A proof of concept for simulating long-term energy system development in a myopic investment detailed operational model

the case of system adequacy

Master of Science in Complex Systems Engineering and Management

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A proof of concept for simulating long-term energy system development in a myopic investment detailed operational model: the case of system adequacy

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"Pursue what is meaningful, not what is expedient."

Jordan B. Peterson

Abstract

In an energy-only market, private investors play a crucial role in realizing the security of supply. However, several specific characteristics inherent to his market design cause concern about whether this market design is suitable for system adequacy. Moreover, due to policy goals aimed at working towards low-carbon energy systems, these concerns are increased. In this light, many countries have implemented a capacity remuneration mechanism to increase the stability of the security-of-supply in their energy system.

While earlier research has been conducted on this topic, we observe two knowledge gaps: 1) from a theoretical perspective, there is debate on the effectiveness of capacity remuneration mechanisms, especially on the role of seasonal storage, 2) from a methodological perspective, we find that there are no models that are equipped to consider myopic investments while having a high enough detailed operational model also to consider investments in (seasonal) storage and the impact of extreme weather scenarios. This research aims to fill these knowledge gaps by presenting a proof-of-concept of a myopic investment detailed operational (MIDO) model. In our thesis, we focus on system adequacy. However, by developing the MIDO model, we hope to enable researchers to analyze any problem related to long-term energy system development with a multi-time scale nature.

At the center of the MIDO model are three sub-models: the investment decision model (ID), the future price (FP) model, and the present price model (PP). Figure 1 shows how these models are connected through a loop. The first step in this loop is the present-price model, which generates highly accurate information on the operation of a market. After running a year in the PP model, information on the performance of all assets in a market is sent to the ID model. With this data, the ID model performs two tasks: invest based on limited information in an iterative greedy process and dismantle assets losing money. The ID model gets the information on the performance of investment assets under consideration from the FP model. The FP model generates less reliable information than the PP, but it does so very fast. After the investment decisions are made, this information is transferred to the PP model, and the loop starts from the beginning. In this way, a market is simulated with investment cycles, delayed responses, uncertainty, and risk upon investment decisions. This process enables the comparison of different forms of capacity remuneration mechanisms and the effect on the security-of-supply in an isolated energy system.

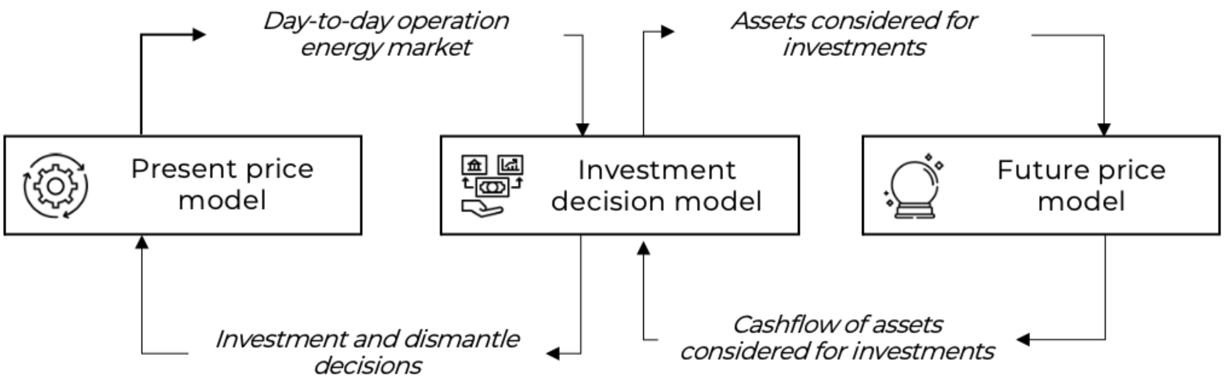

FIGURE 1: Overview of the sub-models in the MIDO model

We explore two distinctly different futures within our thesis to see if there is any added value in a capacity market in any of these futures. Moreover, within these futures, we analyze how a capacity market can help withstand an extreme-weather scenario. From this analysis, we find that a capacity market has added value in all scenarios, from the point of system adequacy but also a total consumer cost perspective. However, because we only have explored two futures, we do not argue that a capacity market will always positively impact the system adequacy within an energy system. Instead, we argue against the notion that seasonal storage on its own is always enough to reduce all shortages created in an energy-only market and disagree with the idea that seasonal storage makes capacity markets redundant.

We identify two avenues for future research. First, researchers interested in generating more and better results should utilize the MIDO model to explore more future scenarios and compare different forms of capacity mechanisms. Second, research aimed at improving the MIDO model should focus on limiting the computational time generated by the investment loop and seek to expand on the model's functionalities.

Acknowledgements

This report represents the conclusion of my Master thesis and thereby the end of my time as a student in Delft. In this section, I would like to express my gratitude to everyone who has been a part of my thesis.

Firstly, I would like to acknowledge my appreciation for my first supervisor, Pieter Bots. If I had to use a Dutch proverb to describe your guidance style, it would be 'hard op de inhoud, zacht op de man'. Thank you for always being extremely critical of my work and pushing me to become a better student while always offering a helping hand and lifting my spirits when I needed it. Furthermore, I would like to thank you for the hours you spent on developing Linny-R, sometimes to match specific needs I had for my model. Without these efforts, I would have quite literally not been able to produce my thesis in its current form. Secondly, I want to thank my second supervisor Laurens de Vries. Your courses in the Bachelor and Master are the primary reason I developed an interest in market design. Moreover, your in-depth understanding of modeling energy systems and market designs was critical in bringing my thesis to succession. Finally, thank you for constantly reminding me to keep the bigger picture in mind and not get stuck in details while modeling.

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Chapter 1

Introduction

1.1 The importance of private investment during the energy transition

"The European Green Deal is Europe's man on the moon moment" with this line, the President of the European Commission signified the importance of the Green Deal for society (European Commission, 2019a). The Green Deal is the response strategy of the EU towards climate and environmental-related challenges. This strategy sets out a vision of a European Union emitting zero greenhouse gas emissions in 2050. Within the EU, the production and use of energy across sectors account for more than 75% of total greenhouse gas emissions (European Commission, 2019b). In line with this goal, many member states plan to transition from a system based on fossil fuels to systems based 100% on renewable energy resources (RES) where variable renewable energy sources (vRES) play a significant role (European Commission, 2018, Zappa, Junginger, and Broek, 2019). vRES are RES that are dependent on external weather conditions to produce electricity Krakowski et al., 2016. According to the European Commission (2019a) to realize the Green Deal's ambitions, there are significant investments needed, and the private sector will be "vital in financing the green transition.". However, many studies argue that the current market structure will not properly incentivize these private actors to make these investments and that this, in turn, will hinder the security of supply of energy and put the set-out policy targets at risk (Sensfuß, Ragwitz, and Genoese, 2008; Djørup, Thellufsen, and Sorknæs, 2018; Hildmann, Ulbig, and Andersson, 2015; Sorknæs et al., 2020; Sorknæs et al., 2019).

1.2 Problems that hinder security of supply in competitive electricity markets

There are two forms of security of supply in a country: capacity adequacy and reliability. (Newbery, 2016). In this thesis, we view adequacy as "the ability of the electric system to supply the aggregate electrical demand and energy requirements of the end-use customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements." (North American Electric Reliability Corporation, 2008). Subsequently, we look at reliability as "the ability to withstand sudden disturbances, such as electric short circuits or unanticipated losses of system components" (Latin and Bureau, 2004).

Looking at the overview of the electricity system as in 2.2 we can see that reliability is a public good supplied through ancillary and balancing serves by a Transmission System Operator (TSO), whereas adequacy could (in theory) be realized only through investments of private actors (Oren, 2000). In this thesis, we chose to look at the security of supply from a long-term adequacy perspective and therefore do not investigate the role of the balancing services offered by a TSO.

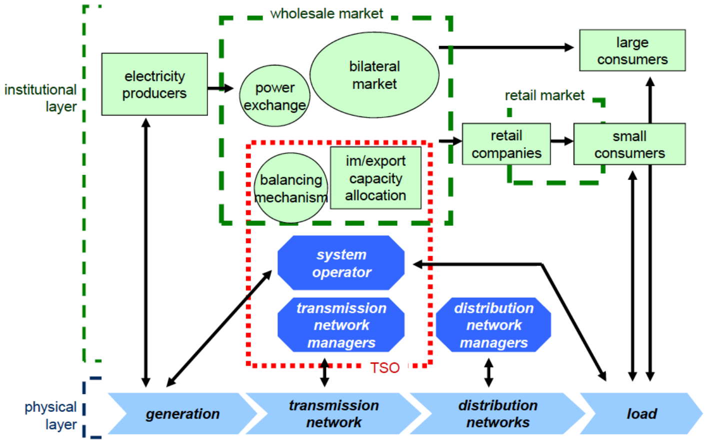


FIGURE 1.1: Overview of the electricity system (from De Vries, Correlje, and Knops, 2013)

1.2.1 Problems inherently caused by the energy-only market

The missing money and missing market problem

In an energy-only market, an asset get gets paid only for the volume of electricity it produces. In a competitive energy-only market, all producers bid according to their marginal price, and the electricity price is equal to the last bid that is necessary to satisfy demand (Gore, Vanadzina, and Viljainen, 2016). So in an energy-only market, investors can earn back the fixed costs of their investment costs through inframarginal rents and scarcity rents. Inframarginal rents are the difference between the marginal cost of an asset and the current market price. Scarcity rents are equal to the price gap when demand exceeds supply and, again, the marginal costs of an asset. In theory, if there is no market failure, these two rents should provide efficient revenues for investors to recover the costs of investments and attract enough new investments to guarantee the security of supply (Gore, Vanadzina, and Viljainen, 2016). These efficient incentives would be the case if the scarcity price would reflect the opportunity costs of a network failure or the value of lost load (VOLL) (Joskow, 2008). However, to prevent market abuse in times of scarcity, regulators have introduced a price cap in times of scarcity (Gore, Vanadzina, and Viljainen, 2016). If the price of this price cap is set too low, then generators do not earn enough money to earn back their investment, and no new investments are incentivized; this is called the "missing-money problem" (Joskow, 2006). In addition, it has been established that estimating the average VOLL is difficult (Willis and Garrod, 1997), and therefore markets across the world struggle with incentivizing investment for a correct VOLL.

Furthermore, even if the VOLL is established at an adequate level, but the revenue is not perceived to be satisfactory by investors, this creates a "missing market" problem (Newbery, 1989). Issues around missing markets become problematic "if risks cannot be efficiently allocated with minimal transaction costs through futures and contract markets, or if important externalities such as CO_2 and other pollutants are not properly priced" (Newbery, 2016).

Imperfect foresight, regulation uncertainties and risk aversion

In addition to the missing money and missing market problem, an energy-only market may not provide investors sufficient incentive to invest in generation capacity due to high investment risk. High volatility of electricity prices, high upfront costs of investments, and long lead time cause high investment risk (De Vries, 2007). If investors were risk-neutral and had access to all relevant information, this should not pose a problem, and investments in generating assets should still be socially optimal, under the assumption of a perfect market (Shahidehpour, 2003). However, this is not the case because it is difficult to determine future revenue. After all, this is strongly dependent on the duration/frequency/height of "rare" price spikes. Moreover, these price spikes are difficult to predict for investors as they are strongly dependent on the development of investments of other actors, demand development, the weather.

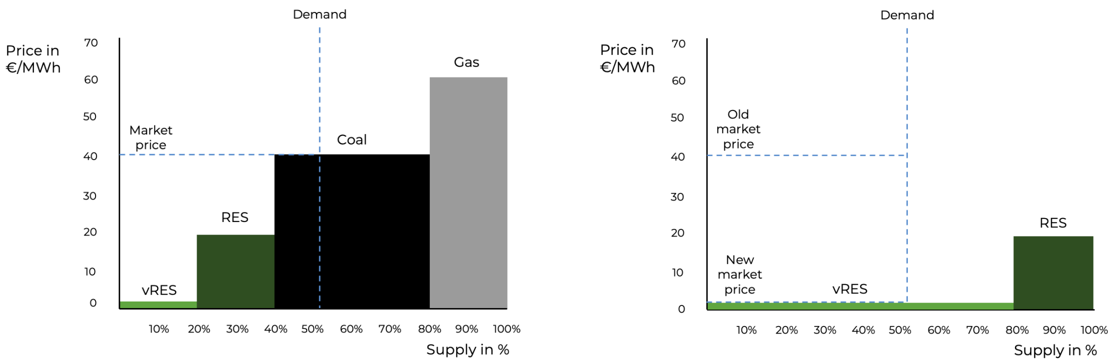
Furthermore, the ability to assess future revenue is hindered even more due to regulatory uncertainty. An example of this regulatory uncertainty may be that a regulator lowers the price cap if there are price spikes or impact on the CO_2 price due to regulatory decisions by policymakers in emission trading schemes (De Vries, 2007). Moreover, considering these investment risks, looking at the entire group of investors in a market, it is worthwhile to under-invest (below the social optimum) as this will lead to high prices and a higher chance to recover their investments. Oppositely, the market does not recover its investment in case of overinvestment and following low prices (De Vries, 2007). For this reason, in an imperfect electricity market, investors are seen as risk-averse and will delay investment until the need for generating capacity is reasonably sure (Neuhoff and De Vries, 2004).

1.2.2 Additional problems that arise due to the energy transition

As discussed in the previous section, multiple issues impact the security of the supply of an energy system. Note that the current problems such as the missing money and the missing market have become more salient during the energy transition (Newbery, 2016). Furthermore, an energy system that transitions towards a low-carbon energy system adds additional obstacles to the security of supply that we will discuss in this subsection.

Merit-order effect

To explain the merit-order effect, we point to the stylized merit in order in figure 1.2. For example, in figure (A), the price-setting asset group is coal, which leads to an electricity price of 40 €/MWh. However, if the market invests in only renewable due to policy or environmental incentives, the merit order of figure (A) transitions to figure (B). If the demand remains the same, this causes the price to drop significantly. This phenomenon is referred to as the "merit-order effect" and forms a barrier for investment into RES by investors.



(A) 40%RES (B) 100%RES

FIGURE 1.2: Merit-order effect due to vRES

Weather dependent RES and seasonal storage

Weather will highly influence a system that transitions from depending on fossil-fueled assets to eventually being 100% backed by RES. Therefore it is increasingly recognized that the key to a low-carbon electricity system is 'flexibility' (Doorman and De Vries, 2017). 'Daily' flexibility can match supply and demand for the day-night pattern up to several days. Examples of assets that can provide this are batteries and demand-side response. However, in addition to the short-term imbalances, there is a need for 'seasonal' flexibility. The need for flexibility will cause this during 'normal' weather circumstances and during the occasional periods where there are weeks or more without any sun or wind (called 'wind drought' or 'Dunkelflaute'). The expectations are that biomass or synthetic fuels, such as hydrogen, ammonia, or methanol, will fulfill these functions in the long term.

It seems that there is a good argument for a business case for 'daily' flexibility; however, the investment risk on the other side of the spectrum for the 'seasonal' flexibility seems high. As we have already explained, there are several reasons why investors are risk-averse. So a valid question to be asked is "who would invest in storage or generation facilities that are expected to be needed only once every several years, especially when its need is weather-driven, while both weather patterns and weather-related electricity consumption patterns (such as how homes are heated) are changing?" (Doorman and De Vries, 2017). Even facilities that are used a few times a year would have high investment risk as they would need to earn back their investment by charging very high prices during a limited amount of hours every year. However, even when such challenging weather occurs, society expects the security of supply of our energy system to be secure (Doorman and De Vries, 2017).

1.2.3 Capacity mechanisms as a solution

As discussed in the previous paragraphs, the missing money, the missing market, high price volatility, long lead times, imperfect foresight, regulatory uncertainty, risk aversion, the merit-order effect, and weather dependent RES all put pressure on the security of the supply of energy in a competitive electricity market. A combination of these arguments has led many scientific authors to conclude that an energy-only market will not be sufficient to incentives investors to invest in enough vRES and back-up capacity to realize the set-out policy targets of the energy transition while maintaining the security of supply (Doorman and De Vries, 2017; Newbery, 2016; Duggan, 2020; Gerres et al., 2019; Holmberg and Ritz, 2020).

For these reasons, many authors point to the use of some capacity remuneration mechanisms to provide incentives for investors to guarantee an adequate level of security of supply. In essence, a capacity mechanism provides generators additional payments for their capacity in exchange for being available Holmberg and Ritz, 2020. In current practice, European countries have introduced four different forms of capacity mechanisms, as shown in figure 1.3.

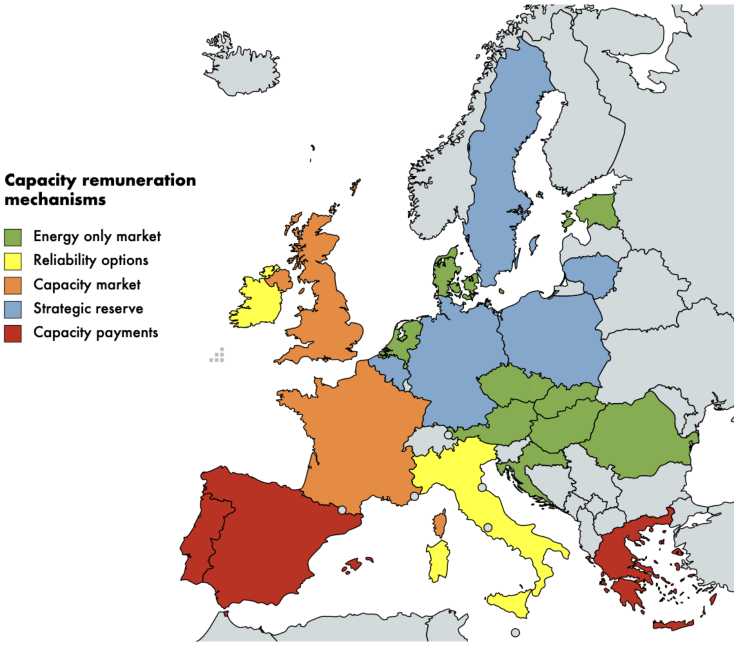


FIGURE 1.3: Capacity Remuneration mechanisms in EU (based on Nouicer and Meeus, 2019)

Price based: capacity payments

Capacity payment is the only mechanism out of the four that is price-based instead of volume-based. In this mechanism, all plants receive a fixed payment (set out by a regulator) for their available capacity (Nouicer and Meeus, 2019). However, since its introduction, it has been unsuccessful in reaching its set out policy targets and has been criticized for its reliability (Bhagwat, 2016). The main problem in implementing this mechanism is the difficulty in determining what capacity payment level is required to ensure enough incentive to realize a level of security of supply that is necessary (Batlle et al., 2007).

Volume based: strategic reserve

In the case of a strategic reserve, a central authority decides the amount of capacity needed to make up for a predicted shortfall by the market a few years in advance. The central authority then proceeds to set out a competitive tendering process to contract this shortfall in capacity (Nouicer and Meeus, 2019). This contracted capacity is not able to participate in the electricity market and is set to deploy at a set 'reserve price', which is higher than the marginal costs of this asset, but below the VOLL (Bhagwat, 2016). The effect on the security of supply is that due to the tightening of supply by the strategic reserves, investments are attracted to the market before physical shortages occur (Vries and Heijnen, 2008).

Volume based: capacity market

In a capacity market, consumers (or an agent representing these consumers, need to purchase capacity credits equal to their peak demand plus an additional margin (determined by a central authority). An auction realizes the purchase process of these credits (Ockenfels, Stoft, and Cramton, 2013). The goal of this auction is to provide additional revenue to power generators and, in turn, help assets return their fixed costs (Joskow, 2008). Moreover, it is the expectation that this additional market provides a stronger and earlier investment incentive signal than the wholesale electricity price (Bhagwat, 2016).

Consumer based: reliability options, reliability contracts and capacity subscription

This last group consist of three in potential effective capacity mechanisms: reliability options (Bhagwat and Meeus, 2019), reliability contracts (Vázquez, Rivier, and Pérez-Arriaga, 2002) and capacity subscriptions (Doorman, 2005a). These capacity mechanisms are all consumer-based. In this consumer-based group, the capacity subscription is the most market-oriented option out of all (Grande, Doorman, and Wangensteen, 2001. Which, in essence, creates a capacity market directly between generating companies and consumers.

1.3 Current gaps in long-term energy system development

1.3.1 Limited understanding of the effect of storage on system adequacy

Section 1.2 showed how a significant long-term challenge in the transition to a low-carbon energy system is how to maintain the security of supply (Doorman and De Vries, 2017). While some countries have already implemented capacity mechanisms to guarantee system adequacy, others still hold on to an energy-only market. There is an extensive body of literature that lays out the arguments for and against capacity mechanisms, e.g., see Chao and Lawrence (2009), Ockenfels, Stoft, and Cramton (2013), De Vries (2004), Joskow (2008), and Duggan (2020). Even though this discussion has been held for some time now, there is still no clear answer, and the debate surrounding capacity mechanisms is still actively going on in scientific literature. As in more recent literature, Bhagwat and Meeus (2019) note, "capacity mechanisms in their different forms have been controversial in theory as well as practice." Holmberg and Ritz (2020) agrees with this by stating that "capacity mechanisms are playing a growing role in electricity markets around the world - and yet their use and design remain hotly debated." Adding to this Kaminski, Höschle, and Delarue (2021) states that "although heavily debated, many authorities assume that the current market design does not attract an adequate amount of capacity investments, and are therefore implementing capacity markets." This discussion around the need or effectiveness of capacity mechanisms which was already being debated is enhanced by the transition towards low carbon energy systems as this has given rise to additional discussion points (Bhagwat et al., 2017). Therefore, the significance and need for capacity mechanisms (especially during the energy transition) remains an unsolved knowledge gap.

Previous studies have already looked at the need for a capacity market in a future energy system, yet these studies still have left several gaps unanswered. Bhagwat (2016) makes an extensive comparison of different forms of capacity mechanisms through the use of an agent-based model. This research shows how capacity remuneration mechanisms positively impact system adequacy in an (isolated) electricity market with a growing share of renewable. However, in this analysis, demand response and storage are left out of the scope. This limitation leads the author to point to two knowledge gaps still being unanswered. The first is, what is these technologies' impact on the long-term development of the electricity market (especially adequacy)? Moreover, what is the impact of these technologies on the effectiveness of and need for capacity mechanisms? The effect of storage technologies and demand response are relevant to research as it might mean that the energy produced by vRES might be available in times of shortages, and flexible demand might reduce the demand at all during shortages. This storage potential would, in turn, reduce the need for generators during this time and therefore make the capacity mechanism redundant (Bhagwat, 2016). Khan et al. (2018) have updated the agent based-model utilized by Bhagwat (2016) to be able to include electrical energy storage and demand response; they conclude that the case for capacity mechanisms is lessened by the demand-side response and electrical energy storage. However, the authors make explicit that this is only the case for medium-term energy storage and that more research is necessary with other types of storage to determine whether, when, and how much share of this flexibility will be enough to remove the need for a capacity mechanism altogether. This question is especially relevant as the authors show how flexibility might negatively impact the legitimacy of a capacity mechanism. However, as we have already argued, seasonal storage might be essential for system adequacy in a low-carbon energy system. In contrast, the investment risks of these types of flexibility are high (Doorman and De Vries, 2017). Thus making a case that capacity mechanisms might be necessary, especially with concerns of extreme weather scenarios (Khan et al., 2018).

From all these studies, we conclude that there is no consensus on the need/effectiveness of capacity mechanisms. Moreover, the energy transition, seasonal storage, and extreme weather scenarios can significantly impact the role of system adequacy in a future energy system. Yet, there is no agreement in the scientific literature on the effect of (seasonal) storage on the need for a capacity mechanism.

1.3.2 Lack of models that include a detailed operational and allow for myopic investment

We have conducted a literature review to understand why the current state-of-the-art models have not been able to generate sufficient insights to solve the limited understanding of the effect of storage on system adequacy. In our review, we found that modeling in many different forms is a core methodology (Hansen, Breyer, and Lund, 2019). However, as Bhagwat (2016) notes, there are two gaps in the current overall body of models: 1) models that can account for the impact of capacity mechanisms are limited and 2) there are almost no models that consider the combined impact of uncertainty, myopic investment (bounded rational investment behavior) and path dependence of an electricity market. In our thesis, we argue that the second point is especially relevant to simulate long-term energy system development accurately. Many of the problems as described in section 1.2 related to system adequacy are based on the investment decisions of private investors. In real-life energy markets, investors' ability to make these decisions is bounded by limited access to information on the future, leading to sub-optimal investments. These sub-optimal investments then, in turn, call for policy measures such as a capacity-market to account for the adverse effects that arise from sub-optimal investments (Bhagwat, 2016).

So, therefore, we only look at modeling studies that simulate long-term energy system development while allowing for myopic investments. Our review finds that most researchers use Agent-Based Modelling (ABM) to integrate this perspective. In this light we find the EMLab-Generation model used in studies such as Bhagwat (2016), Khan et al. (2018), and Chappin et al. (2017a), the PowerACE model utilized in Genoese, Genoese, and Fichtner (2012) and the ABM model used in Keles et al. (2016). Outside of these ABM-based models, several model-based studies also use a myopic investment perspective, such as Hach, Chyong, and Spinler (2016a) and Weiss et al. (2017). In all of the analyzed studies, the operational model does not have a high level of detail. This lack of detail in the operational model leads to the representation of vRES playing a limited role; flexibility not being incorporated at all, or no inclusion of 'seasonal' *and* 'daily' flexibility. The authors of these studies point to several reasons why this is the case.

Firstly, in studies such as Bhagwat (2016) or Hach, Chyong, and Spinler (2016a) the authors state that storage has been left out of the scope, which is a valid reason as no study can en corporate all elements of the energy system. However, we would like to argue here that this also represents a change of view on the importance of storage, especially regarding the role that synthetic fuels play concerning the system adequacy of future energy systems. Previous studies looked at seasonal storage from a different paradigm; therefore, these former models were not conceptualized/built to include these aspects. This change in view means that utilizing these models as a basis and simply 'adding' seasonal storage or extreme weather scenarios is a burdensome task.

Secondly, there are studies where some form of storage has been included; however, the role of storage is limited. For example, in Khan et al., 2018 there is only one form of storage, the investment into storage is not based on return on investment (which is the case for other assets) and there is no room to include rare weather events. The authors justify these simplifications by stating that it is too big a computational burden on their model to take account of these features. The work of Weiss et al. (2017) also only uses one form of storage in the form of batteries; they point to this as a limitation of their work and advise future research to include power-to-gas technologies.

Concluding, we find that the inclusion of storage and extreme weather scenario in myopic investment is not included in other models either because at the time of modeling (seasonal), storage was not perceived to be relevant, or the simulation of a detailed operational electricity market (which is necessary to model storage) made the overall model computationally unfeasible.

1.4 Myopic investment detailed operational model

In section 1.3.1 we argued that there is a need to better understand the role of capacity mechanisms in future energy systems, especially with relation to seasonal storage. Moreover, in section 1.3.2 we showed that there are no myopic-investment models equipped for simulating long-term energy system development with a high enough operational detail as to include (seasonal)storage. To fill these gaps, we aim to present a proof-of-concept of a myopic investment detailed operational (MIDO) model in this thesis that can simulate these effects in a computationally acceptable time.

We aim to enable future researchers to utilize the MIDO model showcased in this thesis as a quantitative backing to the qualitative economic/policy debate on the role of capacity mechanisms. Note that in our thesis, we focus on system adequacy, but the mechanism behind the development of the energy market is the same for a particular class of problems such as the integration of vRES in energy systems (Hu et al., 2018), the role of CO_2 markets (Richstein, 2015) and coupled energy systems (Sorknæs et al., 2020). So in this regard, we hope that researchers who are interested in better understanding any problem in this entire class of problems can benefit from the approach presented in our thesis.

We classify these problems by the multi-time scale approach necessary to simulate these problems in the long-term development of the electricity market. In the overall power system modeling literature, modelers use two conceptually different sub-models to analyze long-term power system development: operational models (short-term) and investment/capacity expansion (long-term). As the names suggest, the first kind of model is used to represent the day-to-day operation of an energy system on a time scale of milliseconds to hours, while the investment/-capacity expansion model simulates investment/changes to power systems on a long term basis (Emmanuel et al., 2020).

In our thesis, we utilize this conceptualization as a basis to create our MIDO model, which is a multi-timescale market simulation based on three coupled models as displayed in figure 1.4. The three sub-models are the future price (FP) model, the present price (PP) model, and the investment decision (ID) model. In its essence, the MIDO model is one big loop that links the information between these three sub-models. The following procedures are executed to run one year in the overall model. Firstly, the present price model runs to simulate the day-to-day operation of the energy market for a year. The information that is generated in this sub-model is then sent to the investment-decision model. The investment-decision model, which represents the behavior of all investors in a country, then determines if it has the cash to invest in new assets. To create sub-optimal investments based on limited information, the investment decision model utilizes the data from the future prices model. The future prices model is a model that can simulate the operations of the entire market in some future year. In this way, the investors make rational investment choices based on limited information. After the investment decision model makes the investment and dismantles choices, a new year is initiated, and the loop starts.

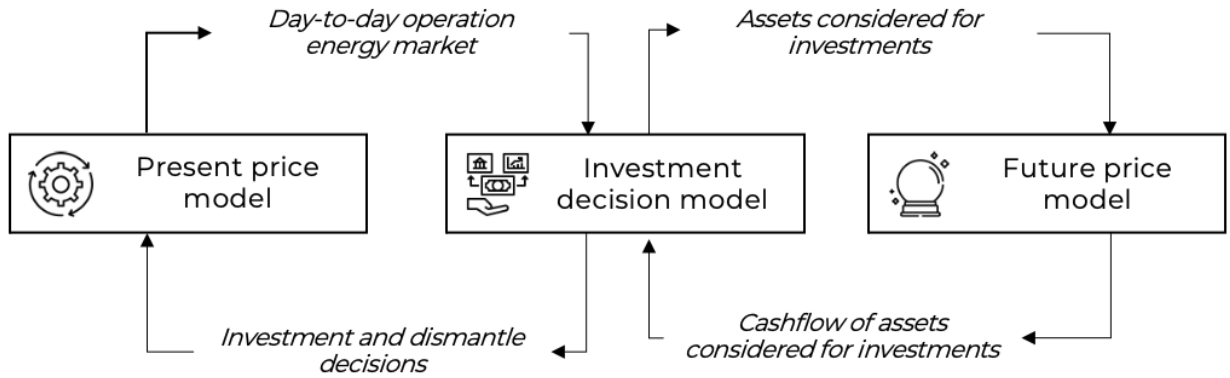


FIGURE 1.4: Overview of the sub-models in the overall myopic investment detailed operational model

1.5 Research questions

To deliver upon a proof-of-concept of the MIDO model, we ask ourselves the following main research question for this:

"How can we simulate long-term energy system development in a myopic investment detailed operational model?"

We formulate six sub-questions that enable us to answer our main research question:

1. What are the requirements for the investment-decision, present-price, and future-price model?
2. How are the requirements of all the sub-models reflected in the current state-of-the-art models?
3. How can we develop the present-price model?
4. How can we build the future-price model?
5. How can we construct the investment-decision model?
6. How does a capacity mechanism perform in a (semi) isolated energy system that is transitioning to a low-carbon system when taking into account seasonal storage and extreme weather scenarios?

1.6 Thesis structure

Chapter two aims to answer our first two sub-questions by conceptually arguing for the requirements necessary in all sub-models and looking at how these requirements are reflected in the current state-of-the-art models. Chapter three explains the MIDO model in detail, enabling us to answer sub-questions three, four, and five. Chapter four introduces the case on which we apply the MIDO model. Chapter five presents our results, which allows us to answer sub-question six. In the following chapters, we give our conclusion, discussion, and recommendation.

Chapter 2

Myopic investment detailed operational model conceptualization

The goal of this chapter is to conceptualize all the elements necessary to develop the MIDO model. First, in section 2.1 we define the requirements of all the sub-models in the MIDO model. After we have specified the requirements of all sub-models, we will argue in section 2.2 which elements in power system models we find necessary to include in the MIDO model to answer our main research question. After having established this, we compare the set-out requirements with the state-of-the-art models in section 2.3. Based on this review, we can determine what elements we can implement from existing models and which features we need to build from the ground-up during our thesis.

2.1 Requirements of all the sub-models

In our thesis, we look at the functional and non-functional requirements. We define a functional requirement as "the services and functions that the system should provide, the things it should do, or some action it should take" (Faulconbridge, Ian, and Ryan, 2014). A non-functional requirement is defined as "the qualities, properties, or attributes that the system must possess" (Faulconbridge, Ian, and Ryan, 2014). To make the difference between a functional and non-functional requirement clear, in our thesis, we formulate functional requirements as something that the system "must" do and non-functional requirements as something that the system "shall" do. We formulate the requirements of all our sub-models, based on every sub-model's input and output data. Figure 2.1 shows the input and output data of every sub-models in the MIDO model.

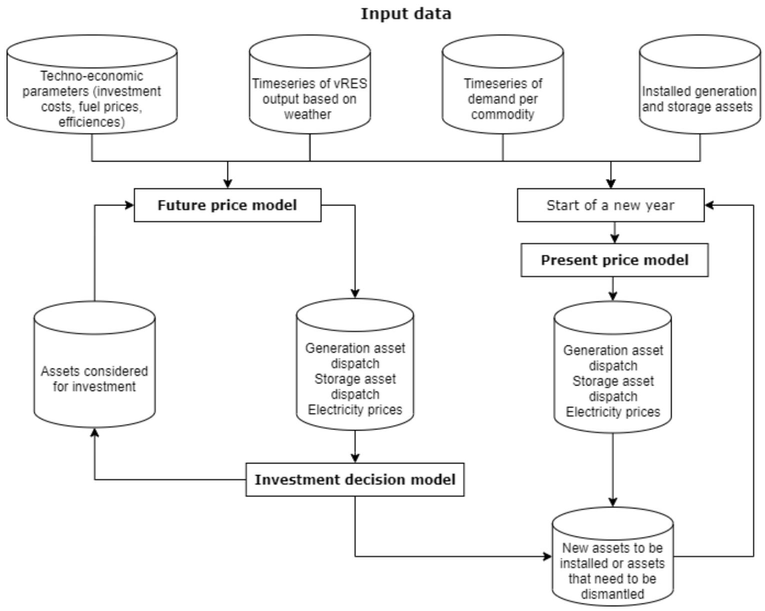


FIGURE 2.1: High-over: interconnected ID + PP + FP model

2.1.1 Investment decision model requirements

The primary goal of the ID model is to represent rational investment and dismantle choices made by the market as a whole based on imperfect information in different market designs. Table 2.1 shows all the requirements of the ID model.

Requirements 1 - 6 reflect how the primary goal of the ID is realized. Firstly, requirements 1-2 state the model must make an investment or dismantle decisions every year, and requirements 3-4 state that these decisions must be rational. However, requirement 5 dictates that while these decisions are rational, they must be based on limited information. The primary driver behind the modeling choices of requirements 1-5 is the theory behind investment decisions as laid down in section 1.2. In section 1.2 we argued that while investors in the energy market are rational, they have limited information on which to base their investment and dismantle decisions. This lack of information poses a problem for these investors as there are many aspects of the energy system that are uncertain. Therefore, we argue that it is essential to include this aspect in our model as these investment decisions based on limited information lead to the sub-optimal portfolio from a societal perspective. So in this way, our model should simulate the system development as observed in real-life energy markets, which in turn calls for different forms of market design or policy measures to influence the asset portfolio of the market (Bhagwat, 2016). Finally, through requirement 6, we argue how the investment decisions should be made in an energy-only market but should also consider market designs with capacity remuneration mechanisms.

To simulate this behavior, the ID model bases all its dismantle decisions on the past performance of assets which is output data of the PP model. All the investment decisions are based on the performance of assets in future years, which are calculated by the future price model.

Requirements ID model	Description
#1	The ID model must make decisions on in investing in new assets every year
#2	The ID model must decisions on dismantle existing assets ever year
#3	The ID model must make rational investment
#4	The ID model must make rational dismantle decisions
#5	The ID model must make decisions with limited information
#6	The ID model must make investment decision in different market designs

TABLE 2.1: Requirements investment decision model

2.1.2 Present price model requirements

The main goal of the PP model is to represent the day-to-day operation of the energy system with a high degree of accuracy. We argue that the model should have a high degree of accuracy as the PP model runs every year and reflects the actual operation in the energy market. Therefore, this model should be highly accurate to analyze the impact of system adequacy on an energy system. With this goal in mind, the data generated by the PP model is utilized by investors to assess what assets have been earning and determine the overall budget they have to invest. The requirements the model has to realize this goal is shown in table 3.1.

The generation of the electricity price and the dispatch of generation and storage assets in requirements 1-4 are the minimum information an investor needs to determine how assets have been performing and calculate their investment ability (Richstein, 2015). Furthermore, requirements 1-4 state that the PP model needs to output data on an hourly level for all hours in a year. We argue that an hourly temporal resolution is necessary, as the main goal is to simulate the operation of the market with a high degree of accuracy. We argue for this based on three reasons. First, the investment decision on which the investors base their decision is dependent on the electricity price, which is decided on hourly based (Kath and Ziel, 2018). Second, at least hourly simulations are necessary to accurately simulate the weather-dependent behavior of vRES (Emmanuel et al., 2020; Zappa, Junginger, and Broek, 2019). Third, hourly price spikes during times of a shortage in supply are crucial for the investment behavior of investors (De Vries, 2007). This time resolution is especially relevant for the possible shortages that can arise in a system highly dependent on vRES in the case of a Dunkelflaute (Doorman and De Vries, 2017). Moreover, in requirements 3 and 4, we explicitly mention that the PP model must be able to output hourly storage of all storage assets and must be able to reflect hourly weather input for weather scenarios based on chronological input data. We discussed in section 1.3.1 and 1.3.2 why there is a need for models that include these aspects. Finally, requirement 5 states that the model shall be highly accurate, and 6 we state that the model shall be computationally feasible. So, this means that even though we aim at a high degree of accuracy, we still want the PP model to be computationally feasible and, therefore, look for a trade-off between accuracy and computational time.

Requirements PP model	Description
#1	The PP model must output hourly electricity price for a year
#2	The PP model must output hourly dispatch of all generation assets for a year
#3	The PP model must output hourly dispatch of all storage assets for a year
#4	The PP model must base the vRES dispatch based on chronological hourly weather input
#5	The PP model shall be highly accurate
#6	The PP model shall be computationally feasible

TABLE 2.2: Requirements present price model

2.1.3 Future price model requirements

The goal of the FP model is to generate the cash flows of assets in one or multiple future years. By producing this information in the FP model, the ID model can determine whether assets that are considered for investment are worth the investment. Table 2.3 shows the requirements for the FP model.

Almost all the requirements for the FP are the same as the PP model. This similarty is expected because both models produce the same output. However, there are two differences between these models from a requirement standpoint—the first different arises from requirement 5: the computational feasibility. In the PP model, we know that we will have to run the PP model once every year of the total number of years we plan to simulate. However, for the FP model, we do not know how many years the model needs to run as this is based on the logic behind the ID model. So based on the reason we determine in the ID model, the computational feasibility requirement might lead to different modeling choices for the FP model compared to the PP model. The second difference arises from the accuracy requirement. The FP model does not necessarily have to be highly accurate because it is utilized to predict future cash-flows. We argue that real-life investors also would use models and predictions to determine these cash-flows, moreover, this future is inherently uncertain, so in this regard, a certain error margin is accepted. So, for these reasons, there is no requirement that the FP model should be highly accurate.

Requirements PP model	Description
#1	The FP model must output hourly electricity price for a year
#2	The FP model must output hourly dispatch of all generation assets for a year
#3	The FP model must output hourly dispatch of all storage assets for a year
#4	The FP model must base the vRES dispatch based on chronological hourly weather input
#5	The FP model shall be computationally feasible

TABLE 2.3: Requirements future price model

2.2 Choice of included elements in power system model

Before we look at the current models in the literature, it is essential to make explicit what aspects are within our modeling scope. The primary differentiation between models is found in the temporal and spatial resolution that are included in a model (Schaber, 2013). Next to these temporal and spatial dimensions, one can identify an additional dimension: the inclusion of market dynamics and uncertainty. Every modeler has to choose their modeling depth based on the available computational power, the time to build their model, and the elements that are deemed to be relevant to include (Schaber, 2013).

Figure 2.2 shows the main elements that can be included in all power system models, the elements that are in bold we argue to be relevant to include in our model.

