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Cost-Optimal Transition of the Dutch Electricity System From 2030 to 2050

Development of a Myopic Electricity System Optimisation Model

TUDelft

Cost-Optimal Transition of the Dutch Electricity System From 2030 to 2050

Development of a Myopic Electricity System Optimisation Model

By

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Summary

An important process for navigating the uncertainties associated with the energy transition is power system planning. Energy system models are considered to be useful tools for supporting the power system planning process but are limited in several ways. Firstly, energy system models often have a high computational burden, limiting the possibility of conducting a large range of experiments. Secondly, to reduce their computational burden some energy system models have limited temporal detail, resulting in overestimation of VRE capacity in the system, underestimation of VRE curtailment, and undervaluation of flexible resources. Thirdly, many energy system models are considered to be 'black boxes' due to their high complexity and limited transparency.

To address these problems related to models for power system planning, the Operation and Planning Model (OPM) has been developed in this study. The OPM is a myopic electricity system cost-optimisation model with a high level of temporal detail and a relatively low computational burden to allow for exploring the development of a national energy system, focussing on the interplay between demand, supply, and storage of electricity.

The OPM has been applied to a reference case and two targeted experiments on the development of the Dutch electricity system from 2030 to 2050. The reference case showed that in case natural gas-fired power plants with carbon capture and storage are included in the OPM, the electricity system becomes highly dependent on this technology for the provision of electricity and flexibility. If this technology is not included in the OPM, the maximum number of additional generation and storage units per year is shown to have a major impact on system development. In case this factor is sufficiently high to not limit investments, the system becomes mainly dependent on onshore wind for the provision of electricity and energy storage in underground hydrogen storage facilities for flexibility. In case this factor is limited to a lower level, the system develops a more balanced technology mix.

Multiple recommendations are made for future research continuing on the work presented in this report.

1. Applying the OPM to more experiments can result in more in-depth insights into factors influencing the development path of the Dutch electricity system. This could entail analysing scenarios with variations of the costs for the different technologies to assess under which cost levels the system develops a favourable or unfavourable technology mix.
2. The spatial scope of the OPM can be expanded to assess the importance of cross-border trade for ensuring system reliability and gaining insights into the co-evolution of interconnected electricity systems.
3. The demand side is assumed to be inflexible in the OPM. Including demand side flexibility can result in a more accurate view of the electricity system's development between 2030 and 2050.
4. The used time series data is based on a single year. An alternative approach is suggested in which time series data from multiple years is used which would better represent that perfect forecasting of capacity factors and electricity demand for a future year is not possible.

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List of Abbreviations and Acronyms

AF	Annuity Factor
CAGR	Compound Annual Growth Rate
CAPEX	Capital Expenditure
EAC	Equivalent Annual Costs
EENS	Expected Energy Not Served
KPI	Key Performance Indicator
LOLE	Loss of Load Expectation
LP	Linear Programming
M&S	Modelling and Simulation
MILP	Mixed Integer Linear Programming
NPE	Nationaal Plan Energiesysteem (National Energy System Plan)
OPEX	Operational Expenditure
OPM	Operation & Planning Model
PV	Photovoltaic
RES	Renewable Energy Sources
TSO	Transmission System Operator
UC	Unit Commitment
VoLL	Value of Lost Load
VRE	Variable Renewable Energy

Nomenclature

AF_i	Annuity factor for technology *i*
b	Binary variable indicating the OPM stage (*b* = 0 in Operation stage, *b* = 1 in Planning stage)
$CO2_i$	Carbon emissions per unit of electricity produced for technology *i* (ton CO_2/MWh)
$CO2_y^{MAX}$	Carbon emission cap for year *y* (ton CO_2)
EAC_i	Equivalent annual costs for technology *i* (EUR)
d_i	Depreciation period, i.e., the lifetime technology *i* (year)
η_i^{th}	Thermal efficiency for technology *i*
FC_i^{CAPEX}	Fixed cost for capital expenditures for technology *i* (€)
FC_i^{OPEX}	Fixed costs for operational expenditures for technology *i* (€)
i	Type of technology
I	Set consisting of all generation and storage technology types
$inv_{i,y}^{solver}$	Number of additional units of technology *i* invested in by the model solver in year *y*
$k_{i,t,y}$	Curtailment for technology *i* in timestep *t* in year *y* (MWh)
$ll_{t,y}$	Loss of load for in timestep *t* in year *y*
$L_{t,y}$	Load in timestep *t* in year *y* (MWh)
$OU_{i,y}$	Number of operational units for technology *i* in year *y*
$p_{i,t,y}$	Electrical power supplied by technology *i* in timestep *t* in year *y* (MW)
p_i^{MAX}	Maximum power output for technology *i* per unit(MW)
r_i	Discount rate for technology *i*
$sl_{i,t}$	Storage level of electricity storage technology *i* at timestep *t* (MWh)
sl_i^{MAX}	Maximum storage level per storage unit for storage technology *i* at timestep *t* (MWh)
t	Timestep (e.g. hours or days)
T	Set with all timesteps in a run for each stage year
VC_i^{fuel}	Variable costs for fuel for technology *i* (€/MWh_{th})
VC_i^{OPEX}	Variable cost for operational expenditures for technology *i* per unit of electricity supplied (€/MWh)
$VoLL$	Value of lost load (€/MWh)
y	Current year
Y	Total number of years in the optimisation problem

1. Introduction

In 2015 the Paris Agreement was established to restrict global warming to levels below 2 degrees Celsius of preindustrial times, under the United Nations Framework Convention on Climate Change (UNFCCC, n.d.). To address climate change, signatories of the agreement must prepare and present their plans for climate action. In partnership with five sectors, the Dutch government developed the *Klimaatakkoord* (Climate Agreement) as their plans and goals for reaching the Paris Agreement goals (Klimaatakkoord, n.d.). The Dutch government's target for the electricity sector under the *Klimaatakkoord* is to generate 70% of electricity from renewable energy sources (RES) by 2030, with a 100% target for 2050 (Rijksoverheid, 2019; RIVM, n.d.). The *Klimaatakkoord* also sets the target to reach a 55% reduction of carbon emissions in 2030 compared to 1990 levels (Rijksoverheid, 2019). To reach these targets, major changes to the Dutch electricity and energy system must be made in terms of developing renewable electricity generation capacity, electrical energy storage and other supporting infrastructure, requiring over 300 billion euros in investments, which will take years to develop (Duyster & Terwel, 2021).

To ensure that these necessary investments and developments happen, the Minister of Energy and Climate, Rob Jetten, announced that the Dutch government will take on a more proactive role compared to the last decade (Hensen & van der Walle, 2023). As part of these efforts, a draft version of the *Nationaal Plan Energiesysteem* (NPE, National Energy System Plan) was published. This is a plan that presents the government's long-term vision for the climate-neutral Dutch energy system in the year 2050 (Ministerie van EZK, 2023b; RVO, 2023). The draft version of the NPE contains a description of the five main problems on which decisions have to be made and on which the Dutch government wants to act more pro-active to reach the envisioned energy system of 2050, being:

1. Maximisation of renewable energy supply and development of required supporting infrastructure.
2. Implementation of energy-saving measures.
3. Allocation of available energy and infrastructure to where it is most needed from a systems perspective.
4. International cooperation and increased interconnectedness of the European energy system.
5. Allow for participation and initiatives from citizens in the decision-making process.

One of the goals for electricity production in a supporting document to the draft NPE is to have a net-zero emission electricity system in 2035, which could include natural gas-fired power plants with carbon capture and storage (CCS) if the rate of development of renewable capacity is not sufficient (Ministerie van EZK, 2023a). While the NPE outlines the Dutch government's desired direction for the development of the energy and electricity system up to 2050, it is important to acknowledge that this path will not be without challenges and uncertainties.

Exogenous uncertainties. The draft NPE indicates factors exogenous to the energy system that increase the uncertainties related to the development of the Dutch energy system, such as the transition to more circular production, changes in the labour market, demographic developments, and climate adaptation (Ministerie van EZK, 2023b).

Endogenous uncertainties. The draft NPE also lists factors which are endogenous to the electricity system which result in uncertainty, such as the development of hydrogen production capacity, sustainable fuels, and other technological innovations (Ministerie van EZK, 2023b).

Security of supply. The increasing rate at which operational thermal generation capacity is being decommissioned and variable renewable energy (VRE) electricity generation capacity is being developed, results in a decline in the security of electricity supply. The electricity system becomes more weather-dependent and reliant on flexibility measures such as electrical energy storage and demand response (TenneT, 2022).

Investment planning. The decisions and investments that have to be made in the transition towards 2050 are highly interconnected and have to be made by both public and private parties, which poses a planning and coordination problem between the different stakeholders. The problem entails determining what the optimal mix of energy supply and storage is to meet electricity demand in the year 2050. Additionally, it entails determining how the optimal mix changes over time in the transition from the current system towards the system in 2050 and therefore, how the investments should be timed to maintain an optimal mix. Furthermore, it entails determining which actors are responsible for the realisation of the investments and development of the technologies to realize this optimal mix. To navigate the planning and coordination problem of the energy transition, a long-term and consistent policy strategy of the government is considered to be necessary (Ministerie van EZK, 2023b). However, since the electricity and gas markets are liberalised to a large extent, the level of influence the government has on the developments in these markets is limited.

Investment incentives. There are concerns that the design of the current liberalised electricity market provides insufficient incentives for investing in generation capacity. In a perfect energy-only market, rising electricity prices during times of scarcity should provide the market signal to investors to invest in new generation capacity (Ringler et al., 2017). The characteristics of VRE compared to conventional power plants result in a distortion of this market signal. Negligible marginal costs for electricity production from VRE technologies such as wind and solar power result in an adjusted merit order of generation capacity (Nicolosi & Fürsch, 2009; Sensfuß et al., 2008). VRE technologies are intermittent, which combined with their negligible marginal costs can result in higher price volatility and lower electricity prices in wholesale markets (Cevik et al., 2022; Lund et al., 2015). The combination of higher price volatility and lower price levels increases the investment risks for investing in new electrical generation capacity since there is more uncertainty about the expected returns on the investment. High investment risks may result in risk-averse investors deciding not to invest in new electrical generation capacity or postpone it until the need for new capacity is reasonably sure (Neuhoff & De Vries, 2004). Therefore, the Dutch government must develop policies to reduce these risks, to ensure that sufficient investments in VRE generation capacity are made to transition to the envisioned future energy system while maintaining the security of supply at an acceptable level.

1.1. Power System Planning

An important process for navigating the uncertainties associated with the energy transition is power system planning, which is "a process in which the aim is to decide on *new* as well as *upgrading existing* system elements, to adequately satisfy the loads for a foreseen future" (Seifi & Sepasian, 2011, p. 7). The system elements that are considered in this process are amongst others the generation facilities, substations, and transmission lines (Seifi & Sepasian, 2011). The system can also be subdivided into four functionally independent subsystems that are interconnected, being the generation, transmission, distribution, and consumption subsystems (Demir & Hadžijahić, 2018).

Short-term planning studies have time horizons of up to one year and consider issues such as economic dispatch, unit commitment, and day-ahead markets (Gaur et al., 2019; Seifi & Sepasian, 2011). Long-term studies have time horizons ranging between one year and up to a few decades and typically consider issues such as transmission and generation expansion planning, investment decisions, and policy development (Gaur et al., 2019; Seifi & Sepasian, 2011). The increasing share of decentralised intermittent VRE generation and decreasing share of centralised thermal power plants increases the complexity of the power system planning process and increases the importance of considering short-term system operations in long-term power system planning (Deng & Lv, 2020; IEA, 2022b).

Power system planning studies are being conducted by both private and public actors, such as consulting firms, government agencies and academic institutions (e.g. DNV (n.d.), NREL (n.d.), Tallinn University of Technology (n.d.)). However, in the context of the current European liberalised electricity market, the decisions regarding investments in generation facilities are mainly made by actors from the private sector (Meeus, 2020). Therefore, the government does not have a direct influence on how the generation requirements of the system are met and in which generation technologies will be invested (Seifi & Sepasian, 2011). Through the development and implementation of energy policies, policymakers attempt to steer the decisions of these private sector actors to ensure that their energy policy goals are met.

The Dutch government indicated in the concept NPE that its policy goals for the current and future energy system are that it is affordable, reliable, safe, sustainable, equitable, and participatory (Ministerie van EZK, 2023b). These goals overlap to a large extent with the European Commission's energy policy goals that are based on three pillars, being secure, sustainable, and competitively priced energy for Europe (European Commission, n.d., 2020). The combination of these three energy policy goals is often referred to as the 'energy trilemma', since the goals can be competing with each other and trade-offs have to be made (Heffron et al., 2015). Therefore, policymakers should assess how policies affect the three pillars integrally and not focus on developing policies for each pillar in isolation. As earlier discussed, the current developments in the electricity sector result in an increase in price volatility, lower prices, higher investment risk, and therefore more uncertainties in the process of power system planning. This results in an increasing need for decision support tools, such as quantitative energy systems models, to navigate these uncertainties.

1.2. Energy System Modelling

Energy system modelling is an important tool for supporting long-term power system planning, analysis of energy transition pathways, and for deducing policy advice (Mier & Azarova, 2021; Poncelet, Delarue, Six, Duerinck, et al., 2016). Energy system modelling allows decision-makers to evaluate the performance of alternative power system designs over a range of scenarios, such as changes in demand, the introduction of new technologies, and the integration of renewable energy sources.

1.2.1. Differentiation Between Energy System Models

The work of Siala et al. (2022) compared energy system models and more specifically power market models based on four characteristics, being the model type, the planning horizon, the temporal resolution, and the spatial resolution.

Differentiating based on types of models results in the distinction between models that use either an optimisation or a simulation framework (Siala et al., 2022). In the case of an optimisation framework, the model attempts to minimize the overall system costs, consisting of investment costs, fixed operation and maintenance costs, and variable costs. Such models are based on the fundamental assumptions of a perfectly competitive market in which symmetric firms seek to maximise profits, which would lead to a minimisation of system costs in a perfectly competitive market (Siala et al., 2022). In reality, these assumptions do not always hold in electricity markets, since they show characteristics of oligopoly markets with imperfect competition (Ahlqvist et al., 2022). On the other hand, simulation models do not necessarily follow the fundamental assumptions of a perfect market and determine dispatch and investment decisions on heuristics (Siala et al., 2022). This allows for simulating strategic behaviour, such as firms seeking scarcity rents during periods when available generation capacity is limited. However, using a simulation model is a less suitable approach in case the purpose of a planning study is to determine the least-cost system configuration.

Differentiation based on planning horizon relates to the foresight period a model has for determining the dispatch and investment decisions (Siala et al., 2022). A distinction can be made between two types of models. Firstly, there are perfect foresight models that have complete knowledge over the entire time horizon of the power system planning problem (Cuisinier et al., 2022; Poncelet, Delarue, Six, & D'Haeseleer, 2016). Some authors refer to these models as intertemporal models, since they consider all the periods of the entire planning problem simultaneously (Siala et al., 2022). Secondly, there are myopic models, which have a limited foresight period (Cuisinier et al., 2022; Poncelet, Delarue, Six, & D'Haeseleer, 2016). The term myopia is the medical term for near-sightedness (Foster & Jiang, 2014). In myopic models the optimisation problem is divided into sub-problems that are being solved consecutively, meaning that the investment and dispatch decisions within the period of foresight are made without information about later periods (Lopion et al., 2018; Siala et al., 2022). The results from the earlier sub-problems are then used as inputs for the later sub-problems.

Distinguishing between model types based on temporal resolution relates to the number of timesteps to reflect fluctuations in supply and demand within a year (Siala et al., 2022). There are roughly two approaches, either using 8760 hourly timesteps for an entire year or using a heuristic or clustering algorithm for selecting representative hours or days. The advantage of a representative time-step approach is that it reduces the complexity of a model and therefore lowers the computational burden (Pfenninger, 2017; Siala et al., 2022). However, using 8760 hourly timesteps will result in model results showing more accurate storage behaviour (Nahmmacher et al., 2016; Siala et al., 2022).

In the study by Siala et al. (2022), the spatial resolution of a model refers to the number and shape of the geographical regions that are modelled within the European power market based on the wholesale markets. However, when using a broader definition for the concept of spatial resolution, it can also relate to the spatial distribution of the demand and supply within a region, and whether to include constraints into the model resulting from network topology and available capacity on transmission lines, distribution grid, and interconnectors (Frew & Jacobson, 2016; Hess et al., 2018). Including these constraints allows for assessing the impact of limited infrastructure transport capacity on the functioning of the system but increases the computational burden. When these constraints resulting from transport infrastructure are neglected, the electricity system in the model can be considered to be a 'copper plate' (Hess et al., 2018).

1.2.2. Balancing Trade-Offs in the Design of Energy System Models

Although energy system models are considered useful tools for supporting decision-making, it is shown that these models have shortcomings and that trade-offs have to be made when selecting or developing an energy system model. Energy system models used for conducting long-term planning studies often have limited temporal details to reduce the computational burden resulting from their large size and long planning horizon (Gaur et al., 2019; Kannan, 2011). Not sufficiently accounting for these short-term operational constraints can result in an overestimation of VRE capacity in the system, underestimation of VRE curtailment, and undervaluation of flexible resources (Deane et al., 2012; Gaur et al., 2019). To address these shortcomings, studies have assessed the effect an increase in time resolution and the addition of unit commitment constraints in long-term planning models has on simulation outcomes. These studies showed that there are significant differences in the generation mix that is the outcome of a long-term model when including short-term operational factors (Haydt et al., 2011; Palmintier & Webster, 2011; Pina et al., 2011).

A different approach to address the problems related to the limited temporal detail in the models used for long-term planning studies is by soft-linking of models to iteratively integrate a long-term system planning model with a short-term or operational model that addresses aspects such as hourly dispatch and intermittent VRE generation (Brouwer et al., 2015; Deane et al., 2012; Poncelet, Delarue, Six, Duerinck, et al., 2016). However, since the models used in such an approach are linked and not developed in an integrative fashion, the basic functioning of the linked models often differ, which can result in solutions not converging and the outcome being sub-optimal (Gaur et al., 2019; Helistö et al., 2019). Therefore, it is important to develop integrated energy system models that allow for long-term planning and account for detailed operational factors, without resulting in an excessive computational burden.

Next to the drawbacks related to the lack of limited temporal detail, some energy system models can be considered 'black boxes' according to Mier & Azarova (2021). The first reason is that these models often consist of large numbers of variables and equations, which makes it hard or nearly impossible to trace back differences in model results to specific assumptions or equations (Mier & Azarova, 2021). Secondly, a majority of the models are not publicly available and often very little to no descriptions or source codes are provided (Mier & Azarova, 2021). This reduces the possibility for model comparison and replication of results, which is often indicated as a key reason for differences between results of similar studies or policy analyses based on different models (Mier & Azarova, 2021; Morrison, 2018; Müller et al., 2018). Moreover, Moallemi & Malekpour (2018) indicated that it is important that models used in the power system planning process are transparent and easy to work with to have private and public stakeholders and decision-makers make use of them. Therefore, energy system models must be transparent and not excessively complex, to allow for a clear understanding of the influence of assumptions and equations on the model outcomes and to allow for inter-model comparison.

When addressing the influence of the level of foresight of models, it is useful to consider two concepts from the field of transition studies, being path dependency and technological lock-ins. Path dependency refers to the idea that past investment decisions shape future opportunities and can limit future options (Teece et al., 1997). This is related to the concept of a technological lock-in, which occurs when an existing technology becomes dominant and difficult to displace due to the infrastructure and investment already committed to it (Arthur, 1989; Teece et al., 1997). These concepts have been widely used in transition literature for describing, identifying, and analysing mechanisms or variables that affect transition pathways (Goldstein et al., 2023).

Intertemporal models can avert path dependencies and lock-ins since these models examine the entire time horizon, which is not the case for myopic models (Siala et al., 2022). In a real-world situation, the bounded rationality of investors may also lead to investment decisions that are myopic and therefore may result in suboptimal achievement of policy goals (Bhagwat et al., 2017). Although the intertemporal models with perfect foresight are useful for finding cost-optimal solutions, the results from myopic models with limited foresight are more likely to be close to the real economy and market behaviour (Lopion et al., 2018). An additional advantage of myopic models is that in general, they have a lower computational burden compared to models with perfect foresight, which makes them more usable for conducting analyses with higher temporal, spatial, or technological resolutions, while maintaining manageable computational times (Babrowski et al., 2014; Mier & Azarova, 2021; Poncelet, Delarue, Six, & D'Haeseleer, 2016).

Sánchez Diéguez et al. (2021) present the IEASA-Opt model, an optimisation model used for analysing the impact of cross-sectoral flexibility for the energy transition in the Netherlands. The model comprised amongst others the simultaneous optimisation of the hourly dispatch for the power system of 20 European countries and the multi-year planning of investment decisions for developing transport infrastructure, generation capacity, and energy storage. The run time of the IESA-Opt model for the transition from 2020 to 2050 took 8 hours per run, while only performing a run for the year 2050 took 30 minutes[1]. Extensive models such as IESA-Opt consider a wide range of factors, which makes them well suited for conducting in-depth and detailed analyses on the development of a national energy system. However, their high computational burden limits them in the possibility to perform a high number of runs consisting of a longer range of consecutive years, since this results in the need for a computer with high computational power or conducting all the runs will become a very time-consuming process.

1.3. Research Objectives

The main objective of this research is methodological in nature and aims to develop an energy system optimisation model for exploring the transition of a national electricity system, focusing on the interplay between demand, supply, and storage of electricity. The model needs to optimise both short-term operational and long-term investment decisions. The model must have a limited computational burden, to allow for running a range of runs within a manageable timeframe. Moreover, the working of the model has to be transparent and not overly complex, to ensure comprehension of how assumptions shape model outcomes.

To assess whether the developed model is suitable for exploring the transition of a national electricity system, it will be applied to a reference case on the development of the Dutch electricity system from 2030 to 2050 to assess whether the model is fit for purpose. Additionally, it will be applied to two targeted experiments to assess potential alternative development paths for the Dutch electricity system. The two targeted experiments will focus on the effect of excluding CCS as a technology and varying the rate at which additional generation and storage capacity can be developed for the development of the Dutch electricity system from 2030 to 2050.

1.4. Research Questions

To guide the methodological objective for the development of the cost-optimisation model in this study, the following question will be answered:

1. *What is a suitable design for a cost-optimisation model for exploring the development of a national electricity system?*

Two additional research questions will guide the application of the model to a case study on the development of the Dutch electricity system from 2030 to 2050:

2. *Does the model provide credible results for the development of the Dutch electricity system from 2030 to 2050?*
3. *How does the exclusion of CCS and variations in the rate of development of additional generation and storage assets affect the development of the Dutch electricity system from 2030 to 2050?*

The next chapter will discuss the methodology used to reach the research objectives and answer the research questions. Additionally, the next chapter discusses the steps taken in this modelling study and how this results in the structure of the report.

1 The researchers used a computer with “a six-core processor, 32 GB of RAM, and an unblocked solid state drive” (Sánchez Diéguez et al., 2021, p. 25).

2. Methodology

This study will use a quantitative research approach to address the research objectives and answer the research questions. More specifically, a modelling approach will be used as the research method. The study consists of two parts. The first part of the study entails constructing a cost-optimisation model for exploring the development of a national electricity system. In the second part of the study, this model is applied to a case study of the development of the Dutch electricity system from 2030 to 2050, consisting of a reference case and two targeted experiments.

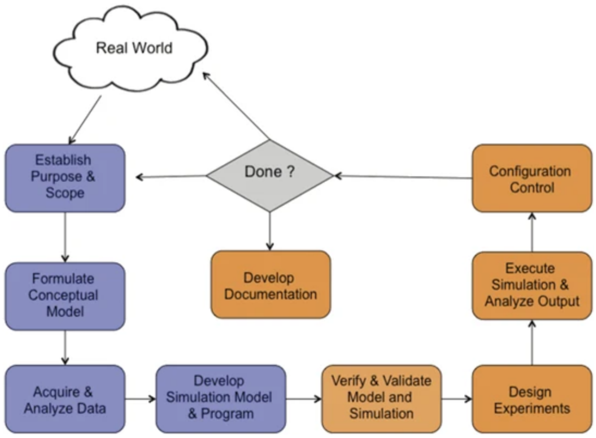


Figure 1: Modelling and simulation process. From Loper (2015).

To guide the model development process, the modelling and simulation (M&S) life cycle process framework of Loper (2015) is used. A visual overview of the nine steps is shown in Figure 1.

1. ***Establish the purpose and scope.*** This entails developing a problem statement, based on a real-world problem to be solved. This is presented in chapter 1, in which the societal problem is introduced, literature is discussed, research objectives are stated, and the resulting research questions are presented.
2. ***Formulate the conceptual model.*** Loper (2015) distinguishes between an informal conceptual model and a formal conceptual model. The informal conceptual model is an abstract version of the real-world system which is being studied and described using natural language. The development of the informal conceptual model will be discussed in chapter 3. The formal conceptual model only contains an unambiguous description of the model, this will be presented in chapter 4 of this thesis report.
3. ***Acquirement and analysis of data.*** The data used as input for the reference case is presented in chapter 6.
4. ***Develop a simulation model and program.*** This consists of the implementation of the formal conceptual model into a programming language, a simulation language, or other computational software, which will be presented in chapter 5.
5. ***Verification and validation of the model*.** Verification is the process of determining whether the model represents the conceptual description and specifications. Validation is the process of determining the degree to which a model and its outputs accurately represent the real-world system. This will be presented in section 5.5.
6. ***Design of experiments.*** This entails determining the design of the different scenarios that will be simulated. In this study, the design of the reference case will be presented in chapter 6 and the design of the experiments will be presented in chapter 7.
7. ***Execution of experiments.*** This consists of running experiments with the model and analysing the outputs. The results and analysis of the reference scenario and the experiments will be presented in chapters 6 and 7.
8. ***Configuration control.*** This is the process of keeping track of different versions of a model that is under development. This happened during the model development process, but only the finalised version of the model will be presented in this thesis.
9. ***Model documentation.*** This is the report which presents all the M&S framework steps taken for developing the model and analysing results. In the case of this study, the model documentation is this entire thesis report.

The next chapter will discuss the conceptualisation of the developed model.

3. Conceptualisation

3.1. Spatial Scope and Resolution

The objective of the study is to develop a cost-optimisation model for exploring the development path of a national electricity system, which will be applied to the Dutch electricity system. Therefore, the spatial scope of the optimisation model is the Dutch electricity system. It is assumed that there is no interconnection capacity with neighbouring countries. The advantage of this approach is that it reduces the complexity and computational burden compared to a model in which all interconnected electricity systems are modelled.

However, in reality, the Dutch electricity system is interconnected with Denmark, Belgium, Germany, Norway, and the United Kingdom (CLO, 2022). TenneT (2022) reported that the interconnection capacity with the UK and Norway specifically will have an important role in ensuring the security of supply for the Netherlands in the years after 2030 when there are higher levels of intermittent VRE generation capacity. This is because these countries are less likely to have shortages in electricity supply simultaneously with the Netherlands compared to Germany, Belgium, and Denmark. Therefore, interconnection capacity has an important role in the functioning of the Dutch electricity system, which will become increasingly important in the post-2030 electricity system. As a result of the modelling assumption that the Dutch electricity system is an isolated system, more electricity generation and storage assets are required compared to what can be expected in the real-world system.

Next to the spatial scope of the model, the spatial resolution of the model has to be determined. It will be assumed that the electricity system functions as a copper plate, meaning that there are no constraints resulting from network topology or available capacity on the transmission and distribution grid. This also means that the spatial distribution of supply and demand is not taken into consideration. Similar to the assumption to model the national system in isolation, this assumption was made to reduce model complexity and the computational burden of the model. The disadvantage is that factors such as grid congestion cannot be accounted for, which is becoming an increasingly large problem for the development of solar photovoltaic (PV) projects in certain regions in the Netherlands (RVO, 2022; van den Berg, 2019). Hess et al. (2018) included the constraints resulting from grid capacity and the costs for grid expansion in a scenario study for a 100% renewable German energy system in 2050 and found that the grid makes up 12% of the total system cost. The model which is developed for the study presented in this thesis report will not be able to consider the grid constraints, nor the grid expansion costs that are necessary for increasing the share of VRE. However, this is considered to be outside the scope of this research.

3.2. Technological Scope

The model only includes domestic electricity supply and demand, and the assumption is made that the grid functions as a copper plate. From a technological perspective, this means that the model does not include transmission or distribution infrastructure, nor interconnectors with the electricity systems of other countries. The electricity demand in the model is aggregated on a national level, meaning no distinction is made between the electricity demand for specific purposes, industries, or geographic regions. Similarly, the electricity supply is aggregated on a national level, meaning that the location of generation and demand, and potential grid congestion are not considered.

In principle, the model always tries to meet electricity demand. However, in case the costs for delivering the load are higher than the value of lost load (VoLL), the model will decide to shed the load. In EU Regulation 2019/943 the VoLL is defined as "an estimation in euro/MWh, of the maximum electricity price that customers are willing to pay to avoid an outage" (European Parliament, 2019, p. 12).

The main technological components which are included in the model are generation and storage assets. Three groups of electricity generation technologies will be included in the model, being VRE generation technologies, thermal generation technologies with carbon emissions, and thermal generation technologies without carbon emissions.

The VRE technologies that are included are PV, offshore wind, and onshore wind. The thermal generation technologies with carbon emissions that are included are biomass and waste-fired power plants, and combined cycle gas turbines (CCGT). Coal-fired power plants are not included in the model, since the Duch government banned the use of coal for the generation of electricity starting from 2030 (Eerste Kamer der Staten-Generaal, 2019; Rijksoverheid, 2018). The thermal generation technologies without carbon emissions that are included are nuclear power plants and combined cycle gas turbines with carbon capture and storage (CCGT CCS). In a supporting document to the draft NPE, it is indicated that CCS may have a role in the energy transition as a backup, but that focus should be on the maximisation of the VRE capacity (Ministerie van EZK, 2023a). For CCGT CCS the specific operational characteristics and limitations of the storage of CO_2 have not been included in the model, since this is outside of the scope of this study.

A distinction will be made between storage assets for daily and seasonal storage. The conceptualisation of daily storage assets in the model is based on lithium-ion batteries. The conceptualisation of seasonal storage in the model is based on the conversion of electricity into hydrogen using electrolysers, underground hydrogen storage (UHS) in salt caverns and depleted gas fields, and the conversion of hydrogen into electricity using fuel cells.

The conceptual model presenting the spatial and technological scope is shown in Figure 2.

