Capacity Mechanisms

ensuring long-term system adequacy during the energy transition in the electricity market

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The Woman in the Arena

"*It is not the critic who counts; not the woman who points out how the strong woman stumbles, or where the doer of deeds could have done them better. The credit belongs to the woman who is actually in the arena, whose face is marred by dust and sweat and blood; who strives valiantly; who errs, who comes short again and again, because there is no effort without error and shortcoming; but she who does actually strive to do the deeds; who knows great enthusiasms, the great devotions; who spends herself in a worthy cause; who at the best knows in the end the triumph of high achievement, and who at the worst, if she fails, at least fails while* ***daring greatly****, so that her place shall never be with those cold and timid souls who neither know victory nor defeat.*"

Theodore Roosevelt

Abstract

Electrification by means of renewable energy sources in electricity production (RES-E) is a key strategy to meet global climate goals established in the Paris Agreement. The increasing share of RES-E as a result of this has significant implications on the functioning of the electricity system and the adequacy of the electricity market design, as these technologies exhibit different characteristics compared to conventional generators. Their intermittent output combined with near negligible marginal costs has an effect on electricity price formation and will lead to an increased demand for flexibility services to level out these fluctuations. These trends will induce an increased investment risk for flexible generation capacity. This increased investment risk feeds into the risk-averse behaviour of investors that is already present due to market failures that exist in electricity markets. It remains unclear whether the liberalised neoclassical electricity market design provides sufficient incentives to invest in generation capacity in order to maintain system adequacy during the energy transition.

One possible market design option that is proposed to address this increased investment risk are *Capacity Mechanisms*. Capacity Mechanisms allow for an adequate remuneration of (flexible) generation capacity, by providing a steady income stream to firm capacity on top of revenues obtained from selling electricity. The purpose of this thesis is to evaluate the effectiveness of a capacity market - a specification of a capacity mechanism - in maintaining system adequacy in a system with an increasing share of RES-E. Additionally, it aims to fulfil the need for electricity system models that allow for performing robustness analysis as this it is seen as increasingly important to adequately account for uncertainty that is inherently related to the unfolding of the energy transition. This research was carried out by extending an existing quantitative model of the Dutch electricity system, referred to as Myopic Optimisation Detailed Operational (or MODO), with a capacity market. The methodology applied relies on myopic optimisation. Conceptualisation of the capacity market model is based largely on the design of the NYISO Installed Capacity Market (NYISO-ICAP), as this design is relatively simple whilst being considered a successful capacity market. A thorough literature review on the NYISO-ICAP was performed to establish a profound understanding of real-world capacity market dynamics and how these can be translated to the model. The conceptualisation of the capacity market forms a basis for formalisation and is used to establish the formal rules of the capacity market model complying with the basic structure of linear programming problems. This serves as input for the implementation of the extension of the capacity market in MODO, and thus in Linny-R.

With the resulting model, the effectiveness of a capacity market in maintaining system adequacy was assessed on the performance of several Key Performance Indicators. These encompass the Supply Ratio, the average annual volume of Energy-not-Served [MWh], the average Electricity Price [€/MWh] and the total Consumer Spending [€]. A comparative analysis was performed between the performance of the energy-only market and the capacity market on the identified Key Performance Indicators in four pre-specified scenarios. The four scenarios are varied on key uncertainties underlying the unfolding of the energy transition to explore the robustness of results, such as weather conditions and the level of risk aversion of investors.

From this thesis, it can be concluded that a capacity market can be an effective and robust policy instrument to maintain system adequacy during the energy transition at a lower cost to consumers. This can specifically be seen in the increased number of investments in peaking generators compared to the energy-only market when forecasted revenues of the capacity market are sufficient, which has a positive effect on the electricity system's robustness to different weather conditions. Furthermore, when the level of a risk aversion of investors is high, a capacity market is more robust in ensuring system adequacy compared to an energy-only market. Nonetheless, a capacity market can be prone to investment cycles which can have a negative influence on the effectiveness of a capacity market to maintain system adequacy at all times. These investment cycles are a result of the bounded rationality and myopia experienced by investors, ultimately leading to imperfect forecasting of the revenues of the capacity market. Results of this thesis have shown that in *busts* of investment cycles, investments in generation capacity can be insufficient to maintain system adequacy.

To conclude, a capacity market can be a viable option in order to maintain system adequacy in the energy transition. However, whether it is the most suitable option to maintain system adequacy is not clear. Novel flexibility options such as storage could potentially serve a significant role in maintaining system adequacy. If additional flexibility options have a lower perceived investment risk compared to flexible generation units, the electricity market can potentially continue to rely on its initial liberalised neoclassical market design whilst maintaining system adequacy. This requires further exploration in future research.

Furthermore, MODO and its capacity market extension fill the need for electricity system models that allow for performing robustness analysis, as it has a relatively low computation burden. Hence, an interesting avenue for future research is to evaluate the effectiveness of a capacity market in many possible futures.

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The thesis that lies before you is the final product of the masters programme Complex Systems Engineering and Management and symbolises the end of an era: my time as a student in Delft. I would like to express my gratitude for everyone who has offered their support and help during this research project, ultimately playing an important role in the fulfilment of this thesis.

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Nomenclature

μ_j	Energy conversion efficiency of technology type *j*
$B_{i,j,y}^{price}$	Price of capacity bid in the yearly capacity market of asset *i* of technology *j* in year *y* [€/MW]
$B_{i,j,y}^{volume}$	Volume of capacity bid in the yearly capacity market of asset *i* of technology *j* in year *y* [MW]
$c_{i,j,y}$	Capacity sold in the capacity market by asset *i* of technology *j* in year *y*
$D_{peak,y}$	Electricity peak demand in year *y*
$D_{r,y}$	Demand requirement of capacity market in year *y*
$f_{j,y}$	Fixed costs of technology type *j* in year *y* [€/MW/y]
$f_{j,y}^{O\&M}$	Fixed Operation and Maintenance costs of technology type *j* in year *y*
$g_{i,j,y,t}$	Electricity output of asset *i* of technology *j* in year *y* at time *t*
i	Asset in a technology stack
$I_{j,y}^{annuity}$	Annuity for an investment in technology *j* in year *y* [€/MW/y]
$I_{j,y}^{threshold}$	Investment threshold for technology *j* in year *y*
$ICAP$	Installed Capacity
j	Type of technology
LM	Lower margin of capacity demand in yearly capacity market [MW]
$P_{i,j,y}$	Profitability of asset *i* of technology *j* in year *y*
$P_{j,y}^{threshold}$	Profitability threshold for investment in technology *j* in year *y*
$p_{y,t}$	Market clearing price in the electricity spot market in year *y* [€/MWh]
pc_{cap}	Price cap of yearly capacity market [€/MW-year]
pc_y	Market clearing price of yearly capacity market in year *y* [€/MW-year]
$pc_y^{forecast}$	Forecast of the market clearing price of the yearly capacity market in investment run of year *y*
r	Installed Reserve Margin (IRM)
$s_{i,j}$	Standard generation capacity of asset *i* with technology *j*
t	Time unit (e.g. hours or days)
$UCAP$	Unforced Capacity
UM	Upper margin of capacity demand in yearly capacity market [MW]
$v_{j,y}^{fuel}$	Fuel price of technology type *j* in year *y*
$VoLL$	Value of Lost Load [€/MWh]
$volume_{cm,y}$	Volume of capacity procured in the capacity market in year *y*
y	Year

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1 Introduction

The energy transition is one of the most profound challenges of the 21st century and has risen to the top of political agendas. The report of the Intergovernmental Panel on Climate Change (IPCC, 2022) presents that the effects of anthropogenic climate change are already widespread and significantly harm both nature and lives of billions of people. Therefore, the reason for global political leaders to aim for the goals set in the Paris Agreement to curb greenhouse gas emissions to limit climate change to 1.5 degrees Celsius compared to pre-industrial levels, is all the more present.

A key strategy to meet global climate goals established in the Paris Agreement is electrification based on renewable energy sources in electricity production (RES-E) (Keramidas et al., 2020). Electrification can be widely applied in different sectors, such as transportation, heating (IRENA, 2020) and industry (Wei, McMillan, et al., 2019). It shows great potential to aid in the reduction of greenhouse gas emissions, as it could reduce emissions of the European industry - one of the challenging sectors to decarbonise - by 78% (Madeddu et al., 2020). Along with electrification, potential deployment of hydrogen at scale will induce an increased demand for green hydrogen produced by electrolysis based on RES-E (Gielen et al., 2019), The Sustainable Development Scenario – a strategic pathway to reach these climate goals – of the IEA (2019) shows that electricity demand is projected to grow from a share of 18% to 31% of the global final energy consumption by 2040. This requires the share of RES-E to increase.

The increasing share of RES-E has implications on the functioning of electricity system and the adequacy of the electricity market design, as these technologies exhibit different characteristics compared to conventional, fossil-fuelled electricity generators. One major challenge is the intermittent nature of variable renewable energy sources such as solar and wind. The variable output of these RES-E will lead to an increased demand for flexibility services to level out their fluctuations. Furthermore, the marginal costs of variable RES-E are negligible. The intermittent output combined with negligible marginal costs may lead to both volatile and suppressed electricity prices. These trends will induce an increased investment risk for flexible generation capacity.

Although the increasing share of RES-E aggravates investment risk, the question whether the energy-only market will provide sufficient incentives to invest in generation capacity to maintain system adequacy, does not stem from this newly developing trend. The liberalisation of the electricity market was the starting point of concerns of regulators on whether the market will induce sufficient investment in generation capacity in order to meet demand at all times (Read et al., 1999). Following neoclassical-economic theory, energy-only markets - which only remunerate the electricity that is produced - should be able to incentivise investment in generation capacity by displaying high price peaks during scarcity resulting in the coverage of costs for generation units (Gore et al., 2016; Petitet et al., 2017). This applies when several key assumptions are met: (1) there exists perfect competition in the market, (2) market participants are rational and (3) market participants attain a risk-neutral attitude (Caramanis et al., 1982; Oren, 2005; Schweppe et al., 2013; Stoft, 2002). However, electricity markets exhibit imperfections and therefore these assumptions are somewhat unrealistic. As a result of these imperfections, market failures arise which negatively affect the willingness of investors to invest in generation capacity. The increased investment risk induced by the rising share of RES-E adds to the risk-averse behaviour of investors that is already present due to these market failures.

Thus, it remains unclear whether the liberalised neoclassical electricity market design provides sufficient incentives to invest in (flexible) generation in order to maintain security of supply during the energy transition. This question holds true for the Netherlands. The current electricity market design may be reconsidered as a result of the planned phasing out of 4 GW of coal-fired power plants and the increasing reliance on variable RES-E (Söder et al., 2020), which will ultimately affect the reliability of the Dutch electricity system.

One possible market design options that is proposed to address this increased investment risk is referred to as *Capacity Mechanisms* (L. J. De Vries, 2007). Capacity mechanisms allow for an adequate remuneration of (flexible) generation capacity, by providing a steady income stream to firm capacity on top of the revenues obtained from selling electricity on the market (Hawker et al., 2017). A widespread type of capacity mechanism is the capacity market, and has been implemented in Europe in, amongst others, the UK (Department of Energy and Climate Change (DECC), 2014), Belgium (ELIA, 2022) and France (Leiren et al., 2019). It is considered a plausible consideration as to ensure system adequacy in the Netherlands. In conclusion, policy-makers have to make decisions concerning the adjustment of the electricity market design that will allow for the accommodation of a large share of RES-E and these decisions are inherently related to the success of the energy transition.

1.1. State-of-the-Art Literature on Capacity Mechanisms

As a rising share of RES-E aggravates investment risks in generation capacity, system adequacy has increasingly gained attention in scientific literature. As a result of the increasing share of RES-E, capacity margins are becoming smaller which will ultimately lead to more unserved demand (Jaehnert & Doorman, 2014; Lynch et al., 2019). Capacity mechanisms are considered a viable option to address part of these investment risks (Bublitz et al., 2019).

Although the importance of maintaining system adequacy is widely recognised in scientific literature, there exists no consensus on the need for and effectiveness of capacity mechanisms. Several authors advocate neoclassical economic theory, such as Hirth and Ueckerdt (2014), who state that an energy-only market with scarcity pricing should provide sufficient price signals to stimulate investment in generation. Furthermore, Zappa et al. (2021) question whether the empirical evidence that expresses the need for a capacity mechanism is present.

The effectiveness of capacity mechanisms within interconnected electricity systems is disputed, as this may lead to cross-border leakage (Bucksteeg et al., 2019; Jaehnert & Doorman, 2014). Within integrated electricity systems, the benefits of capacity mechanisms may leak to other countries, leading to free-riding and increased load curtailment within the country that has implemented the capacity mechanism.

Additional to the existing debate on the effectiveness of capacity mechanisms, a key knowledge lacuna that is identified from literature is the relatively limited number of robustness analyses that have been performed when evaluating the effectiveness of capacity mechanisms by using energy system models. The use of a modelling approach is suitable to evaluate the dynamic long-term effects in electricity markets (Hary et al., 2016). Models allow to address uncertainty related to the unfolding of the energy system. However, as the energy transition is inherently related to deep uncertainty, it is of fundamental importance that this uncertainty is adequately accounted for when evaluating modelling results. This uncertainty stems from the many different factors that influence the unfolding of the energy transition. The effectiveness of capacity mechanisms in an electricity system with an increasing share of RES-E is, for example, highly dependent on weather conditions. Thus, Zeyringer et al. (2018) stress that solely using a single weather-year or averaging several weather years can significantly influence the robustness of the outcomes. Currently in literature, several authors - Khan et al. (2018) and Kraan et al. (2019) - choose to use limited number of scenarios and exclude rare weather events. This could lead to severe issues as operational inadequacy of the electricity system and inability to reach climate goals. Hence, there is a need for electricity system models with a low computational burden as to allow for performing robustness analyses when assessing the effectiveness of capacity mechanisms under uncertainty.

1.2. Research Questions

From the state-of-the-art literature on capacity mechanisms, it becomes apparent that two knowledge lacunae exist:

1. There is no consensus on whether capacity mechanisms are necessary to ensure system adequacy;
2. There is a need for electricity system models that allow for performing robustness analysis to evaluate the effectiveness of capacity mechanisms and hence, have a low computational burden

The geographical scope of this research is set to the Netherlands, with a time-span from 2030 till 2050. As the capacity market is considered a plausible option of the types of capacity mechanisms and due to time limitations, this thesis will focus on the capacity market and not on other types of capacity mechanisms. This thesis will aim at addressing the above-mentioned knowledge gaps, therefore the following main research question is derived:

What is the effect of a capacity market on system adequacy of the electricity market in the Netherlands until 2050, when uncertainties such as weather conditions are taken into account?

To answer the main research question, two sub-research questions are formulated that will both allow to gather the required information and provide structure to the research.

1. What is the effect of a capacity market on system adequacy in a system with a high share of RES-E?
2. How is the performance of a capacity market affected under uncertainties, such as weather conditions?

The research approach that is applied to answer the identified research questions is described in the next chapter (2).

1.3. Thesis Outline

This thesis is structured as follows. First, chapter 2 describes the selected research method and argumentation behind this. This chapter is followed by chapter 3 which provides a comprehensive theoretical background on the functioning of the energy-only-market and the logic behind the implementation of capacity mechanisms. Chapter 4 presents the conceptualisation of the capacity market based on the NYISO-ICAP, which serves as a basis for the formalisation in chapter 5. The formalisation represents the mathematical logic behind the implementation of the capacity market in MODO and thus Linny-R, as described in chapter 6. The latter also presents a verification and validation of both the energy-only market and the capacity market. Furthermore, chapter 7 describes the Key Performance Indicators at which the capacity market will be assessed, followed by assumptions and scenarios that serve as input for the sensitivity and scenario analysis. Results of these analyses are presented in chapter 8 and are interpreted. The conclusion of this thesis, insights for policy-makers and recommendations for future research are described in 9. This is followed by a critical discussion of the results in chapter 10. Lastly, a personal reflection of the research project is presented in chapter 11.

2

Research Methodology

This chapter will elaborate on the research methodology that will be applied to answer the research questions stated in section 1.2. First, argumentation behind the choice of the modelling paradigm will be provided in section 2.1. Then, within this paradigm, a research method is proposed, namely myopic optimisation with high operational details. The suitability of myopic optimisation to meet the modelling purposes of this thesis is explained in section 2.1.1. Additionally, limitations of this method are defined in section 2.1.2. Furthermore, a description of the model in which the capacity market will be implemented is described in section 2.2.

2.1. Research Approach & Methodology

The energy transition and an increasing share of RES-E will have significant implications on the functioning of the electricity market. The energy transition is inherent to complexity and deep uncertainty (Moallemi & Malekpour, 2018). The use of a modelling approach is suitable to evaluate the dynamic long-term effects in electricity markets (Hary et al., 2016). Models allow to address uncertainty related to the unfolding of the energy system. Results from energy system models can be helpful for policy-makers to make robust decisions (Pye et al., 2018). This thesis will aim at extending an existing quantitative model of the Dutch electricity market with a capacity market, that will allow to simulate long-term dynamics and assess the performance of the capacity market under uncertainty. The latter will explore robustness of results. Furthermore, this thesis will attempt to act as a bridge between quantitative modelling results and qualitative policy-making.

As the reasoning behind the choice for the modelling paradigm has now become clear, an overview will be provided of research methods within this paradigm that have been applied in literature concerning capacity mechanisms. From this overview, a research method for answering the research questions will be selected. Selection criteria for a specific research method are related to its adequacy for answering the research questions and thus fulfil the aim of this thesis. The aim of this thesis is to model a capacity market and analyse its long-term performance during the energy transition. Therefore, the method should enable modelling large shares of RES-E. Furthermore, as mentioned in the introduction (section 1.1), the selected modelling method should enable accounting for the uncertainty inherently related to the energy transition, and thus also the effectiveness of capacity mechanisms. The focus in the overview will be on methods that accommodate both of these purposes.

2.1.1. Selection of Research Method

As mentioned in the introduction (chapter 1), the problem of maintaining system adequacy has increasingly gained attention in literature, thus the effectiveness of capacity mechanisms is an extensively debated topic to which a wide range of modelling methods has been applied. Amongst these methods are system dynamics (L. De Vries & Heijnen, 2008; Hary et al., 2016; He et al., 2008; Petitet et al., 2017), agent-based modelling (Chappin et al., 2017; Keles et al., 2016; Khan et al., 2018), optimisation modelling (Mastropietro et al., 2016; Tennbakk et al., 2016) or equilibrium modelling (Gurkan et al., 2013; Meyer & Gore, 2015). To fulfil the modelling purposes, the research method should enable accommodating a large share of RES-E for which it is crucial to include a high temporal resolution, while still limiting the computational burden to allow for robustness analyses. It is therefore proposed to apply a novel *myopic optimisation* modelling technique with high operational details.

Optimisation models can differ in the assumed knowledge that is available to decision-makers concerning future events within the model. A distinction can be made between myopic optimisation and optimisation with perfect foresight. In a perfect foresight model, decision-makers have perfect knowledge concerning future events, meaning that they know the exact developments of e.g. fuel prices and demand over the whole time frame of the model. The characteristics of perfect foresight are therefore twofold: (i) the decision-makers have definite expectations without any uncertainty and (ii) these expectations are correct (Bray, 1990). As a consequence, the solution of such a model represents an ideal, optimal transition pathway for energy systems.

Contrastingly, in a myopic optimisation model, it is assumed that decision-makers do not possess such a *crystal ball* that allows them to perfectly predict the future. Myopia is defined as “lack of foresight”, meaning that the knowledge decision-makers have concerning future developments is limited to a particular time frame smaller than the total time frame of the model. The difference between the so-called *window of foresight* of perfect foresight and myopic foresight is visualised in figure 2.1, assuming a time frame of 2030-2050 and a myopic foresight limited to 5 years. An important implication of myopic optimisation is that the optimisation problem is split up into multiple smaller optimisation problems equal to the length of the window of foresight (Babrowski et al., 2014). In the example, this would result in optimisation problems that each represent a 5 year period.

As the energy transition emerges, so does the need for energy system models that accommodate a high temporal and operational resolution while limiting the computational burden as to perform extensive scenario analysis. Furthermore, the rise of the energy transition has implications on the behaviour of decision-makers that should be accounted for in models. There are several reasons why myopic optimisation can be applied to - partly - fill this gap. First, it allows for a more realistic representation of the short-sightedness of investment decision-makers compared to perfect foresight, which is especially true due to the energy transition. As mentioned before, optimisation models with perfect foresight are specifically suited for determining the optimal cost-efficient pathway for the energy system. Nevertheless, the assumption of perfect foresight does not fully reflect the reality of decision-making by investors, which is restricted by bounded rationality and imperfect foresight (Iychettira et al., 2017; Simon, 1990). Additionally, in the following years, the complexity of the electricity system will increase as a result of the increasing share of RES-E (Nagl et al., 2011). With this comes an increased uncertainty, which is elaborated in more detail in section 3.2.1. Therefore, optimisation models with perfect foresight may result in one-sided outcomes that do not optimally reflect reality. Hence, myopic optimisation provides an opportunity to account for this (increased) uncertainty experienced by investors.

Second, the computational burden that rests with myopic optimisation is significantly less compared to optimisation with perfect foresight, as a result of the smaller time frame that is to be optimised (Babrowski et al., 2014; Nerini et al., 2017; Poncelet, Delarue, Six, & D’haeseleer, 2016). This facilitates the possibility to increase the level of temporal and technical detail, which are both essential for

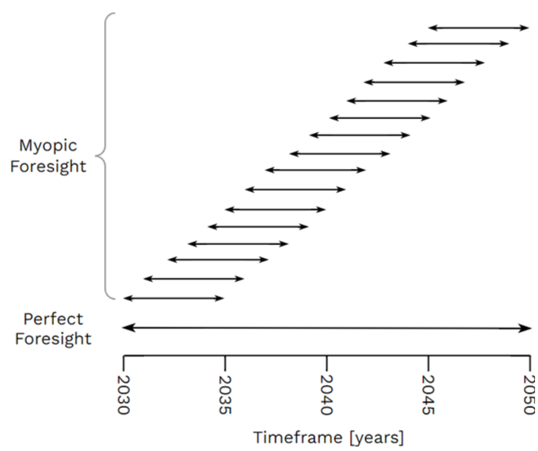


Figure 2.1: Differences between *window of foresight* of Perfect Foresight and Myopic Foresight, adapted from Poncelet, Delarue, Six, and D’haeseleer (2016)

incorporating the full effects of the integration of RES-E (Deane et al., 2015; Pina et al., 2013; Poncelet, Delarue, Six, Duerinck, et al., 2016).