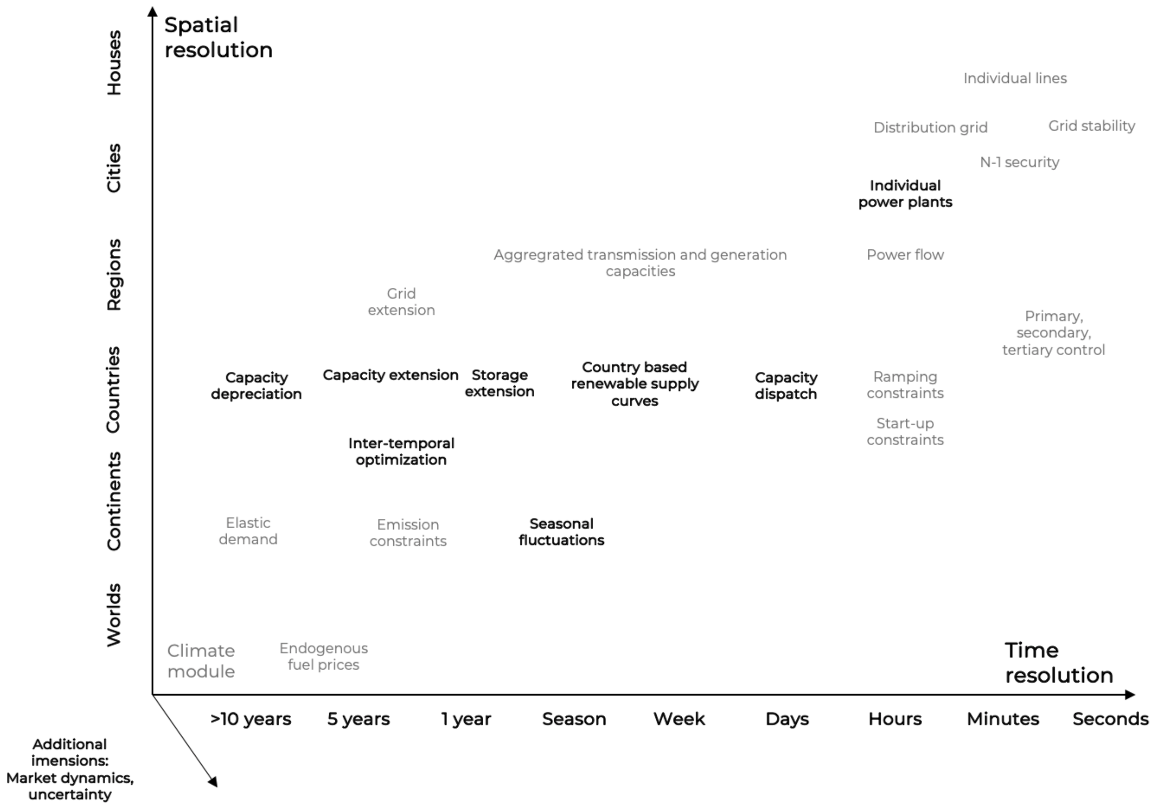


FIGURE 2.2: Classification of model features that can be included in power system models (modified from Schaber, 2013; Haller, 2012)

We are interested in developing a MIDO model that can be utilized to simulate long-term energy system development. This aim has led us to argue in section 2.1.2 that at least an hourly time-resolution is necessary to model the operation of the energy market. Moreover, in section 1.2 we defined how we look at system adequacy and reliability in our thesis. Anything below the hourly resolutions does not fit our aim of modeling adequacy, as this is focused on reliability/system balancing and, therefore, is out-of-scope. Moreover, given our aim and all the requirements of our sub-models, we argue that all grid-related elements (individual lines, distribution grid, transmission grid, grid extension, grid stability, power flows, and N-1 security, control) are too detailed to include for the aim of our model. Primarily because we have a limited time to develop the overall MIDO model, within this time, we argue that we can create an overall model that includes all the requirements of the sub-models without having to include grid-related aspects explicitly. Firstly, we assume that the TSO/DSO in a country will always enable enough infrastructure for energy to flow freely. Second, in our model, we include the construction time after an investment decision is made and before an asset is active. During this delay, we assume that TSO/DSO has enough time to guarantee enough infrastructure for electricity to flow where it is necessary, and therefore we argue that we already account for a part of the problems that arise for investors related to infrastructure. However, please note that in real life, the infrastructure does play an important role, and grid congestion can be a bottleneck for the development of the energy system (Hadush and Meeus, 2018). We will reflect on this in our discussion. The other elements that are out of scope related to the short-term are the ramping constraints and the start-up constraints of assets; we explain this in section 3.1.1. While we run the PP and FP model on an hourly basis, we argue that we need to look at a timescale of multiple decades to observe the long-term development and path dependency of investment (Schaber, 2013).

From a spatial resolution, as can be seen in figure 2.2 we will mainly look at the system from a country point of view. Of course, the individual plants are, in reality, installed on a city/region scale. However, since we do not include the role of elements related to the electricity grid, this does not impact the simulation in the model. Our thesis will look at the electricity grid from an isolated-grid perspective, meaning we will not include any interconnections to other countries. Note that the interconnection between countries can have significant consequences for electricity prices (Rafiee, 2020). Similarly, there are cross-border effects of capacity mechanisms that can influence the effectiveness of these mechanisms (Meyer and Gore, 2015). However, because of time limitations, we exclude these aspects. We will reflect on the implications of these simplifications in our discussion. Lastly, we do not include the long-term impact of climate or endogenous prices as we do not deem these to be highly relevant aspects of answering our main research question.

The last dimension to consider is an additional dimension that a modeler can argue to be relevant for the research objective. We have already explained in section 1.2, 1.3.2 and in the requirements of our sub-model, why it is essential in our research to consider the combined impact of uncertainty, myopic investment (bounded rational investment behavior), and path dependence on the development over time of an electricity market in our thesis.

2.3 Comparison of requirements with existing models

Having now specified what elements we wish to include in our model, we look at the models that have been developed in previous research. Based on these models, we can determine what features we can build on and what aspects must be built from scratch. We organized these models in three groups based on the classification as laid out in Schaber (2013). Firstly, operational models have a high temporal and spatial resolution, usually have a sizeable technological depth, and are technology explicit. In addition, these models typically focus on dispatch or grid simulation. Second, inter-temporal optimization models are used to look at the long-term development of energy systems. These models look at different system configurations for a considerable period (e.g., 50 years) and optimize investment decisions for the entire period. This approach enables modelers to compute optimal decarbonization pathways, for example, or to display long-term energy system development drivers. The last group is the hybrid-optimization models covering an extensive range of timescales, from hours to multiple years. These models combine the operational aspects of the operational model (with a lower degree of resolution) and the grid/storage/asset expansion of the inter-temporal models (Schaber, 2013). The MIDO model can be classified as a hybrid model, based on the spatial and temporal elements we we have argued to be relevant in section 2.2. Within the hybrid models, we classify two types of models: optimization and simulation models. In optimization models, one single objective is maximized or minimized. The class of simulations models, however, enables to address several market participants' profit maximization simultaneously (Weiss et al., 2017).

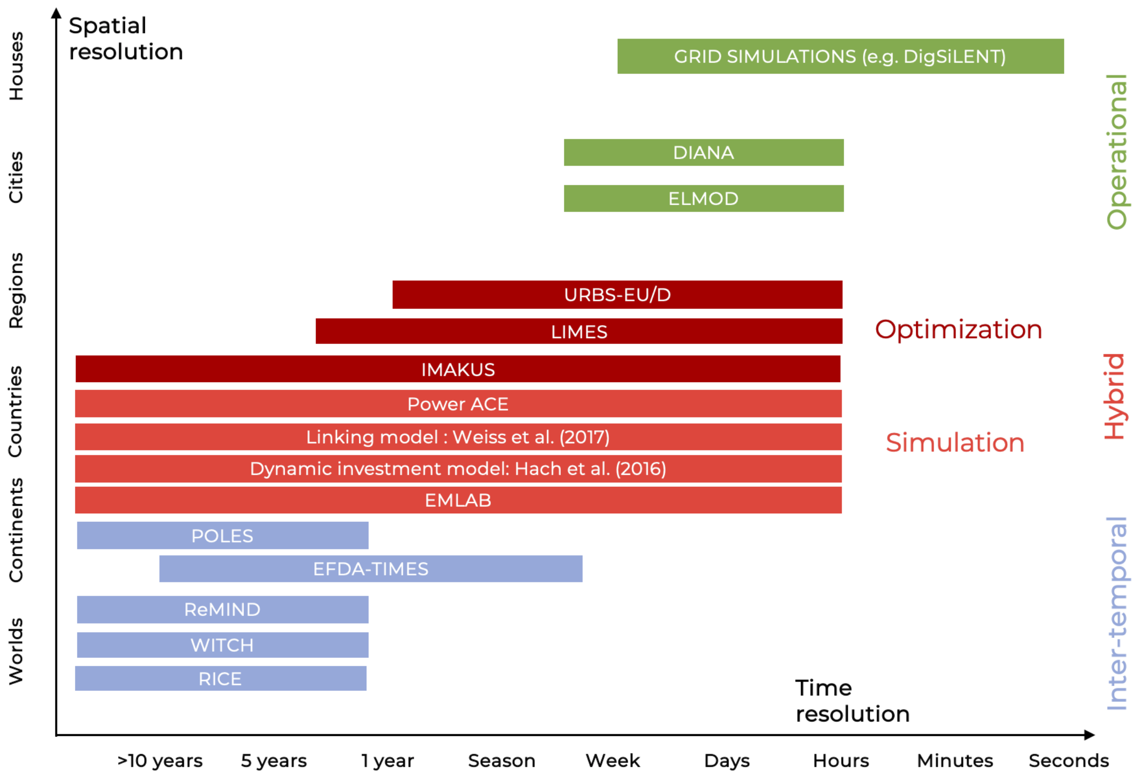


FIGURE 2.3: Overview of selected models used to conceptualize (modified from Schaber, 2013)

2.3.1 Investment decision model conceptualization

Requirements	The model must make decisions on investing in new assets every year	The model must make decision on dismantling~ existing assets ever year	The model must make rational investment decisions	The model must make rational dismantle decisions	The model must make decisions with limited information	The model must make decisions in different market designs
Model	#1	#2	#3	#4	#5	#6
IMAKUS	No	No	Yes	No	No	No
LIMES	No	No	Yes	No	No	No
URBS-EU/D	No	No	Yes	No	No	No
EM-LAB-model	Yes	Yes	Yes	Yes	Yes	Yes
Power-ACE	Yes	No	Yes	No	Yes	Yes
Hach et al.	Yes	Yes	Yes	Yes	Yes	Yes
Weiss et al.	Yes	No	No	No	Yes	Yes

TABLE 2.4: Comparison ID requirements and existing models

Table 2.4 shows an overview of the requirements of the ID model and how this is represented in the models we have reviewed. We have reviewed three hybrid optimization models: LIMES (Haller, 2012), URBS-EU/D (Schaber, 2013) and IMAKUS model (Kühne, 2016). All the optimization models do not fulfill requirements 1, 2, 4, 5, and 6. Requirements 1 and 4 are not fulfilled because investment decisions are incorporated in the objective function to minimize total system costs in all optimization models over the entire simulation period. In this way, optimization models simultaneously determine the investments and operational decisions which maximize the total economic and consumer surplus (Poncelet, 2018). Requirements 2 and 5 are not realized because the optimization models do not consider dismantlement or include the salvage value of an asset in the optimization. Lastly, requirement 6 is not satisfied because all models only optimize for an energy-only market.

Looking at the simulation models, we see that all models fulfill the investment-related requirements (1,3,5,6). Firstly, we see that requirement 1 is realized in all models by allowing the investors to invest in new assets only once a year. Also, requirement 3 is fulfilled as all models assume rational investment behavior where the investment only occurs if the Net Present Value (NPV) is positive for an investor. In the model of Hach, Chyong, and Spinler (2016b) strategic bidding behavior is also considered. However, most models disregard this. Therefore, we also do not include this in our thesis.

Furthermore, requirement 5 is realized in all models by letting actors make the investment decisions iterative through a set of decision rules, where investors have limited access to information. The information on which they base this decision is the electricity prices, the existence of other assets, the market share of these assets, the effect of different policies (such as CO_2 price or capacity remuneration mechanisms), and the expected growth in demand. In the reviewed models, this data reflects either one 'reference-year' or multiple future years. A reference-year is some year in the future that the investors assume is representative enough to base their investment decision. In our thesis, we will utilize only one reference year, on which our investor bases his investment decision. In section 1.3.2 we argued that the current simulation models do not include storage because this requires computationally expensive methods. We have already explained that we will include storage, and therefore we can assume that the operational model utilized in our thesis is computationally more costly than other models. This additional dimension means that by basing the investment decision on multiple years instead of one reference year, our run time would increase more than other models. Given our more computational intensive model and the fact that this simplification has been proven to be an effective method in many different models (Bhagwat, 2016; Keles et al., 2016; Hach, Chyong, and Spinler, 2016a), we also utilize one 'reference-year'. Furthermore, this conceptualization makes sense from our reasoning that actors are risk-averse. We assume an investor has all the information on what assets will be dismantled before this reference year (due to technological age) and what assets are currently under construction. With this knowledge, the actor can make a reasonably conservative estimation of his investment under consideration. Because, in reality, there can only be fewer assets because our actors know about all the current assets, and in the future, only more assets could be dismantled due to these assets not making enough profit.

Moreover, the information that investors utilize to make their decision is inherently uncertain. Since the investors do not precisely know the long-term price development, this is related to what other actors do. Therefore to realize requirement 5, in all the reviewed simulation models, a simplified solution is utilized where the first agent considers only the investments and decommissions available at the time of his decision. However, the next agent receives information about the investment decision made by the previous agent (Keles et al., 2016). In all reviewed models, the iteration occurs greedily, meaning that all the actors invest in the assets they can afford, compare the NPV of this investment, and choose the highest NPV. In the EMLAB model, Weiss et al. (2017) and the PowerACE, this iteration occurs until there is no more budget to invest in or the NPV of all assets is negative. The PowerACE model also has an additional investment volume stop to prevent market power abuse. In the model utilized in Hach, Chyong, and Spinler (2016b) the iterations stop if the Pearson correlation shows that a new investment results in small electricity price changes. In our model, we will also utilize an iterative approach to reflect limited information during investments. However, we will not model individual agents, as we are only interested in the behavior of the market as a whole and, therefore, will assume that one investor with the budget of the entire market can replicate this behavior. So we will include the effect of having multiple agents that can influence each other in this sense, without explicitly modeling it. We will stop this iterative process based on the same approach utilized in the EMLAB model and Weiss et al. (2017).

Additionally, all simulation models realize requirement 6 by allowing for bidding or additional income through a capacity remuneration mechanism at each iteration after regular bidding on the energy-only market. The MIDO model also will incorporate this by first simulating the energy-only market in the PP and FP models. Afterward, the ID model simulates the bids for the whole market in some form of capacity remuneration mechanism. We could insert any capacity mechanism in this part of the ID model. However, as our thesis aims to compare the behavior of the energy-only market with a form of capacity mechanism rather than to compare them all, we chose to model only one capacity remuneration mechanism: a capacity market. We base this choice on the work of Bhagwat (2016) who compares multiple capacity mechanisms and concludes that a capacity mechanism performs better in an isolated energy system. The logic on which this capacity market operates is based on the capacity market utilized in New York Independent State Operator-Installed Capacity Market (NYISO, 2018) and the EMLAB model.

Lastly, the simulation models differ in their inclusion of dismantling decisions. The PowerACE and Weiss et al. (2017) do not include any dismantle decisions and therefore do not fulfill requirements 2 and 4. Contrarily, we see that the EMLAB-model and Hach, Chyong, and Spinler (2016b) do include dismantle-decisions. We have argued in section 1.2 why it is relevant to include dismantle-decisions based on the theory on investments in energy systems. Moreover, there are many examples in real-life energy systems where this has had a significant impact on the energy system (see e.g. Bloomberg, 2013; Platts, 2013). In both EMLAB and Hach, Chyong, and Spinler (2016b) the dismantle decisions are mainly based on the expected cash-flows an asset can generate. If an asset's cash flow is below a certain level for too long, the assets get dismantled. We will utilize a similar approach in our thesis.

2.3.2 Present price model conceptualization

Requirements	**The model must output hourly electricity prices for a year**	**The model must output hourly dispatch of all generation assets for a year**	**The model must output hourly dispatch of all storage assets for a year**	**The model must base the vRES dispatch based on chronological hourly weather input**	**The model shall be highly accurate**	**The model shall be computationally feasible**
Model	#1	#2	#3	#4	#5	#6
IMA-KUS	Yes	Yes	No	No	No	Yes
LIMES	Yes	Yes	Yes	Yes	No	Yes
URBS-EU/D	Yes	Yes	Yes	Yes	No	Yes
EMLAB-model	Yes	Yes	No	No	No	Yes
Power-ACE	Yes	Yes	No	Yes	Yes	No
Hach et al.	Yes	Yes	No	Yes	Yes	No
Weiss et al.	Yes	Yes	No	Yes	Yes	No

TABLE 2.5: Comparison ID requirements and existing models

We compare the requirements of the PP model with the existing models in literature in table 2.5. All reviewed models meet the requirement 1 and 2, so all the models represent the operation of an electrical system on an hourly level. However, on the other requirements, there are big distinctions between the models.

In the previous section, we showed how all simulation models were able to represent investment and dismantle decisions in a way that aligned with the requirements in our investment-decision model. Contrarily, we observe that none of the simulation models is able to fulfill requirement 3. The reason for this is mainly due to the chosen operation model representing the day-to-day operation or the market clearing. The operational model utilized in the EMLAB-model in Bhagwat (2016) is based on an abstraction of the demand based on "load blocks." An essential advantage of this method is that it allows for a short run time (Richstein, Chappin, and Vries, 2014). However, it does cause a loss of a temporal relationship. Therefore it is not able to simulate storage (Wogrin et al., 2014). The EMLAB-model has been updated to include storage by changing the market-clearing to a linear optimization problem in a more recent study. However, this method only included medium-term storage, and no investment in storage was possible in this set-up(Khan et al., 2018). The PowerACE model works similarly; in this model, the day-ahead market is cleared based on blocks of bids of agents. These bids do, however, include elements such as start-up costs or an additional mark-up based on stochastic calculations (Genoese, Genoese, and Fichtner, 2012). Again, similar to the EMLAB-model, some studies have already put effort into further developing this model to include some form of storage. Mainly by adding a unit commitment (UC) model; however, in its current form, the authors in the studies note, "the focus of this analysis is to assess the value of storage units operated with hourly or daily cycles. The modeling approach is less useful to measure the value of long-term storage technologies, e.g., hydrogen storage" (Genoese and Genoese, 2014). The dynamic investment model in Hach, Chyong, and Spinler (2016a) utilizes an hourly clearing mechanism for all hours in a year; however, it does this only for vRES, nuclear, coal, and gas. Lastly, in the linking model of Weiss et al. (2017) we see an approach with a market-clearing module, which can consider battery, however again, they note that in the future, their methodology needs adaptation to be able to include power-to-gas technologies. From this, we conclude that the operational models utilized in the simulation models cannot incorporate long-term storage or would have a computational burden that would be unpractical to do any form of experiments.

Looking at the simulation models, we see two models that are able to meet requirement 3: the LIMES and URBS-EU/D model. To fulfill this requirement, both models utilize a UC model. UC is one of the most important and critical problems in the power industry (Abdou and Tkiouat, 2018). The goal of a UC model is "to meet and satisfy system demand, reserve requirements, and electricity market context in an optimal, cost-efficient manner for the total scheduling period. It is also subject to system reliability, system capacity, transmission, and environmental constraints (Abujarad, Mustafa, and Jamian, 2017).". Typical inputs consist of demand, vRES production, marginal costs of producing units, physical limitations, and network constraints. The typical output consists of generation prices, loss load, fuel consumption, and curtailment. Moreover, flexibility is a vital aspect of future energy systems and can be modeled in a UC (Emmanuel et al., 2020). An UC is a highly accurate representation of an energy system; because of this accuracy, a significant drawback of this method is that it is computationally costly (Poncelet, 2018). However, we find that the LIMES and the URBS-EU/D model do not have the same computational burden that the simulation models are faced with. The reason for this is that these models do not optimize dispatch decisions for every hour of the year, instead focus on optimizing dispatch decisions for a limited number of representative time slices (Nahmmacher, Schmid, and Knopf, 2014).

The choice to model a UC without modeling all hours in a year leads to the fulfillment of requirements 3 and 6. However, the simplification of the temporal resolution in these models means that requirement 5 is not satisfied because the models are not highly accurate. For the model to be highly accurate, we argue that all hours should be modeled. The argument for including all hours is based on the notion that periods of shortages are critical for investors to determine the performance of their assets. By only modeling certain time-slices, the accuracy drops as there is a chance that the moment of shortage hours are not captured; this might have a significant impact. To prevent this from occurring and increasing the confidence in the accuracy of our present-price model, we will model a UC model that includes all hours in a year. However, as this automatically increases the computational time, we will have to implement other measures to reduce the overall computational time.

2.3.3 Future price model conceptualization

Requirements	The PP model must output hourly electricity prices for a year	The PP model must output hourly dispatch of all generation assets for a year	The PP model must output hourly dispatch of all storage assets for a year	The PP model must base the vRES dispatch based on chronological hourly weather input	The PP model shall be computationally feasible
Model	#1	#2	#3	#4	#5
IMA KUS	Yes	Yes	No	No	Yes
LIMES	Yes	Yes	Yes	Yes	Yes
URBS-EU/D	Yes	Yes	Yes	Yes	Yes
EM-LAB-model	Yes	Yes	No	No	Yes
Power-ACE	Yes	No	No	Yes	Yes
Hach et al.	Yes	No	No	Yes	Yes
Weiss et al.	Yes	No	No	Yes	No

TABLE 2.6: Comparison FP requirements and existing models

Table 2.6 shows the comparison of the reviewed models and the FP requirements. As we already explained in section 2.1.3, the PP and FP models have similar requirements. The only difference is found in the accuracy and computational time requirement. Again, as we already alluded to in section 2.1.3, there is a different trade-off with regards to computational feasibility and accuracy. In section 2.3.1 we determined the the logic of the investment-model. Our chosen logic is based on an iterative approach. Now that we have determined the investment logic, we can specify the impact of the computational time requirement in the FP model.

Let us assume that we have one investor with an investment budget of 100€ to invest in new assets. Moreover, our investor can utilize this budget to finance the investment in ten unique assets, and that every asset costs our investor a maximum of 10€. Therefore, our investor must know the NPV of ten different possible assets to make an informed decision. From this overview of NPV, the investor than would chose the asset with the highest NPV. This data can only be generated by running the operational model for a year for all ten investments. After this initial investment, our investor would have a 90€ investment budget left and, in theory, could need another 90 runs (in the worst case from a computational time perspective) to spend its entire budget. Based on this logic, we need 100 runs to determine the investment opportunities in one year. So, a bulk of the computational efforts arise from the data that needs to be generated in the FP model.

In the previous section, we argued for the inclusion of all hours in a year in the UC model utilized in the present-price model. However, due to the fact that the FP model has to run more often than the PP model, we argue that running a UC based on all hours in a year would make the model computationally unfeasible. Moreover, as we already have argued for in section 2.1.3 the FP model can be less accurate than the PP model as this model only services to predict future cash-flows, which is inherently uncertain. For this reason, in the FP model in our thesis, we utilize some form of time-slicing method to reduce the computational time of our overall model.

There are two main options offered by literature which we will now compare: semi-dynamic time-slicing methods (with increased resolution) and semi-dynamic time-slicing methods with representative days. Note that there are also other options out of these common two. However, these lead to a loss of chronological information, and therefore can't include storage (e.g. integral time-slicing methods Bhagwat, 2016 or enhanced integral time-slicing methods Poncelet, 2018). We do not consider these options as the modeling of storage is crucial in our thesis.

The most common way utilized to model long-term energy planning models is the semi-dynamic time-slicing method (Poncelet, 2018), displayed in figure 2.4. This method splits a year into four seasons, every season consists of a weekday and a weekend, and finally, every day has a daytime and nighttime. The value that a certain time slice has is the average of all the time-slices that belong to that group. There are many configurations in this method reaching from 4 to 48 time-slices. While this method reduces the computational time and preserves chronological information, it does also does not sufficiently capture the variability of vRES. The reason for this is that by taking the average, periods of very high and very low vRES are smoothed out (Poncelet, 2018). A way to cope with this smoothing effect has been to increase the number of temporal slices that are taken into consideration (e.g. Haydt et al., 2011; Pina, Silva, and Ferrão, 2011; Pina, Silva, and Ferrão, 2013). Furthermore, the time slices are increased by considering the difference between Saturday and Sunday and by averaging based on the hour instead of a day. This increases the up to 288 time-slices. However, again this does not fundamentally solve the problem related to averaging out (Poncelet, 2018).

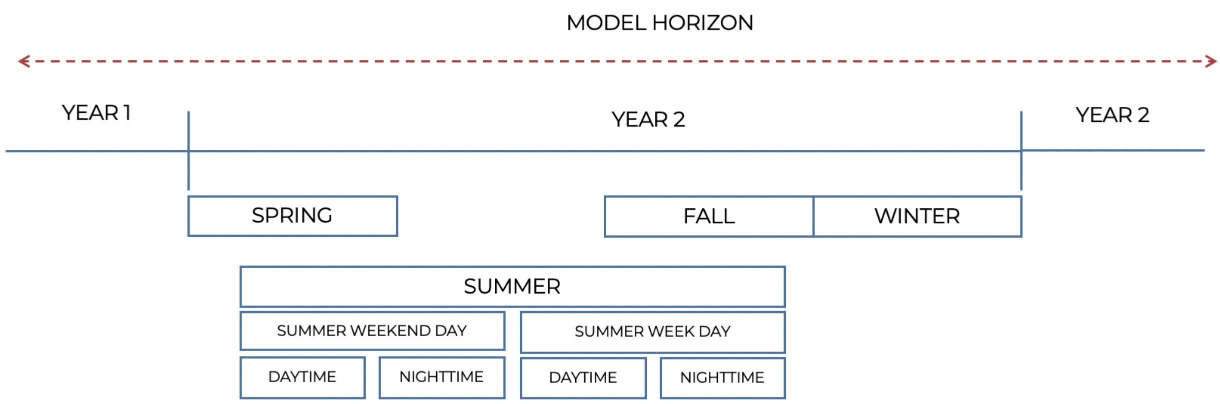


FIGURE 2.4: Semi-dynamic time-slicing method

A way to partly solve the smoothing problem mentioned above is by selecting an X amount of representative days to represent a period in a year. In this method, the actual days present in the input data are selected instead of creating a time slice by averaging all the input data attached to a specific period in a year. The advantage of utilizing this method is that smoothing is avoided. Thus the variability of vRES/demand or any other time series can be somewhere between the observed ranges. Simultaneously, the chronological information is preserved. However, the main issue is that it is challenging to select a set of representative days that can accurately represent an entire year (Poncelet, 2018). Given the positives of avoiding the smoothing effect in the time-slice methods, we chose to utilize representative days in this thesis.

Chapter 3

Myopic investment detailed operational model explained

In this chapter, we explain the workings of the three sub-models we have conceptualized in the previous chapter. Moreover, after explaining more precisely how the sub-models work, we will also validate the working of our model. In section 3.1 we explain the workings of the PP model. In section 3.2 we lay out the working of the FP model. In section 3.3 we thoroughly describe the ID model.

3.1 Present price model

3.1.1 Main assumptions present price model

Temporal representation

For any UC model, two main factors contribute to the computational time of the model: the technical representation of the system and the temporal representation. The analysis of Poncelet (2018) shows that the simplification of temporal and technical detail used in models that analyze transition pathways to high VRES systems leads to an underestimation of the operational costs, overestimation of the uptake of vRES, and overestimation of the level of base-load generation. For a high level of vRES (above 25%), the temporal representation is the dominant factor causing this (Poncelet, 2018). Therefore, as we have argued before, to increase the reliability of the investment decisions made in our overall model, we accept a higher computational time for the PP model than for all the other models. For this reason, the temporal resolution of the UC model in the PP model is hourly, meaning that every year consists of 8760-time steps.

Before we explain how we plan on reducing the computational to solve the UC-model due to the temporal representation, we need to explain the working of the solver utilized in our thesis. The solver optimizes LP problems with a rolling-horizon approach. This approach is illustrated in figure 3.1. The entire simulation horizon (T) is split up into N stages in the rolling horizon approach. Each stage n consists of two parts, the block length (with length L) and the look-ahead (length M). The block length represents a reliable (short-term) forecast, while the look-ahead period represents a less reliable (medium-term forecast). The solver operates in line with the successive stages and, so first, the stage n=1 is solved with block length L. However, in this solution, the solver considers the information from the look-ahead with length M. This is repeated until the solver has gone through all stages. The longer the block length, the more information the solver has to optimize; however, this increases the computational time. In case the block length is reduced and the look-ahead is increased, the overall reliability of the prediction is decreased (Lu, Ying, and Chen, 2016).

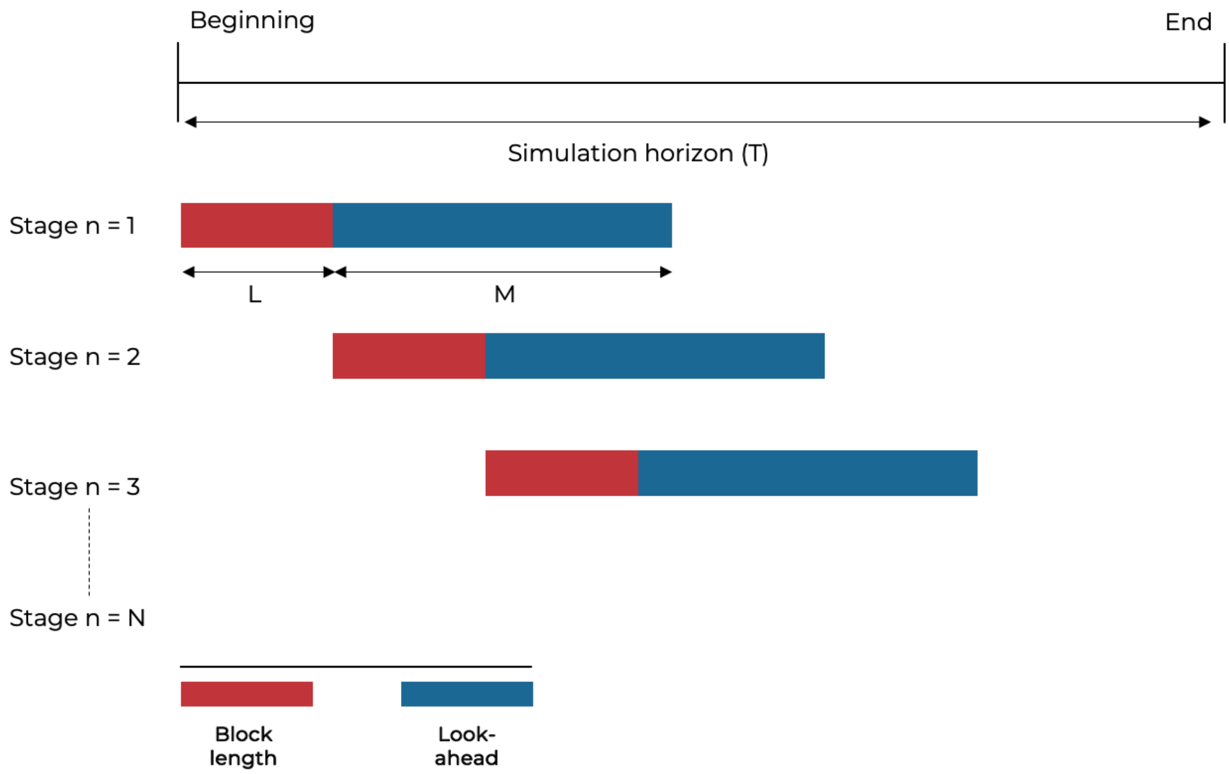
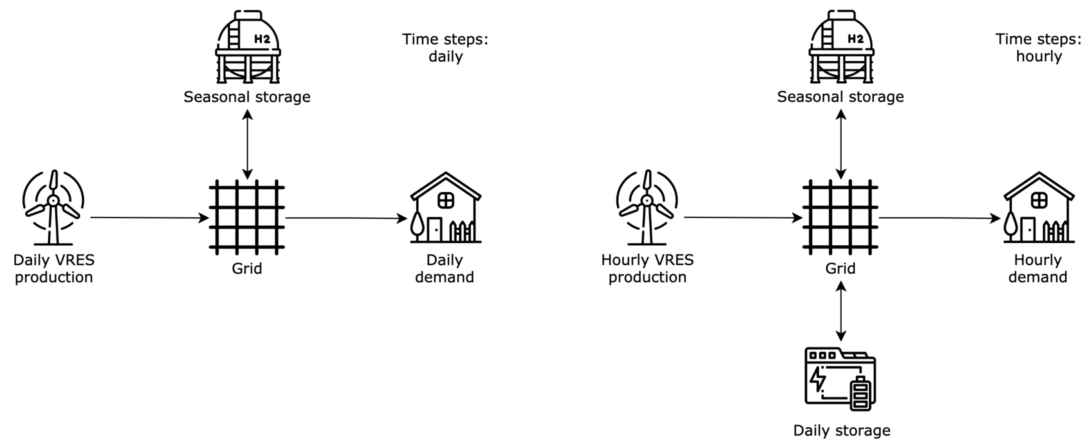


FIGURE 3.1: Rolling horizon approach (adjusted from Lu, Ying, and Chen, 2016)

Please note that most of the modeling choices we have made in this section are based on the computational power of the open-source solver lp _solve (Berkelaar, Eikland, and Notebaert, 2004). This solver has limited computational power, and this section should be read with these constraints in mind. Halfway through our thesis, we switched to a more powerful commercial solver, the LP-solver Gurobi (Inc, 2012). In the discussion, we reflect on the implication this has for our results.

While we want to simulate all hours in a year, it is not computationally feasible for the solver lp _solve to optimize the entire simulation horizon (8760-time steps) at once. In theory, the rolling horizon approach could offer a solution where we would only optimize the block-length of, e.g., a few days or a week with a look-ahead of a week. However, this would limit the model only to consider week-to-week effects wheres, in a future energy system, the impact of seasonal hydrogen storage could be significant (Gabrielli et al., 2018).

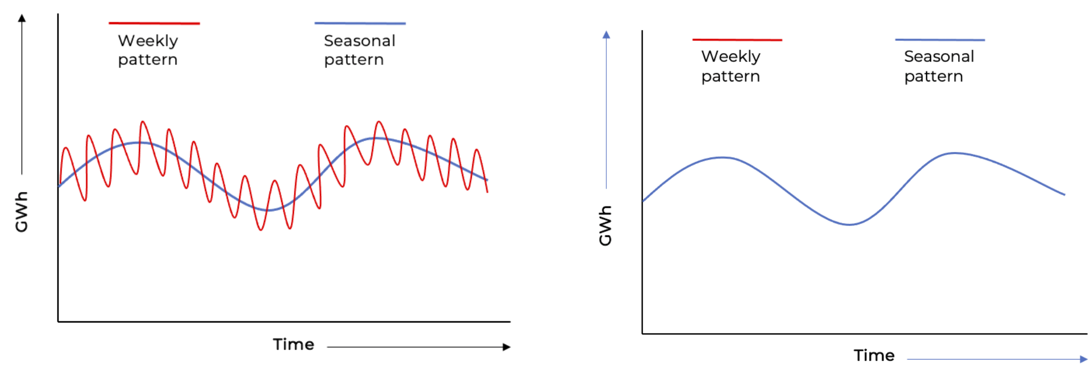
We propose a novel method to account for seasonal hydrogen storage in a UC model while also accounting for daily/weekly storage based on an approach to derive inter-temporal targets for ample pumped hydro energy storage (Deane, McKeogh, and Gallachoir, 2013). In this approach, we focus on realizing empirically valid targets for 'seasonal' flexibility while keeping the computational time of the solver feasible. Although in doing so, we introduce a margin of error as the solver will not find the optimal solution, we accept this error as to our best knowledge; there is currently no other solution offered to solve this problem without significantly increasing our computational time. Moreover, by optimizing long-term storage in this manner, we use the seasonal storage not necessary from a market point-of-view which bids to make the most amount of profit; instead, energy is stored from a TSO-perspective to reduce total system costs (Deane, McKeogh, and Gallachoir, 2013). To realize the above-stated goal of finding seasonal storage targets, we utilize two types of UC models. The conceptual difference between both models is shown in figure 3.2. The seasonal UC model operates on a daily time resolution, and the only option of the system to unlock flexibility is through some form of seasonal storage. Contrarily, the daily UC model runs on an hourly time resolution and can utilize both daily and seasonal storage.



(A) Seasonal UC model (B) Daily UC model

FIGURE 3.2: Conceptual difference between seasonal and daily UC model

To combine the insights created from both models, we follow the steps as shown in the flowchart in figure 3.4. To find the demand for seasonal storage in our system, we first need to 'filter out' all the properties related to day/weekly behavior. We realize this through smoothing of the time series by applying a rolling average of a week. After this smoothing, we will be only left with seasonal effects. Figure 3.3 shows this effect based on a stylized time series. We assume that there are more efficient ways to cope with storage on a week-to-week time scale and therefore argue that it is empirically valid to assume that these effects can be 'filtered' out of the seasonal UC model. Although there might be effects that occur not necessarily on a week-to-week level in real life but are not needed to be solved through seasonal storage (some form of medium storage might be more efficient), we do not take this into account.



(A) Before rolling average (B) After rolling average

FIGURE 3.3: Rolling average effect

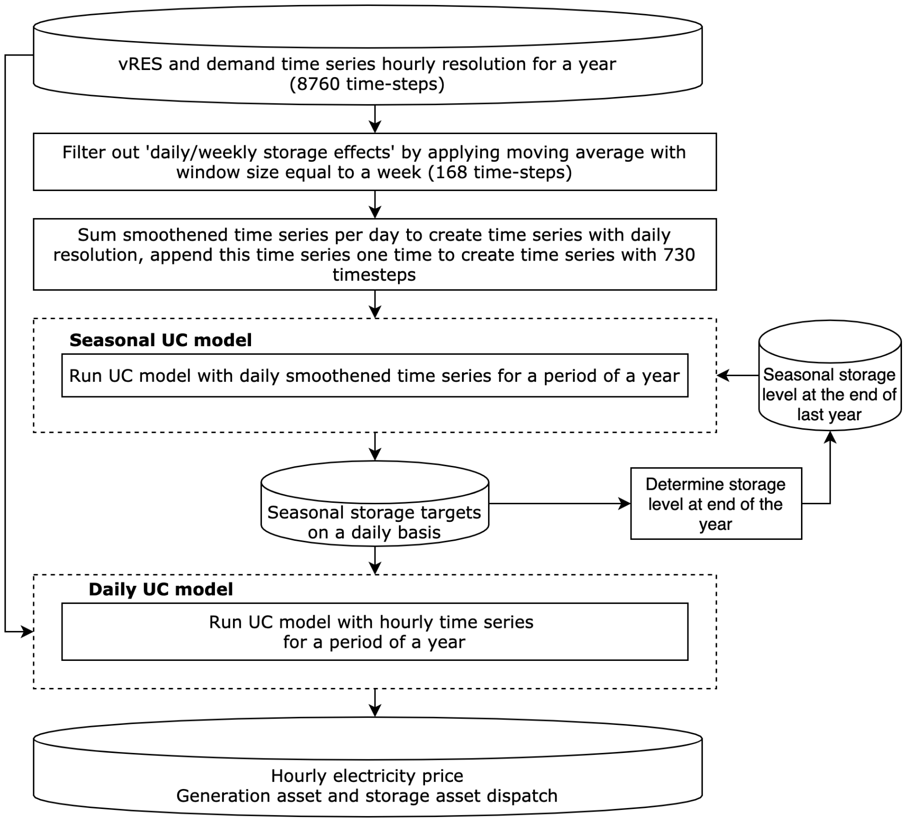


FIGURE 3.4: Flow-chart seasonal UC

The rolling average is applied to all the input time series; these are our model's vRES and demand time series. After having smoothed the time series, we sum the time series to create daily time series instead of hourly time series. The change of time resolution is because lp _solve cannot optimize half a year on an hourly basis in a computationally feasible time. This optimization would result in a block length of 4380 time-steps and a look ahead of 4380 time-steps. However, it is possible to solve half a year on a daily basis as this would mean a block-length of 183 time-steps with a look-ahead of 183 time-steps.

At this point, one could make the argument that if the goal is to reduce the computational time, it might be more efficient instead of going with a smoothed time series of a day to sum the time series to weekly data as this would result in a block-length of 26 time-steps that need to be optimized, with a look-ahead 26. Table X shows an overview of the difference in computing time in both set-ups. We argue that the slight difference in computational time between both configurations is not significant. The bulk of the reduction in computational time is realized by scaling down from a block-length and look-ahead of 4380 time-steps to a block-length and look-ahead of 183 time steps which the solver can calculate in a matter of seconds.