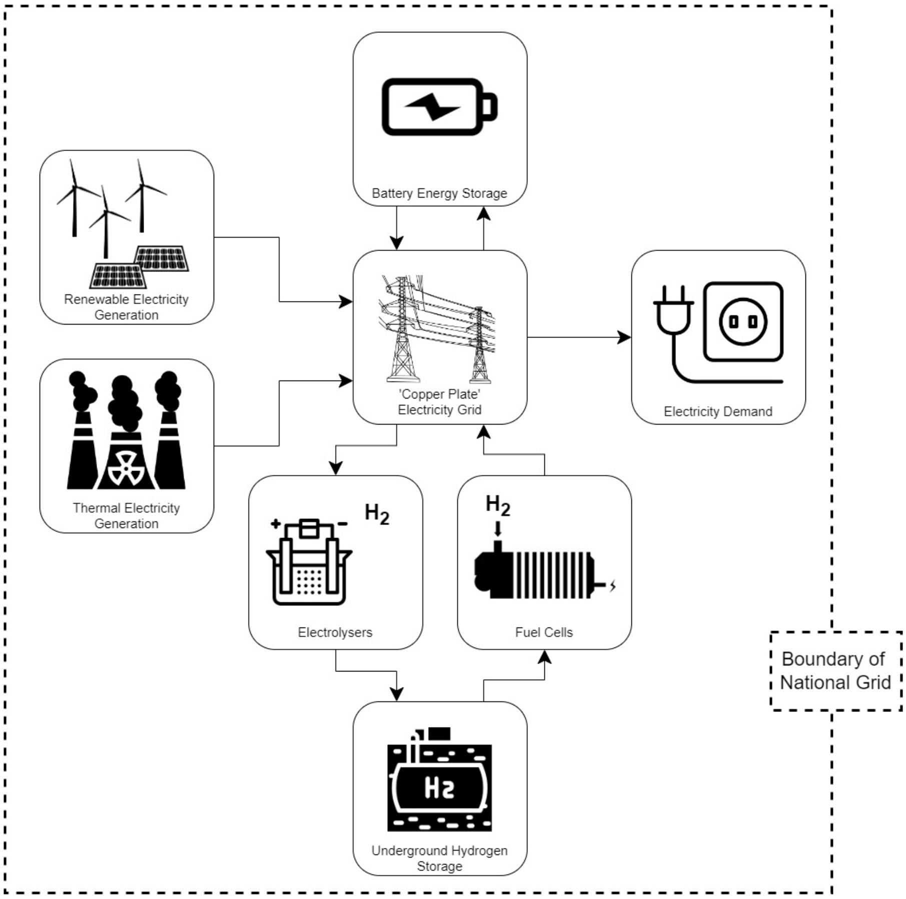


Figure 2: Conceptual Model Technological System

3.3. Conceptualisation of Model Stages

To allow for the optimisation of both short-term operational and long-term investment decisions, the developed optimisation model consists of two consecutive stages. The first stage of the model focuses on the operational short-term functioning of the system and the second stage focuses on investment planning. Therefore, the names of the stages are the Operation and Planning stage, and the name of the model is the Operation & Planning Model (OPM).

The Operation stage aims to minimise costs for the generation of electricity and the charging and discharging of storage technologies to meet demand for a full year. The Planning stage focuses on a future year for making investment decisions for the additional generation and storage assets that are required for that year to minimise the costs of meeting electricity demand.

The longest lead time for all technologies included in the model as an investment option is four years[2]. Therefore, the Planning stage focuses on a year four years into the future. This ensures that the nearest

2 The lead times of the different technologies are presented in Table 13 in appendix B.

possible year in the future is considered for which it is possible to develop each investment option, given that the maximum lead time for developing each technology is four years.

The two stages form an iterative loop in which the Operation stage and the Planning stage each move one year forward after solving the optimisation problem for their respective year. Both stages will have a limited amount of foresight outside of the stage it optimises. This is by the implementation of a look-ahead period of two months into the next year to prevent storage units from emptying at the end of the year. Figure 3 shows how the OPM moves through this iterative loop for three consecutive rounds. The designed optimisation approach is a rolling horizon approach, since the decisions made in both stages are based on the information available within the stage and a period of foresight outside of the stage (Cuisinier et al., 2022; Mier & Azarova, 2021). Since the foresight period outside of the stage is limited and does not stretch till the end of the entire optimisation period, this optimisation approach can be considered a rolling myopic horizon approach (Mier & Azarova, 2021).

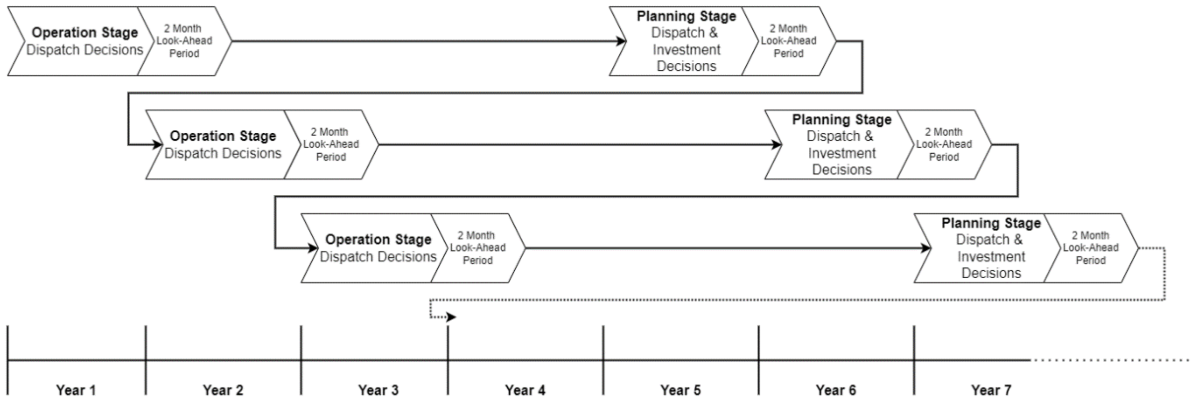


Figure 3: Conceptual Model Flow Diagram

3.4. Key Performance Indicators

When assessing the model outcomes based on Key Performance Indicators (KPIs), a distinction will be made between primary and secondary KPIs. This distinction has been observed in publications from the fields of public policy and business management (Chae, 2009; Cunningham & Pomfret, 2007). Primary KPIs are the most crucial metrics that directly reflect system performance. Secondary KPIs are supportive metrics that provide additional insights and context to the primary KPIs. While secondary KPIs might not have a direct impact on the core objectives of the system, they contribute to a deeper understanding of the factors influencing performance.

The most important system performance characteristics for this study are the costs and reliability of the system. Therefore, the following four primary KPIs will be assessed.

1. **Annual Total System Costs**. The objective of the optimisation model is to minimise total system costs while meeting all constraints, therefore the annual total system costs are the first primary KPI.
2. **Cost per MWh of Electricity Demand.** To allow for easier comparison of system costs between years with different levels of electricity demand, the cost per MWh of electricity demand will be calculated. It is not expressed as cost per MWh of electricity delivered or generated, since loss of load and curtailment are possible.
3. **Expected Energy Not Served (EENS).** To analyse the amount of lost load in a year, the EENS is assessed.
4. **Loss of Load Expectation (LOLE).** To analyse the number of hours with loss of load during a year, the LOLE is assessed.

TenneT (2022) states that the EENS and LOLE are the most important indicators for analysing the security of supply for the electricity system. The performance standard for the Dutch electricity system is a LOLE of four hours per year (TenneT, 2022).

Next these four primary KPIs, two secondary KPIs will be assessed to develop an understanding of the development of the system and its performance.

1. **Electricity Delivered to the Grid per Technology.** To analyse the usage of the electricity generation and storage assets, the electricity delivered to the grid per technology is assessed.
2. **Installed Capacity per Technology**. To analyse the development of the structural system, the installed electricity generation capacity and installed power capacity from storage technologies are assessed.

It is important to explicitly note that the KPIs are only assessed for the Operation stages of the model, since those stages represent the actual day-to-day operation of the electricity system, while the Planning stage represents the decision-making process for investments in assets that become operational four years in the future. An overview of the KPIs with their respective units is presented in Table 1. Since the KPIs are considered to be straightforward, the formulas are not presented in this section but can be found in appendix A for reference.

Table 1: Overview of the Primary and Secondary KPIs

	Metric	**Unit**
Primary KPI 1	Annual Total System Costs	€
Primary KPI 2	Cost per MWh of Demand	€/MWh
Primary KPI 3	Expected Energy Not Served (EENS)	MWh or GWh
Primary KPI 4	Loss of Load Expectation (LOLE)	hours/year
Secondary KPI 1	Electricity Delivered to the Grid per Technology	GWh or TWh
Secondary KPI 2	Installed Capacity per Technology	GW

In the next chapter, the formalised model will be presented.

4. Formalisation of the Model

4.1. Formalised Model Flow

In this section, the formalised model flow of the OPM will be discussed to explain what inputs are used and what outputs are generated during each stage of the model. A diagram showing the detailed steps of the model is shown in Figure 4. The layout of this diagram is inspired by the model flow diagram of Groenewoud (2022).

In the Operation stage, the model will solve an economic dispatch problem for the current full year with a two-month look-ahead period. Based on the results of solving this problem, the KPIs are calculated. To reduce the computational burden of the model the temporal resolution consists of four-hour timesteps, as will be further discussed in section 5.4.1. The model uses six groups of data inputs for the Operation stage.

1. Time series data which consists of data on hourly electricity demand and the capacity factors for the VRE technologies.
2. Data on the number of operational units available in the first year per technology.
3. Techno-economic data for the different technologies, such as the installed capacity per operational unit, the variable costs, and the carbon emissions per unit of electricity produced.
4. The carbon emission cap for the current year.
5. Development schedule of new units becoming available in the current year per technology.
6. Decommissioning schedule for the units being decommissioned in the current year per technology.

Note that there are two development schedules indicated in the model flow diagram in Figure 4, one being the 'predefined development schedule' and one being the 'solver development schedule'. The first contains the development schedule for new assets as an input dataset which can be adjusted for conducting experiments. The second contains the investment decisions made by the model while solving the optimisation problem. The decommissioning and development schedules are used to adjust the number of operational units per technology each year.

The Planning stage also uses a four-hour timestep resolution and a two-month look-ahead period. In contrast to the Operation stage, this stage focuses on a year which is in the future, i.e., the focal year. For this year, the model solves an economic dispatch problem to determine what the cost-optimal usage is of the generation and storage units which are operational and possible additional units which can be invested in.

At the start of the Planning stage, the same six groups of input data used for the Operation stage are updated. The input data used during this stage represents the focal year in the future instead of the current year. This means that the Planning stage accounts for the development in electricity demand and the change in operational assets in the system resulting from the decommissioning and development schedules.

If the model decides to use new assets of a certain technology during the focal year, it will update the dataset which contains the development schedule of that technology. By doing so, an investment in the selected additional asset happens, which will become available at the start of the Operational stage four years in the future. After finishing the Planning stage, it will be checked whether additional years have to be optimised. If so, the model continues with the Operation stage in the next year. If the model has reached the last year of the entire optimisation problem, it stops.

If the scope for an optimisation problem using the OPM is for example the years 2030 to 2050, the model should be run for the years from 2027 to 2050. Since the Planning stage decides to invest in units for a focal year that is four years in the future, starting the model in 2027 results in the first additional units becoming operational in 2031. The installed capacity mix that is set for 2030 is considered the start situation and therefore additional assets become available after this first year. If the model had been run from 2030 to 2050 instead of 2027 to 2050, there would be a gap in the years from 2030 to 2033 in which no additional units can become available yet, but in which decommissioning of operational units can already happen based on input data.

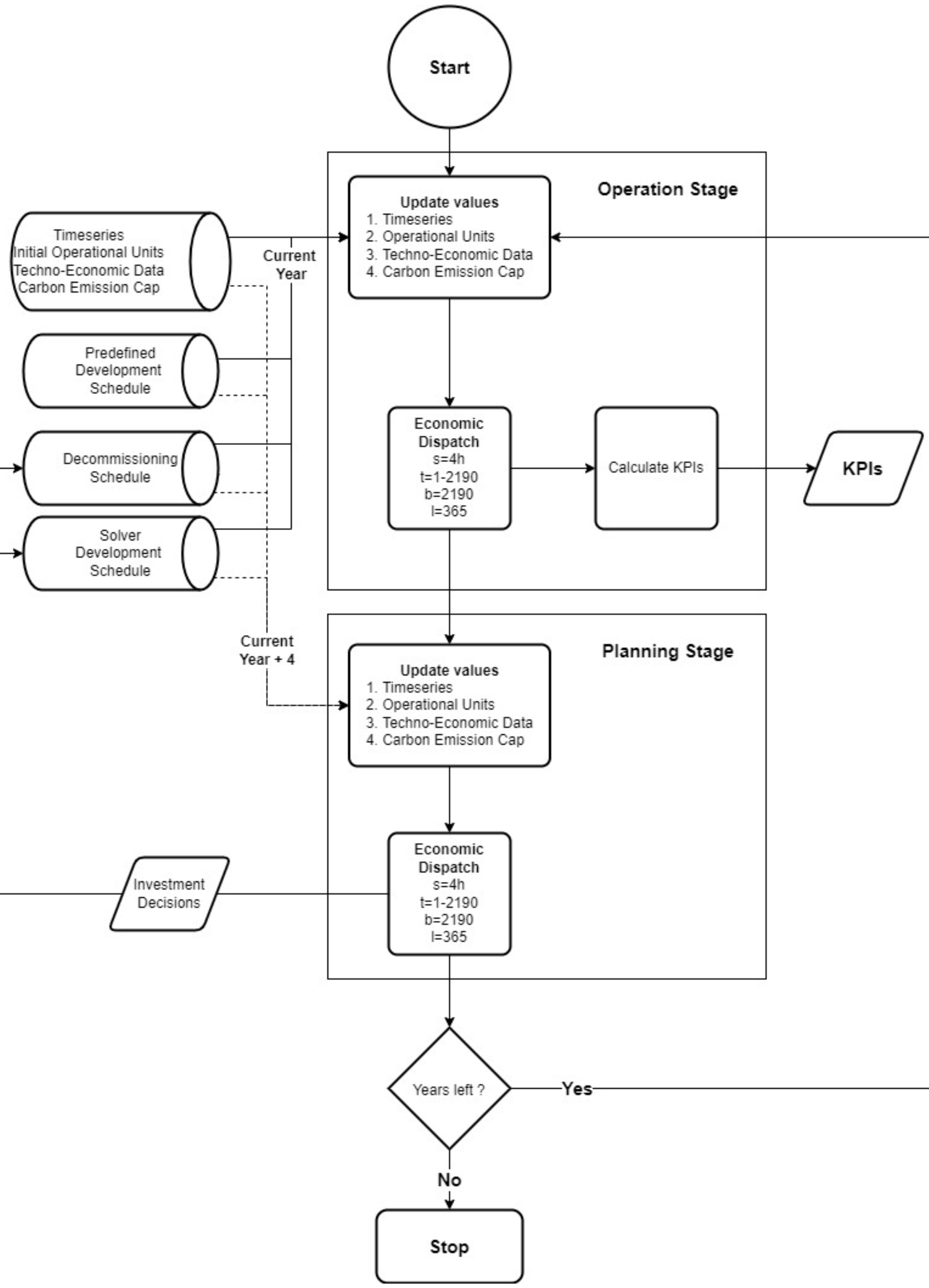


Figure 4: Formalised Model Flow Diagram[3]

3 The letters in the economic dispatch process blocks indicate the model settings during the respective stage. ‘s’ = time step, ‘t’ = optimisation period, ‘b’ = block length, ‘l’ = look-ahead

4.2. Representation of Assets in the OPM

In the OPM, generation and storage technologies are represented as single processes that represent all generation or storage capacity for that specific type of technology. Investments in additional units or decommissioning of operational units happen in discrete steps based on the standard unit capacity of the respective technology. For example, when one unit of a technology is decommissioned, the installed capacity of the process representing the technology is reduced by one time the standard unit capacity. The standard unit capacities used will be presented in section 6.3.1

4.3. Decision Variables

The first decision variable in the OPM is the level of electricity generation from the generation technologies and the level of charging or discharging of electrical energy from the storage technologies which is shown in Equation 1. The decision to invest in an additional unit of a technology by the model during the Planning stage is represented by the decision variable presented in Equation 2. The exact meaning of the terms in the formulations for the decisions variable, objective functions, and constraints that will be presented are listed in the Nomenclature list and will therefore not always be indicated or explained in the text in this section and the next few sections.

Equation 1: Level of electricity generation, charging or discharging by technologies

$$p_{i,t,y} \qquad \forall\ i \epsilon I\ \ \forall\ t \epsilon T\ \ \forall\ y \epsilon Y$$

Equation 2: Number of additional units invested in by model solver

$$inv_{i,y}^{solver} \qquad \forall\ i \epsilon I \quad \forall\ y \epsilon Y$$

4.4. Objective Function

The objective function of the OPM is to minimise the total cost of meeting electricity demand, through a combination of dispatching generation assets, charging and discharging of the storage assets, and loss of load. The objective function also contains the costs for investment in additional units by the model solver, expressed as equivalent annual costs (EAC) for additional units and multiplied by a binary variable b. During the Operation stages, only the assets operational in that year can be used and therefore the binary variable b is zero during the Operation stages. During the Planning stages, it is also possible for the model solver to invest in additional units, therefore b has a value of one during the Planning stages. The objective function is formalised in Equation 3.

Equation 3: Objective Function of the OPM

$$Minimise\ \ (Total\ Variable\ Costs + b \cdot (EAC\ Costs\ for\ Additional\ Units))$$

$$Total\ Variable\ Costs = \sum_{t}^{T}((\sum\nolimits_{i \epsilon I} p_{i,t,y} \cdot (\frac{VC_i^{fuel}}{\eta_i^{th}} + VC_i^{OPEX}) + VoLL \cdot ll_t)$$

$$EAC\ for\ Additional\ Units = \sum\nolimits_{i \epsilon I} EAC_i \cdot inv_{i,y}^{solver}$$

The objective function contains all variable costs for electricity generation, charging and discharging of storage, costs for loss of load, and the EAC for additional units. Note that the objective function does not indicate a summation over all years of the optimisation problem, since the separate model stages are myopic and optimise for each year independently without considering later years. Only the two-month look-ahead period is considered for preventing the emptying of the storage assets at the end of the year.

The threshold for investment in the objective function is the EAC, which accounts for both the capital expenditure (CAPEX) discounted over the lifetime of the asset and the fixed annual operational expenditures (OPEX). The EAC is similar to an annuity but also incorporates the fixed OPEX next to the CAPEX. The formalisation of the EAC as an investment threshold is based on Kenton & Kindness (2020) and is presented in Equation 4. The annuity factor used for the calculation of the EAC is shown in Equation 5. The lifetime of a technology in years is represented as d_i and the discount rate as r_i.

Equation 4: Equivalent Annual Costs

$$EAC_i = \frac{FC_i^{CAPEX}}{AF_i} + FC_i^{OPEX}$$

Equation 5: Annuity Factor

$$AF_i = Annuity\ Factor_i = \frac{1-(1+r_i)^{-d_i}}{r_i}$$

4.5. Constraints

The first constraint to which the optimisation problem is subject is the energy balance constraint which dictates that the supply of electricity must always meet demand. The constraint is shown in Equation 6. The left-hand side of the equation includes the generation of electricity and charge or discharge from storage assets, curtailment, and loss of load. The right-hand side is the load per timestep. Charging of storage assets is represented as negative generation on the left-hand side of the equation.

Equation 6: Energy Balance Constraint

$$\sum\nolimits_{i\in I}(p_{i,t,y} - k_{i,t,y}) + ll_{t,y} = L_{t,y} \qquad \forall\ t\epsilon T\ \ \forall\ y\epsilon Y$$

The next constraint ensures that output from generators and storage technologies cannot exceed the installed capacity. During the Planning stage, the binary variable b has a value of one, which allows the use of additional units invested in by the solver. This is formalised in Equation 7.

Equation 7: Power Capacity Constraint

$$p_{i,t,y} \le p_i^{MAX} \cdot (OU_{i,y} +\ b \cdot inv_{i,y}^{solver}) \qquad \forall\ t\epsilon T\ \forall\ i\epsilon I\ \forall\ y\epsilon Y$$

The number of operational units per technology in a year is indicated by $OU_{i,y}$. During the Operation stage, the number of operational units is determined by first taking the number of operational units in the Operation stage one year earlier, subtracting the number of units to be decommissioned, and adding the number of units to be developed. The number of units to be developed consists of the number of units invested in by the solver during the Planning stage four years ago and the number of units that were scheduled to be developed in that year as part of an experiment.

During the Planning stage, the number of operational units is determined by taking the number of operational units in the Operation stage of the current year, subtracting the number of units to be decommissioned in the four upcoming years, and adding the number of units from the development schedule in the four upcoming years.

The next constraint ensures that the level of energy stored in the storage assets cannot exceed the installed energy storage capacity from the operational units. During the Planning stage, the additional units that the model solver decides to invest in during that stage are also available. It is shown in Equation 8.

Equation 8: Storage Capacity Constraint

$$sl_{i,t,y} \le sl_i^{MAX} \cdot (OU_{i,y} +\ b \cdot inv_{i,y}^{solver}) \qquad \forall\ t\epsilon T\ \forall\ i\epsilon I\ \ \forall\ y\epsilon Y$$

The last constraint is the carbon emissions cap, which is presented in Equation 9. The level of the carbon emissions cap is not equal each year. Therefore, the carbon cap is formulated with an index for the year that is being optimised.

Equation 9: Carbon Emissions Cap

$$\sum_t^T \sum\nolimits_{i\epsilon I} p_{i,t,y} \cdot CO2_i \le\ CO2_y^{MAX} \qquad \forall\ y\epsilon Y$$

The next chapter will present the implementation of the formalised model into Linny-R.

5. Implementation of OPM in Linny-R

5.1. Why Linny-R

The OPM is implemented in Linny-R, which "is an executable graphical specification language for mixed integer linear programming (MILP) problems, especially unit commitment problems (UCP) and generation expansion planning (GEP)" (Bots, 2023a). The Linny-R software has the advantage that it offers a high level of transparency due to the graphical visualisation of all processes, products, and flows in the model. Additionally, the Linny-R software is freely available (Bots, 2023a).

The software is still being further developed and updated versions with new features are published quite frequently (Bots, 2023b). During the process of developing the OPM, this resulted in the advantage that some adjustments to the software were made on request. The disadvantage was that sometimes bugs were encountered when new versions of Linny-R were released. However, in most cases, these bugs were fixed within a few hours after reporting.

A disadvantage to note is that the documentation on Linny-R is limited. There is a documentation website that contains a user guide explaining the functionalities, the graphical user interface (GUI), and the language reference for Linny-R (Bots, 2022). The information provided through this documentation website should be sufficient to understand how Linny-R works and how to develop models. Next to the documentation provided here no other formal materials are available. However, the advantages of using Linny-R are considered to largely outweigh these disadvantages.

5.2. Key Concepts in Linny-R

In Linny-R three basic modelling concepts are used for creating models: processes, products, and links. In the GUI of Linny-R, four main visual components are used, being processes, products, links, and clusters. The description of these components in this section is based on the information provided by Bots (2022).

Products represent something which can be consumed and/or produced by processes. The product can be a tangible good, such as fuel or electricity, but also intangible information or data, such as carbon credits. At each timestep, the product has a certain level. Additionally, a product can be constrained by an upper and lower bound. Lastly, a product can have a certain price. Next to default products, there are four alternative types of products, being stocks, sinks, sources, and data products.

- Stocks function as storage and can retain a certain level over multiple timesteps.
- Sinks function as the destination or receiver in a model.
- Sources function as the point of origin or the supply in a model and provide the necessary inputs into the system.
- Data products represent intangible information and can be either default data products, stocks, sinks or sources. A visual representation of the different product types and their characteristics in Linny-R is shown in Figure 5.

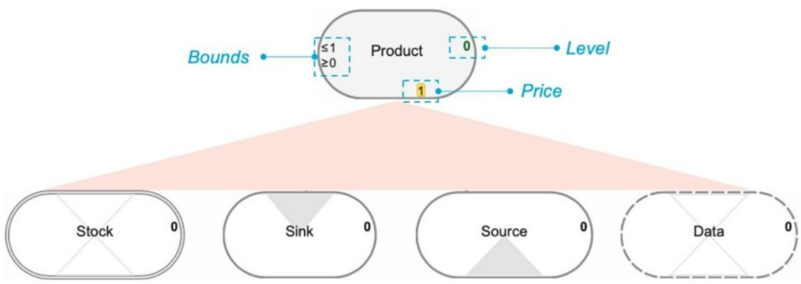


Figure 5: Products in Linny-R. From Groenewoud (2022).

Processes represent the conversion of products into other products. For it to hold significance within a model, a process must be connected to at least one product. At each time step, a process has a production level, which may be constrained by a lower and upper bound. Additionally, a process may have a cost price. Figure 6 shows how a process is represented in Linny-R and how it is linked to products.

Links represent the potential flow of products or data. When a link is present from a product into a process, the process uses the product. When a link is present from a process to a product, the process produces the product. A link has a rate, which determines the efficiency of conversion of an input product into an output product. An overview of how processes, products, and links are represented in Linny-R is shown in Figure 6.

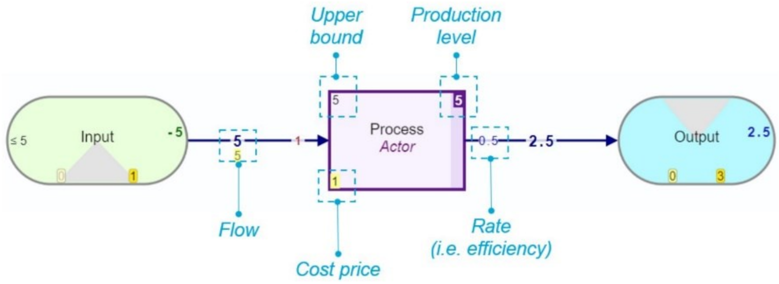


Figure 6: Processes, products, and links in Linny-R. From Groenewoud (2022).

The last relevant Linny-R component to introduce is the cluster, as shown in Figure 7. Clusters can be used to group processes in a subsystem, which helps create a clearer overview of a model but does not affect the optimisation problem itself. Processes can only be a part of one cluster, while products can be part of multiple clusters. Additionally, it is possible to have clusters within clusters to create multiple levels within a model.

Figure 7: Cluster in Linny-R

5.3. OPM Components

5.3.1. Top Cluster of OPM in Linny-R

The top cluster of the OPM as shown in Figure 8 contains all system components of the electricity system. The central component of the OPM is the ‘Grid balance’ product, which represents the ‘copper plate’ electricity grid. All generation technologies can deliver electricity to the ‘Grid balance’ product. Storage technologies are also able to use the ‘Grid balance’ product for charging the storage. The process ‘Electricity Consumption’ is only constrained by a lower bound which is set by a dataset that contains the time series data for the electricity consumption. Through the ‘Grid balance’ product the required electricity is supplied. The ‘Grid balance’ has a very small value for its lower and upper bound ($-1*10^{-8}$ and $1*10^{-8}$) to ensure proper solver functionality when running the model without slack.

In case the generation technologies and storage assets are not able to meet demand, the ‘Accept Loss of Load’ process can supply to the ‘Grid balance’ to ensure that the energy balance constraint is met (Equation 6). The costs for loss of load are determined by the ‘VoLL’ data product, which represents the value of lost load. Therefore, the solver will only opt for loss of load when it results in lower costs than dispatching operational units, discharging the storage assets, or investing in additional units.

During timesteps in which VRE generation exceeds demand, the solver has the option to either store the electricity in one of the storage technology units or curtail it. The curtailment of all operational units is combined in the ‘Total Curtailment Operational Units’ and the curtailment of all potential additional units during the Planning stage is combined in the ‘Total Curtailment Operational Units’ data product.

Lastly, the top cluster of the OPM also contains a cluster ‘Total System Costs’. This cluster contains a range of data products for the calculation of the annual total system costs.

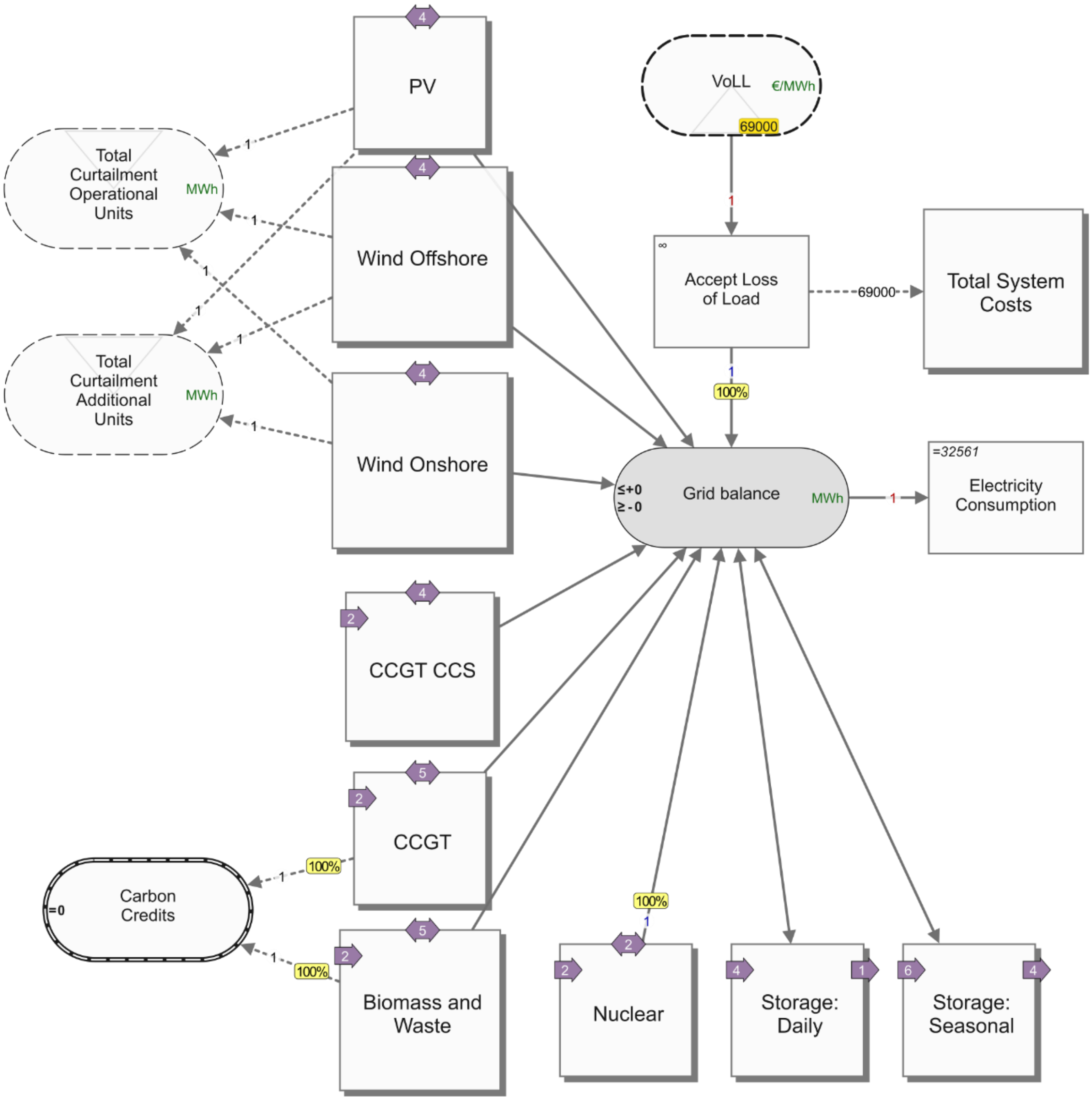


Figure 8: Top Cluster of OPM in Linny-R

5.3.2. Thermal Generation Assets

The cluster for the CCGT units is used as an example of the design of the clusters for the thermal generation assets and is shown in Figure 9. To distinguish between the electricity generation from the existing operational units and the additional units which can be invested in during the Planning stage, two processes in the cluster deliver electricity to the grid, 'CCGT: Commit Operational Units' and 'CCGT: Commit Additional Units'.