As a result of the above-mentioned reasons, myopic optimisation models can provide additional insights to policy-makers to support policy choices. In a like manner as described above, policy-makers are subject to bounded rationality, which results in a limited decision horizon combined with imperfect foresight on the long-term developments of policy decisions (Keppo & Strubegger, 2010). In myopic optimisation models, there is an increasing focus on the short-term as it is assumed there is no knowledge concerning future developments outside this short-term. This reflects both the short-sightedness of investment decision-makers and policy makers. Myopic optimisation provides the possibility to assess the implications of a short-term focus on the fulfilment of long-term goals. This can be illustrated by research of Keppo and Strubegger (2010) and Nerini et al. (2017), who both find that increasing myopia could result in postponed investments in new technologies, compared to perfect foresight. Results of the former research indicated a stronger reliance on fossil fuels in the myopic approach compared to the perfect foresight approach. Thus, myopic optimisation can provide insights in how imperfect foresight of decision-makers may affect the transition pathway of the energy system, and what effect this has on reaching long-term goals similar to the goals set in the Paris Agreement. Complementary to the optimal transition pathways identified by perfect foresight models, myopic optimisation models can provide probable scenarios of the development of the electricity system (Hedenus et al., 2013).

As mentioned above, myopic optimisation is a novel approach that has been recently applied to model energy systems (Babrowski et al., 2014; Groenewoud, 2022; Keppo & Strubegger, 2010; Nerini et al., 2017; Poncelet, Delarue, Six, & D'haeseleer, 2016). However, to this date, to the author's knowledge, myopic optimisation has not yet been applied to study the effectiveness of capacity mechanisms. A state-of-the-art myopic optimisation model of the Dutch electricity system is the *Myopic Optimisation Detailed Operational* - or in short, MODO - developed by Groenewoud (2022). This thesis will aim at extending MODO with a capacity market, to add to the debate on the effectiveness of capacity mechanisms by providing additional insights on the effect of myopia combined with capacity remuneration on investment decisions through myopic optimisation. A detailed description of MODO can be found in section 2.2, which is followed after the identification of limitations of myopic optimisation in section 2.1.2.

2.1.2. Limitations of Research Method

As the advantages of myopic optimisation have now been extensively described in the previous section (2.1.1), it is also important to identify the limitations of a modelling approach in general, and specifically, of myopic optimisation. By identifying the limitations of an approach beforehand, they can be more adequately accounted for when interpreting results. First, limitations of the modelling paradigm in general will be addressed, followed by the limitations of myopic optimisation.

The quality of model results is highly dependent on the quality of input data and assumptions. It is necessary to make these assumptions as it is impossible to model complex systems in full, because the behaviour of these systems is more than the sum of their components (Batty & Torrens, 2001). Another limitation is that when interpreting the results, one becomes overly reliant on quantitative results when assessing the effectiveness of capacity mechanism. To minimise the impact of these limitations, it is proposed to frequently consult in-field stakeholders. These consultations are aimed at validating and verifying the assumptions and input data. This will also help prevent becoming overly reliant on quantitative results by obtaining qualitative, in-field insights.

A major limitation of myopic optimisation is identified by Poncelet, Delarue, Six, and D'haeseleer (2016). They state that within myopic models, investment decisions are based on short-run averaged profits of the period of optimisation, which are implicitly extrapolated to all remaining periods in the time frame of the model. Going back to our example in the previous section, this would mean the investment decision is based on averaging the profits of the five year-window of foresight and then extrapolating these averaged profits to the remaining years outside this period. However, say in year one, the profits are €100k, but these decline every consecutive year and will become negative in year 5. Then this observed trend is not extrapolated outside the window of foresight and therefore, it is not accounted for. Hence, investment decisions within myopic optimisation models also do not fully capture the reality of decision-making.

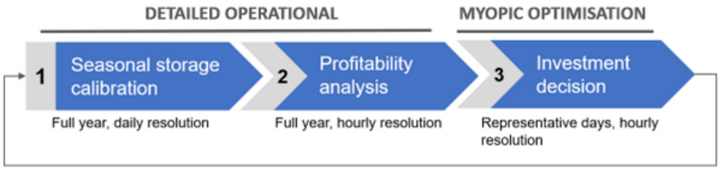


Figure 2.2: Conceptualisation of MODO: three stages with differing temporal settings and input data

2.2. Myopic Optimisation Detailed Operational model

As mentioned in section 2.1.1, the current state-of-the-art myopic optimisation model is the *Myopic Optimisation Detailed Operational* - or MODO - model developed by Groenewoud (2022), in which the capacity market will be implemented. The main purpose of MODO is to simulate long-term myopic investments in European electricity systems, whilst including high shares of variable RES-E, batteries and seasonal storage, in order to support decision-making for both policy-makers and investors. MODO encompasses the electricity spot market where perfect dispatch is assumed, as the spot market is seen to provide an adequate approximation of revenues of assets and can therefore provide insights on the profitability of investment decisions. For simplification reasons, in MODO, a single electricity spot market is modelled, assuming no imports and exports of electricity. This electricity spot market is optimised from the perspective of a single investor. To adequately inform decision-makers from public and private backgrounds, it is important that the model facilitates the performance of robustness analysis. Hence, computational efficiency is an important objective of MODO.

The conceptualisation of MODO is based on a multi-stage multi-timescale form and relies on the Myopic Investment Detailed Operational - or MIDO - model of Sagdur (2021). The model essentially can be divided into three stages: seasonal storage calibration, profitability analysis and investment decision, which are visualised in figure 2.2. These stages can each be classified as *Detailed Operational* or *Myopic Optimisation* based on their temporal settings and input data. For every stage, the structure of the model, i.e. a unit commitment model of an electricity market, remains unchanged. All three stages are consecutively conducted for every simulated year, where the output of the last stage of the former year serves as input for the following year. The three sequential stages form the model flow of MODO, which will be elaborated on in more detail now.

Stage 1, the seasonal storage calibration, can be divided into two sub-stages with each a different purpose. In these sub-stages, first, a suitable initial level for seasonal storage is determined and second, seasonal storage effects are simulated. Both outputs serve as an input for the second stage.

The purpose of stage 2, the profitability analysis, is, as the name suggests, to determine the profitability of the assets that have been invested in during the investment run. As investment decisions in the investment run are based on simulating representative days, it is necessary to run the model with an hourly resolution to assess the actual profitability of these assets and their effect on the overall system performance.

Stage 3 concerns the investment run. In this run, the optimal investment decisions are determined by optimising the investment options next to the already existing assets in a spot market dispatch based on a number of representative days. As the solver of MODO seeks to minimise total societal costs, first, it is determined which investment options realise larger savings to the system as a whole than their accompanied investment costs. The investment options[1] elected by the solver therefore provide an optimal mix to minimise total societal costs. However, as MODO aims to simulate realistic myopic investment behaviour, the elected investment options are evaluated on their profitability using the *Number of Profitable Units (NPU)* function. It is important to note that in MODO, electricity generation units of a technology type are modelled as a stack. Thus, standardised capacities of individual assets are stacked on top of each other resulting in a single decision variable, as visualised in figure 2.3. If an investment option is considered, the capacity of this additional generator will be added to this stack. The NPU of this stack will then be calculated by the following procedure. For every investment option, the profitability is determined by multiplying its production level with the difference between the asset's

[1] The maximum number of investments per technology in MODO is equal to 7 as increasing the number has a significant negative effect on computational efficiency

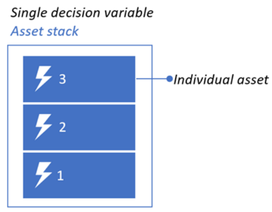


Figure 2.3: Visualisation of an asset stack consisting of standardised capacities and solely one decision variable

marginal costs and the electricity market clearing price. It is then evaluated whether the summed revenues exceed a pre-specified threshold - an annuity - for the asset to be considered profitable. Thus, the investment options provided by the solver will only be implemented when they obtain sufficient revenues to be considered profitable. The rationale behind implementing the NPU function and the assets stacks is that it increases the computational efficiency by, respectively, reducing the number of computationally intensive if-statements and decision variables.

As mentioned above, computational efficiency is an important objective of MODO. To ensure this, several assumptions have been made that still allow to adequately model myopic investment behaviour in electricity generation, but ensure some simplification and abstraction. Technical and geographical details are reduced by not taking into account ramping or network constraints. Furthermore, demand side response is also not included.

MODO is implemented in Linny-R, a graphical specification language that allows for the solving of linear programming problems and especially unit commitment problems (Bots, 2021). The visual representation of products, processes and flows within Linny-R adds to the intuitive understanding of the system behaviour that is being modelled, in the case of this thesis, the clearing of an electricity spot market. Graphical characteristics are inherently related to both intuition and transparency, resulting Linny-R to be a suitable tool to inform policy-makers on quantitative insights that are obtained when modelling policy options. A more detailed description of MODO can be found in Groenewoud (2022).

3

Theory on Energy-Only Markets & Capacity Mechanisms

This chapter provides a comprehensive theoretical background on the functioning of Energy-Only Markets and the logic behind the implementation of capacity mechanisms. As a basis for this theoretical background, the concept *Security of Supply* in electricity systems is addressed and a distinction is made between different sub-concepts of Security of Supply. This research will focus on the sub-concepts *Market Adequacy* and *Generation Adequacy*. Next, the functioning of the electricity market is described and several market failures are identified, followed by the effect of an increasing share of RES-E on the adequacy of the electricity market design. Lastly, theory on the working principle of capacity mechanisms is provided. The main types of capacity mechanisms are described. The insights gained from this theoretical background will allow for an adequate assessment of the performance of capacity mechanisms on how they address the identified market failures.

3.1. Security of Supply

Security of supply is a main policy objective in modern electricity systems due to the limited availability of substitutes for electricity (IEA, 2002). Eurelectric (2006) provides the following definition:

“Security of electricity supply is the ability of the electrical power system to provide electricity to end-users with a specified level of continuity and quality in a sustainable manner, relating to the existing standards and contractual agreements at the points of delivery.”

The definition of security of supply is broad and it can be divided into several mutually exclusive sub-concepts, as visualised in figure 3.1. Security of supply can first be split up into two branches based on time frame: short-term and long-term security of supply (Eurelectric, 2006). Short-term security of supply refers to the operational security, thus the ability of the system to deliver electricity in case of sudden failures of individual components.

Long-term security of supply refers to the ability of the system to meet demand at any time. In the long-term, the definition of system adequacy applied in this research is aligned with the definition provided by Billinton and Khan (1992):

“System adequacy is defined as the ability of the system to supply its load taking into consideration transmission constraints and scheduled and unscheduled outages of generators and transmission facilities”.

This encompasses both generation and network adequacy. Next to the adequacy of the electricity system, the adequacy of the market design affects the long-term security of supply. The reason for this is that the market should provide sufficient incentives for investors to invest in generation or network adequacy, to maintain long-term system adequacy.

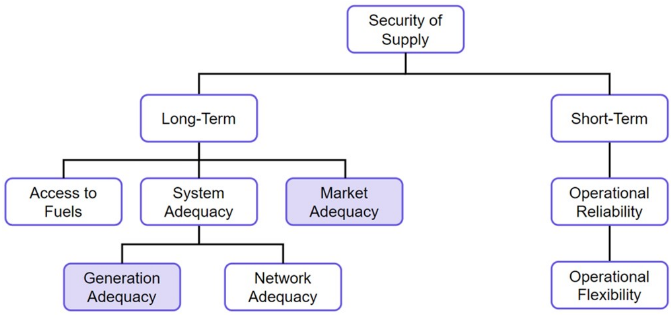


Figure 3.1: Security of Supply: subconcepts adapted from Eurelectric (2006), Höschle (2018), and van Stiphout (2017)

The focus of this research, as sketched in the introduction (ch. 1), is on the interplay between market adequacy and generation adequacy. The increasing share of RES-E has implications on the functioning of the electricity market design and therefore, it inherently influences investments in generation adequacy.

3.2. Investment risk in electricity generation capacity

The liberalisation of the electricity market has been the start of concerns of regulators on whether the market will induce sufficient investment in generation capacity in order to supply demand at all times (Read et al., 1999). Investment in generation capacity is considered sufficient when system adequacy is maintained. This is important to regulators as it can be argued that system adequacy possesses characteristics of a public good: the market may lead to suboptimal investments from a consumer perspective (Finon & Pignon, 2008).

According to economic theory, energy-only markets should provide sufficient incentives for investors to invest in generation capacity until the optimal level is reached, by displaying high price peaks during scarcity resulting in the coverage of costs for generation units (Gore et al., 2016; Petitet et al., 2017). However, this theory is based on certain assumptions. A key assumption is that the price consumers pay for electricity during scarcity should rise sufficiently in real time for consumers to cut back their demand (Hobbs et al., 2001). However, electricity markets do not clear like this.

Next to the arguably shortcoming assumptions that underlie the economic theory of markets, other problems arise that influence optimal investment in generation capacity: market failures. Different types of market failure can occur in electricity markets (based upon L. J. De Vries and Hakvoort (2004) and Hobbs et al. (2001)), which each will be briefly elaborated on.

- **Price caps:** price caps are implemented to protect consumers from high electricity prices during scarcity. However, the price cap should represent the Value of Lost Load (VoLL) and it is difficult to determine the optimal level (Abujarad et al., 2017; Willis & Garrod, 1997). Price caps limit the revenues for generations and will generate less incentives for investments (Vazquez et al., 2002).
- **Risk-averse behaviour by investors:** investors take on a risk-averse attitude when investing in generators that will serve the peak load, as these generators need to recover their costs in relatively few operational hours a year. The volatility of the revenues of the generator will increase the risk concerning this investment (Vazquez et al., 2002).
- **Imperfect information:** To make optimal investment decisions, investors need information concerning future supply and demand and this is lacking (Hobbs et al., 2001).
- **Regulatory uncertainty:** regulatory uncertainty adds to investment risk and therefore to the risk-averse attitude of investors (L. J. De Vries & Hakvoort, 2004). An example is the implementation of a price cap or lowering the existing price cap in periods of scarcity and high electricity prices due to, for example, political pressure. This has significant implications on the revenues of generators.
- **Regulatory restrictions to investment:** these restrictions are related to the permitting process of electricity generators. This can be a lengthy process, thus negatively influences the responsiveness of investors to an increased demand, through which investment cycles may occur (L. J. De Vries & Hakvoort, 2004).

If, during scarcity, electricity prices are too low - e.g. as a result of price caps - and due to this, investors will take on a risk-averse attitude which results in investments in generation capacity that lie beneath the social optimum, this is referred to as the *missing money problem* (P. C. Cramton & Stoft, 2006). However, if these revenues are adequate, but investors do not recognise these revenues as adequate, this is referred to as the *missing market problem* (Newbery, 1989). The latter problem becomes problematic once investors perceive they can not efficiently allocate risks via futures or contract markets, or when externalities such as greenhouse gases are not adequately internalised (Newbery, 2016).

3.2.1. Effect of an increasing share of RES-E on investment risk

As the energy transition progresses, electricity generation by RES-E is expected to increase and could reach a share ranging from 64 percent to 97 percent of overall electricity generation, if the transition pathway follows the Energy Roadmap 2050 of the European Commission (2012). This has implications on the functioning of the electricity market design, as RES-E exhibit different characteristics compared to conventional fossil-fuelled generation technologies. Variable RES-E, such as solar and wind energy, are subject to the intermittency of weather conditions. Their output therefore needs to be levelled out by flexibility services, such as flexible generators, storage or demand response. Short periods of low output of variable RES-E can generally be overcome by these flexibility services. However, long periods of low variable RES-E - also referred to as a *Dunkelflaute* - have to be overcome by flexible generators with very low operational hours, in which the fixed costs of the generation units have to be recovered (Doorman & De Vries, 2017).

Furthermore, as variable costs of solar and wind energy are negligible and they are prioritised during dispatch, RES-E could potentially depress average market clearing prices. This is described as the *merit-order effect* (Sensfuß et al., 2008).

These two developments cause increasing uncertainty concerning the future, that feeds into the risk aversion of investors. Newbery (2016) states: “Absent a futures market with a credible counter-party it is hard to be confident that future electricity prices will be remunerative for unsubsidized generation, and harder to convince bankers or shareholders of the credibility of investment plans based on forecast revenues.” The increasing share of RES-E may therefore exacerbate both the missing money and missing market problem.

3.3. Capacity Mechanisms as a solution

As described earlier, theoretically, the energy-only market should provide sufficient incentives to invest in generation capacity. However, as a result of the above-described market failures and recent developments in the energy transition, the debate on ensuring system adequacy is intensified. One proposed solution that can partly alleviate these investment risks are capacity mechanisms. Capacity mechanisms allow for an adequate remuneration of (flexible) generation capacity, by providing a steady income stream compared to the volatile revenues obtained in the electricity market (See et al., 2016).

Two types of capacity mechanisms can be distinguished according to the European Commission (2016): price-based and volume-based mechanisms. These mechanisms differ in which variable is set by the regulator. In a price-based mechanisms, the price of capacity is determined by the regulator and the volume is an outcome of the market mechanism, whereas in a volume-based mechanisms, a target volume is determined by the regulator and the price is an outcome of the market mechanism. Within these two categories, variables can be varied to generate different capacity mechanism, creating a whole range of different mechanisms. Different types that have been implemented in Europe will be briefly elaborated on. The classification of each type that will be described is visualised in figure 3.2.

3.3.1. Capacity Payments

Capacity payments is the only price-based mechanism that has been implemented. A capacity payment is a fixed price that is set by a regulator which will be paid to eligible capacity (Bublitz et al., 2019). The types of generators that are considered as eligible capacity differs per country. For example, in Ireland, all capacity receives capacity payments, whereas in Spain only new and selected types of generators receive capacity payments (Hach & Spinler, 2016).

The effectiveness of capacity payments has been criticised. The mechanism is relatively expensive

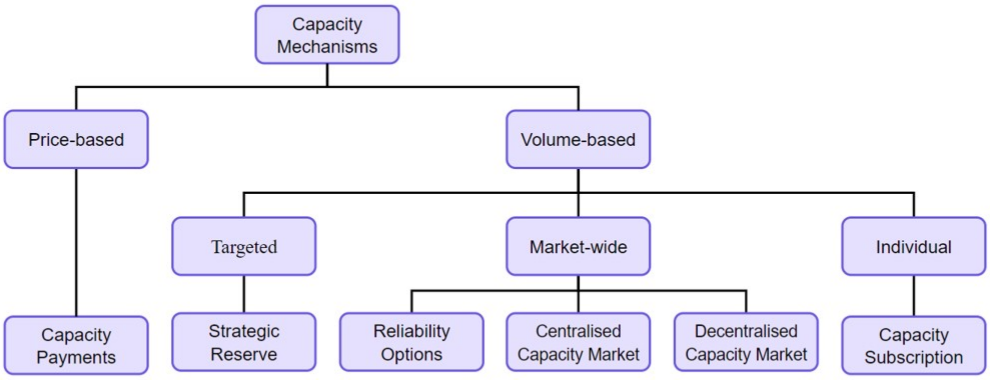


Figure 3.2: Classification of Capacity Mechanisms, adapted from (Agency for the Cooperation of Energy Regulators, 2013; CREG, 2012; Höschle, 2018)

and it fails to guarantee that there will be investments in sufficient capacity to maintain system adequacy and thus be able to meet demand at all times (Batlle et al., 2007).

3.3.2. Strategic Reserve

A strategic reserve is distinguished as a volume-based capacity mechanism. A strategic reserve is a volume of generation capacity, typically a generator with high operating costs, that is contracted by the TSO and will be dispatched during moments of scarcity. Therefore, the strategic reserve only participates in the electricity market when the TSO deems it necessary (Rodilla & Batlle, 2013). The strategic reserve will be dispatched at a high enough price for it to recover its fixed costs, and raise average electricity prices to stimulate investments in capacity (Bhagwat, Iychettira, et al., 2017).

As stated in European Parliament (2019), member states of the European Union should first evaluate whether a strategic reserve is capable of ensuring system adequacy in their market, before evaluating other types of mechanisms. A strategic reserve causes minimal market distortions (Meyer & Gore, 2015), which is considered an advantage.

3.3.3. Centralised Capacity Market

A centralised capacity market is distinguished as a volume-based mechanism, as the required quantity of capacity is administratively determined by a regulator. This quantity of capacity is then procured by a central body, such as the TSO, on behalf of consumers. Consumers are obliged to buy capacity that equals their expected peak demand plus a reserve margin that is set by a regulator (Agency for the Cooperation of Energy Regulators, 2013; P. Cramton et al., 2013).

This amount of capacity is then procured through a bidding process in a capacity auction. Suppliers of capacity bid into the capacity market so as to recover their fixed costs, taking into account expected revenues from the energy-only market.

There exist different types of centralised capacity markets, of which three main types will be discussed. These types essentially differ in the lag period of the contract and reliability product that is procured in the capacity auction. Differences in the lag period of the contract are represented by the distinction between a yearly or a forward capacity market. In a yearly capacity market, such as implemented by the New York Independent System Operator (2022), power plants that are allowed to participate in the capacity auction have to be available in the following year for which the capacity is procured. Contrastingly, in a forward capacity market, eligible capacity has to be available within a specified amount of time, e.g. in the forward market of the UK, generation capacity has to be available in four years ahead (Department of Energy and Climate Change (DECC), 2014).

Next to differences in lag periods, a second distinction can be made concerning the reliability product that is auctioned. The capacity mechanism *Reliability Options* is a specific type of centralised capacity market in which the reliability product is constructed similarly to the financial option (Vazquez et al., 2002). Again, a central body, such as the TSO, procures a quantity of capacity on behalf of consumers. However, in Reliability Options, this capacity is purchased in the form of call options. The central body obtains the right to receive the difference between the spot market price and the pre-specified strike price, from the seller of capacity. If the generator of electricity fails to produce electricity during this moment of scarcity, he is still required to pay this difference without being able to compensate this with revenues from the energy-only market. Therefore, the reliability option employs an explicit penalty.

3.3.4. Decentralised Capacity Market

A Decentralised Capacity Market is another market-wide volume-based mechanism, and is also referred to as *decentralised capacity obligations*. The concept is similar to a Centralised Capacity Market, however, there is one significant difference. In a Decentralised Capacity Market, the process of procurement of capacity does not take place on a central level. Load Serving Entities are obliged to procure capacity based on the forecasted peak demand of their consumers (Bublitz et al., 2019). This procurement takes place via negotiations of individual contracts, not via a central bidding process. An advantage of this is that it promotes both investments in generation capacity and demand response (Leiren et al., 2019). Decentralised obligations have been implemented in France.

3.3.5. Capacity Subscriptions

Capacity Subscription can be seen as the next step after Decentralised Capacity Markets to promote demand response, and in this case essentially of end-users. Capacity Subscriptions are a market-wide mechanism that is implemented on an individual scale. (End-)Consumers are obliged to individually purchase a quantity of capacity that they deem adequate to cover their demand during scarcity (de Vries & Doorman, 2021). Let us assume a certain household has purchased a capacity subscription at the level of 4 kW. This consumer is then ensured (s)he can consume electricity up to this level at any time. However, if this consumer wants to consume electricity at a higher level than 4 kW, his/her consumption will be restricted. The system operator activates a device that limits the consumption of this consumer, referred to as Load Limiting Devices (LLDs). Capacity Subscriptions is a novel capacity mechanism that has not yet been implemented.

