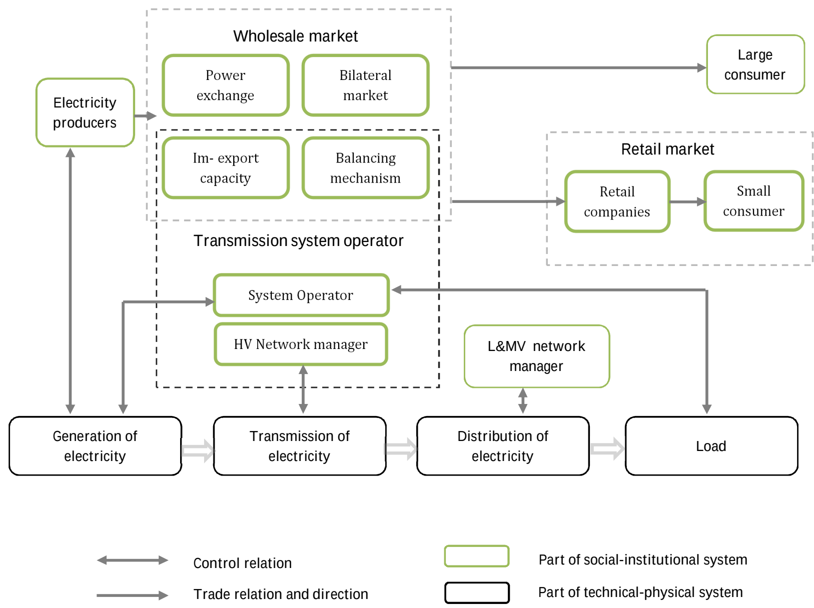


Figure 2.1: Visualization of the Dutch electricity system adapted from [1]

The social-institutional elements include for example the stakeholders of the system like the markets and the regulator. The regulator is not specifically visible in figure 2.1 but has an important role in terms of law and regulation which is interwoven in various parts of the figure. The generation of electricity is performed by mainly private owned power producers. The central production is generated by large power plants operated by electricity producers as Electrabel, Essent or Nuon [2] (2.3). De-central produced electricity is generated by various large and medium scale industrial companies and households mainly for own use. An example is the large life sciences multinational DSM N.V. which generates a part of its own electricity demand for multiple strategic reasons. The transmission of electricity is performed by the transmission system operator. This TSO is Tennet in the Netherlands and also maintains the network [45]. Tennet is a 100 percent state owned company. Besides this network operator role, the TSO also function as the system operator by ensuring the balance on the network. The distributed system operator maintains and operates the low voltage networks. Large DSOs are Liander, Enexis and Stedin [47–49]. The wholesale market is where the large amount of electricity are traded on the spot or bilateral market. The sport market in the Netherlands is the APX-ENDEX [50]. Power producers are selling their electricity on these markets. Retail companies are also buying electricity on the wholesale market and sell it on the retail market to the small consumers. A more in detail description of the electricity system is presented in chapter A.1 of the Appendix.

The development of an electricity system is dependent on the investments done [51]. The

[2] All these companies are taken-over by larger companies as GDF Suez (Electrabel), Vattenfall (Nuon) and RWE AG (Essent).

dependency on investment decisions is declared by the capital intensiveness and long lead times of power plants [27]. Taken into account that an average plant has a lifetime of 25-30 years implies that an investment decision now will have path dependent consequences for the coming decades. From figure 2.3 is known that around 75 percent of the Dutch total yearly electrical output in 2010 was generated by only a small selection of different companies. The 75 percent includes also the de-central generated electricity. This shows the limited number of investors that determine a large share of the present technology mix (see 2.2). Although decentralization is one of the trends observed at the moment, the percentage of centrally produced electricity in large power plants is still dominant. This means that a limited number of power plants determine the development of the present technology mix of the electricity system.

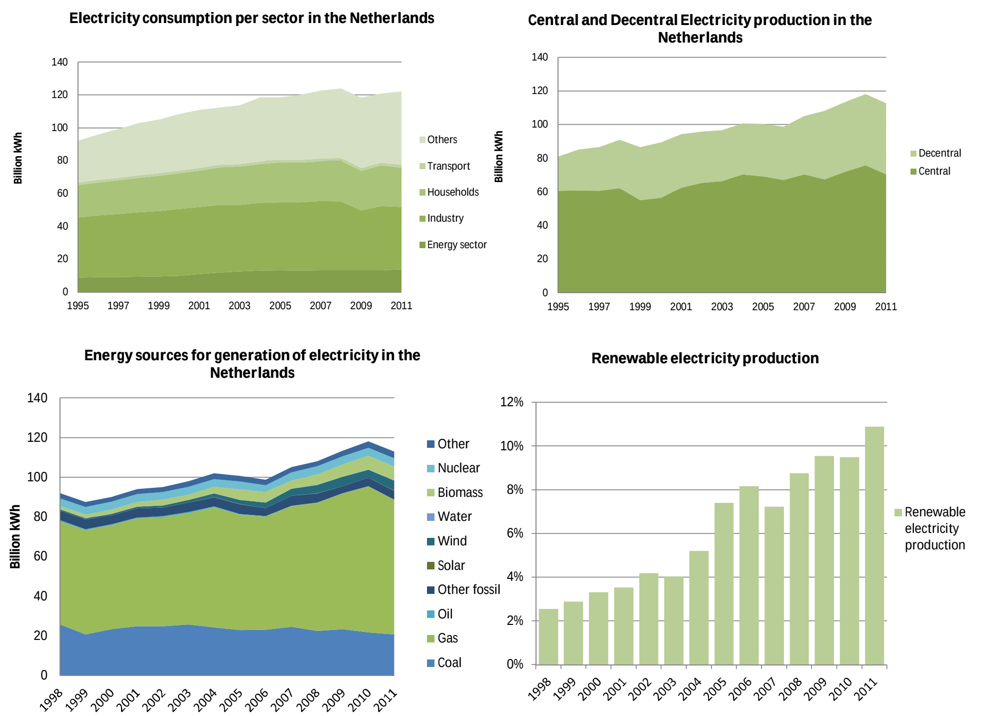


Figure 2.2: Dutch electricity market data [2, 3]

The present situation of electricity generation capacity in the Netherlands is as follows: the average lifetime of generation facilities is around 25-30 years which means that decisions now about installing new capacity will influence the future market situation significantly [52]. This could be explained by the present situation in the Netherlands where new coal fired power plants are being constructed. These power plants could have implications for the position of the other plants in the merit order. The average investment cost in a electricity generation facility include around 500 to 1.000 per KW resulting in capital intensive transactions [10]. The present installed capacity in the Netherlands in 2010 was around 23.650 MW resulting in an electrical output of 118.000 million kWh [45]. In 2010 the average age of the installed capacity in the Netherlands was 21 years. This age distribution reveals the need for new capacity investments taking an expected increase of future demand into account. These observations clarify the impact of investment decisions on the dynamics of electricity markets. When policy makers attempt to obtain insight in the development of electricity systems, investment behaviour plays an important role.

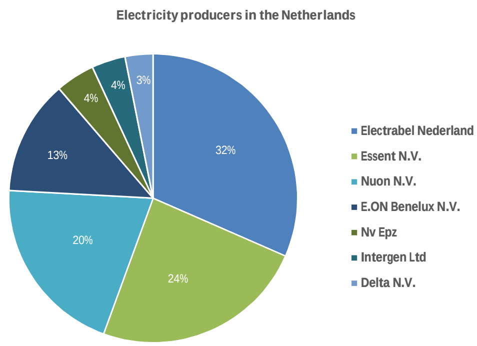


Figure 2.3: Largest electricity producers in the Netherlands [4]

Power plant investment: two perspectives

Modelling large scale power plant investment behaviour is the central subject within this thesis. To introduce the subject this paragraph discusses the "glasses" to look at power plant investment behaviour. It is possible to look at electricity generation investment from various perspectives. A first approach is the theoretical one. This approach includes social-economic, econometric and other theoretical attempts to describe the decisions that investors make. Examples of theories are neo-classical economics and bounded rationality. Another approach is the empirical approach where ordered data is collected on how specific interviewed investors run through their investment evaluations. The empirical data in this research is anonymous and used in an aggregated format.

Scope and assumptions

This section elaborates on the scope and assumptions underlying that scope. The research is performed under the following general assumptions:

1. This research will focus on the investment behaviour of centrally produced electricity which counts e.g. for 63 percent of the total electrical output in the Netherlands[3]. This percentage is without taking imports into account. The de-central production is not taken into account due to the divergent character of the investors and the small scale of the investments.
2. The investment algorithms will be developed according to empirical data obtained from earlier research to investment processes among large scale investors in the North-West European market.

2.2 Empirical data and algorithm design framework

This chapter includes an explanation on the empirical data, the basic investment algorithm and design framework for the development of the algorithms.

Empirical design variables

The additions to the current investment algorithm are retrieved from table 2.1. This table contains the drivers of investment processes and are based upon empirical data [8]. This quali-

[3]This is just presented as an example to give a feeling of the impact of central generation

tative research performed by [8] focussed on power plant investment processes and interviewed a representative number of investors in the North-West European electricity sector. Some of the non-confidential aggregated empirical outcomes are design variables of the investment algorithms in this research. The results provide insight in the way different sorts of investors evaluate energy projects. The results are made anonymous, which implies that no company names will be used in the section where the investment algorithms are described. Table 2.1 shows the variety of drivers that steer investment decisions in the North-West European market. These drivers are the starting point for the additional investment behaviour included in this thesis. The categories are used as design variables. The three categories of design variables are: financial performance, securing continuity and technology preferences [4]. The ideal investment behaviour does not exist, but implementing all the drivers mentioned in table 2.1 for all investors specifically could represent an ideal case. This research intends to implement some of these drivers[5]. In the coming subsections the driver categories are explained.

Categories	**Variables that drive investment processes**
Financial performance	1. Business case attractiveness 2. Perceived level of attractiveness 3. Meeting the hurdle rate 4. Outcome of discounted cash flow model 5. Internal rate of return (IRR)
Securing continuity	1. Acceptance of risk assessment outcomes 2. Minimizing opportunity costs 3. Not to do worse than the competitor 4. Maintain a healthy cash position
Others and technology preferences	1. Meeting strategic goals 2. Meeting sustainable criteria 3. Portfolio considerations 4. Local employment 5. Wish of outperforming 6. Goal reasoning and intra-organizational dynamics 7. Political influence

Table 2.1: Drivers of investment processes adapted from [7, 8]

[4] Also including more, but technology preferences embody most of the drivers

[5] The drivers are sometimes overlapping, but are all specifically mentioned during interviews [8]. This implies that the driver has an individual interpretation

Financial performance

The financial performance is related to the profitability of the project or investment. According to interviews with investors this financial performance is often analysed in terms of an business case containing e.g. net present value (NPV) estimations, comparisons of internal rates of return (IRR) and the estimation of the weighted average cost of capital (WACC) [53]. The internal rate of return in the context of an power plant investment is explained by the discount rate where the NPV equals zero. The internal rate of return could numerically be calculated by the following sectant method [53]:

$$R_{n+1} = R_n - NPV_n \left(\frac{r_n - r_{n-1}}{NPV_n - NPV_{n-1}} \right) \tag{2.1}$$

Here R_n is the n^{th} estimation of the IRR. The WACC is often used to discount the NPV calculations in the North-West European market [7]. Here the weighted average cost of capital defined by the estimated cost of the financing structure of the company [54]. In mathematical terms explained by:

$$WACC_i = \frac{E_i}{V_i} \cdot k_{e,i} + \frac{D_i}{V_i} \cdot k_{d,i} \tag{2.2}$$

Here the $WACC_i$ is the weighted average cost of capital of investor i [55]. The E_i is the market value of the equity share of investor i and D_i the market value of the debt of investor i. V_i represents the total of the equity and debt together. The $k_{e,i}$ represents the investor specific return on equity and $k_{d,i}$ the debt interest rate. These financial measures are used to evaluate the investment project in a business case. According to the interviews performed by the research of [7] the specific WACC value is confidential information for every investor in the electricity market. An investor would have an knowledge advantage in case they would know the specific WACC value of another competitor. To avoid this investors keep their WACC values secret. In the investment algorithms in this thesis the WACC values are calculated using parameters for the rate on equity.

Securing continuity

A second category of drivers is related to the continuity of the investor. The most important drivers in this category are; the outcomes of risk assessments, the liquidity of the company, to do not worse than competitors and the minimizing of opportunity costs [8]. The outcomes of risk assessments are clearly related to the risks associated with the particular investments. The liquidity of the company is related to the cash position of the company and could be measured by the quick liquidity ratio. This is mathematically described by:

$$L_i = \frac{Ca_i}{Cl_i} \tag{2.3}$$

Here the L_i is the liquidity ratio and Ca_i the value of the current assets of investor i. Cl_i are the current liabilities of investor i. The value should be normally around one. The last driver of this category is related to the costs of projects that are not exploited or equal projects of competitors that are exploited. In the context of this thesis this is explained by the following situation: Company x decides not to invest in combined-cycle and gas turbine (CCGT) while company y does invest in this technology. When company y is making profits, the sum of these profits are defined as the cumulative opportunity costs.

Others and technology preferences

The last selection of drivers has divergent underlying reasons and is therefore labelled with "others and technology preferences". Some drivers are: meeting strategic goals and meeting sustainable criteria [8]. Both drivers include technology preferences. Strategic goals are investments in certain technologies to hedge risks in the portfolio ot to meet the green attitude of the company. Meeting of sustainable criteria are for example related to the calculated CO_2 emissions emitted by the potential power plant.

Design framework

Section 2.2 presented the design variables for the investment decisions of electricity producers. In this section the procedure for developing the additional algorithms is described. The steps are as follows;

1. The first step is the selection of **relevant** design variables of investment decisions resulting in additional investment decisions. The considerations for choosing driver(s) of investment processes are:
   - The driver is mentioned in the interviews performed by [8].
   - The implementation of the driver(s) is considered computationally do-able.
   - Additions are considered useful for future research and other projects.
   - There is theory available to operationalize the behaviour
2. The second step is to develop universal investment behaviour for the selected driver(s) regarding investor specific characteristics.
3. The last step is the operationalization of the behaviour which enables investor specific investment behaviour. In the next chapter the operationalization will be described conceptually. The investment algorithms are designed in such a way that they are modular and flexible.

Figure 2.4 visualizes the design procedure.

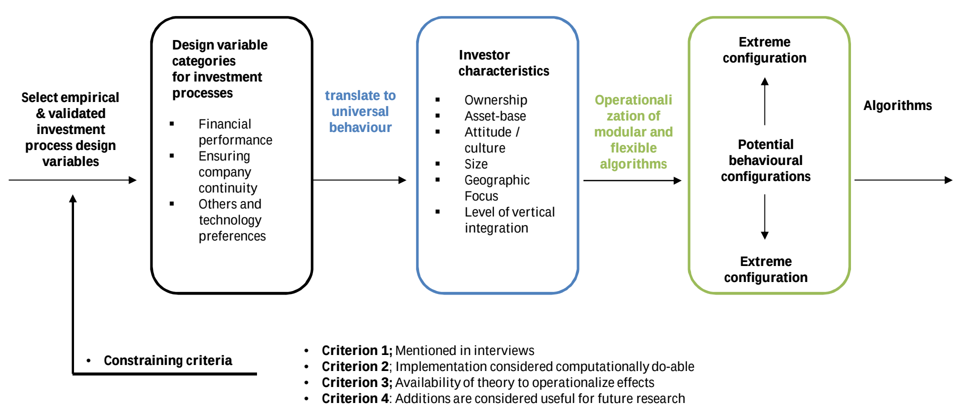


Figure 2.4: Framework for the development of the conceptual investment algorithms

2.3 Description of conceptual algorithms

This chapter describes the conceptual investment algorithms that are modelled. All the investment algorithms build upon the current investment algorithm of an existing model named EMLab-generation [6]. This implies that the developed algorithms represent the current algorithm including additional elements. The constructed algorithms include optional extensions to the current algorithm in the EMLab-generation model. The current investment algorithm of EMLab-generation is utilized as a basis because it includes considerations that are useful for all investors in the market according to interviews performed by [8]. An example is the approximation of a NPV calculation performed by the electricity producers in the model. Although the approximation in EMLab-generation is simplified it is a useful and universally applied financial measure to support decision-making. Figure 2.5 visualizes the structure of the investment algorithms that are modelled in this research.

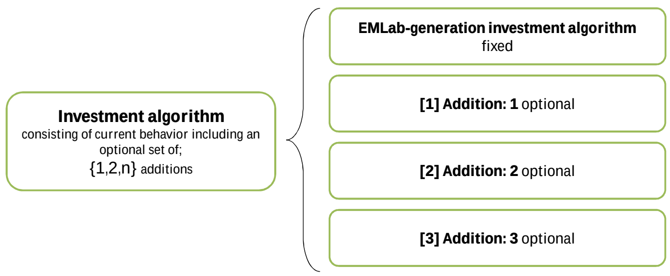


Figure 2.5: Conceptual structure of the investment algorithm

Figure 2.5 shows that new additional investment process elements are modelled. The additional investment behaviour will be modelled in such a way that for every simulation a set of different options is available. From table 2.1 three investment behavioural elements are selected as optional extensions[7]. These additions are chosen in conformity with the design framework in figure 2.4. The three selected algorithm extensions are:

1. **Technology preferences**: the technology preferences are mainly retrieved from two design variables in table 2.1: meeting strategic goals and sustainable criteria. There are however more design variables where technology preferences play a role, but strategic goals and sustainable criteria embody them best.
2. **Credit-risk considerations**: Credit-risks are retrieved from the business case attractiveness and the outcome of discounted cash flow model. Also for the credit-risk counts that more drivers include elements of this consideration.
3. **Risk-averse behaviour**: the last extension, risk-averse behaviour, is retrieved from the portfolio considerations and acceptable risk assessment levels[8].

[6]In chapter 3.1 this model will be explained in detail. EMLab-generation is the model used in this research.

[7]The choice for three algorithms is based on the available time and confidence that it is a sufficient number to answer the research question.

[8]The acceptable risk outcomes belong to the category of ”securing continuity”, but is overlapping with drivers from the category of technology preferences

All these additional extensions of investment processes have an impact on the investment decisions of investors[9]. One example is the preference of an investor to invest in clean technologies due to the idealogical company attitude. Another example is an investor with a very large debt-value in relation to the present assets. For this investor it could be very expensive to accept the loan offer from a creditor.

Basic algorithm

The current investment algorithm of the EMLab-generation model is explained generally to support the understanding of the conceptual models in the coming section. The algorithm is explained in more detail in section 3.1. The basic algorithm generally follows the following main steps:

1. In every simulation round, an investor is randomly chosen which is able to invest first. The question is whether the investor i is capable of paying the down-payment for a certain investment I_i and for what reference year is the investment planned.
2. The investor makes forecasts of the demand levels for the reference year and the years of operation (supply, demand model). This supply demand model incorporates the plants under construction and planned to be decommissioned.
3. The investor predicts the fuel prices (coal, gas, uranium and CO_2) for the reference year on the basis of growth models. Also the electricity prices are calculated.
4. The investor determines the costs and revenues for all investment options. Calculate the weighted average cost of capital for all investors and calculates the NPV outcomes of the investment options.
5. When there are investment options that have a sufficient return on investment the investor invests in the most profitable technology option.

This basic explanation should provide enough information to understand the conceptual descriptions in the coming section. When this is not the case it could be helpful to read chapter 3.1 first.

[9] E.g. due to the subjective preference criteria or additional limitations except only profit.

Technology preferences

The investment decisions of power producers are influenced by the attitude or vision of the company. This is coming forward in the interviews performed by [8], but is also recognized in other reviewed publications. Examples of publications are [56] and [57] who elaborate on the presence of subjective environmental criteria among investors. This subjective attitude is influencing the investment decisions that investors make[10]. To elaborate on possible technology preferences, two extreme stereotypes[11] of investors are described. All the stereotypes in between are also possible.

The environmentalist

This first universal stereotype is describing the investors which tend to invest earlier in green sustainable technologies on behalf of the vision of the company. A public owned company with a green vision on their operations is one example[12]. The public ownership could force the company to include and serve the public interests like ensuring a limited CO_2 footprint of production. The environmentalist grants higher weighting values to sustainability criteria for an selection of profitable investments. In contrary, when a project is able to return the investment, profit will be less important.

The conservativist

The second universal stereotype is the conservative investor. These investors are like the environmentalist considering cleaner technologies, but profit remains decisive. These investors could have a reticent attitude towards large CO_2 polluting technologies, but this attitude is more based on the increasing support of society to limit coal capacity in the European technology mix. The vision of the company is aimed at satisfying the shareholders which are mainly interested in their dividend expectations.

These stereotypes are two examples of investors with technology preferences. These preferences can be based upon a rich variety of criteria. So is it also possible that investors prefer plants which use low price volatile fuels or prefer plants which have more ramping flexibility.

Weighted multi-criteria decision analysis

The question is how to operationalize the technology preferences of a particular investor. In this research a multi-criteria decision analysis (MCDA) method is utilized. In [59] is concluded that the classification of investment opportunities is a typical MCDA issue. In literature, like in [60], MCDA is used to describe multi-criteria investment problems. The main advantage of MCDA is that it is possible to include subjective factors in the investment decision. Besides that, the MCDA is able to deal with investment decisions based upon multiple criteria. The MCDA method is designed by considering a selection of design steps. The steps to design the MCDA are described in [59] and stated in subsection A.2 of the Appendix. In the following subsection the MCDA method is described.

Multi-criteria decision method

The first step is the selection of the criteria. These criteria provide the opportunity to analyse investors with divergent attitudes. The selection of criteria is a good way to distinguish more

[10] See also [58]. Here also more examples of subjective criteria are mentioned.
[11] or configuration
[12] There are also mainly private owned companies with a green vision, but public ownership could be an additional incentive to invest in more sustainable technologies.

environmental or conservative investors. The criteria imply that every investor i has a selection of $\{c_n, c_{n+1}, c_N\}$ criteria. A optional selection is:

Criteria	**Include**
c_1 **MIN**	The CO_2 footprint in t_{CO_2}/MWh. This enables investors to assign higher values to investments with a lower footprint. A smaller footprint means less costs for CO_2 emission and less pollution
c_2 **MAX**	The NPV_p: a higher $NPV > 0$ This means that a investment is expected to be more profitable. This criterion enables that investors can have a high or lower preference for profitability.
c_3 **MAX**	Efficiency of a plant %. This implies that it is possible that some investors tend to value more efficient investments as more attractive.
c_4 **MAX**	Actual lifetime in years. This implies that an investor is able to assign more value to investments with a longer average lifetime. It could also be that an investor prefers investments with a shorter average lifetime due to more flexibility. A nuclear plant should for example at least run one and a half decade to return the investment cost which includes a significant risk factor.
c_5 **MIN**	Price volatility fuels in σ. This enables that investors can show averse behaviour towards investments which using very price volatile fuels.
c_6 **MAX**	Ramping up / down speed in hours. This enables investors to assign higher values to investments with the ability to ramp-up quickly.
c_7 **MIN**	Investment cost in EUR. Investors which have liquidity problems are now able to include a preference for power capacity with a lower investment cost.

Table 2.2: Optional MCDA criteria

The second step is the gathering of alternatives. The alternatives are the generation technologies in the EMLab-generation model listed in table 2.3. Examples are an Integrated Gasification Combined Cycle (IGCC) and Combined Cycle Gas Turbine (CCGT). The alternatives are fixed, but not all available at the same time. CCS technologies for example will be available after a period because CCS sequestration is not viable at the start of the simulation time. The assumption is made that no new technologies are entering the market.

The third step is the evaluation of criteria on the alternatives. Every particular investor will have a weighting factor ψ_n to make a certain criterion more or less important. This implies that every investor i has a set of weighting factors $\{\psi_n, \psi_{n+1}, \psi_N\}$[13] belonging to the criteria $\{c_n, c_{n+1}, c_N\}$. In the case of a environmental oriented investor the CO_2 footprint[14] of an investment will play an important role[15]. At the other side, the other extreme stereotype, the conservativist, will weight profit as a more important criteria in the decision-making process. These weighting criteria are modelled as properties of the electricity producer. These weight factors should be scalable and are therefore parametrized[16]. The assumption is made that the attitude of an investor remains fixed during the simulation. The cumulative sum of the weighted criteria form the utility or propensity of a technology. The higher the propensity of a certain technology relatively to the other investment options, the higher the chance that the particular

[13]Here defined as: what the investor finds more important than another goal (e.g. profit vs CO_2 emissions)

[14]One of the criteria

[15]The importance means a higher weighting factor than average

[16]Discuss the parameter space

Technology	Initial investment cost	Capacity
Coal-PSC	1.365.530	758
Lignite	1.700.000	1000
IGCC	1.724.880	758
Coal-PSC-CCS	2.457.950	600
IGCC-CCS	2.501.080	600
CCGT	646.830	776
CCGT CCS	1.164.290	600
OCGT	359.350	150
Biomass	1.703.320	500
Wind	1.214.600	600
Wind-Offshore	2.450.770	600
PV	2.048.300	500
Nuclear	2.874.800	1000

Table 2.3: Available technologies in the model retrieved from [6]

investor will invest in that technology. The utility or propensity indicates the relative value of a certain investment p for investor i. The propensity ω_p is calculated by:

$$\omega_p = \frac{c_{n,p} \cdot \psi_n}{\sum c_{n,p...P}} + \frac{c_{n+1,p} \cdot \psi_{n+1}}{\sum c_{n+1,p..P}} + \frac{c_{N,p} \cdot \psi_N}{\sum c_{N,p..P}} \tag{2.4}$$

Here ω_p is the propensity of investing in power plant p. $c_{n,p}$ is the value of criterion n for technology p and ψ_n the associated weight-factor. The fourth step in the multi-criteria decision is calculating a probability of investing in a particular technology based upon the normalized propensity value. The weighted propensity is normalised between an lower and upper border by:

$$n_{\omega_p} = \omega_p - \mathbf{min}(\omega_{p..P})/\alpha \cdot \frac{1}{\alpha \cdot \mathbf{max}(\omega_{p..P}) - \mathbf{min}(\omega_{p..P})/\alpha} \tag{2.5}$$

α [17] is here a normalisation parameter to ensure that both values both represent a value between zero and one. The probability of investing in technology p is than mathematically defined by:

$$\upsilon_p = \frac{n_{\omega_p}}{\sum n_{\omega_p}} \tag{2.6}$$

Here υ_p is the probability of investing in power plant p. This calculation is performed for all power plants which have a $NPV > 0$. After all the probabilities $\{\upsilon_p, \upsilon_{p+1}, \upsilon_P\}$ are calculated a discrete probability mass function is established. On the basis of this probability mass function the final investment decision is made. In case of the environmentalist it is now more likely that they invest in technologies which suit the overall company criteria the best. There is a threshold included since the technology preferences are introduced in the model at the moment the $NPV < 0$ investments are filtered.

$$\sum_{p \in P} f(p) = 1 \tag{2.7}$$

From this discrete distribution randomly an investment is selected. The technology preferences of an investor are characterized by the weighting factors for the selection of criteria.

[17] If $\mathbf{min}(\omega_{p..P})$ would be a negative value it should be multiplied instead of divided by α. Since this outcome is not expected (negative utility outcomes) it is not incorporated in the equation above. In the algorithm it will be included.

The value of an investment is measured by multiplying the weight factor and the proportional[18] criteria value relatively to the values of all investments. A investment opportunity will then embody a utility value which enables the calculation of a probability to invest in that technology. This simply implies that an investment with the largest cumulative value will have the highest probability of investment. This means that the chance that the particular investor will invest in that technology is the largest. There are however also limitations of using MCDA (also see section 3.2). These method **limitations** are:

1. It is difficult to operationalize and interpret a strong or weak preference. The discussion here is whether it is possible to quantify preferences on a discrete scale. This remains however a discussion in modelling subjective factors.
2. This method does not automatically include interdependency among criteria[19]. Some criteria are however overlapping. One example is investment costs and profitability. Although these criteria are different they both deal with the financial details of the investment opportunity.
3. This method is not able to overcome the problem of incomparability (see also argument one).
4. This model is not able to deal with changing attitudes over time, but this could be added in a later stage. This limitation is also discussed in section 3.2 and 5.3.

As reflection on these limitations some arguments can be argued. The first argument is that this method is considered a sufficiently realistic way to include subjective factors and differentiate the decisions of investors. A second argument is that the method is a good try to include the behavioural effect which is used often by scientists which are modelling multi-criteria investment decisions [59]. To finalize the conceptualization of this conceptual model two static examples are presented one the next page. These examples give a understanding on how the investment decision of an investor is biased by subjective criteria.

[18] The percentage of the value with respect the cumulative of all investments

[19] This is however partly done by using thresholds. The MCDA is performed after the NPV positive projects are selected.

Summarizing the model description

For two extreme universal stereotypes an example is described in the examples below. Further every possible attitude is possible along the N criteria dimensional space. This MCDA will be performed after the selection of profitable investment opportunities. This implies that there is a threshold included before technology preferences play a role. A project has to be estimated profitable by the particular investor before the subjective criteria will play a role. The general conceptual model of the technology preferences of investors is summarized in words. In section 3.3 this conceptual behaviour will be translated into a computer readable investment algorithm. The current algorithm only took profitability into account with this multi-criteria decision method, additional subjective considerations based upon the company attitude will be included in the model.

Example one *Investment decision example of a environmentalist*

The investors with this stereotype have a strong preference for renewable investment, especially with an $NPV > 0$. This preference means that the probability of investing in renewable technologies is larger than in conventional energy source based technologies. When renewable capacity is no economical option in the case of $NPV < 0$, there is a stronger intention to look for another most clean technology measured by e.g. CO_2 footprint. The implication is that these companies will more often prefer cleaner investments than higher profits. When there is only a coal or nuclear based investment opportunity, there is a chance that the investor will not invest because the technologies do not suit the sustainable strategy of the company.

Imagine that there are two investment options wind and CCGT. The criteria values are as following: $c_{1,wind} = 100$ and $c_{1,CCGT} = 150$ and $c_{2,wind} = 1.25$ and $c_{2,CCGT} = 0.75$ the investor has the specific weighting factors $\psi_1 = 2$ and $\psi_2 = 1$ than the propensity of investing in the two technologies is:

$\omega_{wind} = \frac{100 \cdot 2}{250} + \frac{1.25 \cdot 1}{2}$ $\omega_{CCGT} = \frac{150 \cdot 2}{250} + \frac{0.75 \cdot 1}{2}$

After normalizing with $\alpha = 1.15$ ω_{wind} and ω_{CCGT} the environmentalist has a probability of 36 % of investing in wind technology and 64 % investing in CCGT technology.

Example two *Investment decision example of a conservativist*

For the investors of this type profit is the most important criterion, but also sustainable criteria like the CO_2 footprint plays a role in the decision-making. This implies that these companies include a reticent attitude towards power plants with large emissions, but economical advantages are more decisive. Imagine now that there are three investment options wind and CCGT and Coal. The criteria values are as following: $c_{1,wind} = 100$ and $c_{1,CCGT} = 100$ and $c_{1,coal} = 150$ and $c_{2,wind} = 1.25$ and $c_{2,CCGT} = 0.75$ and $c_{2,coal} = 2.00$ and $c_{3,wind} = 5$ and $c_{3,CCGT} = 2$ and $c_{3,coal} = 3$ the investor has the specific weighting factors $\psi_1 = 2$ and $\psi_2 = 1$ and $\psi_3 = 3$ than the propensity of investing in the two technologies is:

$\omega_{wind} = \frac{100 \cdot 2}{350} + \frac{1.25 \cdot 1}{2} - \frac{5 \cdot 3}{10}$ $\omega_{CCGT} = \frac{100 \cdot 2}{350} + \frac{0.75 \cdot 1}{2} - \frac{2 \cdot 3}{10}$ $\omega_{coal} = \frac{150 \cdot 2}{350} + \frac{2.00 \cdot 1}{2} - \frac{3 \cdot 3}{10}$

After normalizing with $\alpha = 1.15$ [a] the conservativist has a probability of 2 % of investing in wind and 34 % investing in CCGT and 64 % in coal.

[a]adapted for the negative value, the **min** value should get more negative and a negative **max** value should get less negative after using α

Credit-risk considerations

The second conceptual algorithm includes the credit-risk considerations of the investor. The credit-risk embodies the risk that the investor will fail to pay the debt back to the creditor [5,53]. Depending on the credit risk of the investor a loan for a particular investment is granted by the bank. The credit-risk of the investor also influences the discount rate of the granted loan. From the perspective of the investor the consideration is easy to understand: *is this offered interest rate competitive enough for my financial situation.* This credit-risk determination is based upon concepts from credit-risk theory of Black-Scholes and an earlier implementation described in [5]. Important concept here is the financial structure of the investor. Depending on this financial structure the loan and the credit risk are determined[20]. Since there is only one type of bank included in the model weight factors are not included[21]. The financial structure of the investor is determined by the following criteria:

1. c_1 The total value of assets of investor i at time t
2. c_2 The total value of debt of investor i at time t

Black-Scholes debt pricing model

This research utilizes the debt-pricing model of Black-Scholes to determine the price of debt. This model is proven suitable for modelling investment decisions in power generation [5]. This model assumes that an investor defaults when during a certain time period t the total value of the assets of the investor is lower or equal than the value of debt. The value of the debt is calculated by:

$$d_{i,t} = \exp^{-(r_f + r_{p,i}) \cdot (T-t)} \cdot D_{i,t} \tag{2.8}$$

Here $d_{i,t}$ is the total value of the debt of investor i discounted for the interest-rate consisting of the risk-free rate r_f and the investor specific dependent risk-premium $r_{p,i}$. $d_{i,t}$ and $D_{i,t}$ are required for the calculation of the investor specific interest-rate. This risk premium is a representation of the default probability of the investor. Equation 2.8 is than transformed in such a way that the interest-rate can be calculated.

$$r_f + r_{p,i} = \frac{-1}{T-t} \cdot \mathbf{ln}\left(\frac{d_{i,t}}{D_{i,t}}\right) \tag{2.9}$$

Before calculation of the interest-rate it is necessary to know the current nominal value of debt and perceived value of debt including the credit-risk of the investor. This will be explained later this chapter. The debt is priced in this thesis by:

$$d_{i,t} = A_i - E_i \tag{2.10}$$

Here the A_i equals the asset value on the moment of investment decision t. E_i is the market-value of the equity at moment t. This market value of equity will be determined by using the Black-Scholes solution for the calculation of a call option. A call option could be seen as a contract between two parties, the investor and the bank. Here the equity is seen as a call option owned by the investor on the assets with the present value of the total debt as the strike price. This equity valuation is a task performed by the bank. The information however is utilized by the investor to accept the loan or not. In this model the assumption is made that the asset value is evolving as a normal diffusion process[22]. In figure 2.6 the Black-Scholes model of default is

[20] There are various options to estimate the credit-risk. This is a structural approach where the ability of the investor to pay back the debt is issued.
[21] This could be useful for further research: analysis for different types of banks
[22] Geometric Brownian motion

visualized. When the value of debt of an investor is below the total value of assets during the period $T-t$, the investor is considered default. This risk is quantified in the figure. The larger the probability of default the lower the priced value of equity and the larger the interest-rate.