When generating electricity, the processes use fuel and have other variable costs, which are represented by the input products 'CCGT: Fuel' and 'CCGT: Variable O&M'. Additionally, output data products for keeping track of the variable costs of operational units are included as well for calculation of the total annual system costs during the Operation stages. When units of fossil fuels are used, CO_2 is emitted through the 'CCGT: Emissions' data product. In turn, this results in the 'Carbon Credits' data product filling up, which is capped on an annual basis for the entire OPM.

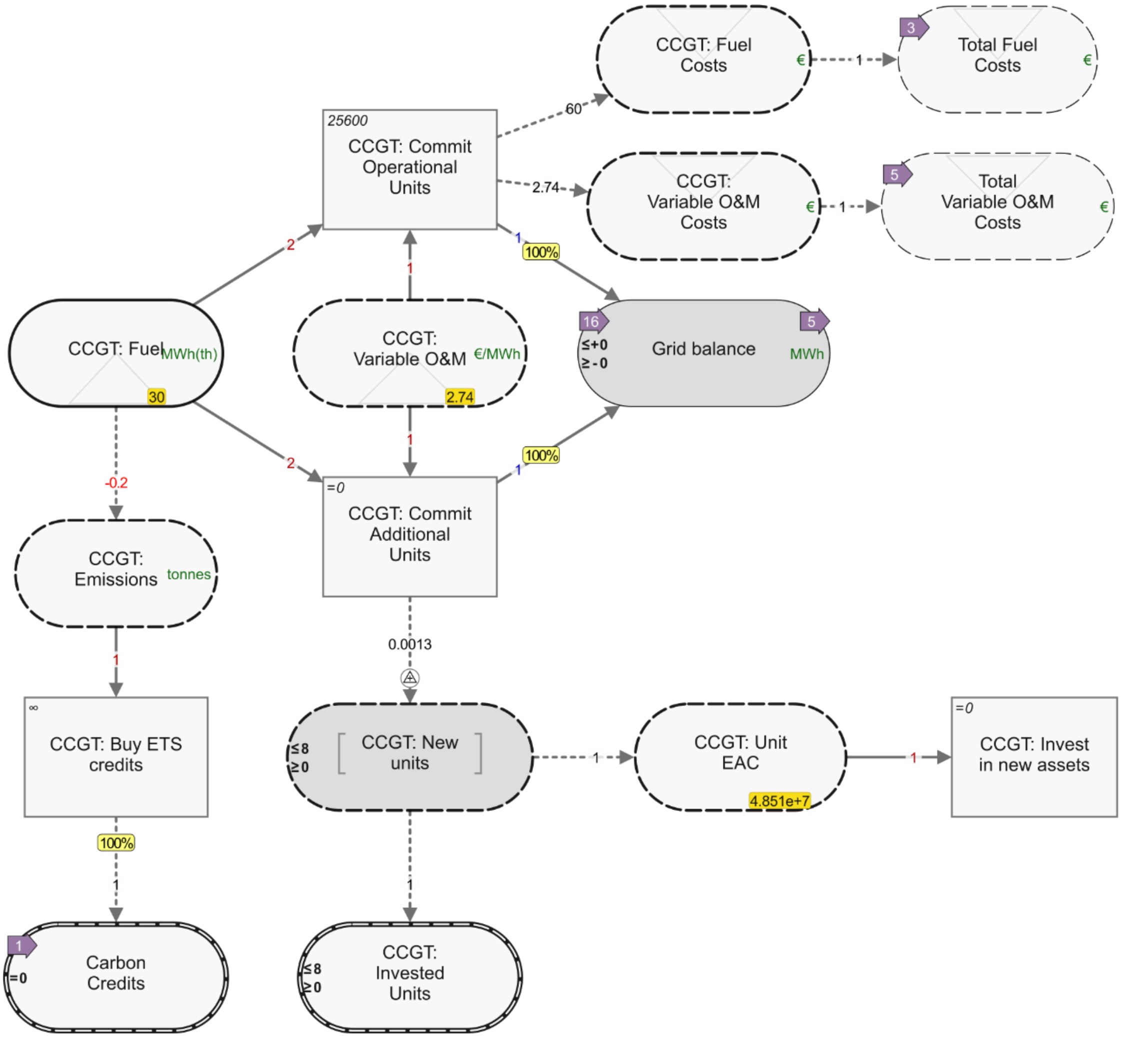


Figure 9: Thermal Generation Assets in OPM (CCGT)

Since investment in new assets is only possible during the Planning stage, the upper bound of the 'CCGT: Commit Additional Units' process is zero during the Operation stages. During the Planning stages, the process has an upper bound set at the maximum number of additional units multiplied by the standard unit capacity of the technology. Investment in an additional unit is triggered when the 'CCGT: Commit Additional Units' process is used. More units are invested each time the output level of the process surpasses a level which is a multiplication of the standard unit capacity. This is implemented through the use of the 'peak-increase' link between the 'CCGT: Commit Additional Units' process and the 'CCGT: New units' data product. The 'CCGT: Invested Units' stock data product is for keeping track of the number of invested units in the current optimisation block. The 'CCGT: Unit EAC' represents the EAC for an additional operational unit, which allows the model to determine which technology is the most cost-effective investment if an additional generation unit is required.

The clusters for CCGT CCS and nuclear generation deviate slightly from the CCGT cluster. For CCGT with CCS, it is assumed that all CO_2 emissions are captured and stored, which results in no emissions from the use of fossil fuels by this technology.

Nuclear energy is a controversial energy source for electricity generation and social acceptance is low in the Netherlands (Sánchez Diéguez et al., 2021). Whether new nuclear plants will be developed depends highly on how public support and government policy develops. Therefore, nuclear generation is not included as an investment option for the solver. Accordingly, the nuclear cluster does not have a process for electricity generation from additional units, as can be seen in Figure 10. The only option for the development of additional nuclear power plants is through the predefined development schedule dataset, which allows for a predefined number of nuclear power plants to become operational in a certain year as part of an experiment.

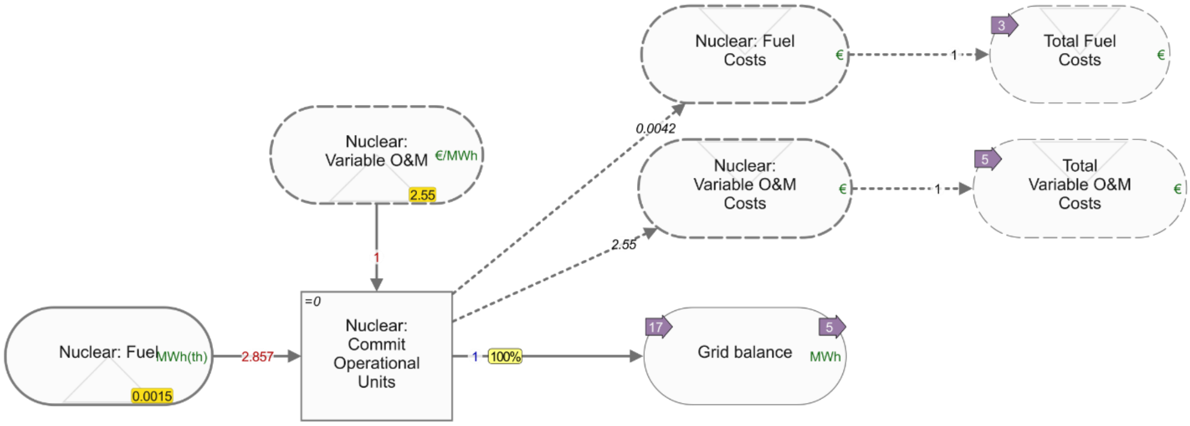


Figure 10: Nuclear Generation in OPM

5.3.3. VRE Generation Assets

The cluster for PV generation is used as an example for explaining the design of the VRE generation asset clusters and is shown in Figure 11. The main difference between the design of the cluster for VRE generation assets compared to the thermal units is that the capacity factor determines the output. The data product representing the capacity factor is linked to the products ‘PV: Installed output’ and ‘PV: Max. available capacity’.

The value of ‘PV: Installed output’ is the maximum PV output possible from the operational units during a timestep. Since curtailment must be possible, the ‘PV: Installed output’ product is a sink that is connected to a data product for curtailment and the process which feeds into the electricity grid. This gives the process ‘PV: Commit Operational Units’ the option to use any fraction of the maximum PV output during a timestep to the grid, allowing for curtailment.

The product ‘PV: Max. available capacity’ represents the maximum possible PV output per timestep if the maximum number of additional units is invested during the Planning stage. Similar to the process for the operational units, the process for additional units can decide how much of this maximum available capacity per timestep is delivered to the grid, allowing for curtailment. To determine the number of investments in additional PV units required to deliver a certain amount of electricity to the grid, the data product ‘PV: Committed Additional Units’ is included. The level of this data product is determined per timestep by dividing the level of ‘PV: Commit Additional Units’ by the standard unit capacity and the capacity factor. The highest level this data product has during a Planning stage determines the number of additional units invested in. During the Operation stages, investment is not possible and the level of the process ‘PV: Committed Additional Units’ is zero by definition.

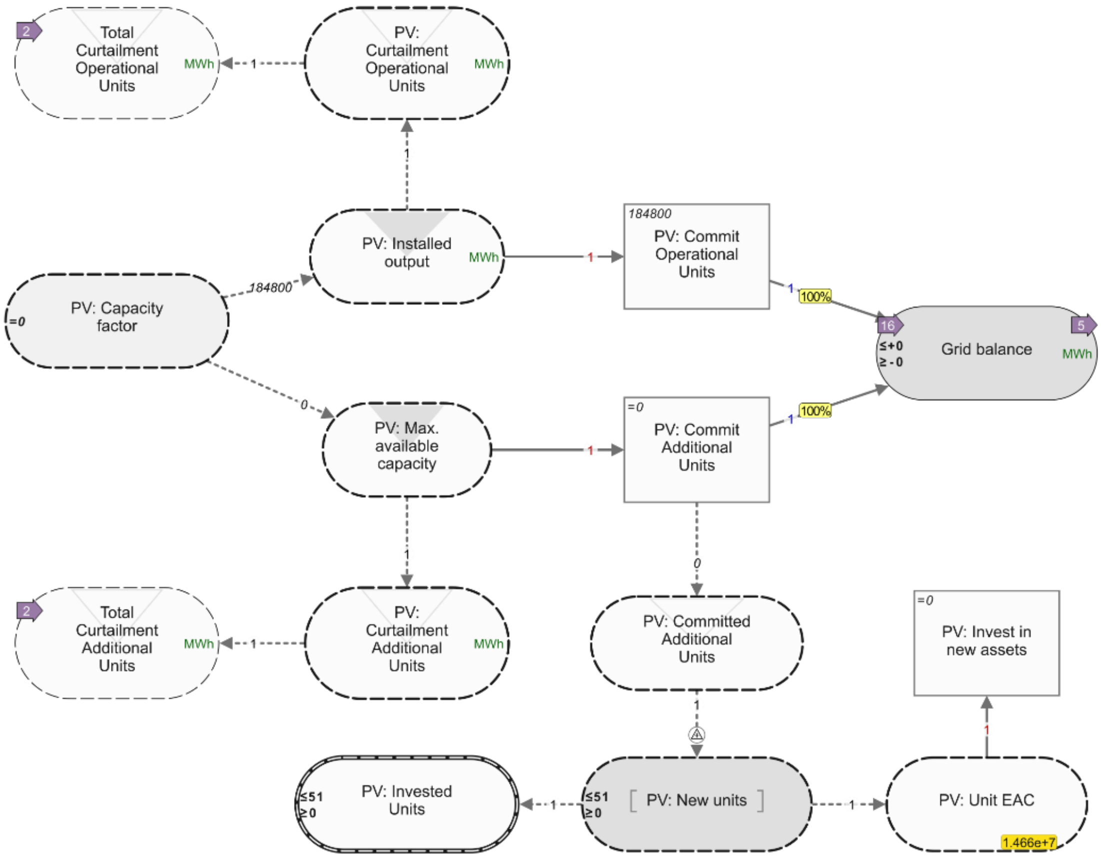


Figure 11: VRE Generation Assets in OPM (PV)

5.3.4. Daily Storage Assets

The highest level of the cluster for daily storage assets is divided into two subclusters, the 'Storage: Daily: Operational' cluster and the 'Storage: Daily: Additional' cluster as shown in Figure 12.

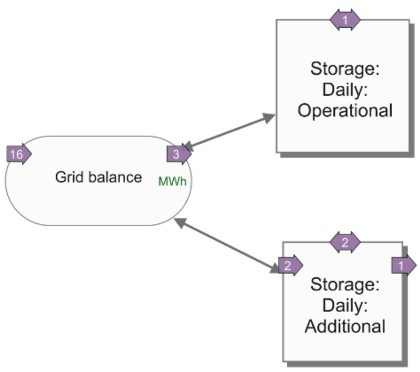


Figure 12: Daily Storage Assets in OPM – Overview Cluster

The cluster which represents the operational units is shown in Figure 13. The conceptualisation for the cluster design is based on a lithium-ion battery storage system. It consists of a process for charging the storage, a data product for the stored electrical energy and a process for discharging the storage and delivering electricity back to the grid. The rate of the links between the processes for charging and discharging the electricity and the stock product for storage represents the charging and discharging efficiency. Additionally, a process and product are included which represents the self-discharging losses of the daily storage.

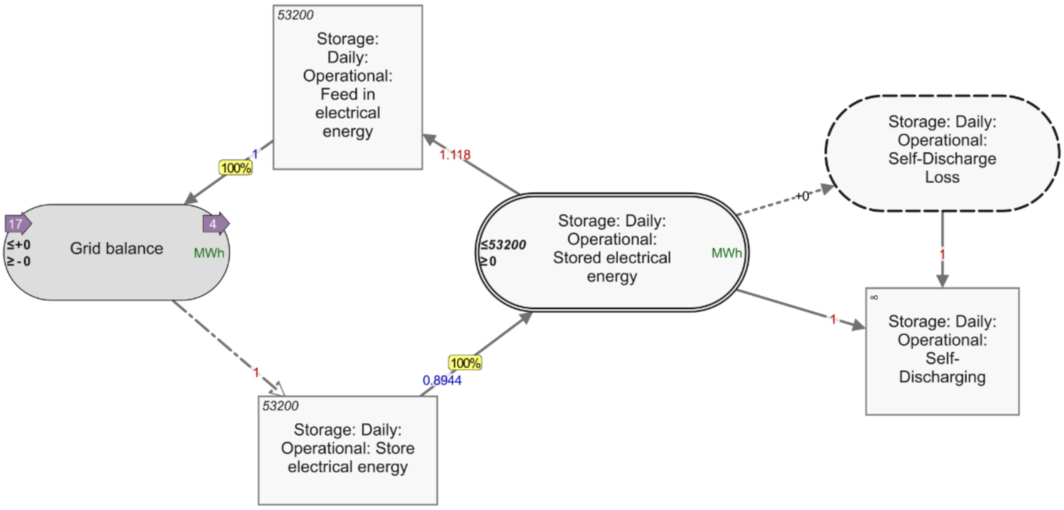


Figure 13: Daily Storage Assets in OPM – Operational Units Cluster

The configuration of investments in daily storage is slightly more complex compared to the configuration for the investment in generation technologies. The two processes for charging and discharging the storage and the stock product for storing the electrical energy can all three trigger investment in an additional storage unit. In case the 'peak-increase' link for triggering an investment was only linked to one of these three components, the level of the other two components could reach levels that would require an additional investment to happen, without triggering this additional investment.

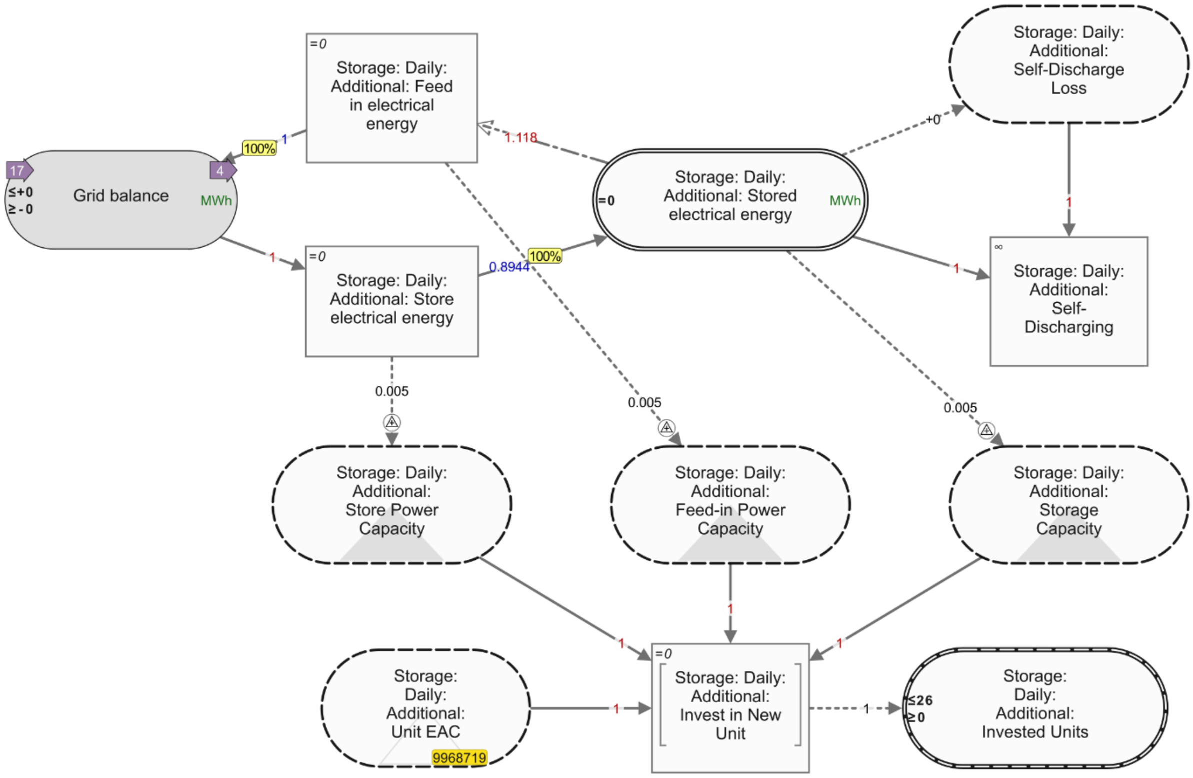


Figure 14: Daily Storage Assets in OPM – Additional Units Cluster

5.3.5. Seasonal Storage Assets

Similar to the daily storage assets, the highest level of the cluster for seasonal storage assets consists of two sub-clusters, as shown in Figure 15.

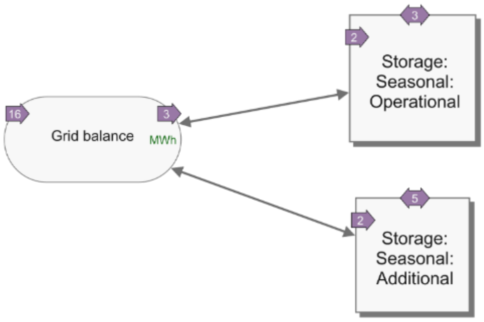


Figure 15: Seasonal Storage Assets in OPM – Overview Cluster

The operational cluster for seasonal storage is presented in Figure 16. The conceptualisation for the cluster design is based on a hydrogen-based storage system consisting of an electrolyser, fuel cell, and UHS. The efficiency of the electrolysers in converting electricity into hydrogen by the electrolyser is incorporated into the link between the electrolyser process and the storage. The efficiency of converting hydrogen back into electricity is incorporated into the link between the fuel cell and the grid balance. The operational cluster for seasonal storage also includes input products for representing the variable costs for the electrolyser and the fuel cells. Additionally, output data products for keeping track of the variable costs for calculating the total system cost KPI are included as well.

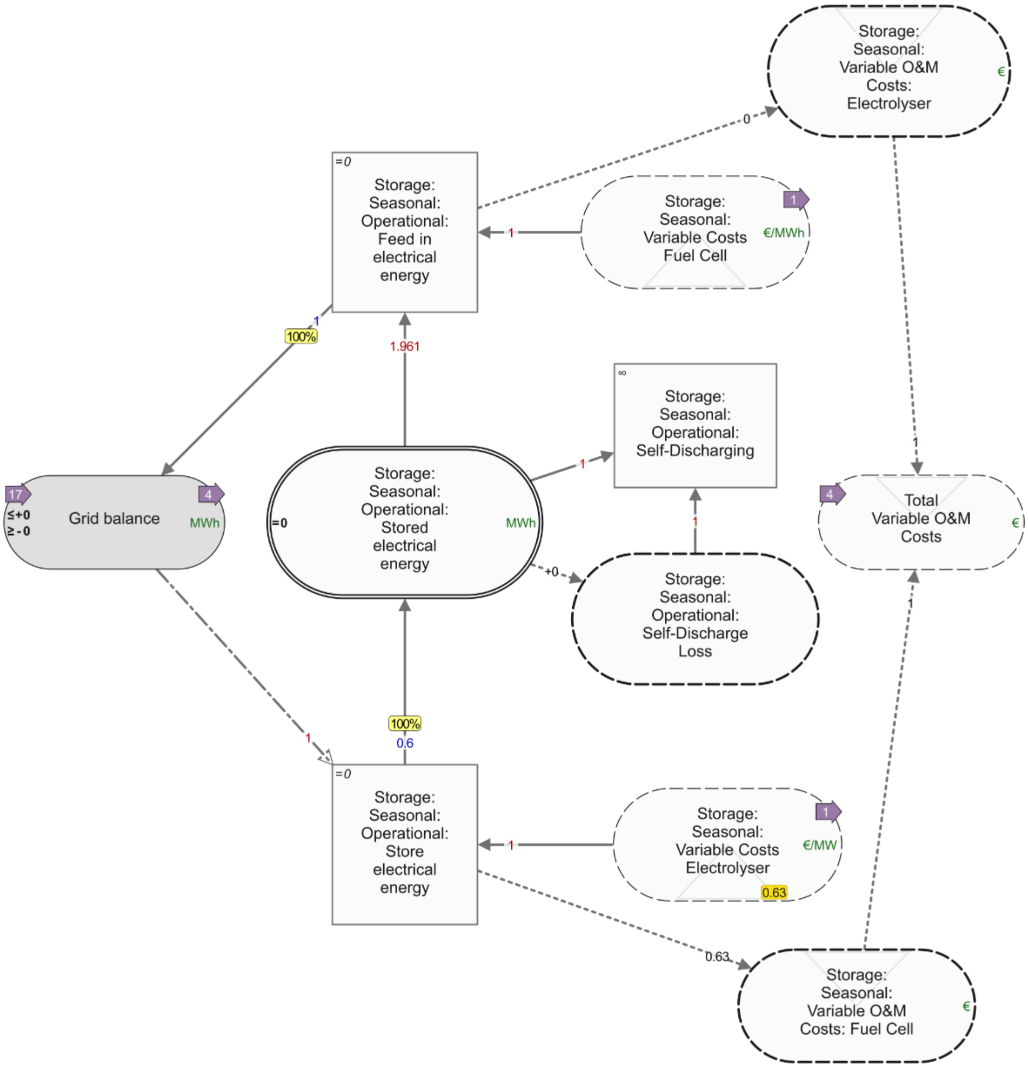


Figure 16: Seasonal Storage Assets in OPM – Operational Units Cluster

The configuration of the cluster for the investment in additional assets is shown in Figure 17. For seasonal storage, the solver can invest in additional fuel cells and/or electrolysers. Development of UHS facilities is not included as an investment decision but is determined based on an input dataset that dictates the available capacity in the UHS facilities in a certain year.

There are multiple reasons for not including it as an investment decision in the model. Firstly, it is expected that the provision of flexibility in the system by a UHS project is not valued sufficiently in the current market to result in a viable business case (van Gessel, Huijskes, et al., 2021). Secondly, the development of such large-scale infrastructural projects requires the development of sufficient societal support and supportive policy frameworks (van Gessel, Huijskes, et al., 2021). Lastly, while the production of hydrogen through electrolysis is mainly considered an activity for market participants and not for system operators, a larger role is expected for system operators in the development of UHS facilities (Ministerie van EZK, 2022). This is also apparent from the fact that the first large-scale UHS facility in the Netherlands is currently being developed by HyStock, a subsidiary of the Dutch gas system operator Gasunie (Gasunie, n.d.; HyStock, n.d.; Ministerie van EZK, 2022). Therefore, it is assumed that the government and system operators will have such a large role in the development of UHS, that it will not be considered as an investment decision in the OPM. Section 6.2.2 will further elaborate on how the available UHS capacity per year is determined for the reference case.

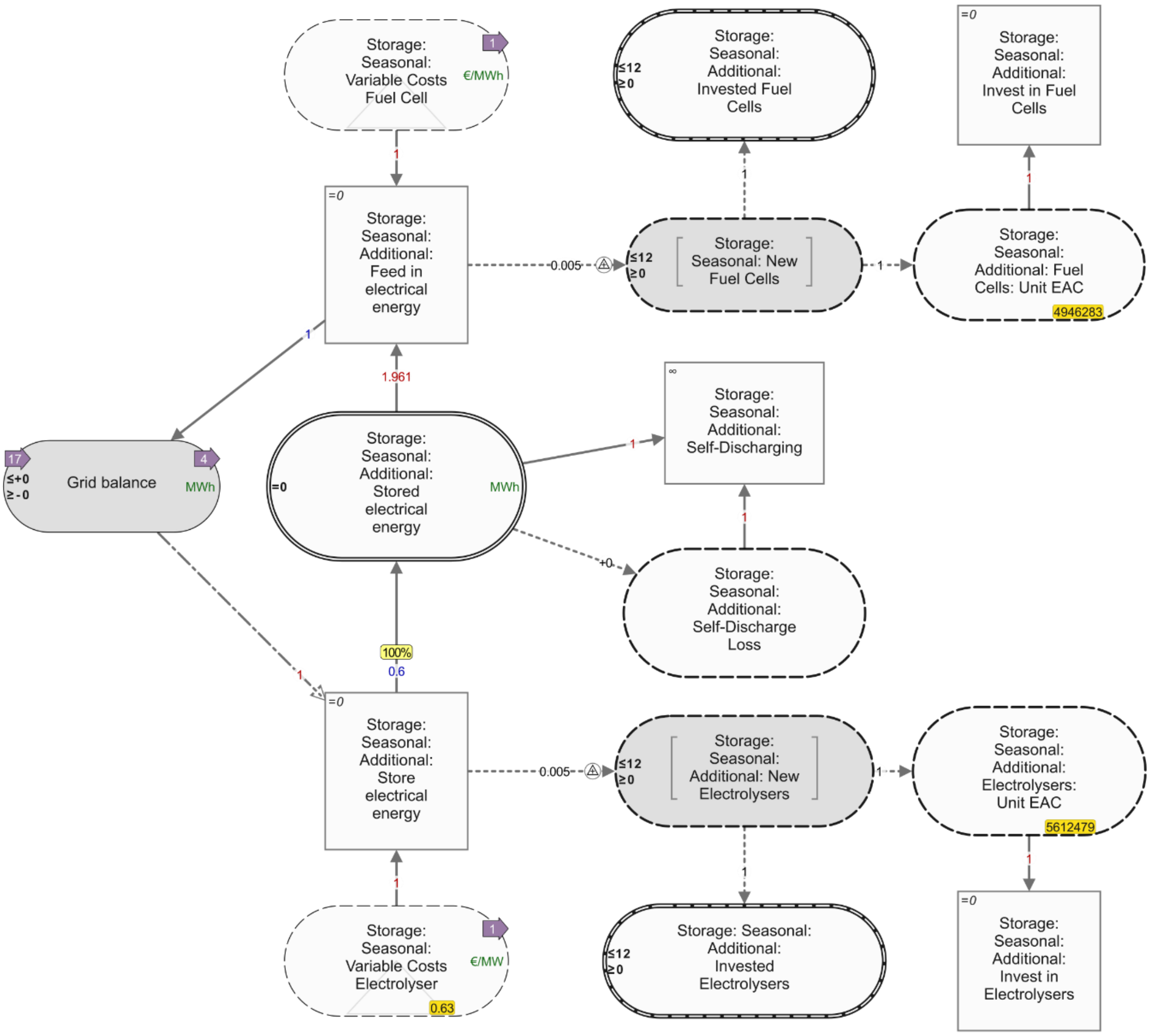


Figure 17: Seasonal Storage Assets in OPM – Additional Units Cluster

5.3.6. Total System Costs

The last OPM cluster to discuss is the cluster for the total system costs. It consists completely of data products and does not affect solving the optimisation problem; it is merely added to visually represent the calculation of the total system costs. Linny-R does offer the possibility to calculate such costs using equations that are not visually shown in a model. However, it was decided to include it in the OPM in a visual way to increase transparency. The overview of the cluster is shown in Figure 18. The cluster with all fixed costs for the EAC payments for the operational units of each technology is shown in Figure 19. Lastly, the cluster for all variable costs is shown in Figure 20.