4 Conceptualisation

This chapter presents the conceptualisation of the capacity market. The conceptualisation is performed by applying a set of generic design criteria of capacity mechanisms to the capacity market. These design criteria combined with the generic working principle of capacity mechanisms are first described. These design criteria are then specified for the capacity market. As capacity markets have been implemented by various TSOs, capacity markets vary in how design criteria are specified. Hence, the choice is made to focus on one particular capacity market that has been implemented, namely the yearly NYISO-ICAP (New York Independent System Operator, 2022). This is chosen as the design of the NYISO-ICAP is relatively simple and does not include any forward bidding, whilst being considered a successful capacity market (Bhagwat, Marcheselli, et al., 2017). Therefore, it can be more easily be implemented in MODO within the limited amount of time.
Furthermore, both institutional and financial relations between actors within a capacity market are identified. This is followed by a detailed description of three important aspects of the capacity market: the demand side, the supply side and the market clearing and auctions. The conceptualisation provides the basis for the formalisation and model implementation of the yearly capacity market.

4.1. Capacity mechanism: working principle and design variables

Capacity mechanisms are considered market design options that are introduced to ensure a specified level of system adequacy. Capacity mechanisms is defined by (Doorman et al., 2016) as:

"A capacity mechanism is a mechanism to value generation or demand response capacity, generally but not always leading to a revenue stream to owners of such capacity in addition to revenues from the energy market."

The working principle of a capacity mechanism can generically be described as follows. A capacity mechanism remunerates the instantaneous availability of firm capacity, as opposed to the energy-only market, where the produced amount of electricity is remunerated. It thus provides an additional income stream for investors in generation capacity. This remuneration is typically valued in €/MW (Höschle, 2018). The aim of capacity mechanisms is to provide a steady income stream for investors so as to ensure sufficient investment in generation capacity to maintain system adequacy. The remuneration of capacity mechanisms is less fluctuating compared to the remuneration of the spot market, which involves volatile electricity prices. The market signal for investments is therefore adjusted to become less risky.

Within a capacity mechanism, there are two types of actors. The first category can be distinguished as the buyers of firm capacity. When entering a contract within the capacity mechanism, the buyer of capacity obtains the right to use the contracted capacity. The second category of actors are the sellers of capacity. When entering a contract within the capacity mechanism, the seller is obliged to instantaneously provide the contracted capacity. These contracts are typically established in an auction for capacity. These institutional relations are visualised in figure 4.1.

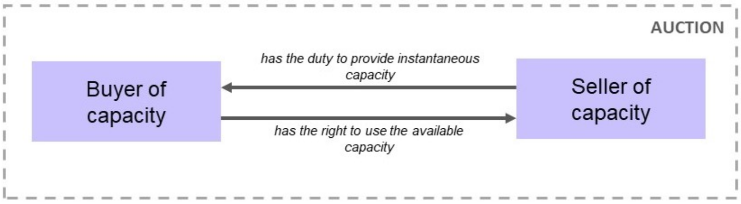


Figure 4.1: Simple representation of the institutional relations between actors in a capacity mechanism

A taxonomy of capacity mechanisms can be presented on the basis of design variables. These design variables constitute of different characteristics of capacity mechanisms that are decided on by the regulator and are adjusted to fit the electricity system into which the capacity mechanism is implemented. Differentiating between design variables will thus lead to different types of capacity mechanisms that will fit different types of electricity systems. The following list of design variables is adapted from Mastropietro (2016) and will serve as a basis for the conceptualisation of the Yearly Capacity Market:

- **Buyers of capacity**: who (or what type of demand) will be obliged to buy capacity, or on whose behalf will the regulator buy capacity?
- **Sellers of capacity:** who are allowed to submit bids in the capacity mechanism?
- **Level of centralisation:** is capacity procured through a centralised auction? And which party is responsible for estimating the demand forecasting? This can be determined centralised by the regulator or decentralised by agents who are required to buy capacity.
- **Lag period:** what is the duration of the period between signing the contract and when the contract comes into effect?
- **Contract duration:** what is the period for which the contract is valid?
- **Reliability product:** what is the type of capacity product the regulator purchases within the capacity mechanism?

Mastropietro (2016) mentions several other secondary design variables such as indexation methods and financial warranties, but for simplification reasons, these are not taken into account. In the next section, first, an introductory overview of the design variables of the yearly capacity market will be provided. This is followed by a detailed description of the important elements of the capacity market, namely the demand side, the supply side and the auction clearing.

4.2. Yearly Capacity Market

A yearly capacity market is a type of capacity market in which the market is cleared annually for the next year (Bhagwat, Iychettira, et al., 2017). Therefore, power plants who participate in the capacity market need to be available the following year (Couto et al., 2021). The conceptualisation of the yearly capacity market is based on the *Installed Capacity Market* of the New York Independent System Operator, also referred to as NYISO-ICAP (NYISO, 2010).

In the yearly capacity market, the transmission system operator (TSO) is the buyer of capacity and will do this on behalf of load serving entities (LSEs). The costs of capacity are therefore passed onto consumers in the form of an additional charge. The sellers of capacity can only participate when their power plant assets are available in the coming year. The yearly capacity market takes on the form of a centralised auction, in which the TSO acts as a central buyer on behalf of LSEs. The lag period is minimal, as the capacity market is held annually for the next year. As the auction is conducted annually, sellers of capacity are awarded with one-year contracts. The reliability product that is exchanged is a capacity credit. The above-mentioned actors and their interdependencies within a yearly capacity market are visualised in figure 4.2. After having provided this general overview of the specification of design variables in the yearly capacity market, the demand-side, the supply-side and the market clearing will now be further specified. For each of these three important aspects of the capacity market, a translation of the real-world concept to the model will be provided.

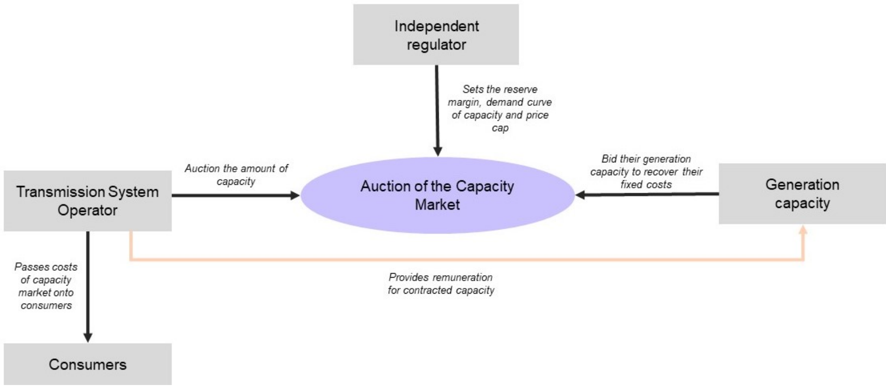


Figure 4.2: Interdependencies between different actors in a yearly capacity market

4.3. The Demand Side

In the yearly capacity market, the TSO procures capacity on behalf of LSEs. The quantity of capacity the TSO is required to purchase depends on the demand requirement that is set by an independent regulator. To calculate the demand requirement (D_r) for the current year, the regulator determines the expected peak demand (D_{peak}) and the Installed Reserve Margin (IRM, r). The latter is the required margin of extra capacity that will limit the loss of load expectation (LOLE) to the reliability standard. In the NYISO-ICAP, this is a LOLE of once every 10 years. The demand requirement is then calculated as follows (equation 4.1):

$$D_r = D_{peak} * (1 + r) \tag{4.1}$$

To procure this quantity of capacity, a sloping demand curve is utilised by the TSO. In the NYISO-ICAP, the preference was given to a sloping demand curve instead of a vertical demand curve, as this will limit price volatility and thus stabilises the capacity market. A vertical demand curve would lead to bipolar prices: prices close to the price cap in periods of insufficient capacity, and prices close to zero in periods of sufficient capacity (Pfeifenberer et al., 2012). The slope of the demand curve is dependent on four variables set by the regulator, namely, the demand requirement (D_r), the lower margin (*lm*) the upper margin (um) and the capacity market price cap (pc_{cap}). The sloping demand curve has two line segments. The first segment is a horizontal line at the level of the price cap, ranging from zero to the lower margin (equation 4.2). The second segment is a sloping line ranging from the lower margin to the upper margin of capacity (equation 4.3).

$$LM = D_{peak} * (1 + r - lm) \tag{4.2}$$

$$UM = D_{peak} * (1 + r + um) \tag{4.3}$$

On the sloping line, the reference point is located. The reference point has a price equal to the annual levelised embedded cost of a new peaking plant minus the expected revenues from energy and ancillary services, i.e. the net Cost Of New Entry (net CONE). The volume related to the reference point is equal to the demand requirement. The price cap is generally set to a multiplication of the net CONE. In the case of the NYISO-ICAP, this is 1.5 times the net CONE (NYISO, 2022). An illustration of the sloping demand, including the above-mentioned aspects, is presented in figure 4.3.

The demand curve is implemented in the capacity auction so that the TSO bids according to the demand curve. In the NYISO-ICAP, the sloping demand curve is only implemented in one type of auction, i.e. the spot auction. There exist three types of auctions in the NYISO-ICAP which will be further discussed in section 4.5.

4.3.1. Translation to Model

In the model, the demand curve for capacity is constructed according to the above-defined equations. The demand curve thus consists of two segments:

1. **The horizontal segment**: when the volume of procured capacity falls below the lower margin LM, generators will receive a price equal to the price cap pc_{cap}. This price cap is set to 2 times

the CONE. The CONE is set at the fixed operation and maintenance costs of a new peaking unit - a OCGT plant - with a value of 29000 €/MW-year. The fixed operation and maintenance costs are assumed to be 5% of the investments costs of an OCGT plant based on International Energy Agency (2020).

2. **The sloping segment**: for the sloping demand curve, an equation (4.4) is determined that adheres to the characteristics described above. However, modelling demand elasticity in Linny-R is challenging and therefore this demand function is implemented in a stepwise manner. This is further elaborated in section 5.3.1.

To forecast the revenues of the capacity market to be able to incorporate them in investment decisions, an abstraction is made concerning the demand curve for capacity. It is assumed that, only during the forecasting of revenues, the demand curve of the TSO takes on a linear form. This is further described in section 6.2.1.

The default value of the Installed Reserve Margin is set to 9.5% as based on Bhagwat (2016). The expected peak demand (D_{peak}) is determined by taking the maximum value of the electricity demand of the previous year.

$$pc_y = \frac{pc_{cap}}{LM - UM} \cdot volume_{cm,y} - \frac{pc_{cap} \cdot UM}{LM - UM} \tag{4.4}$$

4.4. The Supply Side

The supply side of the capacity auction concerns the bids of generation capacity in price (€/MW) and volume (MW) pairs, submitted by each electricity generation unit. The price generators bid is determined by subtracting the expected revenues from the electricity spot market and ancillary services from the fixed operating and maintenance cost of the generator. If the expected revenues recover the fixed operating and maintenance costs, then the generator will bid at a price of zero as no additional revenue of the capacity market is required for the generator to stay online. However, if the expected revenue is inadequate to recover the fixed operating and maintenance costs, the generator will bid the difference. The additional revenues of the capacity market are then the minimum of extra income required for the generator to remain operational.

In the NYISO-ICAP, the volume of capacity suppliers are qualified to offer is determined by the NYISO and is referred to as Unforced Capacity, or UCAP. This capacity is different from the nominal capacity of generators, or referred to by the NYISO as Installed Capacity (ICAP), as it is adjusted for the availability of the generator during peaking hours. The UCAP is calculated as follows (equation 4.5):

$$UCAP = ICAP * (1 - Derating\ Factor) \tag{4.5}$$

The Derating Factor is determined based on the historical availability of generators that is calculated by the Equivalent Forced Outage Rate (EFORd). The EFORd "represents the portion of time a unit is in demand, but is unavailable due to forced outages and forced derates" (NYISO, 2022). As a result

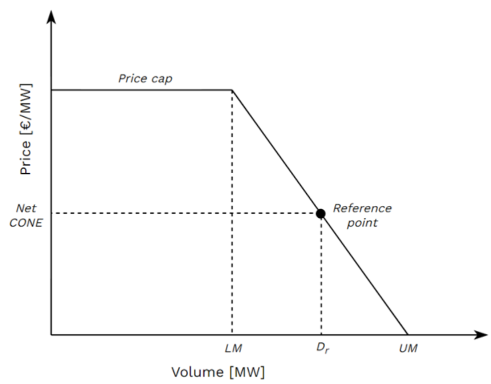


Figure 4.3: Illustration of a sloping demand curve based on Bhagwat (2016) and NYISO (2019)

of using the Derating Factor, each type of generator, including variable RES-E, can participate in the Capacity Market.

4.4.1. Translation to Model

Within the model, it is assumed that no strategic bidding will be employed. This as the sloping demand curve for capacity eliminates much of the chances for strategic bidding (P. Cramton & Stoft, 2005). The price at which capacity is offered is determined by calculating the revenues of the electricity spot market of that year, and then subtracting the revenues from the fixed operation and maintenance costs of that particular asset. For simplification reasons, no forecasting of revenues is performed and no additional revenues of other services, such as ancillary services, are taken into account.
The volume - or UCAP - of capacity that is offered is limited by a plants availability. As no forced outages or forced de-rating is assumed in the model, conventional generators can bid their full nominal capacity. However, the UCAP of variable RES-E is limited by its real-world Derating Factor. It is chosen not to base the Derating Factor of variable RES-E on its average availability during the model sequence as this would structurally over-estimate the contribution of variable RES-E to meet demand during peaking hours. Hence, the Derating Factor that is assumed within the model is based on Derating Factors as identified in literature by Zappa et al. (2021). For wind energy, a Derating Factor of 88% is applied and for solar, this is 95%.

4.5. Market Clearing & Auctions

As mentioned in section 4.3, the NYISO-ICAP consists of three auctions: the Capability Period Auction, the Monthly Auction and the Spot Auction. The Capability Period Auction and the Monthly Auction are both auctions at which LSEs actively participate, whereas on the Spot Auction, the TSO purchases capacity on behalf on LSEs. An advantage of holding multiple auctions is that the procurement of capacity is more flexible and it allows for multiple moments at which market participants can adjust themselves in order to meet the requirements of the NYISO-ICAP.

The Capability Period Auction is a 6-month Auction - sometimes also referred to as the Strip Auction - and has two intervals: a Summer Capability Period Auction and a Winter Capability Period Auction. These auctions offer the ability for LSEs to procure capacity at a single price for a 6 month period.

Contrary to the Spot Auction, the Monthly Auction is voluntary and is organised every month 15 days prior to the start of the month for which the LSEs are purchasing capacity, referred to as the Obligation Procurement Period. Both bids or offers that remain after the Capability Period Auction can be submitted and this does not have to concern the procurement of capacity for a whole capability period. LSEs can also purchase capacity for one month.

The Spot Auction is an auction in which the NYISO purchases capacity to meet the requirement on behalf of LSEs. The Spot Market Auction applies to one Obligation Procurement Period and it allows the excess demand and supply of capacity - resulting from the other two auctions - to be procured. This auction functions by clearing the demand and supply side like described in section 4.3 and 4.4. On the supply side, the bid pairs submitted by generators are sorted in ascending order. The sorted bids are accepted until the cumulative volume of the bids is satisfactory to meet demand. The intersection of the capacity supply and demand curve determines the market clearing price, and this is the price each

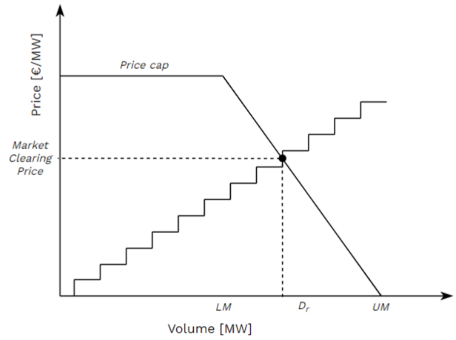


Figure 4.4: Illustration of the Market Clearing of A Capacity Auction

generator will receive for the volume of their accepted bids. An illustration of this process is presented in figure 4.4.

4.5.1. Translation to Model

In the capacity market that is modelled in MODO, the process of multiple auctions is abstracted to a single auction, namely the Spot Auction. This abstraction is expected to have limited effect on the outcome of the capacity market and thus its overall performance. Although with one type of auction, the main function of the capacity market remains unaltered. On the supply side, the volume-price bid pairs are sorted in ascending order. These sorted bids are accepted until the cumulative volume of the bids meets the demand curve. Each accepted bid will receive a uniform price equal to the price of the highest accepted bid.

5
Formalisation

The previous chapter (4) has provided an extensive conceptualisation of important concepts regarding the yearly capacity market, which will serve as input for this chapter concerning the model formalisation. In this chapter, the formal relationships between variables and parameters are identified and described in the form of equations. As with any linear programming (unit commitment) problem, the objective function and the constraints will be identified. These will solely encompass adaptions or additions to equations originated from the initial MODO model of Groenewoud (2022). For a detailed description of the objective function and constraints that apply to stage 1, 2 and 4, please refer to Groenewoud (2022).

5.1. Model Stages and Initial Conditions

As described in section 2.2, the conceptualisation of MODO relies on a multi-stage multi-timescale form. In order to extend MODO with a yearly capacity market, it is necessary to include an additional stage once more accompanied with a different timescale. This stage is referred to as 'Profitability Analysis: CM' - where CM refers to capacity market - and is classified as *Detailed Operational* instead of *Myopic Optimisation*, as visualised in figure 5.1. The profitability analysis is conducted during two stages, namely stage 2 and stage 3. The purpose of this analysis is to determine the profitability of the investments that have been selected in the investment stage 4. By extending the model with a capacity market, this analysis becomes twofold, as the profitability of assets is assessed in both the electricity spot market (ESM) and the capacity market (CM). Hence, the stage in which the capacity market is run, i.e. stage 3, becomes a component of the profitability analysis.

The conceptualisation of the yearly capacity market in chapter 4 has shown that the market clearing of the capacity spot market is conducted annually and cleared at once. Consequently, the timescale at which the 'Profitability Analysis: CM' operates within the model is equal to a single time step in which only the capacity market is cleared. Hence, no compromises have to be made regarding the operational details of the capacity market to ensure computational efficiency, so this stage can be classified as *Detailed Operational*. As can be derived from figure 5.1, the 'Profitability Analysis: CM' stage has implications on the model flow, however, these will be further elaborated on in section 5.2.

Throughout all stages concerning the electricity spot market (stages 1, 2 and 4), the modelled structure of the electricity market is universal and solely the timescales and the input data vary. This

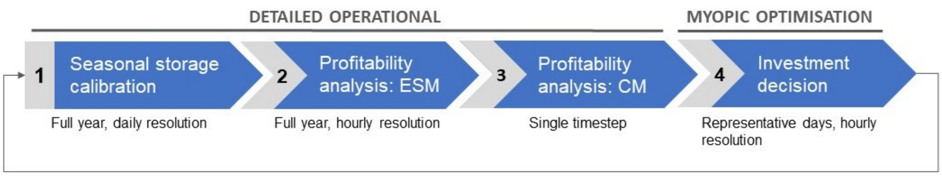


Figure 5.1: Multi-stage multi-timescale conceptualisation of MODO extended with 'Profitability Analysis: CM' stage, adapted from Groenewoud (2022) and Sagdur (2021)

structure is based on the physical unit commitment structure of the electricity market. However, the model structure of the yearly capacity market is different. This is due to the following reason. One major implication of capacity mechanisms is that the remunerated product differs from the electricity product that is traded in the energy-only market. In the yearly capacity market, instantaneous availability of firm capacity, referred to as a capacity credit, is remunerated as opposed to solely remunerating produced electricity in the energy-only market. Intuitively, one may realise that the characteristics of this capacity credit differ from the standard electricity product. Contrary to electricity, capacity credits are intangible and hence, cannot be traded via the same physical model structure, i.e. unit commitment, in which electricity is traded. As a result, the structure of the yearly capacity market is independent from the physical structure of the electricity market. The model structure of stage 3 in which the capacity market is cleared is therefore different from the unit commitment model in the other stages. Although the structures of the unit commitment and capacity market are separate, it is important to note that there still exist interdependencies between the unit commitment stages and the 'Profitability Analysis: CM' stage, as data resulting from each stage serve as input for other stages. For example, the volume of capacity the investor can bid in the capacity market is dependent on the installed capacity in the electricity market.

Besides setting the stages and timescale, there are other initial conditions concerning the yearly capacity market that have to be set. These are essentially the parameters of the yearly capacity market, usually set by an independent party or TSO, which are identified during conceptualisation (chapter 4). These parameters are identified and described in table 5.1.

5.2. Model Flow

By extending MODO with an additional stage that allows running the yearly capacity market, the initial model flow is adjusted as visualised in figure 5.2. This section will focus on how the model flow is changed through the including of the 'Profitability Analysis: CM' stage, but will not go into details of the aspects of the model flow that are not affected. A detailed description of the unchanged aspects - initial model flow - can be found in section 2.2.

First, it is important to note that the sequence of stages that encompasses the model flow is changed. The 'Profitability Analysis: CM' stage is included between the 'Profitability analysis: ESM' stage and the Investment decision stage. This causes the Investment decision stage to move up one term in the sequence, becoming the fourth stage. The placement of the 'Profitability Analysis: CM' stage in the third position is based on the fact that this stage requires input of the 'Profitability analysis: ESM' stage, as it needs the spot market revenues in order to calculate the 'Profitability Analysis: CM' bidding prices of generator types. Furthermore, as the 'Profitability Analysis: CM' stage is classified as *Detailed Operational* and it is considered part of the profitability analysis, it seems logical to place it in the third term, before the investment decision process. From this, it can be derived that stage 1 concerning seasonal storage calibration remains unaffected and therefore, this stage will not be further addressed. The model flow of stage 2, 3 and 4 will be now further elaborated on to gain both insights in their functionalities and interdependencies.

Stage 2 performs an hourly unit commitment run to assess the profitability of the invested assets in the electricity spot market. In this run, the revenues the investor gains from dispatch for each generator are calculated. The calculated revenues from the electricity spot market serve as input for determining the bidding price of each generator type in stage 3, the 'Profitability Analysis: CM' run.