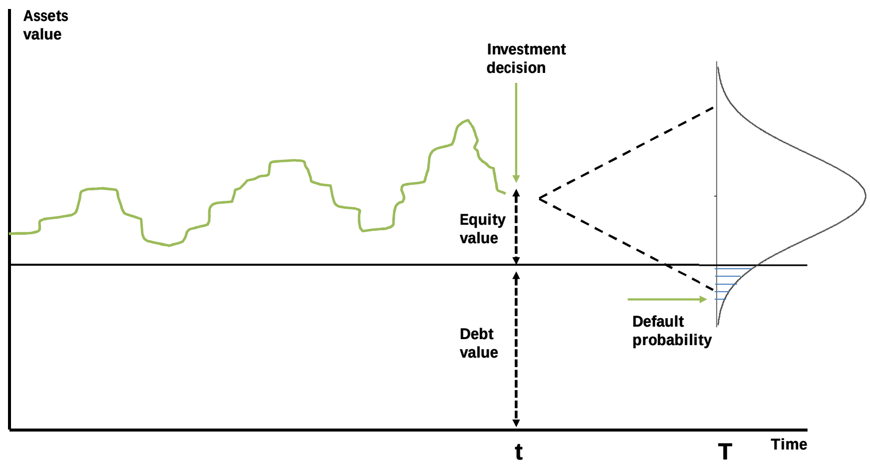


Figure 2.6: The default model of Black-Scholes adapted from [5]

The calculation of the call option is than as follows:

$$E_i = A_i \cdot N(d1) - D_{i,t} \cdot \exp^{-r \cdot T - t} \cdot N(d2) \tag{2.11}$$

Here $N(d1)$ and $N(d2)$ are a N(0,1) distribution function. These functions are defined as:

$$d1 = \frac{log(\frac{A_i}{D_{i,t}}) + r_f + \frac{\sigma^2}{2} \cdot (T-t)}{\sigma \cdot \sqrt{T-t}} \tag{2.12}$$

$$d2 = d1 - \sigma \cdot \sqrt{T-t} \tag{2.13}$$

With equation 2.11, 2.12 and 2.13 it is possible to calculate $d_{i,t}$. Than the interest-rate $r_f + r_{p,i}$. Some assumptions needs further explanation:

1. The calculation of debt in the model is done by looking at the situation when the investment decision is made, so the current status of debt and asset-value. This implies that the decision does not take future investment expectation into account. This could be included in future research.
2. Due to the modelling choice, the Black-Scholes implementation is only working for models with relatively big investors. Since all the investors in the model include a significant portfolio this is not considered problematic. For non oligopolistic markets this Black-Scholes implementation would not be applicable.
3. For future research another model could be implemented to analyse credit-risk. One example is including credit-ratings for companies which score less on a selection of criteria like the cash position and the previous performances.

Two simple static examples are presented below where the BS-debt pricing model is explained.

Example one *Investment decision example of an investor in default*

The investor is of this stereotype has a worse cash position and low value of assets. The total debt-value of the investor is however high which implies that the investor has a significant chance of failing to pay back debts. Now on time t this investor i has the possibility to invest in a coal plant for 2.000 million euro how is the interest-rate determined according to Black-Scholes credit theory?

The required data is as follows; the total value of assets $D_{i,t} = 4.800$ million euro and the total value of debt is 7.800 million euro besides that the volatility σ_i of the assets of investor i is 20% and the risk-free rate r_f is assumed 3%. The debt is considered to be paid back in 10 years from now. The credit-risk is than determined in the following steps:

- $d_{1,i} = \frac{log(\frac{4.200}{7.800})}{+0.03+\frac{0.2^2}{2}\cdot(10)} 0.2\cdot\sqrt{10}$
- $d_{2,i} = d_{1,i} - \sigma\cdot\sqrt{T-t}$
- Than $d_{1,i} = -0.19$ and $d_{2,i} = -0.82$
- The value of the equity is than defined: $E_i = 4.200\cdot 0.43 - 7.800\cdot \exp^{-0.03\cdot 10}\cdot 0.21$
- $E_i = 596.62$ and the price of debt is determined 4.200 - 596 = 3.603
- The interest-rate is than: $r_f + r_{p,i} = \frac{-1}{10}\cdot \mathbf{ln}\left(\frac{3.603}{4.200}\right)$
- Than $r_f + r_{p,i} = 7,72\%$
- Investor i decides to accept the loan offer based upon a parametrized property, it is possible to add an investor which accepts higher interest-rates.

Example two *Investment decision example of an investor with a prime performance*

The investor is of this stereotype has a sufficient cash position and high value of assets with respect to the total value of debt. The relative value of debt is low which implies that the chance that the investor is not able to fulfil his obligations is considered small. Now on time t this investor i has the possibility to invest in a IGCC plant for 1.500 million euro. how is the interest-rate determined according to Black-Scholes credit theory?

The required data is as follows: the total value of assets $D_{i,t} = 7.800$ million euro and the total value of debt is 4.800 million euro besides that the volatility σ_i of the assets of investor i is 20% and the risk-free rate r_f is assumed 3%. The debt is considered to be paid back in 10 years from now. The credit-risk is than determined in the following steps:

- $d_{1,i} = \frac{log(\frac{7.800}{4.800})}{+0.03+\frac{0.2^2}{2}\cdot(10)} 0.2\cdot\sqrt{10}$
- $d_{2,i} = d_{1,i} - \sigma\cdot\sqrt{T-t}$
- than $d_{1,i} = 1,55$ and $d_{2,i} = 0,93$
- The value of the equity is than defined: $E_i = 7.800\cdot 1,55 - 4.800\cdot \exp^{-0.03\cdot 10}\cdot 0,93$
- $E_i = 4.409$ and the price of debt is determined 7.800 - 4.409 = 3.390
- the interest-rate is than: $r_f + r_{p,i} = \frac{-1}{10}\cdot \mathbf{ln}\left(\frac{3.390}{7.800}\right)$
- than $r_f + r_{p,i} = 3,48\%$
- Investor i decides to accept the loan offer based upon a parametrized property, it is possible to add an investor which accepts higher interest-rates.

Risk averse behaviour

The third conceptual algorithm includes risk-averse behaviour. According to interviews performed by [8] there are investors who tend to show risk averse behaviour. Risk averse behaviour is defined by the preference of investing in more certain lower profits than in investments with higher riskier profits. This algorithm is linked with the driver: outcomes of risk assessments. These assessments represent the amount of risk while investing in a certain technology. Risk averse behaviour embodies different behavioural patterns. A first example is that investors show risk averse behaviour for a specific technology due to experienced problems in the past. A second example is that an investor aims to diversify the portfolio to overcome fuel price risks. This could imply that a certain investor would prefer investing in a pulverised coal fired plant instead of another more profitable technology because of hedging risks in the portfolio. For this algorithm some concepts from the Modern Portfolio Theory of H. Markowitz are used[23]. Before is elaborated on the conceptual model first a short explanation on Modern Portfolio Theory is presented.

Modern Portfolio Theory

The Modern Portfolio Theory of H. Markowitz suggests one way to quantify risks. Here the all the power plants owned by a certain investor i are seen as the portfolio of the investor. The additional investment behavioural consideration here is that the investor aims at minimizing the portfolio risks. The specific investment risks are measured by σ_p [54]. The minimization of the portfolio risk implies that the electricity producer is risk-averse. The risk-averse behaviour is an assumption of the model. In order to estimate the portfolio risks, first the expected investment return is calculated as follows:

$$\sigma_{t,p} = \sqrt{E(R_p^2) - E(R_p)^2} \tag{2.14}$$

Here R_p means the return per annum and $E(R_p)$ the expected return per annum for a certain investment p. $\sigma_{t,i}$ is the standard deviation for investment i in year t. The expected return for a whole portfolio is than described by:

$$\mu_i = \sum w_p * \mu_p \tag{2.15}$$

Here the μ_i is the expected return of the portfolio of investor i including p investments where w_p is the proportion of the investment in the portfolio and mu_p is the expected return. The standard deviation of the portfolio return for two investments is than described by:

$$\sigma_i = \sqrt{w_p^2\sigma_p^2 + w_{p+1}^2\sigma_2^2 + 2c_{p,p_x}w_p w_{p+1}\sigma_p\sigma_{p+1}} \tag{2.16}$$

Here the σ_i denotes the standard deviation of the portfolio of investor i. $c_{p,p+1}$ is the correlation coefficient between technologies p and another technology p_x. The correlation coefficient is mathematically defined as follows:

$$c_{p,p_x} = \frac{\sigma_{p,p_x}}{\sigma_p\sigma_{p_x}} \tag{2.17}$$

Coal and IGCC for example will be positively correlated because the technologies utilize similar fuels and have similar generation characteristics[24]. The other elements of the formula are explained by equation 2.14 and 2.15. The minimization of portfolio risk is one way to model risk averse behaviour. A example where the portfolio model is implemented in a electricity market

[23] The model itself is not implemented completely due to the circumstances in the model which are not ideal for the portfolio model. This will be explained later this chapter in more detail.

[24] Think of position in the merit-order etcetera

simulation is [61]. The portfolio model described by the equations above will not be implemented in its pure form due to some reasons. The first reason is that the determination of expected returns is considered computational difficult. The second reason is that this portfolio model makes the simulation slow. This is the case because every specific investor has an additional endogenous predictive model. A third reason is that the portfolio model is less applicable for smaller investors in the market which may prefer a very specific portfolio in stead of a very diverse portfolio. The last reason is that this research is more focussed on the operationalization of the risk-averse behavioural effect than on the implementation of a sophisticated portfolio model. Therefore only some concepts of this portfolio model will be utilized. Besides that the operationalization will be designed in such a way that diversification is not a fixed property for all investors in the market, but that diversification is a flexible behavioural addition depending on the market situation. The following expressions of risk-averse behaviour are taken into account.

1. Investors show technology specific risk-averse behaviour. One example is where investors showing averse investment behaviour against nuclear technology due to the societal pressure.
2. Investors tend to diversify the portfolio or stick to conventional proven technologies.

Technology specific risk-averse behaviour

The operationalization of the technology specific risk-averse behaviour addresses the discounting mechanism of the net present value (NPV) calculation. An investor which has bad previous experiences regarding a certain technology might be unwilling to invest in that technology in the future. The proposed operationalization is therefore to include a technology specific risk-premium when determining the weighted average cost of capital (WACC) which is used to discount the NPV calculation. The new WACC is than mathematically determined as follows:

$$WACC_i = \frac{E_i}{V_i} \cdot k_{e,i} + \frac{D_i}{V_i} \cdot k_{d,i} + r_{i,p} \tag{2.18}$$

Then the $r_{i,p}$ is the technology specific risk-premium. This premium will be parametrized which makes it possible to analyse different levels of specific risk-averse behaviour. Besides that it is also possible to include risk-takers by making the premium negative[25].

Portfolio diversification

The operationalization of the portfolio diversification is a first attempt in the direction of the portfolio theory. A first important element is that only market players with a significant portfolio tend to diversify the portfolio. In order to include this threshold the market-share of the investor is determined during the simulation. The market-share $S_{i,t}$ of investor i on time t is mathematically defined by:

$$S_{i,t} = \frac{\sum(V_{p,i,t})}{\sum(V_{p,c,t})} \tag{2.19}$$

Here $\sum(V_{p,i,t})$ is defined as the sum of generation capacity of investor i at time t and $\sum(V_{p,c,t})$ as the cumulative generation capacity in country c at time t. The market-share is defined as the present available generation capacity excluding the power plants that are under construction or planned for decommissioning. When an investor is considered significantly large it will tend to diversification. What is defined significantly large depends on the investor specific parameter κ_i. Another way to implement the definition of an significant large investor is comparing the portfolio capacity with the largest investors in the North-West European market. Both

[25] For this effect is no empirical indication present.

methods are considered applicable. The first option using the parameter κ_i includes flexibility and a threshold in the model.

$$\gamma_{S_{i,t}} = \begin{cases} TRUE & \text{if } S_{i,t} \geq \frac{\sum S_{i..I,t}/\kappa_i}{\sharp\{S_{i,t}, S_{i+1,t}, S_{I,t}\}} \\ FALSE & \text{if } S_i < \frac{\sum S_{i..I}/\kappa_i}{\sharp\{S_{i,t}, S_{i+1,t}, S_{I,t}\}} \end{cases}$$

When γ_{S_i} equals $TRUE$ the investor tends to invest in the technology which is not included in the portfolio at time t. The progressive diversifying investor first gets the selection of profitable projects $\{p_1, p_2, p_3$ and then checks what technologies are hold in the portfolio. The investor then normalizes the $NPV > 0$ technologies among each-other depending on the market-share between 0 and 1.

$$n_{i,p} = S_{p,i} - \mathbf{min}(S_{p..P,i})/\alpha \cdot \frac{1}{\alpha \cdot \mathbf{max}(S_{p..P,i}) - \mathbf{min}(S_{p..P,i})/\alpha} \tag{2.20}$$

Like in the MCDA is α a normalisation parameter to ensure that both values both represent a value between zero and one. The chance of investing in a certain technology is than mathematically defined by:

$$p_{i,p} = \frac{1 - n_{i,p}}{\sum_{p \in P} n_{i,p..P}} \tag{2.21}$$

Here $p_{i,p}$ is than the chance of investor i investing in technology p. When the portfolio of the investor includes all available technologies there is a trend towards the technology which counts for the smallest fraction in the portfolio. The portfolio diversification is assumed inferior when there are also technology preferences included[26].

[26]With the current formalization it is not possible to integrate these two behavioural considerations. When both are present, technology preferences are assumed superior in the decision making.

Example one *Investment decision example of an investor with technology specific risk-averse behaviour*

Investor i has bad experience with coal technologies. The government has an in-stable regulatory regime which forces this investor to be more risk-averse regarding technologies using coal as an energy source. At time t there are three investment opportunities with a comparable net present value. The NPV calculation however is determined on the basis of a return on equity of 4,5% and a interest-rate of 4,8%. The debt value is 2.000 and the equity value is 5.800. The investor has to decide between $NPV_{wind} = 5.850$ and $NPV_{CCGT} = 5.800$ and $NPV_{IGCC} = 5.900$. The investor has a specific risk-premium of 2.5 % on coal based technologies. How is the decision influenced considering a simple NPV estimation over 1 year? The new weighted average cost of capital for the IGCC is:

$$WACC_{IGCC} = \frac{5.800}{7.800} \cdot 0,045 + \frac{2.000}{7.800} \cdot 0,048 + 0,025 \tag{2.22}$$

The new $WACC_{IGCC}$ is than 7,08 % which adjusts the NPV calculation. This value is now $NPV_{IGCC} = 5.762$ This made the IGCC less attractive than the other options.

Example two *Investment decision example of an progressive investor willing to diversify the portfolio*

This investor has a significant market-share in country A of 35 % which causes a trend towards portfolio diversification. The investor now has four profitable investment options. The available options are $p_{Wind}, p_{CCGT}, p_{Coal}, p_{Nuclear}$ the investor owns currently the following shares in the portfolio $p_{Wind} = 35\%, p_{CCGT} = 10\%, p_{Coal} = 25\%, p_{Nuclear} = 30\%$ Than chance of investing is than determined by normalizing the portfolio shares in the first place, here an example for p_{Wind}:

$$n_{i,Coal} = 0,25 - 0,10 \cdot \frac{1}{0,35 - 0,10} \tag{2.23}$$

The normalized value of coal is than $n_{i,Coal} = 0,4$. The chance of investing in coal is than mathematically defined by:

$$p_{i,Coal} = \frac{1 - 0,4}{1,6} \tag{2.24}$$

The investor has than 62,5% chance of investing in a CCGT plant, 25 % chance of investing in a coal plant and 12,5 % of investing in a nuclear plant.

Conclusions conceptualization

The first research question was: *How are investors in North-West European power generation evaluating investment opportunities based upon empirical data, and how to operationalize these evaluations?*. The question is answered in the previous pages. In section 2.2 is described what processes drive investment decisions. The design framework in figure 2.4 was used to develop three conceptual models with universal investment behaviour. The conceptual models are summarized in table 2.4.

Algorithm	Behavioural expression and operationalization
Technology preferences	• **Behavioural expression:** investors include subjective criteria in their decision-making process. The weight factors of the investor describe the attitude of the investor. Two potential extremes are the environmentalist and conservativist. • **Operationalization:** The subjective factors of investors are included by utilizing a multi-criteria decision method. The method includes the calculation of a utility function based upon $\{c_n, c_{n+1}, c_N\}$ criteria.
Credit-risk considerations	• **Behavioural expression:** Depending on the financial structure of the investor the bank decides upon a certain interest-rate for the external financing of the new power plant. The investor with financial limitations could decide to refuse the loan. • **Operationalization:** The debt-pricing model of Black-Scholes is implemented. This implementation implies the pricing of the equity based upon a probability of default.
Risk-averse behaviour	• **Behavioural expression:** Investors tend to diversify their portfolio or stick to conventional technologies. There are also investors which show risk-averse behaviour towards certain technologies. • **Operationalization:** Concepts are used from the Modern Portfolio Theory of H. Markowitz. Investors with a significant portfolio tend to diversify the portfolio in an attempt to lower the portfolio risks.

Table 2.4: Conclusions on the conceptual algorithms

Chapter 3

Modelling Investment Algorithms

3.1 EMLab-generation: the modelling laboratory

The modelling in this research is performed within an existing model named EMLab-generation. The essential elements of this model are explained first in the coming sections.

Introduction

EMLab-generation is a model of the electricity market and based upon the ABM framework AgentSpring [6]. AgentSpring is developed as a open source ABM framework tool. AgentSpring is used to make the model more easy to operate and maintain. One example of the included features is the predefined "agent" which enables to quickly programme all the market parties involved in the system like the consumer and regulator. Furthermore it is also possible to easily expand the model due to the modular characteristics. In order to understand algorithms developed in this stage of the research some previous knowledge of the current investment algorithm in EMLab-generation is mandatory. The generic steps of the algorithm where already discussed in section 2.3, but this chapter will present a more in-detail explanation.

EMLab description

EMLab-generation is initiated by the TU Delft [6,62]. This research utilizes this model because it is capable of exploring the long-term effects of interacting energy policies. Further, this model is able to cope with heterogeneity, imperfect expectations and investment behaviour in non-ideal situations. EMLab-Generation contains a base model which simulates two interconnected European electricity markets. It is possible to analyse i.e. the amount of CO_2 emissions, the price of electricity and the effect upon investment in renewable generation.

Objective

According to the model documentation the objective of the model is to: "*analyse the aggregate effects of investment decisions of generation companies under different policy experiments and market designs in order to assess the possible effects of different policy instruments on the long-term development of European electricity markets*" [6]

Model structure

The EMLab-Generation model structure consists a model engine and model behaviour see figure 3.1. The engine describes how the simulator works and the behaviour shows the included model behaviour on a long, medium and short term basis. For this research the long-term behaviour is of interest. This is because investment is a long-term activity.

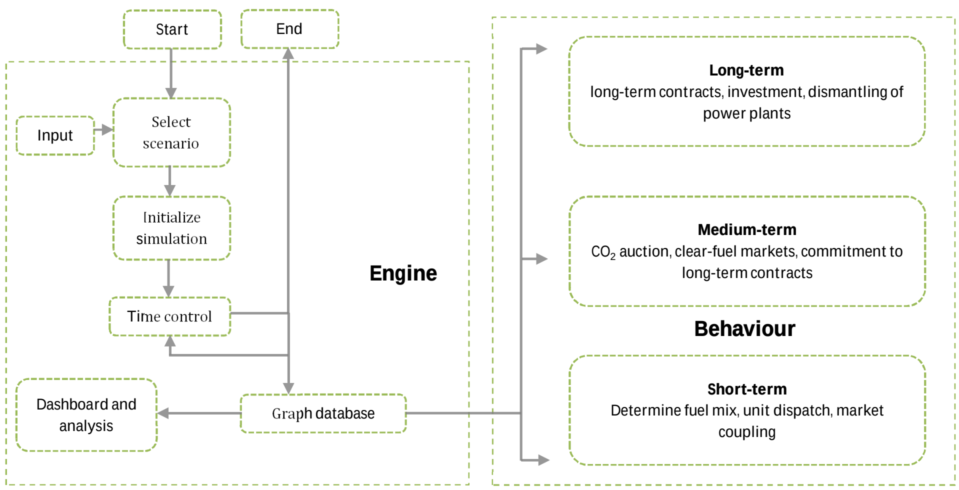


Figure 3.1: Structure of the EMLab-generation model [6]

Model elements

The main elements of the model are presented in. The most important so called "agents" are the power producers or generation companies which produce electricity and invest in new capacity when needed. Other features are the CO_2 en electricity wholesale market where the electricity and emission rights are sold. The model also contains a policy measure which enables to analyse the effects of an emission trading scheme on investment in power generation.

Relation to this research

The modelling work within this thesis focusses on the long-term behavioural aspects of the model. The other behavioural elements are seen as fixed. An example is the dispatching and market clearing mechanism. The investment related behaviour is located in a specific part of the model. The engine and further structure of the model keeps equal as presented in 3.1. In the following section the present investment algorithm is discussed and explained. This investment algorithm will be adjusted in this thesis.

Investment algorithm

The current investment process starts with evaluating whether any of the producers in the model is willing to invest. When this is not the case the process is ended. Every simulation

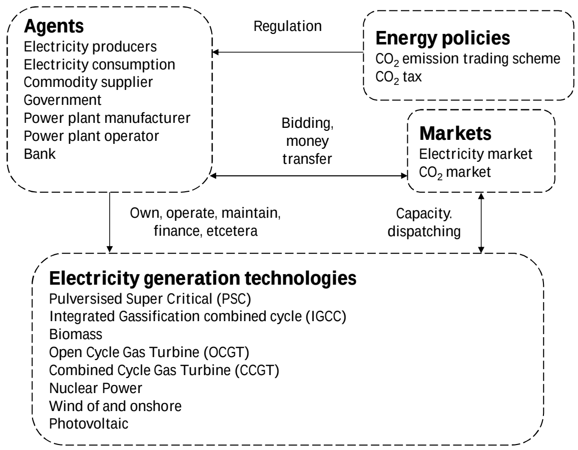


Figure 3.2: General visualisation of the EMLab model elements [6]

tick, another investor will decide first upon investing or not[1]. This is done because investors decisions to invest depend upon decisions of other investors. The decision process structure of the investor is presented in figure 3.3. The producer first gathers the investment options which are present. On the basis of physical and financial constraints is determined what the expected revenues will be for the base year. Electricity producers pay for a certain percentage with own capital and also borrow money from the agent "bank". All the electricity producers calculate every time step the expected profitability of the available technologies. The profitability enable the NPV calculations for each type of technology. So in step by step electricity producers:

1. **Start algorithm**
2. Select the first investor i to invest, this happens randomly every tick. The number of investors are manually determined in the experiment file.
3. The investor makes an estimation of the demand by averaging the expected demand growth rate over the last five years. For each segment of the load-duration function (divided in s segments) the demand is estimated as follows: $\hat{D}_{s,c,t+n} = D_{s,c,t} \cdot (1+h)^t$. Here $\hat{D}_{s,c,t+n}$ is the estimated demand in year t+n, segment s and country c.
4. The investor i makes market predictions for coal, gas, uranium and CO_2 prices in the same way as the demand function in the previous step.
5. Now the electricity price is calculated for each segment of the load duration function and a comparable price duration function is established.
6. Is the investor capable of paying a potential down-payment. This is around 30 percent of the capital cost.
7. Calculation of the running hours of the potential investment on the basis of the future electricity prices and variable costs and the sector availability rate. Check whether the number of potential running hours are sufficient. (e.g. a nuclear plant has to run 5000 hours minimal)
8. Check, whether the power plant (investment) is in the merit order. In other words are the variable costs smaller than the expected prices.
9. The investor estimates the plants cash flow by subtracting the plants variable costs from the estimated market price for each segment of the load duration curve. For the final cash flow for the fixed costs of the power plants are also subtracted.

[1] This is randomly determined to prevent bias

10. calculation of the net present value of the investment discounted for the weighted average cost of capital (see equation 2.2)

    .

    $NPV_p = \left(\sum_{t=0...t_b} \frac{-I_p/t_b+1}{(1+WACC)^t} + \sum_{t=t_b+1..t_b+t_D} \frac{\hat{CF}_{p,t+1}}{(1+WACC)^t} / k_p \right)$
11. Select the all the investment options which have an $NPV > 0$ and rank them according to their value relatively to the invested money.
12. invest by paying the down-payment and starting up the construction of the power plant.

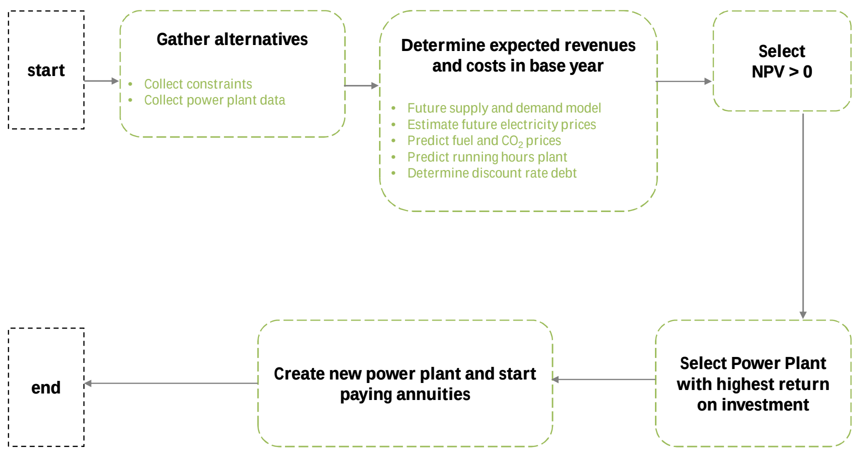


Figure 3.3: Structure of current investment algorithm [6]

This summarizes the current investment algorithm at the moment. This algorithm is the basis for the investment algorithms modelled in this research. Now there is a understanding of the EMLab-generation model the formalization of the conceptual algorithms will be described in the following paragraphs.

3.2 Modelling choices, limitations and assumptions

This section will elaborate on the limitations and assumptions in the investment algorithms. The conceptualization already described some choices which are made for the scope of this research. The first choice was that the algorithms describe the investment behaviour of large scale North-West European investors. Furthermore are the algorithms based upon empirical data of North-West European investors. Modelling choices are:

1. One of the choices is the 40 year simulation time which is an equal time frame to other studies in the field. This time frame is sufficient to come up with a comprehensive answer on the research question. It is also a common time frame in for fuel-price and demand forecasts.
2. The algorithms are analysed for a North-West European electricity market context because the empirical data which is used to design the algorithms is retrieved from North-West European investors.

3. Three deterministic fuel-price forecasts are used from the DECC [39] to explore the influence of exogenous factors.
4. The investment algorithms are implemented in a modular and flexible way.
5. Spring-source is chosen as editor. The algorithms are modelled in Java which is the language of EMLab-generation.
6. The three flexible modular investment algorithms are modelled within an existing agent-based model named EMlab-generation. This implies that EMLab-generation is seen as the "modelling population". This makes it essential that comparable research in the future is performed on different simulation models. This research is considered as a first step in studying the effects of different investment algorithms on the outcomes of energy policy analysis.

Limitations of the investment algorithms are:

1. A first important limitation is that the algorithms are only a first step in analysing the effect of different investment behavioural patterns on the outcomes of policy analysis. The algorithms could be enriched with more variables and behavioural considerations that investors make. Examples are locational factors which might be important for investors, or relational factors between investors and other stakeholders. Due to limited time choices had to be made, the research has to leave more factors out of the scope, this is however not considered problematic.
2. The attitude configuration of the investor remains fixed during the simulation time while it could be possible that in 40 years the attitude changes. This could be included in future research by changing the weight-factors in time based upon indicators in the market. These effects are however not considered problematic. This will be discussed in the discussion section in 5.3.
3. The comparison of subjective factors in the multi-criteria analysis is not considered possible in reality. How to compare two paradigms is still a philosophers problem. The MCDA is however a proven technique to include more criteria and calculate a cumulative utility.
4. In the calculation of the asset-value, good-will of a investor is not incorporated which embodies a significant value in reality. A more sophisticated estimation of the financial situation of an investors is not part of the scope of this research, but is proposed for future work.
5. A limitation of the models is that the running is time intensive (1.5h for one experiment to run once). This implies that the simulation time is long, due to the large number of experiments. A large number of experiments is required due to the exploratory character of the research. This is a limitation since the research has to be performed intentionally within 5 months.

3.3 The model formalization and pseudo-code

This chapter contains the model formalization. The formalization includes the pseudo-code of the investment algorithms. First is visually (in figure 3.4, 3.5 and 3.6) explained how the new algorithm fits in the current algorithm of EMLab-generation. Secondly the pseudo-code is presented. The research includes recapitulating three new algorithms: one algorithm including technology preferences, an algorithm which includes credit-risk considerations and an algorithm which contains risk-averse behaviour. All the algorithms include investor specific behaviour as mentioned in the conceptualization chapter. The behaviour is partly dynamic and therefore able to change over time[2]. It is also possible to combine a mixture of behaviours, therefore an integrated figure is presented in figure 3.7 which includes all possible evaluation steps.

Technology preferences

In figure 3.4 the technology preferences of an investor is positioned in the current investment decision process. The technology preferences will play a role after the selection of profitable projects. This is done on purpose to include a decision threshold. The expected profitability of a project is considered mandatory. The formalization of the technology preferences includes two aspects in the EMLab-model: 1. new properties for every investor and 2. additional commands in the algorithm.

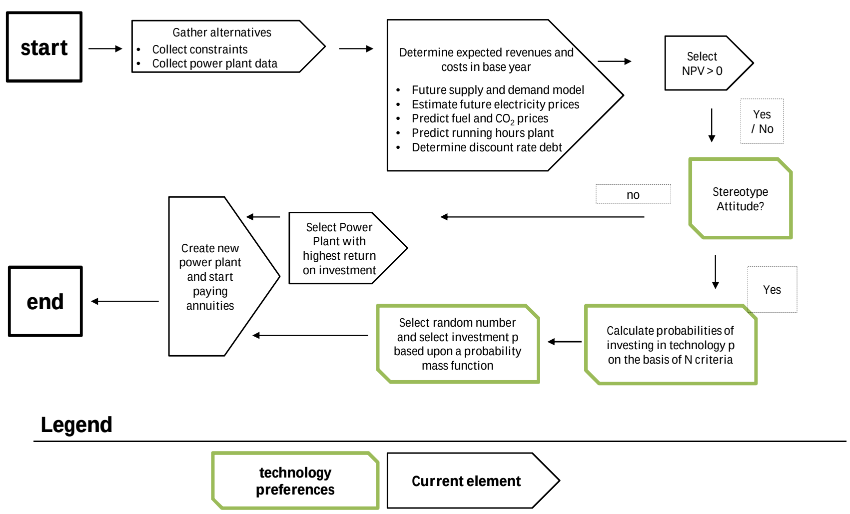


Figure 3.4: Technology preferences positioned in the current algorithm

The pseudo-code of the algorithm including the technology preferences is described on the next page. The pseudo-code does not include the exact code, but shows the main steps to follow.

[2] Changing interest-rates etcetera.

Algorithm 1 Technology preferences: multi-criteria decision analysis

Require: Run the current algorithm described in section 3.1 up to the estimation of the $NPV_{p..P}$

for all Investors **do** get $\{c_n, c_{n+1}, c_N\}$ and $\{\psi_n, \psi_{n+1}, \psi_N\}$
  for all Technologies **do** calculate $\sum c_{n..N,p}$ and save the technology specific multi-criteria score $c_{n,p}$.
    if $\{\psi_n, \psi_{n+1}, \psi_N\} = 0$ **then** Select the investment according to $\mathbf{max}(NPV_{p..P})$.
    end if
  end for
  if number of profitable technologies >= 2 **then** calculate

$$\omega_p = \frac{c_{n,p} \cdot \psi_n}{\sum c_{n,p...P}} + \frac{c_{n+1,p} \cdot \psi_{n+1}}{\sum c_{n+1,p..P}} + \frac{c_{N,p} \cdot \psi_N}{\sum c_{N,p..P}} \tag{3.1}$$

    if min & **max** (ω_p) **then** Save variable
    end if
    for all Propensities **do** calculate

$$n_{\omega_p} = \omega_p - \mathbf{min}(\omega_{p..P})/\alpha \cdot \frac{1}{\alpha \cdot \mathbf{max}(\omega_{p..P}) - \mathbf{min}(\omega_{p..P})/\alpha} \tag{3.2}$$

    end for
    for all Probabilities **do** calculate

$$\upsilon_p = \frac{n_{\omega_p}}{\sum n_{\omega_p}} \tag{3.3}$$

    end for
    Establish a discrete probability distribution.

$$\sum_{p \in P} f(p) = 1 \tag{3.4}$$

  end if
  Option 1: Select a random number and "role a die" select the technology to invest based upon the earlier established discrete probability distribution.
  Option 2: Invest in the technology with the highest propensity
end for

Credit-risk considerations

In figure 3.5 the credit-risk of the second algorithm is incorporated in the current algorithm. The credit-risk consideration plays a role before the calculation of the weighted average cost of capital (WACC). Before the investor is requesting a loan from a bank first the current financial structure of the investor is analysed. This implies the valuation of debt and assets. The value of debt at time t is determined by the sum of debt minus the already paid annuities. The value of the assets is determined by the invested capital in the portfolio plus the cash position minus the depreciation of the plants in the portfolio. The assumption here is that the financial structure is analysed from a accounting perspective. In reality the goodwill of a certain investor could also represent a certain value. This is not taken into account in the model.