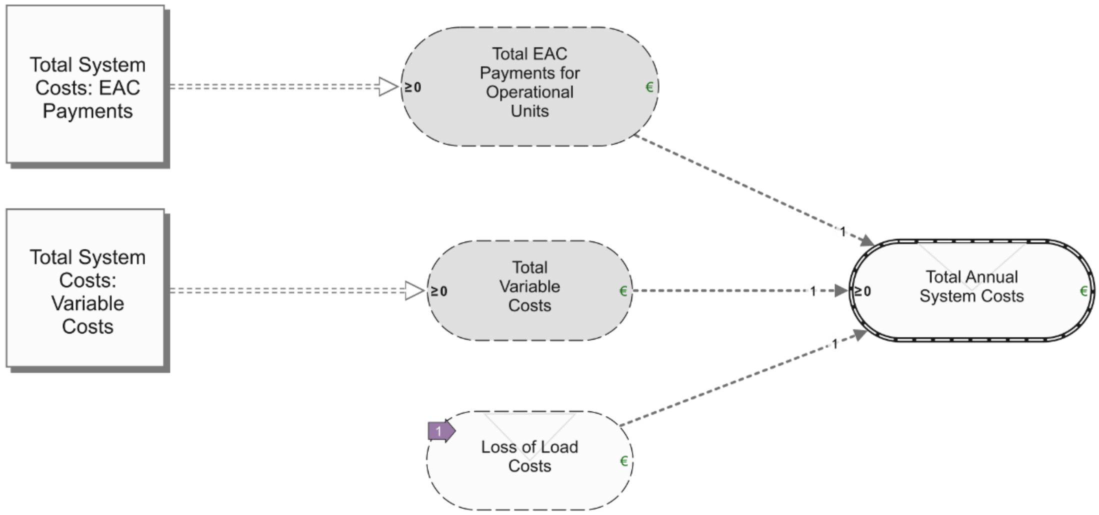


Figure 18: Total System Costs in OPM – Overview Cluster

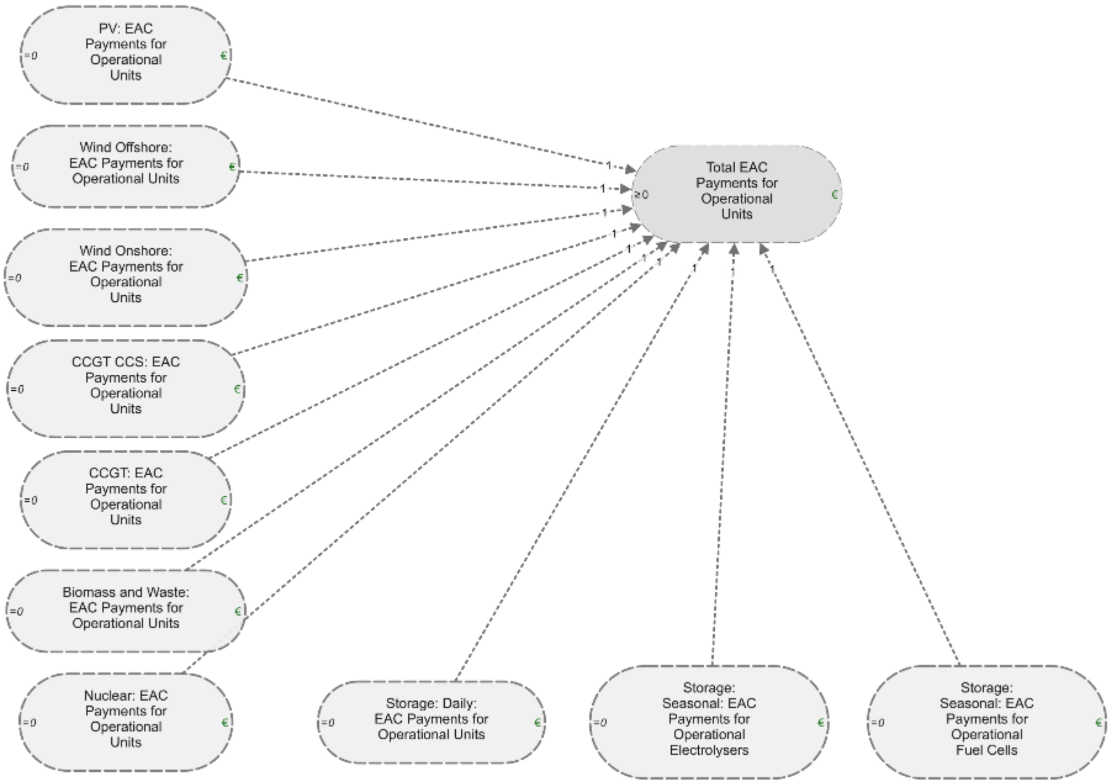


Figure 19: Total System Costs in OPM – EAC Payments Cluster

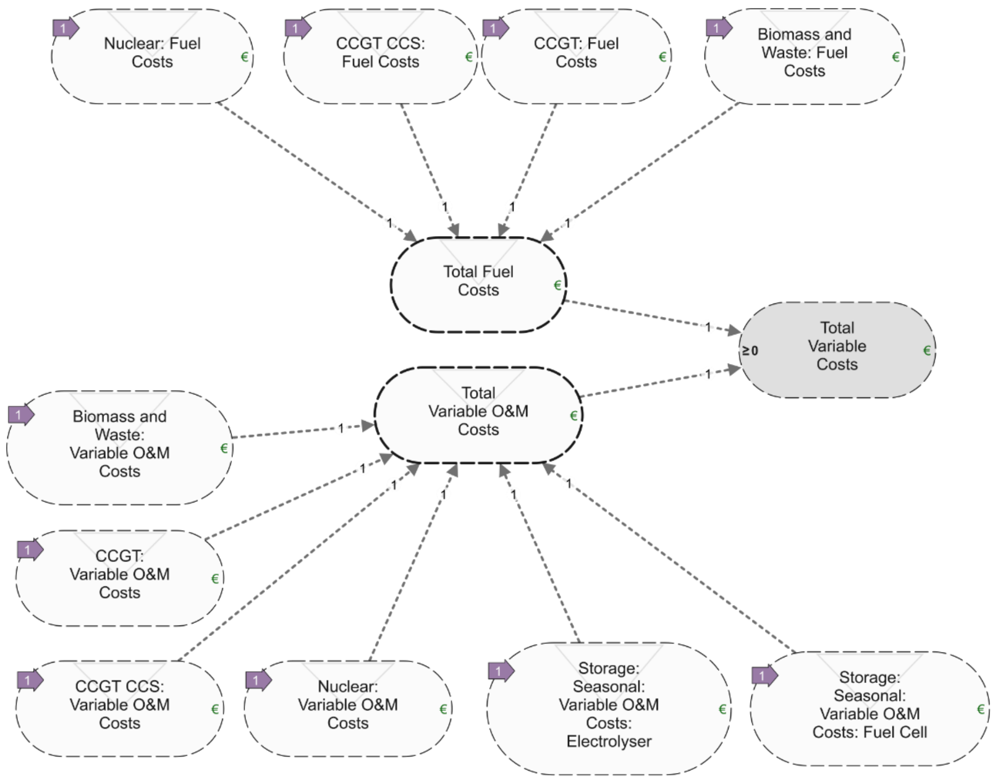


Figure 20: Total System Costs in OPM – Variable Costs Cluster

5.4. Model Settings for the OPM Stages in Linny-R

The Linny-R software allows for selecting model settings for solving the optimisation problem of the model. Determining which model settings to use for solving an optimisation problem is crucial since it has a significant impact on the efficiency, accuracy, and feasibility of the solution process. Within Linny-R there are four main model settings to set before running a model.

1. ***Temporal resolution:*** This determines the size of each timestep in the model. It can range from a certain number of seconds to a certain number of years per timestep. A smaller timestep results in increased accuracy and detail but increases the computational burden.
2. ***Optimisation period:*** This determines the specific time frame or duration over which the optimisation is performed. A longer optimisation period will result in a higher computational burden since it increases the number of timesteps for which the level of decision variables must be determined.
3. ***Block length:*** This determines the number of timesteps in an optimisation block. An optimisation block is a sub-problem of the larger optimisation problem for which the solver will determine the level of decision variables for reaching an optimal solution. A longer block length results in a larger number of timesteps for which the decision variables and the impact on the outcomes have to be assessed, which increases the computational burden.
4. ***Look-ahead period:*** This is the period following the end of the optimisation block for which the solver will consider the consequences of decisions made within the optimisation block. Increasing the look-ahead period results in a higher computational burden similar to when the block length is increased.

5.4.1. Temporal Resolution

A temporal resolution of one-hour timesteps for the highest resolution possible, since the time series data used for demand and capacity factors are hourly data. Therefore, the model outcomes for the run with a one-hour timestep resolution for both stages will be considered the benchmark for comparing the other temporal resolution settings. The OPM has been run for the period from 2027 to 2050 using the same input data as has been used in the reference case presented in chapter 6.

The impact of lowering the temporal resolution on total run time, average annual system costs, and the two loss of load metrics for the period from 2031 to 2050 are shown in Figure 21. The year 2030 is not included since the first additional units invested during the Planning stage of 2027 become available in 2031. Therefore, there is a disproportionate amount of lost load and very high system costs in the year 2030 for all runs, which skews the data for average costs, EENS, and LOLE.

It can be observed that the run time of the OPM is significantly higher when using a one-hour timestep resolution compared to the lower temporal resolutions. While the run time is 271 minutes for a one-hour timestep resolution, a four-hour timestep resolution results in a 90% lower run time of 26 minutes[4]. This major reduction in computational burden improves the usability of the model. However, it is important to assess the effect of reducing the temporal resolution on the accuracy of the model outcomes.

Average annual total system costs reduce slightly when a lower temporal resolution is used. Using a one-hour timestep resolution results in average annual total system costs of 28.6 billion euros, which reduces by 6.9% to 26.6 billion when using a four-hour timestep resolution, which is considered to be within a reasonable margin.

Average annual EENS from 2031 to 2050 is reduced to a large extent by changes in temporal resolution. Reducing the timestep resolution results in a smoothing effect on the fluctuations in electricity demand and VRE capacity factors. Therefore, this has a direct effect on EENS and LOLE in the system, as can be observed in Figure 21. It decreases from 22.5 GWh when using a temporal resolution of one-hour timesteps to 2.6 MWh when using a temporal resolution of four-hour timesteps. It has to be noted that the high values for average annual EENS for the one-hour and two-hour temporal resolutions are skewed by high EENS in 2031, which were respectively 422.1 GWh and 102.2 GWh. However, reducing the temporal resolution does result in a decrease in EENS compared to the one-hour timestep resolution.

The average annual LOLE reduces with temporal resolutions lower than a two-hour timestep. However, considering that the LOLE used as a performance standard for the Dutch electricity system is 4 hours per year (TenneT, 2022), the average annual LOLE for all temporal resolutions can be considered to be within a reasonable range.

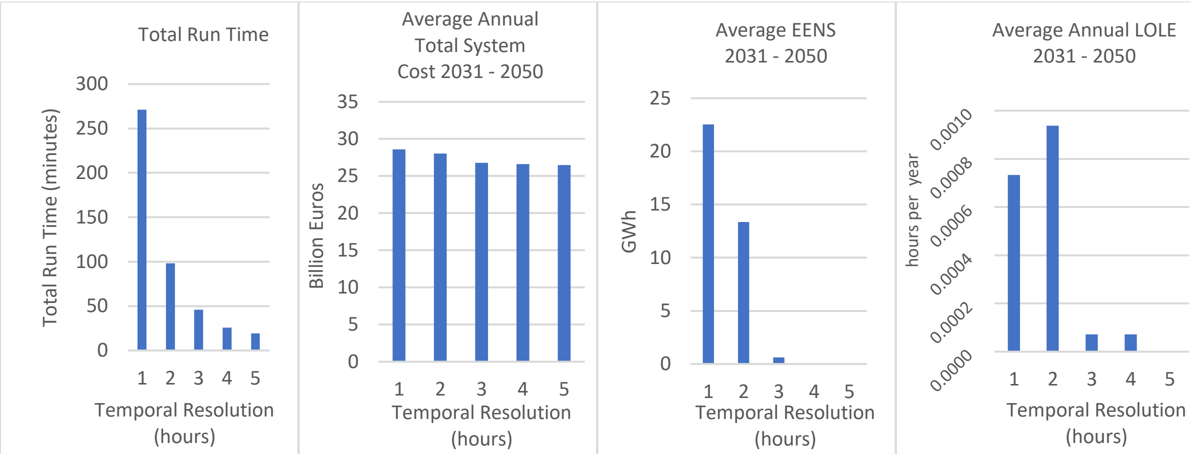


Figure 21: Impact of Temporal Resolution on Run Time, Total System Costs, Loss of Load, and LOLE

The impact of lowering temporal resolution on the average electricity generation mix is shown in Figure 22. Compared to a one-hour timestep resolution, average annual generation from CCGT CCS units is slightly higher for a two-hour timestep resolution but reduces when lower temporal resolutions are used. However, the effect of reducing the temporal resolution on the overall electricity generation mix is limited.

4 The used computer runs on an Intel Core i7 – 7700HQ CPU 2.80 GHz with 16 GB RAM.

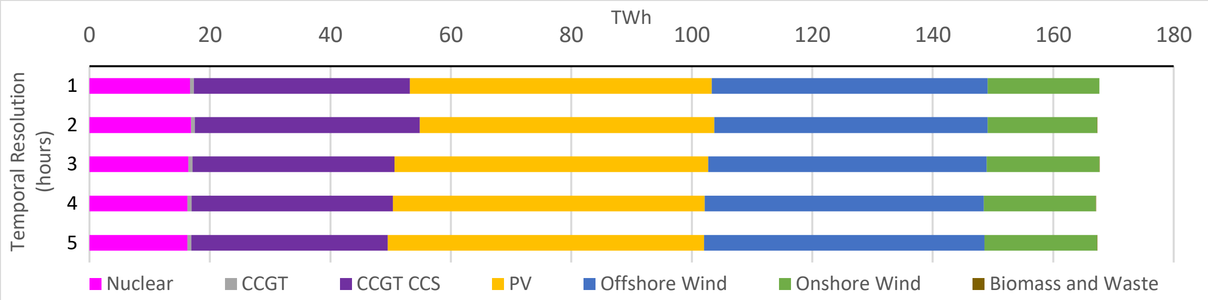


Figure 22: Impact Temporal Resolution on Average Electricity Generation Mix (2031 - 2050)

The average annual feed-in to the grid from daily and seasonal storage units is shown in Figure 23. The values for daily storage units are shown as negative values on this graph. Since daily storage units are designed to charge and discharge within short periods, the smoothing effect on the fluctuations from VRE capacity factors and demand results in a lower feed-in from daily storage units when the temporal resolution is reduced. Average annual feed-in to the grid from seasonal storage units is only affected to a small extent.

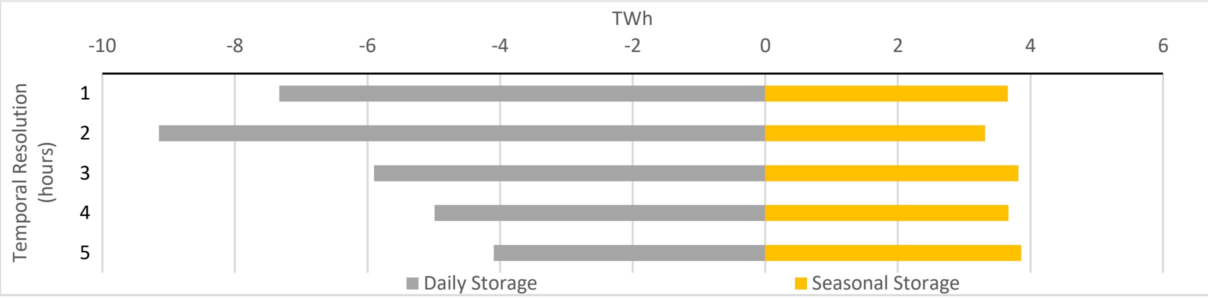


Figure 23: Impact Temporal Resolution on Average Annual Feed-In from Storage Technologies (2031 - 2050)

The impact of reducing the temporal resolution on the average installed capacity mix in the period from 2031 to 2050 is shown in Figure 24. The installed power capacities from storage technologies are shown as negative values in this graph. As can be expected based on what is discussed on the lower average annual feed-in from daily storage units when temporal resolution is reduced, the average installed capacity from daily storage units in the period from 2031 to 2050 is also lower when the temporal resolution is reduced. The impact of the reduction of temporal resolution on the average installed capacity from other technologies is limited.

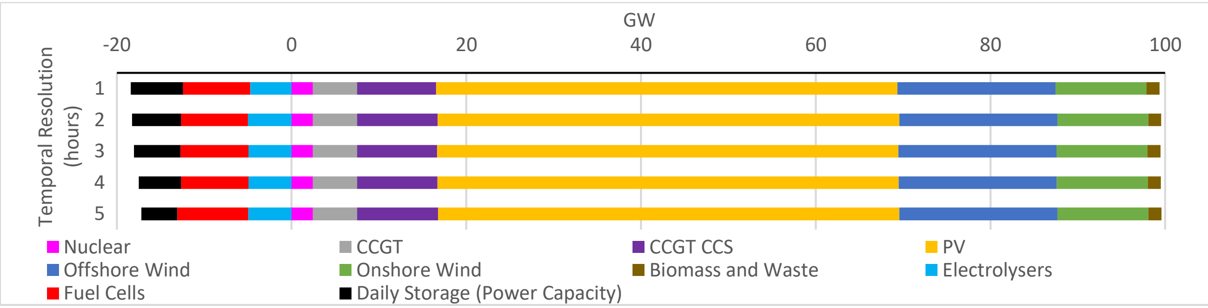


Figure 24: Impact Temporal Resolution on Average Installed Capacity Mix (2031 - 2050)

The major reduction in computational burden when using a four-hour timestep resolution compared to one-hour timesteps is considered to outweigh the reduction in the accuracy of the model. Therefore, a four-hour timestep resolution will be used for running the OPM when conducting the model runs for the reference case in chapter 6 and the experiments in chapter 7.

5.4.2. Optimisation Period and Block Length

The entire optimisation problem in the OPM consists of multiple years. The Operation and Planning stage for each year are optimised in separate consecutive experiment runs in Linny-R. Therefore, the optimisation period of each stage is one entire year. Since the OPM has a temporal resolution of four-hour timesteps, this results in 2190 timesteps in a year.

The block length covers the entire length of the optimisation period of each stage. Hence, the block length will have an identical number of timesteps as the optimisation period of a stage in the OPM, i.e., 2190 timesteps.

5.4.1. Look-Ahead Period

When the model does not have a look-ahead period, the model solver will empty all stock products, such as the energy storage assets, at the end of the optimisation period. This results in the storage assets being empty at the start of each optimisation period as well. For daily storage, this will likely not have a major influence on its functioning, since daily storage levels are fluctuating more in the short term than seasonal storage does. Seasonal storage is mostly used for storing electricity from VRE generation during longer periods of high VRE generation and feeding back into the grid during longer periods of low VRE generation. Therefore, preventing the emptying of storage at the end of an optimisation block is mainly relevant for the proper functioning of the seasonal storage units.

Historical data on VRE capacity factors for the year 2019 from Pfenninger & Staffell (n.d.) and Staffell & Pfenninger (2016) has been used for assessing the seasonal variation in capacity factors for the VRE technologies. This is also the data used as input data for the reference case. Figure 25 shows that from the end of September (around hour 6500) till mid-March (around hour 1800) the weekly rolling average PV capacity factor is lower than the annual average PV capacity factor, except for a short period at the end of February (around hour 1250).

Figure 26 and Figure 27 show that the weekly rolling average capacity factors for offshore and onshore wind are only below the annual average for an extended period during the middle of the year. During the rest of the year, the weekly rolling average capacity factors for offshore and onshore wind fluctuate around the annual average frequently. Given this more consistent fluctuation over the year and the above-average capacity factor levels at the end and beginning of the year, it is considered to affect the required look-ahead period to a smaller extent.

In case seasonal storage is emptied at the end of the year, this may lead to insufficient electrical energy being available to cover the below-average PV generation from the start of the year till the period in mid-March (around hour 1800). Two options are considered for preventing the seasonal storage from being emptied at the end of the year. Firstly, a parameter can be added to ensure that the seasonal storage does not drop below a predefined level at the end of the year. Secondly, a look-ahead period can be used to ensure that seasonal storage at the end of a year is kept at a level that considers the need for stored energy during the look-ahead period at the beginning of next year.

Since the need for seasonal storage depends on the development of the entire electricity system over the multi-year period, it is uncertain what the required amount of energy in the seasonal storage is in the first period of each year. In case the model decides to invest more in CCGT with CCS over the years, less seasonal energy storage is required compared to a case in which more investments in PV capacity happen. Therefore, the need for energy storage must be determined dynamically, to ensure that the storage level at the end of the year is determined based on the need for energy storage resulting from system development rather than that it is based on a predefined parameter value.

Therefore, it is considered more suitable to opt for a look-ahead period than a predefined minimal level for seasonal storage at the end of a year. A look-ahead period of two months is selected, which covers the majority of the period in which there is low PV capacity at the beginning of the year. The two-month look-ahead period corresponds to 1460 hours or 365 four-hour timesteps. A longer look-ahead period is expected to increase the computational burden without adding much benefit for setting the seasonal storage level at the end of the year, based on the capacity factor patterns observed in Figure 25 to Figure 27.

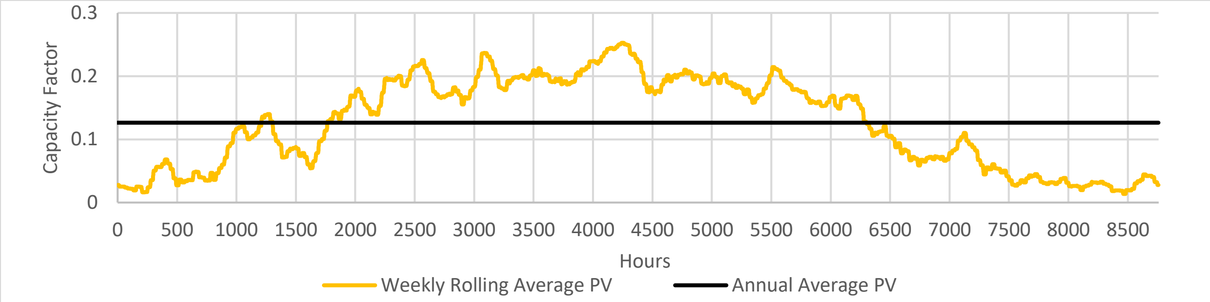


Figure 25: Capacity Factor PV in the Netherlands in 2019. Data from Pfenninger & Staffell (n.d.) and Staffell & Pfenninger (2016).

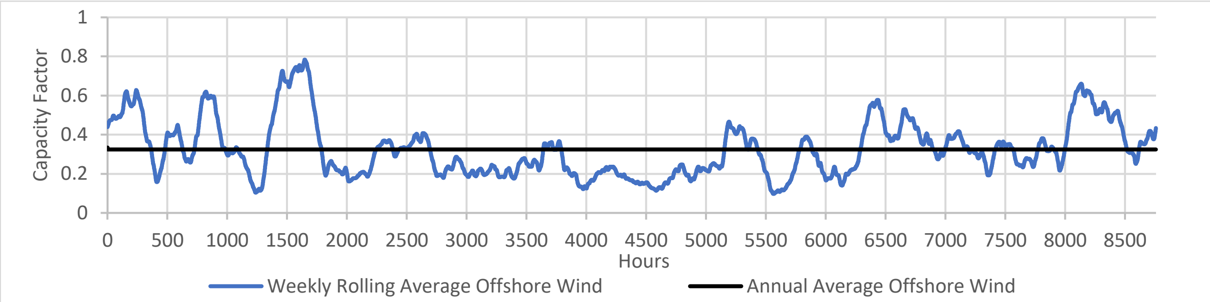


Figure 26: Capacity Factors Offshore Wind in the Netherlands in 2019. Data from Pfenninger & Staffell (n.d.) and Staffell & Pfenninger (2016).

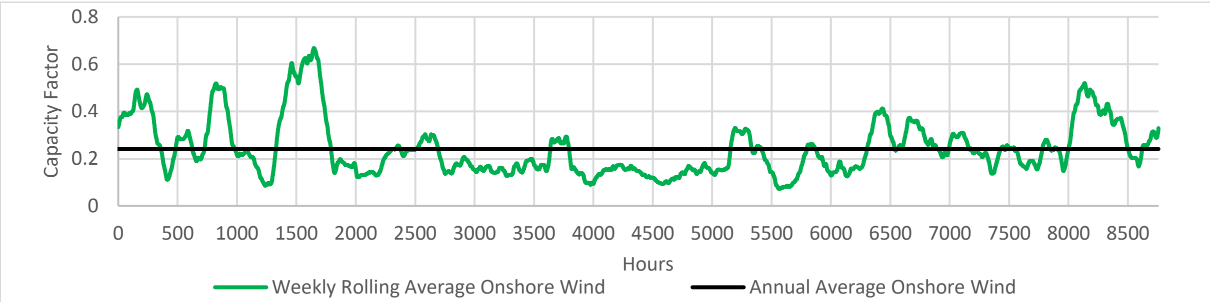


Figure 27: Capacity Factor Onshore Wind in the Netherlands in 2019. Data from Pfenninger & Staffell (n.d.) and Staffell & Pfenninger (2016).

5.5. Verification and Validation of the OPM

Verification involves assessing whether the model accurately represents the conceptual description and specifications. Throughout the process of implementing the OPM into Linny-R, test runs have been conducted to assess whether the model is still working correctly when adjustments are made. The results from the most important verification tests will be presented, being the verification of investment decisions in generation assets, investment decisions in daily storage assets, and investment decisions in seasonal storage assets. The input data that is used for verification of the model is the same as is used for the reference case as will be presented throughout chapter 6. In case other data is used, it will be indicated explicitly.

The process of validation involves assessing the extent to which the model accurately captures the real-world system being modelled. Since the Dutch electricity system consists of a largely liberalized market, it can be expected that the actual development and operation of the Dutch electricity system is not cost-optimal, while the rationale behind the OPM is to dispatch and invest to minimise total system costs. Therefore, it should not be expected that the outcomes of the OPM can directly be compared to historic developments in the real-world system. The OPM is intended as a tool for supporting 'what-if' scenarios and assessing how variations in variables affect the cost-optimal development of the electricity system. Therefore, validation in the context of this study is interpreted as assessing whether the model is developed in a way that allows for reaching the objective of this research. This will be assessed by applying the model to the reference case in chapter 6.

5.5.1. Verification of Investment Decisions in Generation Assets

The verification of the functioning of investment decisions in generation assets is conducted using a simplified version of the model in which all clusters are ignored except for the CCGT CCS cluster. As a result, only the processes for electricity demand and loss of load, and the cluster for CCGT CCS units are operating. The CCGT CCS cluster is selected to verify investment behaviour since the technology is not affected by a carbon emissions cap or a capacity factor. Therefore, results can be analysed clearly.

The verification run consists of the Operation and Planning stages for the years 2027 to 2031, with no CCGT CCS units being pre-installed. This allows us to assess whether the investment decision in the Planning stage of 2027 for units that become operational in the Operation stage of 2031 is logical. Total electricity demand in 2031 is based on the data presented in section 6.4.2, resulting in total electricity demand for 2031 being 136.2 TWh and peak demand in one four-hour timestep being 84,656 MWh. The standard unit capacity for a CCGT CCS plant is 377 MW (see section 6.3.1). This results in the need for 57 units to meet peak demand.

The result of the verification run was that the model solver decided to invest in 56 CCGT CCS units, which equals an installed capacity of 21,112 MW and a maximum output of 84,448 MWh in a four-hour timestep. This is lower than the peak demand of 84,656 MWh and therefore resulted in 206.5 MWh of lost load. Since the VoLL is €69,000 per MWh, the costs incurred for this loss of load is 14.2 million euros. Considering that the EAC for a CCGT CCS unit is 94.8 million euros, the decision to not invest in the 57th unit can be considered logical investment behaviour by the model solver since the costs of the last unit would be higher than the costs for the loss of load it would have prevented.

5.5.2. Verification of Investment Decisions in Daily Storage Assets

A simplified version of the OPM is used for verifying the investment decisions in daily storage assets. All clusters are ignored by the model, except for the offshore wind cluster and the cluster for daily storage assets. As a result, only the processes for electricity demand and loss of load, the offshore wind cluster and the cluster for daily storage assets are operating. The Operation and Planning stages for the period from 2027 to 2031 are used to assess whether logical investments in daily storage units are made.

To allow for a clear assessment of the functioning of investments in daily storage units some parameter values will be set at specific levels. The electricity demand is set at 120 GWh per four-hour timestep. There are no daily storage units pre-installed in 2027 and there is no limit on investment in additional units. At the start of 2027, there are 100 offshore wind units and investment in additional offshore wind units is not possible. Each unit has an installed capacity of 400 MW, resulting in 160 GWh of maximum output per four-hour timestep. Instead of historic capacity factors, the capacity factor will alternate between 1 and 0.5 every three timesteps, resulting in the output per timestep alternating between 160 GWh and 80 GWh every three timesteps.

This results in electricity generated by offshore wind units during the first interval of three timesteps exceeding demand in total by 120 GWh. During the second interval of three timesteps, generation from offshore wind is in total 120 GWh lower than demand. The cycle efficiency of the daily storage units in the OPM is 0.8 (see section 6.3.6). Therefore, the hypothesis is that if sufficient investments in daily storage units are made to store all excess electrical energy during the first interval of three timesteps, loss of load during the second interval of three timesteps should equal the efficiency losses, which would be 24 GWh.

The verification run resulted in the investment in 537 daily storage units during the Planning stage of 2027, which became operational in the Operation stage of 2031. A plot showing an overview of inputs and outputs to the grid for the first 12 timesteps of the Operational run of 2031 is shown in Figure 28. It shows that no curtailment is happening during the first three timesteps and all excess electricity from offshore wind is being used to charge the daily storage units. During the second time interval, the stored electricity is fed back into the grid and 24 GWh of lost load occurs, as expected. Therefore, the investment decision for daily storage units is considered to be logical.