Configuration	Run time
Smoothened time series Block length: 183 Look ahead: 183	0.03
Summed time series Block length: 26 Look ahead: 26	0.01

TABLE 3.1: Requirements present price model

Before the seasonal UC can run, the last step is to append the input time-series of 365 days to create a time series of 730 days. The reason we need to do this finds its origin in the rolling horizon approach as shown in figure 3.1. If we ran the seasonal UC based on a simulation horizon of 365 days in the last block length, no look-ahead information would be available. For the solver, the rational decision would be to empty all the seasonal storage; however, this would not happen because the operators would consider the following year. To simulate this behavior, we want to give the model a look-ahead into the next year and therefore create a time series of 730.

After preparing all the input data, we run the model for the 365 days + the length of one look-ahead period (183 time steps); this ensures that the seasonal storage correctly accounts for the following year. Overall this does not increase our run time significantly as this only increases the run time of the seasonal UC by several seconds. The seasonal storage at the end of a year is saved and the seasonal storage is filled with this amount at the beginning of a run for the following year. After running the seasonal UC, we now know what the seasonal storage needs to be at the end of every day.

We can now utilize this output data to run the daily UC, with end-of-the-day seasonal storage targets every three days. These storage targets are input time series that need to be met. Based on these targets, the daily UC can decide when to charge/discharge the seasonal storage. Moreover, the daily UC also can store electricity in the daily storage unit if this lowers the total system cost. Next, we run the daily UC with a block length of 72 hours and a look-ahead of 72 hours. This gives an operator of a storage unit almost a week of information to optimize the use of its storage assets. We argue that this is a good approximation of real-life as the daily storage units operate in this range (Zakeri and Syri, 2015); moreover, within a week time, a reasonably accurate estimation can be made of weather conditions that influence the need for storage (Niimura et al., 2012; Matsumoto and Endo, 2021). Finally, these steps allow us to run a UC model and gather the relevant output data: electricity price and electricity output per asset during all time steps of a year.

Technical representation

After the temporal representation, the technical representation is the most significant factor contributing to a UC model's accuracy. The PP model represents our system on the most accurate level, so in this chapter, we analyze at what level it is relevant to include technical constraints. We base the modeling choice on the inclusion of the technical aspects on Poncelet who has compared the impact on computational time and incorporating the following technical constraints: reserve constraints, ramping constraints, minimum stable operating point constraints (enforces if a unit is online, it has to generate at least a certain power level), part-load efficiency losses, start-up costs, and minimum up and downtime constraints.

In this analysis, the comparison is made between a model with all the technical constraints (REF model) and multiple models containing elements of the above technical constraints, all the way to a model without any technical constraints (MO model). The effects of technical constraints are tested by comparing the relative underestimation of system costs without all the technical constraints with a system with all the technical constraints. These models are compared for a plethora of different scenarios ranging (Poncelet, 2018). The relation between the computational time vs. the costs is shown in 3.5. The underestimation of projected costs for the model without any technical constraints (MO) is around 5-10% for every scenario. The only exception comes from the scenarios where the thermal generators have low flexibility (low flex). As all our scenarios will have thermal generators with high flexibility, we argue that underestimating total system costs of 5-10% is acceptable. Especially given the significant reduction in calculation time between the different levels of technical constraints. So the UC model in this thesis will not include any of the above-mentioned technical constraints.

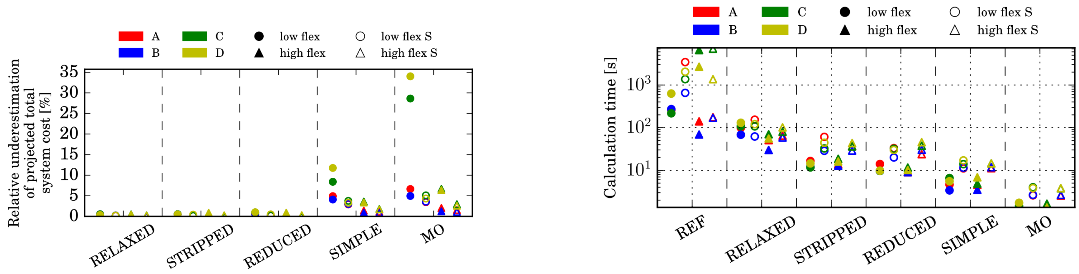


FIGURE 3.5: Comparison of underestimation of costs (left) vs computational time (right) from Poncelet (2018)

3.1.2 Unit commitment in Linny-R

In section 2.3.2 we have established why our PP model should be a UC model. The UC in our thesis is subject to several modeling choices, such as the exclusion of all grid-related elements as argued for in section 2.2 and the little technical details of individual assets in 3.1.1. Several algorithmic methods can be utilized to solve a UC model (we point to Padhy (2004) for an overview of all methods). Given the modeling choices behind the UC in this thesis, our UC can be formulated as a Mixed Integer Linear Programming (MILP) problem (Chang et al., 2004).

One solution to solve a MILP problem is by hard-coding the MILP and then using a solver to solve the code. There are several commonly utilized methods for this, such as direct implementation into MATLAB and coupling a solver with MATLAB (Kühne, 2016) or as a Python Optimization Modeling Objects (Hart et al., 2017). While hard coding is an established method, we will use the UC-modelling tool Linny-R in our thesis. Linny-R is an executable graphical specification language for MILP problems and especially UC problems (Bots, 2021). We argue for the use of Linny-R instead of hard coding based on two arguments. Firstly, because of the ease of use offered by Linny-R. Within our thesis, we have a limited time to reproduce a complex suite of interlinked models. Linny-R enables modelers the ability to built UC models in a matter of several hours. One of the primary reasons this approach is faster than hard-coding is that in Linny-R, a modeler can graphically model all the elements of a UC without modeling the mathematical equations behind a UC model. Second, we argue that a UC in Linny-R is more transparent than hard-coding a model. The reason for this is that, because of Linny-R's graphical nature and ease of use, it is easier for any modeler to understand/experiment with a UC in Linny-R compared to hard-coded UC models.

We will now explain how we have implemented our UC in Linny-R. As we have stated in the previous paragraph, this does not require the inclusion of any formal code or mathematical equation. However, for all readers that are interested to understand our UC from a formal mathematical point of view, we have made our model explicit in appendix A. Figure 3.6 displays a model with all the elements that make up the actual model we have implemented in Linny-R.

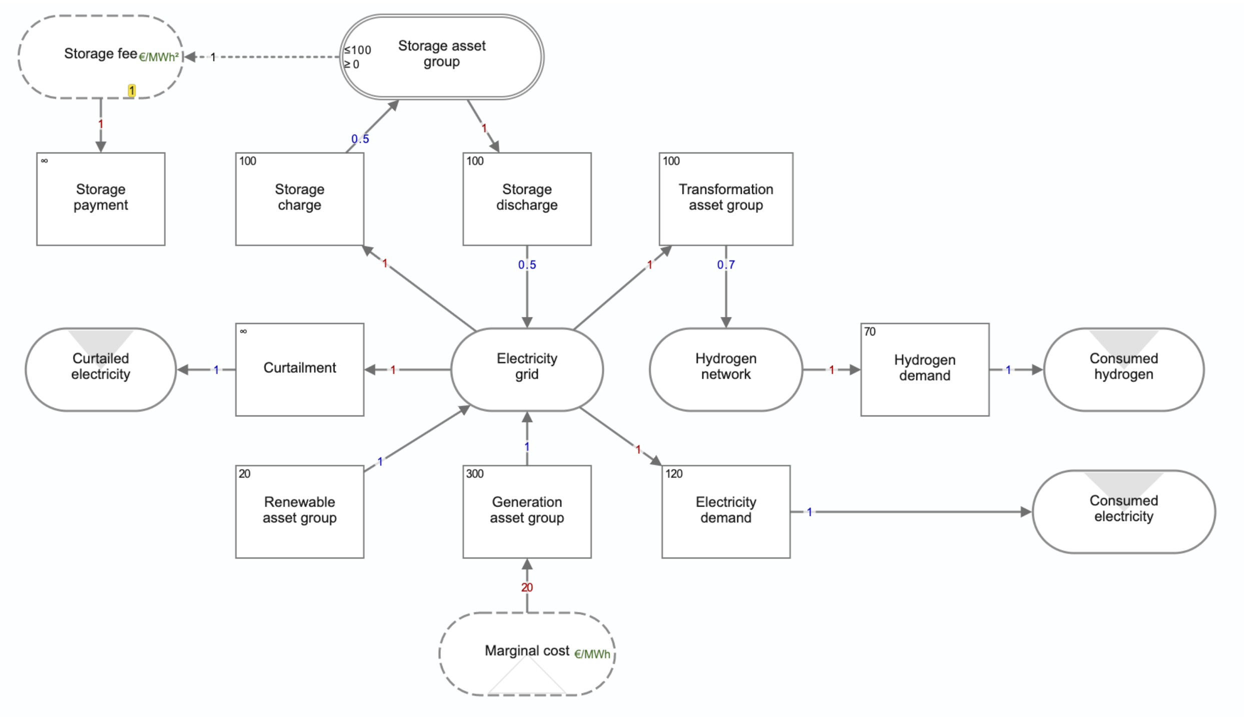


FIGURE 3.6: Linny-R products, processes and links

Looking at figure 3.6 we see that Linny-R consists of three key elements (Hartwig, 2019):

1. Products (the ovals in the figure) consisting of:
    - Sources/sinks: which represent the input of commodities into the system our out of the system
    - Stock: representing the storage of a commodity
    - Data: which represents the input of information into the system
2. Processes (the squares in the figure) consisting of:
    - The generation, transport or transformation of a commodity
3. Links (the lines between all squares and ovals in the figure) consisting of:
    - The relation between processes and/or products

We first look at the supply side in our UC model in Linny-R. Note that because we do not include any technical detail on an individual asset level (as argued for in section 3.1.1) we have decided to model our UC as a cluster unit commitment (CUC) model. In a CUC, all assets are not modeled individually; but instead, they are assigned to an asset group (cluster) (Poncelet, 2018). Our model has four types of assets: generation asset groups, renewable asset groups, transformation asset, and storage asset groups.

Generation asset groups are modeled as processes that have a lower and upper bound. The lower bound of all generation asset groups is 0. The upper bound of a generation asset group is equal to the total installed capacity of the entire asset group, so it is a fixed parameter. The link of a data product models the marginal costs. The renewable asset groups are also modeled as a process. However, this process's upper and lower bound is equal to the output of the total installed asset group during a time step and is not a fixed number but a time series.

Moreover, the renewable asset groups do not have a marginal cost. The transformation asset groups are also modeled as a process with a lower bound of 0 and an upper bound equal to the total installed capacity of an asset group. What separates a transformation asset group from a generation asset group is that the asset group does not produce any energy; instead, it transforms it with a specific efficiency loss denoted by the link going in and out of the asset group. In the example in our figure, the transformation asset group makes hydrogen out of electricity. Lastly, looking at the storage asset group, we see that a process and a product combination model them. The upper bound of the storage asset group reflects the total amount of energy stored in a time step and thus the total size of a reservoir. In the case of implementation of seasonal storage targets as we described in section 3.1.1 the upper and lower bound of storage are set to be equal to the marks at specific time steps. The storage charge or discharge process indicates the power of a storage asset group. The efficiency loss of storage is modeled by changing the link's value that goes in/out the storage charge/discharge.

To match the supply with the demand side, we see that there are three processes: electricity demand, hydrogen demand, and curtailment in figure 3.6 and two products: the electricity grid and hydrogen network. The need for a commodity is modeled as a process with a lower and upper bound equal to the demand for a certain commodity in a time step. We show how we have modeled the demand for hydrogen and electricity as these are the two commodities we consider in our UC. Note that the demand for any commodity could be introduced in a similar fashion. Moreover, we see that there is a process that accounts for curtailment. This process has an unlimited upper bound and transports all excess electricity to the curtailed electricity. Finally, the electricity grid and hydrogen network are products with an infinite capacity; as in our thesis, we assume that the grid has unlimited capacity.

In our UC, we assume that all the installed capacity, the demand, the prices, and the time series of vRES are fixed every year. So when simulating a year in Linny-R, the solver's decision variables are the production of generation asset groups and utilization of storage asset groups. Given these variables, the solver proceeds to execute the objective function behind a MILP: "to meet and satisfy system demand in an optimal, cost-efficient manner for the total scheduling period" (Abujarad, Mustafa, and Jamian, 2017).

As we have explained in the previous section, we use a 'daily-UC' and a 'seasonal-UC' in the PP model. Both these models operate with the same UC model in Linny-R. The only difference between the 'daily' and 'seasonal' UC can be found in the input time-series and the different timescales, as explained in the previous section. All the UC models we utilize in our thesis can be made with the elements as described in this section. For an overview of the actual UC models we have utilized in our thesis, we point to appendix D.4.

3.1.3 Present price model verification and validation

Appendix B.1 gives an overview of all the parameters we have utilized to verify and validate our UC model. For our validation runs, we chose the input data for a projection of the Dutch electricity system in 2050 according to the Energy Transition Model in line with a scenario called: 'National Governance', which is developed by a combined effort of Dutch DSOs and TSO (Netbeheer Nederland, 2021). This data can be accessed in the Energy Transition Models (ETM), which is an open-access database utilized by used by governments, companies, NGOs, and educational institutions in various countries (Quintell, 2010).

We utilize this scenario because in this set-out future, almost all demand in the Netherlands is fulfilled by vRES and seasonal storage in the form of hydrogen plays an important role. Therefore, we argue that if our approach can accurately simulate an energy system with a high degree of seasonal storage, it should also simulate other (less extreme) scenarios. Note that we have chosen to only include seasonal storage in the form of hydrogen in our validation; conceptually, this makes no difference and could be changed into any other form of seasonal storage.

Electricity price generation present price model

As we already explained in section 1.2.1 in an energy-only market, the electricity price is equal to the marginal cost of the highest bid that is necessary to satisfy demand. Therefore, after every run in the PP model, Linny-R automatically displays the electricity price through a formula that per time step sets the electricity price equal to the marginal costs of the most expensive asset needed to match demand. To verify the working of this price generation, we run the PP model without storage, with a fixed amount of vRES production and an increase of demand every time step. Figure 3.7 shows how the price development follows the marginal costs of the assets and thus verifies the price generation of the PP model.

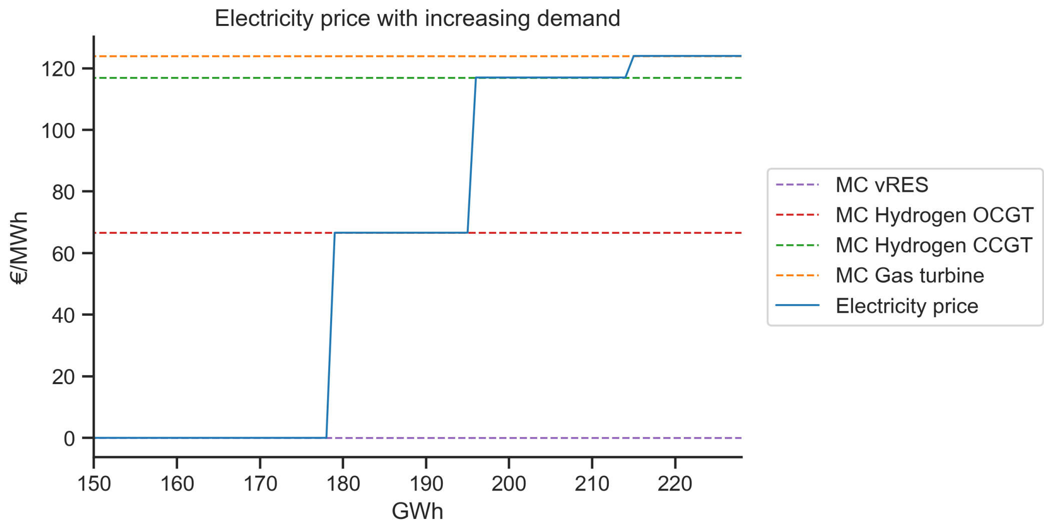


FIGURE 3.7: Electricity price with an increasing demand

Seasonal UC model validation

In the validation of our PP model, we focus on showing that the novel approach as introduced in section 3.1.1 leads to empirically valid 'seasonal' flexibility, while the model shows expected behavior in 'daily' flexibility.

To validate the seasonal UC that is one of the two UC models of the PP model, we formulate a hypothesis based on the input time series. First, we apply a rolling average of a week to the input time series for all input time series and then sum the values every 24-time steps to create a new time series with a daily time resolution. Then, based on these smoothed time series, we make two states for every timestep: surplus or a shortage. The surplus moments are defined as moments where the total supply of all vRES assets is larger than the combined demand for hydrogen and electricity. A shortage is the opposite of a surplus and occurs if the total supply of all vRES assets is insufficient to fulfill the demand. Figure 3.8 shows the shortage and surplus moments based on our input data.

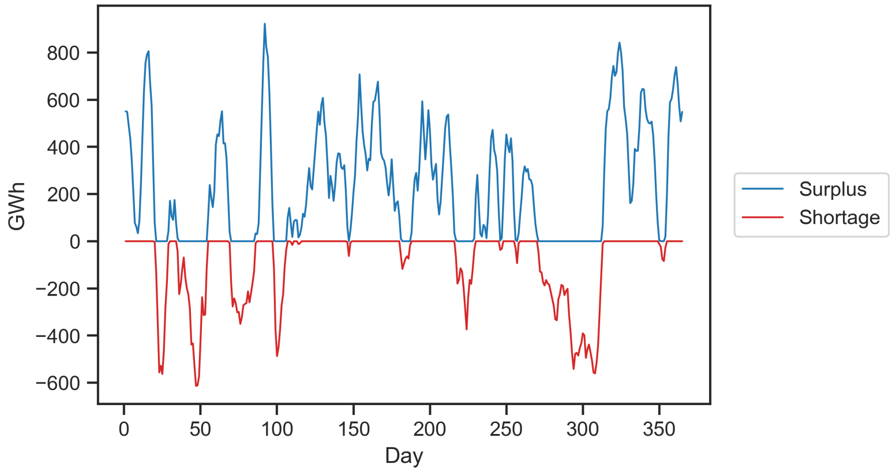


FIGURE 3.8: Shortage vs surplus moments based on input data

Based on this input data, we formulate two hypotheses to validate the working of our model. The first is that the solver should fill the seasonal storage during moments of surplus as here the electricity prices are low or even 0 €/MWh. Oppositely the emptying of the seasonal storage should happen during moments of shortage. Our second hypothesis is based on the pattern of the input data in figure 3.8. From this data, we reason that several surplus moments are spread out over the year, with a larger block in the middle and end of a year. So, the seasonal storage should use these moments and be filled spread out over the year. Consequently, the hydrogen storage should be emptied between these moments since there are dips of shortages. Note that the input data is based on the expected weather scenarios for the upcoming year, so the seasonal storage is filled only for the scenario at hand.

We now run the seasonal UC model to compare the model's output with our two formulated hypotheses. The left-hand side of figure 3.9 shows the surplus moments during a year and the moments that the solver charged the seasonal storage. The right-hand side of figure 3.9 displays all the shortage moments in the system and the discharge of the seasonal storage. Thus, in the left plot, we see that the moments that the seasonal storage is charged occurs during shortages. Similarly, the right plot shows that all the discharge moments of the seasonal storage happens while there is a shortage.

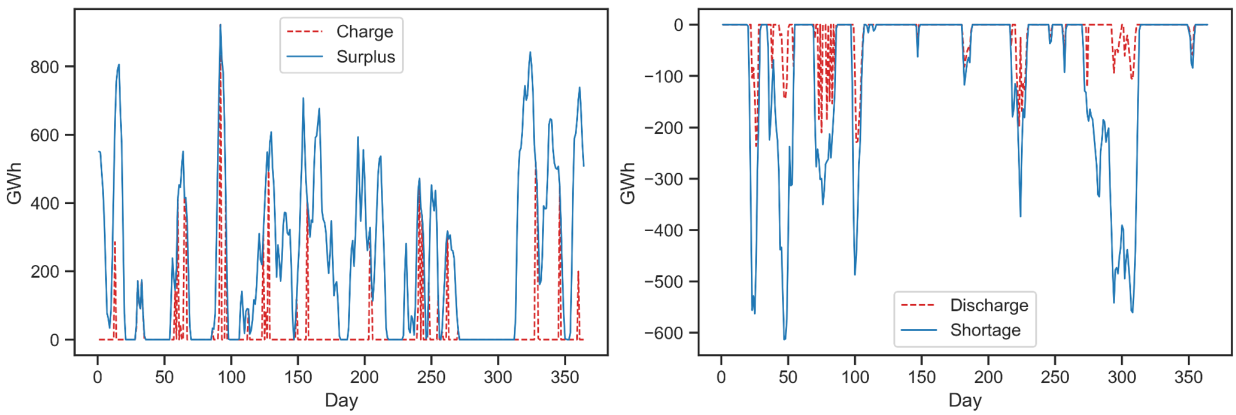


FIGURE 3.9: Surplus moment vs charge moments (left) and charge vs discharge moments (right)

Moreover, we see that there are several moments where the seasonal storage fully utilizes a surplus or shortage moment. To explain this behavior, we point to figure 3.10 where we display the stored energy in the seasonal storage for all days in a year. For example, we see in figure 3.9 that between days 150 and 175, many surplus moments are not utilized to fill the storage. However, in figure 3.10 we see that this is the case because the storage is already full. Comparably, we see in figure 3.10 that between days 250 and 300, there is much opportunity during a shortage that is not fulfilled through discharge. Again, looking at the storage in figure 3.10 we see that around day 300, the storage is empty. This behavior means that there was not enough storage to fill all the shortages through seasonal storage. Therefore, the solver in the seasonal UC has emptied the seasonal storage by spreading it out over this period to minimize the total system costs. Figure 3.11 confirms this by showing that all the hydrogen that is being charged is also discharged, and then the amount that is not discharged is due to efficiency losses. So overall, we conclude that our first hypothesis is confirmed. To verify our second hypothesis, we look at the energy stored in the seasonal storage in figure 3.10. Here we see that in accordance with our hypothesis, the storage is filled spread out over the year. In the days between these surplus moments, the storage is emptied. This behavior thus confirms our second hypothesis.

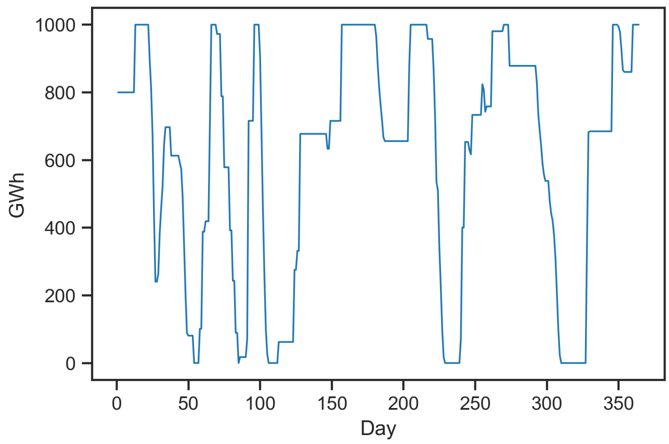


FIGURE 3.10: Stored energy in the seasonal storage

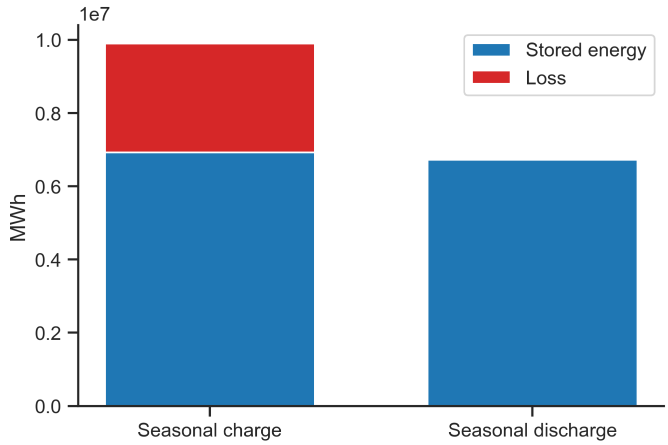


FIGURE 3.11: Comparison of the amount of energy stored vs how much is discharged due to losses

Daily UC model validation

After having validated our seasonal UC model, we now move on to the daily UC model. The input time series for the daily UC is the same as the seasonal UC. The merit order and storage assets utilized in the daily UC can be found in appendix B.1. Again, the merit-order and storage units are the same as the seasonal UC, with the only difference being the addition of Lithium-ion batteries to reflect daily storage assets. For the daily UC, we chose to only include Lithium-ion batteries for these validation runs, but any storage asset can be utilized.

We have two hypothesis we want to confirm to validate the daily UC that is part of the PP model. Firstly, is related to the overall behavior of storage. If the coupling between the daily and seasonal UC operates correctly, the solver should fulfil the seasonal storage target and the 'daily' storage should also correct week-to-week imbalances. Second, if the daily and seasonal UC work according to their goal an increase in storage, ceteris paribus should lead to a lower overall system costs.

Figure 3.12 shows the seasonal storage for a year in the seasonal UC and how this is transformed into weekly storage targets for the daily UC.

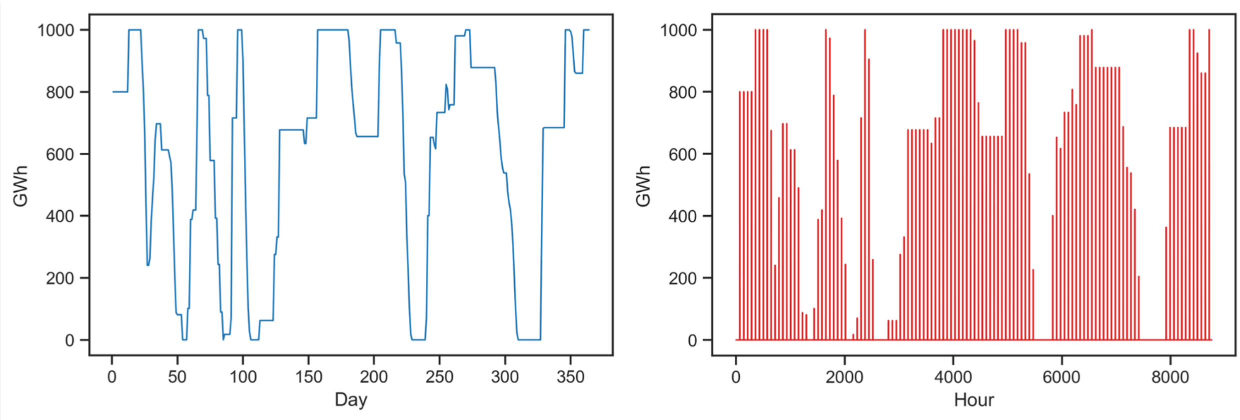


FIGURE 3.12: Comparison seasonal storage vs three day storage targets

Figure 3.13 shows the storage behavior for all the storage units in the daily UC. Both types of storage units are dispatched as expected. The seasonal storage is charged/discharged according to three daily targets and fulfills the seasonal flexibility need. At the same time, the daily storage units are utilized to full fill daily-term flexibility needs and charges/discharges on a day/week level to reduce the total system costs. This overall behavior is in line with our expectations and confirms our first hypothesis.

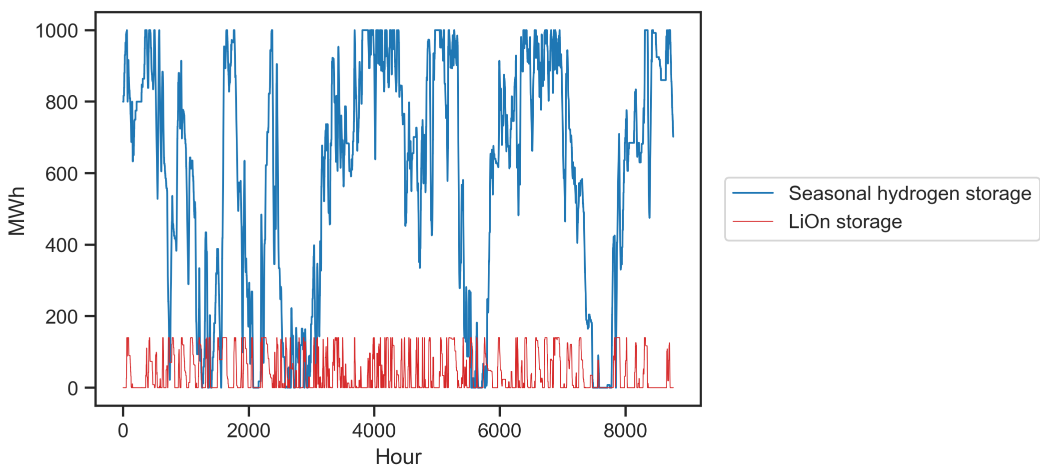


FIGURE 3.13: Daily and seasonal storage behavior overview

We have now shown that the seasonal and the daily storage units behave as expected. As a final form of validation, we now determine the impact on the total system costs when the seasonal and daily storage are reduced. We define the total system costs as the total demand times for all commodities times the electricity price during a time step. Table 3.2 shows an overview of the results. We see that a decrease in the amount of hydrogen storage (1400 to 500 GWh) and lithium-ion storage (140 to 70) leads to an increase in the amount of curtailment, increasing the average electricity price subsequently the overall system costs. This behavior confirms our second hypothesis, that our overall approach leads to system costs reduction.

Hydrogen storage (GWh)	**Lithium-ion storage (GWh)**	**Total system costs (Billion €)**	**Total curtailment (TWh)**	**Average e-price (€/MWh)**
1000	140	8.59	93.6	23.8
500	140	8.9	97	24
1000	70	9.19	94.4	25.5
500	70	9.73	99	27

TABLE 3.2: Effect of installed storage on the total system costs

3.2 Future prices model

3.2.1 Method to select representative days

We will now consider what methods are available to select a set of representative days and how this impacts the analysis, based on the work of Poncelet (2018). In his work, Poncelet compares five different approaches to select representative days:

1. Heuristics (H)
2. Clustering algorithms (CA)
3. Random selection (S)
4. MILP optimization model (OPT)
5. Hybrid approach: random selection followed by optimal weighting (HYB)

For a detailed explanation of all individual methods, we point to the work Poncelet. For our thesis, the significant point is the consideration of the different methods as qualitatively shown in table 3.3. Poncelet (2018) notes that there is no clear-cut best methodology; instead, a modeler should choose a methodology based on the intention of a model.

Criterion	H	CA	RS	OPT	HYB
Accuracy	–	+-	+	++	++
Implementation	++	-	++	–	–
Execution costs	++	+	–	-	-
Flexibility	-	-	+	++	++

TABLE 3.3: Qualitative comparison different methodologies

We first look at the accuracy between the different methodologies. We find that there is only a 5% error difference between all methodologies for the relevant accuracy metrics. So based on this, we could still consider all methods for the FP model. Next, we look at the execution costs, where we find that the RS, HYB, and OPT models have a high execution cost. For example, the OPT methodology can take over 6 hours to find a set of representative days if one wants to find more than two representative days to represent a year. In the FP model, we plan to find representative days for every iteration we run. We argue this is necessary as several factors such as weather years, vRES installed, and demand growth could positively impact the selected days. For this reason, the three methodologies with high execution cost: RS, OPT and HYB do not fit the aim of our model, which leaves the H and CA methodology to consider. The main difference is that the implementation of the CA is higher than the H; however, this would result in a higher degree of accuracy. For this reason, we chose to utilize a form of a clustering algorithm.

The clustering algorithm we will utilize to select representative days in this thesis is the K-means clustering algorithm. The K-means clustering algorithm is a commonly utilized method to select representative days in energy-system models (Tejada-Arango et al., 2018; Yeganefar, Amin-Naseri, and Sheikh-El-Eslami, 2020; Nahmmacher et al., 2016). In figure 3.14 we display the flowchart that leads to the selection of representative days, based on Nahmmacher et al., 2016.

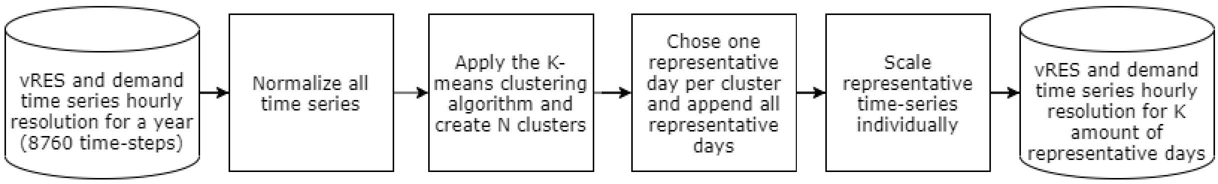


FIGURE 3.14: K-means flowchart

In the first step, we normalize all input time series. The time series need to be normalized since the algorithm clusters days based on their distance from each other. To be able to do this, the time-series need to be measured on the same timescale (Nahmmacher et al., 2016). In the next step, we apply the K-means clustering algorithm according to the following steps (assuming we have input data points x1,x2,x3,. . . ,xn and value K (the number of clusters needed):

1. Chose K elements randomly based on the input data and assign them as elements that are part of a cluster.

2. Calculate the Euclidean distance of all the remaining elements to datapoints K (curren cluster centroids):
   $d(p,q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2}$
   with p = (p1,p2) and q = (q1,q2)

3. Add all the remaining elements to a cluster that is nearest to itself:
   $argquadmin_{c_i \in C} quaddist(c_i, x)^2$

4. Find the new centroid by taking the average of the points in each cluster group:
   $c_i = \frac{1}{|S_i|} \sum_{x_i \in S_i} x_i$
   with S_i is the set of all points assigned to ith cluster.

5. Then the algorithm repeats point two to four until the change in the number of points in a cluster is insignificant or zero.

In the next overall step, we chose one representative day per cluster. Nahmmacher et al. (2016) show in their approach how representative days in clusters more accurately represent the overall system when instead of the cluster's centroid, specific historical days are chosen. We chose our center based on their approach to be the day closest to the cluster centroid, again utilizing euclidean distance. Figure 3.15 shows how 24 representative days are selected based on the input data utilized for the UC validation in the previous section. In the final step, we form the final time-series by appending all the individual selected representative days chronologically. To ensure that technologies' average demand and capacity factors are reflected in our overall time series, we introduce a scaling factor; this is done for all time series individually. This scaling factor is calculated by summing the historical time series of 8760 and the time series consisting of representative days. Next, all individual representative days are multiplied by their weight (w_d). The value of w_d is equal to the amount of time per year the representative period is assumed to be repeated (365/K). Then we divide the sum of the historical time series with the representative-day time series. If the scaling factor is below 1, we scale the representative day time-series to be equal to 1 and vice versa if the representative days have an overshoot.

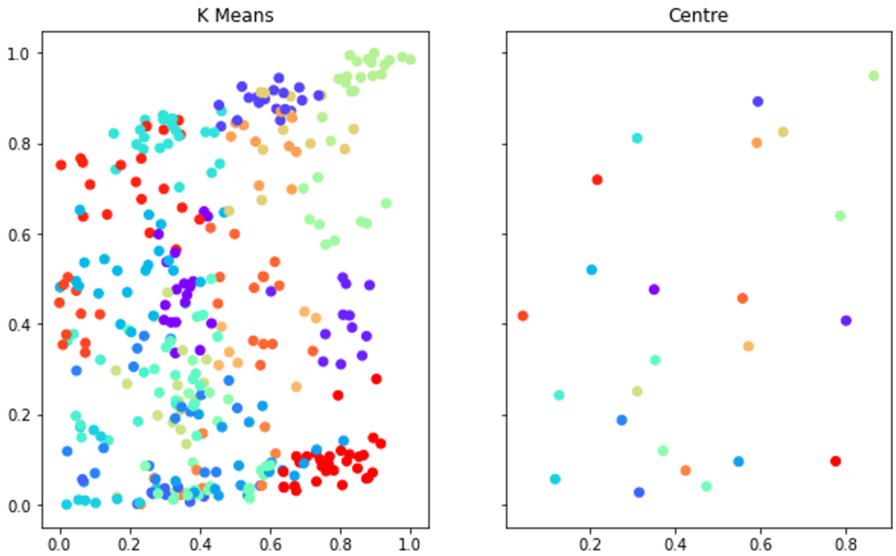


FIGURE 3.15: K-means clustering with centroids

3.2.2 The working of the future price model

Having explained the main difference in temporal representation, we will now describe how the FP model differs from the PP model. The FP model is a UC model; therefore, the FP model is implemented in the same fashion as the PP model described in section 3.1.2. Also, the mathematical formulation, as can be found in appendix A is almost the same. The only difference is that the time series that serves as input data (the output of vRES and the demand) are based on representative days, as described in the previous section. The main difference this causes for the modeling of our UC is that we need to account for the fact that we only run the model based on representative days in the seasonal storage. If the seasonal storage is filled in a modeled period, this needs to be taken into consideration for all the periods that are not modeled; this is displayed in figure 3.16 (Schaber, 2013). Since the seasonal storage at the start and end of a modeled period (24h in our model) can be different. We need to account for this effect and extrapolate the seasonal storage to the next modeled period.

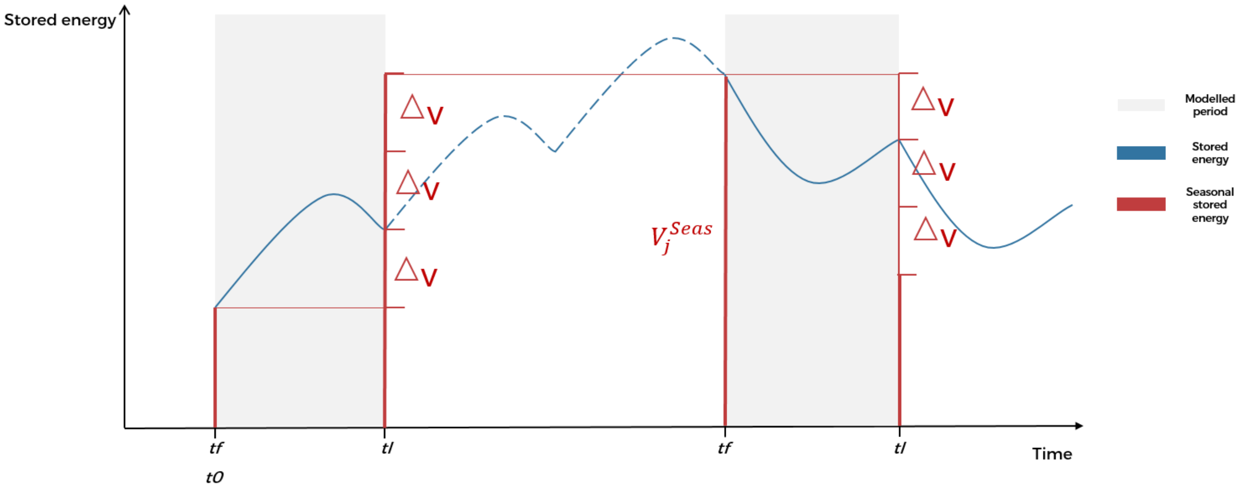


FIGURE 3.16: Seasonal storage (adjusted from Schaber, 2013)

Accounting for seasonal storage and temporal mismatch

$$C_j = C_j / w(t) \qquad \forall t \in T,\ \forall j_{seas} \in J, only\ \ in\ \ seasonal - UC \tag{3.1}$$

$$\Delta_V(tlt) = (V_j(tl_t) - V_j(tf_t)) \qquad \forall t \in T,\ \forall j_{seasonal} \in J, \tag{3.2}$$

$$V_{j,co}^{seasonal}(tl_t) = (w(t) * \Delta_V(tlt)) \qquad \forall t \in T, \quad \forall j_{seasonal} \in J \tag{3.3}$$

$$V_j(tl_t) = V_j^{seas}(tl_t) \quad \forall j_{seasonal} \in J, \quad \forall tl_t \tag{3.4}$$

$$\begin{aligned} &If(w_d - 1) * \Delta_V(tlt) > 0 : \\ &Ej^{in}(tl_t) = ((w_d - 1) * \Delta_V(tlt)) + E_j^{in}(tl) * \eta_j^{in} \qquad \forall j_{seasonal} \in J, \quad \forall tl_t \end{aligned} \tag{3.5}$$

$$\begin{aligned} &If(w_d - 1) * \Delta_V(tlt) < 0 : \\ &Ej^{out}(tl_t) = ((w_d - 1) * \Delta_V(tlt)) + E_j^{out}(tl) / \eta_j^{out} \qquad \forall j_{seasonal} \in J, \quad \forall tlt \end{aligned} \tag{3.6}$$

$$V_j^{seas}(t0) = V_j^{seas}(tl_{t-1}) \qquad \forall t0 \tag{3.7}$$

$$V_j(t0) = V_j^{seas}(t0) \qquad \forall t0, \tag{3.8}$$

$$V_j^{seas}(t) \leq C_j \qquad \forall t \in T \tag{3.9}$$

$$V_j^{seas}(t) \leq CSt_j + (w(t) - 1) * (V_j(tl_t) - V_j(tf_t)) \qquad \forall t \tag{3.10}$$

The first step in deriving seasonal storage targets is to run the seasonal-UC in the FP model in Linny-R. This process is done with the same UC model as the PP model. However, before we start a run, we scale the capacity of the seasonal storage based on the weight of the number of representative days we model, as shown in equation 3.1. Now we run the seasonal-UC model based on the FP model logic. Similar to the PP model, this gives us a time series of seasonal storage as output. We now have to adjust the seasonal storage output to account for only modeling certain representative days. In this way, we create a seasonal storage target for the daily-UC that accounts for seasonal storage correctly.