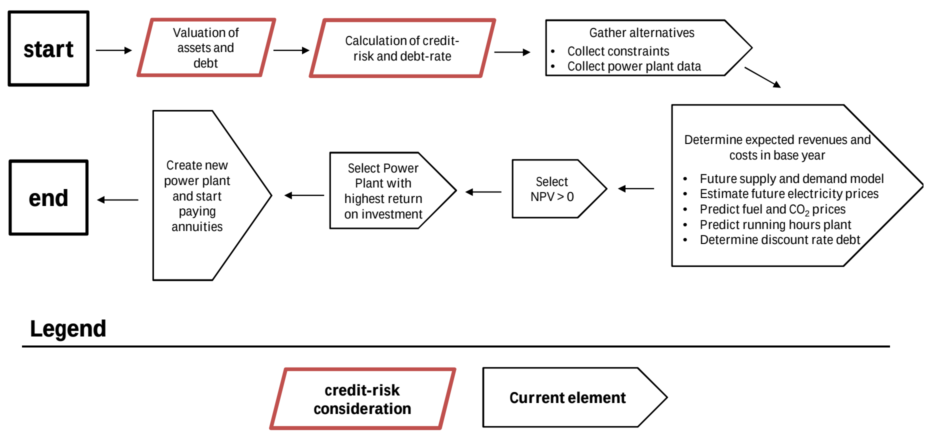


Figure 3.5: Credit-risk considerations positioned in the current algorithm

Algorithm 2 Credit-risk consideration: Black-Scholes debt-pricing model

for all Investors **do** calculate $\sum_{p \ldots P} D_p$ and $\sum_{p \ldots P} A_p$
  for all Powerplants **do** calculate D_p and A_p
  end for
  Determine the probabilities of the standard normal variable

$$d_{1,i} = \frac{\mathbf{log}(\frac{A_i}{D_{i,t}}) + r_f + \frac{\sigma^2}{2} \cdot (T - t)}{\sigma \cdot \sqrt{T - t}} \tag{3.5}$$

$$d_{2,i} = d_{1,i} - \sigma \cdot \sqrt{T - t} \tag{3.6}$$

  Calculate the market-value of equity

$$E_i = A_i \cdot N_{d_{1,i}} - D_{i,t} \cdot \exp^{-r \cdot T - t} \cdot N_{d_{2,i}} \tag{3.7}$$

  Then price the debt

$$d_{i,t} = A_i - E_i \tag{3.8}$$

  Finally determine the interest-rate

$$r_f + r_{p,i} = \frac{-1}{T - t} \cdot \mathbf{ln} \left(\frac{d_{i,t}}{D_{i,t}} \right) \tag{3.9}$$

  The investor decide whether to accept the debt offer yes or no
end for

Risk-averse behaviour

These additions of the risk-averse behaviour are visualised in 3.6. The technology specific risk-averse behaviour is coming forward before the calculation of the net present value. This is the case because technology specific risk-premiums are included in the determination of the weighted average costs of capital. The portfolio diversification decision plays a role after the selection of the profitable projects. On the basis of the market-share the investor decides whether the portfolio is large enough to diversify it.

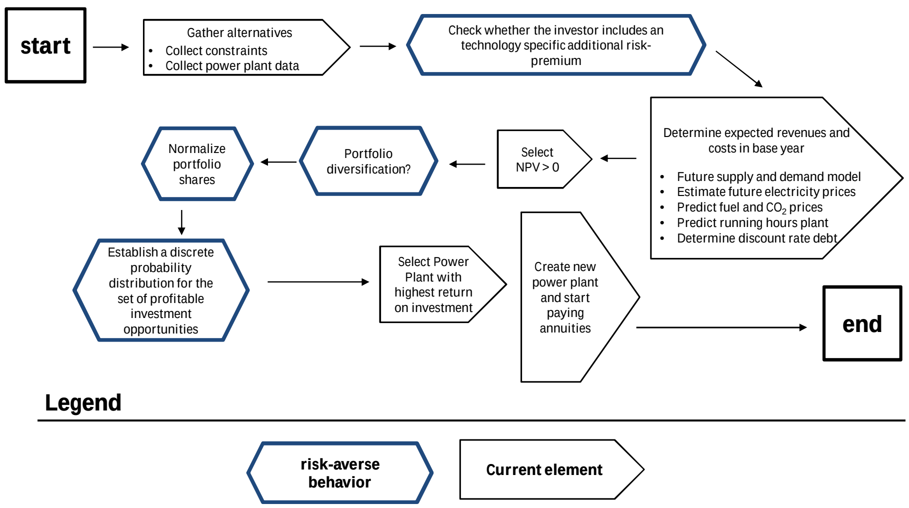


Figure 3.6: Risk-averse behaviour positioned in the current algorithm

Algorithm 3 Risk-averse behaviour: concepts from portfolio theory

Require: Run the current algorithm until the gathering of the alternatives and get $\{p_n, p_n + 1, p_N\}_i$.

for all Investors **do** calculate $S_{p,i}$ technology p portfolio shares of the investor i

$$S_{p,i} = \frac{\sum V_{p,i}}{\sum V_{p..P,i}} \tag{3.10}$$

Than check for r_i and determine the $WACC_i$

$$WACC_i = \frac{E_i}{V_i} \cdot k_{e,i} + \frac{D_i}{V_i} \cdot k_{d,i} + r_{i,p} \tag{3.11}$$

calculate $S_{p,i}$ by:

$$n_{i,p} = S_{p,i} - \mathbf{min}(S_{p..P,i})/\alpha \cdot \frac{1}{\mathbf{max}(S_{p..P,i}) \cdot \alpha - \mathbf{min}(S_{p..P,i})/\alpha} \tag{3.12}$$

.

calculate $p_{i,p}$ by:

$$p_{i,p} = \frac{1 - n_{i,p}}{\sum_{p \in P} n_{i,p..P}} \tag{3.13}$$

Establish a discrete probability distribution.

$$\sum_{p \in P} f(p) = 1 \tag{3.14}$$

Option 1: Select a random number and "role a die" select the technology to invest based upon the earlier established discrete probability distribution.

Option 2: Invest in the technology with the highest propensity

end for

Integrated algorithm and assumptions

Since the algorithms are implemented in a modular way it is possible to combine the modules in one new integrated algorithm containing all decision-making processes described in the algorithms. There are two overlapping elements. The portfolio diversification and technology preferences. When an investor has both behavioural elements included the technology preferences are considered superior.

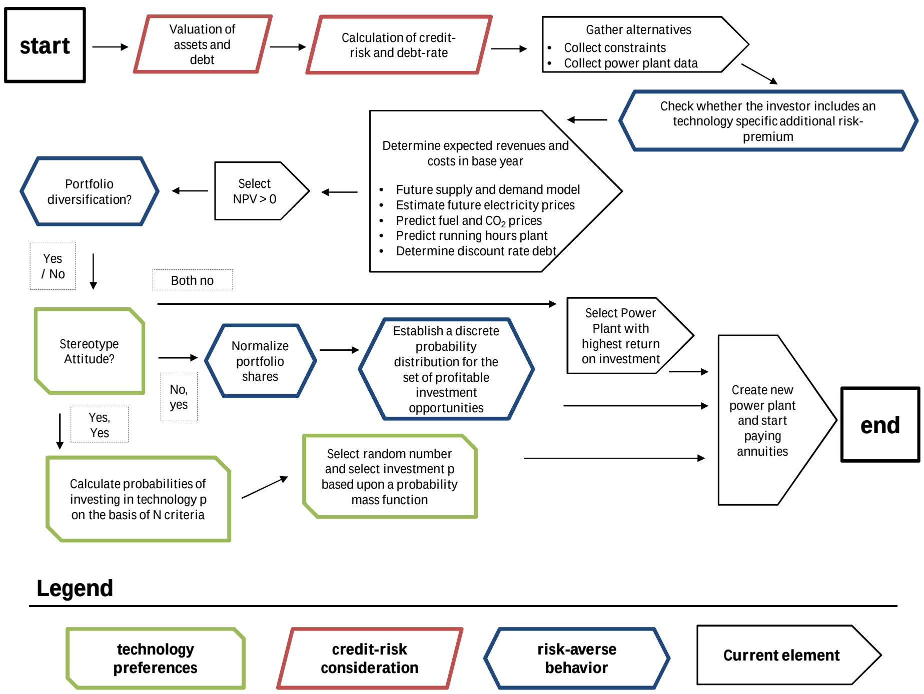


Figure 3.7: Visualization of the integrated investment algorithm

3.4 Java software implementation structure

The algorithms described in the previous chapter are implemented in the EMLab-generation model explained in chapter 3.1. The general code content and structure is visualized in a mind-map in figure 3.8. The general structure of the model is:

An investor owns the **generic investment role** property. The four possibilities are:

1. *InvestInPowerGenerationTechnologies.java*
2. *InvestInPowerGenerationTechnologiesWithRiskAversityRole.java*: extends (1).
3. *InvestInPowerGenerationTechnologiesWithPreferences.java*: extends (1).
4. *InvestInPowerGenerationTechnologiesWithCreditRiskRole.java*: extends (1).

Every investor will have predefined investment behaviour. What the exact combinational mix will be is explained in the experiments section. Within the algorithm the behaviour is dynamic due to changing market shares or financial structures, but the algorithm contents remain fixed. The role as defined above encapsulates investor's behaviour. Roles, which are defined in AgentSpring are modular pieces of behaviour that can be chained and combined to produce more sophisticated behaviours. Here four roles represent behaviour including all algorithms. The mind map in figure 3.8 shows the variables, commands and further constructs in the Java code. It provides a comprehensive overview on the modelling content.

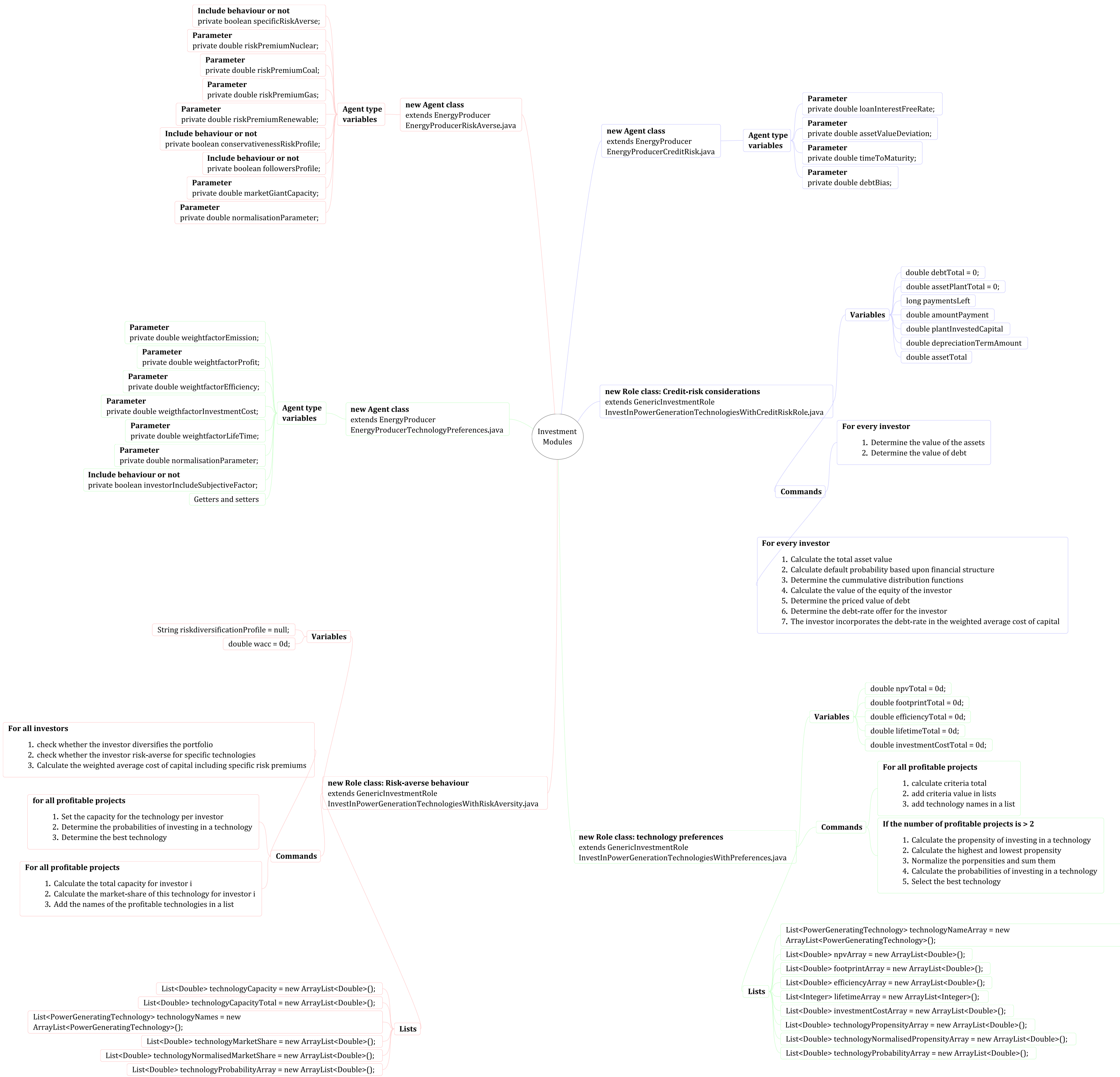


Figure 3.8: Representation of the algorithm content and structure

3.5 Verification of the algorithms

This chapter describes the verification of the model. The verification includes the activity of checking whether the algorithms functions the way they intend to do. To distinguish the verification and validation the following questions are taken into account in this research.

1. **Verification** is the model correctly developed?
2. **Validation** is the model fit for purpose? This will be performed after the experiments.

Verification

The verification of the model includes multiple steps or tests. In [30] four main elements for the verification of an ABM model are suggested. The ABM modelling paradigm requires a specific verification focus due to the modelling characteristics. The first is the recording and tracking of investor behaviour. In this test specific parts of the algorithm are analysed and checked for errors. The second test is the single investor testing where the behaviour of one single investor is verified. A third step is the testing of interaction among investors in a limited model. Here the interaction among different investors is analysed. The last step is the multi investor testing where the model behaviour of multiple investors are examined. In the last step the three algorithms. The steps all include checks for correct coding, dimension analysis and checks for numerical errors.

Tracking and recording of behaviour

The tracking and recording of parts of the algorithms is performed using loggers and testing parts of the code in an isolated environment if possible. The loggers give information on specific parts of the code during the running of the simulation. The loggers are used in specific test classes which makes is more convenient to iteratively "build up" a working model. For the three algorithms some examples of loggers are presented in table A.1. One example of a logger test is the check whether the asset and debt value is correctly calculated by the specific investor. In this code the debt for a single investor is calculated by making use of predefined input information. Another test is the check for the calculation of the propensities of the different algorithms. Below a code example is presented on the verification of the debt valuation. In this situation there is only one market and one investor which owns one plant. The investor has a total debt of 1000 million on the asset which will be paid back by eight annuities of 125 million. In case there are already two payments done the debt value is obviously 750 million. Since the outcome of the logger was 750 million, the calculation is considered correct. This test performed for all kinds of values and made robust for negative values which should not be possible.

Code 3.1: Logger example debt-value calculation

```
double debtTotal = 0;
double assetPlantTotal = 0;
        for (PowerPlant plant : reps.powerPlantRepository.findPowerPlantsByOwner
            (agent)) {
            if (plant.getLoan().getNumberOfPaymentsDone() < plant.getLoan().
                getTotalNumberOfPayments()) {
                long paymentsLeft = plant.getLoan().getTotalNumberOfPayments()
                        - plant.getLoan().getNumberOfPaymentsDone();
                double amountPayment = plant.getLoan().getAmountPerPayment();
                debtTotal += (paymentsLeft * amountPayment);
            }
            }
            logger.warn(agent + " debt value is " + debtTotal);
```

Single investor test

The correct coding of the model is tested by using so called "JUnit" tests. JUnit is a open-source Java oriented testing framework. The framework provides the tool kit to test the developed algorithms. It is for example possible to use assertions for testing expected values and annotations to identify the tested methods. The functionality of the JUnit test is visualized in 3.9. For the algorithms slightly adapted JUnit tests are developed due to the large number of required inputs. This means that some already verified parts of the algorithm are simplified to reduce the amount of work. This simplification does not affect the added value of the test. In table A.2 of the Appendix examples are presented of the single investor tests. All the tests are performed multiple times and under different parameter settings. Besides normal settings the model robustness is also checked for very extreme settings like enormous debts and very extreme attitude configurations.

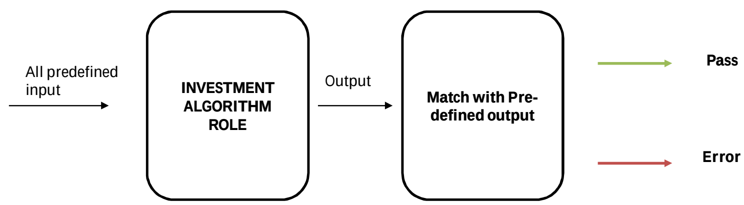


Figure 3.9: JUnit functionality

Interaction test

Interaction among investors is large and limited at the same time. The investment decision of one investor influences the investment decision of the other investor because a new build plant has impact on the market. The interaction could therefore be large via the market. How large the impact is depends on the size of the market and the plant. It is likely that in a market where some of the investors are only investing in base load plants other investors tend more to invest in flexible peak load plants. The interaction is also limited because investors are not interacting with each other directly.

Multi investor test

The last step of the verification is testing the algorithms together. This implies experiments where multiple investors include very different investment behavioural configurations. Here the model is verified for a large parameter sweep doing a significant number of runs. These tests did not result in unexpected outcomes. A first example is the following experiment: in the market there are investors which have a huge debt resulting in a situation where lending money is almost impossible due to the weak financial situation. Taken into account that all investors start with a certain initial capacity the expectation is that the investors with large debts will slowly loose their market-share. The process is slow because the average lifetime of the (newer) power plants is around 30 years. In figure 3.10 this experiment is visualized. In the figure, 2 patterns are visible. The first pattern is the increasing amount of capacity of a selection of investors (D,F,G,H and I), the second pattern is the decreasing amount of capacity by a selection of investors (A,B,C and E). After twenty years the difference between the two groups of investors becomes significant.

This result is considered desired behaviour because investor A,B,C and E have a fixed debt of 100 billion resulting in interest-rate offers above 45 percent. This percentage is to high to enable profitable investments.

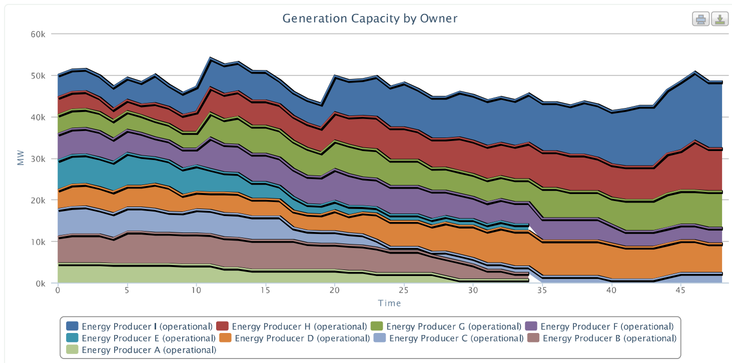


Figure 3.10: Verification: investors in default

Another extreme multi investor test is a market where all the investors are extreme risk-averse for renewable electricity capacity. This non realistic experiment implies that it is likely that investors are only investing in non renewable technologies. This experiment is visualized in figure 3.11. The presented experiment includes just a arbitrary, non realistic parameter configuration, so the visualization is purely to show that there are no investments in renewable capacity.

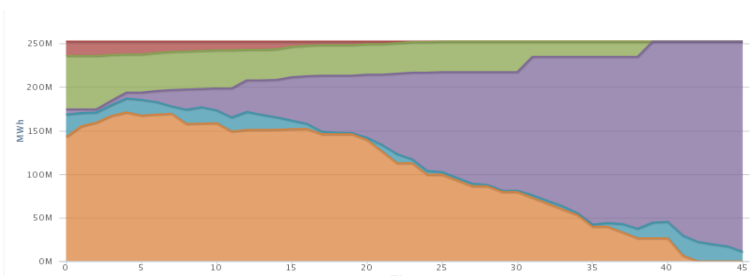


Figure 3.11: Verification: extreme risk-averse towards renewables

3.6 Modelling conclusions

The question was: *how are different conceptual models of investment behaviour translated into a set of investment algorithms within EMLab-generation?*.

Algorithm	Model formalization details
Technology preferences	• **Model formalization**: Investors include criteria and weight-factors $\{c_n, c_{n+1}, c_N\}$ and $\{\psi_n, \psi_{n+1}, \psi_N\}$ to calculate the utility of an investment option. • **Software translation**: New Java classes in EMLab-generation are implemented. The first class includes the new investor which also takes subjective factors into account and the second class includes the new investment role where the utility function is calculated. The MCDA is defined after the selection of the list of profitable investments.
Credit-risk considerations	• **Model formalization**: Investors price their equity and debt to estimate their probability of default. This gives them a certain risk-profile with a associated interest-rate offer. This is included in the net present value calculation. • **Software translation**: Like in the first algorithm this implies two new classes where the properties and investment role of the investor which incorporates credit-risk are defined. The code which enable investors to reflect on their own financial position is positioned before the calculation of the net present value of the investments.
Risk-averse behaviour	• **Model formalization**: The risk-averse investors include additional risk-premiums in their net present value calculation and tend to diversify their portfolio when they reach a certain size in the market. • **Software translation**: Two classes again implement the described formalization. This remains equal to the previous algorithms. The first part of the code is positioned at the determination of the weighted average cost of capital. The second part of the code including the portfolio diversification is placed after the selection of profitable projects.

Table 3.1: Conclusions on the formal algorithms

Chapter 4

Simulation

This chapter includes the design of experiments, analysis and validation of results. The design of experiments (DoE) includes what experiments are performed, why and how. The design of experiments is related to chapter A.3 of the Appendix. The results section includes the data-analysis and statistical tests. This part is related to A.4 of the Appendix. The chapter starts with the design of experiments and ends with the validation of results. The outcomes which support answering the research question are translated to conclusions in the synthesis chapter.

4.1 Design of experiments: what, why and how?

The design of experiments is performed by making use of the design steps described in [30]. This book elaborates on the design of experiments for agent-based models which is suitable for this research. According to [30] there are multiple considerations in the design of experiments. These considerations will be followed schematically to structure the design. This research includes four hypotheses. Hypothesis H1, H2 and H3 answer whether investment decisions are substantially sensitive for the assumed investment algorithm in an EU-ETS governed energy market simulation. This is an important first step in providing an answer on the research question.

If the experiments for H1, H2 and H3 prove that more realistic investment models have substantial effect on the investments done in relation to the base-case, it could provide a signal that the effectiveness of the EU-ETS is affected. When more realistic investment models do not influence investment substantially, it is an indicator that the effectiveness of the EU-ETS mechanism is unaffected. The first step is therefore to analyse the investments, the second step is to look at the EU-ETS mechanism.

1. **H1** The incorporation of credit-risk considerations, risk-averse behaviour and technology-preferences in investment decisions result in substantial differences in investments[1].
2. **H2** There is a significant negative correlation between investments in the capital-intensive technologies and the sensitivity for credit-risk.
3. **H3** There is a significant positive correlation between investments in renewable technologies and the green tendency of investors in the market.
4. **H4** The incorporation of credit-risk considerations, risk-averse behaviour and technology-preferences in investment decisions result in substantial CO_2 emission right price volatility.

[1] In relation to the base-case including homogeneous profit only behaviour.

The chosen benchmark is a two country liberalized electricity market governed by the EU-ETS mechanism. The effectiveness of the EU-ETS mechanism will be measured by the CO_2 price volatility of an emission right. This volatility is an indicator for the stability of the investment signal and is used in previous studies addressing the effectiveness of the EU-ETS [63].

The design of experiments for hypothesis H1, H2 and H3 is different than for hypothesis H4. This has to do with the character of the hypothesis. Hypothesis H1, H2 and H3 are more exploratory oriented, hypothesis H4 is more confirmatory. The first experimental design for hypothesis H1, H2 and H3 will support the falsification of exploratory hypotheses and therefore includes a larger parameter space and more experiments[2]. This experiment space consists of the multi-dimensional grid formed by the number of parameters in the algorithms. One point in the experiment space represents an experiment. The results of hypothesis H1, H2 and H3 will also be used as validation of the results. The 4th hypothesis includes a more specific policy hypothesis regarding the effectiveness of the EU-ETS mechanism for different more realistic investment algorithms. The DoE and sub-hypotheses are described in the following paragraph.

Design of experiments procedure

1. Determination of the main benchmark experiment.
2. Selection of the parameters that will be varied in the investment algorithms.
3. Determination of plausible ranges and intervals of parameter values[a].
4. Selection of plausible collections of parameter values. This is done by making use of a latin-hypercube where correlation among parameters is taken into account.
5. Writing a r-script to generate the experiment files [b].
6. Determination of the key-performance indicators and save them as "queries"
7. Running the experiment files [c].

[a] If possible, ranges are determined by data from theory. In case of doubts a larger parameter sweep is selected. One example is the risk-free rate for power producers. This rate will not fall below 1% or 2% and will not go above 10% looking at historic data.

[b] To complete this step a script is written in R to generate quickly N experiments including the intended parameter values generated by latin hypercube sampling.

[c] This is done on a high performance cluster to lower the simulation time

The benchmark experiment

The experiments are schematically described in table 4.1. The selected benchmark experiment is the connected Dutch and German electricity market governed by the EU-ETS mechanism. The investors in this market include homogeneous profit only investment behaviour. This benchmark is chosen because it reflects the North-West European market for a certain extent. The experiment does not include renewable energy policies like the SDE+ or other feed-in tariff measures, but does include the carbon EU-ETS mechanism. The initial portfolio situation reflects the German and Dutch technology portfolio. The fuel-price time-series are based upon three DECC forecast [39]. The DECC time-series include low, medium and an high fuel-price experiment. A second reason for the selected benchmark experiment is that the investment algorithms are based upon empirical data of North West European investors.

[2] Also called "experiment or experiment space"

The experiments

The experiments are divided in 5 groups. The first group includes experiments where investors evaluate investments options only based upon profit. These experiments are the base-case experiments. There are three groups of experiments where the three algorithms are analysed individually, these experiments will be mainly used as validation. The last group of experiments includes a combination of behaviour. The parameter configuration includes the more plausible experiments. The parameter sweep setup is described in detail for every particular group of experiments in chapter A.3 of the Appendix. The groups with experiments are generally described:

1. **Base case including the basic algorithm**: This experiment includes the base-case where the regular investment algorithm is used to simulate the EU-ETS governed market model. The EU-ETS benchmark model includes a limited number of stochastic elements and parameters (like debt/equity ratio for new investment) are fixed. The base-case simulation is replicated 75 times to ensure that stochastic effects are averaged out. The 75 runs require 112.5 running hours including 3,000 observations. There are three main base-case experiments. One including low fuel-price time series, one including central fuel-price time series and one including high fuel-price time series. These fuel-price forecasts are retrieved from [39].
2. **Algorithm including technology preferences**: This group consists multiple experiments with different technology preference configurations among investors. The selection of parameter value collections is performed by making use of an adapted latin-hypercube sample. Practically this implies e.g. that there are experiments with a high, lower and a lowest fraction of renewable oriented investors, a high, lower and lowest fraction of profit only oriented investors etcetera. This is made visible in figure 4.1. The parameters are the weight-factors for the different criteria. The weight-factors have a ordinal scale and are selected via an uniform distribution. There are 20 different experiments including different investor configurations. The choice for the number of experiments is based upon the present computational power of the HPC. The experiments are like the base-case replicated 75 times to ensure that stochastic effects are averaged out. The 1,500 runs require 2,250 running hours including 60,000 observations.

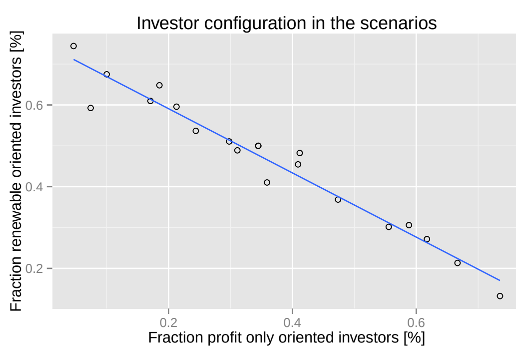


Figure 4.1: Experiments including technology preferences

3. **Algorithm including credit risk considerations**: These experiments include experiments where investors have different sensitivity levels for credit risk. This means that there are experiments where investors are very sensitive for credit-risks and experiments where investors are less sensitive for credit risks. The parameters are the asset volatility, time to maturity, risk free rate and initial debt status. The parameter intervals have a ordinal scale. The number of experiments is 15 and are 75 times replicated. The 1,125 runs require 1.688 running hours for 45,000 observations.
4. **Algorithm including risk averse behaviour**: This group of experiments includes various configurations of risk averse behaviour (towards different technologies). The parameters are the technology specific risk premiums. There are also extreme configurations included to validate the main behaviour of the model. This means that it is the expectation that investors with a nuclear risk premium of one will not invest in nuclear any more due to the enormous risk perception. There are 21 experiments included in this test-group. These experiments are all replicated 75 times. The 1,575 runs require 2,362 running hours including 63,000 observations.
5. **Algorithm including a combination of behaviour**: this group consists of a mixture of the investment algorithms. The parameters include the collection of parameters as described above. A combination of behaviour is used in the experiments to verify the policy-oriented hypothesis H4. The experiments include parameter configurations where the extreme cases are filtered out. An example is that these experiments include one or two investors which rank sustainable criteria in their investment process as very important. In the real world this could be linked to investors like Eneco and Delta. This group includes 30 experiments which are all replicated 75 times. This resulted in 2,250 runs.

Group of experiments	Quantity	Description
Base-case	3	Normal EU-ETS experiment including a low, central and high DECC fuel-price forecast. Investors, which meet constraints, homogeneously evaluate NPV $>$ 0 investment opportunities based on profitability only
Technology preferences	20	Investors evaluate NPV $>$ 0 investments based upon a selection of criteria. There are experiments with different heterogeneous investor attitude configurations. The investors within an experiment judge subjective criteria in different ways. These experiments are used for the validation of the model.
Credit-risk consideration	15	Investors include credit-risks considerations in the investment evaluation. There are experiments with different investor specific sensitivities for credit-risk. Investors here ask themselves "Is this interest-rate competitive for me?". These experiments are used for the validation of the model.
Risk-averse behaviour	21	Investors include technology specific and portfolio risks in the investment evaluation. There are experiments with different levels of risk-averse behaviour and different tendencies for portfolio diversification. These experiments are used for the validation of the model.
Combination mix	27	Investors include subjective preferences, credit-risk considerations and specific risk-averse behaviour towards technologies in their investment decisions. The focus in these experiments is on plausible parameter configurations. This includes mainly experiments without extreme parameter values.

Table 4.1: Description of the groups of experiments

In total the 86 experiments embody 6,450 runs which all took about 1.5 hour per run. On the HPC the simulation ran on 34 machines resulting in about 190 runs per machine. The collection of experiments took about 12 days of simulation time (285 hours). This resulted in about 450 mega bytes of data. The saved data was defined in specific query file containing the code to save the data on a local machine. Some variables are selected as indicators to analyse the hypotheses. The major key performance indicators to analyse the investments made are the technology capacity which indicates in what technologies is invested over time. A second indicator is the total operational capacity minus demand which indicates the capacity margin. A third indicator are electricity shortages which indicate the security of supply. The average electricity price show the responsiveness of investors. The average sensitivity for credit-risks is used to research the relationship between the sensitivity for credit-risk and investments in capital intensive technologies. The green market tendency profile is required to analyse the relationship between the average green tendency of investors in the market and the investments in renewable capacity. The main indicator for the effectiveness of the EU-ETS mechanism is the CO_2 price volatility. The key performance indicators are defined in table 4.2.

Indicator	**Unit**
Technology capacity mix	GW/technology
Electricity shortages	minutes/year
Average CO_2 price	EUR/TON
CO_2 price volatility	%

Table 4.2: Key performance indicators

The most important experiments will be selected for analysis in the main text. The selected experiments include plausible parameter configurations and are described in table 4.3. The experiments include a combination of behaviour. The experiments are performed for three DECC fuel-price forecasts, so in total 3 times 10 experiments will be described in the main text.

Experiment nr.	Experiment content
1 - base	The investors show homogeneous profit only behaviour.
2	10 % of the investors include weighty sustainable criteria in their investment decisions[3]. The investors are little sensitive for credit-risks and up to 40 % of the investors is more risk averse for coal and nuclear technology which are most under societal pressure.
3	20 % of the investors include weighty sustainable criteria in their investment decisions. The investors are little sensitive for credit-risks and up to 40 % of the investors is more risk averse for coal and nuclear technology which are most under societal pressure.
4	10 % of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and large investors[4] are diversifying the portfolio.
5	20 % of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and large investors are diversifying the portfolio.
6	15 % of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and investors are not specifically risk-averse and do not diversify the portfolio.
7	15 % of the investors include weighty sustainable criteria in their investment decisions. The investors are not sensitive for credit-risks and investors are not specifically risk-averse and do not diversify the portfolio.
8	15% of the investors include weighty sustainable criteria in their investment decisions. The investors are little sensitive for credit-risks and large investors are diversifying the portfolio.
9	None of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and investors are not specifically risk-averse and the largest investors in the market are diversifying the portfolio.
10	15% of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and some investors are specifically risk-averse for coal and nuclear technology. The largest investors in the market are diversifying the portfolio.

Table 4.3: Selection of the most interesting experiments

4.2 Data-analysis, simulation and results

This section includes a concise version of the data-analysis and presentation of the results. This section also includes the description of the performed statistical tests to study the hypotheses. A more in detail description of the results can be found in Appendix A.4. The hypotheses will be answered sequentially. In order to understand the schematics of the analysis a procedure is presented in subsection A.4 of the Appendix.