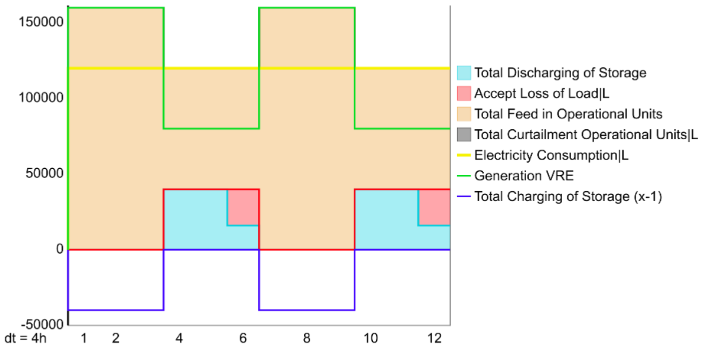


Figure 28: Verification Run Daily Storage - Operation Stage 2031 (s=4h, t=1-12) – Grid Balance

5.5.3. Verification of Investment Decisions in Seasonal Storage Assets

To verify investment decisions in seasonal storage assets, the same set-up is used as presented in the previous section describing verification of investments in daily storage assets. The only difference is that the cluster for seasonal storage will be operational and the cluster for daily storage units will be ignored by the model. There will be zero electrolysers and fuel cells pre-installed in 2027 and there will be no limit on additional investments in these units. UHS capacity will not have an upper bound, to prevent this from being a constraint for investments in electrolysers and fuel cells.

Similar as was the case for verification of daily storage assets, generation from offshore wind units in the first interval of three timesteps exceeds demand in total by 120 GWh and during the second interval generation it is 120 GWh lower than demand. The efficiency of converting electricity into hydrogen using electrolysers is 0.6 and the efficiency of converting hydrogen back into electricity using fuel cells has an efficiency of 0.51, as will be presented in section 6.3.6. This results in the full cycle efficiency for seasonal storage being 0.31. Therefore, the hypothesis is that if sufficient investments in electrolysers and fuel cells are made for storing all excess electricity during the first interval of three timesteps and for reconversion in the second interval, that loss of load per full cycle should equal the conversion losses, which would be 83.3 GWh.

The verification run resulted in the investment in 200 electrolysers and 62 fuel cells during the Planning stage of 2027, which became operational in the Operation stage of 2031. A plot showing an overview of inputs and outputs to the grid for the first 12 timesteps of the Operational run of 2031 is shown in Figure 29. Since no curtailment happens during the first three-timestep interval, all excess electricity is used for converting electricity into hydrogen. During the second three-step time interval, the electricity stored as hydrogen is converted back into electricity. In this interval, 83.3 GWh of lost load occurs, as expected. Therefore, the investment behaviour in electrolysers and fuel cells can be considered logical, since sufficient electrolyser and fuel cell units have been invested in for storing all electrical energy production which exceeded demand and the remaining loss of load can be explained based on the conversion losses.

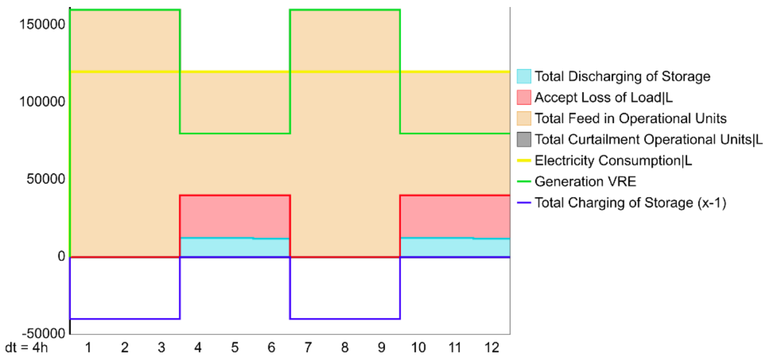


Figure 29: Verification Run Seasonal Storage - Operation Stage 2031 (s=4h, t=1-12) - Grid Balance

Based on the three conducted verification runs, the OPM's investment behaviour in generation assets, daily storage units, and seasonal storage units is considered to be logical and implemented accordingly to its conceptualisation and formalisation.

In the next chapter, the design of the reference case of the development of the Dutch electricity system from 2030 to 2050 will be presented and the OPM will be applied to this case.

6. Dutch Electricity System Transition from 2030 to 2050

In this chapter, the OPM will be used to explore a reference case on the development of the Dutch electricity system from 2030 to 2050. Although the analysis of this case will result in insights into a cost-optimal development path for the Dutch electricity system, the main purpose of this chapter is to assess whether the OPM is fit for exploring the development of a national electricity system.

6.1. Development of the Dutch Electricity System from 2015 to 2022

To provide historical context for the transition of the Dutch electricity system from 2030 to 2050, we will outline the system's development from 2015 to 2022. The development of the capacity mix is shown in Figure 30, which is based on data from ENTSO-E (2022). It shows that a large share of the Dutch capacity mix consists of fossil fuel-fired power plants and that there has been a large increase in capacity from PV systems in recent years. The development of the electricity generation mix is shown in Figure 31, which is based on data from CBS (2022, 2023b, 2023e). Upon comparing Figure 30 and Figure 31, it can be observed that while the share of renewables in the Dutch capacity mix is growing, the country remains heavily reliant on fossil fuels, particularly natural gas, as the primary energy source for electricity generation. This emphasizes the urgency for the Netherlands to increase the rate at which fossil fuels are replaced by renewable energy, to ensure reaching the goals for 2030 and 2050.

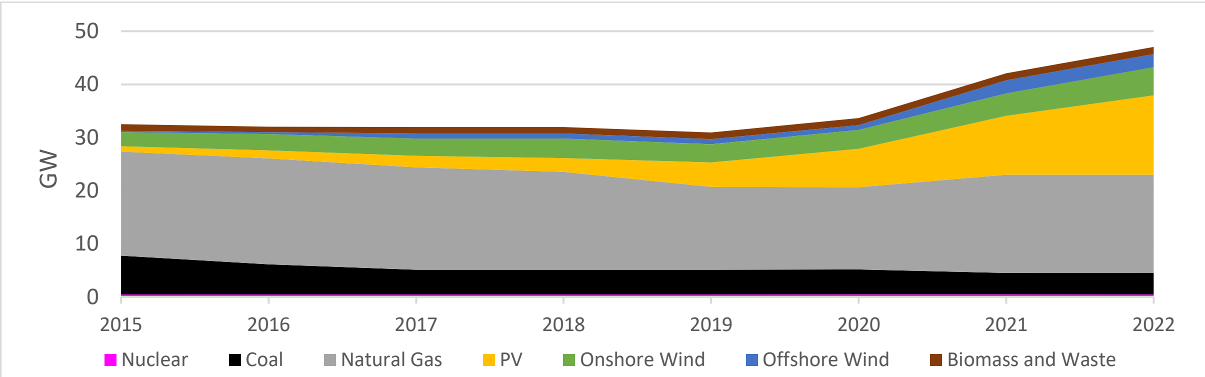


Figure 30: Installed Generation Capacity per Technology in the Netherlands from 2015 to 2022. Data from ENTSO-E (2022).

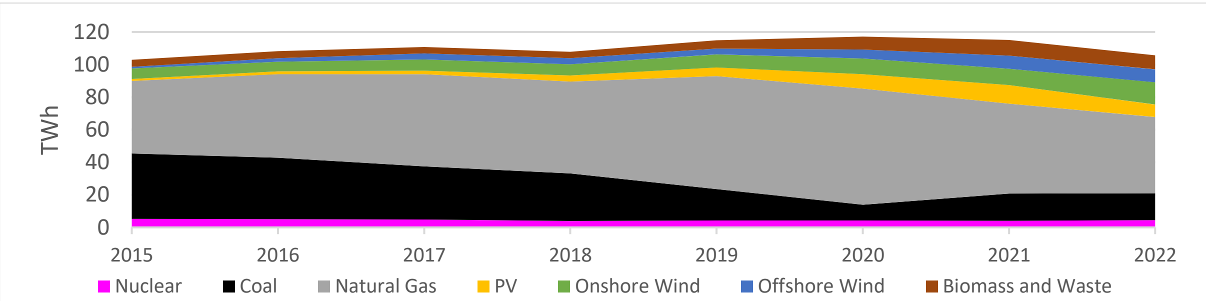


Figure 31: Electricity Generated per Technology in the Netherlands from 2015 to 2022. Data from CBS (2022, 2023a, 2023c).

6.2. The Dutch Electricity System in 2030

6.2.1. Generation Capacity Mix in 2030

To determine the starting point for the development of the Dutch electricity system from 2030 onward, a projection for the installed capacity mix in 2030 based on the "*Hogere Ambitie*" (Higher Ambition) scenario from a report of TenneT (2022) has been used. This scenario is based on the current energy and climate goals of the Dutch government for reaching a 55% reduction in emissions in 2030 compared to 1990 levels. The installed capacity mix based on this scenario is shown in Figure 32 and Table 2. The natural gas-fired power plants are all assumed to be CCGT plants without CCS. Biomass and waste-fired plants are in reality two distinct types of generation technologies. However, in the capacity mix of 2030, they only reflect a small share of the total installed capacity mix. Additionally, biomass can be co-fired in waste incinerators or other power plants, such as coal-fired power plants (CBS, 2021; Rijksoverheid, n.d.-b). Therefore, the two technologies are combined into one asset type in the OPM to reduce the complexity and computational burden of the model. In the OPM, standard unit capacities are used for each technology type, which will be further discussed in section

6.3. Based on these standard unit capacities, the number of standard-sized units per technology in 2030 is determined as input for the OPM.

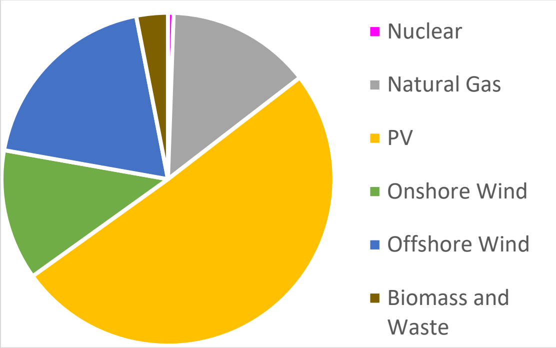


Figure 32: Installed Capacity Mix 2030 in the Netherlands

Table 2: Installed Capacity Mix 2030 in the Netherlands

Technology	Installed Capacity (GW)	Standard-Sized Units
Nuclear	0.5	1
Natural Gas	12.8	32
PV	46.2	308
Onshore Wind	11.6	58
Offshore Wind	17.5	44
Biomass and Waste	2.8	24

6.2.1.1. Nuclear Energy Post-2030

There currently is only one operational nuclear power plant in the Netherlands with an installed capacity of 485 MW, which was intended to be closed at the end of 2033 but will remain operational for a longer duration (Ministerie van EZK, n.d.-a; Rijksoverheid, n.d.-a). Additionally, the Dutch government announced the plan to develop two new nuclear power plants, which are scheduled to become operational in 2035 (Ministerie van EZK, n.d.-b; Rijksoverheid, n.d.-a). It is currently unclear when the existing nuclear power plant will be closed. Therefore, it will be assumed that it will close in 2035 when the new nuclear power plants will become operational.

In a letter to the *Tweede Kamer* (House of Representatives) the Minister of Climate and Energy stated that the two new reactors will each have an installed capacity in the range of 1.0 to 1.7 GW (Jetten, 2022). The standard unit capacity for a nuclear plant in the OPM is set at 485 MW, based on the currently operational nuclear plant. The new nuclear plants will have a combined capacity ranging from 2.0 to 3.4 GW, which would be around four to seven standard-sized units in the OPM. For the reference case, six standard-sized nuclear units are set to become available in 2035 through the predefined development schedule dataset. It has been decided to select a number above the average value in the projected bandwidth since the conservative assumption was made that the currently operational nuclear power plant will close when the new plants become operational.

6.2.2. Daily and Seasonal Storage Capacity in 2030

Similar to determining the generation capacity mix in the Netherlands in 2030, the storage capacity mix also has been determined using the *"Hoger Ambitie"* scenario from TenneT (2022). It is projected that there will be 10.3 GW of installed power capacity from batteries by 2030. As will be indicated in section 6.3, the standard-sized battery units are lithium-ion batteries with an installed power capacity of 50 MW and an installed storage capacity of 200 MWh. Additionally, it is projected that there will be 0.4 GW of installed capacity from electrolysers. It is assumed that the installed capacity from fuel cells will be equal to the installed capacity from electrolysers in 2030. An overview is presented in Table 3.

Table 3: Storage Capacity Mix 2030 in the Netherlands

Technology	Installed Storage Capacity (GWh)	Installed Power Capacity (GW)	Standard Sized Units
Daily Storage (Lithium-Ion Batteries)	41.2	10.3	266
Electrolysers	-	0.4	120
Fuel Cells	-	0.4	120

The seasonal storage cluster is composed of electrolysers, fuel cells, and UHS in salt caverns and depleted gas fields. The practical feasible UHS capacity in salt caverns and depleted gas fields that can be developed in the Netherlands from 2030 to 2050 has been estimated by van Gessel, Juez-Larré, et al. (2021) to be 47 TWh in total. This resulted in the creation of a development schedule for the UHS capacity in which 2.35 TWh of additional capacity would become available annually starting from 2030 onward, resulting in 47 TWh by 2050. Therefore, there is 2.35 TWh of UHS capacity in 2031, 4.70 TWh in 2032, etc. Since the development of UHS is not included as an investment decision in the OPM and the development of the UHS facilities will be 'pushed' by the development schedule dataset based on the practically feasible potential no fixed or variable costs will be included for the development and operation of the UHS facilities.

6.2.3. Decommissioning of Operational Units

The assets operational in 2030 might be decommissioned in the period from 2030 to 2050 when they reach the end of their lifetime. To determine what the expected year of decommissioning is for the units operational in 2030, an estimation of their age in 2030 must be made. Assumptions about the age of units have been made by analysing the development of the installed capacity mix in the Netherlands from 1990 to 2022 by combining data from multiple sources (CBS, 2023a, 2023e; ENTSO-E, 2022). The development of installed capacity from generation and storage units towards 2030 is based on a projection from TenneT (2022). Based on the resulting development pattern from 1990 to 2030 and their typical lifetime as shown in Table 4, it has been determined how much capacity is expected to be decommissioned in which year. Since the OPM uses standard-sized units, the amount of capacity is divided by the standard unit capacity sizes from Table 5. This resulted in the decommissioning schedules as shown in Figure 33 and Figure 34. The decommission schedule is indicated from 2030 until 2054, to ensure that the Planning stage runs properly until the year 2050.

Table 4: Lifetime of Technologies

Technology	Lifetime (years)	Source
Nuclear	40	(EIA, 2020)
CCGT	25	(EIA, 2020)
CCGT with CCS	40	(EIA, 2020)
PV	30	(EIA, 2020)
Onshore Wind	25	(EIA, 2020)
Offshore Wind	25	(EIA, 2020)
Biomass and Waste	40	(EIA, 2020)
Daily Storage (Lithium-Ion Batteries)	10	(EIA, 2020)
Electrolysers	20	(Marocco et al., 2023)
Fuel Cells	20	(Marocco et al., 2023)

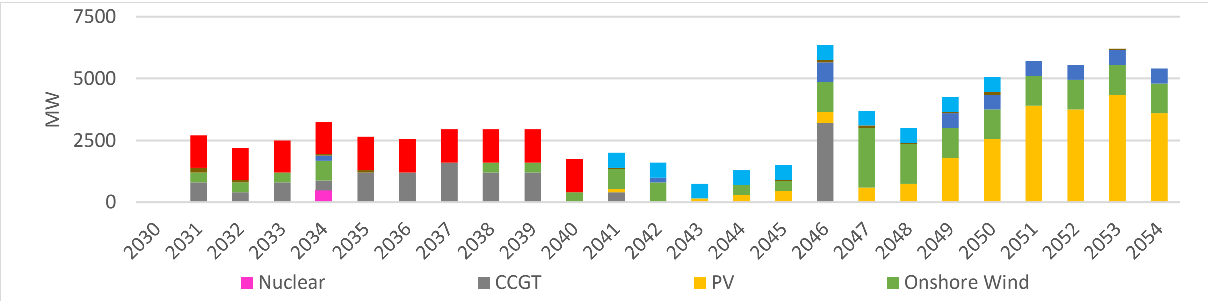


Figure 33: Decommissioning Schedule 2030-2054 in Nominal Capacity

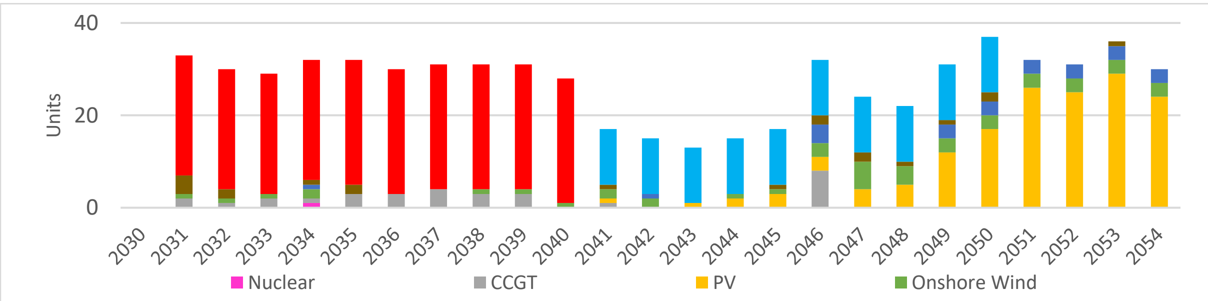


Figure 34: Decommissioning Schedule 2030-2054 in Units

6.2.4. Value of Lost Load in the Netherlands

The average VoLL in the Netherlands has recently been assessed by van Benthem & Kreulen (2022) in a study for the *Autoriteit Consument & Markt* (Authority for Consumers and Markets). It was found that the average VoLL for a typical power interruption in the Netherlands is €69,000 per MWh. This value has been used as VoLL in the reference scenario presented in this chapter.

6.3. Techno-Economic Characteristics

6.3.1. Standard Unit Capacities

An overview of the standard unit capacities for the different technologies is shown in Table 5. The standard unit capacity for electrolysers is based on Luo et al. (2015) and it is assumed that electrolysers have the same standard unit capacity as fuel cells. The standard capacity size of nuclear power plants is based on the only currently operational nuclear power plant in the Netherlands in Borssele (Rijksoverheid, n.d.-a).

Table 5: Standard Unit Capacities

Technology	Standard Unit Capacity (MW)	Source
Nuclear	485	(Rijksoverheid, n.d.-a)
CCGT	400	(EIA, 2023)
CCGT with CCS	377	(EIA, 2023)
PV	150	(EIA, 2023)
Onshore Wind	200	(EIA, 2023)
Offshore Wind	400	(EIA, 2023)
Biomass and Waste	50	(EIA, 2023)
Daily Storage (Lithium-Ion Batteries)	50 (200 MWh storage)	(EIA, 2023)
Electrolysers	50	(Luo et al., 2015)
Fuel Cells	50	(Luo et al., 2015)

6.3.2. CAPEX and OPEX Costs

In Table 5 the used values for the CAPEX and OPEX costs are presented. The values for CAPEX per MW are expressed in thousand euros and the values for CAPEX per standard-sized unit are in million euros.

The CAPEX costs for electrolysers and fuel cells are based on data for proton-exchange membrane (PEM) electrolysers and fuel cells. Different estimates for fixed OPEX costs as a percentage of CAPEX for PEM electrolysers were found, ranging from 4% (KPMG, 2022), between 2% and 4% (Deloitte, 2021), and between 1% and 3% (Christensen, 2020). Based on these numbers it is assumed to be 3% of CAPEX.

Data which was provided in US dollars was converted into euro using the average conversion rate in the period from the 23rd of June 2022 to the 23rd of June 2023, which was 0.956 euros per USD (ECB, 2023).

Table 6: CAPEX and OPEX Costs

Technology	CAPEX per MW (k€)	CAPEX per Standard-Sized Unit (M€)	Fixed OPEX (€/MW/year)	Variable OPEX (€/MWh)	Source
Nuclear	7,094.8	3,441.0	130,889.10	2.55	(EIA, 2023)
CCGT	1,271.5	508.6	15,172.08	2.74	(EIA, 2023)
CCGT with CCS	3,001.9	1,131.7	29,694.07	6.28	(EIA, 2023)
PV	1,384.7	207.7	16,405.35	0.00	(EIA, 2023)
Onshore Wind	2,006.0	401.2	28,336.52	0.00	(EIA, 2023)
Offshore Wind	5,103.3	2,041.3	118,365.20	0.00	(EIA, 2023)
Biomass and Waste	4,776.3	238.8	135,277.3	5.20	(EIA, 2023)
Daily Storage (Lithium-Ion Batteries)	1,270.0	60.7	43,747.61	0.00	(EIA, 2023)
Electrolysers	1,000.0	50.0	30,000.00	0.00	(Christensen, 2020; Deloitte, 2021; KPMG, 2022; Marocco et al., 2023)
Fuel Cells	800.0	40.0	33,126.20	0.63	(Marocco et al., 2023)

6.3.3. Discount Rates

For calculation of the annuity factor as shown in Equation 5, it is necessary to determine the discount rate per technology. The discount rate for most technologies was based on data from IEA (2022c), which provided a range for the discount rate for these technologies. The average value within that range has been used as input data for the model. The three technologies for which no discount rate was provided were lithium-ion batteries, electrolysers, and fuel cells. The discount rate used for these technologies was based on the average value of the entire bandwidth of discount rates provided by IEA (2022c). The used discount rates are provided in Table 7.

Table 7: Discount Rates

Technology	Discount Rate	Source
Nuclear	0.075	(IEA, 2022c)
CCGT	0.075	(IEA, 2022c)
CCGT with CCS	0.075	(IEA, 2022c)
PV	0.045	(IEA, 2022c)
Onshore Wind	0.045	(IEA, 2022c)
Offshore Wind	0.055	(IEA, 2022c)
Biomass and Waste	0.075	(IEA, 2022c)
Daily Storage (Lithium-Ion Batteries)	0.06	Assumption based on IEA (2022c)
Electrolysers	0.06	Assumption based on IEA (2022c)
Fuel Cells	0.06	Assumption based on IEA (2022c)

6.3.4. Maximum Number of Additional Units per Year

There are limitations to the available resources for developing electricity generation and storage assets, such as qualified personnel, machinery, and materials. Therefore, the assumption has been made that there is a maximum number of standard-sized units which can be developed per year, to prevent unrealistic spikes in the development of a single technology in certain years.

The maximum is based on historical data on the development of installed capacity per generation technology in the period from 2015 to 2022 from ENTSO-E (2022). It was assessed what the maximum amount of growth in installed capacity was per technology in a single year. This was converted into the amount of additional standard-sized units in that year. This number has been used as the maximum number of additional units per year for the generation technologies.

A growth projection for the installed capacity from lithium-ion batteries, electrolysers, and fuel cells from 2020 to 2030 is provided in a report by TenneT (2022). The assumption is made that the maximum number of additional units per year is based on the average yearly increase of installed capacity per technology in this projection.

No value will be indicated for nuclear energy since these units can only be developed based on an input dataset with the development schedule. The resulting input data is shown in Table 8. No sources are provided in this table since all values in the table are assumptions explained in this section.

Table 8: Maximum Additional Standard-Sized Units per Year

Technology	Maximum Additional Units per Year	Maximum Additional Capacity per Year (MW)
Nuclear	Not applicable	Not applicable
CCGT	8	3,200
CCGT with CCS	8	3,016
PV	51	7,650
Onshore Wind	6	1,200
Offshore Wind	4	1,600
Biomass and Waste	4	200
Daily Storage (Lithium-Ion Batteries)	26	1,300 (3,200 MWh storage capacity)
Electrolysers	12	600
Fuel Cells	12	600

6.3.5. Other Input Data for Thermal Generation Technologies

A few parameter values are specific for thermal generation technologies, being the thermal efficiency, emission intensity, fuel price, and the annual carbon cap. The data on thermal efficiency, carbon intensity, and fuel prices is shown in Table 9. The sources used are not provided in the table, since determining these parameter values consisted of combining data from multiple sources.

The thermal efficiency of biomass and waste plants, CCGT plants, and nuclear plants is based on the average thermal efficiency of these types of power plants in Germany as provided by Open Power System Data (2020a).

The emission intensity is expressed in tons of CO_2 emitted per MWh produced. The emission intensity of biomass and waste plants is based on data from Vähk (2019), which provided the value for the emission intensity of waste plants. As previously mentioned, a majority of the currently installed capacity of biomass and waste plants is from waste-fired plants, so it is assumed that all plants in the biomass and waste plants technology group have the emission intensity of waste-fired plants. The emission intensity of CCGT plants is calculated using data from Blok & Nieuwlaar (2016) on the energy density and emission factor of natural gas, and the earlier-mentioned thermal efficiency of German CCGT plants.

The fuel price has been expressed in euros per thermic MWh. The fuel price for natural gas is obtained from IEA (2022a), which provided a reference price based on 2021 data. The value for natural gas was provided in USD/MBtu, which was converted into euro per thermic MWh using the tool from Equinor (n.d.). The fuel price for nuclear electricity generation was determined using data from the World Nuclear Association (2021), which provided an estimate of the price of a kilogram of uranium processed for use in a nuclear power plant. Additionally, data from Hore-Lacy (2007) is used to convert this into a value expressed in euros per thermic MWh. It was assumed that only biomass and waste would be used that does not have another purpose and therefore does not have a market price.

Table 9: Thermal Efficiencies and Carbon Intensity

Technology	Thermal Efficiency	Emission Intensity (tons CO_2/MWh_e)	Fuel Price (€/MWh_{th})
Nuclear	0.075	0.0	0.00147
CCGT	0.50	0.4	30.00
CCGT with CCS	0.50	0.0	30.00
Biomass and Waste	0.33	0.6	0.00

In the NPE, the Dutch government indicated the ambition to have net zero carbon emissions in 2035 (Ministerie van EZK, 2023b). Therefore, the annual carbon cap should be zero starting from 2035 onwards. One of the targets in the *Klimaatakkoord* is to reach 55% in carbon emissions reductions for 2030 compared to 1990 levels. In 1990 the level of carbon emissions from electricity generation using fossil fuels was in total 39.6 megatons of CO_2 (CBS, 2023d). The emissions from coal, natural gas, and other power plants were respectively 22.0, 13.3, and 4.3 megatons of CO_2 (CBS, 2023d). It will be assumed that the category of other power plants consists of emissions from biomass and waste-fired power plants. The combined emissions level in 1990 from natural gas-fired and biomass and waste-fired power plants would be 17.6 megatons CO_2. Assuming that the 55% emissions reduction target is linked to specific generation technologies, the carbon emissions cap in 2030 for natural gas-fired and biomass and waste-fired power plants would be 7.92 megatons of CO_2. To stepwise move from a system with 7.92 megatons of CO_2 emissions in 2030 to a net zero emissions system in 2035, the annual carbon cap will be reduced with steps of 1.58 megatons of CO_2 per year.

6.3.6. Other Input Data for Storage Technologies

A few parameter values are specific for storage technologies, being the efficiency of charging and discharging the storage, and the self-discharge rate of the storage. An overview of these values is shown in Table 10.

Table 10: Efficiency and Self-Discharge Rate Storage Technologies

Technology	Efficiency	Self-Discharge Rate per Day	Source
Daily Storage (Lithium-Ion Batteries)	0.8 (full cycle)	0.001	(Kebede et al., 2022)
Electrolysers	0.6	-	(Marocco et al., 2023).
Fuel Cells	0.51	-	(Marocco et al., 2023).
Underground Hydrogen Storage	-	0.00001 (almost zero)	(Luo et al., 2015)

6.4. Input Data Time Series

In this section, the time series data used as capacity factors for the VRE technologies, and the time series data used for electricity demand will be discussed.

6.4.1. VRE Capacity Factors

The time series data for the capacity factors of the VRE technologies has been based on historical data from Pfenninger & Staffell (n.d.) and Staffell & Pfenninger (2016). The data for the hourly capacity factors in the year 2019 has been used for this study. Plots of the weekly rolling average of the capacity factor and the annual average capacity factor for PV, offshore wind, and onshore wind have been presented in Figure 25 to Figure 27. It is important to note that using the data from a single historic year for determining the capacity factors comes with the disadvantage that changes in weather conditions between years and extreme weather conditions that may occur in some years are not accounted for. A *Dunkelfaute* is such a situation, in which electricity generation from both wind and PV is extraordinarily low for a long period.

6.4.2. Electricity Demand

The time series data for the electricity demand is based on a dataset from Open Power System Data (2020b) with data for the Netherlands for the year 2019. Since historic time series data for the VRE capacity and the electricity demand are used, the time series for the same year are selected. By doing so, the used data reflects that fluctuations in electricity usage can be a result of weather conditions and that weather conditions affect capacity factors. The relationship between renewable generation, electricity demand and weather patterns has for example been described for Great Britain by Staffell & Pfenninger (2018) and Thornton et al. (2017).

To include growth in electricity demand due to further electrification of final energy use in the upcoming decades, the historic development trend of electricity demand in the Netherlands from 1980 to 2020 has been assessed using data from CBS (2023f). It is assumed that the development of electricity demand does not follow a linear growth rate, but rather a compound annual growth rate (CAGR). Therefore, data from CBS (2023f) has been used to find a CAGR which reflects the historic development of electricity demand and can be used to extrapolate this trend towards 2050. Figure 35 shows how using a value of 0.015 as the CAGR for the growth of electricity demand starting from the level in 1980 towards 2020 reaches a quite similar level by 2020 as the actual 2020 level.

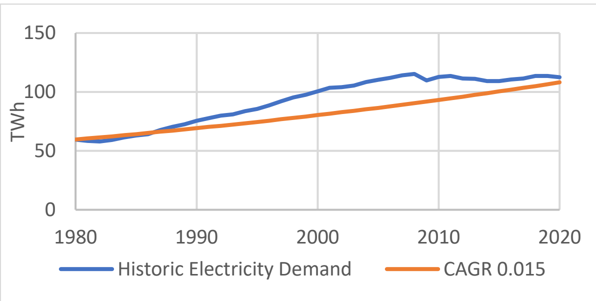


Figure 35: Historic Electricity Demand Development and Development Based on CAGR of 0.015

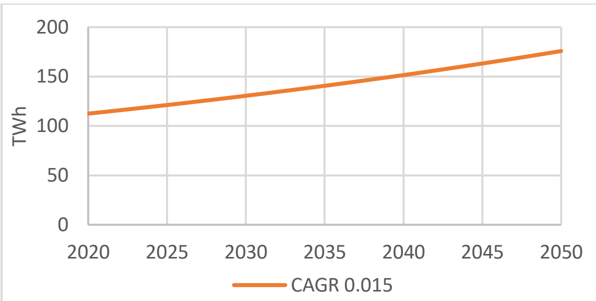


Figure 36: Extrapolation of 2020 Electricity Demand Using a CAGR of 0.015

The CAGR of 0.015 has been used for extrapolation of the historic electricity demand level of 2020 towards 2050, as shown in Figure 36. This has been compared to the projections for future electricity demand for 2025 and 2030 as estimated by TenneT (2022), which are respectively 120.0 and 133.0 TWh. The values found when extrapolating the 2020 demand with the CAGR of 0.015 for 2025 and 2030 are respectively 121.1 and 130.5 TWh. Since these values are comparable to the projections of TenneT (2022) for 2025 and 2030, using the CAGR of 0.015 is considered to be an adequate assumption for this study.