We first determine the difference between the seasonal storage at the beginning of the modeled period and the end of a modeled period for the seasonal storage output of the seasonal UC; this is Δ_V in equation 3.2. Note that a modeled period in our UC is 24h as we work with representative days. After having determined what the Δ_V is, we can now calculate what the seasonal storage is compensating factor V_j^{seas} is in equation 3.3.

The amount of storage at the end of a period in the daily-UC needs to be equal to the seasonal storage if we had modeled all time steps. So in Linny-R terms, the upper bound of the seasonal storage as shown in 3.17 is set equal to the seasonal storage compensating factor V_j^{seas} at the end of every modeled period. We have formalized this in equation 3.4.

At the end of a modelled period, the seasonal storage compensating factor (minus one period) is added (equation 3.5) or subtracted (equation 3.6) from the seasonal storage. In Linny-R, this factor is modeled as a process with an upper and lower bound of zero. Except for at the end of a modeled period, the upper and lower bound get set equal to the compensating factor. The solver can still use the seasonal storage (input or output) in the meanwhile. For all the other time steps, the equations from the daily-UC in the PP-model apply (equation A.4-A.8 apply).

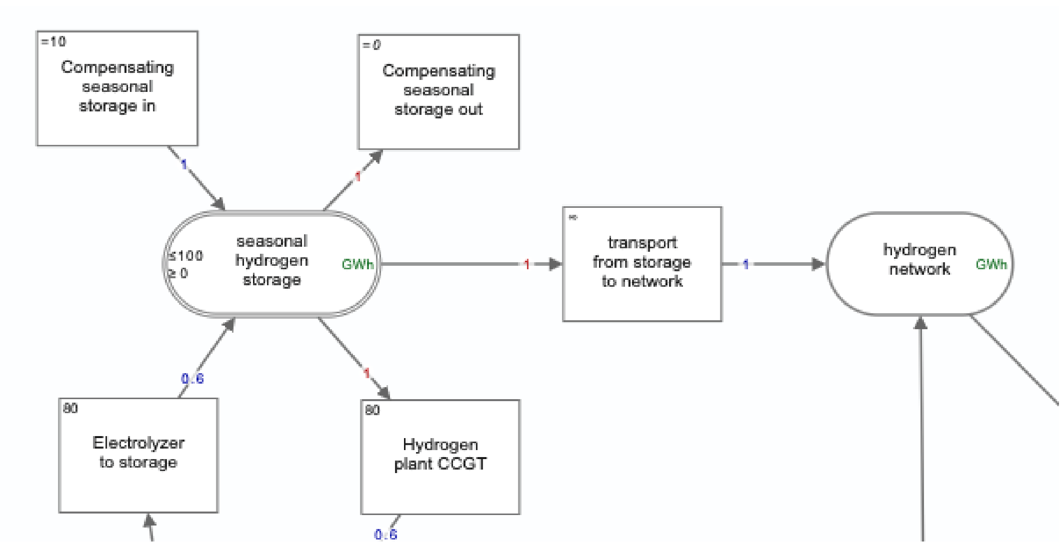


FIGURE 3.17: Seasonal storage in Linny-R with representative days

Equation 3.7 ensures that the seasonal storage compensating factor at the beginning of a year (t0) is equal to the seasonal storage compensating factor at the last time step of the modeled period of the previous year. Equation utilizes this to 3.8 set the seasonal storage level in time step 0 equal to the seasonal storage compensating factor. Thus, again, in Linny-R terms, the seasonal storage in the daily-UC has an initiate storage level that accounts for the previous year.

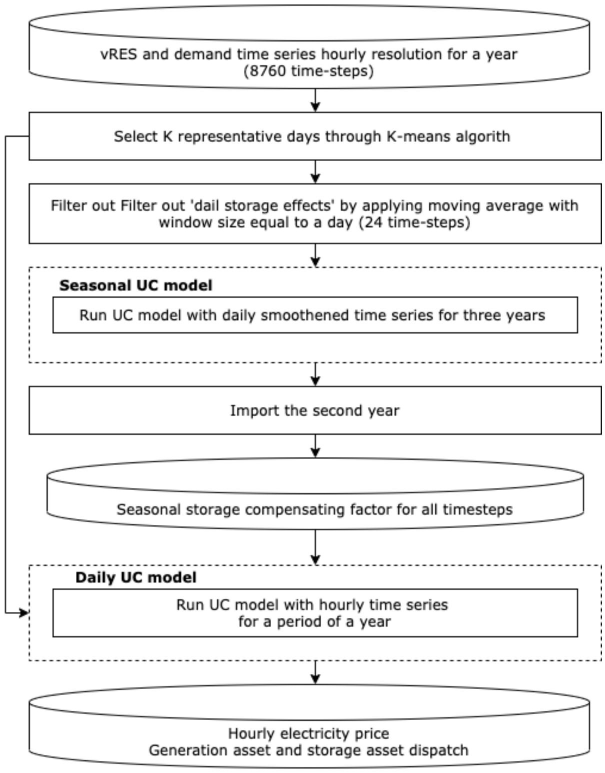


FIGURE 3.18: Flow-chart FP-model

The above mathematical formulations for the seasonal storage targets have an impact on the way we model the FP-model; we have displayed this in figure 3.18. In the first step, we select the representative days based on the k-means algorithm. After this, we want to run the seasonal UC model to create the seasonal compensating factors. The seasonal UC is the same as in the actual prices model; see figure 3.2. Because there are is only seasonal storage installed in the seasonal UC, we need to filter out the effects of the day-to-day storage by applying a rolling average with a window size equal to 24. We could, in theory, also realize this by summing the time-series to daily time series; this would reduce the computational time of the seasonal UC model in the FP-model. However, as shown in the above equations, we need the storage level at the beginning and end of a modeled period. This information would be lost if we summed the hourly time series; therefore, this is unsuitable. Then we run the seasonal UC-model in the FP-model for three years and import the second year. We import the second year as the model behaves differently in a start and stop year. Therefore these years are excluded. After gathering the seasonal storage compensating factors from the seasonal UC model, we can now run the daily UC model with the initial representative days as an input. From the daily UC, we can gather data on hourly electricity prices and the dispatch of all assets. These values need to be multiplied by $w_(t)$, to convert these to the values one would observe in a historical year of 8760-time steps.

3.2.3 Future price model validation and verification

All the parameters that serve as the input data for the FP model can be found in appendix B.2. The input data stems from a system outlook study for the year 2050 done by all the Dutch electricity and gas TSO (Gasunie and TenneT, 2019). This data can be accessed through the ETM model (Quintell, 2010).In this future scenario in 2050, there is a high degree of VRES installed, and therefore the temporal resolution is significant. Consequently, we argue that if the FP model can represent this scenario accurately, it should also depict the operation of systems less dependent on weather input. Since the main factors that are affected by temporal representation are vRES and storage.

The main aim of the FP model is to generate the cash flows of assets in one or multiple future years. Therefore we focus on showing that this goal is accomplished in the validation of the FP model. We aim to realize this by comparing the FP model and the PP model. Note that only the time series differ with regards to the temporal resolution. All the other elements are the same in the FP and PP model. So, if the FP model operates correctly, it should produce similar results for the same year as is realized in the PP model. We formulate two hypotheses we utilize to test the output of the FP model. Firstly, if the PP and FP models operate correctly, the assets should exhibit similar behavior in the season and daily-UC. Second, the main goal of the FP model is to generate cash flow prediction of assets. So the cash flow generated by all assets in the FP and PP should be similar.

Selection of representative days

Before we run the FP model, we need to decide based on how many representative days we will simulate our model. Even though there is no standard method to identify the "right" amount of clusters in any dataset, a commonly utilized method is the elbow method (Almaimouni et al., 2018). The elbow method is a graphical tool that plots the percentage of variance captured as a function of the number of clusters. The elbow mothed is calculated by the following logic (Nainggolan et al., 2019):

1. Set an initial value for K clusters
2. Calculate the sum of error for a value of K. The formula for the sum of error is: $SSE = \sum_{i=1}^{n}(d)^2$ with d = the distance between the data and a cluster center
3. Increase the value of K and run again

To determine the input data for the FP model, we have calculated the SSE for the clusters ranging from 1 day to 365 representative days. The results are shown in figure 3.19. From this, we conclude that there is a clear elbow point after seven representative days. To increase the degree of accuracy in our FP model, we chose to set the representative days at 24 days. We chose 24 days instead of 7 as this minor difference does not significantly increase our computational time, and we will ensure that if the representative days are spread out over a year, we would have almost a whole week in every season.

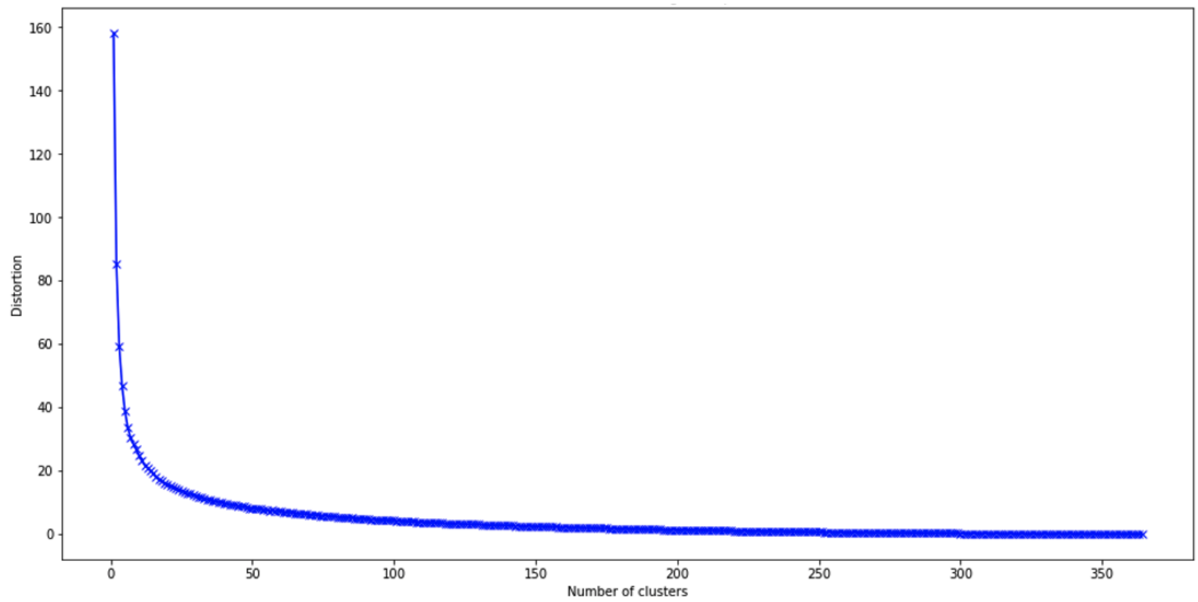


FIGURE 3.19: Elbow methods range 1-365 representative days

Validation and verification seasonal UC model

In the first step, we take all the input time series (based on 24 representative days) of the FP model and apply a rolling average of a day. Similar to the approach utilized in the validation of the PP model in section 3.1.3 we create two states for every time step: shortage and surplus. The plot on the right in 3.20 shows the shortage and surplus moments for all time steps in this input time series for the FP model. We see the shortage and surplus moments of the same time series for all days in a year on the left side. This data is the same input data as we have previously shown in the validation of the seasonal UC in the PP model in figure 3.8. Looking at figure 3.20 we see that the shortage and surplus moments have similar characteristics in both time series. We see surplus moments spread out over the year, with a bigger surplus in the middle and end of a year. While in between of those moments, there are shortages.

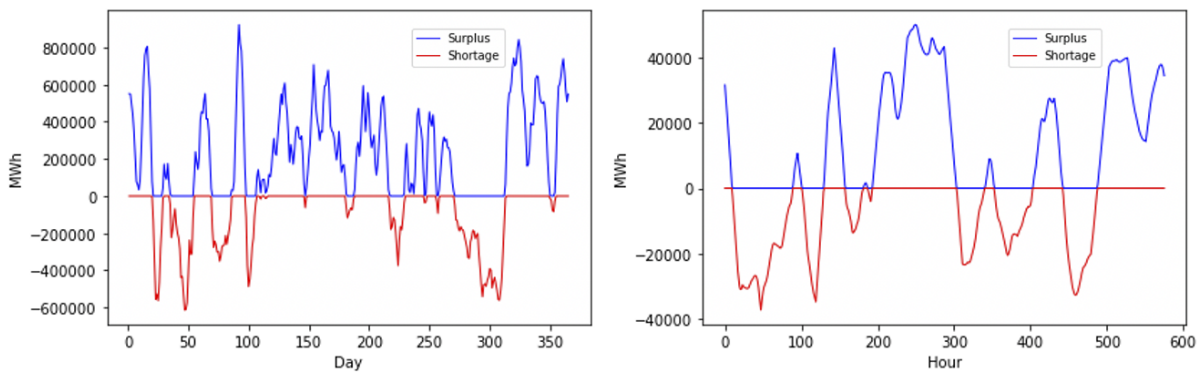


FIGURE 3.20: Comparison of the shortage and surplus in data used for PP model (left) and FP model (right)

We proceed to run the seasonal-UC both in the FP and the PP model. Figure 3.21 displays the difference between the charge and surplus moments for the PP model (left) and FP model (right) in the seasonal UC. We again see similar behavior in that the storage is filled during the surplus moments; however, not all surplus moments are utilized because the storage is full. Moreover, we see that in the FP model, the level of discharge is significantly lower than the PP model; this is expected as in the seasonal UC in the FP model, we only simulate a limited amount of periods and have not yet compensated for this. We explained in section 3.2.2 how account for this.

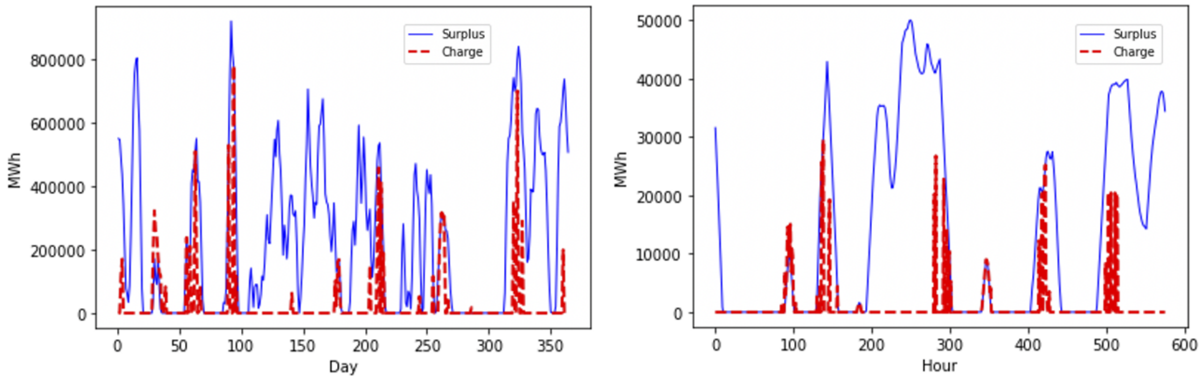


FIGURE 3.21: Seasonal surplus and charge for PP model (left) and FP model (right)

Figure 3.22 displays the seasonal discharge moments in the PP model (left) and FP (model) right. Again, the results are in line with our expectations. The discharge occurs during shortage moments, and not all shortage moments are utilized; the reason for this is that there is not enough storage possible to do so. Again, the difference in the energy discharged is because we have not compensated for the limited amount of modeled periods yet.

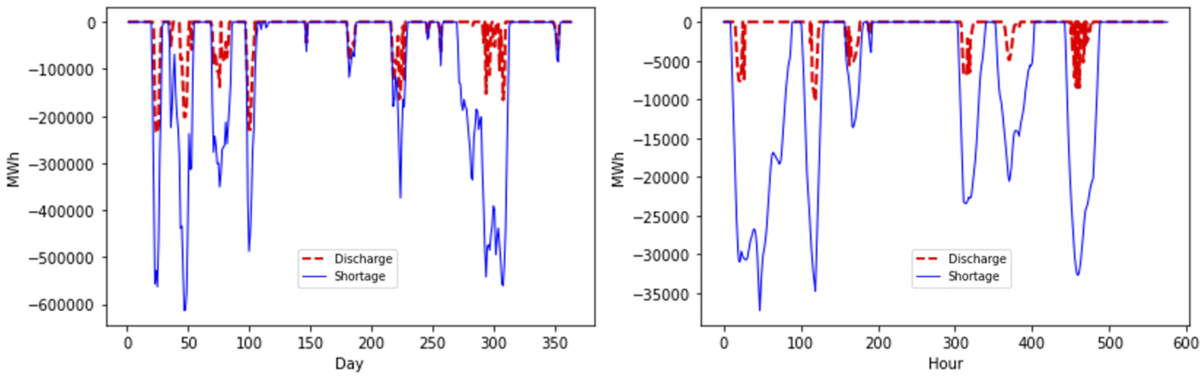


FIGURE 3.22: Seasonal surplus and charge for PP model (left) and FP model (right)

Validation daily UC model

In the next step we create seasonal storage targets for the seasonal storage to fill and charge/discharge compensation targets, based on equation 3.1 - 3.10. In figure 3.23 we show the discharge and discharge compensation factors, this leads to the actual seasonal storage in the daily UC model. We compare the overall storage behavior of the daily UC model in the PP with the FP in figure 3.24. In comparing the overall storage behavior, we see that the discrepancy between the overall energy levels in both models is now dissolved due to the compensation for the modeled periods. Moreover, the behavior of overall storage behaves as expected, with the seasonal storage solving the larger discrepancies over time and the short-term storage in the form of lithium-ion batteries operating on a day-to-day level.

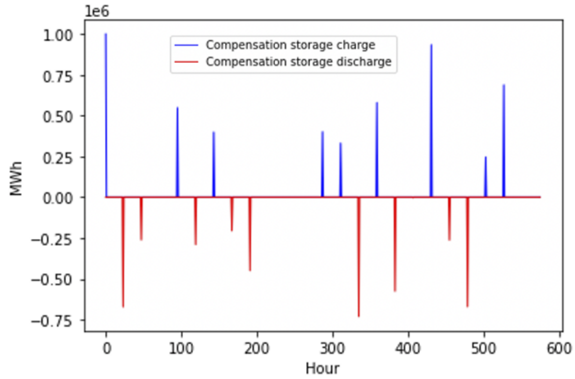


FIGURE 3.23: Storage compensation in the FP-model

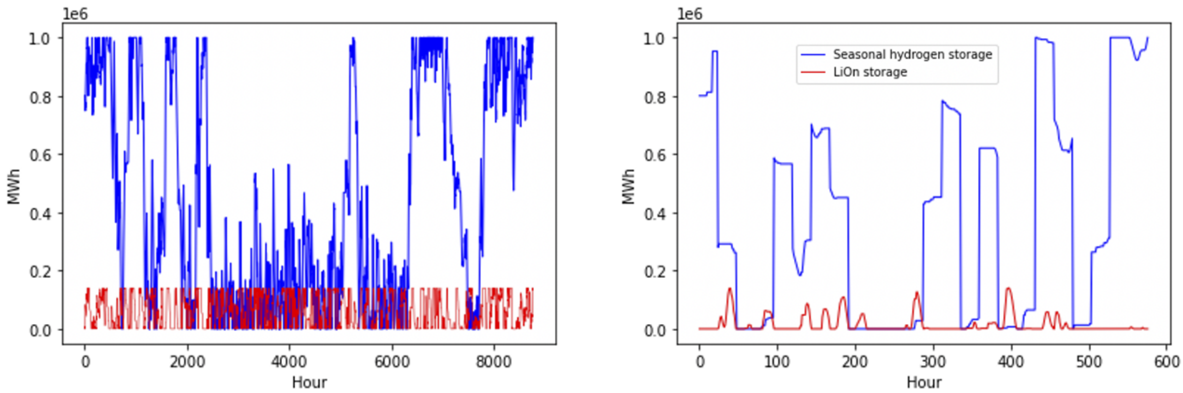


FIGURE 3.24: Storage behavior all storage units for PP model (left) and FP model (right)

The difference between the PP and FP models in the overall storage behavior is that the volatility in the PP model is higher than in the FP model. Partly, this is the case because the FP model only simulates 24 representative days. In reality, all the short-term storage moments on the right need to be multiplied by the weight of those days; this would partly resolve the difference in volatility. So in this way, our first hypothesis regarding the overall system behavior is confirmed.

To take this into account and as a final form of validation, we compare the cash-flow of all assets-groups in both the AP-model and the FP-model in figure 3.25. The cash flow is determined by taking the e-price at a given time step and subtracting the marginal cost of an asset. Overall, we see that the assets have a similar cash flow, and if we compare the total cash-flows in both models, there is only a +/- 10% difference between both models. This confirms our second hypothesis aimed at the cash flow of all assets.

However, there are some differences which we will discuss now. The first big difference is between the offshore profit asset in both models. In selecting the representative days in our model, we choose one day per cluster. We do not consider that some clusters have a smaller cluster size and are less common than other days; this influences the results. In this scenario, there is significantly more offshore wind than any other asset. So the offshore wind assets are affected more by this.

Moreover, because so much offshore wind is installed, this has a significant impact on offshore wind. Furthermore, we see that a relative difference between Lithium-ion storage and hydrogen storage. The reason for this is that the volatility in the PP model is higher because the battery has a chance to optimize over multiple days. Including the different profiles on week en weekend days.

The storage can only optimize over the current representative day in the FP model to prevent any temporal mismatch. However, as the goal of the FP-model is not to 100% accurately represent the market but rather indicate future cash-flows to investors, we argue that the error of margin we see here is acceptable. Finally, we would like to point out that this is a market snapshot in 2050 where the reliance on weather-dependent resources is at its highest and that in cases with fewer weather-dependent resources, the temporal resolutions are less critical, and therefore, the error margin would also be smaller.

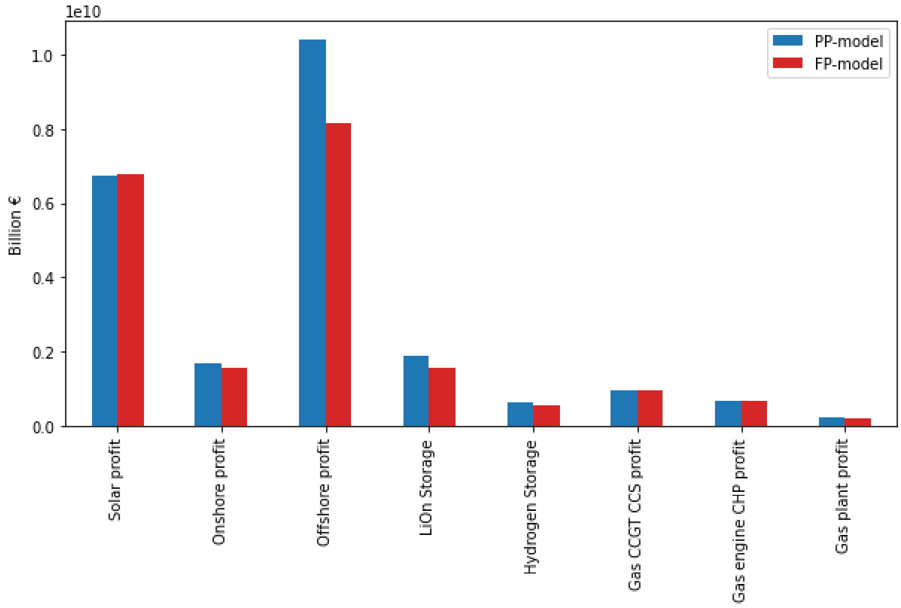


FIGURE 3.25: Cash-flow comparison for PP model (blue) and FP model (red)

3.3 Investment decision model

In this section we explain the working of the code behind the ID model. We will do this by utilizing flow-charts and pseudo-code in mathematical notation. An overview of all the sets, parameters and variables utilized in this section can be found in appendix C. For an overview of the actual python code we utilize to execute the MIDO model, we point to an online appendix, which can be accessed at this url: *www.github.com/ysagdur/MIDO_model*.

3.3.1 Present price model part

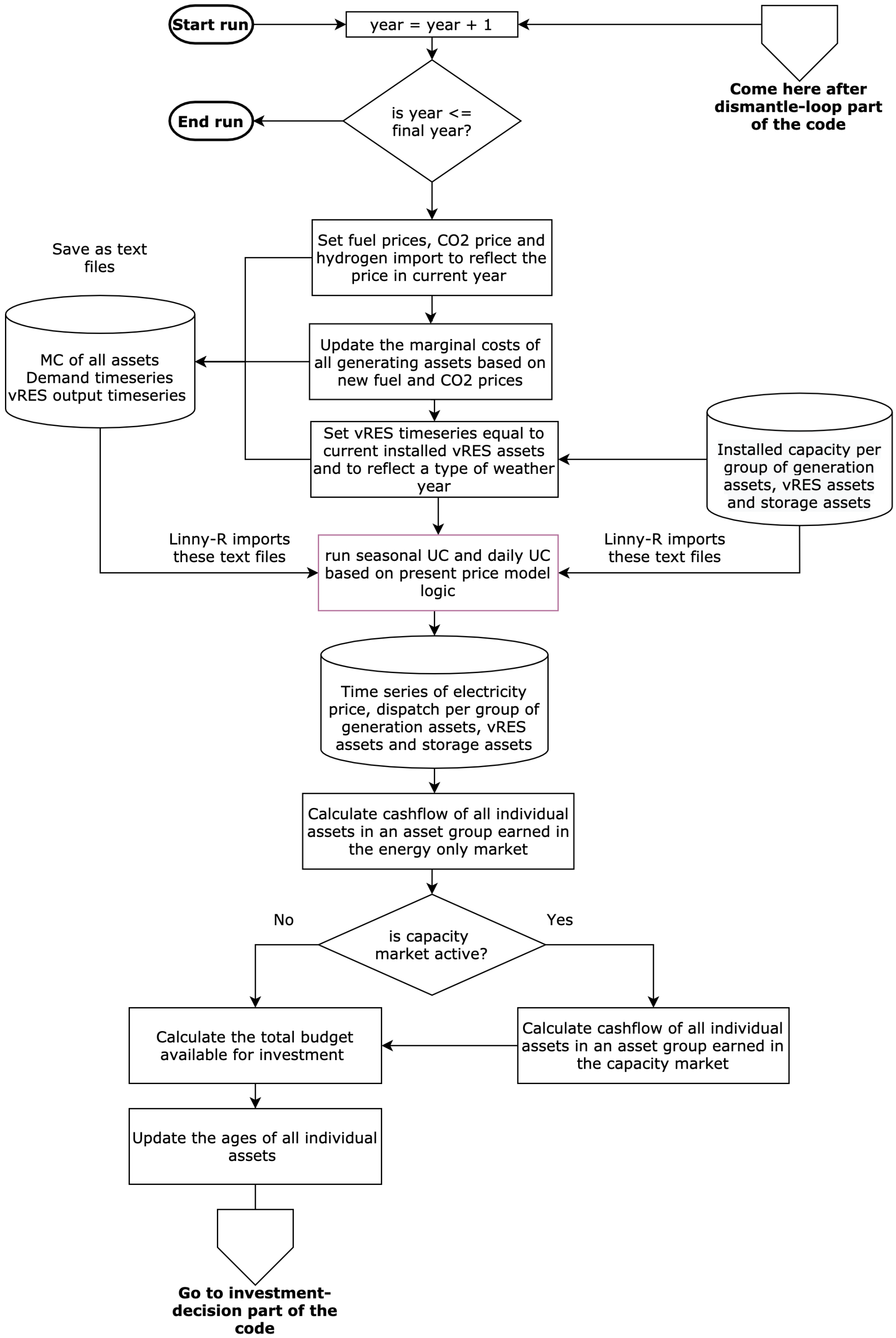


FIGURE 3.26: Storage behavior all storage units for AP model (left) and FP model (right)

Initiating new year

$$p^{fuel} = p^{fuel} + (1 + change^{fuel}) \qquad \forall fuel \in F \tag{3.11}$$

$$p^{CO2} = p^{CO2} + (1 + change^{CO2}) \tag{3.12}$$

$$p^{himp} = p^{himp} + (1 + change^{himp}) \tag{3.13}$$

$$\begin{aligned} k_i^{CO2} &= p^{CO2} * i^{CO2} & \forall i \in I \\ k_i^{fuel} &= p^{fuel} * n^i & \forall i \in I \\ k_i^{MC} &= (k_i^{CO2}) + (p^{fuel} * k_i^{fuel}) & \forall i \in I \end{aligned} \tag{3.14}$$

$$d(co, t) = d(co, t) + (1 + change^{co}) \qquad \forall co \in Co, \forall t \in T \tag{3.15}$$

$$cf_i(t) = \sum_{u=1}^{U} u * (cf_{ss_i, weatheryear}(t)) \qquad \forall i^{vre} \in I^{vre}, \forall t \in T \forall u \in U \tag{3.16}$$

We start the flowchart from the dismantle-loop part of the code or by starting a new run. When we arrive at the beginning of a year, the year counter gets updated. After this, we check if our current year is smaller or equal to the final year, we are interested in modeling. If this is the case, the model keeps on running; otherwise, the run stops. In the first step, in a new year, the model ensures that all fuel prices, the CO_2 prices, and the hydrogen import price are updated to indicate either an increase or decrease in prices depending on the change factors as shown in equation 3.11 - 3.13.

Now that the fuel prices and CO_2 prices are changed, this needs to be reflected in the marginal costs of all relevant assets. The equation shows how 3.14 for all i generating asset groups, the fuel costs are calculated by multiplying the fuel costs times the efficiency of this asset, and the CO_2 costs are calculated by multiplying the CO_2 price times the CO_2 intensity of an asset. These two combined factors make up the marginal costs, so we do not consider other factors such as variable costs. Similar to the change in fuel price, in a new year, all the demand commodities can change by a factor reflecting either growth or decline in demand for a given year, shown in 3.15.

Before we explain the last step, it is essential to explain the difference between asset groups and individual assets. The output of generation or storage assets in the seasonal and daily UC runs based on the installed capacity of an entire I asset group, I^{vre} renewable asset group, and J storage asset group. However, in reality, the capacity of an entire asset group consists of u individual assets, and every asset has a standard capacity size ss_i or ss_j. For an u variable renewable assets I^{vre}, the output for every time step is determined by a capacity factor $cf_{ss_i,w}$ which reflects the output of a standard size vRES unit for every timestep in a particular weather year. Before every run, the algorithm looks at the amount of individual installed vRES assets per asset group i^{vre} and for every timestep, multiplies the output of one standard vRES asset in a given weather year for all individually installed assets.

Running present-price model in Linny-R

During this thesis, additional functionalities have been added by Pieter Bots to Linny-R. Through this addition, Linny-R can be utilized to soft/hard-link information between different models. The linking of data is realized by adding the "receiver" functionality to Linny-R. The receiver has two primary functionalities: (1) look for data in the form of text files to be utilized as the parameters before starting a run, (2) look for a Linny-R model in a directory, and (3) delete the input model and report the data generated by a run in the same directory. So, as can be seen in the flowchart before the Linny-R run, we import all the relevant parameters necessary to execute a run:

the marginal costs of all asset groups kMC i , the demand time series d(co, t), vRES output time series c fi(t) and the installed capacity per asset group ci to Linny-R. After this has been done, the algorithm copies a file of the appropriate Linny-R model into the directory, which the receiver is looking at for a model. If the receiver finds the file, the Linny-R model proceeds to run; once a run is finished, the receiver deletes the model in the receiver's directory and replaces this with the output data generated by a run. The algorithm waits until a model is finished running and the data is generated. Once the data is generated, the script continues. The output of the present-price model is generated according to the logic we have explained in figure 3.4.

Cashflow energy only market

$$
\begin{aligned}
&\forall t \in T, \forall i \in I, \forall u \in U, \forall i \neq I^{vre}: \\
&E^{max}_{i,co}(t) = ss_i \\
\\
&from\ smallest\ to\ the\ largest\ age_u: \\
&if\ \ E^{out}_{i,co}(t) > E^{max}_{i,co}: \\
&rev_u(t) = E^{max}_{i,co}(t) * (p^e - k^{MC}_i)(t) \\
&E^{out}_{i,co}(t) = E^{out}_{i,co}(t) - E^{max}_{i,co} \\
&else: \\
&rev_u = E^{out}_{i,co}(t) * (p^e - k^{MC}_i(t) \\
&E^{out}_i(t) = 0
\end{aligned}
\tag{3.17}
$$

$$
\begin{aligned}
&\forall t \in T, \forall i^{vre} \in I, \forall u \in U \\
&E^{max}_i(t) = cf_i(t) / \sum_{u=1}^{U} (ss^{vre}_i)
\end{aligned}
\tag{3.18}
$$

$$
\begin{aligned}
&\forall t \in T, \forall j^{vre} \in J, \forall u \in U: \\
&E^{max}_i(t) = ssin_j / ssout_j
\end{aligned}
\tag{3.19}
$$

$$
\begin{aligned}
&\forall t \in T, \forall i \in I, j \in J, \forall u \in U \\
&CF^{EOM}_{u/v} = \sum_{t=1}^{T} (rev_{u/v}(t)) - k^{fixOM}_{i/j}
\end{aligned}
\tag{3.20}
$$

Having now run the present-price model, we want to calculate the cash flow of all individual assets; however, since the output data generated by the present-price model is based on asset group, we need some additional data manipulation. The equation necessary to calculate the cash flow is dependent on the type of asset we are dealing with, either a regular generating asset (i), vRES generating asset (i^{vre}), or storage asset (j). To calculate the cash flow for all generating assets that are not vRES assets, we utilize the logic as stated in equation 3.17. For asset i, the maximum output $E^{max}_i(t)$ at a given time-step is equal to the size of the standard capacity of a corresponding asset group. Next, we look at all the individual assets u that are part of asset group i, from the youngest to the oldest. From the output generated by the present price model, we know for every time step what the energy-output (E^{out}_i) is for the entire asset group i. The algorithm checks if this output E^{out}_i is larger than the maximum output of one asset; if this is the case, then the revenue for asset u during time step t is the maximum output times the electricity price minus its marginal costs. Then the energy output E_i^{out} gets reduced by the level of the maximum output, and the algorithm proceeds to repeat the same loop for all assets u. However, if the energy output is smaller than the maximum output, then the revenue for asset u during time step t equals the energy output in a time step multiplied by the electricity price minus its marginal cost. After this, the E_i^{out} gets set to equal, which will result in all the assets u after the current asset u will have no revenue during that time step. For the vRES, we apply the same logic as stated above; however, the maximum output during a time-step is not the size of a standard asset but rather the output during a time step decided by the capacity factor for that vRES asset divided by the sum of the installed individual assets shown in 3.18. Also, the same logic applies for the storage assets; however, the maximum output during a time step is equal to the standard size of the capacity a storage asset j can utilize to charge or discharge (3.19). During a time step (t), an individual storage asset u can either have positive/negative revenue based on if the asset is charging or discharging.

Now having calculated the cash flow for all individual assets in 3.20 we sum the revenue during all time steps for an individual asset and subtract the fixed O&M costs to calculate the revenue earned by this individual asset u in the energy-only market.

Cash flow capacity mechanism

$$\begin{aligned} &if \quad CF_u^{EOM} < 0: \\ &bid_u^{price} = CF_u^{EOM} \\ &bid_u^{volume} = ss_{j/i} \end{aligned} \tag{3.21}$$

$$D_r = D_{peak} * (1 + r) \tag{3.22}$$

$$D_{peak} = max(d(co,t)) \qquad \forall co \in Co \tag{3.23}$$

$$m = \frac{P_c}{UM - LM} \tag{3.24}$$

$$\begin{aligned} UM &= D_{peak} * (1 + r + um) \\ LM &= D_{peak} * (1 + r + lm) \end{aligned} \tag{3.25}$$

$$\begin{aligned} &\forall u \in U: \\ &if \quad bid_u^{price} =< p^{CM}: \\ &CF_u^{CM} = p^{CM} * bid_{u/v}^{volume} \end{aligned} \tag{3.26}$$

If the capacity market module is turned on, there is a capacity market auction at the end of every year. The way the actors bid on the capacity market is shown in 3.21. In the previous step, we calculated the cash flow for all individual assets. If the cash flow of an asset on the energy-only market is negative, it proceeds to bid on the capacity market. The price the bid is made at is equal to the cash flow earned in the energy-only market (as to compensate for its loss). The volume of the bidding block is equal to the standard size of the asset group j/i of individual asset u.

The demand for capacity is determined by a regulator/government actor. This actor can choose several factors that determine the demand: the installed reserve margin (r), upper margin (um), lower margin (D_peak), and the capacity market price cap (P_c). The first three parameters indicate roughly how much capacity the regulator thinks is needed to ensure system adequacy, and the last parameters indicate how much money the regulator is willing to pay for this. The first step to creating the demand curve for capacity is to calculate the demand requirement (equation 3.22, by multiplying the peak demand with the installed reserve margin. The peak demand is calculated as shown in equation 3.23, we assume that the regulator takes into account the demand for all modeled commodities. The slope of the demand curve is calculated in equation 3.24. The sloping line intersects the horizontal line at Point (X= LM, Y = Pc), this is illustrated in figure 3.27. Then the market is cleared at the point at which the supply and demand meet. Finally, in equation 3.26, all the individual assets who have a bid below the market price get the cash flow of the size of their bid times the market price.

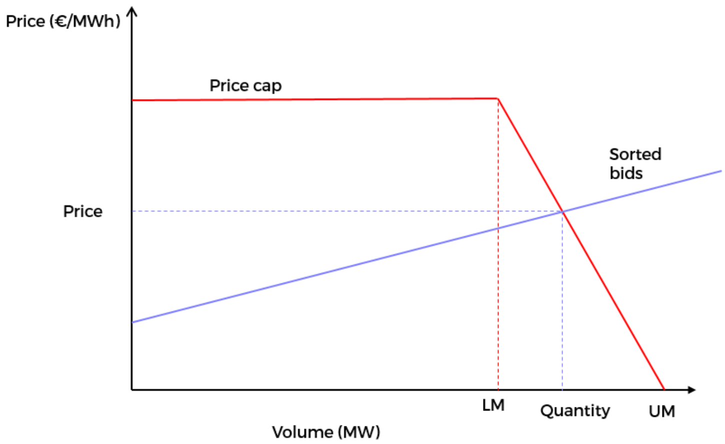


FIGURE 3.27: Capacity market auction (adjusted from Bhagwat, 2016)

Investment budget

$$CF_u(y) = CF_u^{EOM}(y) + CF_u^{CM}(y) \qquad \forall u \in U \tag{3.27}$$

$$budget = budget + \sum_{u=1}^{U} CF(y) - \sum_{u=1}^{U} d_u(y) \forall u \in U \tag{3.28}$$

$$age_u = age_u + 1 \forall u \in U \tag{3.29}$$

In the last part of the present-price part of the code, the model calculates the yearly cash flow earned per individual assets in equation 3.27. Then the algorithm proceeds to calculate the total market has to invest by summing all the yearly cash flows of all individual assets, taking into account any debt that needs to be paid on an individual asset, shown in equation 3.28. Finally, before we go to the investment-decision part of the code, we update all the ages of all individual assets (equation 3.29.

3.3.2 Investment decision part

Figure 3.28 displays the flow-chart utilized in the code that utilizes the present price model logic.