To study this first hypothesis the technology capacity mix development in GW/technology is analysed. The development of the capacity mix indicates in what technologies is invested during the 40 simulation years. In figure 4.2a, 4.2b and 4.2c the base-case experiments are presented showing different capacity development patterns for a low, central and high fuel-price forecast.

The base-case in figure 4.2a including low fuel-prices show that gas technologies will increase their capacity share position and that coal and renewable technologies will play a smaller role in terms of capacity share. More investment can be expected in CCS technologies under the assumptions in the base-case[5]. The main observations are:

1. Gas technologies such as OCGT, CCGT and CCGT-CCS get increasingly dominant due to their competitive fuel-price ratio in relation to coal and relatively low carbon emission.
2. Renewable technologies such as biomass, photovoltaic, wind and wind offshore are not competitive enough which results in a decreasing number of investments. The initial renewable electricity capacity portfolio slowly decreases due to the absence of renewable policies which could increase the attractiveness of these type of investments. This is a comparable pattern with the present situation in North-West Europe looking at central[6] electricity generation capacity [64].
3. Investment in nuclear technology remains stable. Nuclear technology is CO_2 emission free and does not have to compete with a large capacity of renewables in the merit order.
4. There is only investment in coal technologies with CCS sequestration. Coal technologies without CCS sequestration like a conventional pulverized coal plant is no competitive investment option under the assumptions in this base-case.
5. Low fuel-prices result in a market with a high generation flexibility due to the large diffusion of gas technologies.

The base-case including central fuel-prices in figure 4.2b shows for some observations similar results, but in here IGCC-CCS seems to be a larger competitor for gas technologies such as CCGT-CCS and CCGT. The central fuel-price forecast gives coal a more competitive price ratio towards gas which results in more coal investment. Like in the low fuel-price experiment, investment in nuclear technology remains stable for equal reasons. Renewables get slightly more attractive in this experiment since some investment in wind offshore is visible after 25 years. The main observations are:

1. Gas technologies get increasingly dominant in the first 25 years, but IGCC-CCS becomes more competitive after that. It is a confirmation that fuel-prices have substantial effects on the investment pattern.

[5] In all experiments technological improvement factors are included and uniform. The observations here only hold for these assumptions. Further political and institutional factors are not included in the scope.

[6] There is an slowly increasing percentage of renewable electricity, but this is mainly caused by small scale decentral investments

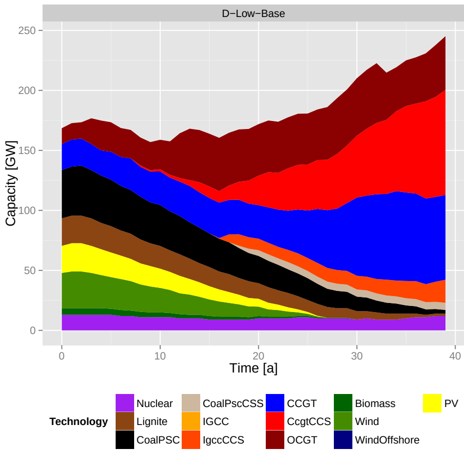
2. Renewable technologies are not competitive enough which results in a decreasing number of investments. For the assumptions in the model on technological development and central fuel-prices are renewables no competitive investment in contrast to for example CCS technology.
3. Investment in nuclear technology remains stable. The first reason is that there is no competition with renewable generation capacity in the merit order and secondly that nuclear technology is carbon neutral.
4. There is mainly investment in coal technologies with CCS sequestration. There is some investment visible in lignite, but this is negligible.
5. Central fuel-prices result in a market with a decreasing flexibility due to the increasing diffusion of IGCC-CCS.

The base-case including high fuel-prices in figure 4.2c shows an investment pattern which could be a result of what is happening in reality at the moment in terms of fuel-prices. Gas technologies are not able at the moment to compete with cheaper coal [65]. This results in gas-based power plants which are not generating electricity at all and therefore cause losses for electricity companies. Only the very flexible OCGT shows stable investment. Figure 4.2c shows that in contrast with the previous base-cases that there is stable investment in lignite. Notwithstanding the high carbon emission of lignite, the technology remains competitive enough in relation to other technologies. The high fuel prices also result in more investment in nuclear technology. Also more investment in renewable technology is visible.

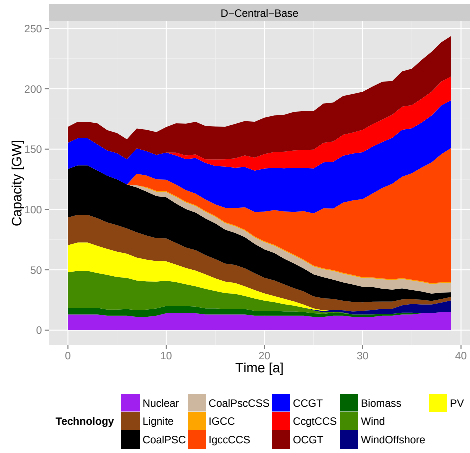
1. Gas technologies cannot compete with IGCC-CCS. Only OCGT shows stable investment.
2. Renewable technologies get attractive after 25 years.
3. Investment in nuclear technology grows.
4. There is not only investment in coal technologies with CCS sequestration, but also in lignite power plants.
5. High fuel-prices result in a market with a low flexibility due to the large diffusion of coal and nuclear technologies.

Now the benchmark or base-cases are analysed it is time to compare the results of the experiments including the more realistic investment models. As mentioned earlier are some experiments selected for analysis which provide the more interesting results. These experiments are presented in table 4.3. The experiments are selected because the include plausible parameter configurations. The total list of experiments can be found in chapter A.4 of the Appendix.

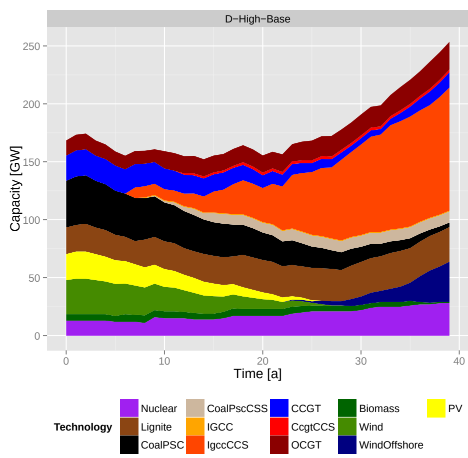
Before the comparison with the experiments is presented is emphasized that the results (investment patterns) are valid for the combination of assumptions on e.g. technological improvements, fuel-prices and demand. The experiments include a wide scale of parameter configurations to ensure that many extreme configurations are analysed and discussed. More information is presented in the discussion chapter on modelling limitations 5.3.



(a) Low fuel-prices



(b) Central fuel-prices



(c) High fuel-prices

Figure 4.2: Base-case capacity mix comparison for three fuel-price forecasts

Hypothesis H1

The results of the experiments will now be analysed and compared with the base-case experiments in the previous section. The first hypothesis is:

> **H1** *The incorporation of credit-risk considerations, risk-averse behaviour and technology-preferences in investment decisions result in substantial differences in investments.*

The experiments with more realistic investment behaviour and low fuel-prices in figure 4.3a shows differences in investments in relation to the base-case. Experiment 2, 3, 4 and 5 show substantial larger investments in renewable technologies like wind offshore, biomass and wind. The fact that investors now also incorporate more criteria than only profit shows a changing investment pattern. This might be logical, but indicates that incorporating sustainable criteria visually seems to have a substantial impact on investments. The higher amount of investments in renewables indicate that there are sufficient profitable investment options in renewable technology available, even in experiments with low coal and gas prices. This can be concluded since the multi-criteria decision analysis becomes active after the selection of the profitable investments. The reason for the absence of renewable investment in the base-case was that renewables are apparently less profitable than other technologies. This is for more realistic investment behaviour obviously no reason to avoid renewable investment opportunities since investors are not only evaluating investment opportunities on their profitability. Experiment 6 and 7 shows less investment in renewables and are more comparable with the base-case. This can be explained by the absence of portfolio diversification in those experiments.There are more equivalences and differences between the experiments with more realistic behaviour and the base-case.

1. The increasing dominance of gas technologies is muted except for experiment 6 and 7. This has to do with the absence of portfolio diversification in those experiments wherefore gas technologies remain more competitive[7].
2. Renewable technologies might not always most profitable due to low prices, but since profit is not the only criterion any more there is more investment in renewables. The percentage of renewables varies between 5 % to 30 % after 40 years. looking at renewable capacity development, wind technology becomes dominant and photovoltaic and biomass remain unattractive.
3. Investment in nuclear technology remains stable similar to the base-case for known reasons. In experiments where investors are more sensitive (experiment 6) for credit-risk there seems substantially less investment in capital-intense technologies like nuclear and IGCC-CCS. This will be studied in hypothesis H2.
4. There is not only investment in coal technologies with CCS sequestration, but now also some investment in standalone IGCC.
5. On average the experiments with more realistic investment behaviour shows less market flexibility because there is a larger diffusion of renewable capacity with a uncertain generation output.

The experiments with more realistic investment behaviour and central fuel-prices in figure 4.3b shows differences in investments in relation to the base-case. Like in the previous experiments with low prices, investment is more distributed among the available technologies in stead of

[7]See table 4.3

one or two very dominant technologies. Although IGCC-CCS gets dominant as in the base-case, investment in this technology is slightly less. This can be explained by the fact that investors in the new algorithms need to borrow money based upon their financial situation. Besides that investors are now also more or less sensitive for this credit-risk. This sensitivity implies that investors are more or less sensitive for potential credit-risks[8]. The credit-risk mechanism in the base-case experiment is that investors need to own 30% of the capital cost as a cash balance in order to invest. The credit-risk algorithm gives investors the possibility to borrow money based on the financial structure of the investor. There seems to be a negative correlation between the sensitivity for credit-risk and the investments in capital-intense technologies. This will be analysed later in this analysis. The further equivalences and differences are:

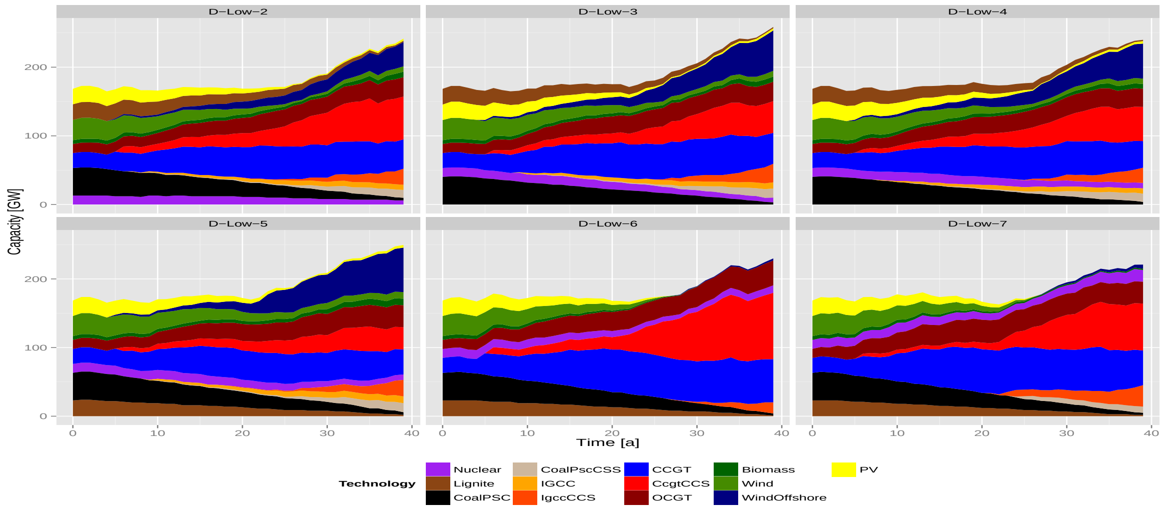
1. Gas technologies are not getting increasingly dominant any more like in the base-case. There is however as in the base-case increasing investments in IGCC-CCS technology.
2. There is substantial more investment in renewable technologies at the expense of IGCC-CCS and gas technologies like CCGT-CCS. In comparison with the experiments with low fuel prices the capacity percentage of renewables fluctuates between 5% to 30%. This is substantially more than in experiments with profit onlt behaviour.
3. Investment in nuclear technology remains stable or grows little.
4. There is mainly investment in coal technologies with CCS sequestration.
5. The market flexibility is comparable with the base-case. There is less inflexible IGCC-CCS capacity, but more renewable capacity with a uncertain generation output.

The experiments with more realistic investment behaviour and high fuel-prices in figure 4.3c shows differences in investments in relation to the base-case such as in the previous cases. The higher prices reduce the investments in gas technologies. Especially in CCGT are substantially less investments. Furthermore show all experiments more investments in renewable capacity. Also experiment 6 and 7 now show substantial investment in renewables for high fuel prices in contrast to the low and central fuel price. Here the effect of the fuel as exogenous factor is clearly visible.

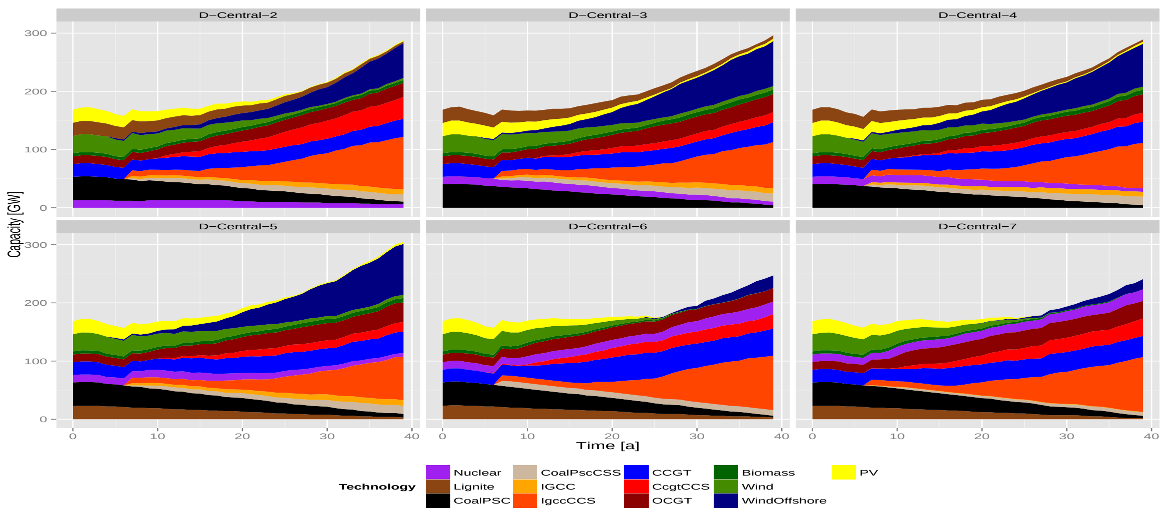
1. Gas technologies cannot compete with IGCC-CCS which is comparable with the base-case. The difference with the base-case is that the capacity share of IGCC-CCS is less dominant.
2. Renewable technologies get earlier attractive than in the base-case. Now investment already grows substantially after 10 years. There is substantial investment in biomass, wind and most of all wind offshore. Some experiments show also investments in photovoltaic, but those investments remain limited.
3. Investment in nuclear technology decreases in some experiments in contrast to the base-case. This can be explained by the investors which are more sensitive for credit-risk. The effect is visible, but less substantial than for example with investments in renewable capacity. Further, there is not only investment in coal technologies with CCS sequestration, but also in lignite power plants. This is similar to the base-case.
4. High fuel-prices result in a market with a low flexibility due to the large diffusion of coal and nuclear technologies. This is also comparable with the base-case.

What these observations mean for the hypothesis will be presented later in this section since this part provides only the descriptive analysis.

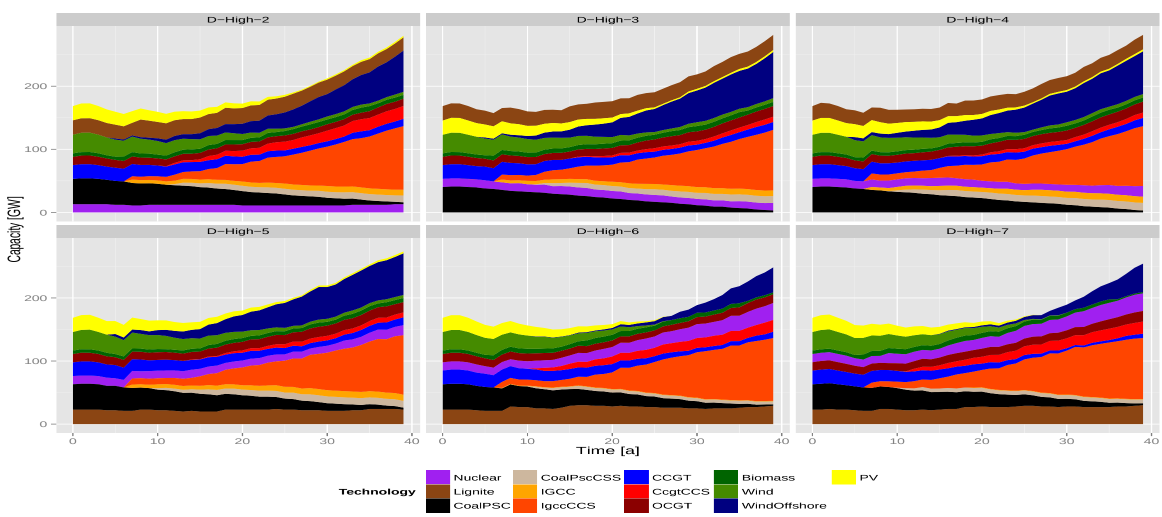
[8] For example: an investor in a weak financial position which is less sensitive for credit risk will still accept loans while an investor which is more sensitive will not accept the offer.



(a) Low fuel-prices



(b) Central fuel-prices



(c) High fuel-prices

Figure 4.3: Technology mix comparison for several experiments

The second step is to use statistical tests to get more insight whether the capacity mix averages over time are indeed substantially different from the base-case. Although differences are already noticed by looking at the graphs, a statistical test can provide an additional argument. The test whether the average capacity between the base-case and the other algorithms is significant is analysed by using independent sample t-tests for every run (forty years simulation time in total). There are some conditions for performing the t-test. These conditions are:

1. The samples are independent
2. The measure scale is ratio/interval
3. The samples are normal distributed

The conditions are met, but a time dependency has to be taken into account. The time dependency is caused by the initial technology portfolio which is the same for all experiments. Due to the building time of plants in the simulation it will take years before patterns are recognizably different. This time dependency is not problematic and averaged out by using box-plots. For every year t-test is used to compare technology capacity mix averages.

Explanation of the box-plot *Every figure (4.4a, 4.4b and 4.4c) shows one graph per experiment (experiment 2 to 7). One graph includes one box-plot per technology, so 13 in total per graph. One box-plot contains 40 t-tests indicating whether a technology has a significant different average capacity in relation to the base-case during the whole simulation. This box-plot makes it possible to measure the overall (over 40 years) differences more accurate than just testing different points in time. When the box (IQR) is above a p-value of 0.025 the technology can be considered not substantially different from the base-case. A visible box therefore means, no substantial difference.*

The box-plots of the most interesting experiments are presented in figure 4.4a, 4.4b and 4.4c. In those figures is immediately visible that all experiments show non substantial and substantial differences in investments. Investments in technologies like photovoltaic, coal , nuclear and lignite remain in almost all experiments non substantially different from the base-case including profit only behaviour. The experiments including more realistic behaviour however also shows substantially different investment in wind offshore, Coal CCS and IGCC CCS.

Table 4.4 shows the cumulative number of substantial different investment patterns for all thirteen technologies. The 6 in the "wind offshore" row in column "low" means for example that the technology was substantially different in all six experiments shown in figure 4.3a. Table 4.4 indicates that wind offshore, OCGT, IGCC and Coal-CCS show the most substantial differences in investments for all fuel price forecasts. The following observations are important for the hypothesis:

1. All experiments show for 1 or more technologies substantial differences in the amount of investments. A exogenous factor such as the fuel-price has also influence on how substantial the difference is. This effect is more influential than the behavioural difference among the algorithms. This is visible by comparing the base-case experiments.
2. The investment pattern changed in the experiments with more realistic investment behaviour, but is not considered very sensitive. There are however substantial differences in investments when experiments include more realistic investment behaviour. This is a signal that the CO_2 price volatility also might be different in relation to homogeneous profit only behaviour in the base-case.

technology	Low	Central	High
N: Nuclear	0	0	5
C: Coal	0	0	0
C+: Coal CCS	5	5	2
I: IGCC	5	5	4
I+: IGCC-CCS	0	2	4
O: OCGT	6	2	3
CT: CCGT	2	2	0
CT+: CCGT CCS	4	3	2
L: Lignite	0	0	0
W: Wind	3	4	0
P: Photovoltaic	0	0	0
WO: Wind offshore	6	6	6
B: Biomass.	5	1	1
Cumulative	36	30	27

Table 4.4: Number of boxplots (LQR) with p-value < 0.025

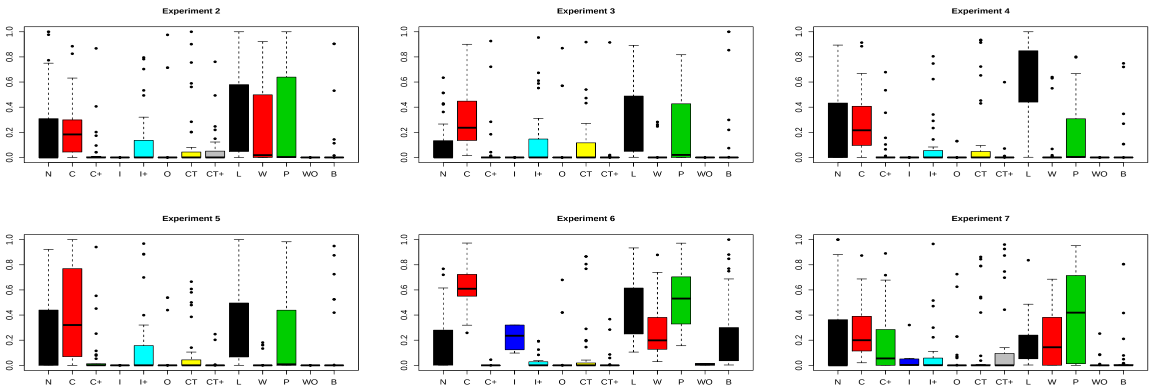
Conclusion on hypothesis H1

Interpretation *From the experiments in figure 4.3a, 4.3b and 4.3c is visible that all experiments show for 1 or more technologies substantial differences in investments. More realistic investment behaviour mainly affects the number of investments in wind offshore, Coal-CCS and IGCC-CCS. For other technologies such as photovoltaic, coal, nuclear and lignite there are fewer experiments with substantial differences in relation to the base-case investment pattern. The fuel-price as exogenous factor showed that it is more influential than behavioural differences among algorithms.*

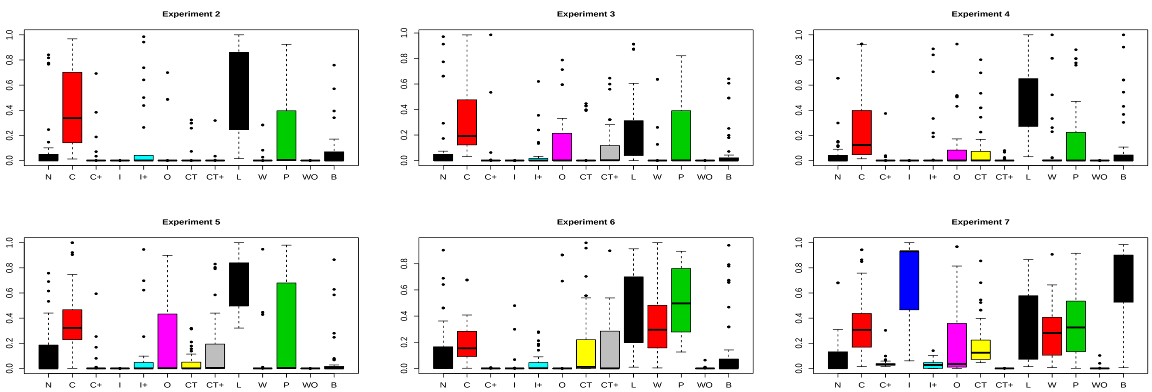
The hypothesis: "The incorporation of credit-risk considerations, risk-averse behaviour and technology-preferences in investment decisions result in substantial differences in investments" is considered not falsified.

This conclusion has implications for the research question. Since hypothesis H1 confirmed that all experiments including more realistic investment behaviour results in 1 or more technologies with substantially different investment patterns, there is now a signal that the CO_2 price volatility also might be substantially different [a]. The experiments including more realistic investment behaviour might provide an new view on the effectiveness of the EU-ETS mechanism. The conclusion on this hypothesis shows the importance of being critical on the implications of the assumed investment behaviour. It could raise the question whether a policy which is evaluated by an simulation model containing one single investment algorithm is robust enough in a electricity market where investors have very diverse investment behaviour.

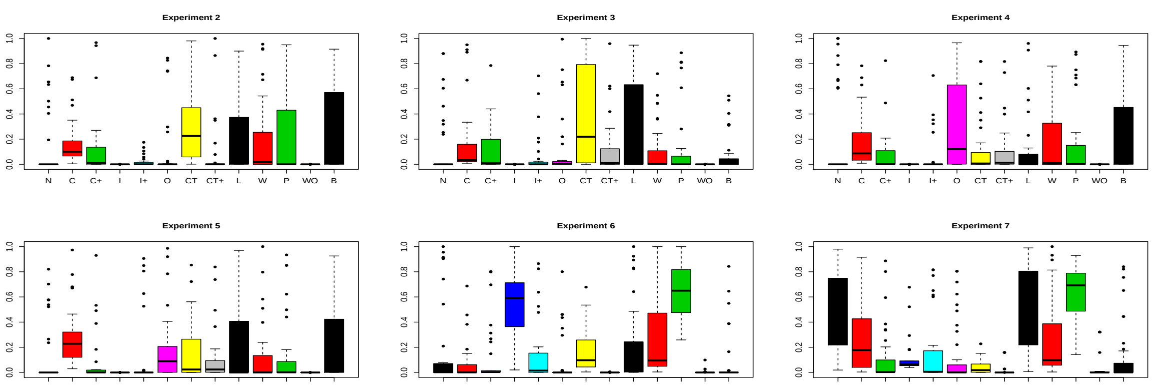
[a] This benchmark experiment is an EU-ETS governed market without renewable energy policies including DECC fuel price forecasts. For experiments which are assuming other values for exogenous variables the outcomes of the hypothesis cannot be guaranteed. The results are however stable for three extreme fuel price forecast scenarios.



(a) Low fuel-prices



(b) Central fuel-prices



(c) High fuel-prices

Figure 4.4: Box-plots with t-tests per technology

The y-axis represents the p-value.

x-axis	technology	x-axis	technology	x-axis	technology
N	Nuclear	I+	IGCC CCS	P	Photovoltaic
C	Coal	O	OCGT	WO	Wind offshore
C+	Coal CCS	CT	CCGT	B	Biomass.
I	IGCC	CT+	CCGT CCS		
L	Lignite	W	Wind		

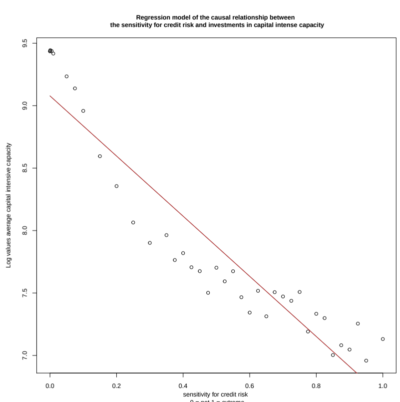
Table 4.5: legend for box-plot plots

Hypothesis H2

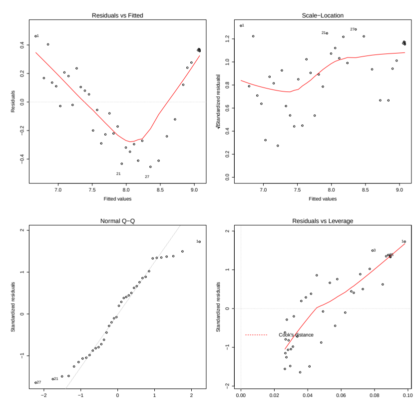
The previous analysis of hypothesis H1 revealed that there seems to exist a correlation between the sensitivity for credit-risks and the investments in capital-intense technologies. In order to study this observation more in detail, single regression analysis is used to research the correlation between the sensitivity for credit-risk and the investments in capital-intensive technologies such as nuclear power and IGCC-CCS. This regression analysis intends to study the following hypothesis.

> **H2:** There is a significant negative correlation between investments in the capital-intensive technologies and the sensitivity for credit-risk.

The designed regression model is a single regression model with one dependent and one independent variable. The independent variable is the sensitivity for credit-risk (also called regressor), the dependent variable is the operational capacity of the most capital-intensive technologies. The sensitivity for credit-risk must be interpreted as follows; a sensitivity of zero indicates that investors borrow money based on their financial structure without asking the question "Is this a competitive interest-rate for me?". On the other hand are investors with a credit-risk sensitivity factor of one answering the question almost always with no. There are four conditions for performing a regression analysis. These conditions are all considered sufficiently met. The first condition is that the variables have a interval/ratio scale. The second condition is that there is a theoretical correlation. The third condition is that the relation is linear and the last condition is that the sample is normal distributed and has an equal variance. The model summary in figure 4.5b also indicates that the conditions are sufficiently met. The linear regression model in figure 4.5a shows that more than 88% of the variation can be explained. Besides that are the constant and the independent variable both significant for a 99% confidence interval.



(a) Regression-model



(b) Regression-model summary

Figure 4.5: Correlation sensitivity credit-risk and capital-intense investments

The details of the model are described in table 4.6. The regression equation is as follows; $\hat{\gamma} = 9.07813 + -2.40 \cdot x$. The F-test statistic has a value of 271.2 with a p-value of 2.2e-16 indicating that the regression-model is significant. Furthermore did a Shapiro-test indicate that the residuals where sufficient normal distributed. The QQ-plot in figure 4.5b shows the normal distribution estimation. The linearity of the model is considered sufficient although there is a minor non horizontal pattern in the standardized residual graph. The Cook-distance figure (4.5b) did not show any outliers with a excessive value implying that no cases are left out of the data set. The only value with a higher leverage than 0.5 is case 21, but since it is the only value it is kept within the data-set.

Output	**Data**
Model	lm(formula = log(value) sensitivity)
Residuals	Min 1Q Median 3Q Max
Values	-0.45 -0.23 0.016 0.22 0.46
Coefficients	Estimate Std. Error t value Pr(>—t—)
Intercept	9.07813 0.08422 107.78 <2e-16
Sensitivity	-2.40 0.146 -16.47 <2e-16
RSE	0.2815
R-squared	0.8828
Adjusted R-squared	0.8796
F-statistic	271.2
P-value	< 2.2e-16

Table 4.6: Statistics regression-model (H2)

The regression-model seems to confirm the observed pattern in figure 4.2a, 4.2b and 4.2c. There is however one important comment. The correlation between the sensitivity for credit-risk and investments in capital-intense technologies includes some experiments (both extreme tails in figure 4.5) which are not likely to happen. An experiment where an investor is so sensitive for credit-risk that he will never invest notwithstanding great expected profits is not considered plausible.

H2: *The hypothesis that there is a significant negative correlation between investments in the capital-intensive technologies and the sensitivity for credit-risk is considered not falsified.*

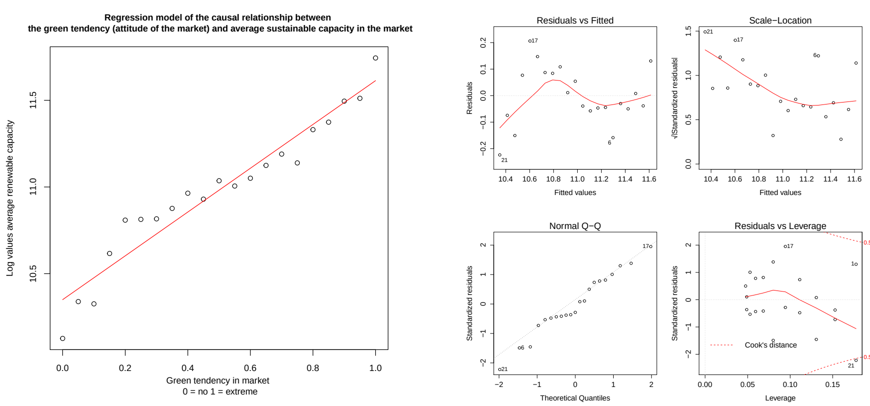
The regression model significance (p-value < 0.01) indicates that for a 99% confidence interval that there is a correlation between the investments in capital-intensive technologies and the sensitivity for credit-risk. The model is able to explain more than 88% of the variation. This conclusion holds for a EU-ETS governed market experiment with DECC fuel-price forecasts. Extreme experiments on the regression line (little sensitive and extreme sensitive) are however not considered plausible in reality. The conclusion on this hypothesis reinforces the earlier observation that more realistic behaviour results in substantially lesser investment in capital-intense technologies.

Hypothesis H3

In section 4.2 was concluded that the "green tendency" of the investors in the market has substantial effect on the renewable capacity in the market. Furthermore a correlation is visible between the fraction of renewable oriented investors and the average capacity of renewables. Like in the previous section, single regression analysis is used to study the perceived correlation between the green market tendency and the average capacity of renewables in the market. Before this is done the definition of the green market tendency is explained. The green market tendency is an indicator between 0 and one which indicates what percentage of investors would select the most sustainable investment from a selection of profitable investment opportunities. The fact that the selection are all profitable investments is an important fact[9]. Like in the previous analysis are all four conditions for performing a regression analysis met. The regression model intends to study the following hypothesis.

> **H3:** There is a significant positive correlation between investments in renewable technologies and the green tendency of investors in the market.

In this single regression model the dependent variable is the capacity of renewables. The independent variable is the green market tendency. The linear regression model in figure 4.6a shows that more than 92% of the variation can be explained. Besides that are the constant and the independent variable both significant for a 99% confidence interval.