Stage 3 concerns the auction clearing of the yearly capacity market. The temporal settings of this stage are set to a single time step as the capacity market is cleared once every year. Therefore, the unit of this time step is *year*. The purpose of this stage is to update the profitability of assets with the

Variable	Unit	Description
$pc_{cap,y}$	€/MW	Capacity Market Price Cap in year y
r	[-]	Reserve margin, value between $0 < r < 1$
lm	[-]	Lower margin, value between $0 < lm < 1$
um	[-]	Upper margin, value between $0 < um < 1$

Table 5.1: Yearly Capacity Market Parameters set by an independent party or TSO

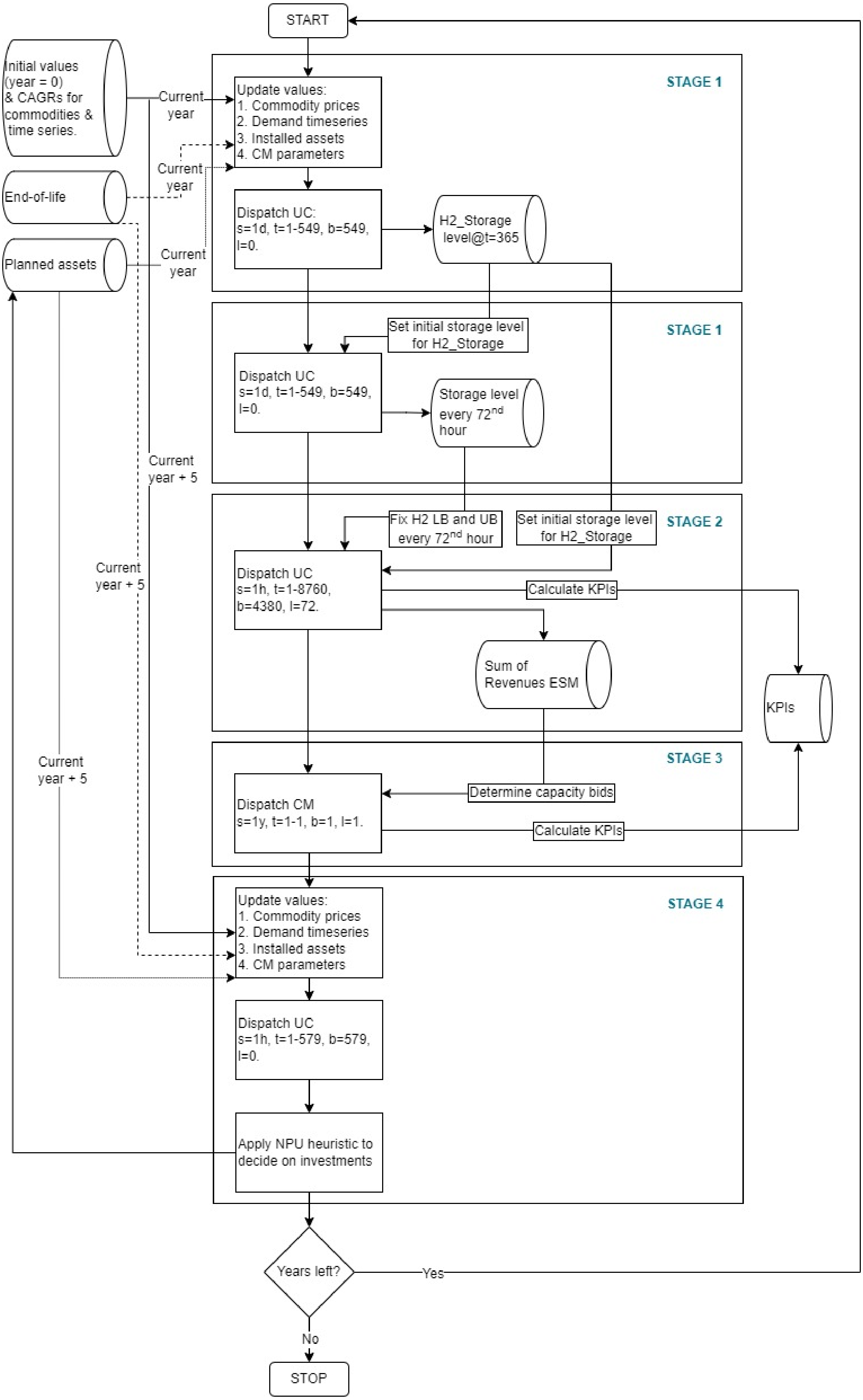
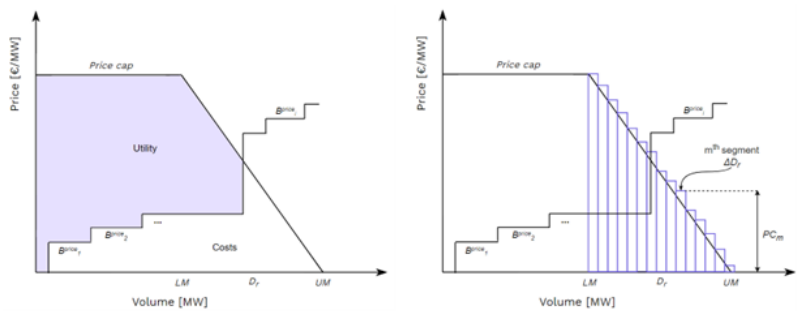


Figure 5.2: Model Flow of MODO extended with a Capacity market, in which solver setting are specified for each stage, these are: 's' = time step, 't' = simulation period, 'b' = block length, 'l' = look-ahead. Adapted from Groenewoud (2022).



(a) Utility (purple) and Costs (white) (b) Stepwise descending demand curve

Figure 5.3: Supply and demand curves of the yearly capacity market considered in the objective function 5.1, adapted from (Opathella et al., 2018)

extra revenues obtained by the procurement of firm capacity in the capacity market.

Stage 4 is where investment decisions are selected and implemented by the solver based on representative days. In this stage, existing assets and investment options are co-optimised to obtain optimal revenues of the electricity spot market. Furthermore, a forecast is performed of the revenues of the capacity market these investment options are expected to obtain. The temporal settings for determining the expected revenues from the electricity spot market are set to representative days due to its computational intensity. The forecast of revenues from the capacity market is performed by calculating the expected revenues based on a simplified linear demand curve of the TSO.

5.3. Optimisation of Yearly Capacity Market in MODO

This section describes the formal relationships between variables to realise myopic optimisation of the capacity market, whilst encompassing profit-seeking investment behaviour.

5.3.1. Objective Function

The objective of stage 3 is to optimally procure capacity from societal point of view by minimising costs and maximising utility. As the solver generally seeks to minimise total system costs, the objective function evaluates the price-volume bid pairs and makes an optimal selection of bids to meet demand. However, the demand for capacity is described by an elastic function and there exists no strict constraint concerning the demand for capacity. If the objective function would solely focus on minimising societal costs, the solver would not procure any capacity as it will not receive anything in return and it is not forced to do so by any constraints. Therefore, the elasticity of demand is implemented in the objective function as additional perceived utility that is obtained by the solver through the procurement of capacity. This will result in the procurement of capacity that will both maximise the utility whilst minimising the costs so as to obtain the solution that is most optimal for societal welfare. Thus, the solver will attempt to maximise the area that is experienced as utility - highlighted area in figure 5.3a, labelled as ‘utility’ - whilst minimised the area that is labelled as ‘costs’. This approach is based on Opathella et al. (2018). The resulting objective function is described in equation 5.1.

$$minimise \sum_{y} \left(\sum_{j} \sum_{i} B_{i,j,y}^{price} \cdot B_{i,j,y}^{volume} \right) - \left(\sum_{m} \Delta D_{r,y} \cdot pc_{m,y} \right) - LM \cdot pc_{cap} \tag{5.1}$$

The first term of this objective function is the area underneath the supply curve in figure 5.3a. In this figure, generic notation of B_i^{price} is used to represent the price at which the accompanied capacity is offered. The second term concerns the sloping part of the demand curve, which is modelled as a stepwise, descending curve as visualised in figure 5.3b. The utility that the solver obtains in this section of the curve is determined by the sum of the utility of each demand step ΔD_r. As the curve is descending, each incremental demand step ΔD_r will have a lower perceived utility. The third term is concerned with the area underneath the horizontal part of the demand curve.

5.3.2. Constraints

To find the optimal solution of the objective function of stage 3 formulated in the previous section (5.3.1), several constraints have to be satisfied.

The first constraint concerns the volume of capacity generators are qualified to bid in the capacity market. As conceptualised in section 4.4, this volume of capacity Unforced Capacity or UCAP is determined by multiplying the nominal capacity of each generator - or Installed Capacity (ICAP) - by 1 minus its Derating Factor. Within the model, the nominal capacity of generators is standardised for each generation type and is referred to as the Standard generation capacity of asset *i* with technology j, or $s_{i,j}$. It is assumed that no forced outages or derates occur, hence, conventional generators are not limited in their availability and their Derating Factor is set to zero. However, for variable RES-E, the volume these technologies are qualified to bid in the capacity market is limited by the Derating Factor. Their Derating Factor is based on their contribution to system adequacy during peaking hours as determined in literature by Zappa et al. (2021). The following constraint can then be derived:

$$B_{i,j,y}^{volume} \leq s_{i,j,y} \cdot (1 - Derating\ Factor) \qquad \forall i,j,y \tag{5.2}$$

The second constraint concerns the upper bound of the demand for capacity of the TSO. The total volume of capacity that can be procured by the TSO cannot exceed the identified upper margin UM, as is presented in equation 5.3.

$$\sum_i \sum_j B_{i,j,y}^{volume} \leq UM \qquad \forall i,j,y \tag{5.3}$$

The third constraint concerns the market clearing price of the capacity market pc_y, which cannot exceed the price cap set by the TSO as presented in equation 5.4.

$$pc_y \leq pc_{cap} \qquad \forall y \tag{5.4}$$

5.3.3. Bidding Strategy

In the previous section (5.3.2), it has become apparent that the volume generators can offer in the capacity market is restricted by their UCAP. The price at which this volume is offered by generators is determined by their bidding strategy. It is assumed that no strategic bidding will be employed as discussed in section 4.4.1. Furthermore, it is assumed that generators will bid the profitability gap, i.e. the gap between their fixed operation and maintenance costs and the revenues obtained in the electricity spot market. When revenues from the electricity spot market suffice for compensating the fixed operation and maintenance costs, the generator will bid at a price of zero.

$$B_{i,j,y}^{price} = \max\left(0; f_{j,y}^{O\&M} \cdot s_{i,j} - \left(\sum_t g_{i,j,t} \cdot (p_{y,t} - \frac{v_{j,y}}{\mu_j}\right)\right) \tag{5.5}$$

5.3.4. Profitability Assessment: *Number of Profitable Units*

Capacity mechanisms allow for an adequate remuneration of generation capacity by providing a steady income stream on top of revenues obtained from selling electricity in the spot market. As a result of this additional income stream, including a capacity market within the model has implications on the profitability of assets. First, a definition for profitability of each asset will be provided (equation 5.6). This definition for profitability will form a basis for the assessment of profitability of assets, both during the stages of profitability analysis and the investment decision.

$$P_{i,j,y} = \left(\sum_t g_{i,j,t,y} \cdot \left(p_{y,t} - \frac{v_{j,y}}{\mu_j}\right)\right) + c_{i,j,y} \cdot pc_y - s_{i,j} \cdot f_{j,y} \tag{5.6}$$

The first term of this definition is concerned with the net revenues from the electricity spot market, the second term with the revenues of the capacity market and the third term with the fixed costs of this specific asset. When the outcome of this equation is larger than zero, the concerned asset is considered profitable. This definition will serve as a starting point for the evaluation of each asset's profitability.

As defined in section 5.2, stage 2 and 3 both perform a profitability analysis on the assets that have been invested in during the investment decision run, stage 4. This profitability analysis is performed by applying the Number of Profitable Units (NPU) function as described in 2.2. In stage 2, the NPU function determines the hourly marginal revenue of each asset that is committed and evaluates ex-post whether the summed marginal revenues exceed a certain threshold for each asset to be considered profitable. To enable this function, six arguments have to be identified:

1. The process concerned with the technology asset stack
2. The standardised asset size
3. The marginal costs
4. The electricity price
5. The profitability threshold
6. The option to analyse the NPU per time step instead of over the total run

Thus, the outcome of the NPU function in stage 2 provides insights in the profitability of assets when solely considering revenues from the electricity spot market. However, in stage 3, extra revenues are gained from the capacity market which has implications on the Number of Profitable Units per technology type. Therefore, an additional calculation of the Number of Profitable Units is performed. This is done by summing both total revenues of the electricity spot market and the capacity market of a technology stack and then dividing that by the total installed capacity multiplied by its fixed costs. The outcome of the NPU calculation in stage 3 provides insights in the profitability of assets when considering both revenues from the electricity spot market and the capacity market.

Furthermore, in the investment run, investment options are evaluated on their profitability using the NPU function. The fifth argument of this function is adapted to facilitate the incorporation of forecasted revenues of the capacity market in the final decision to implement an investment option. The forecasted revenues of the capacity market are implemented as a discount on the profitability threshold. The profitability threshold of an investment is defined as the annuity costs. When the forecasted revenues of the capacity market are subtracted from the investment threshold, an asset will be sooner considered profitable. This is described by equation 5.7.

$$I_{j,y}^{threshold} = I_{j,y}^{annuity} - pc_{y}^{forecast} \tag{5.7}$$

6

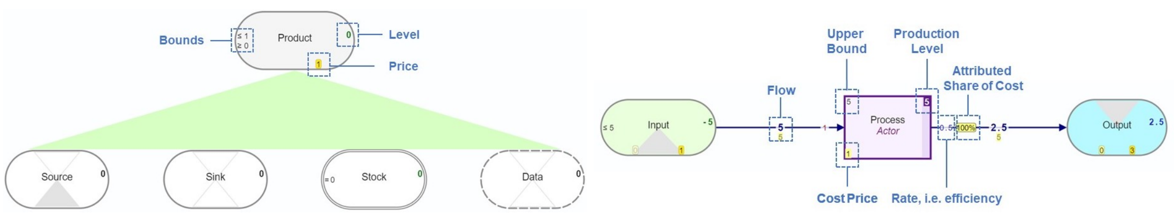
Implementation

The formalisation of relationships between variables and parameters in the previous chapter provide the mathematical logic behind the implementation of the capacity market in MODO. This chapter will describe how both conceptualisation and formalisation will be translated to conform with the structure of Linny-R and thus MODO. Furthermore, a verification and validation will performed on both the models of the energy-only market - additional to the validation provided by Groenewoud (2022) - and the capacity market.

6.1. Introduction to Linny-R

The purpose of this section is to provide an overview of the basic components that are included within Linny-R. A basic understanding of these components will make it easier to interpret visualisations of the capacity market in Linny-R. As described in section 2.2, the rationale for the use of Linny-R lies within its graphical quality that complements intuitive understanding and transparency concerning the system that is being modelled. This graphical quality is realised by visualising the structural components of the system in the user-interface of Linny-R. These structural components constitute the main "building blocks" of any model in Linny-R, besides non-structural entities, such as data sets and equations. There exist three types of structural components:

- A **Product** is an entity that can either be produced, consumed or both. Essentially, there are four different types of products that can be modelled: a source, a sink, a stock and a data-product (figure 6.1a). The latter refers to an intangible product, or information, whereas the others refer to tangible products.
- A **Process** is an entity in which a transformation occurs of a certain input to a certain output. In Linny-R, this is visualised as a rectangle (figure 6.1b).
- A **Link** connects a product to a process by allowing a product flow to go over the link. When a link has its origin in a product and flows towards a process, then this denotes that this process consumes this product. However, when a link has its origin in a process and flows towards a product, this denotes that this process produces this product.



(a) Four product types

(b) Basic model transforming input to output

Figure 6.1: Visualisations of structural components in Linny-R, adapted from (Groenewoud, 2022)

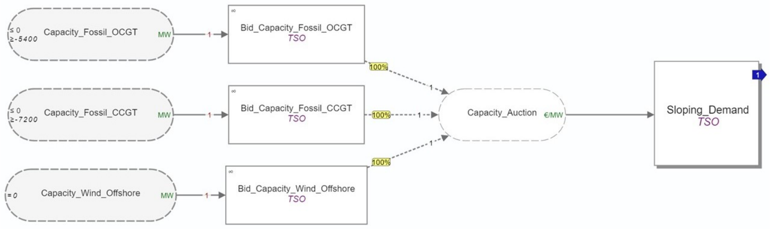


Figure 6.2: Implementation of Capacity Market in Linny-R

A simple representation of a model that consumes an *Input* and produces an *Output* is visualised in figure 6.1b. Attributes of products, processes and links are identified by dashed blocks in figures 6.1a and 6.1b with a description that can be intuitively understood.

6.2. Capacity Market in Linny-R

The conceptualisation of the capacity market auction (chapter 4) and the formalisation of its optimisation (section 5.3) will now be translated to conform with the standard components of Linny-R, as presented in figure 6.2. This will be done by means of a simple model with only three generator types, which will also be used for verification and validation of the capacity market. However, for validation of the energy-only market, historical data of installed generators is used and not this simple model. It is important to note that this simple model can easily be extended to include more technology types, by simply replicating the products and processes that are concerned with technologies. Each aspect of figure 6.2 will now be linked to its concept defined in chapter 4.

The three products on the left, characterised by *Capacity_x*, essentially compose the step-wise supply curve of capacity. Each product is a volume-price bid pair of a generator type. The quantity of the volume and price of each bid are determined based on data of the previous stage in the same year, stage 2. The volume of the thermal technologies is the nominal capacity of the previous stage and the volume of the variable RES-E technology is determined by multiplying 1 minus the Derating Factor of the technology type with its nominal capacity. The price is determined by summing the hourly marginal revenues of the technology in stage 2 and subtracting that from the predefined fixed operation & maintenance costs. The capacity is then offered at the determined price to the auction - *Capacity_Auction* - via the process *Bid_Capacity_x*. The square box with a shadow on the right is a so-called cluster (*Sloping_Demand*). A cluster does not have any transforming features and is rather used to group pro-

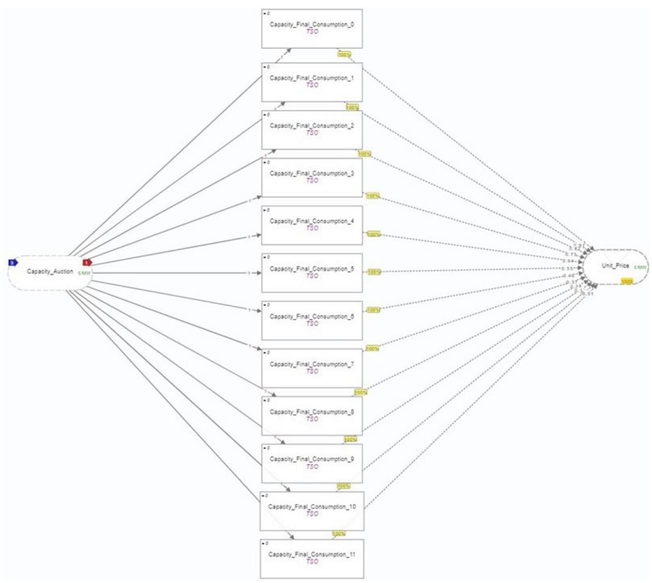


Figure 6.3: Stepwise demand function of capacity in Linny-R

cesses to make the visualisation more appealing. This cluster contains the stepwise sloping demand curve of capacity that is set by the TSO, as presented in 6.3.

In section 5.3.1, it was described how the solver attempts to maximise utility through the procurement of capacity, whilst minimising the costs. For each incremental demand step ΔD_r, the perceived utility decreases. Hence, this is correspondingly implemented in Linny-R. In figure 6.3, each incremental demand step ΔD_r is visualised by a process that is linked to a unit price. The first process, *Capacity_Final_Consumption_0*, represents the horizontal segment of the demand curve. Consequently, this process has an upper bound equal to the *Lower Margin*. As this is the minimal level of capacity the TSO strives for, the utility that the solver obtains through this process is maximum. This utility is determined by the data-product *Unit_Price* with a price equal to the price cap pc_{cap}. As the utility that the solver obtains for the procured capacity beneath the Lower Margin is maximum, the link towards the unit price has a flow of 100%. Thus, when capacity is procured below the level of the lower bound of the first process, this offered capacity will receive the price cap pc_{cap}. For each incremental process following the first process, the perceived utility decreases by 9%, resulting in a range of 100% to 1%.

To ensure that the capacity market is only cleared during stage 3, an actor is defined for each process concerned with the capacity market. This actor is defined as *TSO* and this feature is visualised in purple italic writing underneath the name of a process. By defining an actor, one can prevent processes from changing production levels during other stages of the model. Thus, the actor *TSO* is solely permitted to vary its process levels during stage 3. This will hinder the capacity market from interfering with the clearing of the electricity spot market in other stages.

6.2.1. Forecasting revenues of the capacity market in Linny-R

As argued in section 5.3.4, it is necessary to forecast the revenues of the capacity market in order to incorporate them in the final decision to implement an investment option. Forecasting revenues of the capacity market in the year the investment option will be implemented, is inherent to complexity. This is as the height of the forecasted capacity price is dependent on other investments that will be made and their bidding prices, and thus a high level of uncertainty. In reality, investors cannot forecast with full certainty the investment decisions of other actors, therefore, limiting their prediction capabilities.

As it is still necessary to include the forecasted revenues in the assessment of an investment option's profitability, an abstraction of this complex system behaviour is established.

Limitations of the functionalities of Linny-R have guided the choice for the type of abstraction. In Linny-R, it is difficult to iterate over all technology types which would be required to determine the optimal investments so as to obtain the most revenues from the capacity market. Iteration over multiple technologies is challenging as Linny-R can only make a distinction based on entities such as processes and products. Hence, this option is abstained from. This is further elaborated in chapter 11.

The abstraction that is chosen to be implemented has two functionalities. First, a linear demand curve of capacity is implemented in the investment run. When an investment option is elected by the solver, its capacity will serve as supply to meet this linear demand curve. It is assumed that the capacity

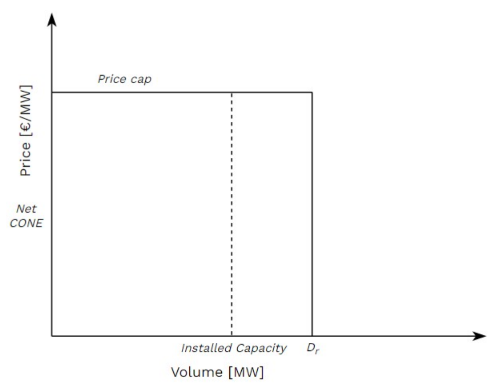
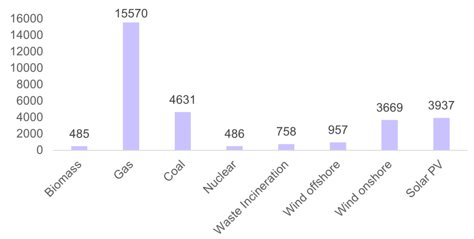
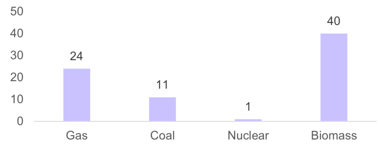


Figure 6.4: Assumed Linear Demand Curve for Forecasting the Revenues of the capacity market



(a) Installed Capacity in 2019 in MW per production type



(b) Commodity prices in 2019 in €/MWh: coal and gas prices based on PBL (2019), nuclear and biomass based on Trinomics (2020)

Figure 6.5: Input data for base case validation

that is already installed all bid their total capacity at a price of zero, meaning that the residual linear demand curve starts from the point of the volume of the total installed capacity, as visualised in figure 6.4. For capacity of investment options that is sold below the target capacity, the solver will receive the price cap of the capacity market. The solver will receive this remuneration only during one time step as the remuneration is provided once a year. Through this mechanism, the solver will include the revenues of the capacity market in providing investment options.