Scaling the demand time series with a CAGR factor for representing the development of electricity demand does not account for changes in demand patterns which may happen due to further electrification of energy use and because of technological innovations. Demand response, smart grid technologies, power-to-X, and other innovations change how the future electricity system functions. However, these technologies are outside the scope of this research. When assessing the results of runs conducted in the OPM, this is an important limitation to consider.

6.5. Results Reference Case

6.5.1. Primary KPI 1 & 2 – Total Annual System Costs & Cost per MWh

The development of total annual system costs in the reference case for the period from 2030 to 2050 is shown in Figure 37. The first additional units which are invested in by the solver in 2027 become operational in 2031, which explains the disproportionately high system costs in 2030, which results from the high amount of lost load in this year. When the first additional units become operational in 2031 the system costs stabilise at a lower level.

To gain a better understanding of the development of the total annual system costs for the period from 2031 to 2050, the decomposition of the annual system costs for these years is shown in Figure 38. The total system costs show a slight decrease over time from 25.3 billion euros in 2031 to 24.3 billion euros in 2050. It is apparent from this graph that the EAC payments, which consist of the fixed OPEX costs and the annuity payments, are a large majority of the system costs.

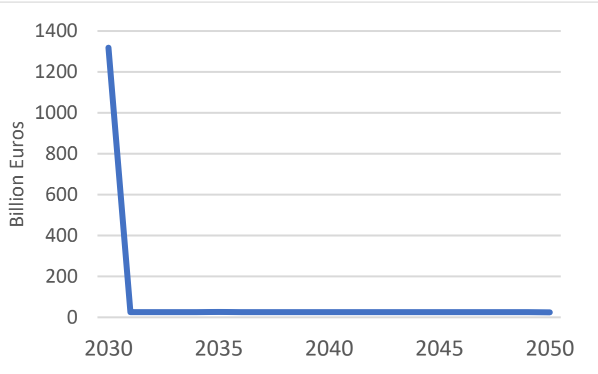


Figure 37: Total Annual System Costs - Reference Case (2030 – 2050)

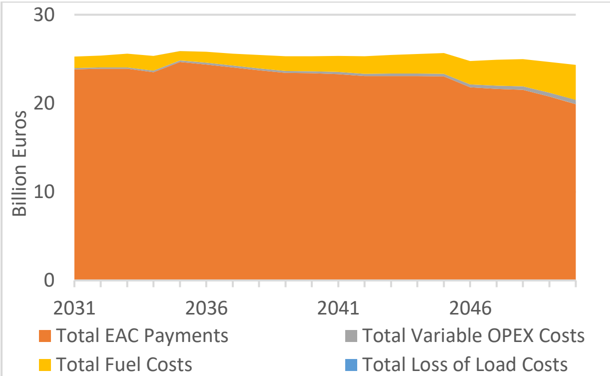
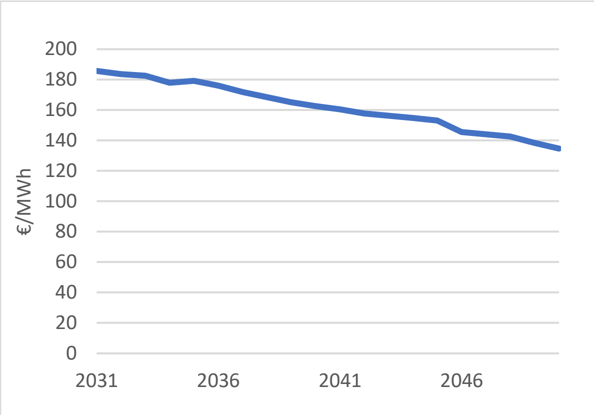


Figure 38: Decomposition of Total Annual System Cost – Reference Case (2031 - 2050)

Figure 39 shows that the development of the cost per MWh of electricity demand decreases from €186 in 2031 to €135 in 2050. To assess whether the resulting costs per MWh are within a valid range, it will be compared to the average monthly consumer electricity prices in the Netherlands in 2021 and 2022, based on data from CBS (2023g). Until September 2021 the average electricity price was below €100 per MWh and increased to a peak of €658.80 per MWh in October 2022 as shown in Figure 40. The large increase in the electricity price from September 2021 to October 2022 is a result of the European gas crisis. Although this data does not directly reflect the costs for electricity generation, it does indicate an order of magnitude for electricity generation costs. The cost per MWh from 2031 to 2050 in the reference case ranges between €135 and €186. This is higher than the average consumer electricity price before September 2021, but still lower than the electricity prices during 2022. Therefore, the results for systems costs in the reference case from 2031 to 2050 are considered to be within a valid range.



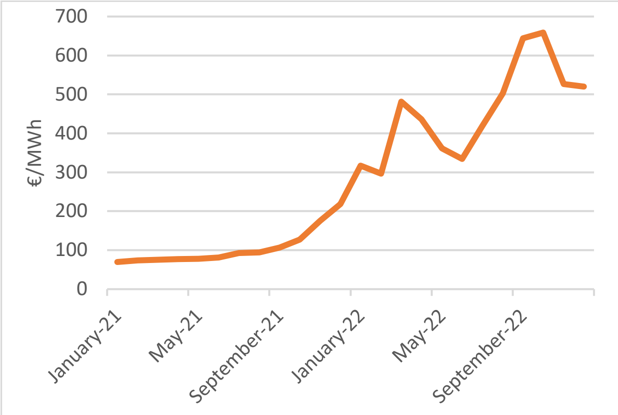


Figure 39: Development of Cost per MWh - Reference Case (2031 – 2050)

Figure 40: Average Consumer Electricity Price in the Netherlands in 2021 and 2022. Data from CBS (2023g).

6.5.2. Primary KPI 3 & 4 – EENS & LOLE

The annual loss of load expressed as EENS is shown in Figure 41. Since the first additional units which are invested in during the Planning stage of 2027 become operational in 2031, there is a disproportionately high amount of lost load in 2030. To get a clearer view of the development of EENS in the years 2031 to 2050, only the results for these years are presented in Figure 42. Note that the values in Figure 41 are expressed in GWh and Figure 42 in MWh.

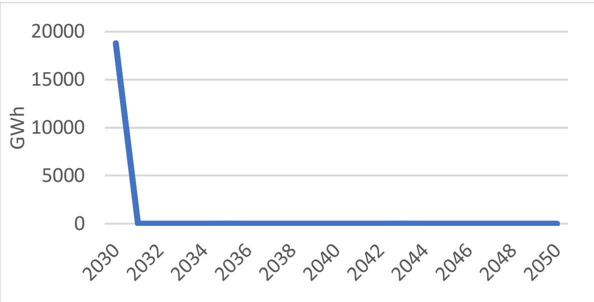


Figure 41: EENS - Reference Case (2030-2050)

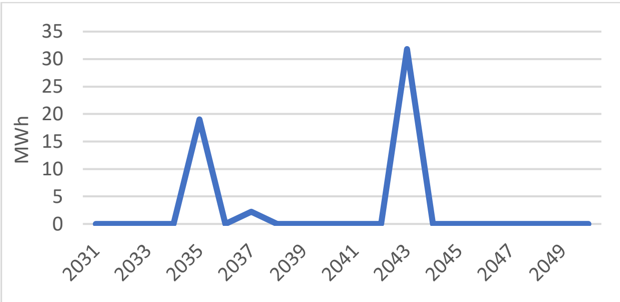


Figure 42: EENS – Reference Case (2031 - 2050)

Figure 42 shows that there were occurrences of lost load in three years, which all occurred in single timesteps. Table 11 shows that the EENS during these years represents a negligible amount when expressed as a percentage of total annual demand for those years. Due to the temporal resolution being a four-hour timestep, it is not possible to determine whether the loss of load happened during all four hours within a timestep or a lower number of hours. Therefore, it will be assumed that the LOLE for these years is 4 hours with loss of load per year. The LOLE which is used as the performance standard for the Dutch electricity system by TenneT (2022) is 4 hours per year with lost load. Therefore, the system meets this performance standard for all years from 2031 to 2050.

Table 11: Loss of Load in Reference Case (2031 - 2050)

Year	EENS (MWh)	EENS as Percentage of Annual Demand	Timesteps with Lost Load	LOLE
2035	19	0.00001%	1	4
2037	2	< 0.00001%	1	4
2043	32	0.00002%	1	4

6.5.3. Secondary KPI 1 – Annual Electricity Delivered to the Grid per Technology

The development of the annual electricity generation mix is shown in Figure 43. It is important to note that the electricity generated from VRE technologies does not include the electricity that is curtailed, but only the electricity delivered to the grid by generation technologies. Over the entire period from 2030 to 2050, there is a large increase in the share of electricity generated from CCGT CCS. The development of CCGT CCS units is limited to an additional eight units or 3.0 GW per year, without limitations on the amount of emissions captured and stored. Generation from CCGT CCS units increases each year, except for 2035 when new nuclear units become available, which have a lower variable cost for generation. In the year 2050, the CCGT CCS and nuclear units generated respectively 35.7% and 11.5% of electricity delivered to the grid by generation technologies. In the year 2030, the electricity generated by VRE technologies accounted for 89.9% of electricity delivered to the grid by generation technologies. This share decreases to 52.7% by the year 2050, due to the increase of electricity generation by CCGT CCS and nuclear units.

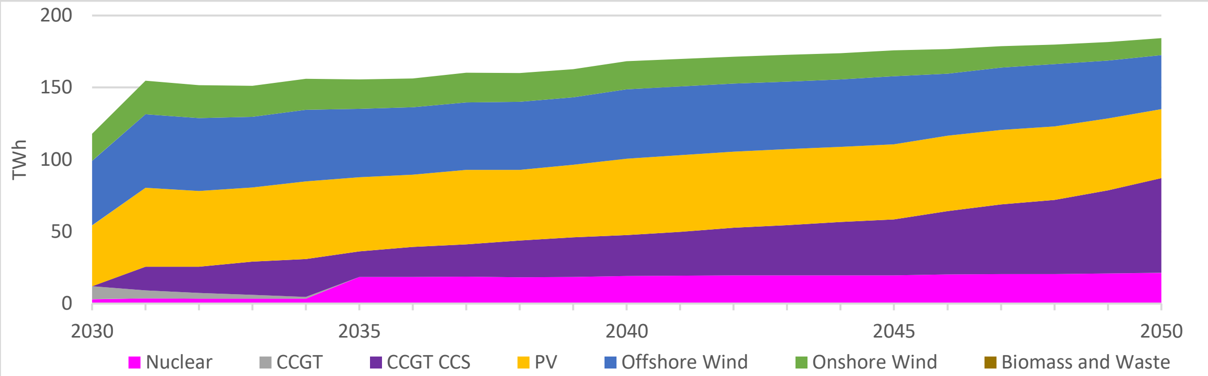


Figure 43: Electricity Generation Mix - Reference Case

The electricity generated from CCGT units decreases from 8.9 TWh in 2030 to zero in 2035 as a result of the carbon emissions cap reducing from 7.92 megatons of CO_2 in 2030 towards zero in 2035. Biomass and waste plants were only operational in the years 2032 and 2034, in which they generated respectively 0.01% and 0.02% of electricity demand in these years. During 2032 and 2034, the CCGT units accounted for 2.57% and 0.79% of electricity delivered to the grid. However, the variable generation costs for CCGT plants are €62.74 per MWh and only €5.20 per MWh for biomass and waste plants. The negligible usage of the biomass and waste units can be explained by their emission intensity, which is 1.5 times higher than the emission intensity of CCGT plants, based on the data presented and assumptions made in section 6.3.5. This difference in emission intensity is the cause for the model solver's decision to dispatch the CCGT plants. If more electricity was generated using biomass and waste plants, a lower amount of electricity could be produced from flexible thermal generation assets before the annual carbon emissions cap was reached. Therefore, the model solver decides to mainly use the CCGT units which have a higher variable cost, but a lower emission intensity compared to biomass and waste plants. By doing so, it prevents loss of load from occurring, which has a high cost of €69,000 per MWh.

The total annual feed-in to the grid from storage technologies is shown in Figure 44. For the period from 2030 to 2050, it shows an overall declining trend for the feed-in of electricity from storage technologies to the grid. This can be explained by the large increase in the share of flexible electricity generation by CCGT CCS units, which reduces the importance of storage in the system for providing flexibility.

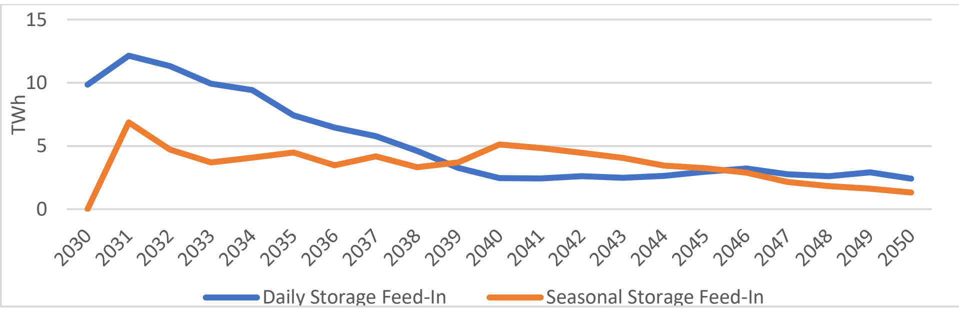


Figure 44: Total Annual Feed-In from Storage Technologies - Reference Case

Additionally, Figure 44 shows that there is an increase in feed-in for both technologies from the year 2030 to 2031. This increase in feed-in from the seasonal storage units results from the first chunk of UHS capacity becoming available in 2031, as explained in section 6.2.2. Therefore, no seasonal storage capacity is available in the year 2030. There is no increase in storage capacity from daily storage units from 2030 to 2031. Therefore, the increase in total feed-in from daily storage results from the increase in electricity generated in the system from 2030 to 2031. This results in more electricity being available to store in these units and feed back into the system at later timesteps.

6.5.4. Secondary KPI 2 – Installed Capacity per Technology

Figure 45 shows the development of the installed capacity mix from 2030 to 2050. As can be expected based on the observed development pattern of the annual electricity generation mix, the share of installed capacity from CCGT CCS and nuclear power plants increases most clearly.

CCGT CCS capacity increases to 15.1 GW by 2050, which is 17.1% of the total installed capacity in 2050. The installed capacities from PV, offshore wind, and offshore wind increase slightly from 2030 to 2031 due to investments made by the model solver. However, no additional investments happen in these technologies in later years and their installed capacity decreases slightly over time due to their end-of-lifetime decommissioning schedules.

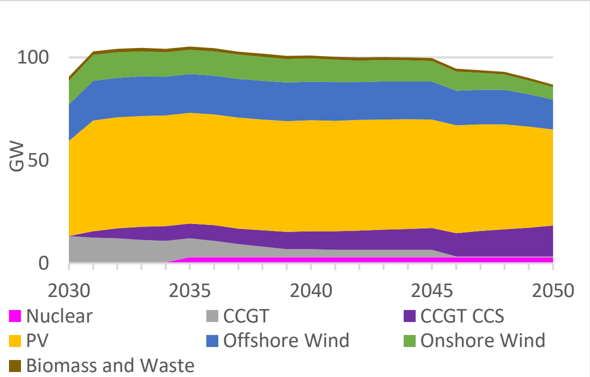


Figure 45: Installed Capacity Mix - Reference Case

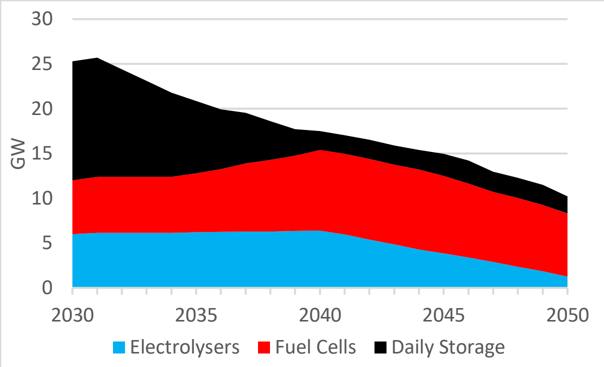


Figure 46: Installed Power Capacity Storage Assets - Reference Case

The development of the installed capacity from storage technologies is shown in Figure 46. Most of the daily storage units are being decommissioned between 2030 to 2040 due to them reaching the end of their expected lifetime. However, some investment happens, which results in a small amount of daily storage units being operational in the period from 2040 to 2050. The installed power capacity from electrolysers decreases from 2040 to 2050, when units start to be decommissioned due to them reaching the end of their expected lifetime. The installed capacity from fuel cells increases slightly from 2030 to 2040 and stays stable towards 2050. The declining installed power capacity from storage units can be explained due to the large role of CCGT CCS units in the reference case for providing flexibility in the system. Therefore, the role of provision of flexibility by the daily storage units with relatively low storage capacity per unit and the seasonal storage with high conversion losses diminishes over time.

6.6. Conclusions Based on the Reference Case

The main findings based on applying the OPM to the reference case of the development of the Dutch electricity system in the transition from 2030 to 2050 relate to the role of CCGT CCS. This technology plays a major role in the functioning of the system in the reference case, due to its ability to provide flexible and emission-free electricity. This causes the role of storage technologies for the provision of flexibility in the system to reduce over time when the share of CCGT CCS capacity is increasing. Additionally, it was found that the cost per MWh in the reference case decreased from €186 in 2030 to €135 in 2050, which can be considered to be in a valid range when compared to historic Dutch consumer electricity prices. From 2031 to 2050, the amount of EENS was negligible during the three years in which loss of load occurred. During each of those three years, the LOLE had a level of four, which is within the performance standards expressed for the Dutch electricity grid as indicated by TenneT (2022). In the reference case, no system behaviour or patterns in system development were observed which are unexplainable or illogical. Therefore, it can be concluded that under the assumptions and input data used for the reference case, the OPM provides credible results.

In the next chapter, the design of the two targeted experiments will be presented and the results of applying the OPM to these experiments will be compared amongst each other and with the reference case.

7. Experiments

Based on the input data and assumptions made for the reference case, it was found that the Dutch electricity system becomes heavily reliant on CCGT CCS capacity for electricity generation and provision of flexibility. In a supporting document to the draft NPE, it was indicated that the storage capacity for CCS is limited and that the focus should be on the maximisation of generation capacity from VRE technologies (Ministerie van EZK, 2023a). Therefore, CCGT CCS will be excluded as technology for both experiments to investigate potential alternative trajectories for the Dutch electricity system to reach the zero-emission goal for 2035 and further development to 2050 without the use of CCS. Furthermore, the maximum additional units of VRE and storage technologies per year will be varied between the two experiments to assess the impact of the rate at which additional assets can be developed on the transition path of the Dutch electricity system.

In the first experiment, the maximum number of additional units invested per technology per year is doubled compared to the values used for the reference case. For the second experiment, the maximum number of additional units is set to a sufficiently high number to ensure that it does not pose a restriction on investments in certain technologies. The arbitrarily high number of 1000 additional units is used, which did not pose a limit on investment in any technology during the entire run. Therefore, the first experiment will be referred to as "x2" and the second experiment as "1000". The resulting maximum additional units and capacity per year for the two experiments are shown in Table 12.

Table 12: Maximum Additional Units per Year for Experiments "x2" and "1000"

Technology	Maximum Additional Units per Year		Maximum Additional Capacity per Year (GW)	
	Experiment "x2"	Experiment "1000"	Experiment "x2"	Experiment "1000"
CCGT	16	1,000	6.4	400
CCGT CCS	0	0	0	0
PV	102	1,000	15.3	150
Onshore Wind	12	1,000	2.4	200
Offshore Wind	8	1,000	3.2	400
Biomass and Waste	8	1,000	0.4	50
Daily Storage	52	1,000	2.6	50
Electrolysers	24	1,000	1.2	50
Fuel Cells	24	1,000	1.2	50

7.1. Comparison of Results Reference Case and Experiments

In this section focus is on the comparison of results of the experiments and the reference case, rather than elaborately discussing the results per experiment in-depth. More detailed results of the experiments are provided in appendix C.

7.1.1. Primary KPI 1 & 2 – Total Annual System Costs & Cost per MWh

To analyse the differences in total annual system costs and the cost per MWh, the development in the period from 2033 to 2050 will be compared for the different cases. This period has been selected for comparing costs since system costs in the "x2" experiment are disproportionately high from 2030 to 2032. The exclusion of CCGT CCS as a technology results in a lower total generation capacity being operational in 2030. The limited possibility for additional investment per year in the "x2" experiment results in a longer period before sufficient investments are made to reach a lower stable system cost level. In the "1000" experiment this lower stable system cost level already is achieved in 2031 when the first additional units become operational. Therefore, focusing on the period from 2033 to 2050 prevents the high values for the "x2" experiment from 2030 to 2032 from distorting the analysis.

The development of total annual system costs is shown in Figure 47 and the cost per MWh in Figure 48. It clearly shows that system costs are lowest in the reference case, higher in the "1000" experiment and highest in the "x2" experiment. The development of total annual system costs and cost per MWh for the reference case shows a stable progression over the considered period, while the two experiments show years with higher costs due to loss of load occurring. Cost per MWh in the "x2" experiment ranged between €276 and €216, while it ranged between €200 and €168 in the "1000" experiment. However, the cost per MWh for all three cases is within the range of the average Dutch consumer electricity prices observed in the period from 2021 to 2022 as previously shown in Figure 40.

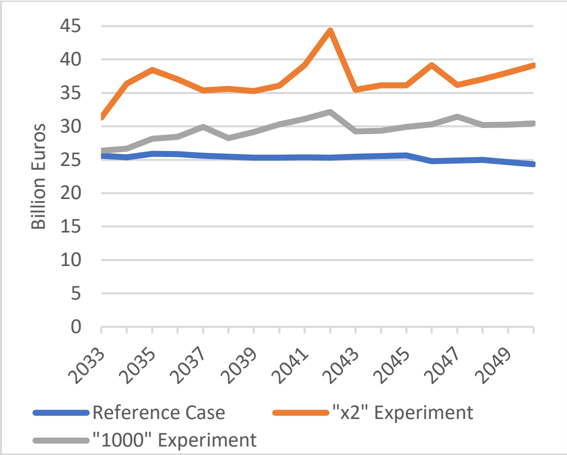


Figure 47: Total System Costs - Reference Case and Experiments (2033 - 2050)

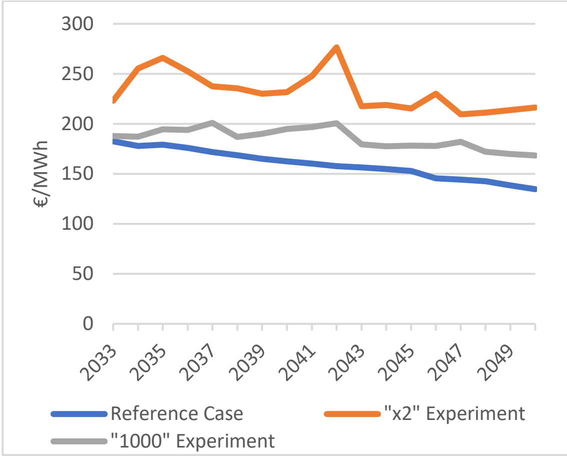


Figure 48: Cost per MWh - Reference Case and Experiments (2033 - 2050)

7.1.2. Primary KPI 3 & 4 – EENS & LOLE

The development of EENS and LOLE for the three cases is presented in Figure 49 and Figure 50. While EENS in the reference case was limited to three years with a LOLE of 4 and a sum of EENS of 54 MWh, the experiments showed years with significantly higher EENS and LOLE. This higher level of EENS and LOLE can partly be explained by the exclusion of the flexible generation capacity from CCGT CCS in the "x2" and "1000" experiments. As a result, except for the nuclear electricity generation, all electricity generation from 2035 onwards is from intermittent VRE technologies. During timesteps in which the capacity factor for VRE technologies is low, the storage assets are the main provider of electricity to the grid.

In the reference case and the two experiments EENS and LOLE were zero from 2048 to 2050. Therefore, the development of the electricity system in all three cases does result in a final system composition which manages to meet demand during the entire year. However, they do so at different costs as discussed in section 7.1.1.

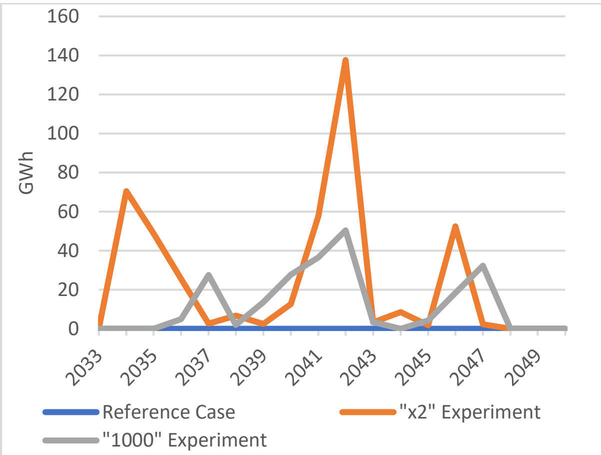


Figure 49: EENS - Reference Case and Experiments (2033 - 2050)

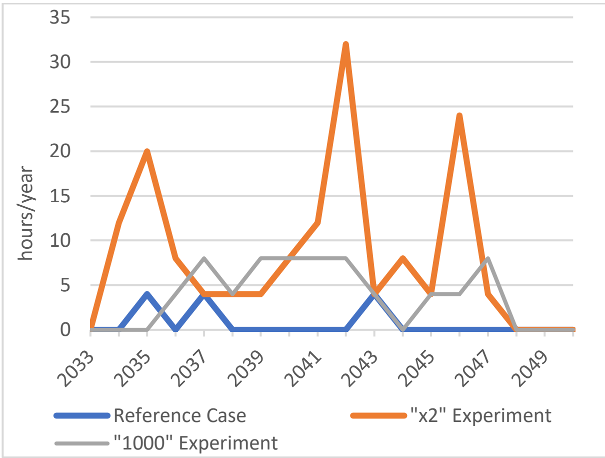


Figure 50: LOLE - Reference Case and Experiments (2033 - 2050)

7.1.3. Secondary KPI 1 – Annual Electricity Delivered to the Grid per Technology

The electricity generation mix and total feed-in to the grid from storage technologies for the two experiments and the reference case will be compared for the year 2050. The aim of focussing on the final year is to assess how differently the Dutch electricity system developed for the three cases at the end of the development trajectory. In Figure 51 the electricity generation mix in 2050 is shown and Figure 52 shows the total feed-in to the grid from storage technologies in 2050. Note that this consist of the electricity delivered to the grid and does not include the curtailed electricity.

In the “1000” experiment, the system becomes mainly dependent on onshore wind for the provision of electrical energy. Additionally, seasonal storage in UHS facilities has become the main storage technology used. The dominance of onshore wind can be explained by its relatively low costs compared to offshore wind and its average capacity factor being higher than the average capacity factor for PV. Since the limit for investments per technology per year is extremely high in this experiment, the model solver decides to mainly invest in onshore wind. Due to the capacity factor of onshore wind fluctuating over longer periods, usage of seasonal storage facilities is more suitable than the daily storage units with limited electricity storage capacity.

The more limited investment options in the “x2” experiment resulted in an electricity generation mix which is more balanced between technologies compared to the “1000” experiment. Similarly, the “x2” experiment resulted in a mix of feed-in from storage technologies to the grid which is more balanced between daily and seasonal storage units compared to the “1000” experiment.

These graphs also emphasize how limited the usage of storage technologies is in the reference case compared to the experiments. This is due to the availability of the flexible generation capacity from CCGT CCS units in the reference case, which reduces the need for storage.

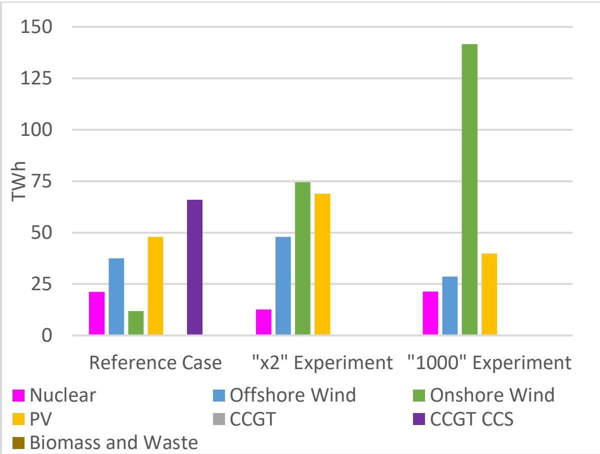


Figure 51: Electricity Generation Mix – Reference Case and Experiments (2050)

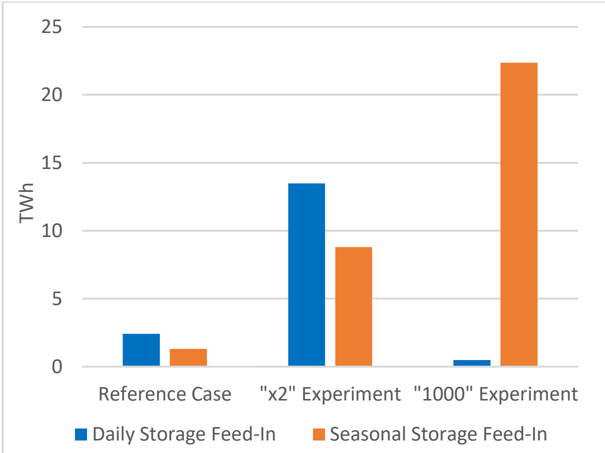


Figure 52: Total Feed-In from Storage Technologies – Reference Case and Experiments (2050)

When comparing the results on electricity generated per technology, it is also important to assess the curtailment per technology in the year 2050 for the different cases, which is shown in Figure 53. This shows that curtailment for all technologies is much higher in the “x2” experiment compared to the “1000” experiment and the reference case.

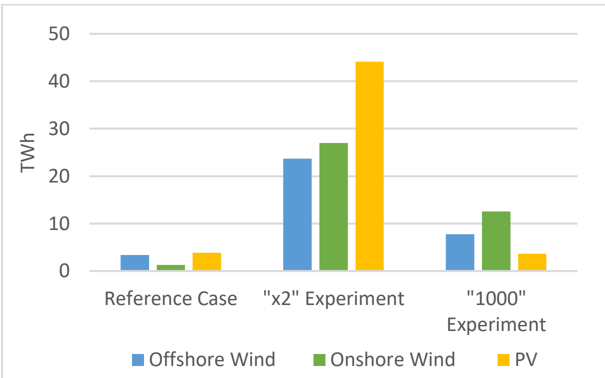


Figure 53: Curtailment per Technology - Reference Case and Experiments (2050)

7.1.4. Secondary KPI 2 – Installed Capacity per Technology

The comparison of the installed capacity mix and the installed power capacity from storage technologies for the different cases will also focus on the year 2050. The installed capacity mix is shown in Figure 54 and the installed power capacity from storage technologies is shown in Figure 55.