(a) Regression model

(b) Regression model summary

Figure 4.6: Correlation green market tendency and renewable investments

The details of the model are described in table 4.7. The regression equation is as follows; $\hat{\gamma} = 10.35025 + 1.26302 \cdot x$. The F-test statistic has a value of 249.3 with a p-value of 2.2e-12 indicating that the regression-model is significant. Furthermore did a Shapiro-test indicate that the residuals where sufficient normal distributed. The QQ-plot in figure 4.5b shows the normal

[9]Furthermore must be taken into account that when a less sustainable investment is significantly more profitable this could result in the fact the "renewable oriented" investor will invest in the most profitable in stead of the more sustainable. Therefore the behaviour is considered as a tendency and not a excluding focus on renewable capacity

distribution estimation. The linearity of the model is considered sufficient although there is a minor non horizontal pattern in the standardized residual graph. The Cook-distance figure (4.5b) did not show any outliers with a excessive value implying that no cases are left out of the data set. The only value with a higher leverage than 0.5 is case 21, but since it is the only value it is kept within the data-set.

Output	**Data**
Model	lm(formula = log(value) Green tendency)
Residuals	Min 1Q Median 3Q Max
Values	-0.22373 -0.04995 -0.03007 0.08413 0.20603
Coefficients	Estimate Std. Error t value Pr(>—t—)
Intercept	10.35025 0.04676 221.34 < 2e-16
Green tendency	1.26302 0.08000 15.79 2.23e-12
RSE	0.111
R-squared	0.9292
Adjusted R-squared	0.9254
F-statistic	249.3
P-value	< 2.229e-12

Table 4.7: Statistics regression-model (H3)

The regression-model seems to confirm the observed pattern in earlier analyses on the correlation between investments in renewable technologies and the green tendency of investors in the market. However in line with the previous linear model a comment on the outcomes is necessary. The correlation between the green market tendency and renewable investments include some experiments which are not likely to happen. An experiment where all the investors in the market have a green tendency or none of the investors have a green tendency is not considered plausible. Besides that, there also seems to be a theoretical cap on the fraction of renewables a market can handle. On this theoretical cap will be elaborated later.

H3: *The hypothesis that there is a significant positive correlation between investments in renewable technologies and the green tendency of investors in the market is considered not falsified.*

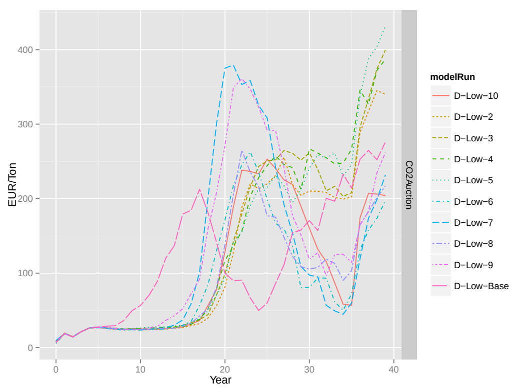
The regression model significance (p-value < 0.01) indicates that for a 99% confidence interval that there is a correlation between the investments in renewable technologies and the green market tendency profile. The model is able to explain more than 92% of the variation. The conclusion holds for a EU-ETS governed market experiment with DECC fuel-price forecasts. Extreme experiments (little/no tendency[a] and extreme tendency) are not considered plausible experiments in reality. Like the previous hypothesis does this conclusion reinforce the earlier observations. The algorithms including more realistic investment behaviour, which means that investors include more criteria, will results in an increasing number of renewable investments.

[a]There is empirical prove that there are always parties with an sustainable tendency although this fraction might be small

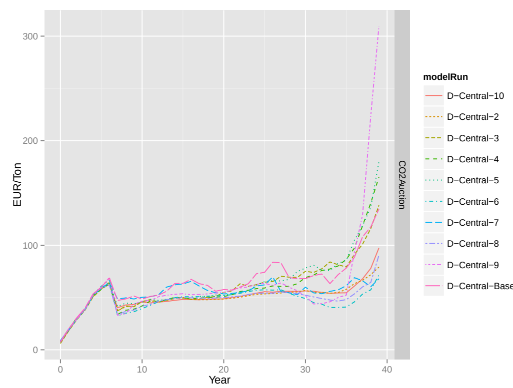
Hypothesis H4

The previous conclusions on the first hypotheses H1, H2 and H3 showed that all experiments with more realistic investment behaviour had effect on the investments done in an electricity market simulation. Furthermore it was already noticed that this observation could provide a warning signal for researchers who are using simulation models for energy policy analysis. It shows the importance of being critical on the assumed investment models. To answer the research question this section will analyse to what extent more realistic investment behaviour results in substantial CO_2 emission right price volatility. This price volatility is a measure for how robust and stable the investment signal of the CO_2 emission right is. The volatility is measured for all experiments by the standard deviation of the average CO_2 price time-series of 40 years. Previous research on the effectiveness of the EU-ETS also used the price volatility as an indicator [63, 66].

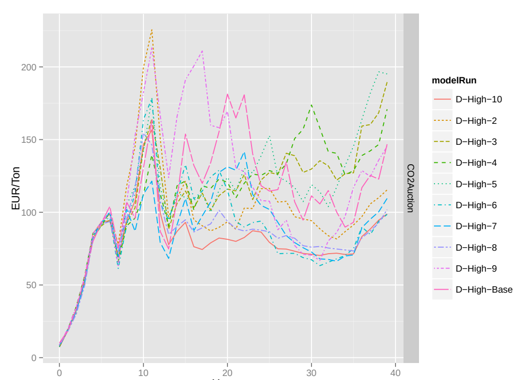
The analysis starts with three figures that show the average CO_2 price development for all experiments in case of three DECC fuel-price forecasts (low, central and high). These figures (4.7a, 4.7b and 4.7c) give insight in the movement of the average emission right price (EUR/ton) in case of the behaviours described in table 4.3.



(a) Low fuel-price forecasts



(b) Central fuel-price forecasts



(c) High fuel-price forecasts

Figure 4.7: Average CO_2 price development for three DECC fuel-price forecasts

It becomes visible that the highest average CO_2 prices are expected in case of low conventional fuel prices (figure 4.7a). The low fuel prices cause that investors remain investing in the conventional technologies such as CCGT and others resulting in an higher demand for CO_2 emission rights. This higher demand automatically results in higher prices. The average CO_2 price movement also shows substantial fluctuation in case of high and low fuel prices. It is remarkable that in case of the high fuel price experiments the average CO_2 price is higher than in the central fuel price experiments. This can be explained by the more competitive position of lignite technology in the high fuel-price experiments in figure 4.3c. It was already discussed that in the DECC high price forecast lignite becomes more competitive. Lignite has however the highest emission ratio of all technologies.

Figure 4.7a, 4.7b and 4.7c indicate that the CO_2 prices show a different pattern than the base-cases. This can be explained by the earlier presented figures 4.3a, 4.3b and 4.3c where various substantial differences in investment patterns were recognized. The experiments are not showing in all cases substantial CO_2 price fluctuations in relation to the base-case. Figure 4.8 provides more insight in the average yearly volatility and average CO_2 price. Experiment number 1 (square in figure) represents the base-case and the further numbers are the experiments (circles in figure) including more realistic investment behaviour.

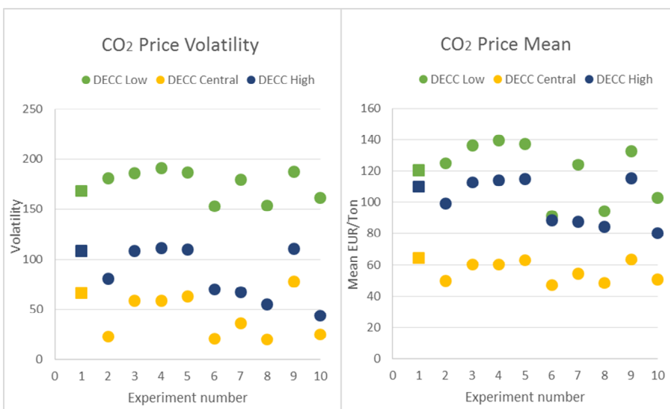


Figure 4.8: Averaged CO_2 price volatility and mean for all experiments

The first observation is that the price volatility between fuel-price (low, central and high) experiments show larger differences than between experiments with the same fuel-prices and different investment behaviours. This is in line with the earlier observation in hypothesis H1 that exogenous factors are more influential than behavioural differences among algorithms. The CO_2 price seems to be very depending on the configuration of exogenous factors (in this case the fuel-prices). Figure 4.8 shows that experiments with more realistic behaviour does not always result in higher CO_2 price volatility. The CO_2 price volatility seems even on average to be lower than in the base-case (4.8 and 4.9) when investors incorporate more considerations in investment decisions. *The question is now* how it is possible that more realistic investment behaviour in the simulation results in a lower CO_2 price volatility.

In the first place this could be explained by the incorporation of more criteria by investors in the investment decision than only profit. In the base-case investors are not looking at plant efficiency, CO_2 emission, portfolio diversification and technology specific risks. This means that investors with more realistic behaviour react on more indicators in an investment decision. A second more simple reason is that a percentage of investors considers sustainable criteria as important resulting in a lower demand for CO_2 emission rights. This will likely result in smaller emission right fluctuations which makes the prices more stable.

Experiment nr.	σ_{low}	% Δ_{base}	$\sigma_{central}$	% Δ_{base}	σ_{high}	% Δ_{base}
1 - base	168		66		108	
2	181	8%	23	-66%	81	-25%
3	186	11%	59	-11%	109	1%
4	191	14%	59	-11%	111	3%
5	187	11%	63	-5%	110	2%
6	153	-9%	21	-69%	70	-35%
7	180	7%	36	-45%	67	-38%
8	154	-9%	20	-70%	55	-49%
9	188	12%	78	17%	111	3%
10	161	-4%	25	-62%	44	-59%
min	153	-9%	20	-70%	44	-59%
max	191	14%	78	17%	111	3%

Table 4.8: Descriptive statistics CO_2 price volatility comparison

Experiment nr.	σ_{low}	% Δ_{base}	$\sigma_{central}$	% Δ_{base}	σ_{high}	% Δ_{base}
1 - base	120		64		110	
2	125	4%	50	-22%	99	-10%
3	137	14%	61	-6%	113	2%
4	140	16%	61	-6%	114	4%
5	137	14%	63	-2%	115	4%
6	91	-24%	47	-26%	89	-20%
7	124	3%	54	-15%	88	-20%
8	94	-22%	49	-24%	84	-23%
9	133	10%	64	-1%	116	5%
10	103	-14%	51	-21%	80	-27%
min	91	-24%	47	-26%	80	-27%
max	140	16%	64	-1%	116	5%

Table 4.9: Descriptive statistics CO_2 price mean comparison

The question is now what this means for the hypothesis H4 presented in subsection 4.1. The analysed figures confirm that substantial CO_2 price volatility can be expected for all experiments including the base-case. This conclusion is in line with previous studies like [63] and [66]. [63] already in 2009 discussed that CO_2 price volatility above 50 % is plausible.

The development of exogenous factors will play an important role in the movement of the CO_2 prices. Low fuel prices will cause higher demand fluctuations for emission rights because conventional fuels remain more attractive. These fluctuations will result in a higher CO_2 price volatility. The most important observation is that more realistic behaviour in most cases resulted in a lower CO_2 price volatility. This reduction went up to 70 %.

H4: *The hypothesis that the incorporation of credit-risk considerations, risk-averse behaviour and technology-preferences in investment decisions result in substantial CO_2 emission right price volatility is considered not falsified.*

More realistic investment behaviour in the simulation showed that substantial CO_2 price volatility can be expected up to more than 100 %. This confirms earlier results from [67], [63] and [66]. The results therefore reinforce the necessity to introduce price stabilizing measures to ensure that the CO_2 price becomes a more stable signal. More realistic investment behaviour in the simulation however also showed less volatility on average in relation to the base-case where investment is based upon homogeneous profit-only behaviour. The results are a confirmation of previous research that CO_2 prices are highly volatile, but more realistic investment behaviour seems to reduce the volatility. Latter indicates that the CO_2 emission right price might be more stable than is assumed at the moment.

The following chapter will include the validation of the model and results.

4.3 Validation: is this a useful model?

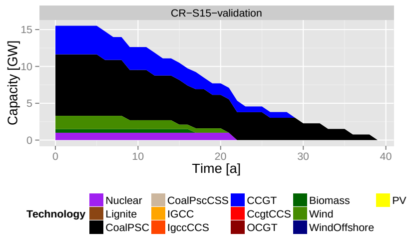
In this section the validity of the model will be described. The validation[10] of an agent-based model is described in [30]. The validation of this agent-based model is hard due to the exploratory character of the hypothesis for which not much real system data exists [11]. Since the hypothesis of this research is more "what if" oriented the focus of the validation is whether the model outcomes are useful and convincing [30]. This research includes structure behaviour tests, expert validation and literature comparisons. The chapter also includes observations based upon individual runs which make the results more convincing.

Structure behaviour tests

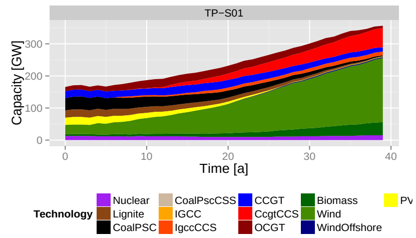
This section includes structural behaviour tests to analyse whether extreme experiments showed convincing investment decisions. In figure 4.9 two extreme decisions are presented to analyse the model outcomes. Figure 4.9a shows an experiment where investors are extremely sensitive for credit-risks. This experiment is not possible in reality, but should result in expected behaviour. This results in investors which answer the question "Is this a competitive interest-rate for me" always with no. This should result in a market where no investment are done. This becomes clearly visible and the prices in the market are rising high due to the shortages. The behaviour is therefore what we would expect. The second extreme experiment includes a market where 100 % of the investors has a extreme green tendency. This means that when an investor gets three investment options, he will always select the most "green" investment. This should result in very high prices since operational capacity is expected to drop. In figure 4.9b and 4.9d is visible that this is the case. More investment decision tests are presented in table 4.10.

[10] Validation is defined by asking the question "Did we build the right thing?" or in [68], "Is the model fit for purpose?". This section should also answer the question; "is this a useful model to answer the research question?"

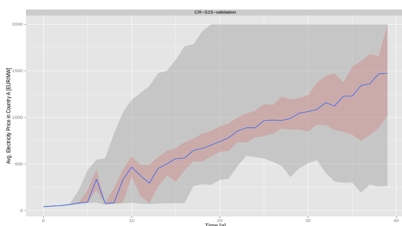
[11] There is data available on historic investments done in a liberalized market and also data on CO_2 price development since the introduction of the ETS.



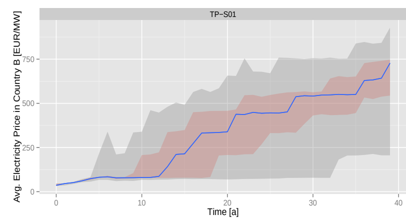
(a) Investment in case of extreme credit-risk



(b) Investment in case of extreme green preferences



(c) Electricity prices in case of extreme credit-risk



(d) Electricity prices in case of extreme green preferences

Figure 4.9: Comparison extreme experiments

Other performed structural behavioural tests are presented in the table below.

Behavioural test	**Outcome**
100 % green investment tendency	Investors select always the most sustainable investment which results in an increasing intermittent capacity. This causes a decreasing operational capacity resulting in larger electricity shortages when the stochastic supply is limited and the demand is high. Prices are rising high. This phenomenon is caused by a model artefact. Investors (newcomers and foreign investors) would react in reality on indicators to prevent such a situation. This falls outside of the scope.
Extremely sensitive for credit-risk	Investors are afraid of investing because there is a strong perception that they cannot fulfil their obligation when they invest. This results in a market where capacity remains decreasing and prices rising to the value of lost load.
Extremely insensitive for credit-risk	Investors keep investing notwithstanding a weak financial structure. Investors build up great debts and extremely negative cash balances. Prices are very low.
Extreme risk-averse for all technologies	The responsiveness of investors on rising prices is low. Only when prices reach a certain level, the investment signals are strong enough to overcome the risk-averse attitude of investors.
Extreme tendency portfolio diversification	Investors always select the profitable investment whose capacity counts for a low fraction of the current investor's portfolio. This results in a market where only the most unattractive technologies (like coal, which is carbon intense) do not have a fraction of the market share.

Table 4.10: Structure behaviour tests

Since there is no real world data available on long term investment patterns which supports the analysis of the first hypothesis, observations are compared with literature. The investment models including more realistic investment behaviour resulted in various observations which can be compared with earlier research. Besides observations of the batch-runs also interpretations of individual runs are included. The following observations will be discussed;

1. More financial space: more capital-intense investments
2. Correlation between sensitivity for credit-risk and capital intense investments
3. Green tendency, green investments and theoretical green cap
4. Correlation between the green tendency of the market and investments in renewable generation capacity
5. Risk-averse behaviour towards nuclear technology: increasing IGCC-CCS and renewables
6. Risk-averse behaviour results in decreasing responsiveness
7. Portfolio diversification strong effect
8. CO_2 price volatility of emission rights

More financial space: more capital-intense investments

From the batch-runs including experiments with credit-risks a significant different investment pattern was recognized in capital-intense technologies. The credit-risk mechanism in the algorithm enables investors to borrow money based on their financial structure instead of a hard cash constraint in the base-case. This more flexible credit-risk mechanism gives the investor an additional opportunity to invest in times when the financial position is weak, although the interest-rate offer from the financier will be much higher than in a financial healthy situation. One observation is that unless the larger financial space the total capacity in the market evolves synchronous with the total capacity in the base-case (see A.8). The total invested capital seems to remain equal in both groups of experiments and more financial space therefore seems not to be a investment signal for more capacity. This could be different in a situation where more interconnection capacity gives an opportunity to serve more foreign demand. Since this increasing interconnection capacity and demand element is not included on the EU-ETS benchmark experiment there is no option to do research to these effects. This also is considered to fall outside the chosen scope of the research.

Another observation is that there are more investments in capital-intensive technologies like nuclear technology and IGCC-CCS. In the base-case an investor would need 30 % of the capital cost of a nuclear plant as his cash balance before he could invest in this technology. Now the investor is able to make a investment decision based upon his financial structure there is more financing flexibility to invest in more capital-intense technologies.

A third observation is that investors with a higher leverage (higher fraction of debt) will invest less depending on the perceived credit-risk uncertainty. Investors in a fragile financial position without a lenient uncertainty perception remain investing, investors with a conservative uncertainty perception will invest less.

Relation to literature: The relation between the perceived financing-risk and the target leverage is researched in the paper of [69]. In the paper is stated that the financial status of the investor plays an important role in leverage / perceived financing uncertainty relations.

According to [70] the effect of leverage on capital investments is negative when there is significant perceived financing uncertainty. These earlier studies show a comparable pattern.

Relationship between sensitivity for credit-risk and capital intense investments

In the previous observation is described that investors which incorporate credit-risks have more financial space and therefore invest in more capital-intense technologies. However, when investors are more sensitive (are more uncertain) for credit-risks less investments in more capital-intense technologies like nuclear technology and IGCC-CCS are expected. This relationship is visible in figure A.8 of the Appendix and verified by the regression-model visualised in figure 4.5a of the Appendix. This regression-model is significant for a confidence level of 99%. Thereby it should be said that certain experiments along the regression line are considered not plausible in reality. It will for example not be likely that investors get so sensitive for credit-risks that they never will invest again.

Green tendency, green investments and theoretical green cap

From the batch-runs including the experiments with technology-preferences is observed that a green tendency in a market has substantial influence on the diffusion or renewable capacity. In the base-case investors make more or less a fully rational decision based on the estimation of an NPV calculation. When investors incorporate more subjective factors (here defined as technology-preferences) a substantial difference in renewable investments can be expected. This outcome seems logical, but indicates that in the used EU-ETS benchmark experiment with DECC fuel-price forecasts is enough profitable investment space for renewable capacity taking market dynamics into account. These profitable investment options are however less attractive than the CCS technologies which are introduced in the market when investors only evaluate projects based on financial indicators. The presence of subjective factors is empirically proven and will influence the development path of generation capacity. How strong this influence is depends on the overall attitude configuration of the market. Private investors can have very different strategies which makes it hard to mimic the configuration profiles of the investors in the Dutch or German market.

A second observation besides the increasing renewable capacity is that there seems to exist a theoretical limit for the intermittent capacity that a market can handle (see figure A.9). This theoretical limit depends on the initial portfolio situation, technological opportunities to solve stochastic power output issues, network evolution (not included in the model) and other extraneous influences.

From the batch-runs including technology-preferences becomes visible that there seems to exits a theoretical cap on the fraction of renewables that a market can handle. This cap is discussed in [71] and [72]. In [71] is argued that extensive investments in transmission networks are required to cope with the stochastic power output of wind-energy when the nominal capacity gets higher than 20 % in the US. In [72] a maximum wind portfolio in 2020 of 8.000 MW_e is mentioned for Ireland.

Relation to literature: From the batch-runs including technology-preferences becomes visible that there seems to exits a theoretical cap on the fraction of renewables that a market can handle. This cap is discussed in [71] and [72]. In [71] is argued that extensive investments in transmission networks are required to cope with the stochastic power output of wind-energy when the nominal capacity gets higher than 20 % in the US. In [72] a maximum wind portfolio in 2020 of 8.000 MW_e is mentioned for Ireland.

Relationship between the green tendency of the market and investments in renewable generation capacity

In addition to the previous observations is analysed whether there exists a correlation between the investments in renewable capacity and the green market tendency profile. From figure A.9 and the significant regression-model in figure 4.6a became visible that there seems to be a relation between the investments in renewable capacity and the green market tendency profile. The regression-model was able to explain more than 92% of the variation of the positive linear relationship. Equal to the earlier described regression-model are there experiments included along the regression-line which are considered not plausible in the current reality. It is empirically proven that there are investors with a strong sustainable preference, but a very high green market tendency seems not plausible.

The reason that there is so little sustainable investment in the Netherlands at the moment can not only be accounted to the non-profitability of investments, but also to not having a real tendency caused by technical, economical and institutional uncertainties.

Risk-averse behaviour towards nuclear technology: increasing IGCC-CCS and renewables

Investors that are risk-averse towards nuclear technology will invest more in IGCC-CCS and even renewables. In the Dutch market where only a small fraction of the total capacity is renewables is enough growth potential for nuclear technology in contrast with the initial German portfolio with a higher renewable capacity, but in case of risk-averse behaviour towards nuclear IGCC-CCS becomes more dominant. The IGCC-CCS is a good option to fill the base-load gap where large-scale plants need to run minimal 5000 hours a year. Due to the EU-ETS mechanism and limited investments in nuclear technology even renewables get more attractive when the years pass by. This shows the competitive relation between renewables and nuclear technology.

The competitive relation between renewables and nuclear technology was observed in the section on data-analysis and interpretation of results. In [73] is described that nuclear technology and intermittent capacity aren't compatible in the current market. The best way to make both technologies compatible is to invest in a transnational or transcontinental power grid. The lock-in effect caused by large base-load plants is described in [74]. This lock-in effect works against a further diffusion of renewables.

Relation to literature: The competitive relation between renewables and nuclear technology was observed in the section on data-analysis and interpretation of results. In [73] is described that nuclear technology and intermittent capacity aren't compatible in the current market. The best way to make both technologies compatible is to invest in a transnational or transcontinental power grid. The lock-in effect caused by large base-load plants is described in [74]. This lock-in effect works against a further diffusion of renewables.

Risk-averse behaviour results in decreasing responsiveness

From the batch-runs including the risk-averse experiments becomes visible that risk-averse behaviour does not result in a very high fraction of substantial average technology capacity differences in relation to the base-case. The argumentation is that risk-averse behaviour mainly causes a decreased responsiveness for investment signals, but does not substantially influence the portfolio technology distribution. The responsiveness includes that investors wait longer with investing until they are more secure about the expected profitability.

Portfolio diversification strong effect

Portfolio diversification seems to be significant in a market where multiple investors include this tendency. In figure A.10 is visible that almost all technologies remain their position in the capacity diagram. This indicates that in the EU-ETS benchmark experiment including the DECC current policies fuel-price forecasts there are sufficient opportunities to diversify the portfolio.

CO_2 price volatility of emission rights

The analysis of the CO_2 price volatility showed that the volatility can rise up to more than 100%. In previous research was already concluded that it is plausible that the volatility can increase up to more than 50%. Historic data shows that the CO_2 price shows heavy fluctuation and dropped 80% from 2007 to 2013 [75]. These comparisons give confidence that the results are plausible.

Conclusion on validity

The model is considered valid for the purpose of exploring how more realistic investment behaviour affects investments in an EU-ETS governed market. The model is also considered valid for the purpose of assessing the effectiveness (In this research defined by the CO_2 price volatility) of the EU-ETS for different investment algorithms. The structural behaviour tests and literature validation indicated that most of the outcomes are convincing to argue that the model and results are valid. There are however also results and model elements for further discussion. This will be done in section 5.3. Further, it is essential for the validity of the results that comparable research is done for different simulation models like EMLab-generation. These results can be seen as a first step in showing the effects of different investment algorithms on energy policy analysis.

Chapter 5

Synthesis

This final chapter includes the answer on the main research question. Furthermore does this chapter include recommendations, a discussion on the model outcomes and a reflection on the research project and process.

5.1 Conclusion on the research question

This research included three objectives. The first one was to explore the influence of more realistic investment behaviour on investments in an EU-ETS governed market simulation. The second was to research how more realistic investment behaviour affects the effectiveness of the EU-ETS mechanism. The last objective was to contribute to current and future projects. During the previous chapters answers where presented on the 4 research sub-questions. By making use of empirical data from investment processes three modular algorithms where designed. These investment algorithms included technology-preferences, credit-risk considerations and risk-averse behaviour towards technologies. Exploratory oriented hypotheses in chapter 4 supported answering the sub-questions. In this section an answer will be presented on the main research question. The main research question defined in chapter 1.2 is:

> "*How is the effectiveness of the EU-ETS mechanism affected by diverse investment algorithms in an energy market simulation model?*"

Answer: In the answers on the sub-questions was concluded that all experiments including more realistic investment behaviour showed for 1 or more technologies substantial differences in investments. More realistic investment behaviour mainly affected the number of investments in wind offshore, Coal-CCS and IGCC-CCS in a low, central and high DECC price scenario. For other technologies such as photovoltaic, coal, nuclear and lignite there where fewer experiments with substantial differences in relation to the base-case investment pattern. The fuel-price as exogenous factor showed that it is more influential than behavioural differences among algorithms. It is however important to notice that the plausible behavioural differences among experiments resulted in substantial different investment patterns.

The analysis of hypothesis H1, H2 and H3 confirmed that all experiments including more realistic investment behaviour results in 1 or more technologies with substantially different investment patterns. This provided a signal that the CO_2 price volatility was substantially different

[1]. The experiments including more realistic investment behaviour gave new insights on the effectiveness of the EU-ETS mechanism.

This research measured the effectiveness of the EU-ETS mechanism by the average yearly standard deviation of the CO_2 emission right price, also called volatility[2]. The main observation is that more realistic investment behaviour, modelled by the three algorithms, in most experiments resulted in a lower CO_2 price volatility in relation to homogeneous profit only investment behaviour. The reduced volatility in comparison with the base-case went up to 70%. This is an indicator that the CO_2 price, although it shows a volatile price movement, might be less unstable than earlier assumed. The CO_2 price volatility however remains substantial in all experiments and was in some experiments even higher than 100%. This outcome is a confirmation of previous work [63] and [67] where was concluded that the CO_2 price is not a robust and stable long term investment signal for non-carbon investment. [63] showed that it plausible when the volatility rises above 50%. The results reinforce the necessity to introduce price stabilizing measures such as a price floor and/or ceiling[3]. Finally the results confirm the importance of being critical on the implications of the assumed investment model used in a electricity market simulation.

To see the results in perspective it is important to notice that exogenous factors showed to be more influential than behavioural differences among the algorithms. This means that the investment pattern in an electricity market is more depending on fuel-prices, demand, technological breakthroughs, institutional changes and for example an economic crisis. Exogenous factors remain therefore more decisive in steering investment patterns. This is however no argument to avoid a reflection on the assumed investment models in energy policy analysis. It is essential for the reinforcement of the results that future research does comparable studies for different simulation models. Two recommendations to deal with the implications of the assumed investment behaviour in models is to design more flexible and modular investment algorithms. Flexibility and modularity in investment algorithms enable and support exploring the effect of different behavioural configurations on outcomes of energy policy analysis. On these recommendations will be elaborated in the following section.

5.2 Recommendations

The problem formulation in this research claimed that energy related policy analysis is incomplete without insight in the implications of the assumed investment behaviour. This statement does not hold for all studies and situations, but intends to provide a warning signal for studies where it could be problematic. The first recommendation is to support further research on analysing the effect of different investment algorithms on the outcomes of energy policy analysis. In North-West Europe and especially the Netherlands are current policies not effective enough to support the transition towards more renewable generation capacity [63]. In order to reach the sustainable energy goals of the authorities in Europe, robust and stable policies are required to support investments in renewable electricity generation capacity. The first step is analyse optional policies such as a price floor and or ceiling for the CO_2 emission right price.

[1] This benchmark experiment is an EU-ETS governed market without renewable energy policies including DECC fuel price forecasts. For experiments which are assuming other values for exogenous variables the outcomes of the hypothesis cannot be guaranteed. The results are however stable (all experiments showed substantial differences) for three extreme fuel price forecast scenarios.

[2] This choice is made because it is an indicator for the stability of the investment signal and used in previous research [63]

[3] This will further be discussed in the recommendation chapter

This type of research is also recommended to explore the effect of different investment algorithms on the effectiveness of back-loading and setting aside emission rights for the period 2013-2020. The European Commission intends to withhold 900 million CO_2 emission rights for this period to increase the price [66]. It could give new insights when this policy is analysed for markets where investors show very diverse investment behaviour.

This research shows the necessity of analysing energy policy options for different investment algorithms to ensure that behavioural differences among investors does not have negative substantial influences on the effectiveness on new polices.

Since the investment algorithms modelled in this research resulted in substantial differences in investments and the effectiveness of the EU-ETS mechanism, this research proposes some handles to monitor the implications of an assumed investment model or algorithm.

1. **Flexibility:** The first recommendation is to include flexibility in investment modelling. The more easy it is to vary parameters and exogenous factors, the easier it becomes to analyse plausible, but very different configurations. More model flexibility helps to reinforce the easiness to explore a large experiment space. The more inflexible a model is the smaller the possibilities to explore different investment behaviours.

2. **Modularity:** The second recommendation is to build modular models. Investment behaviour is proven to be heterogeneous in liberalized electricity markets[4] which calls for coupling of various models. Including modularity in investment modelling will increase the opportunity of analysing heterogeneous and even changing behaviour over time.

One possibility of increasing the flexibility and modularity of investment algorithms is to use more formal languages to construct an investment model. One example is the DEVS formalism, which provides constructs to design modular and hierarchical models in a more mathematical formalism [18]. Another possibility is to use more abstract simulation frameworks such as AgentSpring which is used in this research[5]. Various studies to long term electricity market dynamics and energy policy analysis are using theoretical frameworks in modelling investment behaviour in stead of empirical data. Future research could be done on making theoretical frameworks on investment behaviour more adaptive for flexible and modular modelling.

[4] [7, 8]

[5] `https://github.com/alfredas/AgentSpring/wiki`

5.3 Discussion and reflection: is this research relevant?

This section provides a discussion on the research effort. In line with the model limitations described in section 3.2 will this section discuss the limitations of the results.

The first discussion point is whether the exploratory outcomes of this research are relevant for future research.

Contra: There are arguments to claim that this research is not relevant for future research. The first argument is that exogenous factors proved to be more influential than investment behavioural differences. This could imply that it is more useful to analyse a larger experiment space with diverse exogenous factor configurations in stead of analysing different investment algorithms.

Pro: *it is true that exogenous factors are more influential, but the fact that both factors are substantial make it in my opinion worthwhile to analyse.*

Contra: A second argument to claim that the outcomes of this research are not relevant for future is that more realistic investment behaviour is so specific that you need empirical data before you even can say something about behavioural differences.

Pro: *It is true that empirical data is very important in modelling more realistic behaviour. In my opinion the difficulty of obtaining good data is not a reason to claim that more analysis to the implications of the assumed investment model is not relevant.*

This research claims that it is able to model more realistic investment behaviour, but is this really substantially more realistic taking into account the complexity and uncertainty in modelling investment decisions?.

Contra: An investment decision process can take years before the final decision is made. There are maybe hundreds of factors which are contributing to whether the investment decision is made or not. It is therefore better to generalize investment behaviour to a more abstract level which reduces uncertainty in stead of making algorithms more specific.

Pro: *Although this research claims that it is able of modelling more realistic investment behaviour, it is not the main aim to show that it is substantially more realistic. The purpose of the research is to show what the implications are of more realistic investment behaviour on investments and the effectiveness of the EU-ETS mechanism. The investment models in this research contain considerations which are retrieved from interviews with investors. The validation intended to show that this is the right model ro answer the research question..*

The investment algorithms do not include changing behaviour over time such as learning, but this is not problematic for the results..

Contra: The absence of changing behaviour over time such as learning is problematic because it could affect the results and makes the current behaviour less plausible.

Pro: *It is true that the models at the moment do not include learning effects, but this is considered not problematic for the purpose of the research. Changing behaviour as such is however included in the model. The algorithm including credit-risk ensures for example that investors obtaining interest-rate offers based on their financial position. When investors perform worse, they have to pay more interest, this has a effect on their investment behaviour. The algorithm including technology preferences include the criteria that investors handle during a investment decision process. These preferences are linked to a vision or strategy of an investor and will not change frequently. .*

The unavailability of real data to validate the results is not a problem..

Contra: Without real data to validate results the conclusions are less convincing. This research cannot claim that the investment algorithms show real system behaviour and is therefore a waste of time.

Pro: *It is true in the first place that real data comparisons are traditionally a very good way of validating results and models. This is also partly done with analysing previous results on the* CO_2 *emission right price volatility. Those results where comparable with the results in this study. It remains true that this research has not the possibility of using much real data to validate the outcomes. The character of the first hypothesis (and also partly second) makes traditional validating techniques not applicable due to the absence of real data. This is also the reason that this research uses a different starting point in the validation. This research intended to show that this model is the right model for answering the research question and that the model is therefore fit for purpose. The used techniques in where the comparison of observations with literature, expert consultation and structure behaviour tests. The investment algorithms showed convincing investment patterns, but the fact remains that validation of agent-based models with the used type of hypotheses makes validation though.*

Investment behaviour is studied for ages, but this research includes a new view..