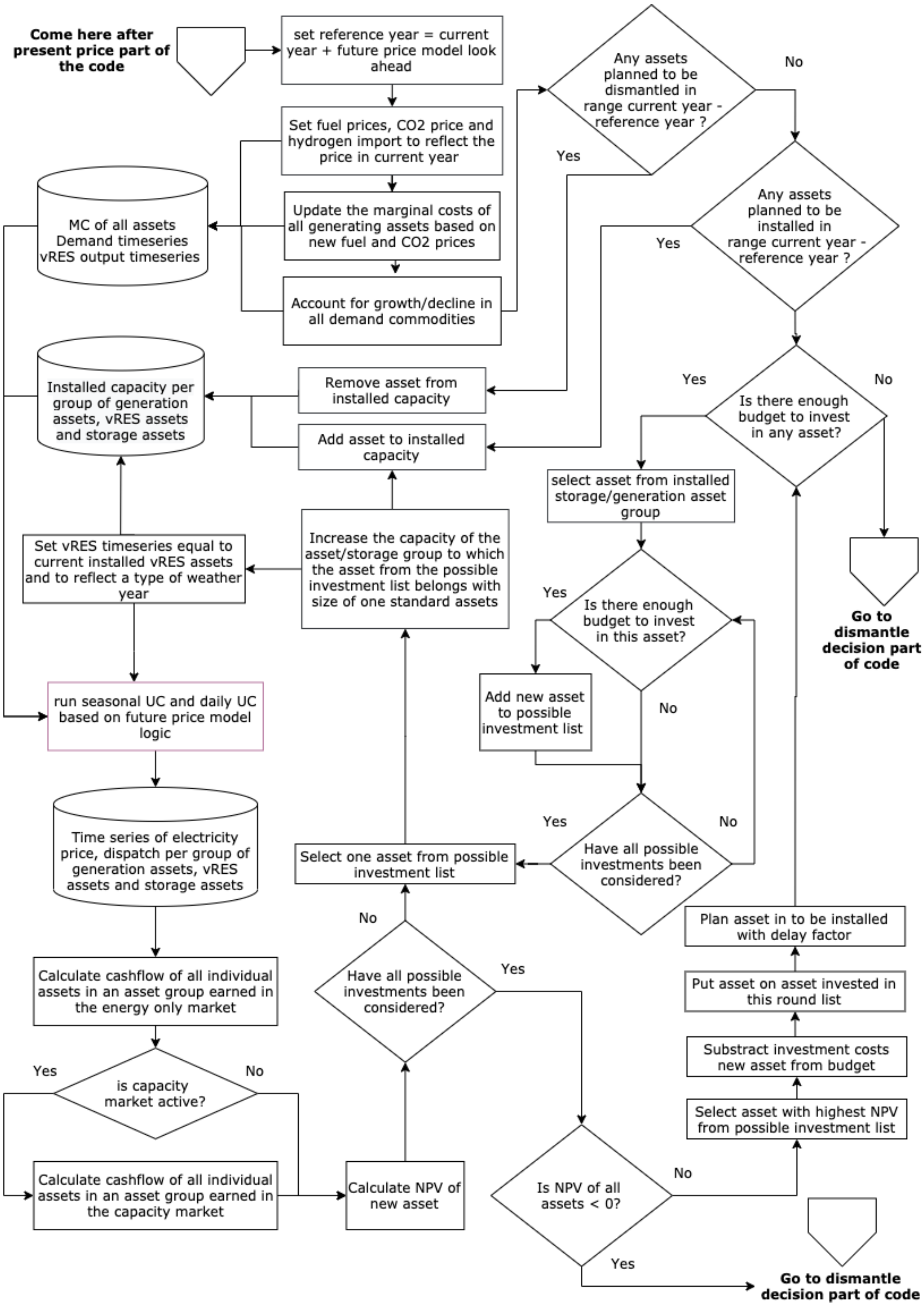


FIGURE 3.28: Investment decision part of the code

Initiating a future price year

$$p^{fuel} = p^{fuel} + (1 + change^{fuel})^{y_{lookahead}} \qquad \forall fuel \in F \tag{3.30}$$

$$y_{ref} = y_{current} + y_{lookahead} \tag{3.31}$$

$$\begin{aligned} &\forall u \in U \\ &if age_u + y_{lookahead} >= age_{i/j}^{technical} : \\ &Ci = Ci - (ss_u)r \end{aligned} \tag{3.32}$$

$$\begin{aligned} &\forall u \in U \\ &if y_{installed,u} <= y_{ref} \\ &Ci = Ci + (ss_i) \;\; or \;\; Cj = Cj + (ss_j)) \end{aligned} \tag{3.33}$$

As we already discussed in the conceptualization of our model, all investments made by the investors are based on a reference year which they assume to represent all future years on which the investment is based. So when initiating a new year in the investment-decision part of the code, we need to perform the same procedure as in equation (3.11- 3.15). However, instead of calculating the change caused by one year, the algorithm the price or demand change for the reference year (3.31) an example of this procedure is shown in equation 3.30. A last vital distinction to be made in the initiation part is related to a weather year. In the PP model at the initiating phase of the code, the capacity factor for all vRES assets gets adjusted based on a weather year. However, the FP model always operates based on the assumption of an average weather year because we assume that investors will not invest based on an 'extreme' weather year that is unlikely to occur.

There are two reasons why an individual asset can get dismantled. One of these reasons is if an asset has reached its maximum technical lifetime. We assume that our investor has knowledge on which assets will be too old to be operational and accounts for this in its assessment of a future market as shown in 3.32.

After an investor has decided to invest in a new asset, the asset does not get installed directly. Instead, it is installed with a delay caused by the construction time and the need to apply for a permit. We assume that our actor knows what assets are currently under construction. So if the installation year of an individual asset is below or during the reference year, the standard size of this asset is added to the overall capacity of the asset group it belongs to reflected by equation 3.33.

Investment loop

$$\begin{aligned} &\forall i \in I, \forall j \in J \\ &if \;\; k_{i/j}^{inv} * f_{equity} >= \frac{budget}{energycompanies} : \\ &add \;\; u \;\; to \;\; possible \;\; investment \;\; list \end{aligned} \tag{3.34}$$

$$CF_u(y_{ref}) = budget + (CF_u^{EOM}(y)) * wd) - (CF_u^{CM} * wt) \tag{3.35}$$

$$CF_u(y = 0) = CF_u(y_{ref}) - (k_{i/j}^{inv} * f_{equity}) \qquad \forall i \in I, \forall j \in J \tag{3.36}$$

$$CF_u(y = 1, .., age_u^{eco}) = CF_u(y_{ref}) - \frac{k_{i/j}^{inv} * (1 - f_{equity})}{age_{i/j}^{eco}} \tag{3.37}$$

$$\begin{aligned}
&\forall t \in T, \forall i \in I, \forall u \in U, \forall i \neq I^{vre} : \\
&E_{i,co}^{max}(t) = ss_i \\
\\
&from\ oldest\ to\ the\ youngest\ u_{thisround} : \\
&if\ \ E_{i,co}^{out}(t) > E_{i,co}^{max} : \\
&rev_u(t) = E_{i,co}^{max}(t) * (p^e - k_i^{MC})(t) \\
&E_{i,co}^{out}(t) = E_{i,co}^{out}(t) - E_{i,co}^{max} \\
&else : \\
&rev_u = E_{i,co}^{out}(t) * (p^e - k_i^{MC}(t) \\
&E_i^{out}(t) = 0
\end{aligned} \tag{3.38}$$

$$NPV_u = \sum_{y=0}^{age_u} \frac{CF_u(y)}{(1+i)^t} \tag{3.39}$$

Now that all the relevant parameters reflect the situation in a reference year, the investor can start investing in an investment round based on an investment loop. The first step in this loop is to calculate if there is enough budget to invest in a new individual asset, displayed in equation 3.34. In this calculation, several assumptions need some clarification. We see that the investment cost of a new generation or storage asset is multiplied by an equity factor (f_{equity}). We assume that every new asset is financed partly directly with the available cash from our investor (the f_{equity}), the other part the actor can lend at the bank and needs to pay back through debt.

On the other side of the equation, we see that the budget is divided by all energy companies. This is because we do not model all individual assets in a market, so one investment actor representing the entire market does all the investments. However, we assume that the maximum available investment budget for an actor's investment equals the budget divided by all energy companies. We have made this assumption because high capital costs of certain assets (e.g., Nuclear) could form a barrier to investment; however, if there is one central actor with all the budget in the market, he could perhaps afford to invest in this asset. While in reality, this would not be the case. So to be clear, our one central investor has access to all the budget; however, within this budget, he only can spend for one new asset what an average energy company in a market could spend. If there is not enough budget to invest in any asset, we go to the dismantle decision part of the code. However, if there is enough budget to invest in at least one asset, the algorithm checks for all assets if there is enough budget to invest in one new asset of that asset group; if this is the case, the asset gets added to a possible investment list.

After this calculation, we now have a list of all investments the investor can afford to build. Now we perform the following part of the code for each of the assets on this list individually. First, we increase the size of the group's capacity (i/j) the individual asset (u) is a part of, with one standard asset. Again, this information is saved as a text file for Linny-R to consider before running the future price model. After this has been done, we update the capacity of the vRES time series with the same equation as in equation 3.16. Then we proceed to run the Linny-R model with the future-price model logic, based on representative days. After running the model, we import the electricity prices to calculate the cash-flows of all assets during our reference year. The logic by which we calculate the cash flow is the same as in the present-price part of the model (equations

3.17-3.26). There are two differences. The first is that in the previous set of equations, the youngest assets always have the first opportunity to earn money from the market (shown in 3.17). In the FP model, however, there is an additional check before the youngest assets earn money. The python script looks if any assets have been invested in, in this investment round $u_{thisround}$, if this is the case, those assets get to earn money first, shown in 3.38. Note that in the logic for the assets in the investment round, not the 'youngest' assets get to earn money first. Because the assets invested at the beginning of an investment round are technically the 'older assets'. Without this logic, our investor would not consider the assets he had invested in in the current investment round. By not considering this, a new investment loop could ruin the business case of his previous invested assets. Also, without this logic, any new investment could have a positive NPV because it simply gets to earn money before any other asset. So the investor would invest in the same investment every investment loop in an investment round. The second difference in generating the cash flow is that the generated cash-flows need to be multiplied by the weight of all the representative days (3.39).

Now that we have the cash-flow for our reference year, we need to calculate the cash-flow during year 0 (equation 3.36) and the cash-flow during all the years of the depreciation time of an asset (equation 3.37). Note that during all the years in the depreciation time of an asset, the investor has to pay back the debt as equally spread out payments over the economic life of an asset. For all the assets that utilize the same weighted average capital costs (WACC) as a discount factor (i)

After calculating the NPV for a new individual asset, we check if we have calculated the NPV of all assets on the possible investment list. If this is not the case, we continue to calculate the NPVs of the assets left. If this is the case, we check if the NPVs of all assets are negative. If this is the case, we go to the dismantle decision part of the code. However, if one or more assets are positive, the model selects the asset with the highest NPV and then subtracts the investment in the new assets (times the equity factor) from the investment budget. Then the model puts the installed asset on the list of assets that have been invested in, in the current investment round. Lastly, the model plans to build the asset with a delay factor equal to its time to build it. We then go back to the beginning of the investment loop until one of the processes sends us to the dismantle decision part of the code.

3.3.3 Dismantle decision part

Figure 3.29 displays the flow-chart utilized in the code that utilizes the decision part of the code.

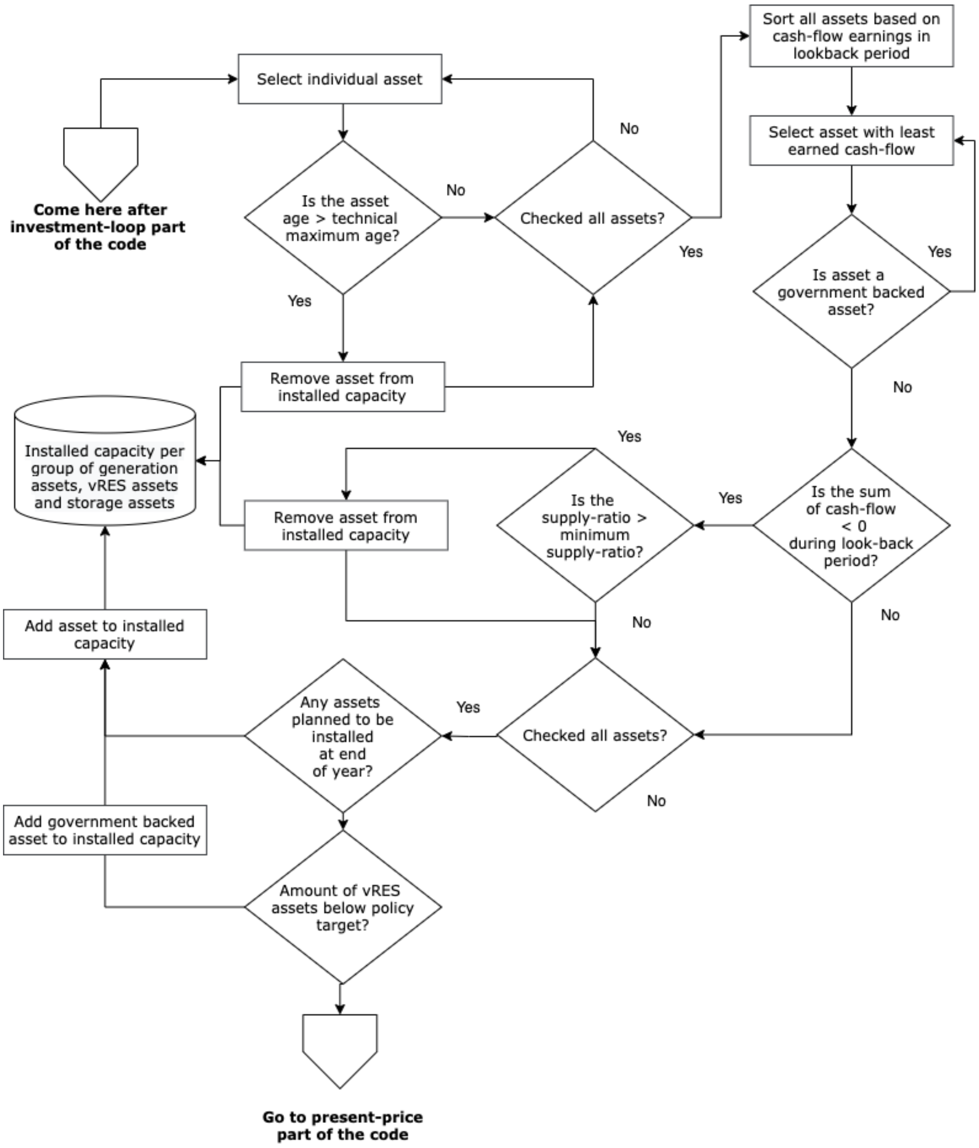


FIGURE 3.29: Dismantle decision part of the code

$$\sum_{y=1}^{y^{lookback}} CF_u \qquad \forall u \in U \tag{3.40}$$

$$sr_{all} = \frac{(Ci) + (Cj)}{\sum_{co=1}^{Co}(max(d(co,t)) - \sum_{t=1}^{T}(cf_i^{vre}(t)))} \qquad \forall i \in I \quad \neq I^{vre}, \forall j \in J, i^{vre} \in I^{vre}, \forall t \in T \tag{3.41}$$

The python script initiates the dismantle loop after the investment loop has no more budget to invest or no attractive investment opportunities. The dismantle loop occurs for all individual assets that are installed. In the first step of the investment loop, the algorithm checks if the age of the asset is bigger than its maximum feasible technical age (the same logic as in equation 3.32). Next, the algorithm proceeds to the sum of the cash-flow earned by all actors in the time equal to the lookback period ($y^{lookback}$). Then the assets get sorted, starting with the assets that have earned the least to the most. Before seeing if an asset can get dismantled, the algorithm checks if the selected asset is a government-backed asset u_g. If this is true, the asset can not get dismantled, and therefore the next asset in the list is chosen. The script then selects the current asset with the lowest cash flow and checks if the cash flow for this individual asset is negative. If this is the case, the asset has been losing money for too long, and the investors get ready to dismantle this asset. However, before this is actually done, the investor proceeds to check if the supply ratio of all the storage and generation assets (sr_{all}) is below the minimum supply ratio (sr_{min}). The minimum supply ratio is a value that the investor himself can decide upon as an investment strategy. Note that the sr_{all} is a different value than the supply ratio, the supply ratio as calculated in **??** only applies to the non-intermittent generation assets.

We argue that if this minimum supply ratio is hit, the investor can reasonably assume that there is a shortage in the market, and therefore there is a high chance that the currently installed assets could have a positive cash flow in the next year. Therefore, if the supply ratio is below the minimum, the asset is not dismantled; otherwise, it gets dismantled. After this has been done for all assets, the algorithm checks if any assets are planned to be installed at the end of the current year. If this is the case, as we are now at the end of the current year, this asset is installed and added to the installed capacity database. Note that this is done for all installation or dismantle decisions, as this information is necessary to run our present-price model accurately in the next year. Finally, the algorithm checks for all renewables if the installed capacity for the upcoming year is below the renewables target i^{vres} set by the government. If this is the case, the government invests in the number of vRES assets necessary to match the set-out policy target. In this fashion, we simulate the current European vRES market, which is strongly subsidized by the government (Khan et al., 2018). After this procedure finishes, the model advances to the beginning of the present price part code.

3.3.4 Investment decision model validation and verification

Simple UC model

Having laid out the logic of the investment-decision model, we now proceed to validate the working of the investment-decision model. In this part of the validation, we want to validate that the logic behind the investment-decision models translates to market dynamics observed in real life. Moreover, we utilize dummy data in a toy model for verification purposes. A run with real-life data has a high computational time and would have many variables to trace; this is not practical following the output of our code and to validate if we have no more bugs left. For this reason, we validate our model by running a simplified UC model. Figure 3.30 shows a conceptualization of our simple UC model.

In our simple UC model, there is only one demand in the form of electricity. The solver ensures that the supply is equal to the demand through one vRES source and the two fossil generators for the least costs possible at all times. Note that the vRES source is a dummy times series not reflecting the real-life generation of a vRES source (such as wind or solar energy). However, the properties of the vRES are similar in that the solver can not turn the vRES on or off; the output of vRES is determined before the model runs through the input data. Storage is represented by a battery with perfect knowledge over the entire run with a round-trip efficiency of 94%. If there is insufficient installed capacity, either the coal plant or the gas plant gets turned on. If there is still not enough electricity to meet demand, a turbine with unlimited capacity produces the remainder of the electricity with marginal costs equal to VOLL. This, in turn, reflects shortage moments during a run. One year has 60-time steps; this is again done to make it simple to follow the model's behavior and limit the computational time.

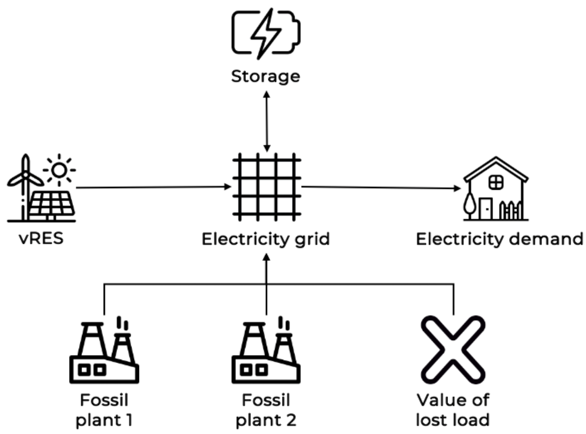


FIGURE 3.30: Simple UC model

The input data for the assets is show in table 3.4 & 3.5. The other model-based inputs are that the model runs for 40 years, the price of VOLL is equal to 400€/MWh, the lookahead is set at five years, the look back is also set at five years, and we assume that there is no supply-ratio minimum. All the other variables that could change over time (e.g., demand growth, technological development, fuel-price costs) are constant. The output data we take into considerations to explain the behavior of the model for all our runs are the average e-price (€/MWh) per year, the supply ratio (installed assets/demand) (MW/MW), and the shortage hours (hours/year).

Asset	Installed capacity year 0	Investment costs	OM costs
VRES	75 MW	40K€	2000 €/year
Coal plant	80 MW	80k€	2000 €/year
Gas plant	40 MW	20k€	2000 €/year
Storage	80 MW	50k€	2000 €/year

TABLE 3.4: Input variables simple UC - 1

Asset	MC costs	Lifetime asset	Installation delay	Age all assets
VRES	0 €/MWh	5 years	1 year	0
Coal plant	50 €/MWh	5 years	1 year	0
Gas plant	150 €/MWh	5 years	1 year	0
Storage	0 €/MWh	5 years	1 year	0

TABLE 3.5: Input variables simple UC - 2

Simple UC model validation

In our first validation run, we will run the model as if only an energy market exists, so assets can not bid on the capacity market. We have two hypotheses that we want to confirm in our validation runs. The first is that if the investment-decision script behaves as expected, it should reflect myopic investment behavior, leading to investment cycles. In these investment cycles, we should see periods of over shortages, which lead to an increase in the investment budget, followed by periods of oversupply, causing lower electricity prices, and finally dismantling assets due to these lower prices. The second hypothesis is that all parameters are constant over time, so we expect equilibrium to emerge in the market with an asset portfolio that fits that equilibrium.

The results of this run are displayed in figure 3.31. The results confirm our first expectation, a classical investment cycle with oversupply and shortages, clearly observed from the results. We start this run with a small amount of oversupply with a supply ratio of 1.2, as can be seen in the middle figure in 3.31. However, after five years, the supply ratio significantly drops from 1.7 to 0.8. This behavior is because all initially installed assets start with the same age (0 years old) and have a lifetime of 5 years. So in the fifth year, all assets that were initially installed are dismantled. This dismantlement causes a significant rise in the average electricity price in year five from 50€/MWh to 175 €/MWh, shown in the image on the left in figure 3.31. However, if all initial assets were dismantled, a logical expectation might be that the electricity price would rise to the level equal to the VOLL (400 €/MWh). This rise in electricity price does not occur because the assets are already dismantled in the reference year on which the investor bases the investments. This forward look is why in the third year, the supply ratio rises from 1.2 to 1.7, and this explains why the electricity prices during year five are below the VOLL. Even though the electricity prices are below VOLL, they are high in year five, raising the investors' investment budget. This causes the investors to invest until the supply ratio is enough to fill all demand fully and there are no more hours of shortage. In line with our second hypothesis, we see a stable behavior emerge after an initialization time of ten years where the model is starting up. After this point, we see roughly every fifteen years the same investment cycle occurring.

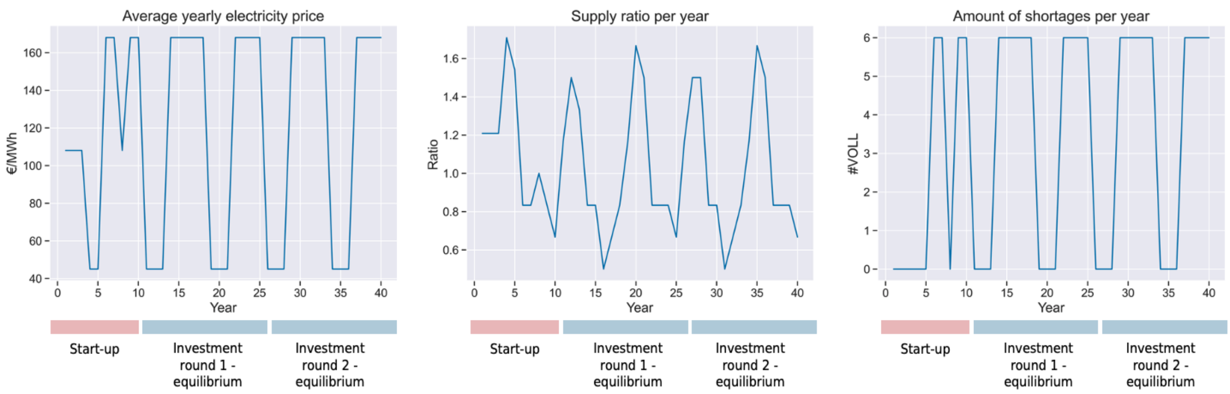


FIGURE 3.31: Energy only market - validation runs

In our second validation run, we look at the impact of a run with and without a capacity market. In this run, all the input variables are the same as the previous validation run, with the only exception being that we changed the VOLL to 250 €/MWh. During this run, we implement a capacity market with a high willingness to pay for extra demand; we have set this value so high that all assets in need of recouping their loss can do so. In reality, such an extreme capacity market is unlikely to be implemented, however for our validation run, we simply want to see if our model performs as expected in such a scenario. For this validation, we again have two hypotheses that we would like to validate. Firstly, if the script is executed as expected in the capacity market, the shortage moments in the energy-only run should be higher than in the capacity market. Moreover, the energy-only run should have a higher average yearly electricity price and a lower yearly supply ratio due to this effect.

In our second validation run, we look at the impact of a run with and without a capacity market. In this run, all the input variables are the same as the previous validation run, with the only exception being that we changed the VOLL to 250 €/MWh. During this run, we implement a capacity market with a high willingness to pay for extra demand; we have set this value so high that

all assets in need of recouping their loss can do so. In reality, such an extreme capacity market is unlikely to be implemented, however for our validation run; we simply want to see if our model performs as expected in such a scenario. For this validation, we again have two hypotheses that we would like to validate. Firstly, if the script is executed as expected in the capacity market, the shortage moments in the energy-only run should be higher than in the capacity market. Moreover, the energy-only run should have a higher average yearly electricity price and a lower yearly supply ratio due to this effect.

The results of this run are displayed in figure 3.32. If we look at both the capacity market and energy, we see different behavior emerging in the first ten years of the run. In the energy only run, we start with a supply ratio of 1.1, and we see this drop-down to 0.0 after then years. This has two reasons. Firstly, all the assets have a technical lifetime of ten years, so all the initially installed assets are dismantled after ten years. Secondly, the investors have a lookback period of three years in which they determine if an asset has been making a profit in those years. If this is not the case, the asset gets dismantled. This explains how after six years already, the supply ratio drops from 1.1 to 0.5. Comparing this with the run with the capacity market, we see completely different behavior; at the ten-year mark, we have an extremely high supply ratio of 3.2. This is caused by the fact that during the first ten years, the investment budget keeps of the investors keeps on increasing due to the fact that any potential loss is recovered in the capacity market. The reference year on which the investors decide to invest is set seven years ahead of the current year. So the investors see that after year 10, assets get dismantled due to their technological age. Having anticipated this effect, the investors already start investing in assets so that once the assets get dismantled in year ten, the number of shortages in a year is significantly shorter. This behavior can be clearly observed in figure 3.32, where we see that for the capacity market after the first ten years every ten years, there are some moments with shortages due to assets being dismantled because of their age. In the energy-only market, we see significantly more years with deficits.

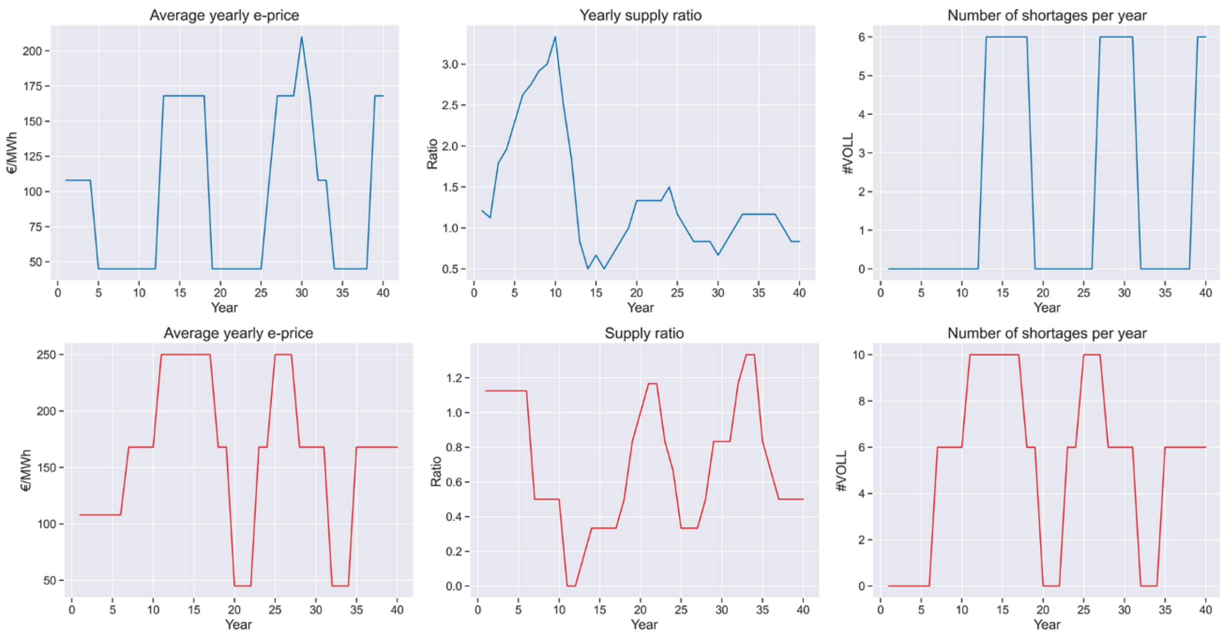


FIGURE 3.32: Energy only market (blue) and capacity market (red) - validation runs

Chapter 4

Case explained: Dutch energy transition

In this thesis, we will apply our proof of concept for the case of the Dutch energy transition. In this chapter, we will describe the input values utilized in our case. We have two different sets of input values. The fixed input values as described in section 4.1. These input values do not change between different scenarios, and we assume these to be constant. The variable input values in section 4.2.1 form the basis of the uncertainty space in this thesis. These are changed in our scenario analysis in chapter 5.

4.1 Fixed input values

4.1.1 Model input values

Table 4.1 shows the standard input values we utilize in the ID sub-model and 4.2 displays the standard input values for present-price and future-prices model. These values are utilized in all runs unless specified otherwise.

The case on which we we apply the MIDO model is the case of the Dutch energy transition. We look at the Dutch energy transition, and we simulate our runs from 2030 till the year 2050. This time frame is chosen to determine the impact of a capacity mechanism on the security of supply we need to simulate multiple decades. Moreover, we want to see how the model behaves in a situation with a high degree of installed vRES. However, we also want to limit our computational time and simulate 20 years, as we can reach our above two objectives within this time frame. The lookahead, lookback period, equity factor, and WACC are all based on Bhagwat (2016) and Richstein (2015). In the scientific literature there is a lot of discussion on the appropriate price for VOLL(Anderson and Taylor, 1986; Baarsma and Hop, 2009; Leahy and Tol, 2011; Linares and Rey, 2013) mostly depending on the location and the nature of the load sources. With values ranging from 2000 €/MWh to 6000 €/MWh (Bhagwat, 2016). Therefore, we assume that the VOLL is equal to 4000 €/MWh.

To calculate the maximum-investment that can be made by our central investor, we need to know the number of energy-companies in a country. As explained in 3.3.2, the maximum investment our central investor can make in a new asset is capped by the equity it would have if there where also other market players available. In the Netherlands, there are currently more than 60 energy companies; however, the market is dominated by three big energy companies who have 75% of the market (Consumentenbond, 2019). For this reason, we assume in our thesis that three energy companies always have an equal share of the market.

The input values that are related to the capacity market, so the upper margin, lower margin, reserve margin, maximum price are all based on the values utilized by Bhagwat (2016). The values in Bhagwat are based on the NYSO-ICAP, on which our capacity market is also based. As explained in section 3.3.3 our central investor dismantles assets, until a minimum supply ratio is reached. Our central investor assumes that if the minimum supply-ratio is reached the installed assets will make a profit in the next year, so dismantlement is not necessary. The minimum supply ratio in our runs is based on looking at the lower limit supply ratios that have been observed in Bhagwat (2016) and Khan et al. (2018); these values were at 0.8 at their lowest. We have set our minimum higher as the values observed in those research were the lowest based on a different bidding strategy, where investors did not have a minimum supply ratio. In their logic as a final step before dismantling an asset, an investor would simulate if an asset was able to make a profit the following year. If this was the case, these assets would not be dismantled. We have not included this final step, and only dismantle based on the cash-flow of the past five years. So this would mean that in our model in the dismantle-loop our central investor would dismantle an asset earlier than in the studies on which we base our minimum-supply ratio. So by setting the minimum-supply ratio a bit higher than the observed minimum supply-ratio, we give our investor a chance to recoup some of the investments made.

Lastly, we need to determine what the investment budget of the market is in our first year. In choosing this budget, we wanted the investors to have enough budget to invest in all assets, except for the nuclear asset, as most companies do not have the budget to invest in a Nuclear plant. For this reason, we chose the initial investment budget to be equal to three times the value of the initial investment costs of the most expensive asset (after the nuclear asset), leading to an initial investment budget of 3900M € for the market.

Table 4.1 shows the input values for the look-ahead and block-length in the UC models we have utilized in the FP and PP model. The input values for the daily UC in the FP models are based on the representative days; the daily model can not optimize two consecutive representative days. As in reality, there are many days between these two days. The daily UC can optimize three days for the PP model with a look ahead of three days to reflect the daily-to-weekly range of lithium-ion batteries. The input values for the seasonal UC model in both the FP and PP-model enable the model to optimize over half a year time, reflect the ability seasonal character of hydrogen storage. The value of 288 reflecting a half-year means that we work with 24 representative days in our model.

Input	**Value**
Simulation years	20 years
Look ahead	7 years
Lookback period	4 years
Energy companies	4
Equity factor	30%
Upper margin	2.5%
Lower margin	2.5%
Reserve margin	9.5%
Max price capacity mechanism	60 K€
Minimum supply ratio	0.93
VOLL	4000 €/MWh
WACC	9%
Budget in year 1	3900 M€

TABLE 4.1: Overview standard input values in the model

Sub-model	Type of UC	Block-length	Look-ahead
FP-model	Daily UC	24	0
PP-model	Daily UC	72	72
FP-model	Seasonal UC	168	168
PP-model	Seasonal UC	288	288

TABLE 4.2: Standard input values UC models

4.1.2 Standard generation and storage assets

As explained in chapter 3 the investment algorithm is only able to invest in standard assets sizes. The standard electricity-producing assets and storage assets are displayed in table 4.3 and 4.4. The standard size of generation assets is based on Bhagwat (2016), and the standard size of the storage assets is based on our own assumptions. In these assumptions, we have assumed that if investments occur in storage assets, they will be roughly in the same order of magnitude as small generation assets. Moreover, every additional asset that is added to the standard generation and storage asset increases the computational time significantly as, during every investment round, the FP model needs to run again to compare the investment potential of this asset. Based on this consideration, we developed four types of storage assets for our central actor to invest in. These assets are intended to reflect all the different types of storage needs the system might have. We have displayed these in figure 4.1.

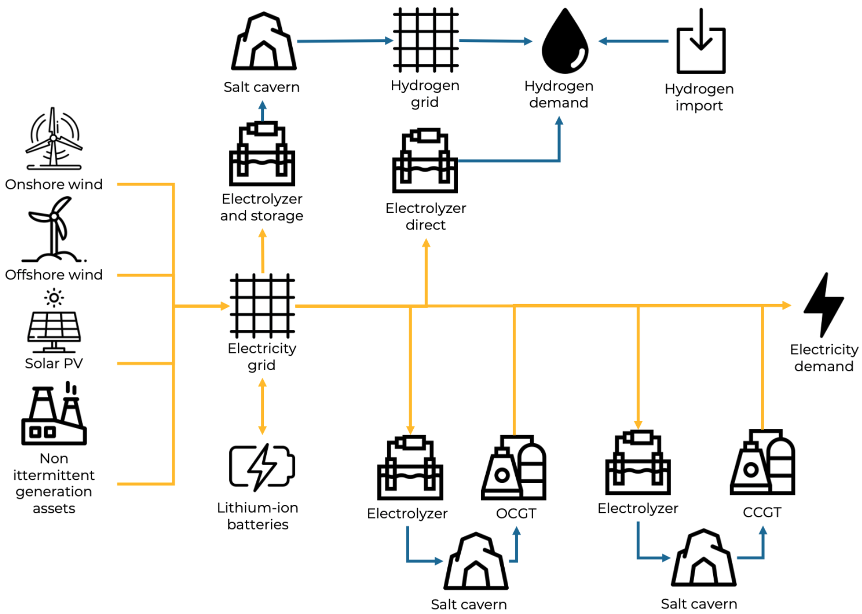


FIGURE 4.1: Conceptual overview of all standard generation and storage assets

First, the only form of daily storage our central actor can invest in are lithium-ion batteries. For the seasonal storage, the actor has three choices. The first asset type is an electrolyzer only utilized to store hydrogen for seasonal storage. This asset is utilized to store hydrogen and then, at a later point, use the stored hydrogen to match hydrogen demand, so no additional conversation into electricity is possible within this asset. The second asset is electrolysis, combining an OCGT asset with hydrogen as its only form of input fuel. This asset is utilized for peak long-term flexibility need. The last asset is CCGT in combination with electrolysis. This asset can be utilized if there

Gen-eartion asset	**Standard size (MW)**	**Fixed OM (%)**	**Efficiency (%)**	**Con-struc-tion time (years)**	**Technical lifetime (years)**	**Deprecia-tion (years)**	**Fuel**
Nuclear	1000	4	33	9	60	25	Ura-nium
Gas CCGT	800	4	60	3	45	15	Natural gas
Gas CCGT CCS	800	4	52	4	45	15	Natural gas
Gas OCGT	200	4	41	2	45	15	Natural gas
Biomass	500	5	42	4	40	15	Biomass
Wind Onshore	600	4	-	2	25	15	-
Wind Offshore	600	4	-	3	25	15	-
Solar PV	600	2	-	3	25	15	-

TABLE 4.3: Standard generation assets

are any long-term seasonal flexibility needs. In all these assets, the investors invest in the same amount of electrolyzer as in the other utilized asset. So a standard hydrogen OCGT electrolysis asset consists of 200MW electrolysis and 200MW CCGT asset. Note that the reservoir size of all hydrogen assets is set at infinity; we assume that there is enough storage in salt caverns possible to store the created amount of hydrogen by an asset if necessary. The costs to store hydrogen in salt caverns in the Netherlands ranges between 2.5 - 3.4 €/MWh (TNO and Berenschot, 2017.) The investor considers these costs when deciding if they should invest in any of the standard storage assets. Lastly, what is not visible in this chart is that there is also an electrolyzer with a capacity set equal to the peak demand of hydrogen commodity in a given year in our model. The investors do not invest in this electrolyzer in our model; instead, we assume that the industry owns these, buying the electricity to create hydrogen themselves.

The other technical assumptions in table 4.3 and 4.4 are based on Pietzcker, Osorio, and Rodrigues (2021), Haller, Ludig, and Bauer (2012), Markewitz, Robinius, and Stolten (2018), Schmidt et al. (2019), Reuß et al. (2017), and Bhagwat (2016).

Storage asset	**Standard size (MW)**	**Reservoir size (MWh)**	**Fixed OM (%)**	**Roundtrip efficiency (%)**	Con-struc-tion time (years)	**Technical lifetime (years)**	**Deprecia-tion (years)**
Lithium-ion batteries	200	258	1	94	2	15	10
Electrolysis + storage	400	Inf	1	70	2	20	15
Hydrogen CCGT + electrolysis	700	Inf	5	39	3	30	20
Hydrogen OCGT + electrolysis	400	Inf	4	27	2	30	20

TABLE 4.4: Standard storage assets

4.1.3 Merit order in 2030

To gather the installed generation and storage assets data in our starting year 2030, we utilize the estimation of Kalavasta made on behalf of Netbeheer Nederland (the trade association for electricity and gas network operators in the Netherlands). This estimation is intended to display a technical target of what would happen if the current policy plans as agreed upon in the Dutch Climate Agreement were realized. (Kalavasta, 2019). Therefore, it provides a good starting point for the system if all current plans are carried out. Again, this data can be accessed through the ETM (Quintell, 2021). All the individual assets associated with an asset group in the merit order have an age-based on historical data on when these assets were installed or based on their projected installement. For an overview of the distribution of all individual assets, we refer to appendix D.2.

Asset	Installed capacity (MW)
Solar PV	26600
Wind onshore	6000
Wind offshore	11400
Nuclear 3rd gen	0
Gas CCGT	14400
Gas OCGT	7800
Biomass	500
Hydrogen CCGT	0
Hydrogen OCGT	0
Gas CCGT CCS	0
Electrolyser + storage	2000
Electrolyser + CCGT	0
Electrolyser + OCGT	200
LiOn batteries	2142

Asset	Storage (MWh)
LiOn batteries	5160
Hydrogen storage	Infinite

TABLE 4.5: Merit order in year 2030 based on (Kalavasta, 2019)

4.1.4 Fuel price and technological development

Table 4.6 shows the development of all the fuel prices utilized in our thesis. The baseline projections values of the fuel prices are based on Pietzcker, Osorio, and Rodrigues (2021) and Strefler et al. (2021). Note that after 2050 all prices are assumed to be constant.