Second, to include the forecasted revenues in the evaluation of the Number of Profitable units, another assumption is made. It is assumed that when the total installed capacity is smaller than the target capacity, the forecasted revenues are equal to the price cap, else they are zero. This mechanism is independent from the outcome of the investment options determined by the solver during the investment run. Thus, each investment option provided by the solver is assumed to receive the price cap of the capacity market when the demand target is not met.

6.3. Verification & Validation

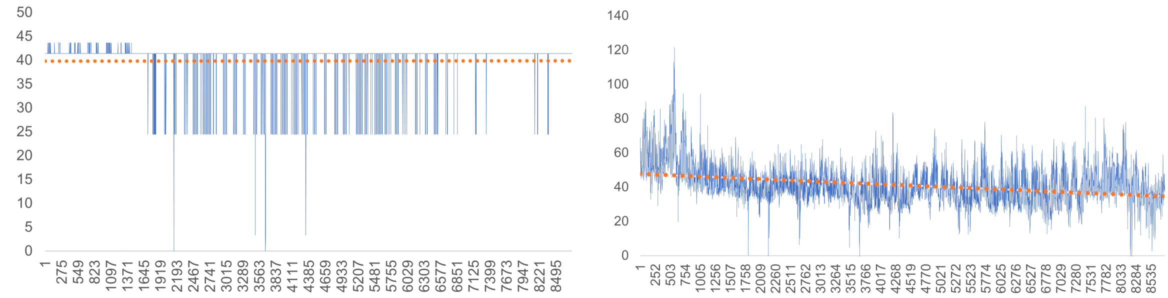
This section will aim at performing additional validation of the energy-only market that is modelled in MODO and a validation of the capacity market extension. These validation experiments aim at extending the validation that is already provided by Groenewoud (2022), which is limited due to time constraints. First, the energy-only market is run with input data based on historical data of the year 2019 and the model output is then compared to the real-world data of that year. Second, to validate the capacity market, the model behaviour of the capacity market will be compared to the dynamics of a real-world capacity market by means of a simple model.

6.3.1. Validation of the Energy-Only Market: Historical data of 2019

As mentioned above, it will first be attempted to validate the energy-only electricity spot market in MODO by applying historical data of the year 2019. By implemented historical data as input for data sets in MODO, it will become apparent whether the model's system performance is comparable to the system performance of the real-world Dutch electricity spot market. Insights that result from potential differences between the real-world and model performance can then be taken into account when interpreting the results.

The following data is used as input. Data on electricity demand is based on the Day-ahead Total Load Forecast of the ENTSO-E. Data on the production of variable RES-E is based on a data set of the Energieopwek, which is, as advised by TenneT, considered the most reliable data source. The assumed total installed capacity per production type and commodity prices are visualised in figure 6.5a and 6.5b. For every generator type, uniform energy conversion efficiency is assumed, expect for gas-fired generators. As can be seen in figure 6.5a, the total installed capacity of gas-fired generators significantly larger than the total installed capacity of any other generator type. In the Netherlands, efficiencies of installed gas-fired generators have a significant range from 40%-60%. Therefore, there are four segments of gas-fired generators in this validation-model, and each segment has an efficiency of, respectively, 40%, 50%, 55% and 58%. The volume of each segment [MW] is determined based on the real-world division in the Netherlands.

An important indicator of the performance of the electricity system is the electricity price in €/MWh, and will serve as a basis for comparison between the modelled system and the real-world. Hence, the



(a) Spot prices in MODO [€/MWh] (b) Day-ahead prices in 2019 [€//MWh]

Figure 6.6: Electricity prices in MODO and the real-world prices in 2019

electricity spot price in MODO and the real-world Day-Ahead price throughout the year are visualised in figure 6.6 to accommodate a comparative analysis. When comparing the modelling results to the real-world data, several dissimilarities occur which can be explicated by simplifications and abstractions within the model. First, it can be noted that spot prices in MODO can change instantly, as no ramping constraints are taken into consideration. Second, an important abstraction of MODO is that units of a generation type are stacked together resulting in plateaus of the electricity price, which do not occur in the real-world. The reason why these plateaus occur is that, due to this stacking of generators, a universal efficiency is attributed to every generation type. For example, every coal-fired power plant is assumed to have an efficiency of 45%. If it is assumed that every coal-fired power plant has a constant efficiency, then this will result in constant marginal costs for every unit of coal generators, i.e. constant bidding prices at the spot market. This has two implications. First, it will result in fewer levels of the electricity prices as bids of a generation type are uniform. Second, when demand is at a height for a consecutive period of time so that the marginal generator to fulfil demand is of the same type, a plateau of the electricity price can occur. An example of this is, in figure 6.6a, between t=7531 and t=8033 where gas-fired power plants are the marginal unit for this consecutive period, and due to identical prices between gas-fired power plants, a electricity price-plateau occurs.

Another important factor that influences the dissimilarities between the electricity price in MODO and the Day-Ahead prices in reality is the assumption that a single electricity market in MODO is modelled. In the Netherlands, the electricity price is heavily influenced by imports and exports of electricity. MODO does not capture this behaviour as no imports and exports are included. Hence, differences in the development of the electricity price are logical.

Third, average spot prices in MODO are slightly lower than the average Day-Ahead price in 2019, respectively 40 €/MWh and 41 €/MWh and less price peaks occur as visualised in figure 6.6. This results in lower Total Consumer Spending in MODO then in the real world, with a €0.25 billion difference. As a result of this underestimation of Total Consumer Spending, MODO might potentially result in structural under-investments.

Asset	**Standard Capacity**	**Installed number**	**CapEx**	**Fuel costs**
Fossil OCGT	75 MW	3	25,000 €/MW	90 €/MWh
Fossil CCGT	100 MW	3	20,000 €/MW	90 €/MWh
Wind Offshore	75 MW	3	40,000 €/MW	-

Table 6.1: Input data concerning assets for simple validation model

Variable	**Value**
VoLL	400 €/MWh
CAGR	2%
pc_{cap}	10,000 €/MW-year
r	0.095
lm	0.025
um	0.025

Table 6.2: Input parameters concerning the electricity and capacity market for simple validation model

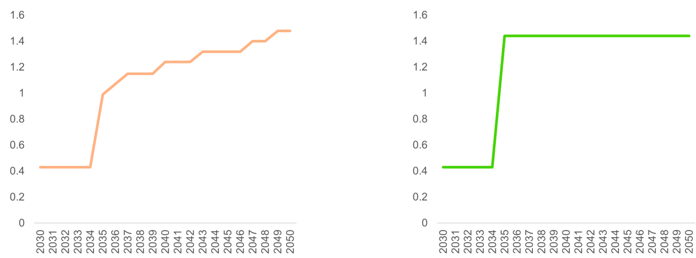
6.3.2. Validation of the Capacity Market

The purpose of this validation is to ensure the model behaviour of the capacity market is similar to dynamics of a real-world capacity market. The model extension of the capacity market will be validated by means of a simple model, as the one visualised in figure 6.2, to reduce the computational burden of validation. The input data concerning the installed assets of this simple model is presented in table 6.1. In this table, the CAGR is the compound annual growth rate of the Dutch electricity demand, which is assumed to be equal to the value estimated by Groenewoud (2022). For each technology type, the fixed operation and maintenance costs are assumed to be 4% of the capital expenditures (CapEx). Furthermore, the initial parameters concerning the electricity spot market and the capacity are presented in table 6.2. The electricity demand is implemented through a fictive data set that is generated following a normal distribution $N(1000, 100)$. The data set of the offshore wind output is a standardised output based on a regular year of Quintel's Energy Transition Model (Quintel, n.d.). It is assumed that fuel prices remain constant and no dismantling of assets occurs. The timeframe at which the model is run is equal to 20 years, the look-ahead is 5 years and a full year is equal to 549 hours, again to reduce the computational burden. The realisation period of investments is assumed to be equal to 5 years, independent of the technology type.

To validate the model of the capacity market, the model behaviour will be tested on multiple hypotheses that are based on the market dynamics of a real-world capacity market. Therefore, the behaviour of a model of an energy-only market will be compared to the behaviour of a model with a capacity market. The first hypothesis is that the model with a capacity market will induce more investments compared to the energy-only market, resulting in a higher Supply Ratio, i.e. the ratio of (available) capacity to peak electricity demand. This is as additional revenues can be gained through the capacity market, resulting in more profitable investments. The second hypothesis is that, due to this higher Supply Ratio, electricity prices with a capacity market will be, on average, lower compared to electricity prices in the energy-only market. Furthermore, the third hypothesis is that, again due to this higher Supply Ratio, the capacity market will result in less hours at which energy is not served and where the price is equal to the Value of Lost Load.

The results of the validation runs are presented in figure 6.7 and 6.8. From figure 6.7, it can be derived that the Supply Ratio of the capacity market run is on average higher than the Supply Ratio of the energy-only market run. The Supply Ratio increases only from 2035, as this is when the first investments are realised. The Supply Ratio increases significantly in year 2035 in the capacity market run as the forecasted revenues of the capacity market in year 2030 are high, and thus, a large number of investments occur. This stabilises after year 2035 as the target capacity set by the TSO is always met during every year, so the forecasted revenues of the capacity market are set to zero. Therefore, the Supply Ratio of the energy-only market slowly converges to a similar level as the capacity market run, as the forecasted revenues of the capacity market solely influence investments in year 2030.

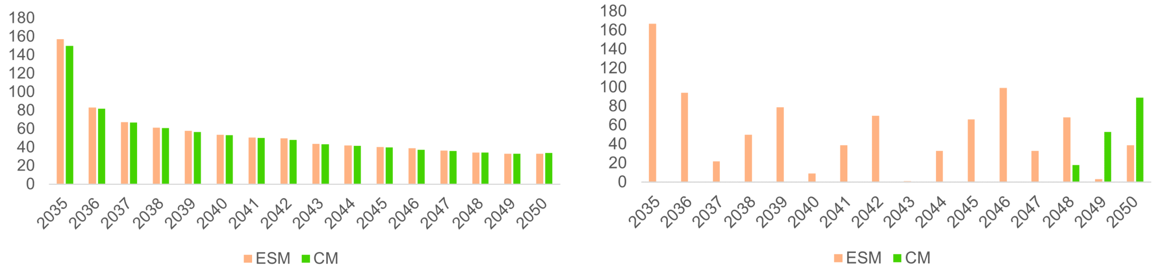
Furthermore, the capacity market run performs as expected when analysing the results presented in figure 6.8. The average electricity price in the energy-only run is slightly higher compared to the electricity prices in the capacity market run. A significant effect of the capacity market can be seen in figure 6.8b, where the total volume of energy-not-served in the energy-only run is 545% higher than the volume of energy-not served in the capacity market run.



(a) Supply Ratio in the Energy Only Market (b) Supply Ratio with a Capacity Market

Figure 6.7: Results of validation runs of the capacity market concerning the Supply Ratio

It can be concluded that the model of the capacity market shows system behaviour as expected. First, forecasted revenues of the capacity market only have effect on the investments when the demand target is not met. This would similarly occur in the real-world as when there is ample capacity, chances are high that the capacity market clearing price would be zero. Second, system behaviour of the capacity market run is in line with the above-mentioned hypotheses.



(a) Average electricity price [€/MWh] (b) Energy-Not-Served [MWh]

Figure 6.8: Results of validation runs of the capacity market concerning the electricity price and ENS

7

Scenario Design

The effectiveness of a capacity market to maintain system adequacy during the energy transition will be evaluated through a scenario analysis. First, several Key Performance Indicators are identified. These will provide a basis for the comparative analysis between the performance of the energy-only market and the capacity market. Second, this chapter describes how the capacity market extension will be tested on its sensitivity to parameters of the capacity market in section 7.2. Third, several scenarios are identified to enable performing a scenario analysis. To answer the research questions identified in section 1.2, these scenarios should allow to analyse the performance of the capacity market under two types of conditions:

- In a system with a high share of RES-E
- Under uncertainties, such as weather conditions

This chapter will describe the assumed system's starting point for the scenario analysis, i.e. a system with a high share of RES-E based on expectations of the electricity system in 2030. Furthermore, it identifies key uncertainties that potentially affect the performance of a capacity market. These uncertainties are cleverly combined to form different scenarios that will serve as input for the analysis.

Besides evaluating the effectiveness of a capacity market in maintaining system adequacy, an analysis will be performed on the effect of storage on the need for a capacity market. This will be done by evaluating the reliability of an energy-only market with and without storage. Input data concerning storage will be described in section 7.5.

7.1. Key Performance Indicators

To evaluate the effectiveness of a capacity mechanism in maintaining system adequacy during the energy transition, several Key Performance Indicators (KPIs) have to be identified. The indicators revolve around two main themes that are concerned with the performance of the electricity system: system adequacy and consumer spending, respectively described in section 7.1.1 and 7.1.2.

7.1.1. KPIs concerning System Adequacy

As identified in section 3.1, generation adequacy as a subdivision of system adequacy is one of the focus areas of this research. One indicator that is broadly applied to evaluate a system's generation adequacy is the *Supply Ratio*. The Supply Ratio is defined as the ratio between the available operation capacity [MW] and the peak electricity demand [MW]. For variable RES-E, their nominal capacity is thus limited by their availability during a peak hour in the Supply Ratio.

A second indicator that can be applied to evaluate generation adequacy is *Energy-Not-Served*. The Energy-Not-Served (ENS) is defined as the amount of electricity demand [MWh] that is not supplied in a given period of time due to inadequate resource availability. Both the Supply Ratio and the ENS are considered suitable indicators for evaluating the reliability of the electricity system.

	Input Parameters	IRM (%)
Sensitivity Scenario 1	Base Case	9.5
Sensitivity Scenario 2	Base Case	12
Sensitivity Scenario 3	Base Case	18

Table 7.1: Sensitivity Analysis

7.1.2. KPIs concerning Consumer Spending

A key indicator of the performance of the electricity market is the average electricity price per year [€/MWh]. This is a first indicator of consumer spending within the model. Next to the average electricity price, the total consumer spending is calculated as a performance indicator. The total consumer spending consists of the total costs to consumers for both the procurement of electricity and capacity. Although procurement of capacity is conducted by the TSO, these costs are passed onto consumers, so it is included within the total consumer spending.

7.2. Sensitivity Analysis

A sensitivity analysis will be performed to test the impact of varying a specific input parameter of the capacity market, namely the Installed Reserve Margin (r). It is chosen to vary this parameter as it is expected to have an effect on the effectiveness of a capacity market to maintain system adequacy in a system with a high share of variable RES-E. Variable RES-E contribute less to system adequacy compared to conventional fossil-fuelled generators due to their intermittent and variable output. Hence, a higher IRM might be required to maintain similar levels of system adequacy in a system with a higher share of variable RES-E compared to a conventional system.

To test the model's sensitivity to the IRM, input data of the Base Case scenario will be employed. This is extensively described in the following section 7.3. These variables are kept constant throughout the sensitivity analysis. The IRM is varied across three different levels, respectively 9.5%, 12% and 18% as presented in table 7.1. These levels are similar to the approach of Bhagwat, Iychettira, et al. (2017).

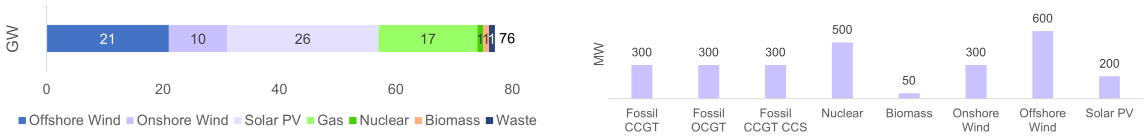
7.3. Base Case: 2030

The year 2030 is the starting point of the analysis to evaluate the effectiveness of a capacity market in maintaining system adequacy. As specified in chapter 1, the analysis will focus on the Dutch electricity system in isolation, without imports and exports of electricity. Therefore, several assumptions have to be made concerning the state of the Dutch electricity system in 2030 and thus the input data for the scenario analysis. Argumentation behind these assumptions is elaborately described in Groenewoud (2022). For the sake of clarity, the input data will be repeated here.

7.3.1. System Description: Generation Technologies

This section will describe the electricity system's context in 2030. It concerns the installed capacity of different technology types. For each technology type that is installed in 2030 or can potentially be invested in during the simulation, assumptions concerning several key characteristics will be described.

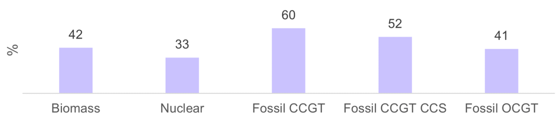
Figure 7.1 presents the assumed capacity per technology type in 2030 and the total installed capacity (left), and the assumed standard capacity per technology type (right), based on Groenewoud (2022). From this figure, it can be derived that the Dutch electricity system is assumed to be predominantly dependent on variable RES-E. Standard capacities are selected to optimally represent the granularity of investment decisions (Groenewoud, 2022).



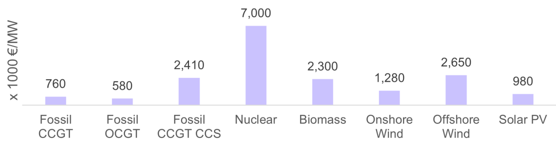
(a) Installed Capacity

(b) Standard Capacity per technology

Figure 7.1: Electricity System in 2030: Installed Capacity



(a) Thermal Efficiency per technology



(b) Investment Costs per technology

Figure 7.2: Characteristics of technologies

Furthermore, assumptions are made considering key characteristics of technologies. These concern efficiencies of thermal power plants - figure 7.2a - and investment costs - figure 7.2b. Thermal efficiencies are identified by Sagdur (2021) who has derived them from literature. Investment costs are based on the report *Projected Costs of Generating Electricity* of the International Energy Agency (2020). Fixed Operation & Maintenance costs are assumed to be 5% of the investment costs per MW. For each investment, independent of its technology type, a realisation period of five years is assumed. The carbon capture rate of the fossil CCGT CCS is assumed to be 100%.

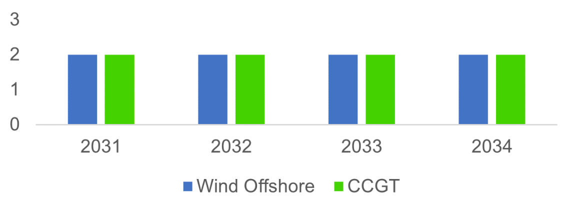
As a result of this realisation period of five years, the investments made in 2030 will only be realised in the year 2035. Therefore, a certain number of pending investments is assumed to mimic realistic investments in the first 5 years of the simulation. The volume of these investments is based on the assumed electricity demand growth factor in the model as described in section 7.4, i.e. a CAGR of 2%. Hence, the installed capacity is assumed to equally increase in the first 5 years with approximately 2% or 1500 MW. To ensure a growth of the installed capacity by approximately 2% per year, investments are assumed in two offshore wind farms and two CCGT plants, as visualised in figure 7.3. As the output of offshore wind farms is limited to their availability, the volume of investments is slightly higher than a 2% increase in installed capacity to maintain similar levels of system adequacy during the first 5 years.

For assets that serve as input data in the model and thus are assumed to be installed before 2030, a dismantlement schedule is assumed based on the installation year of each asset and their technical lifetime. The dismantlement schedule is visualised in figure 7.4.

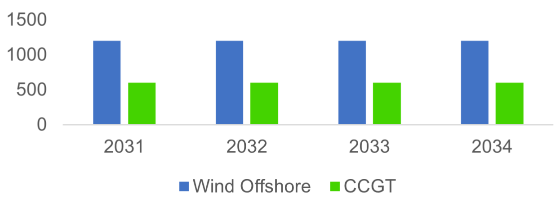
7.3.2. Capacity Market: parameters and input

Besides the input data concerning the electricity system in 2030, several assumptions have to be made concerning the default parameters of the capacity market within MODO. As described in section 4.3, the target capacity and the sloping demand curve are based on parameter values that are set by the TSO. These concern the Installed Reserve Margin, the lower margin, the upper margin and the price cap of the capacity market. For each scenario, these parameters are assumed to remain constant. The values of these parameters are based on Bhagwat (2016) and constitute the following. The Installed Reserve Margin *r* is set to 9.5% and the lower margin *lm* and upper margin *um* are both set to 2.5%. The fourth parameter, the price cap of the capacity market pc_{cap}, is set to a default value of 2*CONE = 2*Fixed Operation & Maintenance Costs of OCGT plant = 2*29000 = 58000 €/MW.

Next to the default values of input parameters of the capacity market that have been defined, assumptions are made concerning the Derating Factor of variable RES-E. For wind energy, a Derating Factor of 88% is applied and for solar, this is 95% both based on Zappa et al. (2021).

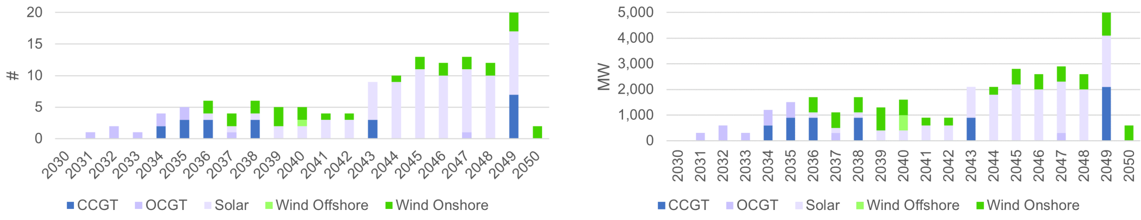


(a) Number of Assets



(b) Capacity

Figure 7.3: Pending investments during the first 5 years of simulation



(a) Number of Assets (b) Capacity

Figure 7.4: Dismantlement of assets installed before 2030

7.4. Uncertain developments from 2030 onwards

Key uncertainties concerning the development of the electricity system from 2030 form the basis for the selection of scenario variables. These scenario variables are varied across different scenarios. Uncertainties concern the development of electricity demand, EU ETS cap, commodity prices and weather conditions.

Electrification is seen to be a key strategy to reach climate goals, hence, the electricity demand is projected to grow significantly the coming decades. The base growth rate of electricity demand is assumed to be a Compound Annual Growth Rate (CAGR) of 2%. This growth rate was determined by Groenewoud (2022) based on data of CBS (2021).

For the developments of the cap of the European Emission Trading System, or EU ETS, an annual decrease of 8 % towards 2050 is assumed with a starting point at a level of 47 million credits in 2025, based on data from Dutch Emissions Authority (2022). This trend is visualised in figure 7.5.