Contra: Investment behaviour is already studied by empirical and theoretical approaches since the thirties. This research is unnecessary and old wine in new bags, to say it literally.

Pro: *Investment behaviour is a sexy subject, no doubts about that. The approach, aim and objective of the research is however different than previous studies in the field. The reason for starting this research is a call from researchers in the field. one example which is also mentioned in the literature review in the Appendix is [20] who argues: "A valuable extension of this work would include consideration of other decision-making behaviours such as naive, forward expectations, forward adaptive expectations, and adaptive moving average". In the field of energy policy analysis where simulation models are used investment behaviour is almost always considered fixed and homogeneous. Since empirical data showed that investors in the liberalized North-West European electrciity market are evaluating investment in a very different way it became interesting to see whether outcomes on energy policy analysis could be affected by different algorithms.*

A citation from Dale W. Jorgenson is as follows *"The number of possible explanations of investment behaviour, which is limited only by the imagination of the investigator, is so* *large that, in any empirical investigation, all but a very few must be ruled out in advance"* [28].

Pro: Taking the statement of Dale W. Jorgenson into account the algorithms could be better designed based on a theoretical framework instead of being based on empirical data which is incomplete.

Contra: *That statement is under discussion various fields of research. This study uses empirical data to feed the algorithms. The exact operationalization is done by using concepts from theory.*

5.4 Reflection on the research-process

After the discussion/reflection on the modelling and results, is this reflection more aimed at the research process. When I started this research the main aim was to finish the work in July. After a discussion with the committee I decided to delay the final presentation date to the 6th of September after the summer holidays. This decision gave some extra time to lay down the work and think well about the reflection en enjoy free time after months of work. I would like to mention first that I am satisfied with the time schedule that I followed. I managed to do the work in around five months which is satisfactory. Early in the research process I found out that finishing the research within five months would be a big challenge especially with the ambition level. The exact definition of a thesis is though. It takes time to convince others and yourself about the way to go. I thought first of some "success" factors that helped me with the research. These success factors where;

1. **Work together:** During the project I worked together with Kaveri and Jeroen. Being together created a stimulating working environment where it was possible to share problems, brainstorm, support each other and have nice discussions. If you work alone, you need even more discipline and structure to keep up the pace. Anyway, working together for me was very stimulating.
2. **Committee:** The supervisors fulfil an important role within the research process. Emile, Servaas en Margot seemed to be a good combination to judge, support and steer my research content. Emile and Servaas in particular helped me to reflect on my own work. Thanks to them I could sometimes do a step away from my work to observe it in a more objective way.
3. **Support:** In my EMLab-generation related research project was a lot of technical support from Jrn and Praduymna. The simulation process (designing experiments, running the model etcetera) of the research was now and then very complex and therefore it was beneficial to have sparring partners for technical difficulties. On moments when you are stuck, it is nice to share problems with people who are working with the same tools.
4. **Tell your story to friends:** You learn a lot about your line of argumentation by explaining it to others. Simple questions from people who do not know your work in detail can help to reflect on your own line of argumentation.
5. **Minimize delay time:** During the process I managed to minimize time delays by making a realistic time schedule. I realised that besides a realistic time schedule you also simply need a bit of luck. It is also important to make appointments with people on time to ensure that you can ask questions.

6. **Balance time/ambition:** Another important factor was seeking the balance between the ambition level and what is possible in five months. In first instance I thought of using the algorithms for looking at substantially different investment patterns (hypothesis H1) in stead of also incorporating a policy perspective. Because the modelling and further process went well, I decided to add the policy dimension to the research. The option to include more depth in the research seemed to be a good option. An important characteristic of the research which made this possible is **scalability**. This gave me the possibility to add additional content to the research.

7. **Spread work:** Work on different parts in your thesis during a working day. It worked for me for example to work during the morning on more content-wise stuff, and use the evening on more hands-on work like running experiments, designing figures etcetera.

Besides "success" factors there are also elements during the process which could have been done better. These points include also things which I would have done differently. These elements are defined as "improvement points". Before I elaborate on these points I must say that the "improvement" and "would have done differently" list of points is very small. This is the case because I am pretty satisfied with the preparation, support, execution and results of the research. Before I started, I knew that within 5 months you will not win a Nobel price with a master thesis. I really tried to make a realistic analysis of what was doable within this time frame. I learned from earlier projects in the bachelor and master to protect myself for the over-ambition. There are however always point for improvement. Some of these points are:

1. **Ask help** The first point is asking people earlier for help, I tended to be an individualist and preferred to figure things out myself. This was however not problematic since I also worked together with people.

2. **Documentation** Another improvement point is the documentation of work done. A lot of work (analysis) was done in my head without document it carefully. This has implications for how observations, results and modelling choices for example are understood by readers of this report. This improvement point is also not considered to problematic, but it could have been much better.

3. **Finishing:** After the green light on the 17th of June, I had to make the choice for graduating before or after the summer holidays. On the one hand it would have been better to finish it before the holiday because everything was fresh in my head. On the other way I now had time to think about the reflection and enhance the quality of writing, but it was not really necessary after all.

4. **More effort and earlier on scope:** The practical aim of this project in the first place was easy. Try to make an enhanced, more realistic investment algorithm for EMLab-generation by using the empirical data of [8]. The current algorithm contained some elements which where very primary such as the constraints on capital and the determination of the weighted average cost of capital. Since I intended to add a policy dimension from the beginning, I really needed to think about how to combine "modelling more realistic investment algorithms" and "energy policy analysis". in the end I think that I did well in combining those elements resulting in a real TPM research effort. An improvement point is that I could have done more in the beginning to define the project on beforehand. On the other hand I cannot be very unsatisfied with how the project definition went in the end.

5. **Work less during nights:** Something which I might would have done differently is working a lot at night. Due to my work and intention to finish the research within five month resulted in "long days" to compensate the missed hours during the day. I decided to work (not research) less in the last 4 months of the research so that there was more time to spend on the research work.

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Appendix A

Appendix

Welcome to the Appendix of this research. This part of the document contains all underlying analyses for the main text. This analysis is fully readable and provides an extensive insight on the work done. The reading guide below summarizes the content of the chapters within the Appendix.

Chapter	Content
1	This chapter contains an article analysis on modelling investment behaviour
2	The development of the algorithms is described here (conceptual + formal)
3	The design of experiments is described here
4	This chapter contains the extended data-analysis and additional figures
5	This chapter contains the algorithm java-code

A.1 Article analysis

To give an overview on the modelling of power plant investment behaviour an significant number of articles is reviewed. The largest part of the reviewed articles focus on the modelling of the long-term electricity market. There are articles that use an empirical approach where some future expectations are presented. The analysis is merged in Table 1. The selected articles are from all kind of universities in the world and all written from different perspectives and with different purposes. The goal is to get a feeling on how scientists are presenting their model shortcomings related to investment behaviour. There is also one paper included which focusses on comparing different theoretical models that described investment behaviour.

Reviewed articles

Below a list is presented with the reviewed articles.

1. In the paper of Gutirrez-Alcaraz (2009), discrete event simulation is used to model the interaction between fuel markets, generation companies and consumers. In their model agents behave like Cournot-Nash players which determine supply to meet the end use consumption. In the model the agents intend to maximize their profits with adaptive expectations of the strategies of the other agents. The article described the model sensitivity for certain parameters and the impacts of varying those. The article does not discuss the impact of other investment behaviour on the model outcomes but suggest the following for future research; "*A valuable extension of this work would include consideration of other decision-making behaviours such as naive, forward expectations, forward adaptive expectations, and adaptive moving average* [20]"
2. In the paper of Clarke et al. (1993) the energy technology mix is predicted by geographically heterogeneous cost distributions. In this approach the market share and the average cost of energy produced by these technologies is derived. The modelled investment behaviour is mainly based upon neo-classical assumptions. The relation between empirical and neo-classical assumptions is discussed [24].
3. In the paper of Karlsson et al. (2008) uses the optimization model of Balmorel. This model is possible to analyse the electricity and CHP markets in the Baltic Sea region with a linear optimization technique considering perfect competition. The agents invest on the basis of prices and demand in a certain year. No further discussion on the investment behavioural sensitivity of the model is presented [76].
4. In the paper of Alishahi et al. (2012) investments are performed within a perfect competitive and uniform market. In this article is mentioned that these assumptions are used as foundation, but no further notion is made on the sensitivity of model outcomes for the investing decisions of producers. There is a very specific description of the multi-staged decision (investment) optimization problem, but without any comments on the sensitivity for the assumptions modelled in this problem [21].
5. In the paper of Arango (2007) investment behaviour is modelled according to a real options approach within a system dynamics model. The model intents to find the critical price which justifies the investment. According to the author the model outcomes corresponds satisfactory to historical data. The author describes the need for improving the model with different modes of investment behaviour. The author states; "Improvements could be made by including the grid in more detail, by taking a different approach to the load

curve for demand during the day, or by using a different investment behaviour model" However, no further discussion is presented on the investment behavioural sensitivity in the model [19, 22].

6. In the paper of Assili (2008) a system dynamics model is developed to analyse an improved mechanism for capacity payments. Investments are performed within a perfect competitive and uniform market. The article describes various opportunities of modelling investment behaviour, but no real discussion is presented on the influence on the model outcomes [77].
7. One example is Zhu (2012) where nuclear power investment is modelled using a simulation based upon a real options approach [16].
8. Another example is Ycel et al. (2012) where simulation is used to analyse plausible development trajectories of the Dutch electricity system [12].
9. The next paper is Pozo (2011) where an iterative market Nash equilibrium model is used to analyse long term equilibriums in electricity markets [78].
10. In the paper of Chappin et al. (2009) an agent-based model is developed to elucidate the effect of CO_2 emission trading. In this model. The consequences of the main assumptions are discussed. An extensive sensitivity analysis is described. Although sensitivity in relation to investment behaviour is not taken into account [15].
11. The next reviewed paper was Ghaderi (2012) where a fuzzy cognitive map was developed to simulate the behaviour of electricity producers. In this paper sensitivity analysis was performed on the factors that influence the decisions of the producers [79].
12. Bernal-Augustin (2007) constructed an model to simulate the day ahead electricity market in Spain. Since the paper is only for short term use, there are no investments included. This article is therefore not so useful for the article analysis [80].
13. Larsen et al. (2010) describes the existence of investment cycles in deregulated liberalized markets. Their hypothesis is that the market has times where is under investment or times with over investment. The model used is a system dynamics model and empirical evidence to confirm that the hypothesis still stands. The authors describes the sensitivity for modelling investment behaviour [22].
14. Johnson (1994) reviews different models who cope with investment behaviour and discusses the insights of these models [23].
15. Hsin-Chin (2011) did empirical qualitative research on the effects of regulation on investment behaviour in the liberalized electricity market in Taiwan [81].
16. Sarica et al. (2012) modelled a decentralized electricity market. The intention was to model the implications of an day ahead market. Since this study was related to a short-term consequences this article was not useful for the analysis [82].

Nr.	Article	Model	Theoretical perspective	Discusses model sensitivity & limitations?
1	Gutiérrez-Alcaraz (2009)	Cournot-Nash model	Neo-classical assumptions including bounded rationality	None, taking also other investment behaviour is suggested as future research.
2	Clarke *et al.* (1993)	Conditional distribution functions	Neo-classical assumptions	Limited. Link empirical and theoretical assumptions is needed. Nothing further about influencing the outcomes.
3	Karlsson *et al.* (2008)	optimization model of Balmorel	Neo-classical assumptions	Limited, model applicable to Baltic sea region. Limitations for assumptions is partly discussed. No real comments on modelling various modes of investment behaviour.
4	Alishahi *et al.* (2012)	Optimization model	Neo-classical assumptions	None
5	Arango (2007)	System dynamics model	Neo-classical assumptions	Limited. Only mention that the model needs potential improvements like using different investment behaviour modes.
6	Assili *et al.* (2008)	System dynamics model	Neo-classical assumptions	The author confirms that the neoclassical assumptions have an effect on the result
7	Zhu (2012)	Monte Carlo simulation using real options approach	Not mentioned but bounded rationality is included	Limited discussion, only reasons related to the future market and the sensitivity of the model results
8	Yücel *et al.* (2012)	System dynamics model Profit estimation (ROI)	Neo-classical assumptions	Limited. Description on how results were established, relation to assumptions.
9	Pozo (2011)	Iterative market Nash equilibrium model	Neo-classical assumptions	None
10	Chappin *et al.* (2009)	Agent-based model	Neo-classical assumptions but also heterogeneity “management styles”	The model outcomes were not sensitive to most parameters, including agents management style parameters. Further major assumptions and their consequences are presented but not related to investment behaviour.
11	Ghaderi (2012)	Fuzzy Cognitive Map	Empirical assumptions	Limited
12	Bernal-Augustin (2007)	Simulation model in VBA	Not mentioned	There is limited notion of the assumptions made in the model. This is logically due to the short term scope of the model.
13	Larsen *et al.* (2010)	System Dynamics model	Neo-classical assumptions including bounded rationality	Provides discusses theoretical and empirical assumptions for testing the stated hypothesis. Citation : “*The simulation models show the occurrence of cycles based on decision rules assumed by the modellers, where the behavior of the investors is still an empirical question*” [41]
14	Johnson (1994)	Qualitative comparison of models CAPM, APT etcetera	Neo-classical assumptions including sunk costs, uncertainties and	“*This paper reviews the assumptions and important insights of the investment theories most commonly suggested as candidates for explaining the apparent 'energy technology investment paradox*”
15	Hsin-Chin (2011)	Qualitative model	Empirical assumptions	The author suggests using a simulation model to test different investment motivations on the long term development of the market.
16	Sarica *et al.* (2012)	Multi-Agent simulation model	Neo-classical assumptions	None, the study was short term oriented and not very useful for the analysis.

Figure A.1: Aggregated list of all the reviewed articles

Conclusion from the article analysis

The conclusion from this article analysis is that in very few cases outcome sensitivity is discussed for the modelled investment behaviour. Often sensitivity analysis is performed on various assumptions within the model like the technological breakthroughs, but not on investment behaviour. Models often assume neo-classical market assumptions and model producers on the basis of bounded rationality. Some articles discuss the modelling sensitivity but are also arguing that the model is fit for purpose. Sometimes reasons are mentioned why not different modes of investment behaviour is required. These reasons are;

1. The assumption that the model is not constructed for a purpose where this sensitivity analysis is needed for.
2. Testing various investment algorithms is time consuming and not always possible within the simulation paradigm.

It is also likely that the following reasons will have an impact, but these reasons are based upon a logical suspicion;

1. It is not likely that scientists will weaken their own findings.
2. Since there is in many studies no real validation possibility
3. It is hard to have a reticence attitude regarding certain outcomes.

The electricity system

This chapter contains a system analysis of the Dutch electricity market. The main elements of this analysis will be presented in the main text. The analysis starts with a more general description of the whole Dutch electricity system. Understanding this system (including the elements) is mandatory for reading the further thesis.

From the philosophy of the faculty of Technology, Policy and Management at the Delft University of Technology where this research project was carried out a systems approach is used to analyse the Dutch power sector. Before is zoomed in on the investments in the power sector first an overview on the whole Dutch electricity system is presented. The Dutch electricity system could be seen as a complex social-technical system [40–43, 83]. This system comprises of technical elements like the physical infrastructure and production plants, but also includes various stakeholders like consumers and producers. Within this system all the different interactions cause a high degree of complexity. In the figure below the electricity system is explained. This is the starting point for zooming in on investment. The green blocks represent the elements that are belonging to the social-institutional part of the system. The black blocks represent the technical-physical elements of the system.

The figure shows all the social-technical elements of the value chain. A description is presented in two parts. First all institutional elements are described and secondly all technical physical element are explained. The regulator as a specific agent is not added but is in reality concerned with law and regulation.

Institutional elements

Energy producers

The energy producers are the owners of the power plants. The main activity of the producer is obvious; producing electricity. Since the increasing number of de-central produced electricity, the number of producers is increasing. There are approximate 800 producers in the Netherlands who produce more than an electrical output of 200 MWh a year. The largest producers in the Netherlands are Electrabel, Essent, Nuon and E.ON. There are all kinds of producers looking at public, private ownership, size, attitude and so on. Because this is also part of sub-question two of the research on this part will be elaborated later. The main source for the data on the difference among producers this information is Enipedia. The 20 largest producers are visualized in the graph below;

In addition on the figure above, here the de-central generated capacity is not included. The division among the de-central and central generated capacity is presented in Figure 7 below. It is visible that the production of electricity was increasing up to in the beginning of 2010 (118 billion kWh). During 2010 the production declined probably due to the economic crisis causing a decrease in demand.

Small and large consumers

The small consumers of electricity are mainly households, small and medium enterprises and other institutions with connections up to 3 x 80 Ampere with a tension level of maximal 1 kV. Large consumers are industrial consumers, transport and horticulture using larger than 3 x 80 ampere connections with a 1 to 50 kV tension level. Above this tension level connections with the HV network is required up to 380 kV. Also the energy industry itself is a large scale user of electricity. A division of the electricity consumption up to 2011 is presented below.

Retail companies

The retail companies deliver electricity and heat to the small consumers. They are buying their electricity on the wholesale market via bilateral contracts or on the Amsterdam Power Exchange (APX). The suppliers or retail companies are not producing electricity themselves. The largest retailers in the Netherlands are Eneco, Essent, Nuon and Oxxio. Some producers are also competing on the retailer market.

Transmission network manager and system operator

The transmission network manager (TSO) operates and maintains the transmission network. It keep the connections online and transports the electricity from the HV network to the LV network. The TSO in the Netherlands is Tennet. The TSO maintains the 110, 150, 220, 380 and 450 kV lines. The 450 kV DC concerns the NorNed and BritNed cable [44–46].

Distribution network manager

The distribution network manager (DSO) maintains the distribution network. It keep the connections online and transports the electricity from the HV network to the end-consumers up to 50 kV. The largest DSOs in the Netherlands are Liander, Enexis and Stedin which have together around 6,5 million customers. In total there were 11 distributed operators in 2010 [47–49].

Power exchange and OTC

The Amsterdam Power Exchange (APX or APX-ENDEX due to merger with ENDEX) is the spot market where demand and supply come together. In this market it is possible to anonymously exchange power which is an advantage for power producers and suppliers. This is an advantage because competitors can keep their trading strategy secret. In 2011 the traded power volume was 108 TWh including all kind of derivatives [50]. APX-ENDEX Holding B.V. which is the 100 percent shareholder of the electricity trading entities like APX-ENDEX Power B.V. and APX-ENDEX Clearing B.V. The shareholders of APX-ENDEX Holding B.V. are inter alia, 56,05 percent Tennet Holding B.V. and 20,88 percent Nederlandse Gasunie N.V. and others 23,07 percent.

Bilateral market

The bilateral market is where buyer and seller agree upon specific contracts. The contracts are often term contracts according to insiders in the market. Data on the volumes is unknown, but the largest volume of electricity is still traded via bilateral contracts with a year-period (or shorter).

Import and export capacity

When there is a difference between supply and demand the TSO keeps the network in balance by import or export (when there is no strategic national fast ramping up reserve). In cases of a surplus it is possible to export electricity to Germany, Belgium, Scandinavia (NorNed) or the UK (BritNed). In cases of a shortage it is possible to buy electricity from these countries. In the Netherlands the in-balances are caused by program responsible parties who did wrong estimations on the expected demand or production. The electricity on the in-balance market is very expensive which intensifies to make good predictions. In 2011 the total import was 20,468 GWh and the total export was 11,834 GWh.

Balancing mechanism

Because it is impossible to predict the exact demands and productions capacities any moment in time to balance the required voltage on the network a balancing mechanism is mandatory. This balancing mechanism is the tool for Tennet, the TSO, the possibility to balance the network. There are various sorts of balancing mechanisms. In the Netherlands the TSO has operating reserves. These operating reserves are some generation facilities which can ramp up pretty quickly and are contracted from the balancing market. This operating reserve is offered by the producers.

Technical elements

Generation

The total production in the Netherlands in 2010 was 118.000 million kWh (37 percent decentral). There are around 800 producers who produce more than 200 MWh a year. The highest production peak according to Tennet in 2010 was 14.727 including import. The technology mix over time is presented in On the next page. It is visible that the percentage of renewable electricity is slowly increasing. Wind and biomass energy are the most important renewable energy sources used generation of electricity.

The percentage of renewable electricity production increased up to 12 billion kWh in 2011 which is approximately 11 percent of the total generated amount of electricity [3].

Transmission

As mentioned before is the electricity transported via the high voltage lines of the transmission system operator(Tennet). In the Netherlands this infrastructure is about 9.700 kilometres long. The following data about the transmission network was obtained from the annual report of Tennet;

Distribution

The total network in the Netherlands in 2010 was 309.502 kilometres long 18. Subtracting the 9.700 of the HV network the L/MV network will be around 300.000 kilometres long. DSOs maintain the LV lines of 0.23 kV, MV lines of 3, 10 and 20 kV, I (intermediate)V lines of 50 kV and sometimes also a small part of HV lines of 110 and 150 kV. In order to get insight in the main aspects of the distribution networks the annual reports of the three main DSOs in the Netherlands are analysed. These DSOs are (Al)Liander B.V., Enexis B.V. and Stedin B.V.

The table above presents the operators of 88 percent of the network. The remainder is distributed by smaller DSOs. Some conclusions from this analysis are;

1. A first conclusion is that investment is of importance for the development path of the electricity system due to the long lead times and capital intensity of investments. An investment in a large coal fired power plant has for example an considerable effect on the portfolio mix for the coming 25 years.
2. A second conclusion is that simulation is often used for the modelling of long-term electricity markets. More than 80 % of the reviewed articles used simulation as their research method (see table A.1).
3. A conclusion from (1 and 2) is that the modelling of investment behaviour could be important in computational modelling of long-term electricity markets to analyse policies [26]. Thereby said that this conclusion is also dependent on the purpose and use of the model.

The information in this chapter should give sufficient overview on the elements within the electricity system. For this thesis at this stage this should enable you as reader to understand the basic insights of the electricity system. The mentioned concepts are important to understand the further thesis description.

Theoretical principles

This chapter provides insight in the theory and empirical data used in this thesis for the development of the conceptual investment algorithms. The chosen theory is i.e. neo-classical economics and modern portfolio theory. Besides the theory empirical data is used [7, 8]. The argument for the neo-classical assumptions are related to the dominant position of neo-classical thinking in the modelling of investment behaviour by other scientists in electricity market models (see figure A.1). The second foundation for the investment algorithms is as mentioned the empirical data. In the coming section the concepts of neo-classical assumptions are explained.

Neo-classical theory

Neo-classical economics was originally introduced around 1900 by Thorstein Veblen in reaction on classical economics [28,31,33]. The neo-classical theory describes in essence that firms intend to maximize their overall present value. The main objective of this theory is describing the phenomenon that capital accumulation is performed under the assumption of profit maximization. Or in the case of an individual optimization of the so called utility. According to the neo-classical theory an economic efficient market is established taking seven assumptions into account. These seven assumptions will be discussed later. Neo-classical theory is aligned with rational choice theory and dominates today's micro-economics. There has been many newer versions of the theory since there is no single consensus on what neo-classical economics exactly is. An example is awareness of economic criteria changes which was suggested as a newer version of neo-classical economics. One of the critiques is that the theory is considered to be adequate in static cases, but could be problematic in long-term simulation meanwhile it is used in various studies. The neo-classical approach focusses on the determination of prices, inputs and outputs. The theory rest on three main assumptions; agents have rational preferences among outcomes, individuals maximize utility and firms profit, agents act independently and on the basis of complete information. Criticism on this theory is that it has a normative bias and wrong assumptions taken rationality into account. Unless the criticism the theory is widespread and used extensively in various studies (see article analysis). All the neo-classical assumptions together are discussed now;

Rational decisions

This assumption says that agents think rational in the sense that they prefer more valuable goods, or less costly depending on the objective function that is prevailing. Applying this idea to the electricity market it would mean that producers intend to invest in more profitable power plants than less profitable power plants. Or in the case of more criteria like environmental friendliness and profitability, producers will prefer the most environmental, profitable power plant. Essential here is that criteria like environmental friendliness have assigned a certain value in order to make the rational decision possible. In the conceptual algorithms the rational choices are made based upon NPV estimations including subjective factors like technology preferences.

Perfect knowledge

The assumption of perfect knowledge means that agents have perfect predictive power. This implies in the case of the electricity sector that producers are able to predict fuel prices in deep detail. This perfect predictive power means that there is no uncertainty on fuel prices, permit procedure delays etcetera. This assumptions enables the power producers to make well founded rational investment decisions which will lead to an equilibrium. In the EMLab generation model agents do not have perfect knowledge.

People act independent and on the basis full and relevant information

This assumption implies that producers are not affected by demand and consumers not by producers of electricity. This could be applied on the electricity market by understanding that the behaviour of consumers will have no influence on the investment decisions of power producers. Or the other way around; the decision of power producers to invest in certain technologies will have no influence on the behaviour of the consumers. This assumption does not hold in the EMLab model. The planned investments of a certain investor i will influence the investments performed by the other investors.

Law of diminishing return

The law of diminishing return is a behavioural hypothesis which simply says that the more agents buy the smaller the increment in satisfaction becomes. From the supplying side this is the same In a neo-classical model this leads to an equilibrium model. This could be translated to the merit order where the first MW_e are very valuable and therefore are the demand prices very high. This assumption holds for the current model. When investors invest in for example a coal fired power plant the possibilities of investing in a new coal fired power plant will decrease because unless demand is increasing tremendously.

Perfect competition or many participants

Perfect competition means the presence of many producers and consumers of electricity. This assumption enables also the most efficient market equilibrium. In the case of the Dutch power sector it is still possible to reach an equilibrium but not the most efficient one. This is the case because there are a limited number of producers, but due to the decentralization and the introduction of the smart meter (which enables everyone with de-central over production to sell their electricity) the number of producers is increasing.

Unique equilibrium

This assumption is related to the fact the agents will converge to one strategy or one way of buying. This will result in an equilibrium. This could be explained by the a certain production function P(price) which is specific for a producer. The consumer has a certain demand function named D(price). For a certain price an equilibrium is achieved where D(price) = P(price). This equilibrium assumptions is not part of the current investment algorithm model.

Freedom to enter

This assumption implies that producers can enter the market without any burden. In the case of the electricity sector this could be explained by the option of new producers to enter the market without any restricting factors like producing minimal capacity. No restrictions in attracting capital, personal etcetera. This new entrance of investors is not incorporated in the model.

These assumptions helping economists to understand the allocation of scare resources in order to maximize profits. In this case how electricity producers are using their money, time, labour to invest in power plants to maximize their profits. The neo-classical assumptions are derived from many other theories like the theory of the firm in the case of profit maximization. Neo-classical economics is all about equilibria because it is argued that these equilibria are the solutions of the maximization problem of the producer. One of the arguments of generalizing the behaviour of producers is methodological individualism. This methodological individualism simply says that economic processes are explained by aggregating the behaviour of producers in this thesis.

A.2 Development of the algorithms

This section includes the design steps for the algorithms.

Conceptual algorithms

The design steps for the MCDA, which is used in the algorithm including technology preferences, are listed below:

Multi-criteria decision analysis method design steps

1. Define the criteria
2. Specification of alternatives
3. Evaluation of criteria on alternatives
4. Choice for the MCDA method
5. Scoring the evaluations
6. Choice of normalization
7. Identification of relative importance
8. Calculation of the preferred choice and ranking
9. Exploration of results
10. Challenging the intuition of the decision-makers
11. Discussion of the results

Pseudo-code

The basic algorithm in EMLab-generation embodies the following steps:

1. **Start algorithm**
2. Select the first investor x to invest, this happens randomly every tick. The number of investors are manually determined in the experiment file.
3. The investor makes an estimation of the demand by averaging the expected demand growth rate over the last five years. For each segment of the load-duration function (divided in segments) the demand is estimated as follows; $\hat{D}_{s,c,t+n} = D_{s,c,t} \cdot (1+h)^t$. Here $\hat{D}_{s,c,t+n}$ is the estimated demand in year t+n, segment s and country c.
4. Investor i makes market predictions for coal, gas, uranium and CO_2 prices in the same way as the demand function in the previous step.
5. Now the electricity price is calculated for each segment of the load duration function and an comparable price duration function is established.
6. Is the investor capable of paying a potential down-payment. This is around 30 percent of the capital cost.
7. Calculation of the running hours of the potential investment on the basis of the future electricity prices and variable costs and the sector availability rate. Check whether the number of running hours are sufficient. (e.g. a nuclear plant has to run 5000 hours minimal)

8. Check, is the plant in the merit order. In other words are the variable costs smaller than the expected prices.
9. The investor estimates the plants cash flow by subtracting the plants variable costs from the estimated market price for each segment of the load duration curve. For the final cash flow for the fixed costs of the power plants are also subtracted.
10. calculation of the net present value of the investment discounted for the weighted average cost of capital (see equation 2.2)

    .
    $NPV_p = \left(\sum_{t=0...t_b} \frac{-I_p/t_b+1}{(1+WACC)^t} + \sum_{t=t_b+1..t_b+t_D} \frac{\hat{CF}_{p,t+1}}{(1+WACC)^t}/k_p\right)$
11. Select the all the investment options which have an $NPV > 0$ and rank them according to their value relatively to the invested money.
12. invest by paying the down-payment and starting up the construction of the power plant.

The integrated algorithm includes:

Algorithm 4 Integrated algorithm: combination of behaviour

Require: Run the current algorithm described in section 3.1 up to the estimation of the $NPV_{p..P}$

for all Investors **do** calculate $\sum_{p...P} D_p$ and $\sum_{p...P} A_p$
    for all Powerplants **do** calculate D_p and A_p
    end for
    Determine the probabilities of the standard normal variable

$$d_{1,i} = \frac{\mathbf{log}(\frac{A_i}{D_{i,t}}) + r_f + \frac{\sigma^2}{2} \cdot (T - t)}{\sigma \cdot \sqrt{T - t}} \tag{A.1}$$

$$d_{2,i} = d_{1,i} - \sigma \cdot \sqrt{T - t} \tag{A.2}$$

    Calculate the market-value of equity

$$E_i = A_i \cdot N_{d_{1,i}} - D_{i,t} \cdot \exp^{-r \cdot T - t} \cdot N_{d_{2,i}} \tag{A.3}$$

    Then price the debt

$$d_{i,t} = A_i - E_i \tag{A.4}$$

    Finally determine the interest-rate

$$r_f + r_{p,i} = \frac{-1}{T - t} \cdot \mathbf{ln}\left(\frac{d_{i,t}}{D_{i,t}}\right) \tag{A.5}$$

    The investor decide whether to accept the debt offer yes or no
end for

$$S_{p,i} = \frac{\sum V_{p,i}}{\sum V_{p..P,i}} \tag{A.6}$$

Than check for r_i and determine the $WACC_i$

$$WACC_i = \frac{E_i}{V_i} \cdot k_{e,i} + \frac{D_i}{V_i} \cdot k_{d,i} + r_{i,p} \tag{A.7}$$

for all Investors **do** get $\{c_n, c_{n+1}, c_N\}$ and $\{\psi_n, \psi_{n+1}, \psi_N\}$
    for all Technologies **do** calculate $\sum c_{n..N,p}$ and save the technology specific multi-criteria score $c_{n,p}$.
        if $\{\psi_n, \psi_{n+1}, \psi_N\} = 0$ **then** Select the investment according to $\mathbf{max}(NPV_{p..P})$.
        end if
    end for

Algorithm 4 Integrated algorithm: combination of behaviour (continued)

if number of profitable technologies >= 2 **then** calculate

$$\omega_p = \frac{c_{n,p} \cdot \psi_n}{\sum c_{n,p...P}} + \frac{c_{n+1,p} \cdot \psi_{n+1}}{\sum c_{n+1,p..P}} + \frac{c_{N,p} \cdot \psi_N}{\sum c_{N,p..P}} \tag{A.8}$$

if min & **max** (ω_p) **then** Save variable

end if

for all Propensities **do** calculate

$$n_{\omega_p} = \omega_p - \mathbf{min}(\omega_{p..P})/\alpha \cdot \frac{1}{\alpha \cdot \mathbf{max}(\omega_{p..P}) - \mathbf{min}(\omega_{p..P})/\alpha} \tag{A.9}$$

end for

for all Probabilities **do** calculate

$$\upsilon_p = \frac{n_{\omega_p}}{\sum n_{\omega_p}} \tag{A.10}$$

end for

Establish a discrete probability distribution.

$$\sum_{p \in P} f(p) = 1 \tag{A.11}$$

end if

Option 1: Select a random number and "role a die" select the technology to invest based upon the earlier established discrete probability distribution.

Option 2: Invest in the technology with the highest propensity

end for

calculate $S_{p,i}$ by;

$$n_{i,p} = S_{p,i} - \mathbf{min}(S_{p..P,i})/\alpha \cdot \frac{1}{\mathbf{max}(S_{p..P,i}) \cdot \alpha - \mathbf{min}(S_{p..P,i})/\alpha} \tag{A.12}$$

.

calculate $p_{i,p}$ by;

$$p_{i,p} = \frac{1 - n_{i,p}}{\sum_{p \in P} n_{i,p..P}} \tag{A.13}$$

Establish a discrete probability distribution.

$$\sum_{p \in P} f(p) = 1 \tag{A.14}$$

Option 1: Select a random number and "role a die" select the technology to invest based upon the earlier established discrete probability distribution.

Option 2: Invest in the technology with the highest propensity

Verification

In the table below the verification of the MCDA is presented. In this verification is analysed how the MCDA method is functioning for different experiments. One example is negative and positive weight-factors. In table A.3 the investment probabilities of three types of investors are estimated with the MCDA method. The outcomes are considered expected.