Fuel prices	2030	2035	2040	2045	2050	2050+
Natural Gas (€/GJ)	7.1	7.8	8.3	8.4	8.9	8.9
Uranium (€/GJ)	1.0	1.2	1.4	1.7	2.0	2.0
Biomass (€/GJ)	6.0	8.0	12.0	16.0	20.0	20.0

TABLE 4.6: Baseline projection values fuel prices

For the technological development, there are only a limited group of assets whose price changes, as shown in table 4.7 and 4.8. We assume that the assets that are not mentioned have already reached technological maturity. For this reason, no significant cost reduction will be realized in these assets. The technological development rates are based on Schmidt et al. (2019), Saba et al. (2018), Pietzcker, Osorio, and Rodrigues (2021), Capros et al. (2012), and Strefler et al. (2021). We assume that after 2050 all these assets have also reached their technological maturity.

Investment costs (€/kW)	2030	2035	2040	2045	2050+
Gas CCGT CCS	1700	1600	1550	1500	1450
Wind onshore	1137	1062	987	955	923
Wind offshore	2102	2000	1900	1800	1700
PV	395	357	340	332	326

TABLE 4.7: Investment costs development for assets

Technology	Type of cost	2030	2035	2040	2045	2050	2050+
Batteries	Power (€/kW)	156	122	108	102	95	95
	Reservoir (€/kWh)	184	144	128	120	112	112
Hydrogen Electrolysis	Power (€/kW)	662	629	596	563	530	530

TABLE 4.8: Investment costs storage related assets

4.2 Variable input values

4.2.1 Scenarios storylines

It is currently uncertain how a 2050 100% RES market will look. For this reason, The Ministry of Economic Affairs, all the Dutch DSOs, TSO and GSOactors have developed four energy scenario's meant to represent "the extreme corners in which the energy transition can take place" (Wiebes, 2020). In our thesis, we take two scenarios with strongly different natures from these extreme corners and compare the role of capacity mechanisms for both these scenarios. In this paragraph, we will explain the storyline behind both scenarios; for an overview of the more technical assumptions behind these scenario's we point to appendix D.8.

The first scenario we will look at is the 'National Governance' (NG) scenario. The storyline of this scenario is that in 2050 the Netherlands is based 100% on vRES and has a high degree of self-sufficiency regarding its energy sources. For this reason, there are no imports from other countries possible. In this National Governance, the renewable targets are realized by subsidies funded by the Dutch Government who plays an active role in this transition. Moreover, there is not a developed worldwide hydrogen market. So import of hydrogen is costly and therefore not utilized. The second scenario is the 'European Governance' (EG) scenario. In this scenario, Europe achieves CO_2 targets and is the world leader in this regard. Europe enables this by enforcing very high CO_2 prices. Because of these high CO_2 prices, the Dutch government does not need to en state high subsidies. Lastly, because of this central Europe position towards renewables, a highly developed world hydrogen market emerges. This means that importing hydrogen becomes available at a feasible price.

In looking at these two scenarios, we aim to provide insights into the functioning of a capacity market with seasonal storage in two extremes.

First, the NG has a strong national character, and therefore the security-of-supply is strongly dependent on national supply. Next, government-provided subsidy adds to the risk regarding the security of supply, as this will lower the electricity price in line with the merit-order effect, thus pushing assets out of the market. Therefore, this could give an insight into a future where a capacity-market where a capacity market has the most added value.

Second, the EG scenario is strongly international orientated. Due to this reason, the energy system can strongly rely on external imports to guarantee their security-of-supply. Here we assume that there is a global hydrogen market. So even if there is a Dunkelflaute, for example, hydrogen import is still possible at the necessary level to guarantee the security of supply. However, we limit the effect of import, partly because we only allow the import of hydrogen for direct consumption. Also, there is no vRES subsidy, so fossil-backed assets can more easily guarantee security-of-supply if the market decides not to invest in vRES. For these reasons, this shows insights into the functioning of a capacity market in a system where it might not be needed as much as the first scenario.

4.2.2 Demand development

As can be seen in table D.8, all assumptions point towards solid growth in electrification and demand for hydrogen in industry, but also other sectors such as heating and mobility. These assumptions are visible in the comparison of the electricity and hydrogen demand in 2030 and 2050 in figure 4.2. The data for the 2030 electricity and hydrogen demand is based on a study done by Kalavasta (Kalavasta, 2019), which is the same study utilized for the merit order in 2030. The data behind this study is open-accessible in the ETM model by Quintell (Quintell, 2010). The electricity and hydrogen data of 2050 can be is based on the NG and EG scenario, which can also be accessed in the ETM model (Quintell, 2010). In our thesis, we assume linear growth from 2030 till 2050. This means that in the NG scenario, we have a yearly electricity demand growth of 2.25% and yearly hydrogen demand growth of 13.8%. In the EG scenarios, these rates are 2.87% for electricity and 16% for hydrogen.

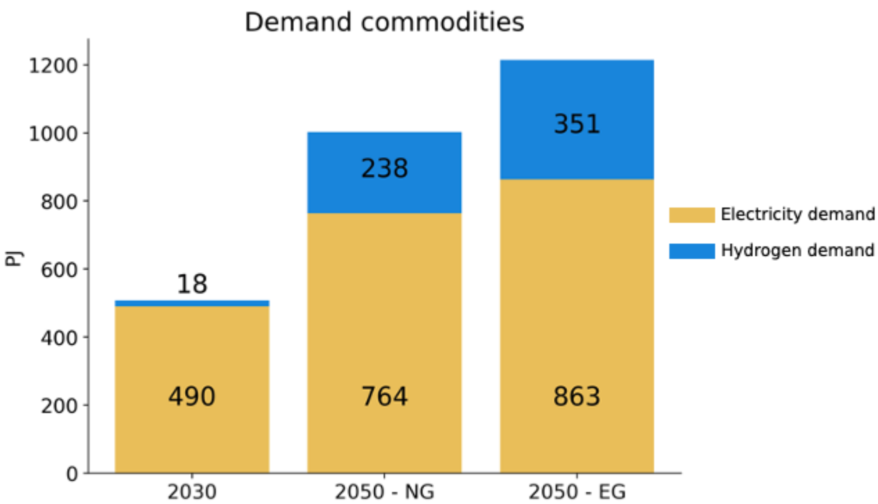


FIGURE 4.2: Demand commodities in 2030 and 2050

4.2.3 Subsidy, CO_2 price & hydrogen import

The other main difference between the NG and EG scenarios can are found in the three areas. Firstly, in the NG scenario, the Dutch government is strongly involved in steering the energy transition, and for this reason, the subsidy module as shown in 3.3.3 is turned on. The policy targets are a linear growth between the merit-order that is the starting point of our runs (table 4.5) and the 2050 merit order in the NG scenario, as shown in table 4.9 (Ouden et al., 2020).

Asset	**Policy target 2050**
Solar	71600
Onshore	20000
Offshore	40200

TABLE 4.9: Policy targets 2050 NG scenario

In the EG scenario, a high CO_2 price incentivizes investment in low CO_2 investments; for this reason, there are no additional subsidy investments. Second, there is a difference in the CO_2 price. As can be seen, the CO_2 price in the EG scenario is significantly higher than in the NG scenarios. The values for the high CO_2 price are based on Fragkos et al. (2017) and Capros et al. (2012), and the low CO_2 price scenarios are based on (Lechner and Steinmayr, 2011). Lastly, the hydrogen import price. During the NG scenario, no global hydrogen market emerges, so in this scenario, no hydrogen import is possible. For the EG scenario, we utilize the same assumptions as in the ETM model (Quintell, 2010). An important point to be made for the import of hydrogen is, as shown in our conceptualization in 4.1 that we model the Netherland as an isolated electricity system. For this reason, we assume that the imported hydrogen can not be stored or utilized to balance the electricity system. In our isolated electricity system, this can only happen through locally produced hydrogen.

Scenario	Category	2030	2050
NG	CO_2 price (€/ton)	35	100
EG	CO_2 price (€/ton)	60	200
NG	Hydrogen import	No	No
EG	Hydrogen import (€/MWh)	60	40
NG	Subsidy	Yes	Yes
EG	Subsidy	No	No

TABLE 4.10: Difference input values EG and NG scenario

4.2.4 VRES and Weather profiles

In our thesis, we will make use of two types of weather years; figure 4.3 shows the comparison between the amount of full-load hours in the different weather years.

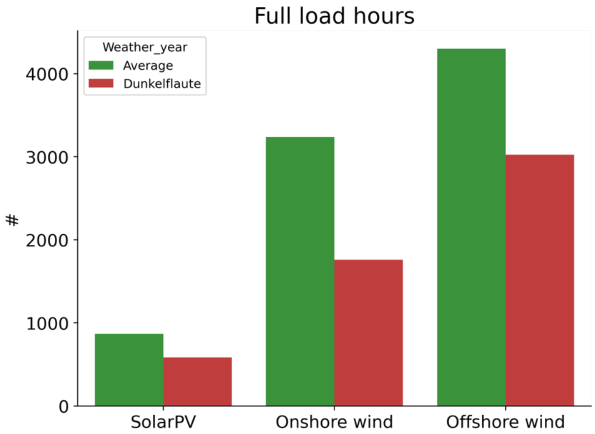


FIGURE 4.3: Comparison of full load hours in average weather year and Dunkelflaute weather year

The time series for all the weather profiles are based on created the ETM model. The ETM model can generate a time series of electricity output for any weather scenario based on an installed capacity of vRES. These generated time series, in their turn, are all based on data from the Royal Netherlands Meteorological Institute (KNMI) (Quintell, 2010). The average weather year profiles reflect the output of vRES assets during regular weather years. Given that sometimes there might be, e.g., more wind and another year there might be less, we assume that these effects should cancel each other out over the long term, and therefore our 'average' weather profile is representative. However, some extreme outliers could severely impact the security of supply during the energy transition. An example of this could be a Dunkelflaute, where there are several weeks where vRES can generate little to no energy. The Dunkelflaute utilized in this thesis is based on a 1997 Dutch weather year where there was a Dunkelflaute for almost the whole month of January and a windless period in November.

4.3 Model key output indicators

The key-output values of the model can be seen in table 4.11. The indicators have two key focuses: the costs and the security of supply. The first group of indicators focuses on the security of supply in our energy system. These are the number of shortage hours that occur in a year, the total volume associated with these shortages, the volume of the capacity reimbursed in some form of capacity remuneration mechanism, and the residual supply ratio. The residual supply ratio is calculated as shown in equation 4.1. The maximum residual supply ratio equals the total installed capacity of all non-intermittent generation assets divided by the residual load. Thus, the residual load is equal to the peak demand that is not served by intermittent generating assets. The minimum residual supply ratio equals the total installed capacity of generation asset assets divided by the residual load. Thus, the residual load is equal to the peak demand that is not served by intermittent generating assets.

The second group of indicators focuses on the costs part of the system. These are the average electricity price in a year, the cost incurred by the consumer due to the capacity that is reserved through the capacity mechanism, and the overall cost to the consumer. The overall cost to the consumer consists of the price paid for the need for any form of a commodity that is modeled and the capacity market.

$$sr_{gen} = \frac{(Ci)}{\sum_{co=1}^{Co}(max(d(co,t)) - \sum_{t=1}^{T}(cf_i^{vre}(t)))} \qquad \forall i \in I \quad \neq I^{vre}, \forall j \in J, i^{vre} \in I^{vre}, \forall t \in T \tag{4.1}$$

$$TC_{consumer} = TC_{demand} + TC_{subsidy} + TC_{CM} \tag{4.2}$$

Metric	**Unit (all per year)**	**Focus of indicator**
Number of shortage hours	(h)	Security of supply
Supply ratio	(MW/MW)	Security of supply
Average electricity price	(€/MWh)	Cost
Total costs subsidy	€	Cost
Total cost capacity market	€	Cost
Total costs to match demand	€	Cost
Total cost for consumer	€	Cost

TABLE 4.11: Total system costs installed storage

Chapter 5

Results

This chapter lays out the results generated by the MIDO model for our case, as described in the previous section. In section 5.1 we perform a sensitivity analysis. We then move on to show the results of the different scenarios in section 5.2. Finally, we compare the output of the MIDO model with a scientifically established myopic investment model in section 5.3.

5.1 Sensitivity analysis

This section performs a sensitivity analysis to see how the model's output changes under the three most significant influences on investment decisions: demand, price, and VOLL. As we have discussed before, the run-time of our model is high, and we are limited in our computational power in the scope of our thesis. For this reason, instead of modeling the ordinary twenty years for a run, we only model twelve years for the sensitivity analysis. We assume that the model will have enough time to have at least one major investment cycle in these twelve years. These cycles are where most investment decisions happen and what influences the results of the model the most. To minimize the uncertainty, we keep all parameters (e.g., fuel-price change, demand growth, and technological development) equal over time unless specified otherwise. All our runs will start with the 2030 input data for the NG scenario as laid out in the previous chapter. The only difference is that the actors have no investment budget in year 0. Table 5.1 shows the sensitivity analysis we will run.

Run	Prices	Demand	VOLL (€/MWh)	CM
1	No change	No change	4000	No
2	No change	No change	2000	No
3	No change	No change	6000	No
4	Baseline projection	No change	4000	No
5	Baseline projection +20%	No change	4000	No
6	Baseline projection -20%	No change	4000	No
7	No change	Baseline projection	4000	No
8	No change	Baseline projection +20%	4000	No
9	No change	Baseline projection - 20%	4000	No

TABLE 5.1: Overview of all the sensitivity runs

5.1.1 VOLL sensitivity

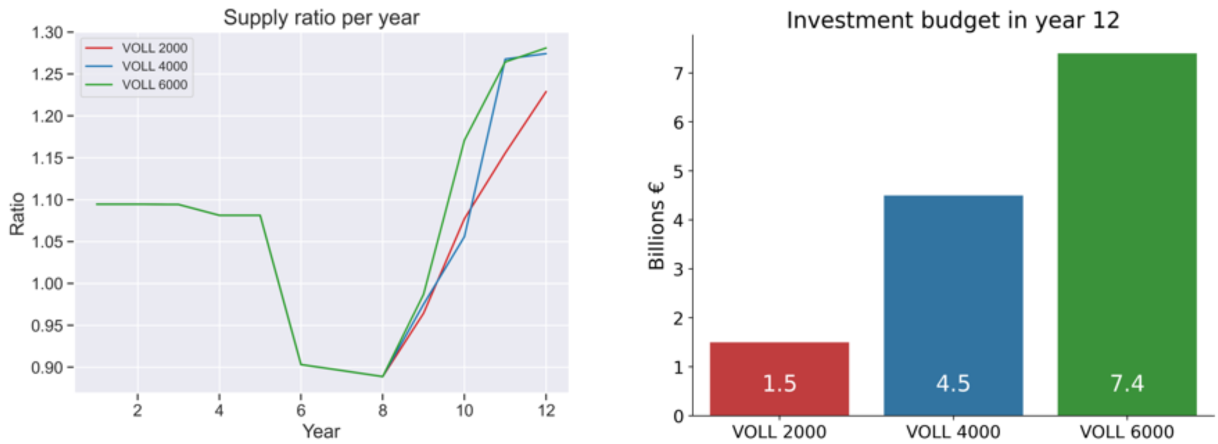


FIGURE 5.1: Supply ratios during sensitivity analysis (left) and the investment budget investors have at the end of year 12 (right)

The left-hand side of 5.1 shows the supply ratio during the three performed runs. Here we see that the model behaves the same for all runs during the first eight years. This is because we start the model run with zero investment budget, and no other factors change. Since we start in an oversupply, the model does not earn enough money to invest and pay of the debt of the currently installed assets at the same time. So the behavior for the three runs is the same for the first five years. After these five years, the model starts dismantling assets because of the look-back period where assets lose money due to this oversupply. Due to this, a shortage arises in the market, and the difference in VOLL plays a role. In the case of 6000 VOLL, the market can invest more aggressively because the shortages create the budget. However, what we also see is that the VOLL 4000 catches up. This is because, during the dip, the investors have enough budget to invest up to the point that the NPV of a different asset is not profitable anymore, which leads both investors to invest to around 1.26 supply-ratio. We also see that in the case of the low VOLL 2000, there is still enough budget to invest up to 1.20 supply-ratio. However, we do see that this happens at a slower pace. Nevertheless, the most significant effect of this single shortage can be seen in the investment budgets that the investors have leftover after year 12. Here we can see that when comparing the VOLL of 2000 with VOLL of 6000, the investors have almost five times more budget to invest after 12 years. Meaning that there is far more capital for investors to anticipate and, in turn, prevent a shortage. However, on the flip side of this, this enables investors in the VOLLL 6000 to over-invest far more and make the supply ratio more volatile.

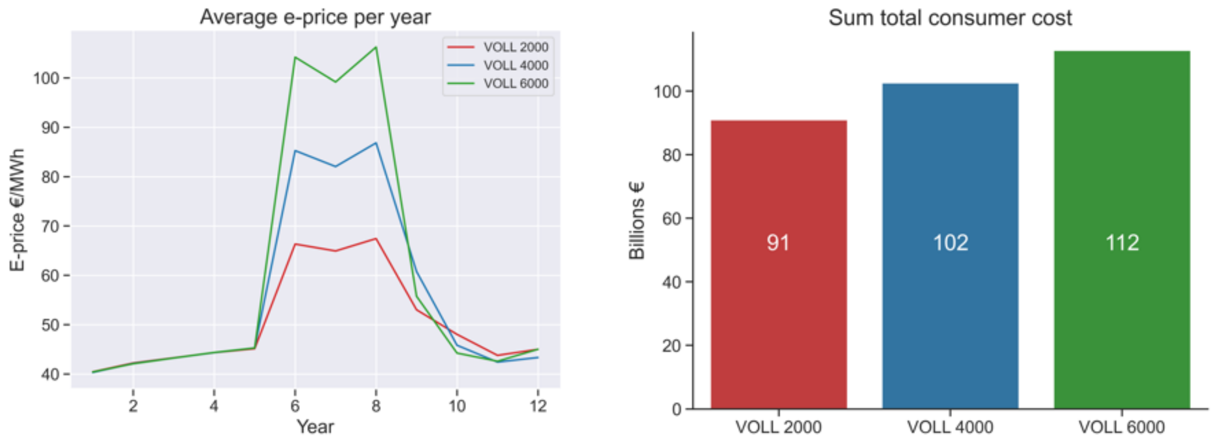


FIGURE 5.2: Average e-price per year (left) and the sum of total consumer costs (right)

What can also be seen from the sensitivity run is the relation between the e-price and the sum of total consumer costs. If the VOLL increases, the e-price during a shortage is higher, directly impacting the total consumer costs.

5.1.2 Fuel and CO_2 price sensitivity

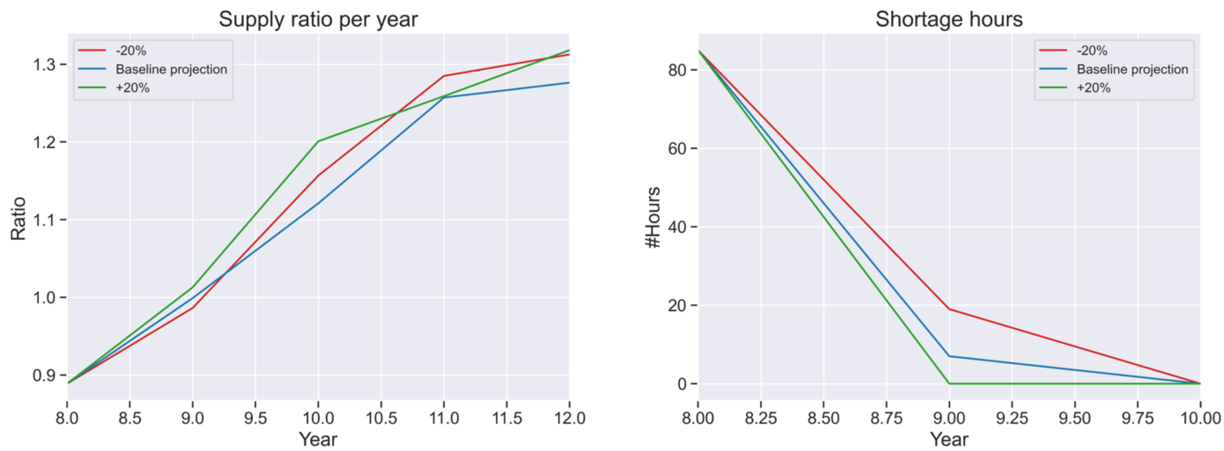


FIGURE 5.3: Supply ratios during sensitivity analysis e-price (left) and the shortage hours (right)

We only display the results after the first eight years as the most noticeable effects happen here. We are looking at the supply ratios (left) for the different electricity prices; the investor has more budget to invest due to higher electricity prices. This higher budget increases their investment opportunity. This can be seen in the number of shortage hours on the right-hand side. In year 9, in the case of 20% higher prices, there are no shortage hours left; in the baseline, there are still has a few shortage hours left, and in the case of -20% lower prices, there are the most shortage hours left. Because the -20% run has the most shortage hours, this gives the investors enough budget to invest, and this results in the supply ratio in year 12 where the +20% and -20% have the same supply ratio.

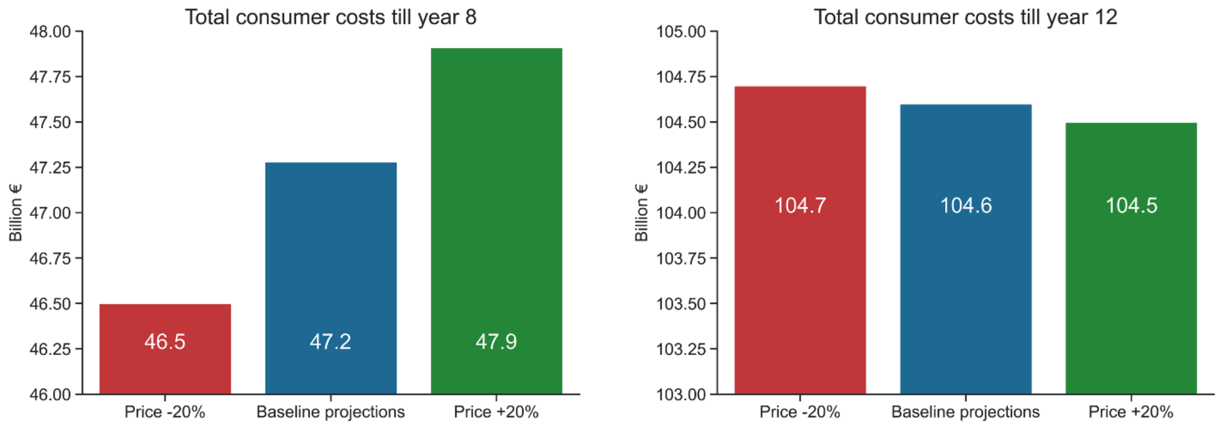


FIGURE 5.4: Sum consumer costs till year 8 (left) and sum consumer costs till year 12 (left)

The expectation would be that in the case of lower fuel prices, the total consumer costs would also be lower; this can be seen in the left-hand side of figure 5.4. This reasoning holds until year eight because the electricity price is lower due to lower fuel costs, translating to lower consumer costs. However, due to the effect of a shortage that lasts longer, because the actors have less budget in case of a lower price, we see that after twelve years, the total consumer costs are the highest in our run with a low electricity price. Regardless of this effect, we see that an increase in electricity price decrease with 20% has a marginal impact on the total consumer costs.

5.1.3 Demand sensitivity

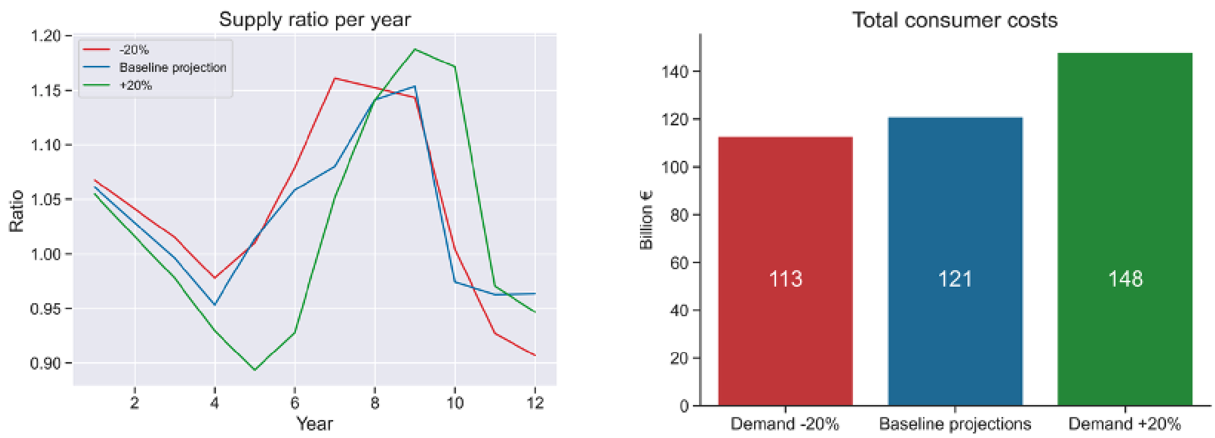


FIGURE 5.5: Supply-ratio (left) and sum of total consumer costs (right)

There are two relevant effects shown in our sensitivity analysis concerning demand. First, in line with expectation, if we compare the baseline projection with the 20% increase of demand growth, the shortages are initially longer in the case with more demand growth. This is expected as the actors come from a situation of oversupply and thus do not have the budget to invest beforehand to prevent shortages, and because of the growing demand rate, the shortages last longer.

The emerging side-effect of this is that because the initial shortage lasts for a longer time, the investors have more budget to invest, which leads to a situation where the over-investment is more extreme after the initial shortage. Second, comparing the baseline with the -20% demand growth, we see that the -20% demand growth can overcome the shortage faster because in the initial shortage, the actors gain a budget to invest and the combination of less demand growth allows them to also over investment more than the baseline scenario. Again, making the oversupply and the following shortages even larger. Looking at the total consumer costs, we see these effects translated in the case with less demand, the actors can better overcome a shortage, and therefore the consumer costs are less high and vice versa.

5.2 Scenario analysis

5.2.1 European governance scenario

Scenario	Shortage hours (h/year)	Supply ratio	Electricity price (€/MWh)	Capacity market cost (billion/year)	Costs to meet demand (billion/year)	Total consumer costs (billion/year)
EG energy-only market	0.5	0.81	56.6	0	12.05	12.05
EG capacity-market	0.0	0.92	53.5	0.4	11.6	12.0

TABLE 5.2: Key indicators in European Governance scenario

In the European Governance scenario, we want to see how a capacity market performs in an isolated electricity system, where hydrogen import to directly match hydrogen demand is possible, and no subsidy is implemented. In table 5.2 we show the results from a twenty-year run; the results are the average of a value over an entire run.

In both market configurations, we see that almost no shortages occur, which is expected given that seasonal and daily storage is possible and that in this run, unlimited import to match hydrogen demand is possible. Moreover, we see that implementing a capacity market increases the supply ratio (from 0.99 to 1.11). Finally, we see that the overall consumer costs are lower in the case of a capacity market, even though the capacity market costs an extra 0.4 billion/year. This phenom occurs because the capacity market also reduces the average yearly electricity price by impacting the installed mix of assets. This effect leads to a total reduction of consumer costs of 0.7 billion per year compared to an energy-only market.

We will now explain how the capacity market can increase the supply ratio and have lower total consumer costs. We start by looking at the supply ratio in figure 5.6. Here we see that the supply ratios in both configurations operate similarly in the initial five years. This is because, in the first five years, the investor does not know what assets to dismantle yet because of costs. After that, however, the investors see that assets will be dismantled because of age and demand is rising. So to prevent a shortage, the model starts investing.

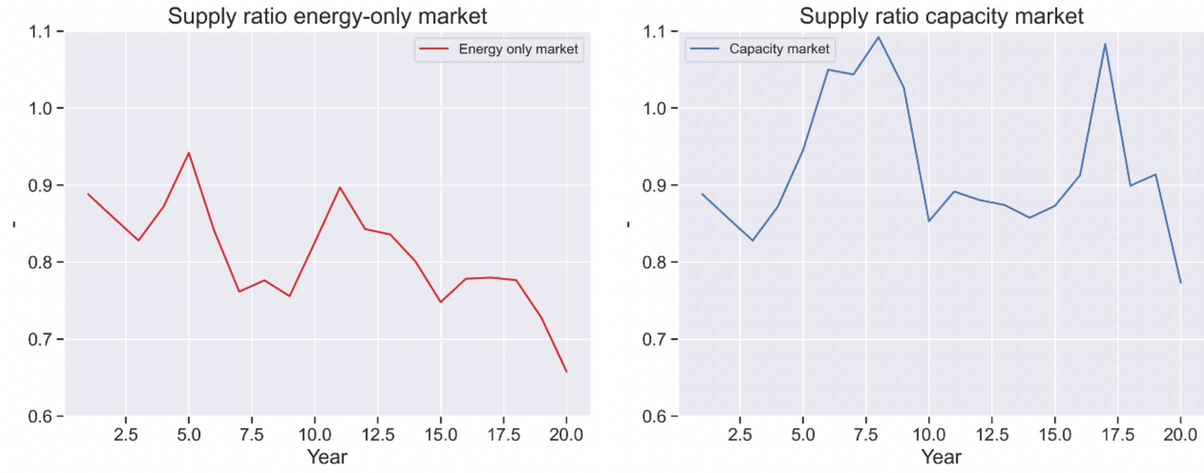


FIGURE 5.6: Supply-ratio in energy-only market (left) and capacity-market (right)

This starting point leads us to year five, where we see that a substantial dip in the installed assets arises in the energy-only market. This dip is because of the high CO_2 price, which impacts the earning potential of the CCGT assets. While this earning potential is being reduced, the CCGT assets still have to pay their fixed O&M. This leads to the dismantlement of CCGT assets. Because these assets get dismantled, we see a substantial dip in the supply ratio. However, as a counter-reaction, CCGT assets get installed again at a fast pace after they have been dismantled, as shown in figure 5.7. The effect of this is an overshoot in the amount of CCGT, which suddenly becomes key in setting the electricity price in the energy-only market. However, due to the high CO_2 price (of around 130 €/ton) around this time, the electricity price becomes high. We see in the capacity market that because these assets have a way to earn back their fixed costs, the GasCCGT assets get dismantled more gradually. In turn, many GasOCGT assets get installed and can be kept active; their income from the capacity market helps realize this. Due to this, we see a high supply ratio because these assets only have to be utilized so often, and therefore they keep the system stable but set the price less often. As a result, we see a lower electricity price in the capacity-market than in this scenario's energy-only market.

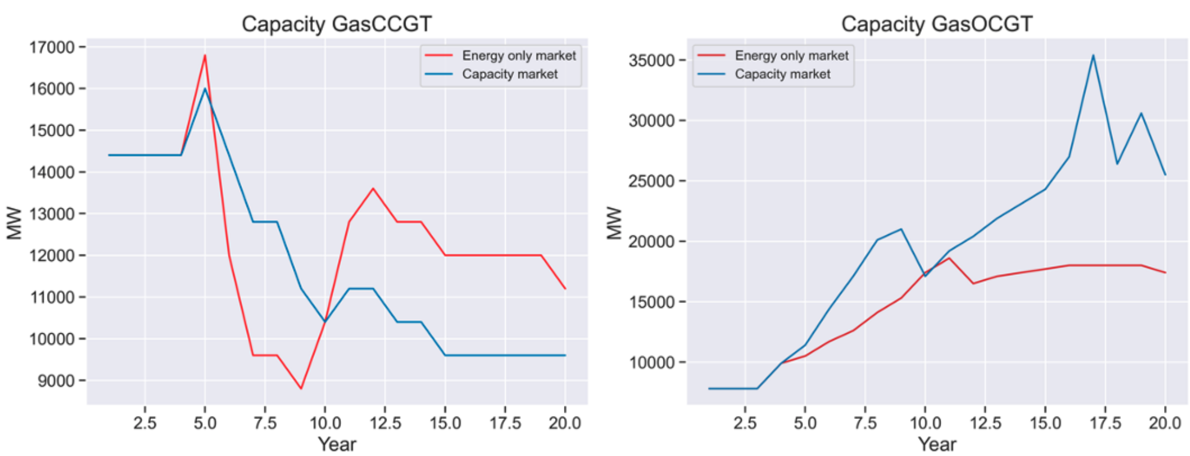


FIGURE 5.7: Installed gas CCGT assets (left) and gas OCGT assets (right)

We observe that long-term seasonal storage is not the main factor in explaining the overall system behavior in this scenario. All storage assets combined in the capacity-market configuration take up around 9% of the total mix and in the energy-only around 7%. In comparison, gas-based assets take up 43% and 36% of the generation-mix in the capacity-market and energy-only configuration, respectively. This limited role of seasonal storage has two reasons. First, because no external subsidy is implemented, vRES only takes up around 50% of the total energy mix in both scenarios. Second, in this scenario, the energy market has unlimited access to hydrogen-import for the direct demand. Additionally, hydrogen import has become very cheap over the years; this is why we see the supply-ratios get less without any shortages arising. More demand is fulfilled through import, and thus, there is less cash flow for installed assets, which means they get dismantled. Therefore, this cheap import of hydrogen means that there is less need for seasonal storage to keep the system in balance.

The combination of the effects of seasonal and daily storage and plenty of available imports would suggest that there is no need for capacity-mechanism in this type of scenario and that an energy-only market is sufficient to guarantee the security of supply. This is confirmed in our results as the energy-only market ensures the security of supply for almost all hours. Still, we see that a capacity market positively influences the security of supply. Moreover, the capacity market prevents the dismantlement of (mostly) CCGT assets, which lowers the average electricity price. This means that even with additional capacity market costs, the overall total consumer costs are lower with a capacity market. Note that we only run one scenario; however, the reduction in consumer costs could be easily nullified in another scenario. This would happen with a slight change in the decrease in electricity price or an increase in the capacity market costs. Overall, these results suggest that even in a future scenario where the security of supply should not be at risk, there could be a role for capacity remuneration mechanisms as supply security increases without any or too many costs.

5.2.2 National governance

Scenario	Shortage hours (h/year)	Supply ratio	Electricity price (€/MWh)	Capacitymarket cost (billion/year)	Subsidy costs (billion/year)	Costs to meet demand (billion/year)	Total consumer costs (billion/year)
NG energy-only market	115	0.85	87	0	4.5	21.2	25.76
NG capacity-market	17.4	1.10	53.5	0.6	4.8	10.5	16.04

TABLE 5.3: Key indicators in National Governance scenario

In the National Governance scenario, we want to observe how a capacity market performs in the case of an isolated energy grid and a strong subsidy towards a low-carbon system. The output of the key indicators in this scenario is displayed in table 5.3. For the energy-only market, we see in table 4.11 that there is a high amount of shortages and an overall low supply ratio. The reason for this is the high level of subsidy invested by the government to simulate vRES. The other government-backed vRES reduces the amount of dispatchable hours of gas assets. Because these dispatchable hours are reduced, we see that gas assets get 'pushed out of the market'. This effect leads to an average of 115 shortage hours per year. These shortages significantly increase the electricity price. This also explains that even though more vRES get installed every year (with a marginal cost of 0), the electricity price does not decline. This can be observed on the left-hand side of figure 5.8. The combination of these forces leads to a high total consumer cost of 25 billion/year.

We will now compare this with the capacity market, where we see a very different market dynamic. On the right-hand side of figure 5.9 we see that initially, the supply ratio is somewhat higher than the energy-only market. However, that after one major shortage (in year 10), the capacity market recovers with a supply ratio that is significantly higher than the energy-only market. Two effects cause this over-shoot. Firstly, we see that the model starts in a situation with a shortage in both scenarios. However, due to the additional cash flow provided through the capacity market, investors can get a positive return on their investment, and fewer assets need to be dismantled. This explains how the capacity market has a 0.10 +/- higher supply ratio in the first ten years compared to the energy-only market. However, we also see that the actors invest all their budget into new assets, yet the supply ratio in the first ten years is that the is still below 1.0 in the capacity market. This means that our central investor does not have enough budget to keep up with a demand that is growing fast and renewable that keeps getting installed and still pushes some assets out of the market. This effect leads to a shortage in year 10, which causes a counter-reaction of an extremely high budget and thus a high supply ratio. So if our investment actor had a higher budget, the shortage would be prevented, preventing the overshoot in supply ratio. We will expand on how this can be implemented in our model in the discussion. The second effect that causes this overshoot we appoint to the construction time of assets. In our thesis, we have assumed that the construction time of CCGT assets (which are the primary assets that get constructed due to the capacity market) is two years. Because the construction time is two years, we see that the shortage lasts longer, which leads to a stronger counter-reaction in more installed assets. This is a model-setting that could be adjusted in any other run.

Overall, we see that the combination of this one significant shortage and a capacity market leads to a significantly better recovery than in the case of an energy-only need. We also see that the market has less incentive to invest in renewable; thus, the subsidy costs are lower in this scenario. However, the effect of preventing the shortages is so high that it more than compensates for the additional subsidy and capacity market costs.

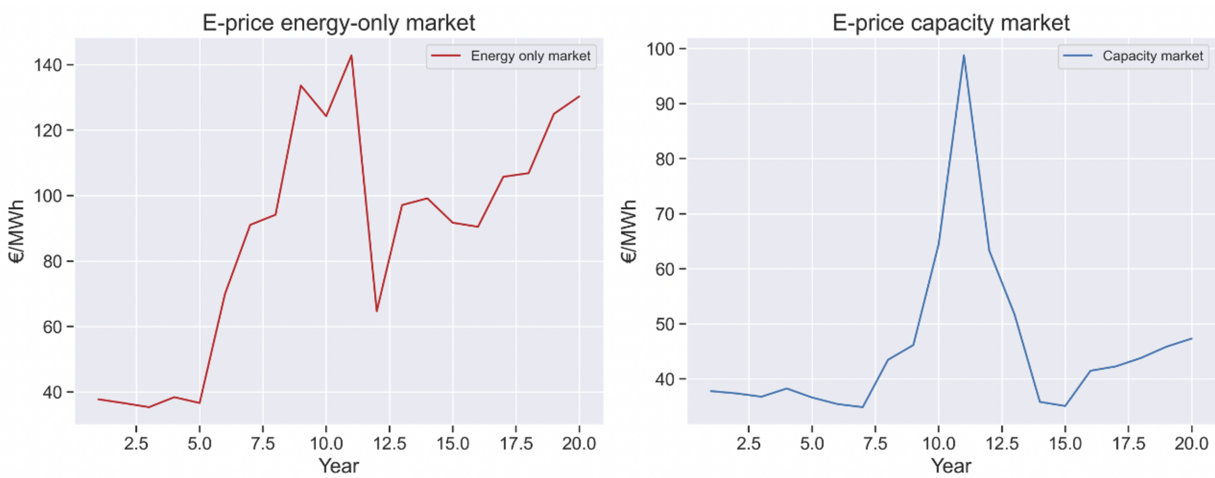


FIGURE 5.8: Yearly average electricity prices in energy-only market (left) and capacity-market (right)

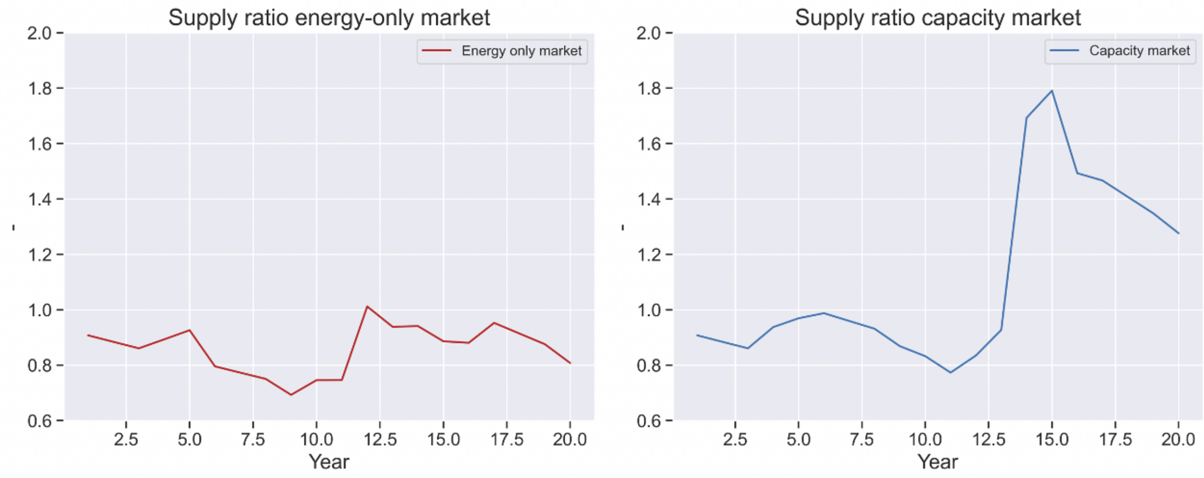


FIGURE 5.9: Supply-ratio in energy-only market (left) and capacity-market (right)

We now look at the overall asset portfolio in both market designs to confirm our initial conclusion set out above. For this we point to figure 5.10. Here we see that the energy supply-mix in our two configurations has two main differences. First, we see that in the case of a capacity market, similar to the previous section, a strong increase in the amount of installed Gas OCGT assets. Again, the reason for this is that the capacity market provides income for these assets to be profitable, even if they are only used scarcity, which makes the use of them in peak demand worth the investment. Second, we see that in the case without a capacity market, a strong investment in seasonal storage occurs. The reason for this is that the electricity prices are high, and more and more vRES gets installed; this provides opportunities for the seasonal storage to profit on. However, even though this is the case, these seasonal storage assets are not enough to remove the shortages that arise in the market. This is because even though these assets get installed, they have to also be filled and discharged. This means that they are not always available, and the efficiency losses that arise in the charge/discharge imply that much more storage needs to be installed in comparison to the installation of a GasOCGT asset.