A key uncertainty concerning the development of the electricity system are commodity prices. This is especially true for gas price developments, as these have seen extreme increases recently (NOS, 2022). For a base value of natural gas prices, a price of 90 €/MWh is assumed based on these recent developments. Furthermore, as a default value, the price of EU ETS credits is set to 50 €/tonne, as identified by Groenewoud (2022). However, a scenario with high commodity prices will be implemented to evaluate their effect on system adequacy. This will be done by increasing the price of natural gas and EU ETS credits. Argumentation behind the choice to analyse the effect of elevated natural gas prices lies in the fact that gas-fired plants are peaking units. Therefore, investments in gas-fired plants have a strong effect on the system's ability to meet demand during peaking hours. Profitability of investments in gas-fired plants is logically influenced by higher natural gas prices. The elevated natural gas price is set to 175 €/MWh, as derived from recent peaks that have occurred in the Dutch TTF (ICE, 2022). The elevated price of EU ETS credits is set to 120 €/tonne of CO_2, based on the *Announced Pledges* scenario of the IEA (2022).

Another key uncertainty is the weather, especially conditions concerning wind and solar intensity. Using a single weather-year or averaging over weather-years can significantly influence the robustness of outcomes, as stated by Zeyringer et al. (2018). Therefore, two weather years serve as input for the scenario analysis, both with diverging weather conditions. The first weather-year is concerned with

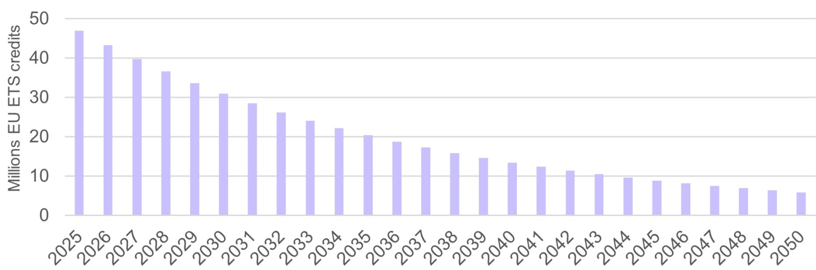


Figure 7.5: Assumed trend of available EU ETS credits in the Netherlands

	Base Case	Dunkelflaute	High Prices & High Risk Aversion	Low Prices & High Risk Aversion
Weather-year	Regular	Dunkelflaute in 2037, 2040 and 2045	Regular	Regular
Gas price [€/MWh]	90	90	175	90
EU ETS price [€/tonne]	50	50	120	50
CAGR	2%	2%	2%	2%
VoLL [€/MWh]	4000	4000	4000	4000
WACC	7%	7%	10%	10%

Table 7.2: Scenario's

representing regular solar and wind output within the Netherlands. The purpose of the second weather-year is to sketch an extreme scenario where long periods with persistently low levels of solar and wind energy occur, referred to as a *Dunkelflaute*. This will have significant implications on the performance of the electricity system, as it is assumed to be pre-dominantly reliant on variable RES-E. As this is not an unlikely scenario, it is also necessary to assess the effectiveness of a capacity mechanism in a Dunkelflaute. For the Dunkelflaute, the Dutch weather year of 1997 is assumed based on data of the Energy Transition Model of Quintel (n.d.). In the Base Case scenario, it is assumed that the input for the weather-year remains constant throughout the entire simulation time-frame and is equal to the regular weather year. In the Dunkelflaute scenario, it is assumed that a Dunkelflaute occurs three times during the simulation, in the years 2037, 2040 and 2045. These years are arbitrarily picked. During the other years, input of a regular weather year is employed. It is important to note, that the Dunkelflaute weather year does not serve as input for the investment runs, as it is unknown to investors when a Dunkelflaute will occur and they cannot be planned for.

Lastly, the level of risk aversion of investors has significant impact on maintaining system adequacy throughout the energy transition. When investors attain a more risk-averse attitude, they are less likely to invest in sufficient capacity to maintain system adequacy. Hence, the effectiveness of a capacity market to maintain system adequacy is evaluated under different levels of risk-aversion. The scenario variable that will reflect this risk aversion is the *Weighted Average Cost of Capital (WACC)*, which serves as the discount rate of the annuity investment threshold. A higher WACC will make capital effectively more expensive, thus investors would require higher profits to meet the investment threshold. Implementing a higher WACC is an approximation of risk-averse behaviour of investors. Argumentation behind this is that more risk-averse investors would expect a higher return for riskier investments. When a higher level of risk aversion is assumed, the WACC is increased to 10%, opposed to regular risk aversion at a WACC of 7%. These rates are based on values estimated by the IEA (2021), concerning the cost of capital in the energy transition.

7.4.1. Scenarios

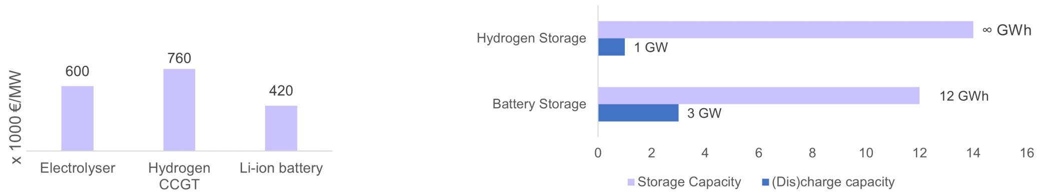
Table 7.2 presents the combinations of levels of scenario variables of each scenario. These scenarios will be analysed to evaluate the performance of a capacity mechanism under different conditions.

7.5. Effect of Storage

The effect of storage on system adequacy in the energy-only market will be evaluated as this influences the need for a capacity market. The following input data will be implemented and is based on Groenewoud (2022). Thermal efficiencies and standard capacities of storage units are displayed in figure 7.6. Investment costs and assumed installed capacity of storage units is displayed in figure 7.7. Due to time limitations, storage is not included in the above-mentioned scenarios.

(a) Thermal Efficiency [€] (b) Standard Capacity [MW]

Figure 7.6: Thermal Efficiency and Standard Capacity of Storage Units



(a) Investment Costs [€/MW] (b) Installed Capacity [GW]

Figure 7.7: Investment Costs and Installed Capacity of Storage Units

8

Results

This chapter will evaluate the effectiveness of a capacity market in maintaining system adequacy through a sensitivity analysis and multiple scenarios that have been identified in the previous chapter (7). The results per scenario are presented based on the Key Performance Indicators and are then interpreted. Furthermore, the effect of storage on system adequacy in the energy-only market is evaluated as it influences the need for a capacity market.

8.1. Results on Sensitivity Analysis

In this section, results on the sensitivity analysis will be presented and interpreted. To perform a sensitivity analysis, the Installed Reserve Margin (r) is varied across three different levels: 9.5%, 12% and 18%. For each level, the average Supply Ratio and total Consumer Spending in euros is visualised in figure 8.1.

A first observation is that the Supply Ratio increases to 1.09 when the Installed Reserve Margin in set to 18%, and remains at a level of 1.03 in the scenarios with an IRM equal to 9.5% and 12%. It can be derived that the model is less sensitive to small changes in IRM, which can be explained by the following mechanism. As a result of the assumption that each investment option will receive the capacity market price cap when the demand requirement is not met, the model is less sensitive to small changes in the IRM. However, when the IRM increases to 18%, the demand target is not met more frequently compared to the other two scenarios resulting in more investments and thus a higher Supply Ratio.

A second observation that can be made is that the average consumer spending drops by 7% in the scenario with an IRM of 18%. Thus, a higher IRM can have a positive effect on maintaining system adequacy at a lower cost to consumers. The reason why the average consumer spending does not vary between the scenarios with an IRM of 9.5% and 12% can be explained by the lack of elasticity in the demand curve of the TSO. As a consequence of implementing a stepwise demand curve for capacity instead of a linear one, the demand for capacity is less elastic causing it to be less sensitive to slight changes in the IRM. This limitation will be further described in section 8.3. To conclude, in a system with a high share of variable RES-E, it might be necessary to implement a higher IRM to compensate for the limited firm capacity variable RES-E have to offer. This could lead to a reduction in overal costs to consumers.

(a) Average Supply Ratio

(b) Average Consumer Spending [€]

Figure 8.1: Sensitivity Analysis Results: Supply-Ratio vs. Consumer Spending

(a) Energy-Only Market (b) Capacity Market

Figure 8.2: Base Case Results: Supply-Ratio

(a) Energy-Only Market (b) Capacity Market

Figure 8.3: Base Case Results: Average Electricity Price [€/MWh]

8.2. Base Case Scenario

In this section, the results of the base case scenario of the energy-only market and the capacity market will be presented and interpreted. Results of the Supply Ratio, average electricity price and the capacity market clearing price are displayed in figure 8.2, 8.3, 8.4, respectively. Average values of results are presented in table 8.1. Lastly, results on the development of the capacity mix are presented in appendix A.1.

A first observation that can be made is that the average Supply Ratio is higher in the capacity market compared to the energy-only market. On average, the Supply Ratio in the capacity market is 1.03 compared to a Supply Ratio of 0.9 in the energy-only market. It can be derived that on average the Installed Reserve Margin of 9.5% is not met, as the supply ratio is 6.5% lower than this target. Nevertheless, the performance on system adequacy in the capacity market is significantly improved compared to the energy-only market. This can especially be observed in the volume of Energy-Not-Served (figure A.2) from 2035 onwards. Due to the realisation period for investments of 5 years, the initial effects of the capacity market experience a lag until 2035. After the first effects of the capacity market on investments are realised in 2035, the system experiences a considerable decrease in Energy-Not-Served until 2050. From 2035-2050, most years in the capacity market have nill Energy-Not-Served compared to significantly higher levels of Energy-Not-Served in the energy-only market. During this period,

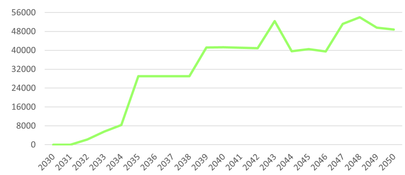


Figure 8.4: Base Case Results: Capacity price [€/MW]

	Base Case - EOM (Average)	**Base Case - CM (Average)**
Supply-Ratio	0.92	1.03
Electricity Price [€/MWh]	80.25	66.88
Energy-Not-Served [MWh]	6.62E+04	3.40E+04
Consumer Spending [€]	1.54E+10	1.28E+10
Capacity Volume [MW]	-	29950
Capacity Price [€/MW]	-	32012

Table 8.1: Base Case Results

Energy-Not-Served is 8 times higher in the energy-only market compared to the capacity market.

As a result of this decreased volume of ENS, electricity price peaks equal to the VoLL occur less frequently having a damping effect on electricity prices, resulting in, on average, lower electricity prices in the capacity market. The costs of the capacity market for consumers do not offset the effect of the lower electricity prices, as average consumer spending in the capacity market is nonetheless lower in the capacity market compared to the energy-only market (table 8.1).

The higher Supply Ratio in the capacity market can generally be attributed to investment peaks that occur in years 2035 and 2047. The reason why a large number of investments occurs in the capacity market in 2035 and 2047, compared to other years, is the following. Due to the assumption that the investor forecasts the revenues of the capacity market based on a linear demand curve, the forecasted revenues of the capacity market follow a bipolar pattern. In year 2030 and in 2042 - five years before the investments are realised - the demand target set by the TSO is not met. Therefore, forecasted revenues of the capacity market are equal to the price cap, i.e. 58000 €/MW. As a result of this high estimation of the revenues of the capacity market, a large number of investments are considered profitable and are implemented. This is visualised in figure A.3 in appendix A.1, where it can be seen that the volume of investments follows a similar pattern as the combined forecasted revenues of the capacity market and the revenues of the electricity spot market from the investment run.

Although the linear demand curve to forecast revenues of the capacity market is a modelling assumption, in reality, investors are similarly bounded by myopia and are unable to perfectly forecast the expected revenues of the capacity market. Hence, in reality a capacity market may result in similar investment cycles as have appeared in the model due short-sightedness of investors. This can be described by the following pattern for which modelling results provide an illustration. The increase in Supply Ratio in the capacity market during the period 2035-2042 causes a decrease in the average electricity price. This negatively influences the profitability of generators, subsequently leading to higher capacity market bidding prices during this period. These increased capacity market clearing prices could potentially lead to a boom of investments. As it takes several years to implement these investments, average electricity prices will stabilise to normal levels. However, when these investments are realised, a similar mechanism as before will repeat itself. Excess capacity will lead to lower electricity prices and simultaneously higher capacity market clearing prices, again stimulating new investment. Parmar and Darji (2020) state that capacity markets can be prone to unstable investment cycles. This is a theoretical concern considering the effectiveness of capacity market in reducing investment risk uncertainty.

Furthermore, the forecasted revenues of the capacity market especially have an effect on the profitability of peaking units: CCGT, CCGT CCS and OCGT plants. It can be observed that in the capacity market, there is a significantly higher uptake of these units, resulting in a higher volume of capacity as presented in the appendix in figure A.4. Due to the additional revenues of the capacity market, these units are considered profitable even when their operational hours are relatively limited. This could have a positive effect on the reliability of the electricity system if a Dunkelflaute were to occur.

A second observation is that the capacity market clearing price is relatively volatile and ranges from approximately 29000 €/MW to 54000 €/MW. This volatility can be attributed to the varying of the Supply Ratio and average electricity prices, ultimately affecting the profitability of generators and their ability to cover all fixed O&M costs. The revenues of the capacity market for the investor follows a similar volatile pattern as the capacity market clearing price, which is presented in figure A.5. This perceived volatility of the revenues of the capacity market can be considered to have a negative effect on the effectiveness of the capacity market in maintaining system adequacy. The main argumentation behind the implementation of capacity mechanisms is to provide a steady income stream compared to the volatile revenues obtained in the energy-only market (See et al., 2016). By providing this steady income stream, perceived uncertainties concerning the return on investment for investors should be reduced, hence, leading to more investments. However, additional volatility of revenues of the capacity market will feed into the risk-averse behaviour of investors that is already present. Thus, when revenues of the capacity market remain volatile, this will negatively affect the effectiveness of the capacity market.

To conclude, it can be stated that the capacity market is effective in maintaining system adequacy with a lower consumer spending compared to the energy-only market. However, a capacity market can be prone to investment cycles as investors are bounded by myopia resulting in imperfect forecasting of revenues of the capacity market. Investment cycles could increase investment risk uncertainty that is perceived by investors and thus negatively influence the effectiveness of a capacity market to maintain system adequacy.

8.3. Dunkelflaute Scenario

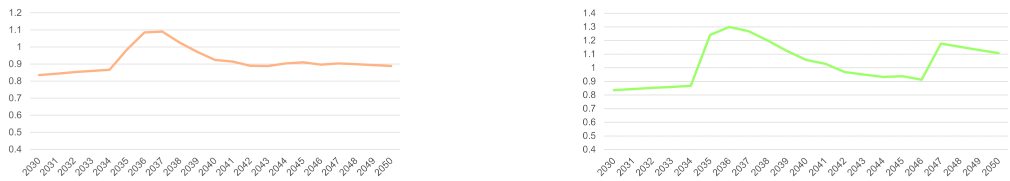
In this section, the results of the Dunkelflaute scenario of the energy-only market and the capacity market will be presented and interpreted. Results of the Supply Ratio, average electricity price and the capacity market clearing price are displayed in figure 8.5, 8.6, 8.7, respectively. Average values of results are presented in table 8.2. Lastly, results on the development of the capacity mix are presented in appendix A.2.

To conduct the analysis of the Dunkelflaute scenario, first, observations will be made and interpreted in a similar manner as in the Base Case scenario (section 8.2). Second, a more close analysis will be conducted on the performance on system adequacy during the years in which a Dunkelflaute occurs, namely 2037, 2040 and 2045.

A first observation that can be made is that the Supply Ratio presented in figure 8.5 follows a similar pattern as in the Base Case scenario, displaying only slight changes when a Dunkelflaute occurs. This system behaviour is expected, as investment decisions are based on the same regular weather year that is employed throughout the Base Case scenario. Hence, in every year during the simulation of the electricity spot market in which no Dunkelflaute occurs, the Supply Ratio should be equal to the Base Case. This can be observed.

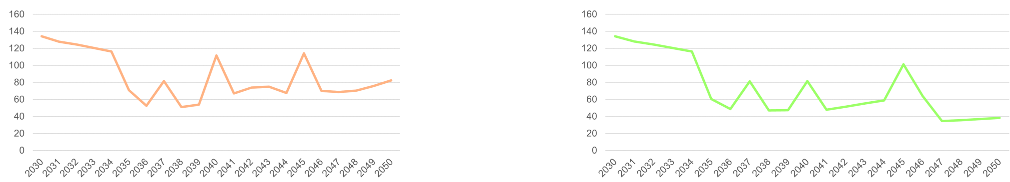
A second observation is that the average electricity price experiences a peak in each Dunkelflaute in both the energy-only market and the capacity market. The electricity peaks that occur in the energy-only market in the years 2040 and 2045 are respectively 37% and 13% higher than the peaks that occur in the capacity market. In the energy-only market, the height of the average electricity price peaks in these two years is higher due to the lower volume of installed capacity, which results in a higher volume of ENS and subsequently, more frequent price peaks equal to the VoLL. The relatively higher Supply Ratio in the capacity market and the larger uptake of peaking units - as displayed in figure A.8 - has a damping effect on the height of the electricity price. Due to the larger capacity of peaking units, the load that would normally be served by variable RES-E during electricity demand peaks can be replaced by these generators, hence limiting the frequency of loss of load hours.

When comparing the results of the Base Case to the Dunkelflaute scenario, it can be observed that the capacity market clearing price and the revenues from the capacity market in the years in which a Dunkelflaute occurs is lower compared to the same years in the Base Case Scenario, as presented in



(a) Energy-Only Market (b) Capacity Market

Figure 8.5: Dunkelflaute Results: Supply-Ratio



(a) Energy-Only Market (b) Capacity Market

Figure 8.6: Dunkelflaute Results: Average Electricity Price [€/MWh]

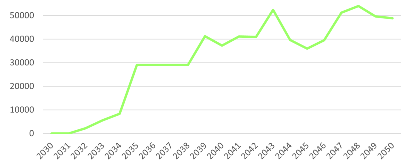


Figure 8.7: Dunkelflaute Results: Capacity price [€/MW]

	Dunkelflaute - EOM (Average)	Dunkelflaute - CM (Average)
Supply-Ratio	0.92	1.04
Electricity Price [€/MWh]	86.24	72.14
Energy-Not-Served [MWh]	6.89E+04	3.44E+04
Consumer Spending [€]	1.66E+10	1.37E+10
Capacity Volume [MW]	-	29950
Capacity Price [€/MW]	-	31600

Table 8.2: Dunkelflaute Results

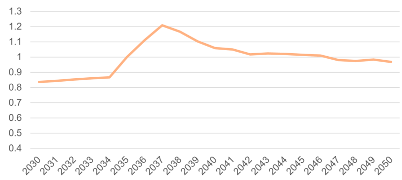
the appendix in table A.1. Due to the higher electricity prices during the Dunkelflautes, the profitability gap of generators is smaller leading to lower bidding prices at the capacity market. This explains the lower average capacity market clearing price in each Dunkelflaute. In reality, it would be expected that the lower average capacity price would result in a higher volume of procured capacity, therefore not leading to lower revenues on the capacity market for investors. However, due to the modelling assumption of the step-wise demand curve for capacity of the TSO, the demand for capacity in the model is less elastic compared the continuous linear demand curve of the TSO in reality. Therefore, the lower capacity price does not lead to higher revenues on the capacity market as the step-wise demand curve is too inelastic to capture these changes. If this were to occur in reality, it would be considered problematic behaviour as it is contradictory to the main purpose of a capacity market. To adequately incentivise sufficient investment in generation capacity, the capacity market should become constrained before the electricity market does. Therefore, the output of the capacity market should be inherently related to the functioning of the electricity market: when the Supply Ratio is low in the electricity market, the capacity market should result in higher revenues to incentivise investments. As this can be attributed to a modelling assumption, it is not expected that similar behaviour would occur in real life.

A closer analysis will now be conducted of the performance on system adequacy during the years in which a Dunkelflaute occurs. To aid this analysis, a comparison of the performance of the capacity market and energy-only market on the Supply Ratio and Energy-Not-Served during each Dunkelflaute is presented in figure 8.8. It can be derived that, as a consequence of the additional investments, the performance of the capacity market on system adequacy during each Dunkelflaute is significantly more satisfactory compared to the energy-only market. In each of the years in which a Dunkelflaute occurs, the Supply-Ratio is higher and the volume of Energy-Not-Served is lower or equal to the amount of the energy-only market. This can be attributed to a similar mechanism as described above, explaining the lower price peaks in the capacity market. As a result of the additional investments that occur due to the forecasted revenues of the capacity market, the Supply Ratio is more adequate and hence, a significantly lower volume of Energy-Not-Served occurs. Furthermore, the more satisfactory performance of

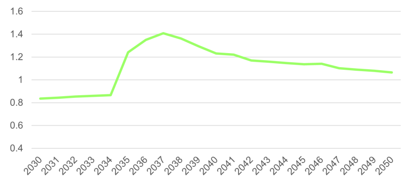
(a) Supply Ratio [-]

(b) Energy-Not-Served [GWh]

Figure 8.8: Dunkelflaute Results: Comparison of the energy-only market and the capacity market on performance on system adequacy in the Dunkelflaute years (2037, 2040 and 2045)

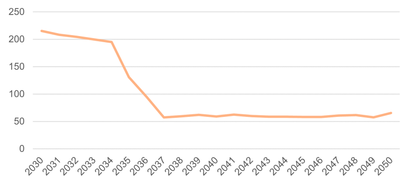


(a) Energy-Only Market

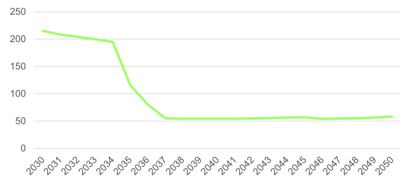


(b) Capacity Market

Figure 8.9: High Commodity Prices & High Risk Aversion Results: Supply-Ratio



(a) Energy-Only Market



(b) Capacity Market

Figure 8.10: High Commodity Prices & High Risk Aversion Results: Average Electricity Price [€/MWh]

the capacity market on system adequacy is realised at a lower consumer costs, as presented in table 8.2.

It should be noted that in the capacity market in the year 2045, the Supply Ratio has dropped below 1 and the volume of Energy-not-Served is not equal to zero. This can be explained by the investment cycles that occur in the capacity market due to the imperfect forecasting of the revenues of the capacity market by investors. It can be seen in figure 8.5b that the Supply Ratio in 2045 is at a low level as it finds itself in a *bust* period of the investment cycles, which will shortly be followed by a *boom*. Hence, the occurrence of investment cycles can have a negative effect on the overall effectiveness of a capacity market to maintain system adequacy at all times.

To conclude, the capacity market provides adequate incentives to invest in more generation capacity - especially of peaking generators - which has a significant positive effect on maintaining system adequacy in the case of a Dunkelflaute. However, due to the imperfect forecasting of revenues of the capacity market, investment cycles might occur which can result in not reaching the adequacy goals during *bust* phases of an investment cycle.