Alternatives	Criteria	Criteria 1 NPV	Criteria 2 CO_2 footprint	Criteria 3 Operating criterium	Criteria 4 Investment lifetime	Criteria 5 Investment cost	Criteria 6 Plant efficiency
IGCC		50	47	5,500	40	88	42
Wind		37	4	5,500	20	52	39
CCGT		45	12	-	30	33	52
OCGT CCS		26	25	-	30	45	52
Total		158	88	11,000	120	218	185
Weightfactor		3	1	-	3	1	1

Weighted propensity		**Criteria 1**	**Criteria 2**	**Criteria 3**	**Criteria 4**	**Criteria 5**	**Criteria 6**
		Max	**Min**	**Min**	**Max**	**Min**	**Max**
IGCC		0.95	0.53	0.00	1.00	0.40	0.23
Wind		0.70	0.05	0.00	0.50	0.24	0.21
CCGT		0.85	0.14	0.00	0.75	0.15	0.28
OCGT CCS		0.49	0.28	0.00	0.75	0.21	0.28

Propensity weighted		**Utility total**	**Normalised**	**Probability**
IGCC		1.239	0.36	24.19%
Wind		1.129	0.25	16.40%
CCGT		1.598	0.74	49.79%
OCGT CCS		1.034	0.14	9.62%
Upper border		1.837		
Lower border		0.899		
Total			1.50	100.00%

Figure A.2: Verification of the multi-criteria decision method

Scenario setting		**Scenario A**	**Scenario B**	**Scenario C**
NPV		3	1	1
CO_2 footprint		1	4	1
Operating criterium		0	1	3
Investment lifetime		3	0	1
Investment cost		1	1	1
Plant efficiency		1	2	3
Explanation		**Profit oriented investor**	**The environmental oriented investor**	**Flexible investor**

Propensity weighted		**Scenario A**	**Scenario B**	**Scenario C**
IGCC		24.19%	4.58%	3.26%
Wind		16.40%	31.53%	10.26%
CCGT		49.79%	37.10%	46.41%
OCGT CCS		9.62%	26.80%	40.07%

Figure A.3: Three types of investors analysed with the MCDA

The second verification includes the Black-Scholes debt pricing model. This model is analysed for different extreme values. Also a sensitivity analysis is performed under ceteris-paribus circumstances. The first verification step includes the calculation of the interest-rate of two extreme stereotypes of investors. In figure A.4 the relation is presented between an increasing asset-value and the price of debt and equity (debt assumed constant 50 million euro). In these figures $\sigma\% = 20$ and $r\% = 3$ and $\Delta t = 10$.

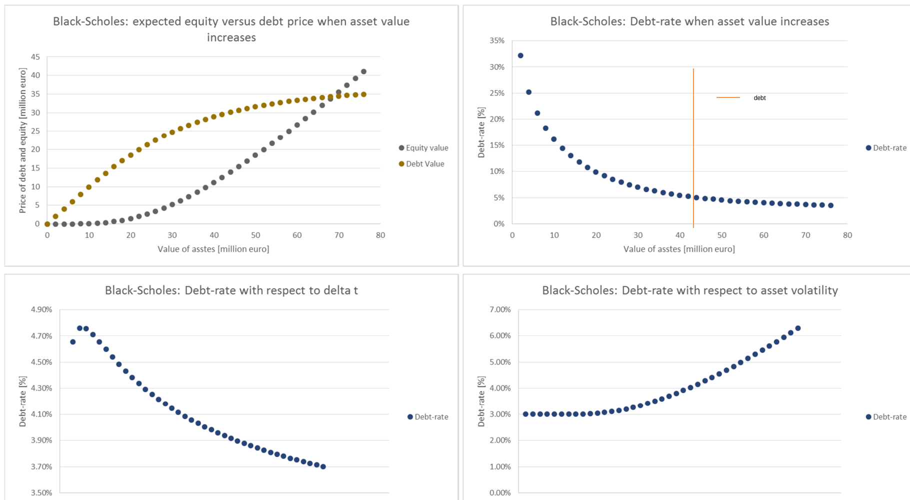


Figure A.4: Debt-pricing model: equity, debt and interest-rate for increasing value of assets

The debt-pricing model of Black-Scholes is also analysed for three experiments in figure A.5. The three types of investors are;

- **Type 1** one investor which has problems to fulfil his obligations
- **Type 2** one investor with a prime performance
- **Type 2** one investor with a normal performance

In the figure is visible how the interest-rate evolves for three situations of investors where the asset value is varied. For the investor with a lot of debt it will take much longer to obtain a loan offer with a low interest-rate from the bank. The interest-rate for the investor with a prime performance are much lower for a whole spectrum of asset values.

The algorithms in EMlab are also tested. Here de code is considered as a black box. Predefined input is inserted in the code which should match expected outcomes.

The second test includes J-Unit tests where the behaviour of one single agent is verified. The performed tests are the following;

Algorithm	Logger
Technology preferences	• Logger(Tell me the value of the propensities): this is the calculated output of the propensity equation to check whether the equation is modelled correct. • Logger.warn(Tell me the outcome of the normalization): this is to check whether the normalization is functioning as expected • Logger.warn(Tell me the probability of investing in technology i)
Credit-risk consideration	• Logger.warn(Tell me the value of debt for all investors) • Logger.warn(Tell me the value of priced equity for all investors) • Logger.warn(Tell me the interest-rate offer of the bank)
Risk-averse behaviour	• Logger.warn(Tell me the calculated weighted average cost of capital per investor i) • Logger.warn(Tell me the market-share per investor and technology) • Logger.warn(Tell me the probability of investing per investor)

Table A.1: Loggers used in the algorithms

	Scenario 1	Scenario 2	Scenario 3
Asset value	[150-530]	[150-530]	[150-530]
Debt value	488	55	181
Risk free rate	3.25%	2.58%	2.95%
Asset volatility	27%	18%	23%
Delta t	10	15	7
Investor type	Investor in default	investor with prime performance	Investor with normal performance

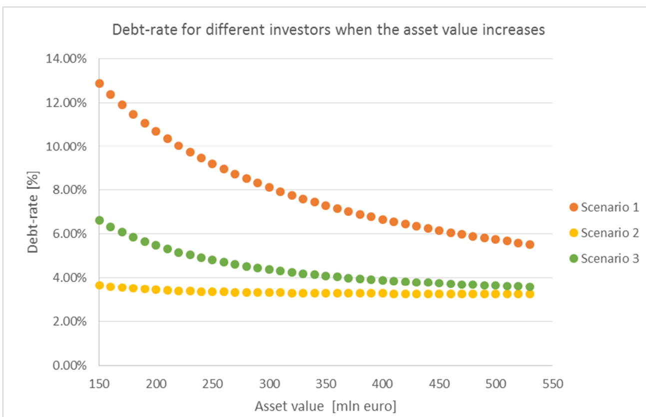


Figure A.5: The interest-rate for three types of investors

Algorithm	Test	Input and output
Technology preferences	Is the investor's decision-making as expected. This implies: is the investor checking correctly whether he is including subjective factors and is he correctly calculating the criteria scores and propensities. Is the normalizing correctly performed and are the probabilities determined as expected. In total; is the investor incorporating the technology preferences by means of the MCDA in the decision-making process a correct way	The inputs were the number of plants, technologies, capacities and further associated information. Also all information for the NPV calculation is included. For the MCDA the weight-factors and normalization parameter was predefined. The output for the agent is; `WARN Energy Producer G includes subjective factors true and has the following probabilities [0.103, 0.251, 0.279, 0.346, 0.019] for the following technologies [CoalPulverized, GasConventional, Biomass, Wind, CoalPulverizedCSS] the best technology is Wind`

Credit-risk consideration	Here is checked whether the agent is including the right interest-rate in the calculation of the weighted average cost of capital. When the financial structure of the investor is weak this should be reflected in the interest-rate offer.	The inputs are the same as in the first algorithm, but here also some parameters for the Black-Scholes debt-pricing model are included. These parameters are the asset volatility, the time to maturity and risk free rate. The outputs are;
		`WARN Energy Producer B debt value is 6.86E9`
		`WARN Energy Producer B the value of the plants is 7.63E9`
		`WARN Energy Producer B gets a interest-rate offer of 6.43% at timepoint 13`
		
		`WARN Energy Producer I debt value is 9.07E8`
		`WARN Energy Producer I the value of the plants is 1.88E9`
		`WARN Energy Producer I gets a interest-rate offer of 3.5% at timepoint 13`

Risk-averse behaviour	In this test is checked whether the investor with risk-averse behaviour indeed includes the expected considerations in the decision-making process.	The inputs are again partly equal to the first two algorithms. Other inputs are risk-averse associated parameters like the border where a investor is considered a giant. This status implies that the investor will diversify the portfolio. One example of output is; `WARN Agent Energy Producer H has chosen the best technology Biomass from the following options [CoalPulverized, GasConventional, Biomass] he diversifies his portfolio true and the market-shares of the potential technologies are [0.416, 0.426, 0.000] his total capacity is [7286.0, 7286.0, 7286.0]`

Table A.2: J-Unit tests

A.3 Design of experiments

In this section the design of experiments is discussed. The experiments, hypotheses and further DoE details are discussed here. The hypotheses are:

1. **H1** The incorporation of credit-risk considerations, risk-averse behaviour and technology-preferences in investment decisions result in substantial differences in investments.
2. **H2** There is a significant negative correlation between investments in the capital-intensive technologies and the sensitivity for credit-risk.
3. **H3** There is a significant positive correlation between investments in renewable technologies and the green tendency of investors in the market.
4. **H4** The incorporation of credit-risk considerations, risk-averse behaviour and technology-preferences in investment decisions result in substantial CO_2 emission right price volatility.

The experiments to provide an answer on the hypotheses is divided in five groups. One group of base-case experiments which includes homogeneous profit only behaviour for diverse exogenous fuel price forecasts. The second, third and fourth group are mainly used as validation experiments. These experiments are used to analyse whether the investment algorithms result in convincing investment patterns. The aggregated table with experiments is:

Group of experiments	Quantity	Description
Base-case	3	Normal EU-ETS experiment including a low, central and high DECC fuel-price forecast. Investors, which meet constraints, homogeneously evaluate NPV > 0 investment opportunities based on profitability only
Technology preferences	20	Investors evaluate NPV > 0 investments based upon a selection of criteria. There are experiments with different heterogeneous investor attitude configurations. The investors within an experiment judge subjective criteria in different ways. These experiments are used for the validation of the model.
Credit-risk consideration	15	Investors include credit-risks considerations in the investment evaluation. There are experiments with different investor specific sensitivities for credit-risk. Investors here ask themselves "Is this interest-rate competitive for me?". These experiments are used for the validation of the model.
Risk-averse behaviour	21	Investors include technology specific and portfolio risks in the investment evaluation. There are experiments with different levels of risk-averse behaviour and different tendencies for portfolio diversification. These experiments are used for the validation of the model.
Combination mix	27	Investors include subjective preferences, credit-risk considerations and specific risk-averse behaviour towards technologies in their investment decisions. The focus in these experiments is on plausible parameter configurations. This includes mainly experiments without extreme parameter values.

Table A.3: Description of the groups of experiments

The experiments are divided as follows:

experiment space in algorithm	Parameter sweep
Basic algorithm.	No parameter sweep here a fixed experiment is chosen
Technology preferences: • parameter weightfactorProfit • parameter weightfactorEmission • parameter weightfactorEfficiency • parameter weigthfactorInvestmentCost	The parameters can have the value no role, a role and significant role. No role implies the value of zero because the criterion is than not incorporated in the decision-making. When the criterion plays a role in the decision-making process it gets the value of one attributed. When the criterion plays an significant role it gets assigned the value of two. This implies that there are 3^3 **= 27 theoretical technology preferences profiles**. Also some experiments can be left out of the simulation due to parameter correlations among each-other. Since the residual amount of possible experiments is still large, latin hypercube sampling is used to select a feasible collections of parameter values. The experiments vary between a very profit only oriented market to a market with a high fraction of renewable investors.

Table A.4: Parameter configuration group 2

experiment space in algorithm	Parameter sweep
Basic algorithm.	No parameter sweep here a fixed experiment is chosen
Credit-risk considerations: • parameter assetValueDeviation • parameter debtBias • parameter loanInterestRiskFreeRate • parameter timeToMaturity	The asset-value deviation differs between 10% and 30%. The debt bias is estimated between 0 and 10 billion. The risk-free rate is ranges between 1% to 5%, but remains fixed in the first run. The time to maturity is estimated to be between 5 and 15 years, but remain also fixed in the first run. These values are chosen based on the earlier implementation done by [5] This results in 4^2 **= 16 potential configurations** in case of 4 intervals. This results in experiments where most investors have a very healthy financial structure to a market where investors have a very weak financial structure.

Table A.5: Parameter configuration group 3

experiment space in algorithm	Parameter sweep
Basic algorithm.	No parameter sweep here a fixed experiment is chosen
Risk-averse behaviour: • parameter riskPremiumNuclear • parameter riskPremiumCoal • parameter riskPremiumGas • parameter riskPremiumRenewable • parameter marketGiantCapacity	The risk-premiums differs between 0 to 10%. The market giant capacity decides whether an investor has a significant portfolio and tends to diversify. The giant capacity is set such that the value mimics a large investor within the European market. One example is Vattenfall or RWE. The experiments differ from a risk-taking market to a very risk averse market. This results in $3 \cdot 3 \cdot 3 \cdot 2$ **= 54 potential configurations** taken into account three or two intervals.

Table A.6: Parameter configuration group 4

Experiment nr.	Experiment content
1 - base	The investors show homogeneous profit only behaviour.
2	10 % of the investors include weighty sustainable criteria in their investment decisions[1]. The investors are little sensitive for credit-risks and up to 40 % of the investors is more risk averse for coal and nuclear technology which are most under societal pressure.
3	20 % of the investors include weighty sustainable criteria in their investment decisions. The investors are little sensitive for credit-risks and up to 40 % of the investors is more risk averse for coal and nuclear technology which are most under societal pressure.
4	10 % of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and large investors[2] are diversifying the portfolio.
5	20 % of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and large investors are diversifying the portfolio.
6	15 % of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and investors are not specifically risk-averse and do not diversify the portfolio.
7	15 % of the investors include weighty sustainable criteria in their investment decisions. The investors are not sensitive for credit-risks and investors are not specifically risk-averse and do not diversify the portfolio.
8	15% of the investors include weighty sustainable criteria in their investment decisions. The investors are little sensitive for credit-risks and large investors are diversifying the portfolio.
9	None of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and investors are not specifically risk-averse and the largest investors in the market are diversifying the portfolio.
10	15% of the investors include weighty sustainable criteria in their investment decisions. The investors are normally sensitive for credit-risks and some investors are specifically risk-averse for coal and nuclear technology. The largest investors in the market are diversifying the portfolio.

Table A.7: Experiments including behavioural combination

The key-performance indicators to study the hypotheses are:

- Technology capacity mix in GW/technology
- Capacity margin in GW/year
- Electricity shortages in minutes/year
- Average electricity price in EUR/MWh
- Average CO_2 price in EUR/MWh
- CO_2 price volatility in %

A.4 Analysis of results

This section of the Appendix includes the analysis of results. First the base-cases are analysed to understand the basic model behaviour. Thereafter are the experiments analysed with extreme parameter configurations as a validation step. Finally the plausible experiments are analysed. The analysis procedure is described in the coming subsection.

The data analysis procedure

Data is analysed by making use of an R-script. This R-script contains the ability to read the data files and provides functions to construct data visualizations. A data-analysis framework is used to schematically analyse the results. This framework which is visualised in figure A.6 structures the analysis.

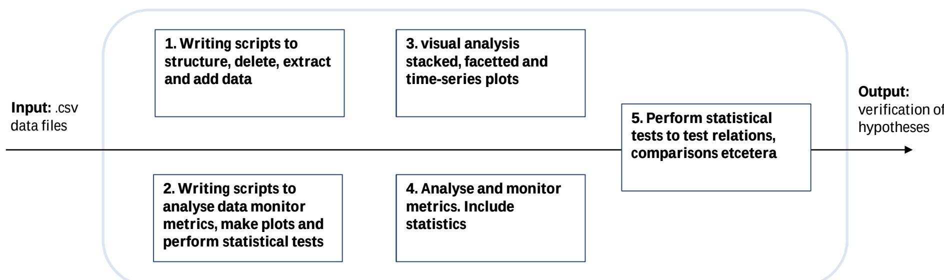


Figure A.6: Data-analysis framework

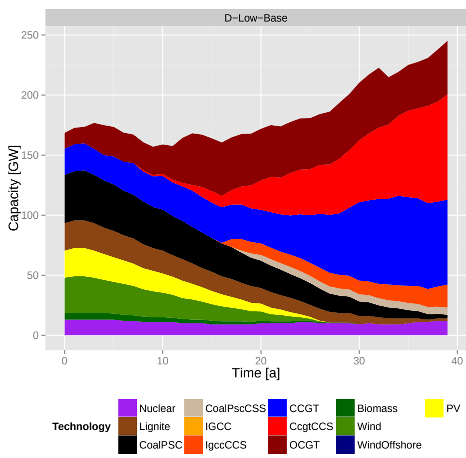
The analysis is presented in a sequential way following the number of the hypothesis. This means that the analysis starts with the analysis of hypothesis H1 and ends with hypothesis H4. The data-analysis ends with the interpretation and validation of results. The interpretation is translated into conclusions in the synthesis chapter. Table A.8 shows the statistical tests which are performed.

What to test	Statistical test
H1 Whether there are substantial differences between the average capacities per technology of the base-case and the three designed algorithms.	t-test
H2 Whether there is a significant correlation between the sensitivity for credit-risks and investments in capital-intense technologies	regression-model
H3 Whether there is a significant correlation between the green market tendency profile and investments in renewable capacity	regression-model

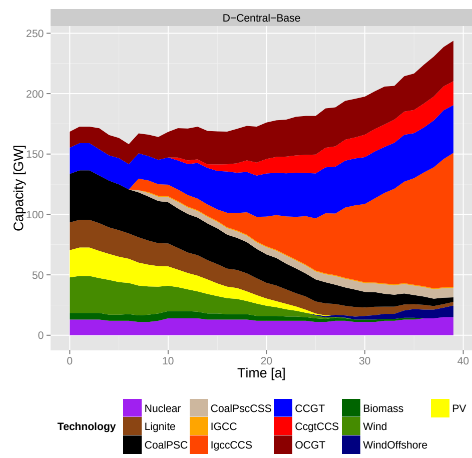
Table A.8: Statistical tests

The experiments are schematically described in the previous chapter of the Appendix. The selected benchmark experiment is the connected Dutch and German electricity market governed by the EU-ETS mechanism. The investors in this market include homogeneous profit only investment behaviour. This benchmark is chosen because it reflects the North-West European market for a certain extent. The experiment does not include renewable energy policies like the SDE+ or other feed-in tariff measures, but does include the carbon EU-ETS mechanism. The initial portfolio situation reflects the German and Dutch technology portfolio. The fuel-price time-series are based upon three DECC forecast [39]. The DECC time-series include low, medium and an high fuel-price experiment. A second reason for the selected benchmark experiment is that the investment algorithms are based upon empirical data of North West European investors.

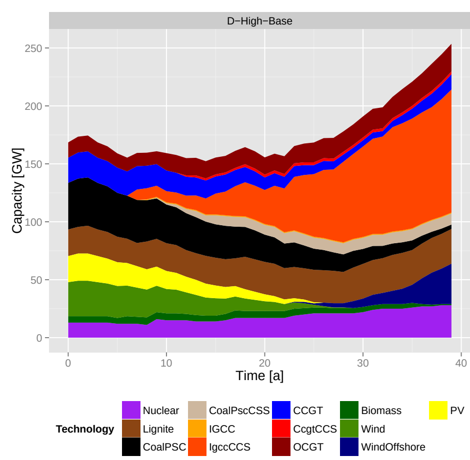
The base-case or benchmark



(a) Low fuel-prices



(b) Central fuel-prices



(c) High fuel-prices

Figure A.7: Base-case capacity mix comparison for three fuel-price forecasts

The base-case in figure 4.2a including low fuel-prices show that gas technologies will increase their capacity share position and that coal and renewable technologies will play a smaller role in terms of capacity share. More investment can be expected in CCS technologies under the assumptions in the base-case[3].

The base-case including central fuel-prices in figure 4.2b shows for some observations similar results, but in here IGCC-CCS seems to be a larger competitor for gas technologies such as CCGT-CCS and CCGT. The central fuel-price forecast gives coal a more competitive price ratio towards gas which results in more coal investment. Like in the low fuel-price experiment, investment in nuclear technology remains stable for equal reasons. Renewables get slightly more attractive in this experiment since some investment in wind offshore is visible after 25 years.

The base-case including high fuel-prices in figure 4.2c shows an investment pattern which could be a result of what is happening in reality at the moment in terms of fuel-prices. Gas technologies are not able at the moment to compete with cheaper coal [65]. This results in gas-based power plants which are not generating electricity at all and therefore cause losses for electricity companies. Only the very flexible OCGT shows stable investment. Figure 4.2c shows that in contrast with the previous base-cases that there is stable investment in lignite. Notwithstanding the high carbon emission of lignite, the technology remains competitive enough in relation to other technologies. The high fuel prices also result in more investment in nuclear technology. Also more investment in renewable technology is visible.

Before the comparison with the experiments is presented is emphasized that the results (investment patterns) are valid for the combination of assumptions on e.g. technological improvements, fuel-prices and demand. The experiments include a wide scale of parameter configurations to ensure that many extreme configurations are analysed and discussed.

Extreme experiments

The analysis of extreme experiments includes the analysis of the experiments of group 2,3 and 4 presented in table 4.1. For all these experiments the investment patterns are presented in the coming subsections. The investment patterns are analysed for the capacity in GW/year.

Experiments including credit-risks

This section elaborates on the results of the experiments including credit-risks. In total 14 experiments are analysed on multiple investment related key-performance indicators. The experiments include an increasing sensitivity for credit-risks. Scenario 1 includes the highest sensitivity for credit-risks and experiment 14 the lowest. There are also experiments included where investors have a fixed initial debt (representing less financial healthy investors). The experiments are replicated more than 75 times to reduce stochastic model effects.

Figure A.8 shows the technology capacity diagram in case of the base-case and the case where investors incorporate credit-risk. A first notice is that it seems when investors incorporate credit-risk the portfolio development remains more **diverse**. There are multiple possible reasons:

1. **Origin**; The base-case investment algorithm includes a hard constraint. Here investors can only invest when they are able of paying the down-payment which is around 30% of the capital costs. The algorithm including credit-risk enables investors invest even when the financial position of the investor is weak. This weak position will result in higher interest-rates due to the lower credibility, but gives the investor more investment options during the simulation.

[3]In all experiments technological improvement factors are included and uniform. The observations here only hold for these assumptions. Further political and institutional factors are not included in the scope.

2. **Origin**; The second expected reason is that investors are more risk-averse for capital intensive investments and therefore invest more in lower scale technologies. This statements seems not to hold for nuclear technology because this capacity is increasing. This is analysed in the second pattern.

The algorithm including credit-risk considerations include experiments where investors include an increasing sensitivity for credit-risk. This sensitivity implies that investors are more or less sensitive for potential credit-risks[4]. The credit-risk mechanism in the base-case experiment is that investors need to own 30% of the capital cost as a cash balance in order to invest. The credit-risk algorithm gives investors the possibility to borrow money based on the financial structure of the investor. In the table 4.3 are the interesting CR experiments listed. Experiment CR-14 is the experiment where credit-risk mechanism is incorporated without any sensitivity, the lower the experiment number the more sensitive investors are. This sensitivity indicates to what extent investors make the trade-off between the obtained interest-rate offer from a financier for a certain investment and the investment benefits. The first notable pattern from figure A.8 is that there is more investment in capital-intensive technologies. The two most capital intense technologies are IGCC-CCS and Nuclear. In figure A.8 is visible that investors which are incorporating credit-risks without being sensitive for those risks start investing in more capital-intense technologies like nuclear and IGCC-CCS. On the other hand is visible that nuclear and IGCC-CCS investments become less popular when investors are more sensitive for credit-risks. There seems to be a negative correlation between the sensitivity for credit-risk and the investments in capital-intense technologies. This will be analysed later in this analysis.

The second analysed pattern are the investments in more **capital-intensive** technologies. The two most capital intense technologies are IGCC-CCS and Nuclear. In figure A.8 the following experiments are presented: experiment "CR-S01" includes investors which are highly sensitive for credit-risks, the higher the experiment "S.." number, the less sensitive the investors are for credit-risks. It is however notable that Coal-PSC-CCS becomes more present in the credit-risk case although it is a capital-intense technology. It is visible that nuclear and IGCC-CCS investments become less popular when investors are more sensitive for credit-risks. The expected reasons is;

1. **Origin**; the expected reason for the lower dominant position of nuclear and IGCC-CCS when credit-risks are taken into account are the evaluation of the credit-risks by the investors. The question "Am I able to fulfil my obligations" will limit the number of investments in these two most capital-intense technologies when investors become more sensitive for these risks.
2. **Origin**; the expected reasons that Coal-PSC-CCS becomes more dominant is followed by the lowered investments in IGCC-CCS. As becomes visible is Coal-PSC-CCS slightly cheaper and includes an higher expected cost improve (see table A.9).

The third analysed pattern includes the generation of electricity for the base- and credit-risk case. This is visualized by using a facetted graph where al technologies are made visible. The first notable pattern is the more dominant position of **renewable electricity**.

1. **Origin**; IGCC-CCS accounts in the base-case for a growth of around 125 GW in total, since credit-risks lower that amount with around 100 GW other technologies will "benefit" from the situation. After twenty simulation years it is visible that renewable capacity

[4]For example: an investor in a weak financial position which is less sensitive for credit risk will still accept loans while an investor which is more sensitive will not accept the offer.

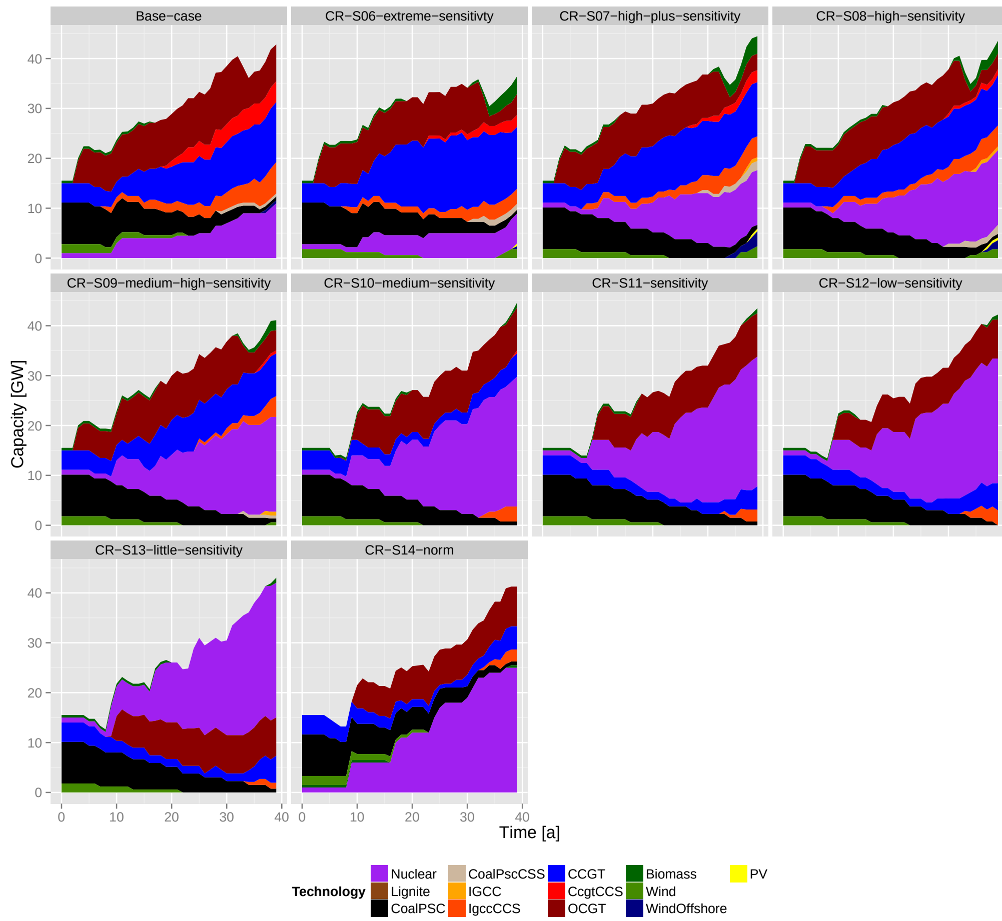


Figure A.8: Capacity mix extreme experiments including credit-risk

becomes more dominant, probably this is caused by a combination of reasons; 1. more investment options due to flexible interest rates, 2. the lower number of investments in IGCC-CCS and 3. the lowering number of available emission rights.

1. **Origin**; the credit-risk considerations of investors imply that investors will be less responsive to electricity price signals.
2. **Origin**; the second expected reason is the more dominant renewable (intermittent) capacity which implies that more shortages are expected. The shortage is caused by the stochastic generation potential of wind and photovoltaic technology. These shortages are visible in figure.

The following behavioural patterns are observed by analysing the experiments and visual plots;

1. **More diversification** incorporation of credit-risks by investors results in more technology

Technology	Initial investment Cost	Cost improvement factor	Capacity MW
CoalPSC	1.365.530	No	758
Lignite	1.700.000	No	1000
IGCC	1.724.880	-0.0036	758
CoalPSC CCS	2.457.950	-0.0098	600
IGCC CCS	2.501.080	-0.0075	600
CCGT	646.830	-0.0075	776
CCGT CCS	1.164.290	-0.0075	600
OCGT	359.350	No	150
Biomass	1.703.320	-0.0044	500
Wind	1.214.600	-0.0017	600
WindOffshore	2.450.770	-0.0205	600
PV	2.048.300	-0.0247	500
Nuclear	2.874.800	No	1000

Table A.9: Investment opportunities

capacity diversification.

2. **Reticent with capital intense investments** incorporation of credit-risks by investors results in a more reticent attitude towards capital intense technologies like IGCC-CCS.
3. **Larger diffusion of renewable capacity** incorporation of credit-risks by investors results in a larger diffusion of renewable technologies.
4. **E-price volatility** investors which incorporate credit-risk seem to be less responsive and prefer lower scale and less capital intense capacity.

The credit-risk consideration experiments show that prices will rise significantly when investors only incorporate credit-risk (in other words; borrow money based on their financial structure) without being sensitive for those risks. In experiments where investors are more credit-risk sensitive the prices converge more to the base-case experiment.

Experiments including technology preferences

Experiment TP-20 for the general content of the experiment includes no investors which have a tendency[5] towards renewable capacity, but only evaluate investments on profit and other financial indicators. Experiment TP-18, TP-16, TP-14 and TP-12 include an increasing fraction of investors which have a tendency to invest in sustainable technologies like wind and biomass[6]. This means that experiment 12 has a higher fraction of renewable oriented investors than experiment TP-14. It is visible that the increasing fraction of renewable oriented investors result in an higher renewable generation capacity. This might be logical, but indicates that a tendency towards renewables visually seems to have a substantial impact on the investments in the current DECC fuel-price experiment. What this observation means for the hypothesis will be elaborated on later in this section since this section provides only the descriptive analysis. CCGT also becomes more attractive at the expense of IGCC-CCS due to the carbon footprint and limited

[5] A tendency means including e.g. the CO_2 footprint and plant efficiency in the investment evaluation

[6] The number of renewable oriented investors in the market with divided by the total number of investors in the market is called the fraction of renewable oriented investors. This fraction is defined as; **the green market tendency fraction**

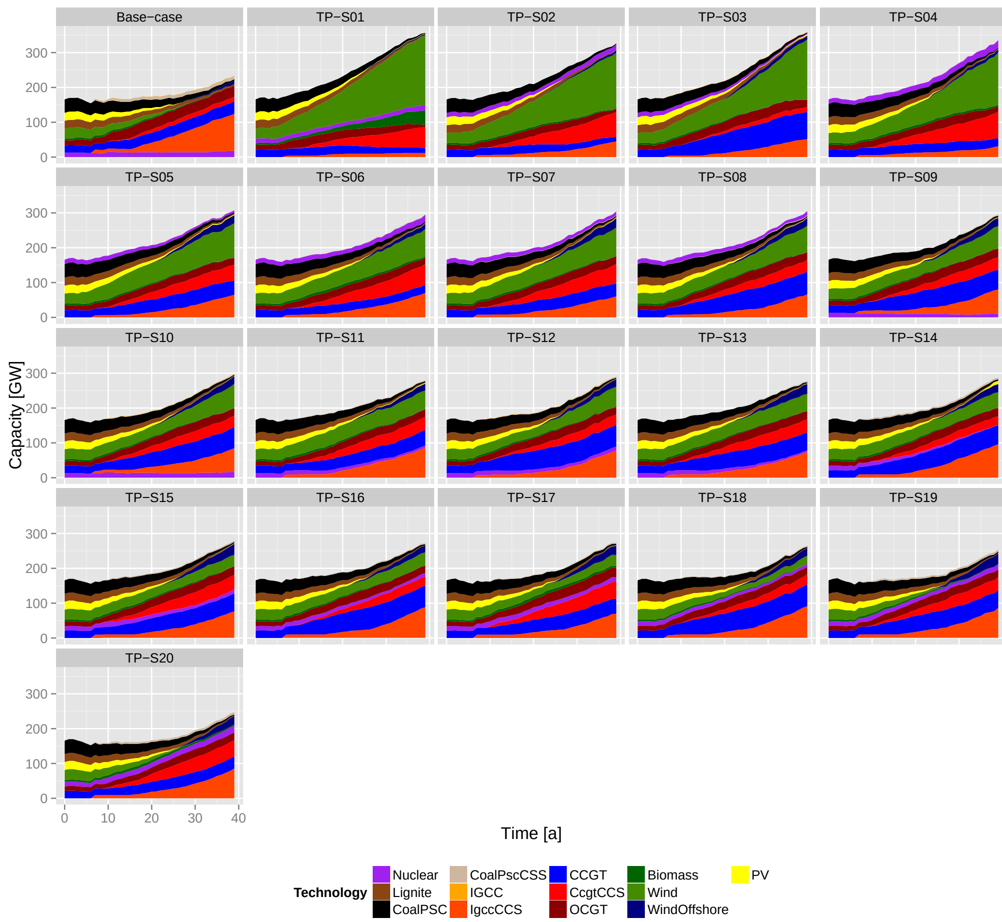


Figure A.9: Capacity mix extreme experiments including technology-preferences

profitability caused by the increasing fraction of renewable generation capacity. In the TP experiments, looking at renewable capacity development, wind technology becomes dominant and photovoltaic and biomass remain unattractive.