In comparison to the EG, we see that in the NG scenario, the overall impact of a capacity market is much more valuable. Because of the subsidy and no additional import, the impact of shortages on the overall system is far greater. In this scenario, the capacity market provides additional value in the form of installed capacity that reduces the shortages, which eventually leads to a saving in the total consumer costs

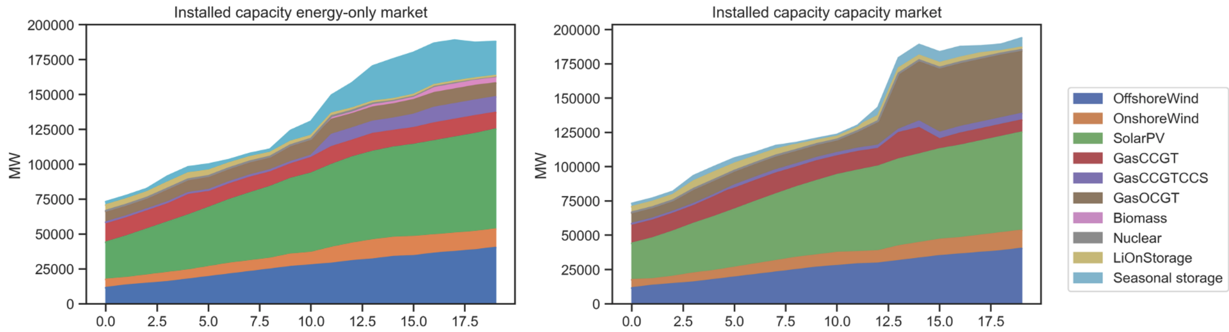


FIGURE 5.10: Installed assets energy-only market (left) and capacity market (right)

5.2.3 Impact of Dunkelflaute

We also want to observe the impact of a Dunkelflaute on the energy system. To realize this aim, we have run the EG and NG scenario in the years 2040 and 2045 with the merit-order present in those years in the runs in the previous sections. Note that to analyze the impact of the Dunkelflaute, we did not simulate an entire transition; instead, we look at what would happen in a stationary year based on our previous observed transition paths.

Scenario	Market design	Year dunkeflaute	Electricity price (€/MWh)	Hours shortage (h)	Shortage volume (GWh)
EG	EO	2040	62	0	0
EG	CM	2040	61.5	0	0
EG	EO	2050	63	0	0
EG	CM	2050	61	0	0

TABLE 5.4: Effect dunkelflaute EG scenario

Table 5.4 that a Dunkelflaute does not have a significant impact on the EG scenario. The reason for this is that in this scenario, there is unlimited import possible. So the Dunkelflaute does not cause any major shortage as any need for energy is replaced by hydrogen import. Moreover, we see a slight price difference between the capacity market and the energy-only market. The same mechanisms cause this price difference as we described in section 5.2.1.

Scenario	Market design	Year dunkeflaute	Electricity price (€/MWh)	Hours shortage (h)	Shortage volume (GWh)
NG	EO	2040	226	369	380
NG	CM	2040	95	88	21
NG	EO	2050	212	297	255
NG	CM	2050	91	0	0

TABLE 5.5: Experiments run to see effects of Dunkelflaute

Based on the results shown in 5.5 we conclude that the effect of a Dunkelflaute is far more significant in the NG scenario than in the EG scenario. This difference is expected as there are more vRES installed, and there is no import possible. Furthermore, we see that the CM significantly reduces the total volume and the hours of shortages. As we explained in the previous section, this prevention of shortage hours is primarily because of the additional OCGT assets due to the capacity market. Finally, we observe that in 2040 this effect is already present; however, in 2050, this effect is so strong that there are no more shortages in the CM market design.

The previous section concluded that the capacity market could increase the supply ratio for both scenarios without high costs as the gains made by prevented shortages outweigh the additional capacity market costs. In this section, we can add to this conclusion that a Dunkelflaute would amplify the shortages, and therefore the positives would occur with a more significant positive system impact.

5.3 Comparison results of the MIDO model with EMLAB

Given the novelty of our MIDO model, we will reflect upon the results in the EG and NG scenario in the previous sections. We will do this by comparing the results generated by our model to the EMLAB-model in similar scenarios. We base this comparison on chapter four in the PhD thesis of Bhagwat (2016). The MIDO model and the EMLAB-model are based on a different conceptualization of the energy system, have different assumptions, and run different scenarios; therefore, we do not expect the results to match one on one. However, by looking at the results generated in scenarios that have a similar essence and comparing the system behavior of both models on a high aggregate, we aim to increase the validity/confidence in the MIDO model.

First, we look at the EG scenario. This scenario is similar to a scenario run in EMLAB, where they have analyzed the effectiveness of a capacity market in the absence of a renewable energy policy. In our thesis, we realized this through the EG scenario, where the government implemented no subsidy for vRES, and a high CO_2 price was observed. An overview of the main results is shown in 5.6. The delta stands for the comparison observed in a run with a capacity market minus the value with an energy-only market.

Here we see that the average supply ratio in the energy-only market was 0.97 for the EMLAB model and 0.81 for the MIDO model. However, by implementing a capacity mechanism, the average supply ratio rises to 1.11 in EMLAB and 0.92 in our model. Here we see similar effects occurring. Moreover, they find that the average electricity price drops by 5 €/MWh when implementing a capacity-market in our model, the electricity price drops by 3 €/MWh. These effects should not be seen based on their numerical value rather than a capacity mechanism in the same type of isolated market that leads to the same overall system behavior. The first main difference is that in their model, in the runs, there are 26 shortage hours/year observed on average with an energy-only-market and 0 zero with a capacity-remuneration mechanism. However, in our model, we see that there are no shortage hours in both the energy only and the capacity market. However, with regards to this point, the EMLAB-model notes "the presence of even small quantity of demand response would lead to a considerable reduction in shortage hours observe in the baseline scenarios" (Bhagwat, 2016). So this difference is expected. Moreover, in their scenario, the overall supply ratio for both market configurations is higher. This can be explained because, in our model, more demand is fulfilled through import, our model starts in a shortage, and the demand rises at a significantly higher rate.

Indicator	EMLAB	MIDO
Δsupply ratio	+0.10	+0.10
Δelectricity price (€/MWh)	-5	-3
Δ shortages	-26	0
Effect on asset portfolio	More GasOCGT	More GasOCGT

TABLE 5.6: Comparison EMLAB and MIDO EG scenario

Second, we look at the NG scenario. This scenario is similar to a scenario run in EMLAB, where they looked at the effectiveness of a capacity market with a growing share of renewables. This is similar because the NG scenario also includes subsidies and operates in an isolated grid. Here we again find similarities based on overall system behavior. First, we see that in this scenario, many yearly shortages occur in EMLAB due to subsidies. The same happens in our model. Second, in the EMLAB model, the investment in additional capacity through the capacity market pays off because the reduction in shortages is significant. Again, similar behavior occurs in our model. Thirdly, we see that a capacity market leads to a substantial increase in investments of Gas OCGT assets; this is similar to our model.

However, we also see some apparent differences. Firstly, the capacity market in EMLAB is more stable than the over-shoot in our model. We argue this is justified because in our model, demand grows to a far greater degree than in EMLAB, and we start our run in a shortage in terms of supply ratio. This all leads to the situation where the capacity market cannot prevent a shortage, and thus a shortage and over-investment occurs. Moreover, in section 5.2.2 we argued how implementing a higher overall investment budget of the market and a lower lead time before a

Gas OCGT asset is installed would lead to a situation where this over-shoot would be prevented/lowered. Second, we see that in this case of our model, the installed generation-mix with and without a capacity market differs when there is also a subsidy. This change in the generation mix is not the case in the EMLAB-model. Again, we argue that this difference is justified because the difference mainly arises from seasonal storage in our model. The EMLAB model does not consider seasonal storage. So, in conclusion, we find that our model has very similar system behavior as in the EMLAB model; however, there are some differences that can be explained by different assumptions, scenarios, some change in model logic regarding investment budget, and the inclusion of daily/seasonal storage.

Chapter 6

Conclusion

In energy-only markets, private investors play a crucial role in realizing the security of supply during the energy transition. However, several specific characteristics inherent to his market design have caused concern on whether this form of market design can deliver on the energy system's socially desired level of reliability. For this reason, many countries have implemented a capacity mechanism to ensure system adequacy. Currently, there is a broad debate on the effectiveness of these capacity mechanisms, especially in extreme weather scenarios and investment risks of seasonal storage. However, this debate has been mainly theoretical, as no model can accurately model myopic investments in combination with a detailed operational model that can include seasonal storage and extreme weather. Our thesis aims to deliver a proof-of-concept of a myopic investment detailed operational (MIDO) model suited to incorporate these missing elements. The presented MIDO model consists of three sub-models: the investment-decision (ID) model, the future-price model (FP), and the present-price (PP) model. These models are linked and utilized to pass data among each other. The first sub-question we ask our self to deliver a proof-of-concept is:

What are the requirements for the investment-decision, present-price and future-price model?

The primary goal of the ID model is to represent rational investment and dismantle choices made by the market as a whole based on imperfect information in different market designs. The requirements for the ID model are that it must make decisions on investing/dismantling assets every year. These decisions must be rational, based on limited information, and must be made in different market designs.

The main goal of the PP model is to represent the day-to-day operation of the energy system with a high degree of accuracy. To full fill this aim, the PP model must output hourly electricity prices for a year. Moreover, the PP model must output hourly dispatch of all generation and storage assets. Furthermore, the output of the vRES assets should be based on chronological hourly weather input. Lastly, the model shall be highly accurate and computationally feasible.

The overall goal of the FP model is to generate the cash flows of assets in one or multiple future years. To realize this objective, the FP model has almost all the same requirements as the PP model. However, there are two differences; firstly, the FP model does not have to be highly accurate, as the output data is utilized to reflect future cash flow projections. Second, the computational feasibility requirement of the PP model is interpreted differently as the FP model runs more than once per year.

Having formulated all the requirements, we proceed to ask ourselves the following sub-question:

How are requirements of the investment-decision, present-price and future-price model reflected in the current state-of-the-art models?

For the ID model, several simulation models fulfill the rational investment and dismantle decisions based on limited information in different market designs requirements. These models let individual agents make iterative-based investments and dismantle decisions through a set of decision rules, where investors have limited access to information. In our thesis, we implement the core of the logic behind this iterative greedy approach. However, because we only have a limited time, we chose not to model individual agents but rather translate the logic to one central investor, representing the aggregate behavior of the market.

For the PP model, we observe that none of the myopic-based investment models can incorporate all requirements. However, we find that several optimizations models can fulfill most of the PP model requirements. This finding leads us to conclude that we can utilize a unit commitment (UC) model that includes all hours of a year to simulate the day-to-day operation of the energy system with a high degree in the PP model. We utilize a UC as the basis for the PP model yet introduce several additions to decrease the computational time to make the PP model computationally feasible.

Also for the FP model, we find that none of the myopic-based investment models fulfill all requirements. However, that there are optimization models that satisfy all the FP model requirements. These optimization models utilize a UC model that is based on some form of time-slicing; we argue for the use of representative days. By adjusting this temporal resolution, we can utilize a UC in our FP model to generate the cash flows of assets in a future year in a computationally feasible way.

Having conceptualized our three sub-models, we now move on to modeling our first operation model, the present-price model. Leading us to the following sub-question:

How can we develop the present-price model?

The PP model aims to be accurate, and therefore, we accept a higher computational time in this operational model. However, we want to limit the computational to be feasible. To realize this objective, we find that we need two connected UC models. One of these models is the 'seasonal' UC model, which we run based on daily time series to create seasonal storage targets. Then these seasonal storage targets are utilized as input values for the second UC model called the 'daily' UC model. The daily UC model is run on an hourly time series to simulate the operations of the energy market with a high degree of certainty. However, we realize a significant reduction in its computational time due to the seasonal storage targets. This model can provide empirically feasible seasonal storage targets for all hours in a year while taking one or two minutes to solve.

Now having modeled our present-price model, we move on to model to the second operational model and ask ourselves:

How can we build the future-price model?

In this model, the aim is the inverses of the PP model. Here we want to simulate a fast model, and to this extent, we want to give up some accuracy, again to a particular limit. To realize this goal, we utilize the previous combination of a daily and seasonal UC model. However, we do not run this model based on all hours in a year to reduce the computational time. Instead, we utilize a K-means approach to select representative days, which we use to simulate a year with significantly fewer time steps. This model can generate similar results as the UC-model with an error margin of 10-20%. However, the model can simulate a year in ten to twenty seconds.

The last sub-question is focused on developing the investment-decision model and is as follows:

How can we construct the investment-decision model?

We developed a Python script that can automatically process the PP and FP model data to create myopic investment and decisions. The investments made by our central investor (who reflects the entire market) are based on a 'reference-year'. The central investor assumes that this year is representative during the asset's economic life considered for investment. In the logic implemented in the ID model, the central investor compares its investment options and consistently pursues the investments with the highest NPV until the investor has no budget to invest or no investment options with a positive NPV are left. Moreover, our investor looks back a specific look-back period to determine if any assets have been losing money for too long. If this is the case, the asset gets dismantled. This logic creates a classical investment cycle. In these cycles, the market over-invest in case of a shortage or dismantles assets if there is a shortage. Moreover, we have implemented a capacity market in the ID model next to the energy-only market based on the NYISO-ICAP. Now that we have developed all sub-models that are part of our MIDO model, we ask ourselves:

How does a capacity mechanism perform in an energy system that is transitioning to a low-carbon system, when taking into account seasonal storage and extreme weather scenarios?

We looked at two distinctively different futures. First, a future with a high European CO_2 price, no subsidy driving renewable investment, and a high degree of hydrogen import. In this scenario, we find that the security-of-supply can be met adequately without a capacity market. However, the security of supply is higher with a capacity market, without increasing the total consumer costs. This points toward a capacity remuneration being valuable, as it shows promise even in a scenario where the security of supply on its own is adequate. Second, we look at a future with a medium CO_2 price, a substantial subsidy pushing renewable investments, and no import. In this scenario, we find that the capacity market has even more added value as it significantly reduces the number of shortages in this scenario. The reduction of these shortages makes the investment in additional capacity through a capacity market more than justified. Again, this adds to the notion that at least some form of capacity remuneration mechanism would be helpful to implement during the energy transition. Lastly, we have looked at the impact of extreme weather on the energy system in both scenarios. In these scenarios, the above conclusions are confirmed. We see that all configurations with a capacity mechanism are superior in handling extreme weather scenarios.

Because we only have explored two scenarios, we can not conclude with a high degree of confidence that any capacity mechanism has added value in an energy system transitioning towards a low-carbon system. However, since we observe that a capacity market has added value in all our scenarios and since we explore two opposite corners of the energy transition, we can conclude that are specific future scenarios where some form of capacity remuneration mechanism can have an added value. Moreover, we conclude against the notion that seasonal storage makes capacity mechanisms redundant. In this line of reasoning, seasonal storage would reduce all shortages observed in an energy-only market. However, our model has shown that this is not always the case.

Having explored several futures by making use of the MIDO model, we can now answer our main-research question:

How can we model long-term energy system development in a myopic investment detailed operational model?

The main aim of our thesis has been to show a proof-of-concept of the MIDO model that can simulate myopic investment-behavior, while also including a detailed operational model that can account for seasonal storage and the effect of extreme weather scenarios. As currently, no other models combine both these aspects. We have argued for the validity of our model by validating all different sub-models and through a sensitivity analysis—these validations were all confirmatory of the underlying mechanisms in the MIDO model to real-world application. Moreover, we have shown how the MIDO model can simulate long-term energy system development within two distinct futures while accounting for seasonal storage and extreme weather scenarios. Lastly, we have cross-validated the results of the MIDO model with the EMLAB model, which showed how, overall, our model produces very similar system behavior as with an established model.

These elements all lead us to conclude that the core logic behind the MIDO model is suitable to be utilized by researchers as a quantitative backing to the qualitative economic/policy debate on the role of capacity mechanisms. Moreover, since the logic behind the MIDO model is flexible, it can be utilized to generate insights into energy transition pathway options for an entire class of problems. However, to increase the suitability of the MIDO model to be used for this purpose, we suggest several improvements in the discussion. These improvements are related to refinements of the model, conceptual aspects that might be changed, and changes that can reduce the overall computational time of the MIDO model.

Chapter 7

Discussion

7.1 Reflection on the MIDO model

7.1.1 Reflection on modeling process

This section reflects why the MIDO model takes 12 hours to complete an entire run (when simulating 20 years) and our overall modeling process. In reducing our model's computational time, our primary efforts have been focused on reducing the time it takes to run the daily-UC, the seasonal-UC, and the actual python code. The first step in realizing this was running all our UC as CUC, which leads to the solver only having to solve for asset groups instead of individual assets. Afterward, we have excluded many technical aspects of asset groups for our UC models. However, the biggest computational gain in the daily and seasonal UC has been realized by utilizing the seasonal and daily UC. Previous research has also utilized a similar method for pumped hydro seasonal storage. However, these did not consider daily storage as well. So by applying smoothing to our time series and filtering out the short-term effect, we argue that we have been able to push this methodology one step further. By doing so, we have made it possible even to consider utilizing the UC in our thesis. Otherwise, solving the UC alone would provide too much computational power (when utilizing an open-source solver) for the MIDO model to even be feasible.

In the next step, we translated this methodology into the realm of representative days. To our knowledge, no other work has utilized this combination in representative days. Since usually, the models that utilize representative days also include the investment into storage assets themselves, and all do this in one model. We have also made a step by utilizing the daily and seasonal-UC method with representative days.

As a final step, the developer of Linny-R Pieter Bots introduced the utilization of the Gurobi-solver instead of the lp _solve solver we had to utilize at the beginning of our thesis. The change of the solver increased our solving abilities by roughly a factor of 10. These efforts all led us to times as shown in table 7.1 to solve our Linny-R models. Note that the times in the FP model are based on 24 representative days.

Model			
PP-model		FP-model	
Seasonal-UC	Daily-UC	Seasonal-UC	Daily-UC
5 second	30 seconds	4 to 5 seconds	1 to 2 seconds

TABLE 7.1: Overview run time UC models utilized

Based on these solve times, we were optimistic about the application of the MIDO model. However, after speeding up the UC models, we were confronted with the methodology we had utilized to process the data generated by the Linny-R model. We had initially built our code for a dummy model for verification purposes. In this dummy model code, we utilized a python package called Pandas to process our generated data. In Pandas, we utilized a loop structure to perform the equations we have laid out in 3.3. However, we noticed that it took our code several minutes to process all the generated data per investment round. This additional time meant that all the work in speeding up the model through increasing the run-time of the UC models had been nullified by the time it took to process the data. This again made our overall model computationally not feasible. To solve this problem, we rewrote all our code utilizing vectorization. Vectorization makes use of NumPy array operations, where each operation involves a loop over array entries efficiently implemented in C (Cai, Langtangen, and Moe, 2005). These efforts decreased the loop-time utilized in our code with a factor of +/- 10000. So in this light, we highly recommend any future work that plans to build upon the code of the MIDO model to continue writing the data manipulation as vectorization. However, even though we undertook all these efforts, we still found an average run-time of 12 hours.

The main contributor in this run time can be found in the investment loop we have utilized in our the ID model. In the EG-scenario with a capacity market, we had +/- 530 'investment rounds'. If we assume in every investment round, we had to compare eight assets; this means that per investment round, we had to run the seasonal and FP model eight times. This would result in roughly 4000 runs of the FP model in only one overall model run. If the total time of the model to run and process the data takes 10 seconds per model. This process already takes 11 hours of the 12, without considering the PP model runs. Before building the MIDO model, we underestimated how many investment rounds would occur in our model. Given this fact, however, we still think it was a solid modeling choice to reduce the computational time of the FP-model and our code as much as possible.

An improvement of only 1 second on the overall method in the investment loop could result in a time reduction of one hour (4000/1/60/60). However, in reflecting, we think it would have been wise to look at ways to reduce its efforts to run through the investment loop. We have a few ideas on how to speed up the investment-round process, which we will discuss in our recommendations for future work.

The last point we want to discuss is related to the overall development time of the MIDO model. In our thesis, we have developed a model that is, in terms of overall functionally, similar to the EMLAB model. We do not claim we can make a model as scientifically validated, verified, and accepted as the EMLAB-model within the time frame of our thesis. Also, we realize that we can utilize the work done by other researchers to conceptualize elements we utilize in our model as a stepping-stone and thus reduce the take it takes to develop our model. Yet, the EMLAB model took multiple years to develop, and in this thesis, we only had several months to work on the MIDO model. We appoint several factors to our short development time. First, most of the models that integrate the myopic-investment principle in long-term system development utilize ABM. However, currently, the impact of ABMs models in this field is limited, among other things, because the development process of ABMs is slow (Chappin et al., 2017b). Within our thesis, we have simulated not the individual behavior of agents but rather aggregated the combined behavior of all actors in the form of one central actor who represents the entire market. In this regard, we were able to simulate the overall behavior of the market but did not have to go through the process of modeling all individual agents, which contributes to the long and complex development time of ABM models. Second, we made use of Linny-R. We identify two elements enabled by the Linny-R tool that contributed to the quick development time of our MIDO model. Foremost, by making use of Linny-R, we were able to generate the bases of our operational models very fast. At the beginning of our thesis, we had no coding experience. Yet, due to the graphical nature of Linny-R, we were able to develop the bases of our UC models in a matter of hours. The operational models took a long time to develop as we spent quite some time researching methods to reduce the computational time of the UC; however, a basic UC model can be created in several hours in Linny-R. Secondary, Linny-R provides a solid basis to link data to Python. In the course of our thesis, Pieter Bots added the 'receiver' functionality to Linny-R. This functionality enables data to be exchanged between Linny-R and Python as described in section 3.3.1. Emmanuel et al., 2020 have conducted a literature review on the need to combine investment and operational models in power systems. He concludes that researchers should develop models that combine the insights of operational and investment models to ensure both instantaneous stability of the power system and long-term security of supply. However, that this gives rise to additional complexity as modelers need to account for the linkage of models with different time resolutions. While there are some co-simulation tools that can combine two models into one framework, Emmanuel et al. (2020) states, "there is certainly room for additional research to advance model integration to maintain computational tractability while providing the ability to assess and verify flexibility options across a broad range of timescales." By delivering a proof-of-concept of the MIDO model, we have shown how the newly "receiver" functionality in Linny-R can be utilized for this purpose. Moreover, we argue that because of the fast development time of the MIDO model, we showed how the link between Python and Linny is flexible and easy to use.

7.1.2 Reflection on methodological contribution

We will now look at the conceptual model aspects of our MIDO model. We made several simplifications due to time limitations that we will now reflect on. Nevertheless, even with all these limits, we argue that the MIDO model provides a solid basis for future work to be built upon for future research.

Firstly, all the investments in our model are made by one central actor. To prevent any unrealistic ability in terms of capital to spend, we have limited the maximum budget our central actor can spend on one new asset. Our central actor's budget for a new asset equals the overall budget divided by the number of energy companies this investor would typically compete with. In this simplification, our central actor can still spend the entire market budget, but the size of the investment of a new asset is limited. We argued that this limitation was necessary, as otherwise, the central actor in our model could invest, e.g., in a Nuclear plant. In comparison, one actor who did not represent the entire market could not spend that much money on a single new asset. Nevertheless, we still kept true to the essence of how the market works, and therefore we argue that our overall model results concerning myopic investments are valid.

However, while we argue that it is valid to limit the spending potential of one investor, we did not consider any external investments that could occur outside of the market. If the national energy companies do not have enough budget, one could make a logical assumption that those (external) energy companies or parties with access to a large amount of capital would make these investments. These investors would invest with a higher interest rate as they are not accustomed to operating in this market and therefore want a more significant return. Not including this aspect is a limitation of the MIDO model. Moreover, implementing this aspect could lead to a higher overall investment budget and prevent some of the shortages/depth of shortages in the energy market. This, in turn, would avoid a high overshoot, as we have observed in our results.

Moreover, another aspect that is lost due to the investment being made by one central actor is the relationship between different energy companies. An element that is therefore lacking in the MIDO model is unique investment strategies related to different investors. If our MIDO model could have multiple investors, we could give all these investors their own set of unique investment strategies and observe the behavior this creates. We know from the literature that investors are risk-averse by nature (De Vries, 2007). We have included this characteristic of investors in our MIDO model by letting the actors invest based on a conservative reference year while considering any other investments already made.

However, a more formal way to realize this could be to introduce an investment strategy based on conditional value-at-risk (CVAR) concepts and constant absolute risk aversion (CARA). Another investment strategy that could be introduced is a 'green-energy company.' Our model assumes that the myopic investor focuses on profit maximization, so only invests in the asset with the highest NPV. However, in reality, green energy companies could realize that their investments do not lead to the highest profit maximization. For example, imagine a situation where the green energy company can choose between two assets: a gas asset and an offshore wind park. If the offshore wind park had an NPV of 10M€ and the gas asset had an NPV of 12M€, the green energy could still choose to invest in an offshore wind park. Lastly, an actor could be implemented that actively abuses market power. All these elements are left out of the scope of our thesis. Nevertheless, including this could lead to interesting market dynamics to observe.

In addition to this point, again, looking back at the literature on market design, we find that policy uncertainty is an essential factor that energy companies take into consideration when investing (De Vries, 2007). In our MIDO model, we have not considered these effects due to time constraints. Reasoning based on the additional dimension this would add to investment choices means an additional dimension of uncertainty. This extra dimension would make investors even more risk-averse and would lead to a situation where they would push back investment until they are more confident that they would make a positive return on their investment. In return, this would mean that the supply ratio would be less stable, and the effect of shortages would be more prominently visible. Looking at our conclusion, this would again confirm that some form of capacity remuneration mechanism is desirable.

Furthermore, looking at the overall choices made in modeling storage, several points deserve some attention. First, our storage assets 'bid' on the electricity market based on overall system cost reduction. Sometimes, this system cost reduction does not benefit the profit made by an asset group. In reality, an operator of a storage asset would probably not utilize it for total-stem costs reduction but rather for profit maximization of his asset. This bidding strategy has the effect that the overall system costs in our model are lower than they would be in real life, and simultaneously the model under invests into storage as these assets have a lower profit. Second, the way how our model can anticipate a 'Dunkelflaute'. The relation between our daily and seasonal UC means that our seasonal UC model determines storage targets for the daily UC. These storage targets in the daily UC are fixed parameters in the form of a time series.

For this reason, the daily UC already considers the effect of a Dunkelflaute to the best of its abilities. This anticipation means that in the seasonal UC, we assume that the operator of any storage facility already sees a Dunkelflaute occurring because our seasonal UC optimizes with the knowledge of the weather condition of the entire upcoming year. While in reality, the seasonal storage might operate based on the expectation of an average weather year, and then halfway in a year is 'confronted' with a Dunkelflaute. For this reason, the results of an extreme weather year are most likely underestimated in our model. Thirdly, the future-price model we utilize in our thesis works is based on representative days. As we have shown in the validation of this method in section 3.2.3 we can make a good approximation of what the revenues would be like if we had run a UC for all time steps. However, we also saw that there was still a margin of error. Our main explanation for this is that effects occur not daily but rather on a week-to-week basis. Lastly, in selecting the representative days in our thesis, we only picked one day based on the number of clusters. However, some days are more common than others, so adjusting representative days for the weight of its cluster could be an additional step to reduce any error margins. By not doing so, we overestimate the importance of 'non' typical days in our thesis.

Moreover, in our thesis, we have considered the hydrogen and electricity demand in a country. In the scenarios we analyzed (due to a focus of electrification and hydrogen related development), 70-80% of the demand in the scenarios was based on electricity and hydrogen. Therefore, due to time constraints, we did not consider the demand development regarding heat and (bio) gas. In the field of research on 100% RES systems, historically, there has been a significant focus on the electricity sector. However, in the last years, there has been a growing amount of research that reflects a paradigm shift moving away from single-sector thinking to a holistic view on the energy sector (Lund et al., 2007; Hansen, Breyer, and Lund, 2019). The reasoning in these papers is that to implement a large share of vRES efficiently, a significant interaction between energy sectors is necessary (Mathiesen et al., 2015). Within our thesis, we have integrated this perspective partly because we also included the role of hydrogen in our model. 'Insert EG and NG'. However, we did not look at the impacts between these sectors and the other sectors. Additionally, we assumed that there was a demand growth in our model. Regardless of the energy sector's investments into the assets necessary to realize this demand. While in reality, one could argue that large-scale hydrogen demand would only develop after the market made investments in many vRES. There could be several interesting connections arising from this, which was out of the scope of our thesis.

Furthermore, we did not look at the role of infrastructure in our thesis. We, for example, assumed that there would be enough electricity infrastructure necessary for the actors to invest in any assets they wanted, that hydrogen could be important at any necessary level and that there would be enough electrolyzers installed to match demand. To prevent confusion with this last point, we only refer to to the required electrolyzers to 'directly' fulfill demand. Not the electrolyzers associated with storage. These choices, again, were all made due to time constraints. However, infrastructure development could play a bottleneck in the energy transition. Relating to the security of supply, one could imagine that the market has a shortage of installed assets. However, because there is not enough grid capacity to allow for new investments, the shortage is extended for some period. These effects are out of the scope of our thesis and could be considered in additional work.

Lastly, within our thesis, we have only looked at the role of security-of-supply and capacity mechanisms in one country. However, incapacity remuneration mechanisms, interesting effects can occur between different countries. For example, imagine that we have two countries that are interconnected through the electricity grid. Country A decides to invest in a capacity-remuneration mechanism, and due to this, they "pay" for a high security of supply. Let us assume that country B does not invest in a capacity remuneration mechanism and is still an energy-only market. Then let us say a Dunkelflaute occurs only in country B and not in A. This effect would provide the chance for country B to 'free-ride on the investments made by country A. With these types of considerations, the results of our thesis could be viewed from a different perspective. However, we only consider the view from an isolated country.

7.2 Reflection on the theoretical contribution

From a theoretical perspective, this thesis aims to contribute to the ongoing discussion in the literature on the effectiveness of capacity remuneration mechanisms during the energy transition. We argue that this primarily qualitative discussion could benefit from an additional quantitative modeling perspective. Through our MIDO model, we hope to enable future researchers to understand better the dynamics that might occur regarding system adequacy. Moreover, we have contributed to this by providing initial insight into system behavior for two opposing scenarios. In this light, we argue that a capacity market has positive effects on system adequacy in both cases. Due to this, we have provided model-based evidence against the theoretical reasoning that seasonal storage reduces all shortage moments in an energy market and that this effect would make a capacity-mechanism always redundant. However, there are several limitations to our contribution to this theoretical debate that we would like to highlight here.

Firstly, it is essential to explain what restrictions in our thesis a reader should interpret our results. An average run of twenty years took around twelve hours to run. Within the scope of our thesis, we had limited access to computing power. We explored several options to increase our computing power. The first solution we looked for to solve this problem was reserving physical computers offered by the TU Delft. However, we were only allowed to reserve three computers for one or two days due to corona measures. With the time it would take to set up and install all our models on one physical machine, we would not have been able to run many more experiments than we currently have. The second solution we looked for was in the form of an online environment Google Collab. Which provides an online environment on which code can be run and thus could provide us with some valuable computing power. In our thesis, we exchange data between our three sub-models through text files. Google Collab did not offer a way to share text files between a local machine and their online environment in a way that would help us with our computing power problem. So we were left with the computing power of our physical machine.

A common approach in running experiments in the class of model we have built is to run Monte-Carlo experiments based on a triangular projection of values that change in future years (e.g., demand growth, fuel-price changes, CO_2 price change, and hydrogen import prices). We initially wrote our code with running these types of experiments in mind; the code utilized in the thesis can be transformed to run these types of experiments in a concise time frame. However, a standard practice in these types of experiments is to run 120 Monte-Carlo runs per scenario. If we wanted to compare an energy-only and capacity market for one scenario, this would take 240 Monte-Carlo runs. Given an average run, this would take 2880 hours with only one physical machine. This was not feasible; even if we would only run a quarter of the runs (which would increase the random factor in the Monte Carlo runs), we would still need to run one physical machine for a month. Due to this reason, we have decided to test our MIDO model in sensitivity analysis and perform our runs within two different scenarios. However, based on the sensitivity analysis and our scenario analysis, we argue that we have delivered a model that a researcher with more computing power can utilize and with minimum effort can adapt the code to be used to run, for example, a Monte-Carlo experiment. This way, create a range of future scenarios all equally likely to occur and then, based on this insight, conclude with more robust results that contribute to the theoretical debate on capacity-remuneration mechanisms and energy-only markets.

Secondly, we have shown how an energy-only market performs compared to a capacity market for two different scenarios. From this, we conclude that some form of capacity remuneration mechanism could benefit the security of supply. From the perspective of our thesis, we have argued that an investor does not invest based on a 'rare' weather year instead of on an 'average' weather year. As shown in our thesis, this provides the investment patterns and can explain how the system is not 'prepared' for an extreme weather year. In this light, one could argue that investors could also consider 'rare' weather-years in their investment decisions. However, in this thesis perspective, we say that the investment risk is too high for an investor to invest in seasonal hydrogen storage or a Gas asset in the year 2030, equipped only to be utilized during a Dunkelflaute. This investor does not know if this Dunkelflaute will occur anywhere in the next ten years. At the same time, this asset would still have to pay his fixed O&M every year and take a loss. This is where a capacity-remuneration mechanism provides added value. So in this way, we argue that our model logic is valid, even though we omit 'rare' weather-years into the investment logic of our central investor.

Another main point that needs to be made regarding the overall theoretical contribution of our thesis is the following. Within our thesis, we wanted to contribute to the academic discussion on implementing any capacity remuneration mechanism and compare that with an energy-only market. In this light, we have chosen to do so for a capacity market as research indicated this would be a solid consideration of a capacity remuneration mechanism (Bhagwat, 2016). However, since many countries have already implemented different forms of capacity remuneration mechanisms such as reliability options, strategic reserves, or capacity payments, a theoretical discussion compares these capacity mechanisms. Moreover, there are also additional capacity remuneration mechanisms such as capacity subscriptions Doorman, 2005b or reliability contracts Vázquez, Rivier, and Pérez-Arriaga, 2002 which we have not discussed. We have not considered the comparison of all these capacity mechanisms because of time limitations. However, previous work has shown that even though there are many differences between capacity remuneration mechanisms, the addition of any capacity mechanism in comparison to an energy-only market has added value Bhagwat, 2016. So in this line, our overall conclusion still is valid.

Lastly, several other factors could influence our results. We argue that these uncertainties could significantly impact the developments in our study because our model has a strong path dependency since we look at multiple decades. This means that a small error margin could have a significant impact over time. We discuss these points here at the 'theoretical contribution' part of the discussion because all these points can be changed in the MIDO model, by changing some basic aspects of the model either in Linny-R or in our code. Or by running some additional experiments. In the previous section, we discussed elements that are similar to these here. However, the previously discussed aspects would take more time to develop.

Firstly, we only looked at what could happen regarding security-of-supply, if instead of the expected 'average' weather-year an 'extreme' weather-year took place in one year. These runs gave us additional insight into the impact of an 'extreme' weather-year on the security-of-supply. While we only have modeled one year, we can empirically argue that if an extreme weather year would happen, this leads to more shortage and thus would create an over-investment in turn. Thus, making the overall system more unstable. Right now, this element is not fully represented in the data of our runs. This would confirm that a capacity remuneration mechanism benefits the security-of-supply without increasing the total consumer costs. Moreover, we did not look at the occurrence of an 'extreme' weather-year in all years for all runs in both an energy-only and capacity-remuneration configuration. However, again, we can empirically argue that we see that the capacity market has a higher security-of-supply in almost all years. So again, we would say running these additional experiments would confirm our initial conclusion.

Second, in the UC models utilized in our thesis in both the PP and FP models, we have simplified the technical dimensions in these types of models. For example, we did not take into consideration: reserve constraints, ramping constraints, minimum stable operating point constraints (enforces if a unit is online, it has to generate at least a certain power level), part-load efficiency losses, start-up costs, and minimum up and downtime constraints. We made this choice as we argued that 5-10% would only underestimate the system's total costs; however, this was only in the light of one year. Again, looking at the effects of path dependency, these could impact the overall results of the system over time. This simplification means that, in reality, the total system costs would probably be higher than a run in our model would suggest.

Third, in our thesis, we only considered the impact of storage by a central investor. In reality, in addition to the market that invests in flexibility, it is also expected that demand-side-response as a 'daily' flexibility option will emerge. In this light, if the demand-side response of, e.g., households or industrial players fully develops, these parties could also offer flexibility. Currently, in our model, these opportunities are captured by the lithium-ion batteries as 'daily' storage. Since the demand-side response would compete for the same flexibility opportunities, this would mean that the 'daily'-storage in our model would be less profitable. Because of this effect, our central investor would have an additional budget to invest, as it could not spend the budget on daily storage as the market already realizes this. This additional budget would, therefore, probably increase the supply ratio in a country.

Chapter 8

Recommendations

Based on the novelty of the MIDO model and the elements we covered in the discussion, there are many avenues to be considered for future research. The first set of recommendations we have focuses on researchers with more computing power than we have and are also interested in generating more accurate results or exploring more futures. These results, in their turn, could be utilized to pursue policymakers to implement or disregard a specific policy option regarding capacity remuneration mechanisms or as a quantitative backing for theoretical debates surrounding capacity remuneration mechanisms. Therefore, the first recommendation is related to the limited scenario analysis we have done in our thesis. To this extent, we recommend that future researchers, who have access to more computing power, run Monte Carlo experiments based on triangular projections in which demand, fuel prices, CO_2 prices, hydrogen import prices/volume, and weather years are all variables that can change. In doing so, the main changing variables that impact the future security of supply could be researched. Through this, a future researcher could add with greater confidence to the capacity mechanisms' theoretical debate. Especially the relation between different types of 'extreme' weather years that occur during other years could be interesting in determining what the 'risks' are of not pursuing a capacity remuneration mechanism as a country.

The second recommendation is focused on the number of representative days we utilize in our thesis. We use 24 representative days as our daily-UC, and seasonal-UC can solve this in a matter of seconds. However, we see that this still leads to some error margins. This could be solved by modeling 'representative weeks' instead of 'representative days.' Future work needs to be conducted to determine the impact of this on the overall running time of the model and the additional accuracy this creates.

The third recommendation focuses on expanding our model with more capacity-remuneration mechanisms. The current code we have utilized in the investment-decision model is highly flexible, and researchers could replace the capacity-market module with any capacity-remuneration mechanism of interest.

Lastly, our model is currently not 'realistic' in several aspects that could be incorporated in future research. The first addition could be done by including demand-side-response while also allowing any investor to invest in storage facilities. The second addition could be made by having more technical aspects of the generation assets. It could be interesting to see if there are any significant differences between our 'relaxed' model in which we have excluded all these elements and a model which includes all these technical aspects. This could provide additional confidence in the results generated by the model.

The second set of recommendations are focused on further developing the nature of our proof-of-concept model. Firstly, within our thesis, we have made a solid effort to reduce the computational time created by the UC models and the code utilized to process the data generated by our models. However, there is an exciting avenue to explore to reduce the computational time created by the investment-loop caused by our investment-decision model. We currently do not have the answer to this question. However, several factors could be taken into consideration.