8.4. High Commodity Prices & High Risk Aversion Scenario

In this section, the results of the High Commodity Prices & High Risk Aversion scenario of the energy-only market and the capacity market will be presented and interpreted. Results of the Supply Ratio, average electricity price and the capacity market clearing price are displayed in figure 8.9, 8.10, 8.11, respectively. Average values of results are presented in table 8.3. Lastly, results on the development of the capacity mix are presented in appendix A.3.

A first observation that can be made is that limited additional investments are made in CCGT and OCGT-gas plants in both the energy-only market and the capacity market, as displayed in figure A.9. This output is consistent with the expectations considering the high gas and EU ETS credit prices. As a result, the uptake of biomass in both situations is relatively high compared to other scenarios, as it replaces the peak load that is normally served by an increased number of gas-fired power plants. Similarly to gas-fired power plants, biomass plants can provide flexible generation to fulfil demand in peaking hours due to relatively low ramp up times (Thrän et al., 2015).

A second observation that can be made is that electricity prices experience a higher peak in the first five years, followed by, on average, higher electricity prices compared to the Base Case scenario in both the energy-only and capacity market. This behaviour is as expected and can be attributed to the higher gas and EU ETS credit prices that prolong from 2030 to 2050. As a result of these relatively higher electricity prices compared to the Base Case scenario, the magnitude of the uptake of peaking generators, in this case especially due to biomass, is on average larger as can be derived from figure A.1 and A.9. Biomass delivers additional firm capacity which has a positive influence on maintaining system adequacy. Hence, Supply Ratios for both the energy-only market and the capacity market are

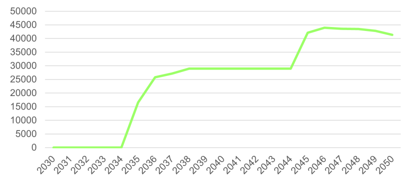


Figure 8.11: High Commodity Prices & High Risk Aversion Results: Capacity Price [€/MW]

	High Prices & High Risk Aversion - EOM (Average)	**High Prices & High Risk Aversion - CM (Average)**
Supply-Ratio	0.99	1.12
Electricity Price [€/MWh]	99.44	95.11
Energy-Not-Served [MWh]	3.01E+04	2.95E+04
Consumer Spending [€]	1.76E+10	1.46E+10
Capacity Volume [MW]	-	31682
Capacity Price [€/MW]	-	25225

Table 8.3: High Commodity Prices & High Risk Aversion Results

higher compared to other scenarios. Furthermore, as a result of the higher electricity prices, consumer spending is increased significantly compared to the Base Case scenario. This results in relatively higher profit margins for generators which do not experience high commodity prices, such as biomass plants. Hence, the high commodity prices offset the effect on the assumed level of risk aversion by investors. The higher assumed WACC effectively makes capital more expensive, requiring higher profits to meet the investment threshold, which are realised by the higher profit margins.

Third, it can be derived from table 8.3 that the capacity market has a more satisfactory performance on maintaining system adequacy at a lower cost to consumers compared to the energy-only market. However, due to the relatively strong uptake of biomass in the energy-only market, the difference on the performance on system adequacy between the energy-only market and the capacity market is limited compared to the Base Case and Dunkelflaute scenarios.

To conclude, high commodity prices seem to have limited effect on the performance of the energy-only market and capacity market on system adequacy, but will essentially result in the development of a different capacity mix. However, the performance of the capacity market on maintaining system adequacy is more satisfactory at a lower cost to consumers compared to the energy-only market.

8.5. Low Commodity Prices & High Risk Aversion Scenario

In this section, the results of the Low Commodity Prices & High Risk Aversion scenario of the energy-only market and the capacity market will be presented and interpreted. Results of the Supply Ratio, average electricity price and the capacity market clearing price are displayed in figure 8.12, 8.13, 8.14, respectively. Average values of results are presented in table 8.4. Lastly, results on the development of the capacity mix are presented in appendix A.4.

A first observation that can be made is that the high level of risk aversion negatively influences the adequacy of the supply ratio, as for both the energy-only market and the capacity market, the value is lower compared to the Base Case scenario as derived from table 8.4. However, the effect of a high

(a) Energy-Only Market (b) Capacity Market

Figure 8.12: Low Prices & High Risk Aversion Results: Supply-Ratio

(a) Energy-Only Market (b) Capacity Market

Figure 8.13: Low Commodity Prices & High Risk Aversion Results: Average Electricity Price [€/MWh]

	Low Prices & High Risk Aversion - EOM (Average)	**Low Prices & High Risk Aversion - CM (Average)**
Supply-Ratio	0.89	1.02
Electricity Price [€/MWh]	95.28	71.30
Energy-Not-Served [MWh]	1.03E+05	3.82E+04
Consumer Spending [€]	1.87E+10	1.35E+10
Capacity Volume [MW]	-	29995
Capacity Price [€/MW]	-	30353

Table 8.4: Low Commodity Prices & High Risk Aversion Results

level of risk aversion is significantly larger in the energy-only market compared to the capacity market. Due to this high level of risk aversion, investments in the energy-only market are lacking. This has a significant effect on the electricity price and the volume of Energy-Not-Served. In the energy-only market, the volume of ENS is on average 70% higher compared to the capacity market. Similarly, the average electricity price is higher due to the more frequent electricity prices equal to the VoLL that occur as a result of the ENS.

The high level of risk aversion has less effect on system adequacy in the capacity market as presented in table 8.4. Revenues of the capacity market fill the gap of the additional profits that are required for the assumed more expensive capital, therefore incentivising more investments in generation capacity. Although the Supply Ratio is slightly lower compared to the Base Case scenario, the difference is significantly smaller compared to the energy-only market. The more satisfactory performance on system adequacy of the capacity market is realised at a lower cost to consumers compared to the energy-only market.

To conclude, the capacity market can be considered to be more robust to the level of risk aversion of investors compared to the energy-only market. Furthermore, if the level of risk aversion of investors is estimated as high, the need for a capacity market to maintain system adequacy increases.

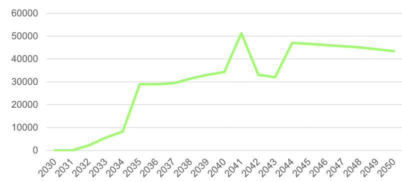


Figure 8.14: Low Commodity Prices & High Risk Aversion Results: Capacity Price [€/MW]

8.6. Results on the Effect of Storage

In this section, the results on the effect of storage on system adequacy in the energy-only market will be presented an interpreted. The results on the Energy-Not-Served are displayed in figure 8.15.

When comparing the total volume of Energy-Not-Served of the energy-only market with and without storage, one can derive that storage can have a significant impact on the electricity system's reliability. In total, including storage in the energy-only market reduces the total volume of Energy-Not-Served by 95%. Thus, including storage can potentially have a positive effect on maintaining system adequacy by levelling out the fluctuations in output of variable RES-E.

To conclude, including storage in the energy-only market could potentially reduce the need for a capacity mechanism to maintain system adequacy.

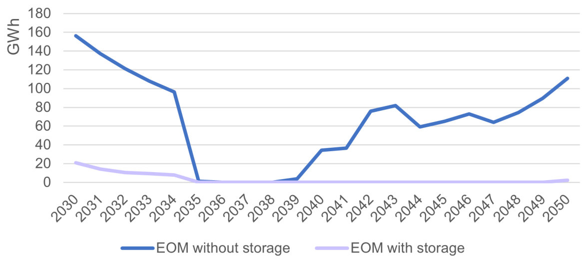


Figure 8.15: Effect of Storage on Energy-Not-Served [GWh]

9 Conclusion

As electrification is a key strategy for policy-markers to pursue climate goals set in the Paris Agreement to limit greenhouse gas emissions, the share of RES-E in electricity production is expected to increase significantly. The increasing share of RES-E has implications on the functioning of electricity system and the adequacy of the electricity market design, as these technologies exhibit different characteristics compared to conventional, fossil-fuelled electricity generators. As a result of their intermittent output and near negligible marginal costs, electricity prices may become volatile and suppressed, causing an increased investment risk for generation capacity that is perceived by investors. This thesis aims to address the question whether a capacity market can aid in providing sufficient incentives to invest in (flexible) generation in order to maintain system adequacy during the energy transition, as compared to the liberalised neoclassical market design.

It does so by attempting to provide an answer to the following main research question:

What is the effect of a capacity market on system adequacy of the electricity market in the Netherlands until 2050, when uncertainties such as weather conditions are taken into account?

An answer was provided to the main research question by extending an existing quantitative model of the Dutch electricity market, i.e. MODO, with a capacity market by providing additional insights on the effect of myopia combined with capacity remuneration on investment decisions through myopic optimisation with high operational details. From this thesis, it can be concluded that a capacity market can be an effective and robust policy instrument to maintain system adequacy during the energy transition at a lower cost to consumers. However, capacity markets can be prone to investment cycles which can have a negative effect on the overall effectiveness of a capacity market to maintain system adequacy at all times. Therefore, it remains unclear whether the capacity market is the best solution for maintaining system adequacy during the energy transition. These statements will further be strengthened by insights that are derived from this research.

From this research, it can be derived that a capacity market is a robust policy alternative to maintain system adequacy. The effectiveness of a capacity market in maintaining system adequacy can specifically be seen in the increased number of investments in peaking generators compared to the energy-only market when forecasted revenues of the capacity market are sufficient. This has a positive effect on the ability of the capacity market to maintain system adequacy during a Dunkelflaute, hence ensuring robustness in different weather years. Furthermore, the capacity market is more effective in maintaining system adequacy with high levels of risk aversion of investors, similarly ensuring robustness.

Nonetheless, the effectiveness of a capacity market is strongly reliant on the ability of investors to accurately forecast the expected revenues of their investments from the capacity market and whether it is perceived to reduce investment risks. Investors are bounded by rationality and limited by myopia, resulting in imperfect forecasting of revenues from the capacity market. Imperfect forecasting of these revenues may result in unstable investment cycles which can negatively affect investment risk uncertainty. Furthermore, investment cycles can have a negative effect on the overall effectiveness of a capacity market to maintain system adequacy at all times. From this thesis, it can be derived that during *busts* of investment cycles, the performance of a capacity market on maintaining system adequacy can potentially be unsatisfactory.

To conclude, a capacity market can be a viable option in order to maintain system adequacy during the energy transition. However, whether it is the most suitable option to maintain system adequacy remains unclear. As a result of the variable output of RES-E, additional flexibility services, such as hydrogen and battery storage are on the rise. If the perceived investment risk of these flexibility services is lower compared to peaking plants, the need for a capacity market reduces. This research identified that storage can serve a significant role in maintaining the reliability in an electricity system with a large share of RES-E. Hence, if additional flexibility options have a lower perceived investment risk, the electricity market can potentially continue to rely on its initial liberalised neoclassical market design whilst maintaining system adequacy.

Besides providing an answer to the main research question, a second objective of this thesis was to fulfil the need for electricity system models that allow for performing robustness analysis to evaluate the effectiveness of a capacity market in many possible futures. It can be concluded that MODO extended with a capacity market successfully fulfils this need. Extending MODO with a capacity market has not significantly affected its computational efficiency. On a personal computer with an Intel® Core i7 processor and 16 GB of RAM memory, run-times are on average 2 hours. Thus, MODO and its capacity market can be utilised to perform robustness analysis, which will be further elaborated on in section 9.2.

9.1. Insights for Policy-Makers

This section briefly presents insights for policy-makers considering the implementation of a capacity market.

- A capacity market can be considered an effective and robust policy instrument to maintain system adequacy during the energy transition.
- The need for a capacity market increases when the level of risk aversion of investors is considered high. When the system would continue to rely on the neoclassical liberalised market design in such conditions, system adequacy standards could potentially not be met.
- In a system with a high share of variable RES-E, a higher Installed Reserve Margin might be required to reach pre-specified reliability targets as the contribution of variable RES-E to system adequacy is limited.
- Before considering the implementation of a capacity market, it is important to assess the willingness of investors to invest in other flexibility options such as storage and the role demand response could play as these could potentially reduce the need for a capacity market.
- It remains unclear whether a capacity market is the most optimal policy instrument to maintain system adequacy during the energy transition. Other capacity mechanisms that have not been the object of focus of this thesis, such as capacity subscriptions - as described in chapter 10 - could potentially reduce investment risk uncertainty by establishing predictable contracts with consumers. Hence, this capacity mechanism may be less prone to investment cycles as capacity remuneration may be more easily forecasted. However, further research on the effectiveness of capacity subscriptions will be required.

9.2. Recommendations

This section describes avenues for future research that could potentially provide interesting additional insights.

On Robustness Analysis This thesis has stressed the importance of performing robustness analysis when evaluating long-term electricity system performance to adequately account for uncertainty that is inherently related to the unfolding of the energy transition. Performing robustness analysis is especially crucial in evaluating electricity systems with a high share of variable RES-E, as the system's performance is strongly dependent on uncertain weather conditions. This thesis has aimed to capture uncertainty concerning parameters by performing a scenario analysis. However, due to the deterministic nature of input data such as weather conditions (further elaborated on in chapter 11), results ensured limited robustness of the electricity market design to maintain system adequacy in different weather years. Therefore, stochastic optimisation is proposed to more accurately represent the stochasticity underlying weather conditions. Results would provide insights in the effectiveness of a capacity mechanism in ensuring system adequacy under diverging weather conditions.

On the Effect of Flexibility Services In electricity systems which are pre-dominantly reliant on variable RES-E, flexibility services such as storage and demand response will play an increasingly large role in maintaining system adequacy. This thesis has shown that storage can have a significant positive effect on the electricity system's reliability. Hence, it is suggested to further explore the effects of storage and demand response on the need for a capacity mechanism. One aspect that can be further investigated is the perceived investment risk that is associated with storage, as this will influence the likelihood of investments. This will ultimately affect the need for a capacity mechanism.

On Cross-border Leakage MODO and its capacity market extension is based on a single electricity system without interconnection capacity. Thus, this thesis does not account for the effects of cross-border leakage of the capacity market. Similarly, this thesis does not account for the effects of imports of electricity on maintaining system adequacy. Future research could investigate how effectiveness of a capacity market is influenced by cross-border leakage and electricity imports, by including interconnection capacity to other electricity systems. Extending MODO with interconnection capacity will also aid in providing more valid results on the energy-only market, especially when modelling integrated electricity systems, such as the Netherlands.

On Risk Aversion of Investors The level of risk aversion of investors in generation capacity has a fundamental effect on the adequacy of the electricity market design to maintain sufficient reliability. Hence, it is suggested to empirically explore levels of risk aversion of investors. Furthermore, it is suggested to apply a more comprehensive method to account for risk aversion as opposed to the method applied in this thesis. Möbius et al. (2021) evaluate the effects of risk aversion through stochastic optimisation, by including a risk measure in the objective function. This could provide additional insights in the effect the level of risk aversion has on robustness of electricity systems.

On Capacity Subscriptions From this thesis, it can be concluded that a capacity market can be prone to unstable investment cycles as a result of imperfect forecasting of revenues of the capacity market, which negatively influence the effectiveness of a capacity market to maintain system adequacy at all times. Other types of capacity mechanisms, such as capacity subscriptions were not evaluated in this thesis, but could potentially provide a solution for the reliance on the ability of investors to accurately forecast revenues of the capacity market. This is further described in chapter 10 where modelling results are compared to literature. Further research could explore the effectiveness of capacity subscriptions in maintaining system adequacy and the likelihood of the occurrence of investment cycles with this type of capacity mechanism.

On Profitability of Mid-Merit Plants In MODO, spot market revenues are seen as an adequate approximation of the profitability of investment decisions. However, consultations with TenneT have provided insights in additional revenues that can be gained outside the spot market, which can have a significant effect on the profitability of mid-merit plants such as CCGTs. To illustrate, mid-merit plants obtain a large share of their revenues from the option value of their plant and futures trading. These revenues are not captured in electricity system models, but are estimated to have a significant effect on the profitability of mid-merit plants and thus on system adequacy. It is proposed to explore the magnitude of these revenues and include more comprehensive revenues in MODO as to obtain more valid results concerning investments and their effect on the system's reliability.

On Technical Constraints Technical details of generation units, such as ramping constraints, are not taken into consideration in MODO and its capacity market extension. Ramping constraints can have significant impact on the ability of the system to meet demand and its operational adequacy. Koh et al. (2014) state that slow ramping rates of conventional plants may cause additional Loss of Load in electricity systems with large shares of wind energy. Therefore, it is proposed to include ramping constraints in MODO to enhance the validity of results concerning system adequacy.

On the Effect of Derating Factors Consultations with TenneT have provided insights in the importance of Derating Factors and their influence on the effectiveness of a capacity market to maintain system adequacy in a system with a high share of variable RES-E. A Derating Factor that overestimates the firm capacity variable RES-E have to offer will have a negative effect on the ability of a capacity market to maintain system adequacy. This is further elaborated on in chapter 10. It is suggested that future research could explore the influence a Derating Factor has on the effectiveness of a capacity market and whether it should be adjusted over time in a system with an increasing share of variable RES-E.

10 Discussion

This chapter will present the discussion of the results of this thesis and situate them in terms of literature. This will be performed along several main themes: validity of MODO and capacity market, reflection of Methodology, Consultations with TenneT and Comparison of results to Literature. It will provide insights on how results can be interpreted in light of identified limitations.

Validity of MODO and Capacity Market MODO and its capacity market extension has proven itself a useful tool for evaluating the performance of a capacity market during the energy transition. An important aspect of its usefulness is that, due to its low computational burden, it fills the need for electricity system models that allow for performing robustness analyses so as to inform policy-makers on robust strategies. However, when reflecting on the modelling results, there exists a key trade-off between the low computational burden and the validity of results. This is true for both the energy-only market and the capacity market. The reason why this trade-off exists will now be elaborated on. One of the main modelling decisions of MODO and the capacity market to reduce the computational burden was to implement electricity generation units of a technology type in the form of an asset stack. The rationale behind implementing these asset stacks is to reduce the number of decision variables, which has a positive effect on the computational efficiency. Furthermore, the modularity of MODO due to this stacking makes it easy to work with, resulting it to be an effective tool to be applied by policy-makers. The decision to stack generation units, however, has implications on the validity of modelling results of both the energy-only market and the capacity market.

In the energy-only market, stacking of assets of a technology type implies that each asset within the stack has an identical thermal efficiency. As a result of this, the total capacity of an identified technology will bid at the same marginal costs. This causes fewer fluctuations in the electricity market clearing price, which does not optimally reflect reality.

In the capacity market, the capacity a technology type can offer is similarly stacked into a single product in Linny-R. Stacking the capacity of a technology type in a single product implies that all assets within the capacity stack bid at the same capacity price. Meaning, if the profitability gap of one asset is bigger than zero, it will assume that all generators in the stack will bid their capacity at this price. This can be illustrated with a simple example. Assume there are two OCGT plants in the model. The first plant is able to recover their fixed operation and maintenance costs. The second plant is not able to recover their fixed operation and maintenance costs and will bid its capacity at a price of 100 €/MW. As a single bidding price is assumed for all OCGT generators, the total capacity of both generators is bid at a price of 100 €/MW. This might result in the total capacity of this bid not being accepted, when the price is considered too high compared the amount of utility the procurement of this capacity is assumed to obtain. In reality, however, the capacity of the first generator would undoubtedly be accepted as it would offer its capacity at a price of zero. Thus, as a consequence of assuming a single price for the total capacity of a technology type, the capacity market in the model structurally presents higher market clearing prices compared to what would be expected in the real-world. To conclude, there exists a significant trade-off between the ability of the model to enable robust results due to its low computational burden and the validity of modelling results.

A further modelling choice that ensures computational efficiency is to optimise investment decision based on a number of representative days instead of a full year with an hourly resolution. Due to this simplified temporal resolution, lower peaks in electricity demand occur in the number of representative days compared to a full year with an hourly resolution. This has an effect on the profitability of peaking generators, as these essentially cover a large share of their costs in peaking hours. Hence, modelling results might display under-investment in peaking generators compared to reality.

Furthermore, one major limitation is the assumption that a single electricity market is modelled and no imports and exports of electricity are taken into account. The Netherlands is a country which relies heavily on interconnection capacity. To illustrate this, imports and exports amounted to around 20 billion kWh in 2019, which is relatively high compared to a net production of around 115 billion kWh (CBS, 2021). An important critique of capacity mechanisms is their effectiveness within interconnected electricity systems. Within integrated electricity systems, the positive effects of a capacity mechanism may leak to other countries, leading to free-riding and increased load curtailment within the country that has implemented the capacity mechanism. Due to the assumption concerning the single market, the effect of cross-border leaking is not considered in this research. Therefore, the effect of a capacity market in the Netherlands may be lower compared to the results described in this thesis.

A further limitation that is identified in this thesis is the less elastic demand curve for capacity of the TSO due to the assumption of a step-wise instead of linear curve. As a consequence of the less elastic demand of capacity of the TSO within the model, the procurement of capacity is less responsive to changes in capacity bidding prices of generators. However, since the beginning of this thesis, Linny-R has seen several advancements of which one can solve the reliance on the stepwise demand curve for capacity. New functionalities of Linny-R facilitate the incorporation of a piecewise linear constraint which can replace the step-wise linear function and substitute it for a continuous linear function.

Lastly, another limitation is the assumption that forecasting the revenues of the capacity market to incorporate them in the investment decision is based on a linear capacity demand curve. Due to this, the forecasted revenues of the capacity market follow a bipolar pattern and are either an overestimation or an underestimation of the actual revenues from the capacity market. This does not reflect the reality of forecasting by investors as more advanced methods will be applied, ultimately leading to a higher accuracy of forecasts. The assumption of the linear demand curve in forecasting has implications on the results concerning the effectiveness of a capacity market. As a result of the linear demand curve, the forecasted revenues of the capacity market follow a bipolar pattern. This has the effect that the forecasted revenues either strongly underestimate or overestimate the actual revenues from the capacity market. As a result of this, the capacity market is more prone to investment cycles compared to when a more accurate forecasting method is applied. This abstraction was implemented due to time limitations. However, it is strongly encouraged to further explore the possibilities of more accurate forecasting methods as this will have a significant impact on the validity of results. Future research could further verify and validate the forecasting of revenues from the capacity market.

Reflection on Methodology Myopic optimisation is a novel approach that has been recently applied to model energy systems. As myopic optimisation has not yet been applied to model a capacity market, this thesis provides a methodological contribution to literature by providing additional insights that add to the debate on the effectiveness of a capacity market. These insights are essentially based on the effectiveness of a capacity market in a situation where investors are subject to bounded rationality and imperfect foresight. Results of this thesis have shown that, as a consequence of imperfect forecasting of revenues of the capacity market, investment cycles may develop. Due to these investment cycles, the adequacy standard set by the TSO was not continuously met throughout the full timeframe of analysis. Hence, the robustness of the effectiveness of a capacity market is negatively affected by the bounded rationality and imperfect foresight that investors exhibit. Thus, myopic optimisation can be seen as a useful method to examine the relationship between the effectiveness of policy alternatives and bounded rationality of actors. Besides having identified the clear advantages of myopic optimisation resulting from additional insights, there exist several limitations.