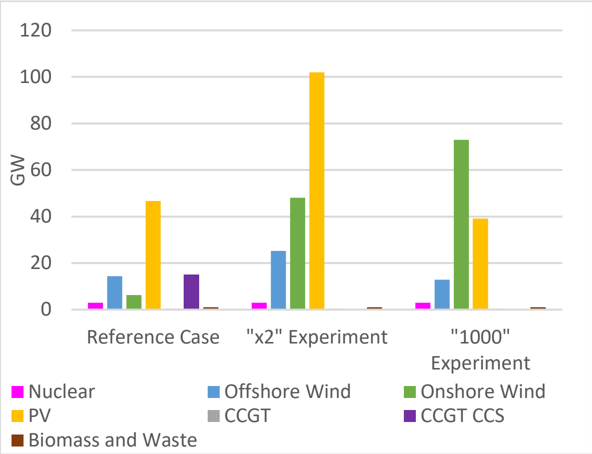


Figure 54: Installed Capacity Mix – Reference Case and Experiments (2050)

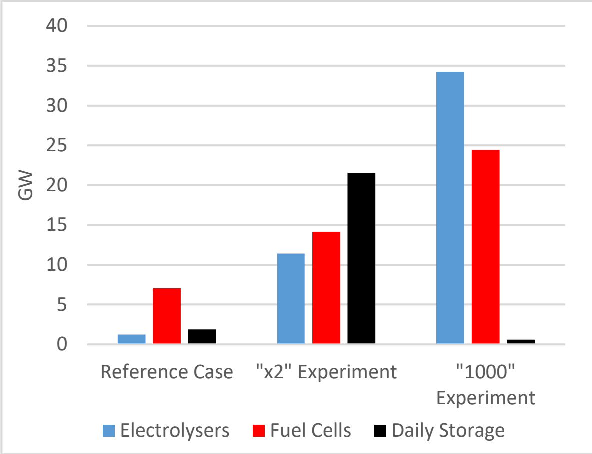


Figure 55: Installed Power Capacity Storage Technologies – Reference Case and Experiments (2050)

As can be expected based on the results presented for the electricity generation mix and the feed-in from storage technologies, the "1000" experiment shows a high level of installed capacity from onshore wind, high levels of installed power capacity from electrolysers and fuel cells, and very limited installed capacity from daily storage units.

The installed capacity mix in the "x2" experiment shows a majority of installed capacity from PV systems. The large share of PV systems can be explained by the fact that the maximum additional capacity per year for PV systems in the "x2" experiment is relatively high compared to the other technologies, as can be seen in Table 12. In the "x2" experiment, it is possible to develop 15.3 GW of additional PV capacity per year, compared to 3.2 GW of offshore wind and 2.4 GW of onshore wind per year. The large installed capacity from PV systems in the "x2" experiment did not result in a large share in the electricity generation mix in Figure 51, due to the high amount of curtailment as shown in Figure 53.

In the "x2" experiment the installed power capacity from storage technologies consists of a majority of daily storage units and a smaller installed capacity from electrolysers and fuel cells. The daily fluctuation of the output from PV units is an explanatory factor for the higher level of installed power capacity from daily storage units. The daily storage units have a relatively small amount of electrical energy storage capacity per unit but have much lower efficiency losses compared to seasonal storage consisting of electrolysers, fuel cells and UHS. This makes the daily storage units more suitable for the frequent charging and discharging of electricity produced by the PV systems.

7.1.5. Conclusions Based on Comparing Results Reference Case and Experiments

The main finding of comparing the results of the two experiments and the reference case is that in case CCGT CCS is excluded, the maximum number of additional units per technology per year results in different development paths. If the maximum of additional units is sufficiently high to not restrict investments, the Dutch electricity system becomes mainly reliant on a combination of onshore wind and seasonal storage units. In case the maximum number of additional units that can be invested in is limited to twice the level of the reference case, a more balanced mix of electricity generation and storage units will develop.

In the year 2050, there is no loss of load in the reference case, nor the two experiments. However, there are differences in the cost per MWh in 2050 for the three different cases. In the reference case, which has a large share of CCGT CCS, the cost per MWh in 2050 is €135. In the "x2" experiment, which has a balanced mix of electricity generation and storage technologies, the cost per MWh in 2050 is €216. In the "1000" experiment, which relies mainly on onshore wind and seasonal storage units, the cost per MWh in 2050 is €168.

The next chapter will present the conclusions of this study.

8. Conclusion

The main methodological objective of this thesis is to design a cost-optimisation model for exploring the development of a national electricity system. The developed model is applied to a reference case on the development of the Dutch electricity system from 2030 to 2050 to assess whether the model provides credible results. Additionally, it is assessed how the exclusion of CCS and variations in the rate of development of additional generation and storage capacity affect the development path of the Dutch electricity system from 2030 to 2050.

To reach the main methodological goal of this thesis, the first research question addressed in the study is:

1. *What is a suitable design for a cost-optimisation model for exploring the development of a national electricity system?*

The design of the model developed in this study conceptualises the national electricity system as an isolated system without grid capacity constraints. The design of the cost-optimisation approach in the model is an iterative loop which optimises the short-term system operation and the long-term investment planning, which resembles a rolling horizon optimisation approach. Since the horizon of foresight does not span the entire optimisation period to 2050, but only two months, the optimisation approach can be considered myopic. This model design results in a low computational burden and allows for conducting model runs for cost-optimisation of the development path of the Dutch electricity system from 2030 to 2050 in a manageable amount of time of 26 minutes[5].

To assess the credibility of the results generated by the model, the second research question addressed in this study is:

2. *Does the model provide credible results for the development of the Dutch electricity system from 2030 to 2050?*

To answer this second research question, the model was applied to a reference case on the development of the Dutch electricity system from 2030 to 2050. This showed that under the assumptions made and with the input data used, the Dutch electricity system would become heavily dependent on CCGT CCS units for the provision of electricity and flexibility in the system. The cost per MWh in the reference case decreased from €186 in 2030 to €135 in 2050, which is in a valid range when compared to the historic Dutch consumer electricity prices in 2020 and 2021. EENS was limited to a negligible amount during the three years that loss of load occurred and LOLE during these three years was within the performance standard as indicated by TenneT (2022). Therefore, the model is considered to provide credible results for the reference case.

To assess alternative development paths for the Dutch electricity system resulting from the exclusion of CCS and varying the rate at which additional investments in technology can be made, the third research question addressed in this study is:

3. *How does the exclusion of CCS and variations in the rate of development of additional generation and storage assets affect the development of the Dutch electricity system from 2030 to 2050?*

To answer this question, the model has been applied to two targeted experiments in which CCGT CCS units were excluded and the maximum of additional units per technology per year was adjusted compared to the reference case. This resulted in two alternative development paths for the Dutch electricity system compared to the reference case:

a. In experiment “x2”, the maximum number of additional units per technology was doubled compared to the reference case. In this experiment, the system developed a balanced mix of electricity generation and storage technologies. The system costs were relatively high and there were years with significantly more loss of load compared to the reference case. The cost per MWh in this experiment ranged between €276 and €216.
b. In experiment “1000”, the maximum number of additional units per technology was set at 1,000, which was sufficiently high to not limit investments made in a technology in any year. In this experiment, the system became mainly dependent on onshore wind for the provision of electricity,

5 The used computer runs on an Intel Core i7 – 7700HQ CPU 2.80 GHz with 16 GB RAM.

while flexibility was provided by energy storage in seasonal storage units. The system costs in this case were in between the level of the reference case and the other experiment. Loss of load did occur in this experiment to a larger extent than in the reference case, but not as extreme as in the "x2" experiment. The cost per MWh in this experiment ranged between €200 and €168.

Therefore, it can be concluded that the exclusion of CCGT CCS and adjustment of the number of possible investments results in different development paths for the Dutch electricity system towards 2050. In the reference case, the system in 2050 mainly relies on CCGT CCS units for the provision of electricity and flexibility, with a cost per MWh of €135 in 2050. In case CCGT CCS is excluded and the maximum number of additional units invested in per technology per year is limited to twice the level of the reference case, it results in a diverse mix of generation and storage technologies, with a cost per MWh in 2050 of €216. In case CCGT CCS is excluded and the maximum number of additional units is sufficiently high to not pose a limitation on investments, the system becomes mainly reliant on onshore wind and seasonal storage units, with a cost per MWh in 2050 of €168.

In the next chapter, the results of the study will be discussed, limitations will be identified, and possibilities for future research will be suggested.

9. Discussion

9.1. Discussion of Results

The reference case and the two experiments presented in this report show that the OPM can be useful for gaining insight into the development path of a national electricity system. This was especially noticeable when comparing the results of the two experiments. It showed that in case CCGT CCS is excluded, a higher rate at which additional units per technology can be invested per year results in lower cost per MWh 2050 and a different system composition. This finding is relevant for policy-makers since it shows that stimulation of the rate at which VRE generation capacity and storage capacity can be developed, can support reaching the energy policy goals for an affordable energy system. Therefore, policy-makers should identify and reduce barriers to the development of the combination of generation and storage technologies which offers the cost-optimal solution for meeting electricity demand. This also supports the importance of the first of the five main problems listed in the draft NPE, which states that the development of renewable energy supply and the supporting infrastructure must be maximised (Ministerie van EZK, 2023b).

The results of the reference case and two targeted experiments are too limited to develop specific policy recommendations on how the electricity system of the Netherlands should develop towards 2050. Additionally, some constraints are not included in the OPM which poses a limitation on the practical feasibility and social acceptability of the model outcomes. An example would be conflicting interests in land usage in a relatively small and densely populated country such as the Netherlands. In the "1000" experiment the installed capacity from onshore wind increases from 11.6 GW in 2030 to 33.0 GW in 2031 and up to 73.0 GW by 2050. However, the maximum potential for onshore wind in the Netherlands is estimated to be between 30 and 60 GW according to studies considering spatial constraints (Generation.Energy & PasadMaxwan, 2020; Vendrik et al., 2023). Therefore, it is important to be aware of such constraints which are not included within the OPM. An optimisation approach that provides more insight into the spatial dimension of future designs of the electricity system is the SPORES method (Lombardi et al., 2020). This method allows for exploring spatially feasible system alternatives that are within a certain percentage of the total system costs of the cost-optimal solution.

One of the objectives for the development of the model in this study was to ensure that the developed model is transparent and not overly complex, to prevent it from being considered a 'black box' and to increase its usefulness for public stakeholders and decision-makers in the power system planning process as suggested by Moallemi & Malekpour (2018). The implementation in Linny-R allows for a clear visualisation of the model, which increases the transparency of the model. However, many of these visualised products, processes and links within the model are defined by lengthy expressions. Therefore, it is debatable whether the functioning of the OPM is truly transparent and not overly complex, since completely understanding its precise functioning by assessing all the expressions embedded in the model would be very laborious work and likely not feasible for someone without modelling experience.

The two targeted experiments showed significantly higher EENS and LOLE compared to the reference case. Although higher EENS and LOLE can be expected due to the exclusion of the flexible generation capacity of CCGT CCS units, other factors likely had an influence. A possible explanation is the decision to select a two-month look-ahead period for setting the storage levels at the end and start of each year. In the reference case with CCGT CCS, these two months resulted in sufficient energy in the storage units to maintain EENS to a negligible level and the LOLE within the performance standards. However, in the two experiments without CCGT CCS, EENS was significantly higher, and LOLE exceeded the performance standards. A test run using a look-ahead period of six months did result in lower EENS and LOLE for the experiments. However, time limitations on the thesis project did not allow for thoroughly assessing what a suitable look-ahead period would be to prevent the loss of load which is attributable to the look-ahead period. Moreover, there could be other unidentified factors that explain a part of the high loss of load in the experiments.

Next to the limited number of experiments conducted, other limitations in the study result from the fact that the OPM does not account for interconnection capacity with other electricity systems, that it does not incorporate demand side flexibility, and the used approach for selecting time series data. Based on these limitations, recommendations are made for future research in the next section.

9.2. Recommendations for Future Research

On experiments and policy recommendations. The first recommendation results from the limited number of experiments conducted in this study. Conducting additional experiments could result in more in-depth insights into the impact of factors influencing the development path of the Dutch electricity system and help shape policy recommendations. An example could be to assess scenarios in which the CAPEX and OPEX costs for the different technologies are varied within a range of possible future cost projections. By doing so, it can be assessed at which cost levels for the different technologies the system starts developing towards favourable or unfavourable technology mixes. These insights can inform the development of policies such as a subsidy scheme to ensure that the developing system meets the *Klimaatakkoord* targets for the share of renewables in the electricity mix.

On spatial scope and interconnection capacity. Expanding the spatial scope of the model by including the electricity system of one or multiple countries which have interconnection capacity with the Dutch electricity system could be a promising avenue for future research. Interconnection capacity is already important for the reliability of the Dutch electricity system, but its importance is expected to grow in the post-2030 electricity system with high levels of intermittent VRE generation. Including other national electricity systems and the interconnection capacity with these countries could result in insights related to the co-evolution of the different interconnected electricity systems and the importance of cross-border trade for ensuring system reliability in systems with high levels of intermittent VRE. Additionally, it would address the fourth main problem that the Dutch government wants to address as indicated in the draft NPE, which is increasing the interconnectedness of the European energy system (Ministerie van EZK, 2023b).

On demand side flexibility. In this study, the demand side was considered inflexible and the demand pattern for all years from 2030 to 2050 was based on the time series data of the Netherlands in 2019. The only flexibility in the system resulted from storage technologies or from flexible electricity generation. It is expected that the electrification of different sectors such as mobility, heating, and industry result in the demand side of the electricity system becoming more flexible through demand response (De Wildt et al., 2022; Sijm et al., 2022). This can be offered by different P2X technologies, such as power-to-hydrogen, power-to-heat in industry, power-to-heat in households, and power-to-mobility (Sijm et al., 2020). Including such technologies in the OPM for the provision of demand side flexibility could result in more realistic insights into the development of the electricity system in the period from 2030 to 2050.

On the use of time series data. For this research, the time series data for electricity demand in each year is based on the 2019 data of the Netherlands which is scaled using a CAGR. Similarly, the capacity factors for the VRE technologies for each year are based on data from 2019. A recommended alternative approach would be to use hourly time series data from multiple different years for the electricity demand and capacity factors in the Operation stage to represent annual differences. The time series data for electricity demand and capacity factors for the Planning stage of the model would be a representative year that is compiled using a representative days method for multiple years (e.g., Poncelet, Delarue, Six, Duerinck, et al., (2016)). Thus, the Planning stage will make investment decisions based on time series data which approximates what will happen in the Operation stage four years into the future. The decisions made during the Planning stage will reflect that it is not possible to know what the exact demand and capacity factor will be for each hour of a year four years into the future. This will result in a more accurate representation of how perfect forecasting is impossible and how hours with extreme electricity demand or VRE supply in a year affect the reliability of the system.

The next chapter will present a reflection on the process of conducting the research for this master's thesis project.

10. Reflection

Before starting this master's thesis project, I had little to no experience with modelling in general and I had no experience yet with developing optimisation models. The courses in the first year of the CoSEM programme did help me develop my quantitative research skills and helped me gain basic knowledge about optimisation problems. Therefore, I considered it a challenge worth taking on to use the master's thesis project as an opportunity to research a topic with optimisation models, since I considered it to be an interesting approach that I wanted to learn more about.

During the first part of the research process for this thesis, the guidance of Pieter Bots was very helpful for understanding how to work in Linny-R and how to better structure my thinking when attempting to capture real-world processes in an optimisation model. The learning curve which I had to go through resulted in the process of model development taking up significantly more time than initially planned. Additionally, I experienced it to be quite challenging to implement some of the model functionalities, while ensuring proper operation of the entire model. When the model becomes more complex over time, thorough investigation of the functioning of the model is crucial but also becomes more demanding. Tracing back unexpected model behaviour to the implementation of a specific model component or an expression used in a certain link or process sometimes felt like looking for a needle in a haystack to me. The meetings I had with Pieter Bots in which I presented problems I encountered during model development were very enlightening for learning how to approach such issues. Unfortunately, not always being sufficiently thorough on the overall functioning of the model resulted in me identifying errors in the model in a late stage of the process, which resulted in an increased time pressure to adjust the model and simultaneously finalise the thesis. As a result, the scope of the thesis became a lot narrower compared to the original plan.

When reflecting on the overall research process of my master's thesis project, spending much time on some side paths and details is one of the pitfalls I fell into. Additionally, I made multiple changes to the scope of the thesis. These two factors combined resulted in a lot of time and effort being put into searching for information and developing model components which were not used for the final version of the model or the thesis. Therefore, it would have been beneficial to make more focused progress during the project if I had established the definitive research questions earlier in the process.

References

Ahlqvist, V., Holmberg, P., & Tangerås, T. (2022). A survey comparing centralized and decentralized electricity markets. *Energy Strategy Reviews*, *40*, 100812. https://doi.org/10.1016/J.ESR.2022.100812

Arthur, W. B. (1989). Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *The Economic Journal*, *99*(394), 116. https://doi.org/10.2307/2234208

Babrowski, S., Heffels, T., Jochem, P., & Fichtner, W. (2014). Reducing computing time of energy system models by a myopic approach. *Energy Systems*, *5*(1), 65–83. https://doi.org/10.1007/s12667-013-0085-1

Bhagwat, P. C., Iychettira, K. K., Richstein, J. C., Chappin, E. J. L., & De Vries, L. J. (2017). The effectiveness of capacity markets in the presence of a high portfolio share of renewable energy sources. *Utilities Policy*, *48*, 76–91. https://doi.org/10.1016/j.jup.2017.09.003

Blok, K., & Nieuwlaar, E. (2016). *Introduction to Energy Analysis*. Routledge. https://doi.org/10.4324/9781315617213

Bots, P. W. G. (2022). *Linny-R documentation*. https://sysmod.tbm.tudelft.nl/linny-r/docs/

Bots, P. W. G. (2023a). *linny-r*. https://www.npmjs.com/package/linny-r

Bots, P. W. G. (2023b). *Linny-R version history*. Github. https://github.com/pwgbots/linny-r/wiki/Linny-R-version-history

Brouwer, A. S., van den Broek, M., Seebregts, A., & Faaij, A. (2015). Operational flexibility and economics of power plants in future low-carbon power systems. *Applied Energy*, *156*, 107–128. https://doi.org/10.1016/J.APENERGY.2015.06.065

CBS. (2021, December 7). *More and more renewable energy from biomass*. Centraal Bureau Voor de Statistiek. https://www.cbs.nl/en-gb/news/2021/39/more-and-more-renewable-energy-from-biomass

CBS. (2022, March 7). *Meer elektriciteit uit hernieuwbare bronnen, minder uit fossiele bronnen*. Centraal Bureau Voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2022/10/meer-elektriciteit-uit-hernieuwbare-bronnen-minder-uit-fossiele-bronnen

CBS. (2023a, February 2). *Elektriciteit; productie en productiemiddelen*. Centraal Bureau Voor de Statistiek. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/37823wkk/table?dl=50A32

CBS. (2023b, March 6). *Aandeel hernieuwbare elektriciteit met 20 procent gestegen in 2022*. Centraal Bureau Voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2023/10/aandeel-hernieuwbare-elektriciteit-met-20-procent-gestegen-in-2022

CBS. (2023c, March 7). *Welke sectoren stoten broeikasgassen uit?* Centraal Bureau Voor de Statistiek. https://www.cbs.nl/nl-nl/dossier/dossier-broeikasgassen/welke-sectoren-stoten-broeikasgassen-uit-

CBS. (2023d, June 2). *Hernieuwbare elektriciteit; productie en vermogen*. Centraal Bureau Voor de Statistiek. https://opendata.cbs.nl/#/CBS/nl/dataset/82610NED/table

CBS. (2023e, June 15). *Elektriciteitsbalans; aanbod en verbruik*. Centraal Bureau Voor de Statistiek. https://opendata.cbs.nl/#/CBS/nl/dataset/84575NED/table

CBS. (2023f, July 13). *Gemiddelde energietarieven voor consumenten, 2018 - 2023*. Centraal Bureau Voor de Statistiek. https://opendata.cbs.nl/#/CBS/nl/dataset/84672NED/table

Cevik, S., Ninomiya, K., Bogmans, C., Gracia, B., Pescatori, A., Schimmelpfennig, A., Shang, B., Stanley, A., & Zhang, Z. (2022). *Chasing the Sun and Catching the Wind: Energy Transition and Electricity Prices in Europe*. https://www.imf.org/-/media/Files/Publications/WP/2022/English/wpiea2022220-print-pdf.ashx

Chae, B. (Kevin). (2009). Developing key performance indicators for supply chain: an industry perspective. *Supply Chain Management: An International Journal*, *14*(6), 422–428. https://doi.org/10.1108/13598540910995192

Christensen, A. (2020). *Assessment of Hydrogen Production Costs from Electrolysis: United States and Europe*. https://theicct.org/p-content/uploads/2021/06/final_icct2020_assessment_of-_hydrogen_production_costs-v2.pdf

CLO. (2022, July 29). *Interconnectiecapaciteit elektriciteit, 2015 - 2021*. Compendium Voor de Leefomgeving. https://www.clo.nl/indicatoren/nl0595-interconnectiecapaciteit-elektriciteit

Cuisinier, É., Lemaire, P., Penz, B., Ruby, A., & Bourasseau, C. (2022). New rolling horizon optimization approaches to balance short-term and long-term decisions: An application to energy planning. *Energy*, *245*, 122773. https://doi.org/10.1016/j.energy.2021.122773

Cunningham, L. S., & Pomfret, M. A. (2007). Partnering contracts in practice at Blackpool, UK. *Proceedings of the Institution of Civil Engineers - Municipal Engineer*, *160*(1), 17–21. https://doi.org/10.1680/muen.2007.160.1.17

De Wildt, B., Quirke, R., & Sijm, J. (2022). *Barriers to demand response*. https://publications.tno.nl/publication/34639482/Gliqt5/TNO-2022-P10368.pdf

Deane, J. P., Chiodi, A., Gargiulo, M., & Ó Gallachóir, B. P. (2012). Soft-linking of a power systems model to an energy systems model. *Energy*, *42*(1), 303–312. https://doi.org/10.1016/j.energy.2012.03.052

Deloitte. (2021). *Fueling the future of mobility: hydrogen electrolyzers*. https://www2.deloitte.com/content/dam/Deloitte/jp/Documents/global-business-support/jp-gbs-fueling-the-future-of-mobility-hydrogen-electrolyzers.pdf

Demir, A., & Hadžijahić, N. (2018). Power System Planning: Part I —Basic Principles. In M. Hadžikadić & S. Avdaković (Eds.), *Lecture Notes in Networks and Systems* (Vol. 28, pp. 178–188). Springer. https://doi.org/10.1007/978-3-319-71321-2_15

Deng, X., & Lv, T. (2020). Power system planning with increasing variable renewable energy: A review of optimization models. *Journal of Cleaner Production*, *246*, 118962. https://doi.org/10.1016/j.jclepro.2019.118962

DNV. (n.d.). *Transmission & Distribution - Power System Planning*. Retrieved 2 August 2023, from https://www.dnv.com/power-renewables/transmission-distribution/power-system-planning.html

Duyster, H., & Terwel, R. (2021). *Een essay over de financiering van de Energietransitie tussen 2020 en 2050*. https://open.overheid.nl/documenten/ronl-b8a8fe39-6d57-4b77-a5de-3ff5fbf71eff/pdf

ECB. (2023). *US dollar (USD)*. European Central Bank. ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-usd.en.html

Eerste Kamer der Staten-Generaal. (2019, December 10). *Kamer stemt in met verbod op kolen bij elektriciteitsproductie*. https://www.eerstekamer.nl/nieuws/20191210/kamer_stemt_in_met_verbod_op_kolen

EIA. (2020). *Capital Cost and Performance Characteristic Estimates for Utility Scale Electric Power Generating Technologies*. https://www.eia.gov/analysis/studies/powerplants/capitalcost/pdf/capital_cost_AEO2020.pdf

EIA. (2023). *Assumptions to the Annual Energy Outlook 2023: Electricity Market Module*. https://www.eia.gov/outlooks/aeo/assumptions/pdf/EMM_Assumptions.pdf

ENTSO-E. (2022, December 14). *Installed Capacity per Production Type*. ENTSO-E Transparency Platform. https://transparency.entsoe.eu/generation/r2/installedGenerationCapacityAggregation/show?name=&defaultValue=false&viewType=TABLE&areaType=CTY&atch=false&dateTime.dateTime=01.01.2015+00:00|UTC|YEAR&dateTime.endDateTime=01.01.2023+00:00|UTC|YEAR&area.values=CTY|10YNL----------L!CTY|10YNL----------L&productionType.values=B01&productionType.values=B02&productionType.values=B03&productionType.values=B04&productionType.values=B05&productionType.values=B06&productionType.values=B07&productionType.values=B08&productionType.values=B09&productionType.values=B10&productionType.

values=B11&productionType.values=B12&productionType.values=B13&productionType.values=B14&productionType.values=B20&productionType.values=B15&productionType.values=B16&productionType.values=B17&productionType.values=B18&productionType.values=B19#

Equinor. (n.d.). *Natural Gas Converter*. Retrieved 22 August 2023, from https://ngc.equinor.com/Home/Price

European Commission. (n.d.). *Energy*. Directorate-General for Energy. Retrieved 11 April 2023, from https://commission.europa.eu/about-european-commission/departments-and-executive-agencies/energy_en

European Commission. (2020). *Strategic Plan 2020-2024 DG ENER*. https://commission.europa.eu/system/files/2020-10/ener_sp_2020_2024_en.pdf

European Parliament. (2019, June 5). *Regulation (EU) 2019/943 of the European Parliament and of the Council of 5 June 2019 on the internal market for electricity*. Official Journal of the European Union. http://data.europa.eu/eli/reg/2019/943/oj

Foster, P. J., & Jiang, Y. (2014). Epidemiology of myopia. *Eye 2014 28:2*, *28*(2), 202–208. https://doi.org/10.1038/eye.2013.280

Frew, B. A., & Jacobson, M. Z. (2016). Temporal and spatial tradeoffs in power system modeling with assumptions about storage: An application of the POWER model. *Energy*, *117*, 198–213. https://doi.org/10.1016/j.energy.2016.10.074

Gasunie. (n.d.). *HyStock Waterstofopslag*. Retrieved 19 August 2023, from https://www.gasunie.nl/projecten/hystock-waterstofopslag

Gaur, A. S., Das, P., Jain, A., Bhakar, R., & Mathur, J. (2019). Long-term energy system planning considering short-term operational constraints. *Energy Strategy Reviews*, *26*, 100383. https://doi.org/10.1016/j.esr.2019.100383

Generation.Energy, & PasadMaxwan. (2020). *Ruimtelijke Uitwerking Energiescenario's*. https://open.overheid.nl/repository/ronl-fdc846f5-8bd8-4734-b337-4e9e65df315c/1/ruimtelijke-uitwerking-energiescenarios/ruimtelijke-uitwerking-energiescenarios

Goldstein, J. E., Neimark, B., Garvey, B., & Phelps, J. (2023). Unlocking "lock-in" and path dependency: A review across disciplines and socio-environmental contexts. *World Development*, *161*, 106116. https://doi.org/10.1016/J.WORLDDEV.2022.106116

Groenewoud, J. (2022). *Myopic Optimisation of Generation and Storage Investment for Long-Term Electricity System Planning* [MSc Thesis, TU Delft]. http://resolver.tudelft.nl/uuid:7f8dbc6d-4c98-4bc4-8685-25edddf3cbc7

Haydt, G., Leal, V., Pina, A., & Silva, C. A. (2011). The relevance of the energy resource dynamics in the mid/long-term energy planning models. *Renewable Energy*, *36*(11), 3068–3074. https://doi.org/10.1016/j.renene.2011.03.028

Heffron, R. J., McCauley, D., & Sovacool, B. K. (2015). Resolving society's energy trilemma through the Energy Justice Metric. *Energy Policy*, *87*, 168–176. https://doi.org/10.1016/J.ENPOL.2015.08.033

Helistö, N., Kiviluoma, J., Holttinen, H., Lara, J. D., & Hodge, B. (2019). Including operational aspects in the planning of power systems with large amounts of variable generation: A review of modeling approaches. *WIREs Energy and Environment*, *8*(5), e341. https://doi.org/10.1002/wene.341

Hensen, C., & van der Walle, E. (2023, July 3). Bij de vergroening van het Nederlandse energiesysteem neemt de overheid een ongebruikelijk dominante rol in. *NRC*. https://www.nrc.nl/nieuws/2023/07/03/minister-jetten-overheid-pakt-hoofdrol-in-verduurzaming-energie-a4168811?t=1690908665

Hess, D., Wetzel, M., & Cao, K.-K. (2018). Representing node-internal transmission and distribution grids in energy system models. *Renewable Energy*, *119*, 874–890. https://doi.org/10.1016/j.renene.2017.10.041

Hore-Lacy, I. (2007). *Nuclear Energy in the 21st Century*. Elsevier. https://doi.org/10.1016/B978-0-12-373622-2.X5000-4

HyStock. (n.d.). *Het project*. Retrieved 19 August 2023, from https://www.hystock.nl/over-hystock/het-project

IEA. (2022a). *Global Energy and Climate Model Documentation*. https://iea.blob.core.windows.net/assets/2db1f4ab-85c0-4dd0-9a57-32e542556a49/GlobalEnergyandClimateModelDocumentation2022.pdf

IEA. (2022b, February 24). *Energy transitions require innovation in power system planning*. International Energy Agency. https://www.iea.org/articles/energy-transitions-require-innovation-in-power-system-planning

IEA. (2022c, October). *Techno-economic inputs – Global Energy and Climate Model*. IEA. https://www.iea.org/reports/global-energy-and-climate-model/techno-economic-inputs

Jetten, R. A. A. (2022). *Nadere uitwerking van de afspraken uit het coalitieakkoord op het gebied van kernenergie*. https://www.tweedekamer.nl/downloads/document?id=2022D53286

Kannan, R. (2011). The development and application of a temporal MARKAL energy system model using flexible time slicing. *Applied Energy*, *88*(6), 2261–2272. https://doi.org/10.1016/j.apenergy.2010.12.066