A foremost approach that could be explored could focus on changing the logic behind the FP model in the MIDO model. The logic of the investment loop could be changed by including new investments in the objective function of the solver. In the same logic as currently is done in the investment loop, the investor could base its investment decisions on a 'reference-year'. In this way, the model accounts for the limited information investors have, as similar to the current ID model, all the information an investor has stemmed from this 'reference-year'. However, by making new investments part of the objective function and letting a solver decide what assets the market would invest in, the investment loop could be changed into one single optimization per year. Looking at the run time of the investment loop in our thesis, if the solver could optimize a 'reference-year' with the possibility to invest in new assets faster than 30 minutes, the overall model would be faster. The inclusion of investment costs as part of the objective function of a solver is implemented in the LIMES-model, which is a long-term electricity system developed by Schaber (2013), or in more recent work on investment in investment in industrial-clusters by Perea (2021). These papers could serve as a starting point to integrate this new investment perspective in the MIDO model. Another direction that could be explored could focus on the current individual assets that our central investor invests in. In this regard, we have chosen 'realistic' standard asset sizes. However, an argument could be made that since our central investor invests as an entire market. There are many years in which an investment in the same asset is made twice or even thrice. So in this regard, a simple solution could be to increase the 'standard asset' size and compare what this does to the results under the same circumstances. A third idea to further explore is moving away from the current 'central investor' logic to a model with multiple investors. In doing so, first, the number of investors would increase, and therefore the number of major large energy companies that could invest in an asset probably decreases. However, we could also imagine that certain investors have limitations on their investment strategy. So that they would not invest in an asset if this would decrease the profitability of their overall portfolio. The last avenue could be based on 'dropping' the investment consideration into an asset if it has had a negative NPV for several loops in an investment round. As these are merely initial suggestions, we invite future researchers to closely look at this central problem in our MIDO (concerning computational time).

Second, as we hinted at in the discussion, an exciting addition could be to replace our central investment actor with many individual investment actors and adjusting the investment strategies. The primary added value would be seeing the different types of dynamics that emerge from this and the impact on the security-of-supply. A first step in realizing this in our proof-of-concept would be to add a loop before every investment loop. In this loop, an investment actor is chosen that then performs the investment loop is currently utilized. After this has been added, these investors could be given different investment strategies. Lastly, we noted that policy uncertainty was not considered in our proof-of-concept. After adding these different types of investment strategies, another addition could be in accounting for policy uncertainty. This could be realized by running different scenarios in which specific investors have confidence in the government's policy and some who do not. For example, if actors do not trust that the CO_2 price will keep rising, they could add a premium to their investments. Again, these are only initial thoughts, and we invite future researchers to consider this.

Third, the research could look at embracing a 100% Smart Energy System view. In light of this view, there are two options to pursue. The first would be to model the heat and (bio)gas sector in a Linny-R model and allow for investments in these sectors with the same logic as in the hydrogen and demand sector as in our proof-of-concept. This could lead to interesting insights on dynamics between industries. The second would be to do the first option and include a relationship between investment and demand. So only after the model invests in large offshore wind parks through subsidies by a central government. Then hydrogen demand emerges, which again has impacts on the other sectors. This would make such a model very complex; however, it could lead to unexpected policy recommendations and insights.

Lastly, researchers could extend the MIDO model to include multiple countries to see the impacts of capacity-remuneration mechanisms. This extension would introduce an additional dimension to consider. These insights could prove highly valuable for policymakers as it is expected that electricity grids will become more and more intertwined in the future.

Appendix A

Mathematical formalization UC model in Linny-R

A.1 Overview of all utilized set, parameters and variables

Symbol		Explanation
Sets	**Size**	
$co, co_{in}, co_{out} \in Co$		Commodities
$Co(de) \in Co$		Demand commodities
$fuel \in F$		Input fuels for generating assets
$i \in I$		Generation asset groups
$j \in J$		Storage asset groups
$j_{daily} \in J$		Daily storage asset groups
$j_{seasonal} \in J$		Seasonal storage types
$i^{res} \in I$	$\mid$ I x Co x $\mid$	Generation unit with variable renewable input
$i^{trans} \in I$	$\mid$ Co $\mid$	Transformation generation units
$t \in T$		Timesteps
$t_{endweek} \in T$		Timesteps at the end of the week
$tf, tl \in T$		First and last time steps for modelled period t
$weathearyear \in Weatheryear$		A type of weather year

TABLE A.1: Symbols utilized in UC

Symbol		Explanation
Parameters	**Domain**	
k_i^{fuel}	I	Fuel costs for generation asset group
k_i^{CO2}	I	CO2 costs for generation
k_i^{var}	J	Variable storage costs
η_i	I	Efficiency transformation asset group
$\eta_j^{in,out}$	J	Efficiency storage asset group in- and output
C_i	I	Generation asset group capacity
C_j	J	Storage asset group storage size
$Cin_j, Cout_j$	J	Storage asset group storage in- and output capacity
cf_i	$I^{vre}xT$	Capacity factor for VREs
$d(co,t)$	Co x T	Demand for a commodity in timestep t
w(t)		Weight of modeled timestep
ss_i	I	Standard size of the capacity of an asset in asset group i

TABLE A.2: Paramaters utilized in UC

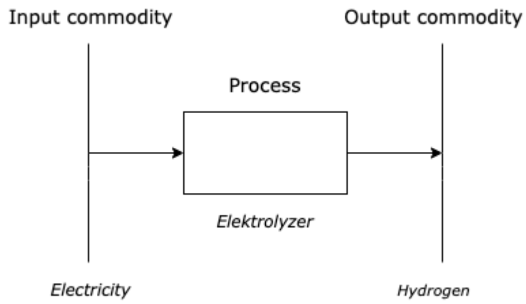
Symbol		Explanation
Variables	Domain	
$E_{i,co}^{in}(t)$	T x I x Co	Energy consumption (input)
$E_{i,co}^{out}(t)$	T x I x Co	Energy production (output)
$V_{j,co}(t)$	J x T x Co	Stored energy
$V_{j,co}^{seas}(t)$	J x T x Co	Seasonal stored energy
$p^{e(t)}$	T	Electricity price at a timestep

TABLE A.3: Variables utilized in UC

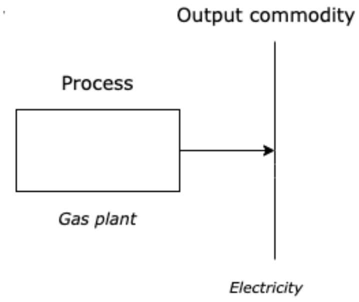
A.2 Overview of all formulas UC

The mathematical formalization of our UC is strongly influenced by the notations utilized in Schaber (2013). An overview of all the symbols utilized in our mathematical formulation can be found in the previous section A.1.

Generation processes



(A) Transformation asset group



(B) Generation asset group

FIGURE A.1: Difference between transformation and generation asset groups

$$E^{out}_{i,co}(t) = \eta_i * E^{in}_{i,co}(t) \qquad \forall i \in I^{trans} \tag{A.1}$$

$$E^{out}_{i,co}(t) \leq C_i \qquad \forall i \in I \tag{A.2}$$

$$E^{out,co}(t) = cf_{i,co}(t) * C_i \qquad \forall i \in I^{VRES} \tag{A.3}$$

The generation process equations A.1-A.3 are valid for all time steps, commodities and generation assets ($\forall t \in T, \forall co \in Co$), unless specified otherwise.

The above equations focus on the process of generating electricity or energy. Our UC model has two types of generation assets groups: generation assets that transform one commodity into another and generation assets that generate electricity. Figure A.1 shows an example of both types of processes. Note that there is no input in the generation asset groups that create electricity (so do not transform a commodity). This input in the form of a commodity is not necessary to produce electricity because we assume this input commodity to be infinite, so therefore it is not modeled.

Equation A.1 applies to all the transformation asset groups only. The equation ensures that the energy generation E^{out}_i of an output commodity co by the transformation asset is equal to the energy input E^{in}_i times the transformation efficiency η of that process.

The energy output is of all processes is capped in equation A.2 that states that the energy production during a time step is equal to or less than the installed capacity of that asset group.

The weather circumstances have to be considered for vRES generating assets such as wind parks or solar PV. This consideration is realized in equation A.3 wherein every time step there is a maximum output possible for every time step $cf_{i,w}$ for every vRES asset. This capacity factor is an input time series for every time step and depends on the weather year w that is assumed to occur in a modeled year.

Storage

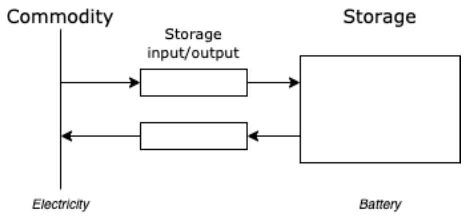


FIGURE A.2: Storage unit

$$V_{j,co}(t) = V_{j,co}(t-1) + Ej, co^{in}(t) * \eta_j^{in} - ES_{j,co}^{out}(t)/\eta_j^{out} \qquad \forall \quad j_{daily} \in J \tag{A.4}$$

$$V_{j,co}(t) = V_j^{seasonal}(t) \qquad \forall j_{seasonal} \in J, \quad \forall t \in T_{endweek} \tag{A.5}$$

$$V_{j,co}(t) \leq C_j \tag{A.6}$$

$$E_{j,co}^{in}(t) \leq Cin, j \tag{A.7}$$

$$E_{j,co}^{out}(t) \leq Cout, j \tag{A.8}$$

Storage equations A.4-A.8 are valid for all time steps, commodities and storage types ($\forall t \in T, \forall co \in Co, \forall j \in J$), unless specified otherwise.

There are two types of storage groups: daily storage groups j_{daily} and seasonal storage groups $j_{seasonal}$, which have different equations. All the storage units work according to the storage process as shown in fig A.2. A commodity is stored and discharged later to reduce the total system costs for every storage unit.

Equation A.4 describes the storage process applicable to all the storage units. The total amount of stored energy is denoted by $V_{j,co}$. The charge and discharge of energy every time step is taken into account by $E_{j,co}^{in}$ and $E_{j,co}^{out}$ respectively. In case energy is either charged or discharged some energy is lost, this is tracked through the parameters η_j^{in} and η_j^{out}.

The seasonal storage units $j_{seasonal}$, have an additional equation described in A.5. At the end of the day of every three days in a simulated year, the stored energy in $st_{seasonal}$ needs to be equal to $V_j^{seasonal}$. We have explained how we derive these seasonal targets in section 3.1.1. Note that this equation only applies to the daily UC since, in the seasonal UC, these targets are created.

Equation A.6-A.8 ensures that the total stored energy and the charge/discharged energy per time step are consistently below the storage capacity.

Energy balance

$$d(co,t) \leq \sum_{i=1}^{I}\left(\sum_{co,in}^{Co,in} E_{i,co}^{out}(t) - \sum_{co,out}^{Co,out} E_{i,co}^{in}(t)\right) + \sum_{j=1}^{J}\left(ESt_{j,co}^{out}(t) - ESt_j^{in}(t)\right) \qquad \forall t \in T, \forall co \in CO^{de} \tag{A.9}$$

Equation A.9 ensures that during every time step t, for all energy commodities co the energy commodity demand d is met. The generation of a commodity can realize this balance in a generation process E^{out} or storage output ESt^{out}. The storage input ESt^{in} and other use of the demand commodity E^{in} have to be subtracted to ensure the balance is kept.

Objective function

$$OBJ = min \sum_i (k_i^{MC}) E_i^{in}(t) + sum_j (k_j^{var} V_j(t)) \tag{A.10}$$

$$k_i^{MC} = k_i^{fuel} + k_i^{CO2} \tag{A.11}$$

All the equations mentioned above are boundary conditions to enable the cost minimization of our solver. The objective of equation A.10 is to minimize the marginal costs of all the variable costs associated with the generation and storage processes that are active at a specific time step.

The marginal costs we take into consideration are shown in equation A.11 our thesis is the fuel costs and the CO2 costs. The level of these costs is set at the beginning of every year. We do not include variable O&M costs, which are taken into account in similar studies; we made a choice to only look at fixed OM costs. The storage processes all have some fictional number of costs associated with them. These costs are set low as not to have a significant impact on the outcome. However, there are some negative costs associated with storage to prevent unnecessary use of storage by the solver.

Appendix B

Input data - FP and PP UC model validation

B.1 Input data - PP validation run

Asset	**Installed capacity (MW)** & cost (€/MW)	
Hydrogen OCGT	6318	66
Hydrogen CCGT	7200	117
Gas plant	Infinite	124
LiOn batteries	116000	0
Hydrogen plant from storage	16000	0
Elektrolyzer available for storage	233333	0
Elektrolyzer available to serve demand	1000000	0
Solar	60000	0
Onshore wind turbines	20000	0
Offshore wind turbines	51500	0

TABLE B.1: Merit order seasonal & daily UC - PP validation

Asset	**Storage capacity (MWh)**	**Variable cost (€/MW)**
Hydrogen storage (cavern)	10000000	0.001
Lithium-ion battery	1350000	0.001

TABLE B.2: Storage units seasonal & daily UC - PP validation

Demand	**PJ**
Electricity	833
Hydrogen	255

TABLE B.3: Demand seasonal & daily UC - PP validation

B.2 Input data - FP validation run

Asset	Installed capacity (MW)	Marginal cost (€/MW)
Gas CCGT CCS	6318	260
Gas engine	7200	285
Gas plant	6540	326
Gas turbine	Infinite	404
Fuel cell	250000	0
Elektrolyzer available for storage	400000	0
Elektrolyzer available to serve demand	1000000	0
Solar	23000	0
Onshore wind turbines	8370	0
Offshore wind turbines	53260	0

TABLE B.4: Merit order seasonal & daily UC - FP validation

Asset	Storage capacity (MWh)	Variable cost (€/MW)
Hydrogen storage (cavern)	10000000	0.001
Lithium-ion battery	1350000	0.001

TABLE B.5: Storage units seasonal & daily UC - FP validation

Demand	PJ
Electricity	833
Hydrogen	255

TABLE B.6: Demand seasonal & daily UC - FP validation

Appendix C

Overview of utilized sets, in investment-decision

Parameter	Unit/content	Description
ss_i	MW	Standard capacity of asset group
$ssin_j$	MW	Standard input capacity of storage group
$ssout_j$	MW	Standard output capacity of storage group
um	-	Upper margin capacity market
lm	-	Lower margin capacity market
r	-	Reserve ratio
Pc	€/MWh	Maximum price capacity market
$y_{lookahead}$	Year	Lookahead in ID-model
$y_{lookahead}$	Year	Lookback in ID-model
f_{equity}	-	Equity percentage
$energycompanies$	-	Amount of energy companies
wt	-	Weight of representative timestep
$age^{eco}_{i/j}$	Year	Economical age asset group
$age^{technical}_{i/j}$	Year	Technical age asset group
sr_{min}	-	Minimum supply ratio

TABLE C.1: Parameters utilized in python code

Set	Description
$\forall fuel \in F$	All input fuels
$\forall i \in I$	
	All asset groups
$\forall i^{vre} \in I$	All vRES asset groups
$\forall co \in Co$	All commodities
$\forall t \in T$	All timesteps
$j \in J$	All storage asset groups
$\forall u \in U$	All individual assets

TABLE C.2: Sets utilized in python code

Variable	Unit/content	Description
p^{e}	€/MWh	Electricity price
p^{fuel}	€/MWh	Fuel price
p^{CO2}	€/MWh	CO2 price
p^{himp}	€/MWh	Hydrogen import price
$change^{fuel}$	-	Factor reflecting fuel price change
$change^{CO2}$	-	Factor reflecting CO2 price change
$change^{himp}$	-	Factor reflecting hydrogen import price change
$change^{co}$	-	Factor reflecting CO2 price change
k_{i}^{CO2}	€/MWh	CO2 cost of an asset group
k_{i}^{fuel}	€/MWh	Fuel cost of an asset group
k_{i}^{MC}	€/MWh	Marginal cost of an asset group
$k_{i/j}^{fixOM}$	€	Fixed O\M of an asset group
$k_{i/j}^{inv}$	€	Investment cost of an asset group
$d(co,t)$	MWh	Demand for a commodity in timestep t
$cf_{i}(t)$	MWh	Capacity factor of vRES asset group in timestep t
$ss_{i,weatheryear}(t)$	MWh	Output of one standard vRES asset in a weather year in timestep t
$E_{i,co}^{max}(t)$	MWh	Max output of an asset group
$E_{i,co}^{out}(t)$	MWh	Output of an asset group
$rev_{u}(t)$	€	Revenue of an individual asset
bid_{u}^{price}	€	Bid submitted to CM market individual asset
bid_{u}^{volume}	MWh	Bid submitted to CM market individual asset
D_{peak}	MW	Peak demand
$CF_{u/v}^{EOM}$	€	Cash-flow individual asset earned in energy-only market
CF_{u}^{CM}	€	Cash-flow individual asset earned in capacity-market
$CF_{u}(y)$	€	Total cash-flow individual asset in a year
$budget$	€	Total investment budget
age_{u}	years	The age of individual asset
$y_{installed,u}$	years	The year in which an individual asset will be installed
y_{ref}	years	Reference year in which the model operates
$u_{thisround}$	[1,....,U]	Individual asset that is invested in current investment-round

TABLE C.3: Variables utilized in python code

Appendix D

Input data Dutch Energy System 2030

D.1 Input demand timeseries - 2030

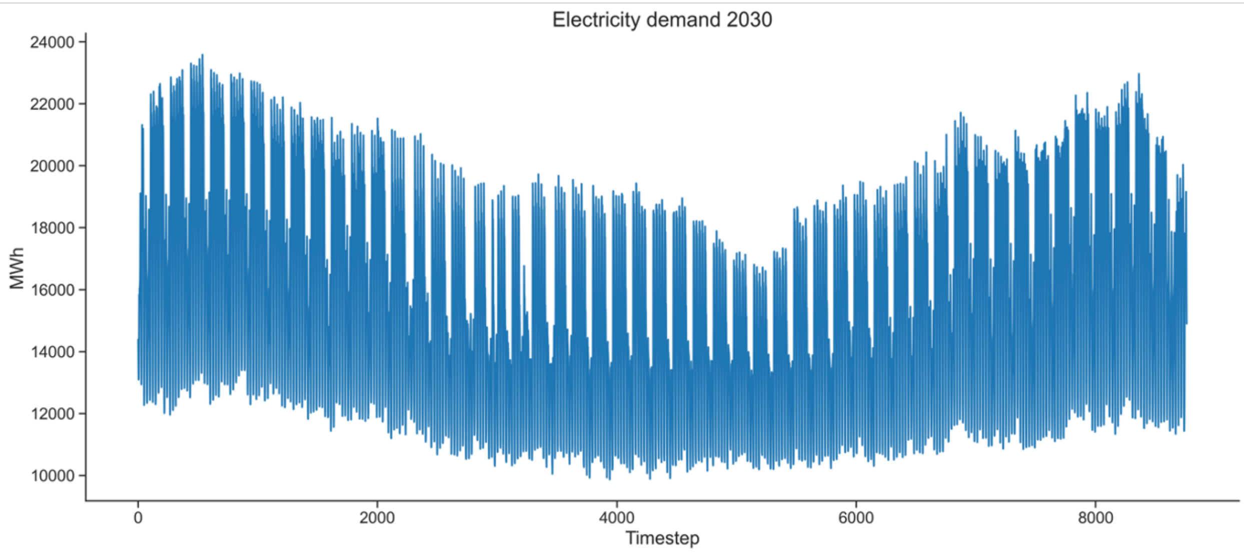


FIGURE D.1: Electricity demand

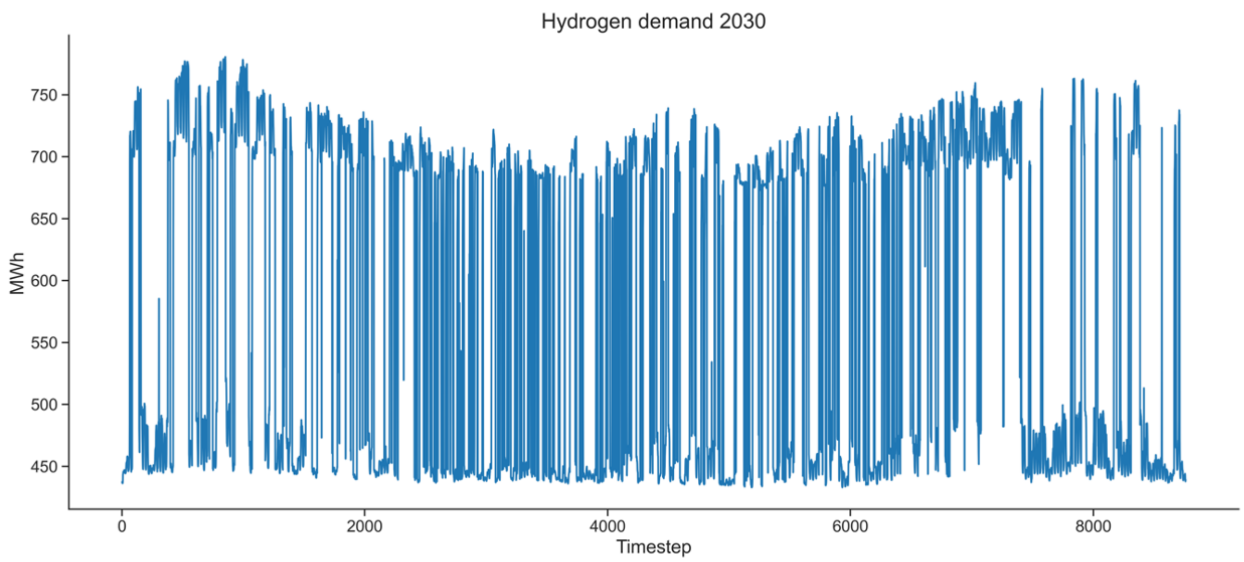


FIGURE D.2: Hydrogen demand

D.2 Ages of all assets

Company	Asset location	Age in 2030
Vattenfall	Magnum	17
Vattenfall	Magnum	17
Vattenfall	Magnum	17
Eneco	Enecogen	18
Eneco	Enecogen	18
RWE	Centrale Moerdijk	18
RWE	Clauscentrale	18
Vattenfall	Centrale Diemen	18
Vattenfall	Centrale Hemweg	18
Engie	Maximacentrale	20
Engie	Maximacentrale	20
EDF/PZEM	Sloecentrale	20
EDF/PZEM	Sloecentrale	20
CCI	Maasstroom Energie	20
Air Liquide	PerGen	23
Uniper	E.ON-centrale Leiden	26
Rijnmond Power	Rijnmond Energie	26
RWE	Centrale Swentibold	31
Nouryon	Delesto	31
Dow	Dow	32
Uniper	Centrale RoCa	33
Engie	Eemscentrale	33
Engie	Eemscentrale	33
Vattenfall	Cluster Velsen	33
Engie	Eemscentrale	34
Engie	Eemscentrale	34
Engie	Eemscentrale	34
Eneco	Lage Weide	35
Vattenfall	Centrale Diemen	35
Air Liquide/Eneco	EuroGen	36
Nouryon	Salinco	37
Eneco	Centrale Merwedekanaal	40
Eneco	Centrale Merwedekanaal	45

TABLE D.1: Age distribution of CCGT assets based on (Wikipedia, 2021a)

Figure D.3 displays the distribution of CCGT asset ages in the year 2030 if all the current installed assets would be kept installed. Based on this distribution, we have assumed the distribution of the CCGT assets in our model (displayed in D.4) and the OCGT assets in our model (shown in D.5).

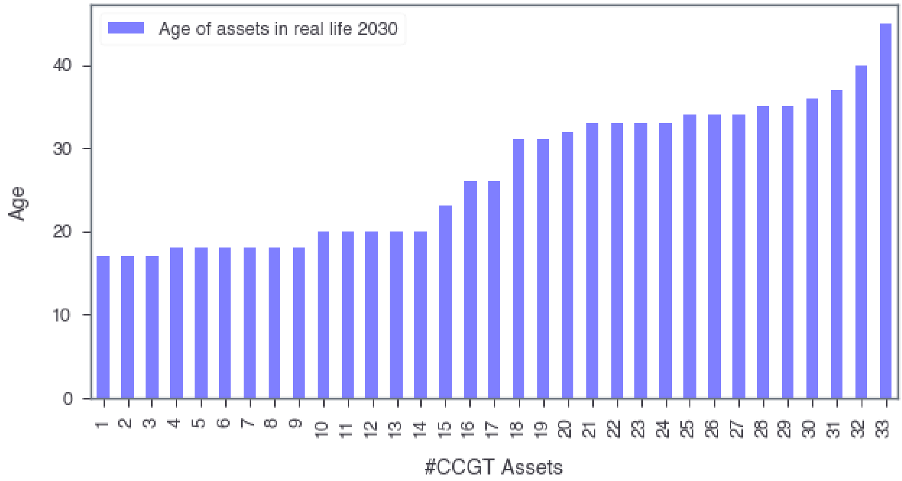


FIGURE D.3: CCGT assets age distribution based on real life data

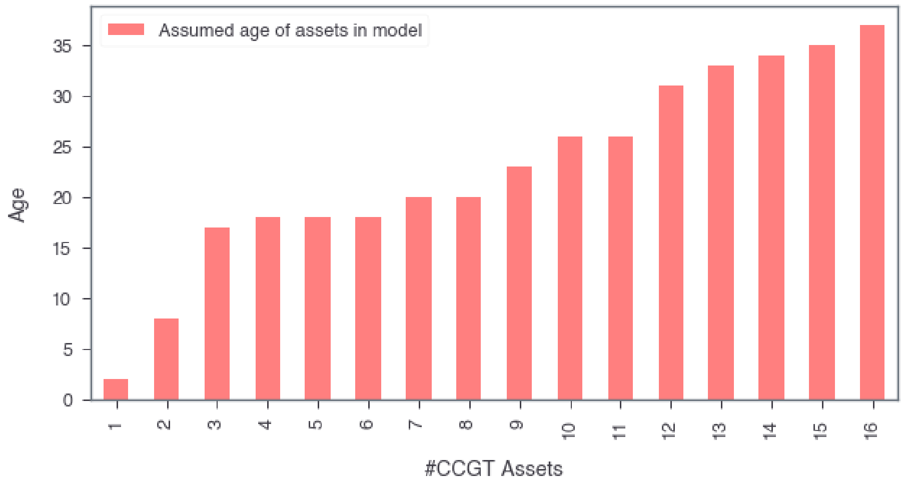


FIGURE D.4: CCGT assets age distribution in model

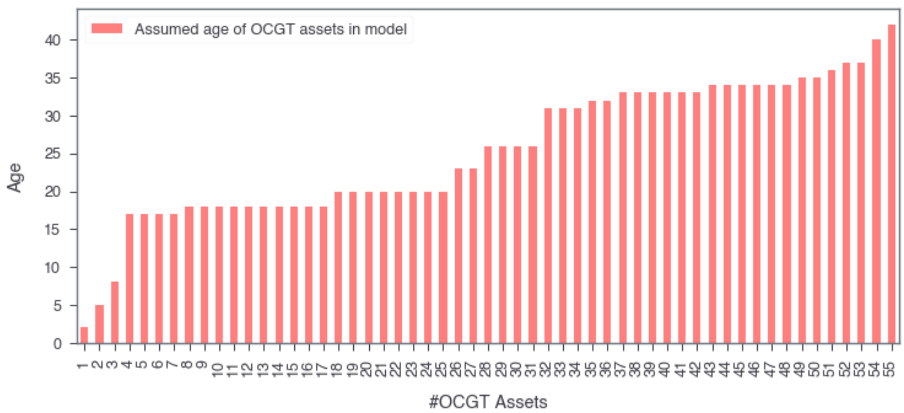


FIGURE D.5: OCGT assets age distribution in model

Producent	Name	location	Age
Cogas	Biomassacentrale Brouwer	Balkbrug	13
Ennatuurlijk	Bio-energiecentrale Strijp T	Eindhoven	14
Brouwer	Centrale Maasvlakte	Rotterdam (Maasvlakte)	14
Twence	Onyx Power	Rotterdam (Maasvlakte)	15
Twence	Biomassa Golden Raand	Delfzijl	16
Eneco	Bioconversie Hengelo	Hengelo	19
BES Exploitatie B.V.	BEC Hengelo	Hengelo	22
BMC	BMC Moerdijk	Moerdijk	22
BECC	Biomassacentrale Twente B.V. Goor	Goor	24
Uniper	Biomassa Energiecentrale Sittard	Sittard-Geleen	25
Onyx Power	Bio-energiecentrale Cuijk	Cuijk	30

TABLE D.2: Age distribution biomass assets (based on Wikipedia, 2021a

We derived from our input scenario, that there is one biomass plant of 500 MW in the merit order in 2030. We assume that this one biomass plant has the average age of all the current installed assets as shown in table D.2.

Offshore park location	Age in 2030
IJmuiden Ver, kavel III	1
IJmuiden Ver, kavel IV	1
IJmuiden Ver, kavel I	2
IJmuiden Ver, kavel II	2
Ten noorden van de Waddeneilanden, kavel I	3
Hollandse Kust (west), kavel VII	4
Hollandse Kust (west), kavel VI	5
Hollandse Kust (noord), kavel V	7
Hollandse Kust (zuid), kavels III en IV	8
Hollandse kust (zuid) I,II	9
Borssele I II	10
Borssele III en IV	10
Gemini Windpark	14
Luchterduinen	15
Prinses Amaliawindpark	22
Egmond aan Zee (OWEZ)	23

TABLE D.3: Ages of offshore windparks based on Ministerie van Economische Zaken en Klimat, 2021

The age of the installed offshore wind park is based on the current offshore wind parks that are already installed and the planned tenders for wind parks on the North sea as shown in table D.3.

Year	Installed onshore asset (MW)
2005	1224
2006	1453
2007	1641
2008	1921
2009	1994
2010	2009
2011	2088
2012	2205
2013	2485
2014	2637
2015	3034
2016	3300
2017	3245
2018	3436
2019	3527
2020	3752
2021	3977
2022	4201
2023	4426
2024	4651
2025	4876
2026	5101
2027	5326
2028	5550
2029	5775
2030	6000

TABLE D.4: Installed onshore windparks based on (CBS, 2021)

Age	#Wind parks
24	2
21	1
16	1
14	1
9	1
6	1
4	1
3	1
2	1
1	1

TABLE D.5: Ages of onshore wind parks

To calculate the age of the onshore wind parks, we have made use of the data on the current installed onshore wind parks. We extrapolated this information until we got to the installed capacity of our 2030 scenario, as shown in D.4. Now that we know in what year how many assets are installed, we can utilize this information to create the age distribution displayed in table D.5.

Year	Installed Solar PV (MW)
2010	88
2011	146
2012	284
2013	646
2014	1,003
2015	1,521
2016	2,129
2017	2,904
2018	4,515
2019	6,867
2020	8,661
2021	10,455
2022	12,249
2023	14,043
2024	15,837
2025	17,631
2026	19,425
2027	21,218
2028	23,012
2029	24,806
2030	26,600

TABLE D.6: Installed Solar PV based on (Wikipedia, 2021b)

Age	10	9	8	7	6	5	4	3	2	1
LiOn assets	5	5	4	4	4	4	4	4	4	4
Electrolyser storage	1	1	1	1	1	1	1	1	1	1
Electrolyser OCGT	0	0	0	0	0	1	0	0	0	1

TABLE D.8: Ages of storage assets

Age	#Solar PV park
20	1
19	0
18	1
17	2
16	2
15	3
14	3
13	4
12	8
11	10
10	9
9	9
8	9
7	9
6	9
5	9
4	9
3	9
2	9
1	9
0	9

TABLE D.7: Ages of solar parks

To calculate the ages of the solar-pv assets, we utilize the same approach as for the onshore wind parks. This leads us to the age distribution for solar pv as shown in table D.7.

There are currently no assets installed at the size we deem as standard in our model for all storage assets. For this reason, we have to make an assumption when assets of this size become available. We assume that this will happen from 2021 on forward, and we assume that these assets will be installed evenly. These assumptions resulted in the age distribution as shown in table D.8.

D.3 Main 'technical' assumptions in scenario - ETM model

Sector	National Governance	European Governance
Built environment	Insulation label A 55% all-electric heat pump 25% heat (geothermal +green gas/biomass) 20% hybrid heat pump green gas LED lighting, induction cooking, efficiency improvement devices, growth number devices Population growth	Insulation label B 40% hybrid heat pumps green gas 20% hybrid heat pumps hydrogen 25% all-electric 15% heat (residual heat +green gas/biomass) LED lighting, induction cooking, efficiency improvement devices, growth number devices Population growth
Mobility	Passenger transport: 95% electric, 5% hydrogen Freight transportation: 50% hydrogen, 25% electric, 25% biofuels	Passenger transport: 70% electric, 30% hydrogen Freight transport: 25% electric, 25% hydrogen, 25% green gas, 25% biofuels
Industry	Similar to current Efficiency 1% per year Circularity important CCS possible Strong electrification, Commitment hydrogen ICT is growing strongly Circular feedstock	Growth 1% per year Efficiency 1% per year CCS important Strong electrification Commitmenthydrogen ICT is growing strongly Fossil feedstock
Agriculture	Strong electrification Emphasis on geothermal and heat pump with storage for heat, biomass boilers and somegreen gas CHPs	Strong electrification Emphasis on geothermal and heat pump with storage for heat
Shipping aviation fuel	Similar to current	Growth 1% per year

TABLE D.9: Main 'technical' assumptions behind scenarios (based on Ouden et al., 2020)

D.4 Linny-R models

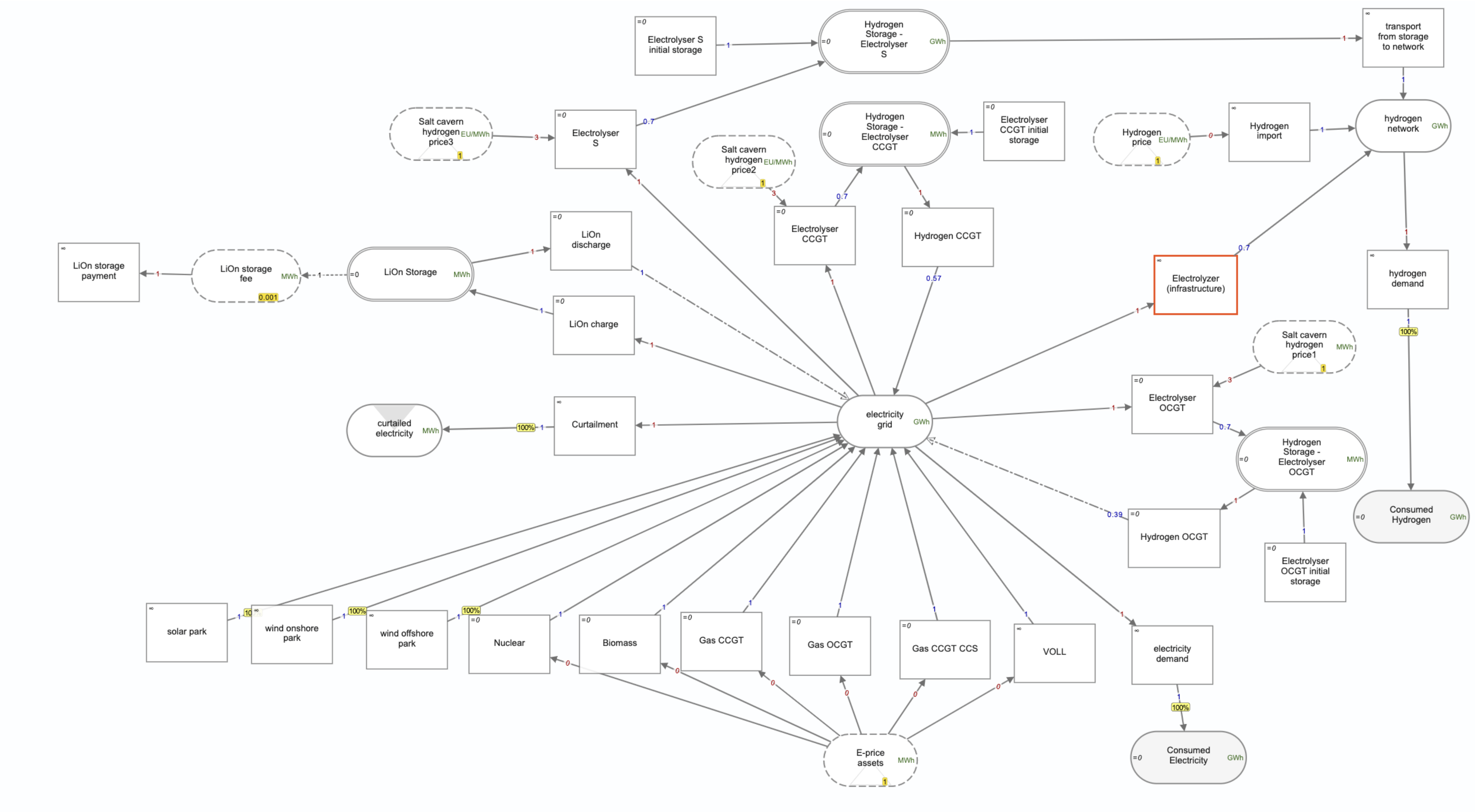


FIGURE D.6: Daily UC in Linny-R

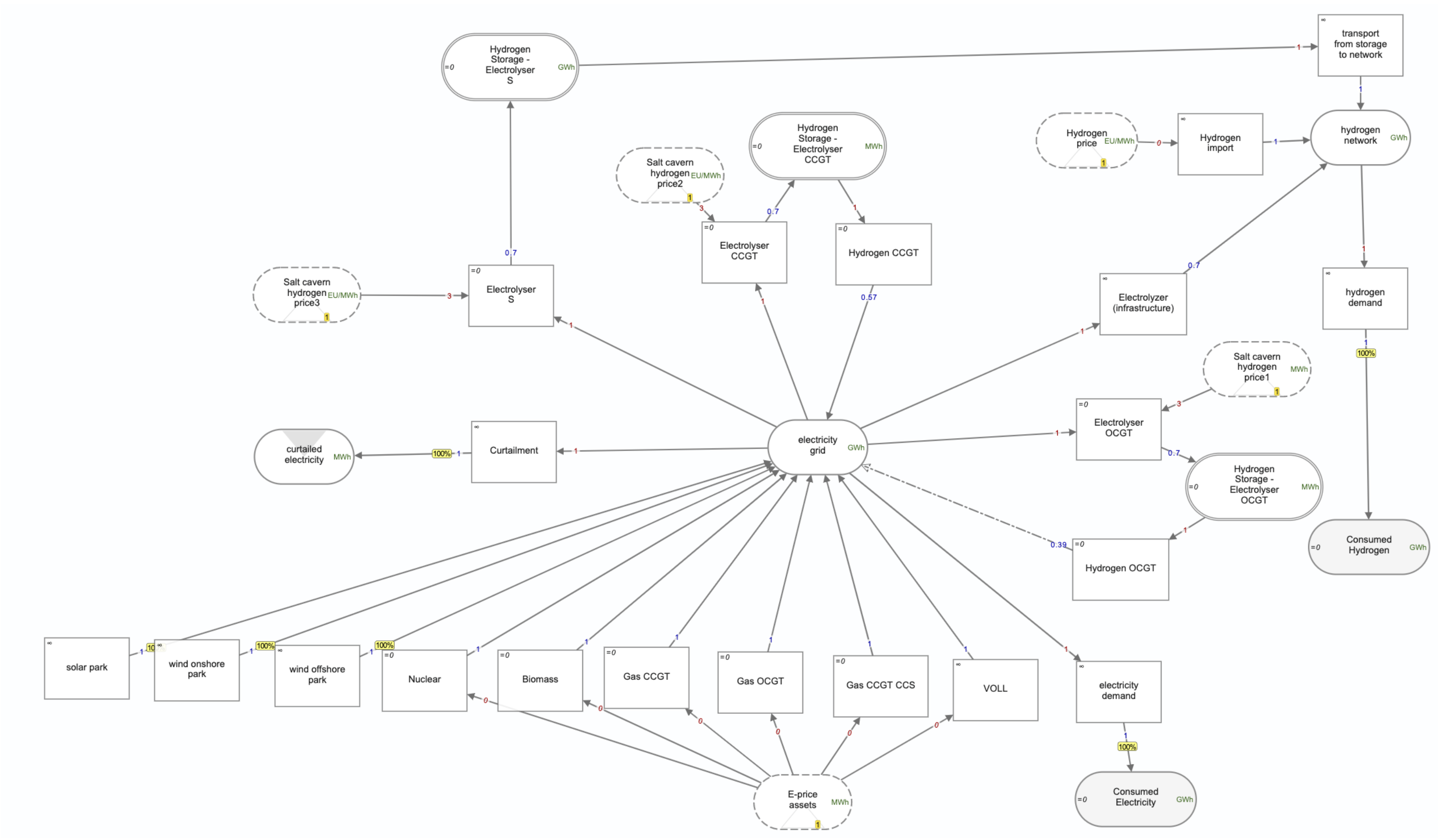


FIGURE D.7: Seasonal UC in Linny-R

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