In case of the experiments including technology-preferences is dependent on the investor's configuration how the price path evolves. It is visible that in the experiments above 40% green market tendency the average prices are rising significantly. This is an indication that with this market attitude a theoretical renewables cap is reached what we can handle in terms of security of supply in the market. When there is to much investment in renewable generation capacity, this will result in operational shortages.

Experiments including risk-averse behaviour

With the algorithm including risk-averse behaviour are 21 experiments performed with different technology specific (or fuel) risk-averse profiles. In figure A.10 the capacity development of a

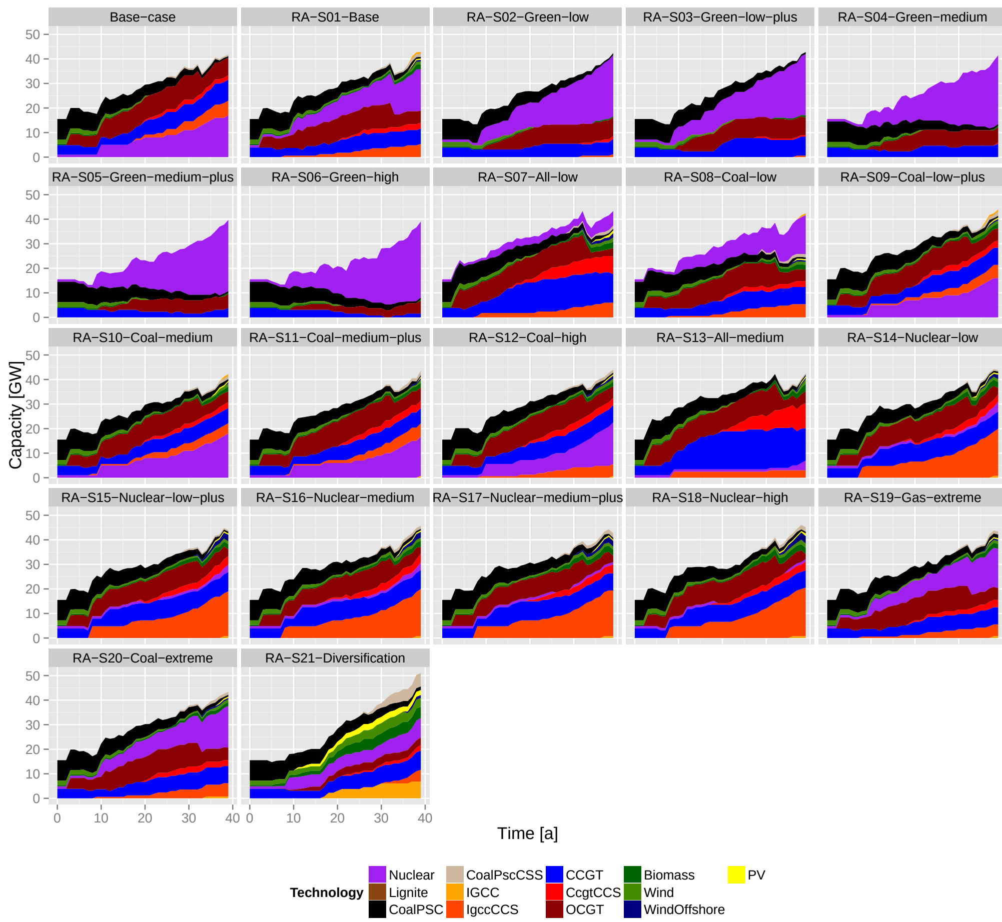


Figure A.10: Capacity mix extreme experiments including risk-averse behaviour

selection of experiments including risk-averse behaviour are presented. The selected experiments are considered interesting cases because they include extreme and plausible experiments. The extreme experiments are visualized to support the validation of the model.

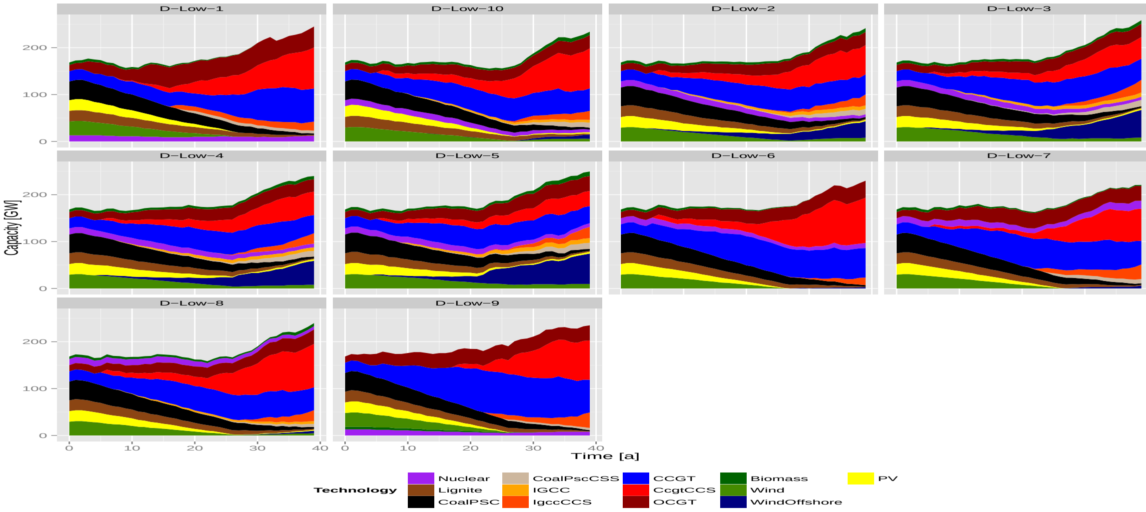
Figure A.10 shows that risk-averse behaviour towards nuclear technology results in almost no new investments in this technology. Risk-averse behaviour towards coal seems to have less effect due to the high fuel price, CO_2 emission cap and low technological expected development which made coal already a non-attractive technology without the CCS sequestration technology. In experiment RA-21 where investors include a strong tendency towards portfolio diversification is visible that the distribution among technologies is more equal. In the experiments including risk-averse behaviour towards renewables the investments in nuclear technology increase intensively. This has probably to do with the large interconnection capacity between the Netherlands and Germany[7]. The high initial fraction of renewable capacity in Germany gives no place for nuclear

[7]This is done to create one market and incorporate dynamic effects between the portfolio's

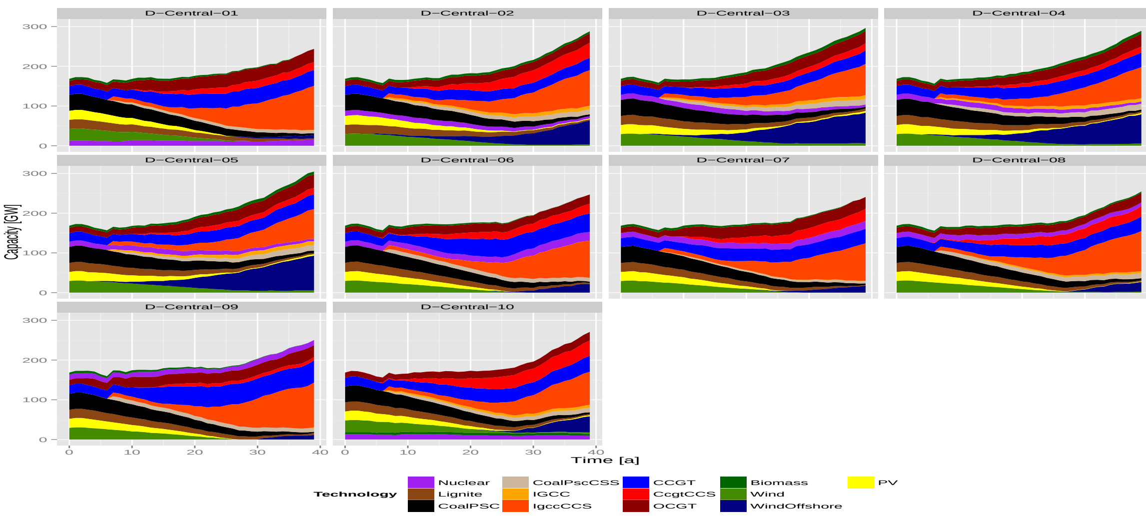
investments which are therefore done in the Netherlands. The experiment including risk-averse behaviour to all investment options results in an increasing capacity for renewables and gas-based technologies. This development emerges at the expense of nuclear technology which gets less dominant than in the base-case. This pattern can be explained by two reasons. The first reason is that nuclear technology incorporates the highest risks and second that the technology competes with the less riskier renewable capacity. Before the mentioned observations will be interpreted, statistical t-tests will be presented to present whether differences in investments are significant or not.

Plausible experiments

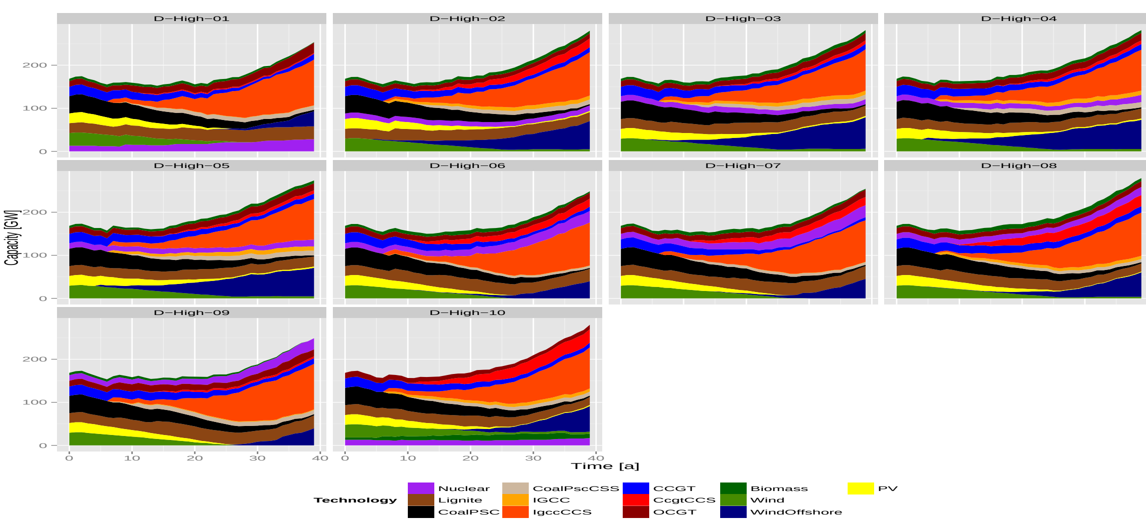
This section includes all the graphs which are used to support the conclusions. The first three graphs include the technology mix comparison for all experiments listed in 4.3. These figures include all experiments.



(a) Low fuel-prices



(b) Central fuel-prices



(c) High fuel-prices

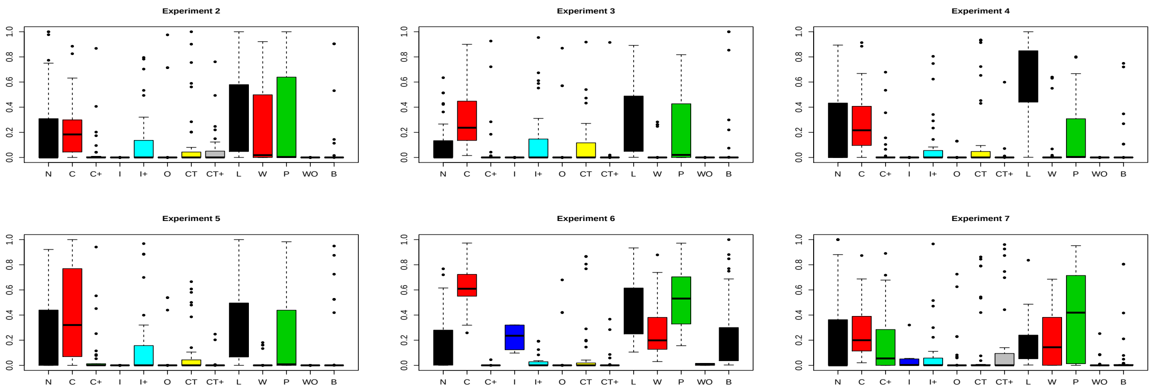
Figure A.11: Technology mix comparison for all plausible experiments

For all these graphs are also t-tests performed which provide insight whether differences are substantially different. A short explanation is presented on the box-plots.

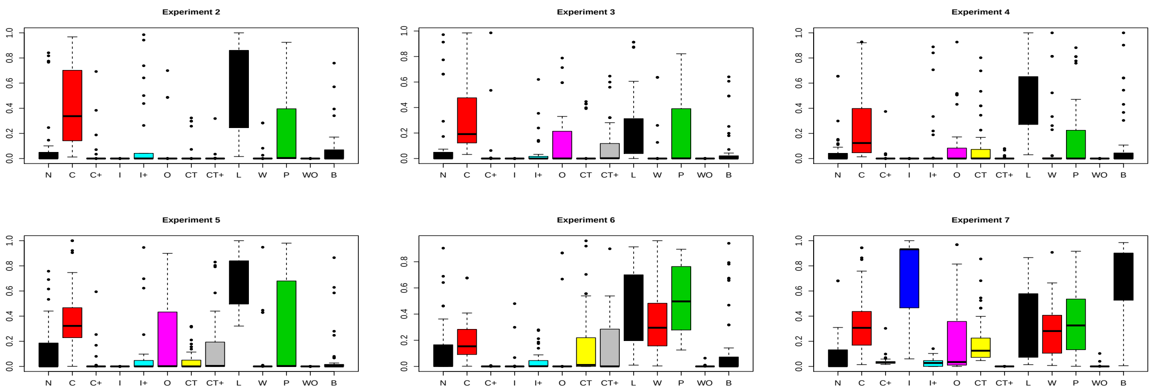
Explanation of the box-plot shows one graph per experiment (experiment 2 to 7). One graph includes one box-plot per technology, so 13 in total per graph. One box-plot contains 40 t-tests indicating whether a technology has a significant different average capacity in relation to the base-case during the whole simulation. This box-plot makes it possible to measure the overall (over 40 years) differences more accurate than just testing different points in time. When the box (IQR) is above a p-value of 0.025 the technology can be considered not substantially different from the base-case. A visible box therefore means, no substantial difference.

technology	Low	Central	High
N: Nuclear	0	0	5
C: Coal	0	0	0
C+: Coal CCS	5	5	2
I: IGCC	5	5	4
I+: IGCC-CCS	0	2	4
O: OCGT	6	2	3
CT: CCGT	2	2	0
CT+: CCGT CCS	4	3	2
L: Lignite	0	0	0
W: Wind	3	4	0
P: Photovoltaic	0	0	0
WO: Wind offshore	6	6	6
B: Biomass.	5	1	1
Cumulative	36	30	27

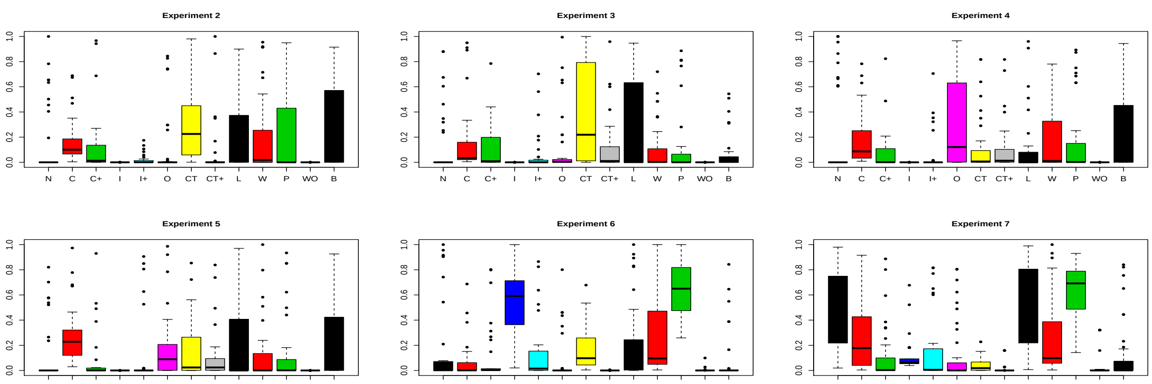
Number of boxplots (LQR) with p-value < 0.025



(a) Low fuel-prices



(b) Central fuel-prices



(c) High fuel-prices

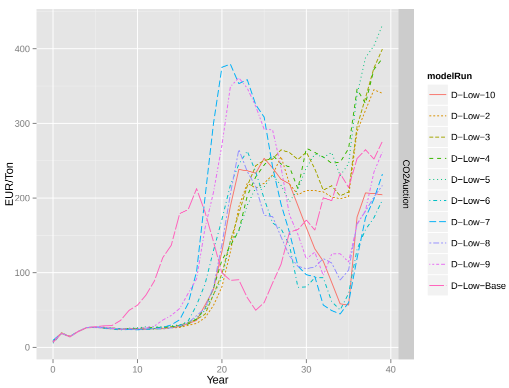
Figure A.12: T-test comparison

The y-axis represents the p-value.

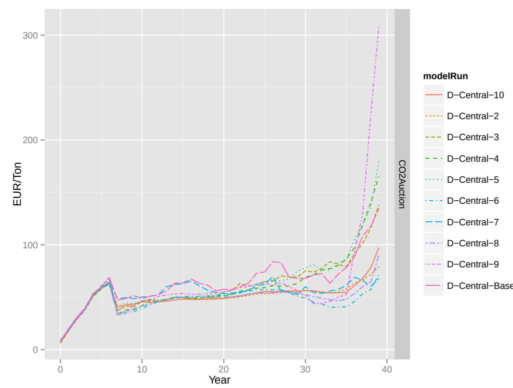
x-axis	technology	x-axis	technology	x-axis	technology
N	Nuclear	I+	IGCC CCS	P	Photovoltaic
C	Coal	O	OCGT	WO	Wind offshore
C+	Coal CCS	CT	CCGT	B	Biomass.
I	IGCC	CT+	CCGT CCS		
L	Lignite	W	Wind		

legend for box-plot plots

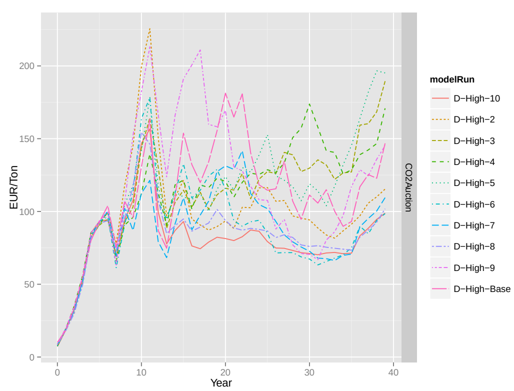
The following graphs show the average CO_2 prices among all experiments. These figures give insight in how the CO_2 price development is for different experiments described in the previous chapter.



Low fuel-price forecasts



Central fuel-price forecasts



High fuel-price forecasts

Average CO_2 price development for three DECC fuel-price forecasts

The following graphs show the average CO_2 price and volatility for all experiments. These figures give insight in how the CO_2 price and volatility is for different experiments described in the previous chapter.

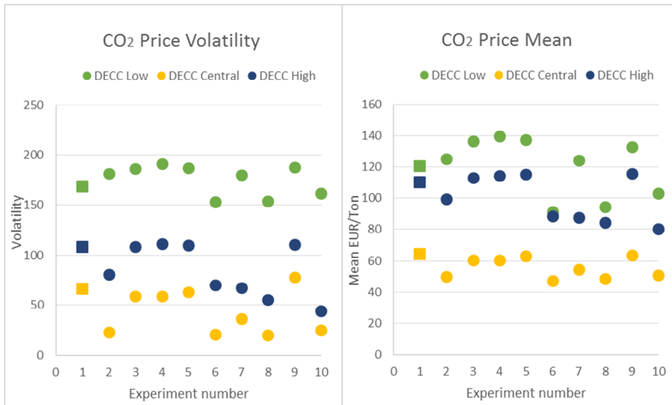


Figure A.13: Aggregated CO_2 price volatility and mean for all experiments

Experiment nr.	σ_{low}	% Δ_{base}	$\sigma_{central}$	% Δ_{base}	σ_{high}	% Δ_{base}
1 - base	168		66		108	
2	181	8%	23	-66%	81	-25%
3	186	11%	59	-11%	109	1%
4	191	14%	59	-11%	111	3%
5	187	11%	63	-5%	110	2%
6	153	-9%	21	-69%	70	-35%
7	180	7%	36	-45%	67	-38%
8	154	-9%	20	-70%	55	-49%
9	188	12%	78	17%	111	3%
10	161	-4%	25	-62%	44	-59%
min	153	-9%	20	-70%	44	-59%
max	191	14%	78	17%	111	3%

Descriptive statistics CO_2 price volatility comparison

Experiment nr.	σ_{low}	% Δ_{base}	$\sigma_{central}$	% Δ_{base}	σ_{high}	% Δ_{base}
1 - base	120		64		110	
2	125	4%	50	-22%	99	-10%
3	137	14%	61	-6%	113	2%
4	140	16%	61	-6%	114	4%
5	137	14%	63	-2%	115	4%
6	91	-24%	47	-26%	89	-20%
7	124	3%	54	-15%	88	-20%
8	94	-22%	49	-24%	84	-23%
9	133	10%	64	-1%	116	5%
10	103	-14%	51	-21%	80	-27%
min	91	-24%	47	-26%	80	-27%
max	140	16%	64	-1%	116	5%

Descriptive statistics CO_2 price mean comparison

Further details on the electricity prices are:

Experiment	Mean	Median	Variance	σ	IQR	MAD
D-Central-10	50.8431	50.83507	621.8471	24.93686	11.87207	8.774321
D-Central-2	50.18444	50.74611	511.8707	22.62456	12.80673	9.482867
D-Central-3	60.53711	51.10411	3464.8881	58.8633	17.87828	13.436991
D-Central-4	60.60996	52.60136	3502.0836	59.1784	17.50013	12.658254
D-Central-5	63.23025	52.83888	3961.3899	62.93957	14.76178	10.825923
D-Central-6	47.40576	50.26837	431.1388	20.76388	19.70461	11.57493
D-Central-7	54.34855	53.32452	1314.4966	36.25599	14.97342	10.016253
D-Central-8	48.68985	50.1846	404.2886	20.10693	13.20836	9.270111
D-Central-9	63.74529	53.85292	6063.5931	77.86908	19.11171	11.40894
D-Central-Base	64.30284	55.48291	4411.5796	66.41972	14.53438	10.566771
D-High-10	80.33422	79.9189	1944.816	44.10007	31.99045	22.132558
D-High-2	99.33539	86.1567	6521.8924	80.75823	36.23848	26.796176
D-High-3	112.95896	85.19361	11851.768	108.86583	56.16065	42.476013
D-High-4	114.1741	84.40208	12358.342	111.16808	60.4946	46.197355
D-High-5	115.11172	85.36672	12031.812	109.68962	58.98939	43.934128
D-High-6	88.68907	81.50553	4900.0698	70.0005	48.00548	34.434998
D-High-7	87.74264	79.6093	4532.6692	67.3251	48.29971	34.879925
D-High-8	84.45784	81.26548	3038.3266	55.12102	31.55058	22.277877
D-High-9	115.88575	85.69923	12232.999	110.60289	68.71139	53.49523
D-High-Base	110.27802	81.68242	11630.284	107.84379	65.91465	50.417007
D-Low-10	103.02792	29.64797	26008.76	161.27232	37.83442	10.701051
D-Low-2	125.19849	29.38324	32870.604	181.30252	64.24314	12.20401
D-Low-3	136.67644	34.56831	34704.944	186.29263	99.90765	19.137378
D-Low-4	139.88223	31.51143	36669.987	191.49409	99.93905	15.045727
D-Low-5	137.38958	34.31221	34977.375	187.02239	98.36319	19.090251
D-Low-6	91.40184	27.55436	23548.65	153.45569	15.50534	6.03173
D-Low-7	124.24213	30.01392	32485.781	180.23812	63.92655	10.415083
D-Low-8	94.35491	28.79363	23666.743	153.83999	30.4672	8.19858
D-Low-9	132.91357	30.78338	35250.767	187.75187	80.81804	10.728544
D-Low-Base	120.34934	32.57982	28298.958	168.22294	76.67134	18.650834

Table A.10: Statistical indicators CO_2 emission right price

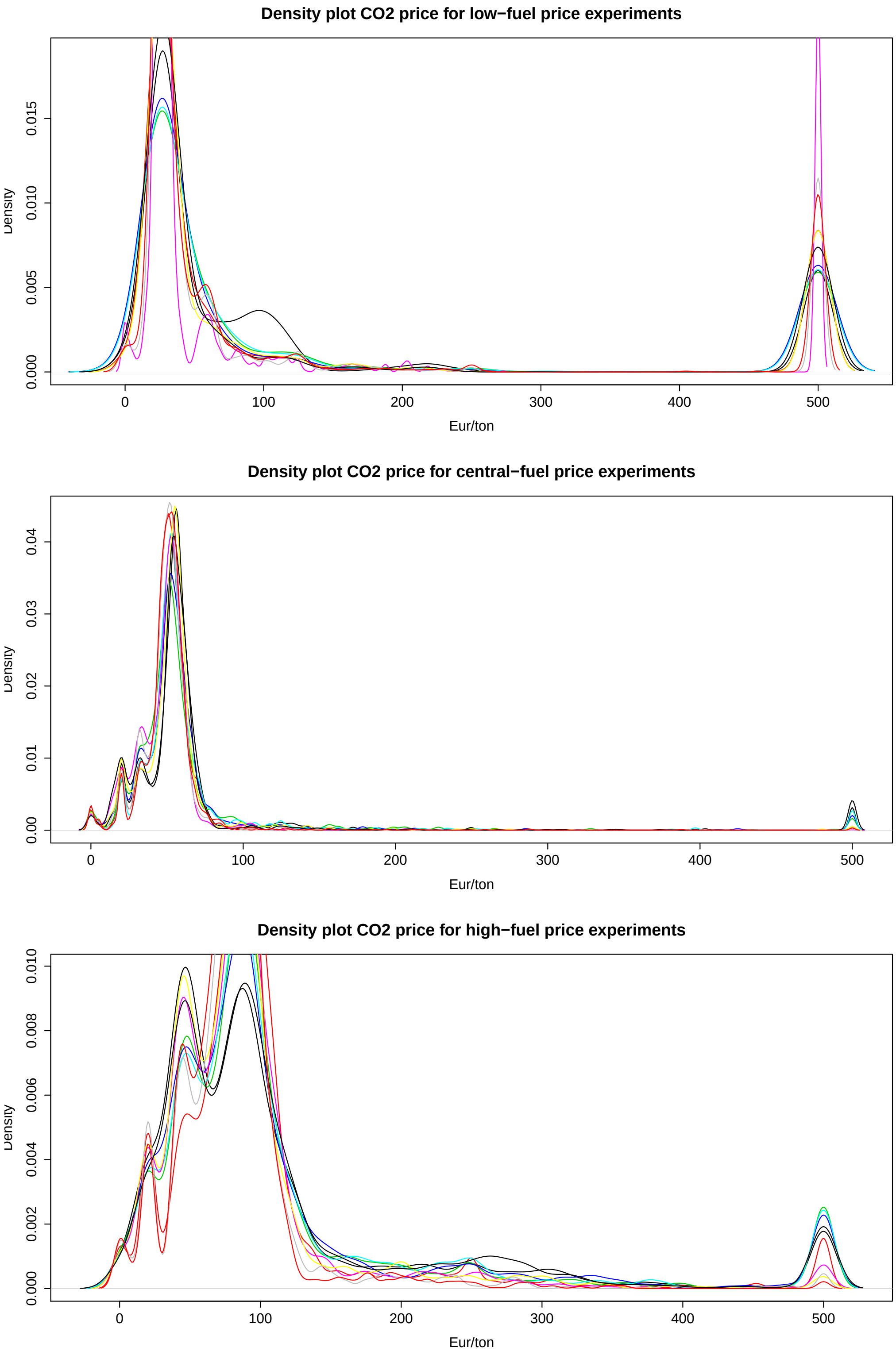


Figure A.14: Density plot CO_2 price for all experiments

Individual observations

Below some observations are presented which fall outside of the scope of the research.

Subjective blindness

From batch-runs including experiments with technology-preferences is a pattern recognized which is called subjective blindness". When a large fraction of investors in the market include a strong homogeneous tendency towards the sustainability of an investment, intermittent capacity gets highly preferred. This results in a situation where a large number of investors remains investing in the intermittent capacity which is considered profitable resulting in a decreasing operational capacity. This ensures that there is enough theoretical nominal capacity to serve the market, but high prices remain dominant due to the shortages caused by the high fraction of intermittent capacity with a stochastic power output. In reality this investment behaviour would not be preferable taking public interests into account. Besides that it is not a plausible experiment that investors remain investing in sustainable capacity due to the economical unattractiveness under the EU-ETS experiment with current policies IEA fuel-price forecasts. However in the experiment where there exists a solution for electricity storage like electrical vehicles, electrolysis and other power to gas solutions, this experiment could be preferable. In this situation the government should intervene to ensure the security of supply.

Relation to observation in reality: In 2003 when the Dutch government introduced the Ministeriële regeling Milieukwaliteit Elektriciteitsproductie, also known as MEP, there was a run on sustainable capacity by investors because the policy gave a strong financial incentive. In the end the government had to stop this policy measure because there was no financial cap and costs grew sky-high, it was considered to successful.

Crucial decisions

From individual runs with experiments including credit-risk often "crucial investment decisions" where recognized. These crucial investment decisions are decisions made by investors in a weak financial position. That means investors with a very negative cash-balance and high fraction of debt in relation to the asset value position. There are two types of crucial decisions recognized. The first is the crucially wrong decisions. This investment decision is recognized when a financially weak investor invests in a technology with unexpected disappointing results. Due to the weak financial position the interest-rate for the loan is high pushing the weak investor further into a even worse financial position due to the high loan-costs. The consequence of this decision is that the market-share of these investors shrink after the crucially wrong decision due to the incompetence to invest in the following years. This incompetence is caused by the high interest-rate wherefore the investor needs to borrow money due to the high probability of default. One important notion is that when this investor has a significant portfolio this could result in a market shock related to prices. In this situation it could take more than five years for the investor to recover from the fragile position. This is because the other investors in the market are (in the first period, where still lower prices are dominant) not able to provide the financial power to invest enough in case of increasing demand. This results in increasing prices and a investment cycle time to recover from shocks. In this situation the assumptions is made that there are no new market entrances.

The second crucial decision is the financially weak investor which is due to the credit-risk mechanism still able to invest in a very profitable technology notwithstanding his weak financial status. When the profits from this investment are even better than expected the investor can draws himself out of the fragile financial position. When this investor owns a significant portfolio in relation to the market a stabilizing market (in terms of electricity prices) is expected.

Relation to observations in reality: The company situation here is comparable with a phoenix company (defined in [84]) that emerged through the "almost" collapse of a former by insolvency. The investor in the simulation did not default, but remained existing. Comparable cases in history in terms of "market-value" are Nokia and DSM. DSM went almost broke in 1970, but invested in chemical industry and became after that investment decision successful again. Another example is Nokia which market value dropped from $40 in 2007 to $2 in 2012. After investing in the Nokia Lumia 920 the market-share is increasing again. Whether such a situation could happen in the electricity sector is doubtful due to the importance of security of supply and strict regulation

First "good" mover advantage

From individual runs with experiments including credit-risk considerations "first good mover advantages" are recognized. There are investment windows for new technologies (e.g. CCS technologies or even turning point between competitive technologies) which can provide large advantages for the investor who invests on the right moment in time. This investment window is the moment that a new innovation becomes economically viable like IGCC-CCS. When an investor invests to early and obtains worse results due to these "bad" timed investments, suffer from that starting position for years. The other investors who invested at the right time seem to have a stronger future financial position and tend to perform better in runs by means of a growing market-share, lower (loan) costs and a more healthy cash position.

Highest significant differences in investments

Looking at the earlier presented t-tests (figure 4.4a, 4.4b and 4.4c) including the verification whether the average capacity over time is considered significantly different from the base case gave divergent outcomes. Scenarios including credit-risks showed that mainly the capital-intense technologies showed significant differences in capacity averages. Interesting observation is that the base-case is almost similar to experiment 8 which includes high sensitivity for credit-risk. This seems understandable since the base-case required 30 % capital cost cash balance before the investor is able to invest. In these experiments, the average capacity of Coal, Wind, IGCC and Biomass are almost never significantly different from the base-case. Scenario's including technology-preferences showed that subjective factors have a very strong effect on changing investments. Almost all technologies showed a significant difference with the base-case. Only photovoltaic and lignite remain insignificant. Scenarios including risk-averse behaviour showed a smaller effect on significant differences in capacities. A reason for the low faction of significant differences is that risk-averse behaviour mainly causes a decreased responsiveness for investment signals.

A.5 EMlab-generation code

The EMLab-generation code can be found by the following url: `https://github.com/RubenVerweij/emlab-generation/tree/feature/investmentBehaviour`. Information about installing and setting up the model can be found to the wiki page (github). The modelling process can be tracked by looking at the code commits `https://github.com/RubenVerweij/emlab-generation/commits/feature/investmentBehaviour?page=1`. One code example which describes how an investor calculates his debt and asset position is presented below:

```
if (agent.getInvestorIncludeCreditRisk().equals("true")) {
            for (PowerPlant plant : reps.powerPlantRepository.
                findPowerPlantsByOwner(agent)) {
                if (plant.getLoan().getNumberOfPaymentsDone() < plant.getLoan().
                    getTotalNumberOfPayments()) {
                    long paymentsLeft = plant.getLoan().getTotalNumberOfPayments
                        ()
                            - plant.getLoan().getNumberOfPaymentsDone();
                    double amountPayment = plant.getLoan().getAmountPerPayment()
                        ;
                    debtTotal += (paymentsLeft * amountPayment);
                } else {
                }
                if (plant.getLoan().getNumberOfPaymentsDone() < plant.
                    getTechnology().getDepreciationTime()) {
                    double plantInvestedCapital = plant.getActualInvestedCapital
                        ();
                    double depreciationTermAmount = plantInvestedCapital / plant
                        .getTechnology().getDepreciationTime();
                    assetPlantTotal += plantInvestedCapital -
                        depreciationTermAmount;
                } else {
                }
                if (debtTotal == 0) {
                    debtTotal = 1;
                } else {
                }
```