The argumentation behind including myopia in optimisation models is essentially based on that it is expected to more realistically reflect the reality of decision-making. However, when reflecting on the research project in this thesis, there arise two arguments why myopic optimisation also does not fully reflect the reality of decision-making.

A first limitation of myopic optimisation has been identified by Poncelet, Delarue, Six, and D'haeseleer (2016). The authors stress that within myopic models, investments decisions are based on short-run averaged profits of the period of optimisation, which are implicitly extrapolated to all remaining periods in the time frame of the model. Results from this thesis strengthen the argumentation behind this limitation, as a similar mechanism can be deduced from the results, which is represented by figure A.6 in the Appendix. In MODO, the forecasted revenues of the capacity market are similarly extrapolated to all remaining periods in the time frame of the model. As the forecast is based on a single-year and does not evaluate multiple periods, the forecasting does not capture any trends in capacity market revenues. Therefore, when the forecasted revenues are estimated equal to the price cap, these revenues are simply extrapolated to remaining years in the simulation. This will result in investments that are not profitable due to lower capacity market revenues compared to the extrapolated values, as can be seen in year 2037 and 2038 in figure A.6. Thus, this does not optimally reflect the reality of decision-making by investors.

Argumentation behind a second limitation that is identified as a result of this thesis will now be provided. A drawback of myopic optimisation is that it is of a deterministic nature. Due to its deterministic nature, weather years that serve as input for the model are similarly deterministic. Output of variable RES-E in the model is determined by these deterministic values. Investment decisions within the model are based on the deterministic output of variable RES-E and hence do not take potential fluctuations into account. Performing a myopic optimisation with a deterministic weather year will thus result in a capacity mix that is optimal for the weather year in question. With an increasing penetration of variable RES-E in the electricity system, the need to account for uncertainty considering their output is present. This is not accurately captured by the deterministic weather years in myopic optimisation. A method that is proposed to effectively capture the uncertainties concerning the output of variable RES-E is stochastic optimisation. Accounting for the stochasticity of weather conditions in electricity system models by stochastic optimisation can provide a promising solution to maintain system adequacy in a system with an increasing share of variable RES-E. Zheng et al. (2014) describe a method of stochastic optimisation in which an uncertain vector is included in the objective function. In this way, stochasticity of variable RES-E output can be incorporated in the optimisation. The outcome of stochastic optimisation is a more robust development of the electricity system, which is optimal for a wide range of weather conditions. Reliability of an electricity system that is pre-dominantly reliant on a large share of variable RES-E is largely dependent on the output of variable RES-E. Hence, modelling a capacity market through stochastic optimisation can provide more robust insights into its effectiveness in many different futures.

Consultations with TenneT Throughout this research project, it was aimed to frequently consult in-field stakeholders to abstain from becoming overly reliant on quantitative results and to validate modelling assumptions and input data. To realise this, frequent consultations with TenneT - the Dutch TSO - and specifically with William Zappa have been performed. Zappa is an expert on energy system research and has (co-)written several publications on the matter (Brouwer et al., 2016; Zappa et al., 2019; Zappa et al., 2021). These consultations have proven to be especially useful for validating modelling assumptions and input data. One of the insights that have been gained from these consultations is the importance of the height of the Derating Factor in maintaining system adequacy through a capacity market. The Derating Factor determines the volume of firm capacity variable RES-E are allowed to offer in the capacity market and thus, what their contribution is to system adequacy. A Derating Factor that overestimates the contribution of variable RES-E to system adequacy will have a negative effect on the effectiveness of a capacity market. An adequate estimation of the Derating Factor of variable RES-E is therefore required to result in a satisfactory number of additional investments in firm capacity to maintain system adequacy. This could provide an interesting avenue for future research, which could focus on the effect of the Derating Factor on the effectiveness of a capacity market and whether this Derating Factor should be adjusted over time in a system with an increasing share of RES-E.

Furthermore, as described in section 9.2, consultations with TenneT have provided insights in additional revenues that can be gained by mid-merit plants atop of revenues from the spot market, such as options and futures trading. These insights place the modelling results in perspective as they do not capture the picture concerning the profitability of mid-merit plants.

Comparison of Results to Literature The theoretical background presented in chapter 3 will provide a basis for a comparison of modelling results and insights from this thesis with literature. First, it was derived from literature that regulatory uncertainty can aggravate investment risk that is perceived by investors. This thesis did not focus on the effect of regulatory uncertainty on investments. However, regulatory uncertainty in a capacity market can have significant effects on the profitability of investments. A striking example is the change in Derating Factor that is experienced by storage units in the Unit Kingdom Energy Storage World Forum (2021). Due to regulatory changes in the capacity market, Derating Factors of the most affected storage types were decreased extremely by 80%. This will influence the profitability of storage. Hence, perceived regulatory uncertainty will add to the risk-averse behaviour of investors. Regulatory uncertainty can be considered an additional scenario variable that can be varied across different scenarios and will therefore provide an avenue for future research.

From this research, it was concluded that the effectiveness of a capacity market is strongly reliant on the ability of investors to accurately forecast the revenues of the capacity market. In this thesis, a yearly capacity market was modelled, meaning that solely existing generators can participate in the capacity market. Another type of a capacity market is the forward capacity market, as for example implemented in the United Kingdom (Department of Energy and Climate Change (DECC), 2014). The forward capacity market could reduce the reliance on the ability of investors to forecast the revenues of the capacity market, as long-term contracts for new investments on capacity remuneration will be established. Theoretically, this could reduce the investment risk that is associated with uncertain revenues of the capacity market and could potentially increase the effectiveness of a capacity market on maintaining system adequacy. However, research of Bhagwat (2016) has pointed out that the performance of a yearly capacity market and a forward capacity market on maintaining system adequacy is similar. Therefore, it remains questionable whether a forward capacity market will be successful in reducing investment risk.

The effectiveness of other capacity mechanisms such as capacity subscriptions (Doorman, 2000) were not evaluated in this thesis. However, when reflecting on the working principle of capacity subscriptions, it could potentially provide a solution for the reliance on the ability of investors to accurately forecast the revenues of the capacity market. By implementing capacity subscriptions instead of a capacity market, system adequacy is transformed into a private good as consumers are required to estimate their willingness to pay for available capacity. Consumers buy this capacity from providers of firm capacity, such as generators in the form of contracts and their demand for capacity can potentially be based on their historical consumption (de Vries et al., 2019). Long-term capacity subscriptions combined with basing their demand on historical consumption can potentially reduce uncertainty concerning the remuneration that providers of firm capacity will receive. Hence, capacity subscriptions can potentially be more effective in maintaining system adequacy and could result in less strong investment cycles.

11 Reflection

A quote of Porter (2017) beautifully stresses the importance of reflection: *"Reflection gives the brain an opportunity to pause amidst the chaos, untangle and sort through observations and experiences, consider multiple possible interpretations, and create meaning. This meaning becomes learning, which can then inform future mindsets and actions."* The purpose of this chapter is aligned with this quote. It will serve as a personal reflection of the research project that is described in this thesis. This reflection will be carried out along two main themes: the process of this research and building on somebody else's work, in this case MODO. Insights that arise from this reflection will hopefully inform and guide future researchers.

Reflection on the Process At the beginning of this research project, I had set a very ambitious scope. I wanted to model multiple capacity mechanisms and perform a robustness analysis on each of the mechanisms to compare their effectiveness on maintaining system adequacy in an extensive number of scenarios. A few weeks into the research project, I realised that I could better start with an initially small scope and then add research aspects when time would allow it. Today, I realise my initial ideas are comparable to the workload of a PhD, at minimum. In the end, I have stayed with the small scope that I adjusted to in the beginning of the research. This scope is concerned with modelling a simple version of a capacity market and analysing its effectiveness through a scenario analysis, instead of a robustness analysis. Even with this adjusted scope, time pressure was still present throughout the project. When reflecting on this, I can conclude that doing research is a slow process and innovation cannot be forced.

One aspect of this thesis that was particularly difficult and time-consuming was to forecast the revenues of the capacity market in the model, in order to be able to include them into the final decision to implement an investment. The difficulty lies in the fact that the forecasted capacity market clearing price is dependent on the number of investments that occur. The initial plan was to include this in the *Number of Profitable Units* function as an iterative loop so as to find the optimal number of investments to gain most revenues from the capacity market. However, when executing this plan, two difficulties arose. First, it would require to determine which investments of a technology type to include first in determining the corresponding capacity market clearing price. This can be illustrated with a simple example. Say the solver provides two types of investment options, 2 Offshore Wind plants and 2 CCGT plants. If all four investments would be made, the capacity price would be lower than if only two investments would be made. Hence, it is necessary to forecast the revenues of the capacity market starting with the technology that is most profitable. The initial idea was to first sort the investment options of a technology type based on their ascending marginal costs. Namely, plants with relatively low marginal costs have a higher profit margin. In the example, this would mean the NPU of Offshore Wind would first be evaluated, followed by the NPU of CCGTs. This is the case as the marginal costs of Offshore Wind are near negligible and the marginal costs of CCGTs are substantially higher. After selecting with which technology to begin the evaluation, the forecasted revenues of the capacity market would be incorporated in the NPU in the following manner. First, the capacity price that corresponds to the offshore wind investment options is calculated. Each investment option has a particular capacity

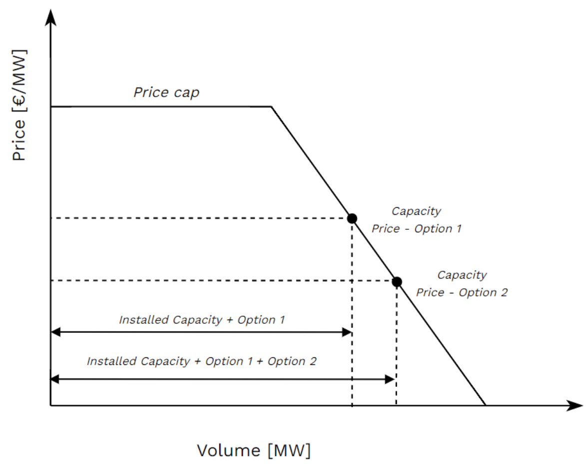


Figure 11.1: Illustration of initial idea of forecasting revenues of the capacity market

market clearing price that it is associated with. It would be assumed that all other generators are price-takers, thus bid at zero. The price of the second option is lower than the price corresponding to the first option, as visualised in figure 11.1. Then, it would add the first capacity price to the revenues of the first option. If this option is profitable, it would proceed to evaluating the second option. This is done by adding the capacity price corresponding to the second option to the revenues of both investment options. The NPU function will then evaluate whether the number of profitable units with the second capacity price is higher, i.e. equal to two, instead of one. If this is the case, it would mean that the lower capacity price corresponding to the second investment option is still sufficient to realise two profitable investments, hence they both should be implemented. If this is not the case, it should only implement the first investment option. After having evaluated the NPU of Offshore Wind, it will continue in a similar way by evaluating the NPU of CCGT.

Both iterating over and sorting of multiple technologies is difficult in Linny-R. This due to the fact that Linny-R does not have any knowledge concerning which components of the model are considered a technology. It merely can make a distinction between processes and products, hence making it difficult to iterate over multiple technologies. Furthermore, a similar difficulty arises when sorting over multiple technologies. Hence, in the end, this idea was not pursued. Due to time limitations, an abstraction of forecasting of the revenues of the capacity market was made. It was decided to base it on a linear capacity demand curve.

Building on somebody else's work As MODO has been developed by a former CoSEM student, Jasper Groenewoud, building on this model has been a unique way of conducting a master thesis, resulting in a work that has been mostly realised by students only. This *passing the baton* from student to student has been motivating for me, but several challenges have arisen during the research project. Building on another student's work can be specifically challenging due to the limited documentation and experts that are available compared to very well-established energy system models. In essence, there is solely one expert concerning the model, i.e. the student, and documentation is limited to the master thesis that has been written.

When reflecting on my research project, documentation and expert consultations are key to understanding the line of reasoning behind the modelling choices and assumptions. A thorough understanding is required to further enhance the model, which can be difficult to establish when documentation is limited. To provide fulfilling documentation, it is important to describe each step in modelling choices clearly and exhaustively, meaning that no steps should be missed. Due to the relatively short amount of time that is prescribed for a master thesis in CoSEM - 6 months - this can form a challenge.

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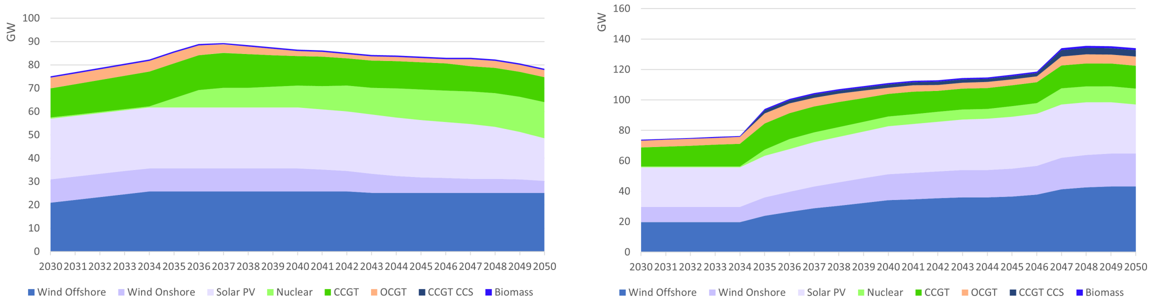
A
Results of Scenario Analysis

This appendix presents additional results of the scenario analysis that have been performed in chapter 8. It concerns the capacity mix developments of each scenario and other additional results. For the Base Case Scenario, it also presents an illustration of a limitation of myopic optimisation, which will serve as an example for the Discussion in chapter 10.

A.1. Base Case Scenario



(a) Energy-Only Market

(b) Capacity Market

Figure A.1: Base Case: Capacity Mix [GW]

(a) Energy-Only Market

(b) Capacity Market

Figure A.2: Base Case: Energy-Not-Served [x10000 MWh]

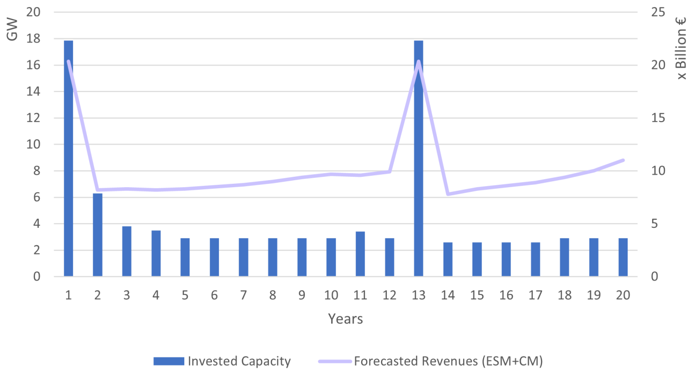
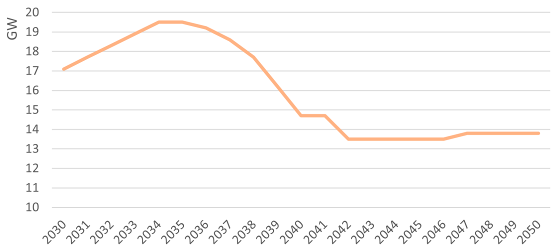
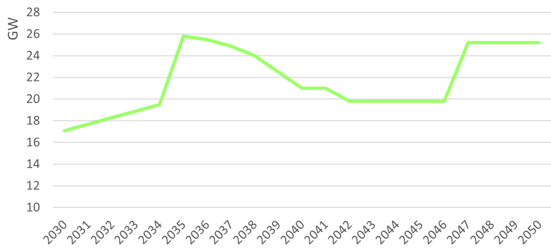


Figure A.3: Base Case: Invested Capacity in GW next to forecasted revenues of the ESM & CM in billion euros for every investment run



(a) Energy-Only Market



(b) Capacity Market

Figure A.4: Base Case: Capacity of Peaking Plants (CCGT, CCGT CCS and OCGT) [GW]

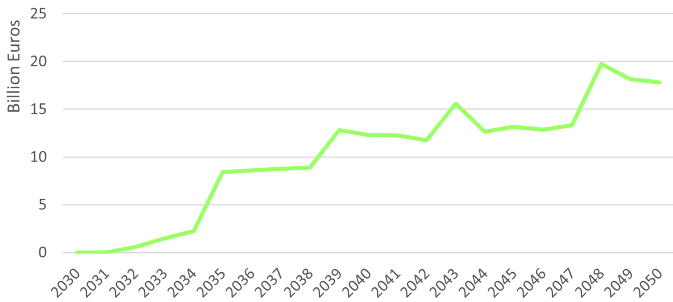


Figure A.5: Base Case: Revenues of the Capacity Market [€]

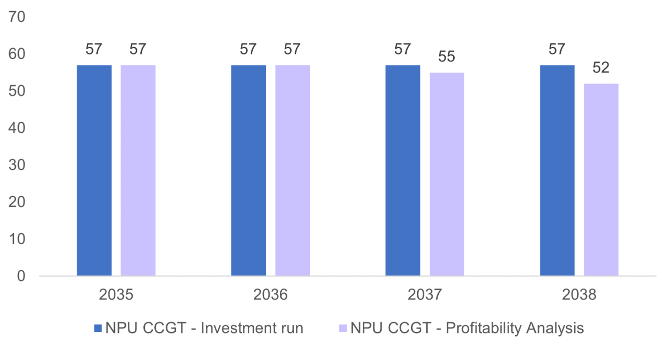
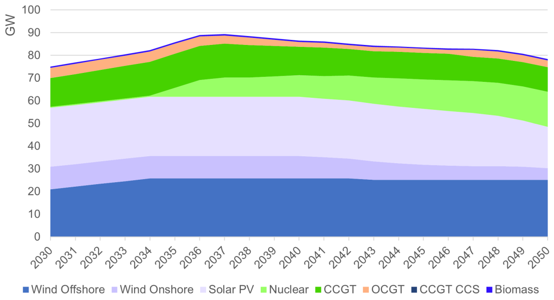
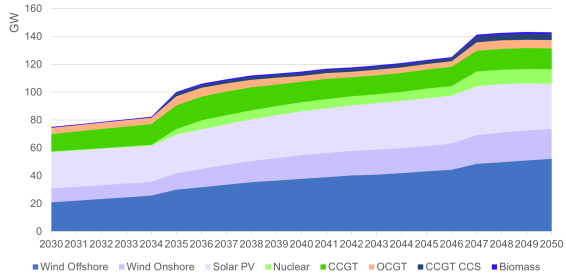


Figure A.6: Effect of myopic optimisation: implicitly extrapolating average revenues to all remaining periods in the time frame of the model, an illustration

A.2. Dunkelflaute Scenario

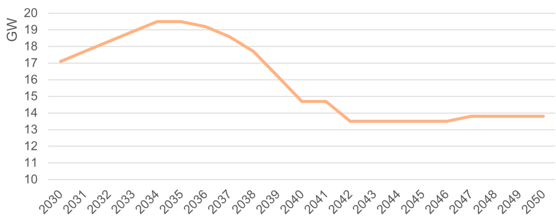


(a) Energy-Only Market

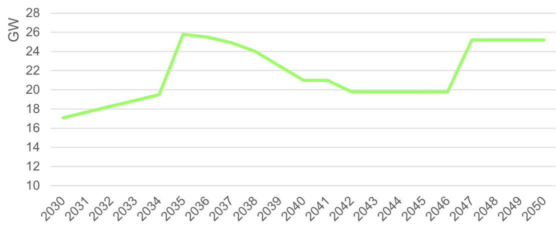


(b) Capacity Market

Figure A.7: Dunkelflaute: Capacity Mix [GW]



(a) Energy-Only Market



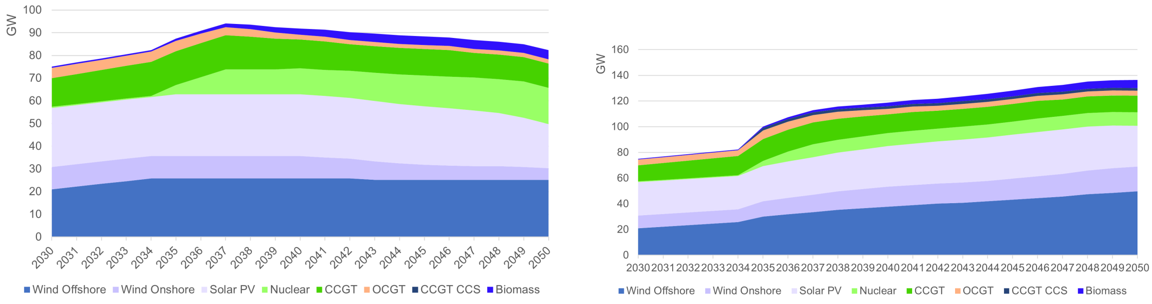
(b) Capacity Market

Figure A.8: Dunkelflaute: Capacity of Peaking Plants (CCGT, CCGT CCS and OCGT) [GW]

	Capacity price [€/MW]		**Revenues from CM [€]**	
	Base Case - CM	*Dunkelflaute - CM*	*Base Case - CM*	*Dunkelflaute - CM*
2037	29000	29000	8.76E+08	8.76E+08
2040	41317	37261	1.23E+09	1.11E+09
2045	40518	35921	1.31E+09	1.17E+09

Table A.1: Comparison of capacity price [€/MW] and revenues of the capacity market [€] of the Base Case and Dunkelflaute Scenario

A.3. High Commodity Prices & High Risk Aversion Scenario

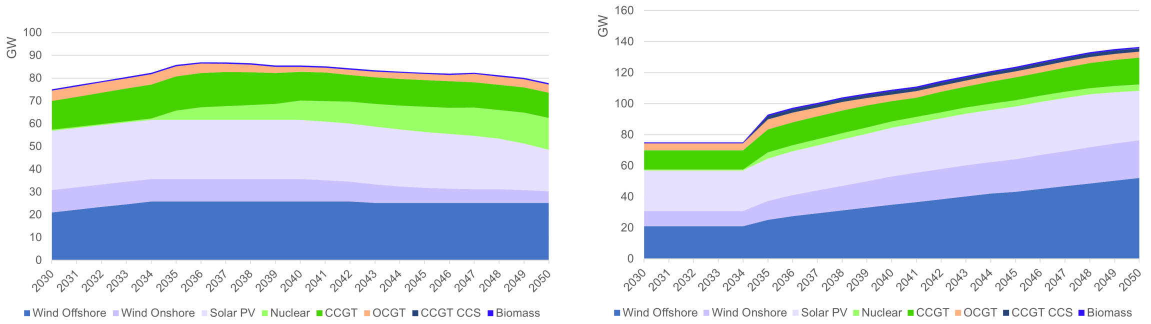


(a) Energy-Only Market

(b) Capacity Market

Figure A.9: High Commodity Prices & High Risk Aversion: Capacity Mix [GW]

A.4. Low Commodity Prices & High Risk Aversion Scenario



(a) Energy-Only Market

(b) Capacity Market

Figure A.10: Low Commodity Prices & Risk Aversion: Capacity Mix [GW]