Kebede, A. A., Kalogiannis, T., Van Mierlo, J., & Berecibar, M. (2022). A comprehensive review of stationary energy storage devices for large scale renewable energy sources grid integration. *Renewable and Sustainable Energy Reviews*, *159*, 112213. https://doi.org/10.1016/J.RSER.2022.112213

Kenton, W., & Kindness, D. (2020, August 23). *Equivalent Annual Cost (EAC): What It Is, How It Works, Examples*. Investopedia. https://www.investopedia.com/terms/e/eac.asp

Klimaatakkoord. (n.d.). *Het Akkoord*. Klimaatakkoord. Retrieved 9 January 2023, from https://www.klimaatakkoord.nl/klimaatakkoord

KPMG. (2022). *How to evaluate the cost of the green hydrogen business case? Assessing green hydrogen production costs*. https://assets.kpmg.com/content/dam/kpmg/be/pdf/2022/hydrogen-industry-1.pdf

Lombardi, F., Pickering, B., Colombo, E., & Pfenninger, S. (2020). Policy Decision Support for Renewables Deployment through Spatially Explicit Practically Optimal Alternatives. *Joule*, *4*(10), 2185–2207. https://doi.org/10.1016/J.JOULE.2020.08.002

Loper, M. L. (2015). The Modeling and Simulation Life Cycle Process. In M. L. Loper (Ed.), *Modeling and Simulation in the Systems Engineering Life Cycle* (pp. 17–27). Springer-Verlag. https://doi.org/10.1007/978-1-4471-5634-5_2

Lopion, P., Markewitz, P., Robinius, M., & Stolten, D. (2018). A review of current challenges and trends in energy systems modeling. *Renewable and Sustainable Energy Reviews*, *96*, 156–166. https://doi.org/10.1016/j.rser.2018.07.045

Lund, P. D., Lindgren, J., Mikkola, J., & Salpakari, J. (2015). Review of energy system flexibility measures to enable high levels of variable renewable electricity. *Renewable and Sustainable Energy Reviews*, *45*, 785–807. https://doi.org/10.1016/j.rser.2015.01.057

Luo, X., Wang, J., Dooner, M., & Clarke, J. (2015). Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Applied Energy*, *137*, 511–536. https://doi.org/10.1016/j.apenergy.2014.09.081

Marocco, P., Novo, R., Lanzini, A., Mattiazzo, G., & Santarelli, M. (2023). Towards 100% renewable energy systems: The role of hydrogen and batteries. *Journal of Energy Storage*, *57*, 106306. https://doi.org/10.1016/j.est.2022.106306

Meeus, L. (2020). The Evolution of Electricity Markets in Europe. In *The Evolution of Electricity Markets in Europe*. Edward Elgar Publishing. https://doi.org/10.4337/9781789905472

Mier, M., & Azarova, V. (2021). *Unraveling the Black Box of Power Market Models* (357; Ifo Working Papers). https://www.ifo.de/en/publications/2021/working-paper/unraveling-black-box-power-market-models

Ministerie van EZK. (n.d.-a). *Langer openhouden kerncentrale in Borssele*. Ministerie van Economische Zaken En Klimaat. Retrieved 22 August 2023, from https://www.overkernenergie.nl/plannen-van-het-kabinet/langer-openhouden-kerncentrale-in-borssele

Ministerie van EZK. (n.d.-b). *Twee nieuwe kerncentrales*. Ministerie van Economische Zaken En Klimaat. Retrieved 22 August 2023, from https://www.overkernenergie.nl/plannen-van-het-kabinet/twee-nieuwe-kerncentrales

Ministerie van EZK. (2022). *Samenvatting openbare consultatie marktordening waterstof*. https://open.overheid.nl/documenten/ronl-35ee832d2f7534a06696262948fd89cf45e22995/pdf

Ministerie van EZK. (2023a). *Concept Nationaal plan energiesysteem - Ambtelijk werkdocument B - Ontwikkelpaden ketens van het energiesysteem*. https://open.overheid.nl/documenten/06cc087f-ccbe-4e42-960f-2c8d317dba7c/file

Ministerie van EZK. (2023b). *Nationaal plan energiesysteem - Concept*. https://open.overheid.nl/documenten/5a6e1180-844e-4f42-ab06-d63a559cd795/file

Moallemi, E. A., & Malekpour, S. (2018). A participatory exploratory modelling approach for long-term planning in energy transitions. *Energy Research & Social Science*, *35*, 205–216. https://doi.org/10.1016/J.ERSS.2017.10.022

Morrison, R. (2018). Energy system modeling: Public transparency, scientific reproducibility, and open development. *Energy Strategy Reviews*, *20*, 49–63. https://doi.org/10.1016/j.esr.2017.12.010

Müller, B., Gardumi, F., & Hülk, L. (2018). Comprehensive representation of models for energy system analyses: Insights from the Energy Modelling Platform for Europe (EMP-E) 2017. *Energy Strategy Reviews*, *21*, 82–87. https://doi.org/10.1016/j.esr.2018.03.006

Nahmmacher, P., Schmid, E., Hirth, L., & Knopf, B. (2016). Carpe diem: A novel approach to select representative days for long-term power system modeling. *Energy*, *112*, 430–442. https://doi.org/10.1016/j.energy.2016.06.081

Neuhoff, K., & De Vries, L. (2004). Insufficient incentives for investment in electricity generations. *Utilities Policy*, *12*(4), 253–267. https://doi.org/10.1016/j.jup.2004.06.002

Nicolosi, M., & Fürsch, M. (2009). The Impact of an increasing share of RES-E on the Conventional Power Market — The Example of Germany. *Zeitschrift Für Energiewirtschaft*, *33*(3), 246–254. https://doi.org/10.1007/s12398-009-0030-0

NREL. (n.d.). *Supporting India's States With Renewable Energy Integration*. National Renewable Energy Laboratory. Retrieved 2 August 2023, from https://www.nrel.gov/international/india-renewable-energy-integration.html

Open Power System Data. (2020a). *Data Package Conventional power plants*. https://doi.org/10.25832/conventional_power_plants/2020-10-01

Open Power System Data. (2020b, October 6). *Data Platform - Time series*. https://doi.org/10.25832/time_series/2020-10-06

Palmintier, B., & Webster, M. (2011). Impact of unit commitment constraints on generation expansion planning with renewables. *2011 IEEE Power and Energy Society General Meeting*, 1–7. https://doi.org/10.1109/PES.2011.6038963

Pfenninger, S. (2017). Dealing with multiple decades of hourly wind and PV time series in energy models: A comparison of methods to reduce time resolution and the planning implications of inter-annual variability. *Applied Energy*, *197*, 1–13. https://doi.org/10.1016/j.apenergy.2017.03.051

Pfenninger, S., & Staffell, I. (n.d.). *About - Renewables.ninja*. Renewables.Ninja. Retrieved 14 December 2022, from https://www.renewables.ninja/about

Pina, A., Silva, C., & Ferrão, P. (2011). Modeling hourly electricity dynamics for policy making in long-term scenarios. *Energy Policy*, *39*(9), 4692–4702. https://doi.org/10.1016/j.enpol.2011.06.062

Poncelet, K., Delarue, E., Six, D., & D’Haeseleer, W. (2016). Myopic optimization models for simulation of investment decisions in the electric power sector. *2016 13th International Conference on the European Energy Market (EEM)*, *2016-July*, 1–9. https://doi.org/10.1109/EEM.2016.7521261

Poncelet, K., Delarue, E., Six, D., Duerinck, J., & D’Haeseleer, W. (2016). Impact of the level of temporal and operational detail in energy-system planning models. *Applied Energy*, *162*, 631–643. https://doi.org/10.1016/j.apenergy.2015.10.100

Rijksoverheid. (n.d.-a). *Kernenergie in Nederland*. Retrieved 13 December 2022, from https://www.rijksoverheid.nl/onderwerpen/duurzame-energie/opwekking-kernenergie#anker-3-2-nieuwe-kerncentrales-bij-voorkeur-in-borssele

Rijksoverheid. (n.d.-b). *Rijksoverheid stimuleert ontwikkeling bio-energie*. Retrieved 24 August 2023, from https://www.rijksoverheid.nl/onderwerpen/duurzame-energie/bio-energie

Rijksoverheid. (2018, May 18). *Kabinet verbiedt elektriciteitsproductie met kolen*. https://www.rijksoverheid.nl/actueel/nieuws/2018/05/18/kabinet-verbiedt-elektriciteitsproductie-met-kolen

Rijksoverheid. (2019). *Klimaatakkoord: Hoofdstuk Elektriciteit*. https://www.klimaatakkoord.nl/binaries/klimaatakkoord/documenten/publicaties/2019/06/28/klimaatakkoord-hoofdstuk-elektriciteit/klimaatakkoord-c5+Elektriciteit.pdf

Ringler, P., Keles, D., & Fichtner, W. (2017). How to benefit from a common European electricity market design. *Energy Policy*, *101*, 629–643. https://doi.org/10.1016/j.enpol.2016.11.011

RIVM. (n.d.). *Energietransitie*. RIVM. Retrieved 4 October 2022, from https://www.rivm.nl/onderwerpen/energietransitie

RVO. (2022, December 15). *Netcapaciteit en netcongestie*. Rijksdienst Voor Ondernemend Nederland. https://www.rvo.nl/onderwerpen/zonne-energie/netcapaciteit

RVO. (2023, July 5). *Nationaal plan energiesysteem (NPE)*. Rijksdienst Voor Ondernemend Nederland. https://www.rvo.nl/onderwerpen/energiesysteem/nationaal-plan-energiesysteem

Sánchez Diéguez, M., Fattahi, A., Sijm, J., Morales España, G., & Faaij, A. (2021). Modelling of decarbonisation transition in national integrated energy system with hourly operational resolution. *Advances in Applied Energy*, *3*, 100043. https://doi.org/10.1016/j.adapen.2021.100043

Seifi, H., & Sepasian, M. S. (2011). Electric Power System Planning. In *Power Systems* (Vol. 49). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-17989-1

Sensfuß, F., Ragwitz, M., & Genoese, M. (2008). The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. *Energy Policy*, *36*(8), 3086–3094. https://doi.org/10.1016/j.enpol.2008.03.035

Siala, K., Mier, M., Schmidt, L., Torralba-Díaz, L., Sheykhha, S., & Savvidis, G. (2022). Which model features matter? An experimental approach to evaluate power market modeling choices. *Energy*, *245*, 123301. https://doi.org/10.1016/j.energy.2022.123301

Sijm, J., Janssen, G., Morales-España, G., van Stralen, J., Hernandez-Serna, R., & Smekens, K. (2020). *The role of large-scale energy storage in the energy system of the Netherlands, 2030-2050*. http://resolver.tudelft.nl/uuid:ecec5529-8f0b-4f41-a062-cacd65e4b027

Sijm, J., Morale-España, G., & Hernández-Serna, R. (2022). *The role of demand response in the power system of the Netherlands*. https://publications.tno.nl/publication/34639481/emVYyq/TNO-2022-P10131.pdf

Staffell, I., & Pfenninger, S. (2016). Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*, *114*, 1224–1239. https://doi.org/10.1016/j.energy.2016.08.068

Staffell, I., & Pfenninger, S. (2018). The increasing impact of weather on electricity supply and demand. *Energy*, *145*, 65–78. https://doi.org/10.1016/j.energy.2017.12.051

Tallinn University of Technology. (n.d.). *Power Systems Research Group*. Retrieved 2 August 2023, from https://taltech.ee/en/power-systems-group

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

TenneT. (2022). Monitoring Leveringszekerheid 2022. In *TenneT TSO B.V.* (Vol. 2022). https://tennet-drupal.s3.eu-central-1.amazonaws.com/default/2023-01/Monitoring%20Leveringszekerheid%202022%20%28V2%29.pdf

Thornton, H. E., Scaife, A. A., Hoskins, B. J., & Brayshaw, D. J. (2017). The relationship between wind power, electricity demand and winter weather patterns in Great Britain. *Environmental Research Letters*, *12*(6), 064017. https://doi.org/10.1088/1748-9326/aa69c6

UNFCCC. (n.d.). *The Paris Agreement*. United Nations Framework Convention on Climate Change. Retrieved 9 January 2023, from https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

Vähk, J. (2019). *The impact of Waste-to-Energy incineration on climate: Policy Briefing*. *September*, 7. https://zerowasteeurope.eu/wp-content/uploads/edd/2019/09/ZWE_Policy-briefing_The-impact-of-Waste-to-Energy-incineration-on-Climate.pdf

van Benthem, M., & Kreulen, K. (2022, June). *De 'Value of Lost Load' van elektriciteit in Nederland*. Ecorys. https://www.ecorys.com/nl/nederland/our-work/de-value-lost-load-van-elektriciteit-nederland

van den Berg, J. (2019, January 11). Kleine speler zit klem met zonnestroom: het netwerk is te krap. *De Volkskrant*. https://www.volkskrant.nl/nieuws-achtergrond/kleine-speler-zit-klem-met-zonnestroom-het-netwerk-is-te-krap~b5df6b10/

van Gessel, S., Huijskes, T., Schroot, B., & Dalman, R. (2021). *Ondergrondse Energieopslag Noodzakelijk Voor Toekomstig Energiesysteem*. https://www.ebn.nl/feiten-en-cijfers/kennisbank/ondergrondse-energieopslag-noodzakelijk-voor-toekomstig-energiesysteem/

van Gessel, S., Juez-Larré, J., Huijskes, T., & Dalman, R. (2021). *Ondergrondse Energieopslag in Nederland 2030 – 2050*. https://www.ebn.nl/wp-content/uploads/2022/10/Ondergrondse-energieopslag-in-Nederland-2030-%E2%80%93-2050-%E2%80%93-Technische-evaluatie-van-vraag-en-aanbod-2.pdf

Vendrik, J., Groenewegen, H., & Rooijers, F. (2023). *Usefulness and necessity of additional onshore wind in 2030 and 2050. Explanation of potential scenarios and assessments*. https://cedelft.eu/publications/usefulness-and-necessity-of-additional-onshore-wind-in-2030-and-2050/

World Nuclear Association. (2021). *Economics of Nuclear Power*. https://world-nuclear.org/information-library/economic-aspects/economics-of-nuclear-power.aspx

Appendices

A. Formulas for Calculation of KPIs

In this appendix, the formulas used for calculating the KPIs discussed in section 3.4 are presented.

Equation 10: Primary KPI 1 - Annual Total System Costs

$$Annual\ Total\ System\ Costs = Annual\ Total\ Fixed\ Costs + Annual\ Total\ Variable\ Costs$$

$$Annual\ Total\ Fixed\ Costs = \sum\nolimits_{i\epsilon I} OU_{i,y} \cdot EAC_i \qquad \forall\ y\epsilon Y$$

$$Annual\ Total\ Variable\ Costs = \sum_{t}^{T} \sum\nolimits_{i\epsilon I} (p_{i,t,y} \cdot (\frac{VC_i^{fuel}}{\eta_i^{th}} + VC_i^{OPEX})) + VoLL \cdot ll_{t,y} \qquad \forall\ y\epsilon Y$$

Equation 11: Primary KPI 2 – Cost per MWh of Electricity Demand

$$Cost\ per\ MWh\ of\ Electricity\ Demand = \frac{Annual\ Total\ System\ Costs}{\sum_t^T L_{t,y}} \qquad \forall\ y\epsilon Y$$

Equation 12: Primary KPI 3 – Expected Energy Not Served (EENS)

$$Expected\ Energy\ Not\ Served\ (EENS) = \sum_{t}^{T} ll_{t,y} \qquad \forall\ y\epsilon Y$$

Equation 13: Primary KPI 4 - Loss of Load Expectation (LOLE)

$$Loss\ of\ Load\ Expectation\ (LOLE) = \frac{number\ of\ hours\ with\ ll_{t,y} > 0}{8760} \qquad \forall\ y\epsilon Y$$

Equation 14: Secondary KPI 1 - Installed Capacity per Technology

$$Installed\ Capacity\ per\ Technology = OU_{i,y} * p_i^{MAX} \qquad \forall\ i\epsilon I\ \ \forall\ y\epsilon Y$$

Equation 15: Secondary KPI 2 - Annual Electricity Delivered to Grid per Technology

$$Annual\ Electricity\ Delivered\ to\ Grid\ per\ Technology = \sum_{t}^{T} (p_{i,t,y} - k_{i,t,y}) \quad \forall\ i\epsilon I\ \ \forall\ y\epsilon Y$$

B. Lead Time of Technologies

Section 4.1 presents that the Planning stage of the OPM focuses on a year four years in the future since this is the longest lead time of the technologies which are included as an investment option, except for nuclear power plants. Section 5.3.2 discusses that nuclear plants are not included as an investment option, due to their controversial nature, low social acceptance, and high dependence on government policies for the development of new units. Although the lead time of units is not included in the OPM as input data, it is presented in this appendix to support making the modelling decision for having the Planning stage focus on a year four years in the future.

Table 13: Lead Time of Technologies

Technology	Lead Time (years)	Source
Nuclear	6	(EIA, 2023)
CCGT	3	(EIA, 2023)
CCGT with CCS	3	(EIA, 2023)
PV	2	(EIA, 2023)
Onshore Wind	3	(EIA, 2023)
Offshore Wind	4	(EIA, 2023)
Biomass and Waste	4	(EIA, 2023)
Daily Storage (Lithium-Ion Batteries)	1	(EIA, 2023)
Electrolysers	3	(EIA, 2023)
Fuel Cells	3	(EIA, 2023)

C. Detailed Experiment Results

C.1. Primary KPI 1 & 2 – Total Annual System Costs & Cost per MWh

The results for the development of annual total system costs for the "x2" and "1000" experiments are shown in Figure 56 and Figure 57. Due to the first additional units becoming available in 2031, there were disproportionate high system costs in 2030 for both experiments. In the "x2" experiment, the more limited number of additional units which could be invested in per year resulted in a longer period before system costs reached a lower stable level, which happened in 2033.

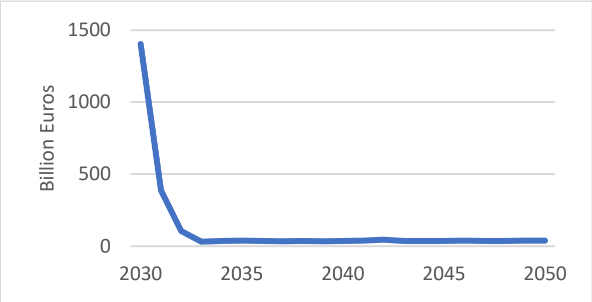


Figure 56: Total System Costs - "x2" Experiment

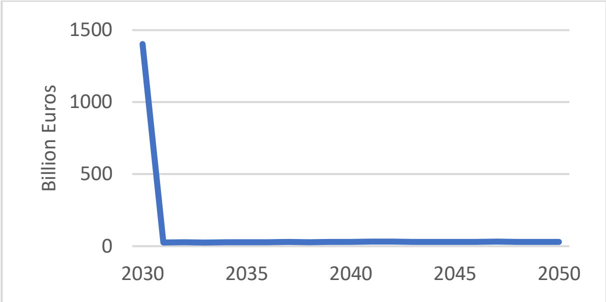


Figure 57: Total System Costs - "1000" Experiment

The decomposition of the total annual system costs for the period from 2033 to 2050 is presented for the two experiments in Figure 58 and Figure 59. Both experiments showed peaks in system costs in multiple years in which loss of load occurred. Total annual system costs in the "x2" experiment increased from 31.3 billion euros in 2033 to 39.1 billion euros in 2050. In the "1000" experiment, the total annual system costs in 2033 were 26.3 billion euros and increased to 30.4 billion euros in 2050.

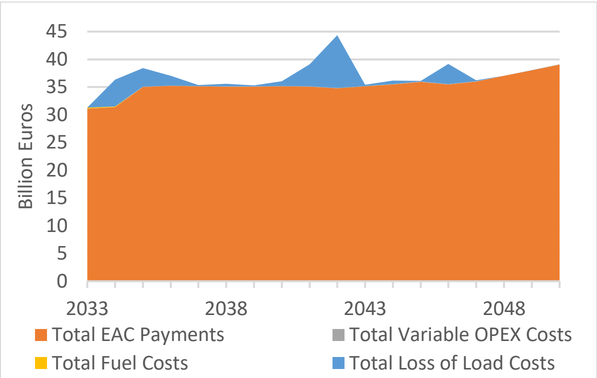


Figure 58: Decomposition of Total Annual System Costs - "x2" Experiment (2033 - 2050)

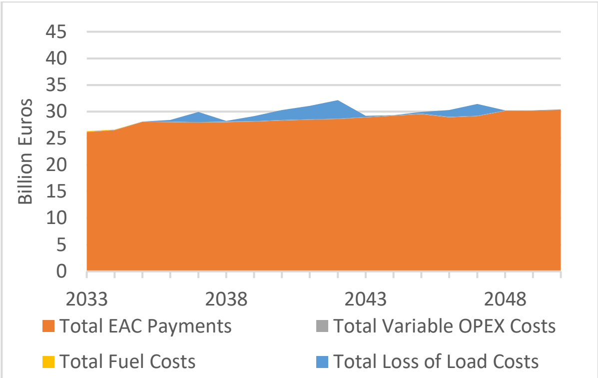


Figure 59: Decomposition of Total Annual System Costs - "1000" Experiment (2033 - 2050)

In Figure 60 the development of cost per MWh is shown for both experiments. Over the entire period from 2033 to 2050 the cost per MWh decreases in both experiments, but higher values are present in years in which loss of load occurs.

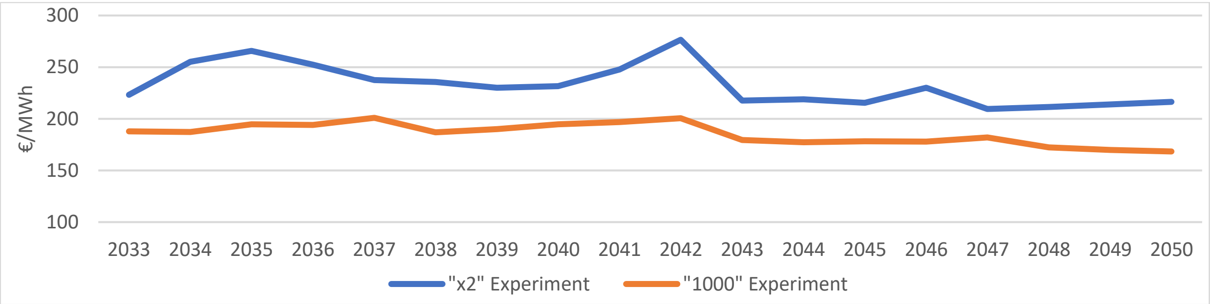


Figure 60: Cost per MWh - "x2"and "1000" Experiment

C.2. Primary KPI 3 & 4 – EENS & LOLE

In Figure 61 the development of the EENS is shown for both experiments. In Figure 62 the development of the LOLE is shown for both experiments. In the “x2” experiment, the peaks for EENS and LOLE are significantly higher than for the “1000” experiment, which is due to the lower possibility for investments in the “x2” experiment.

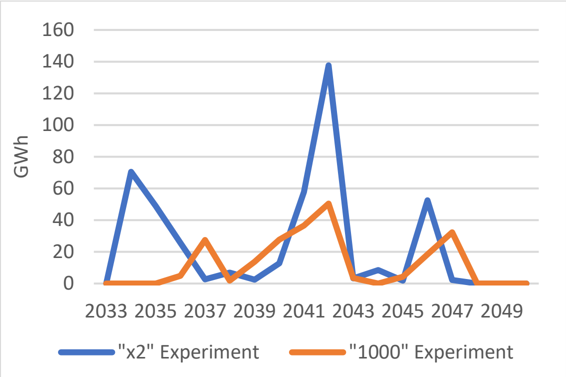


Figure 61: EENS - Experiments (2033 - 2050)

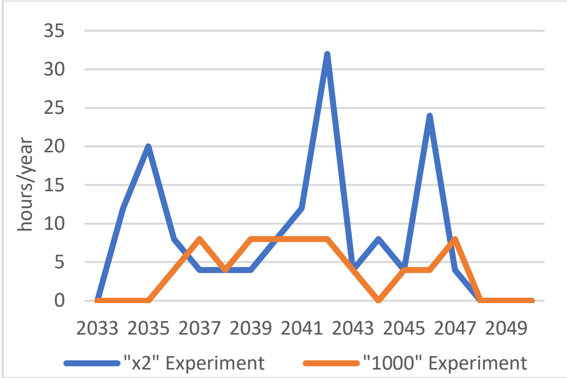


Figure 62: LOLE - Experiments (2033 - 2050)

C.3. Secondary KPI 1 – Annual Electricity Delivered to the Grid per Technology

In Figure 63 the development of the electricity generation mix for the “x2” experiment is shown and Figure 64 shows the development of the electricity generation mix for the “1000” experiment.

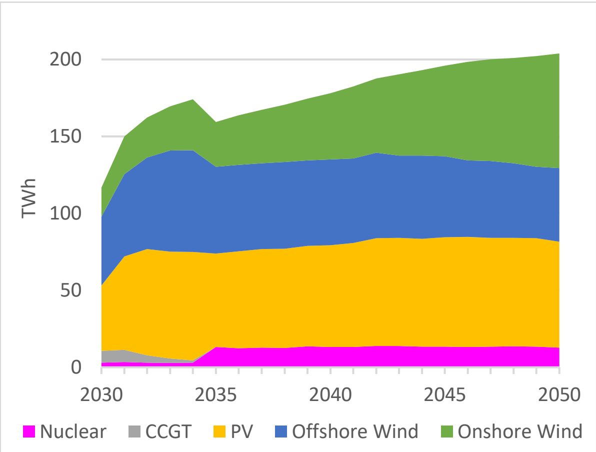


Figure 63: Electricity Generation Mix - "x2" Experiment

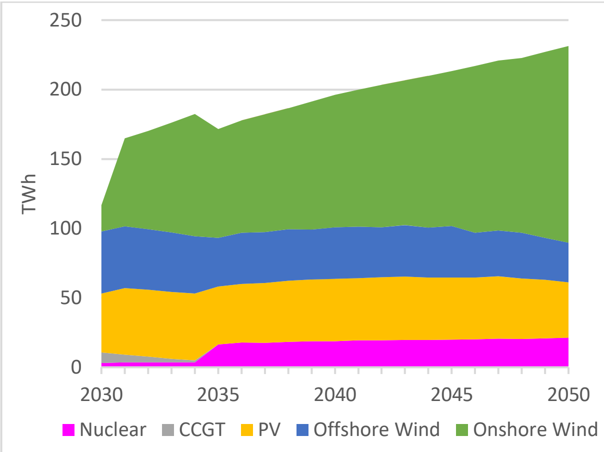


Figure 64: Electricity Generation Mix - "1000" Experiment

The total annual feed-in to the grid from storage technologies is shown for the “x2” and “1000” experiments in respectively Figure 65 and Figure 66.

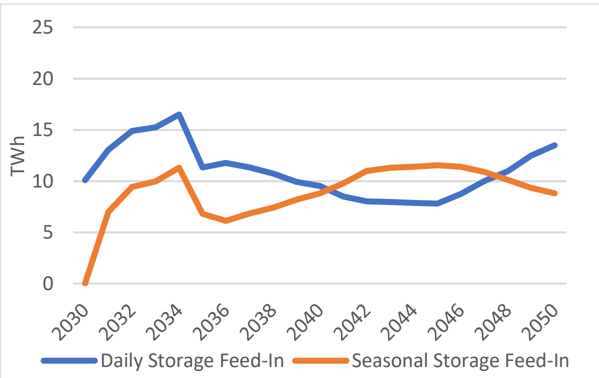


Figure 65: Total Annual Feed-In from Storage Technologies - "x2" Experiment

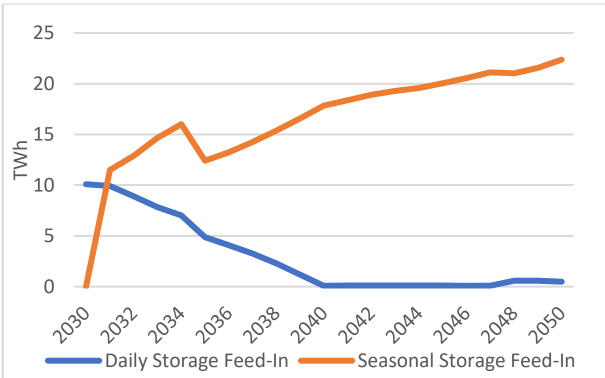


Figure 66: Total Annual Feed-In from Storage Technologies - "1000" Experiment

C.4. Secondary KPI 2 – Installed Capacity per Technology

The development of the installed capacity mix from 2030 to 2050 for the “x2” and “1000” experiments is shown in Figure 67 and Figure 68. The development of the installed power capacity for storage technologies from 2030 to 2050 for the “x2” and “1000” experiments is shown in Figure 69 and Figure 70.

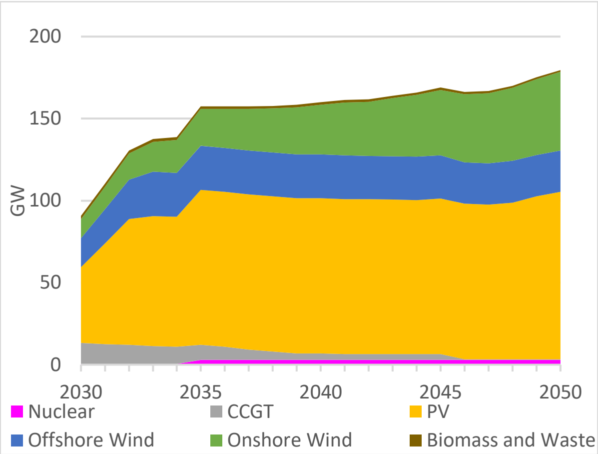


Figure 67: Installed Capacity Mix - "x2" Experiment

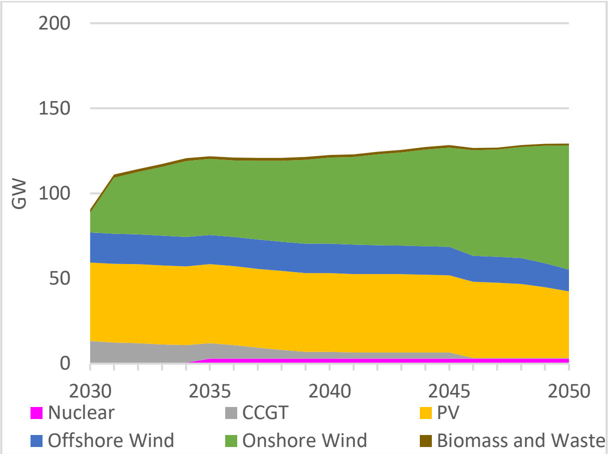


Figure 68: Installed Capacity Mix - "1000" Experiment

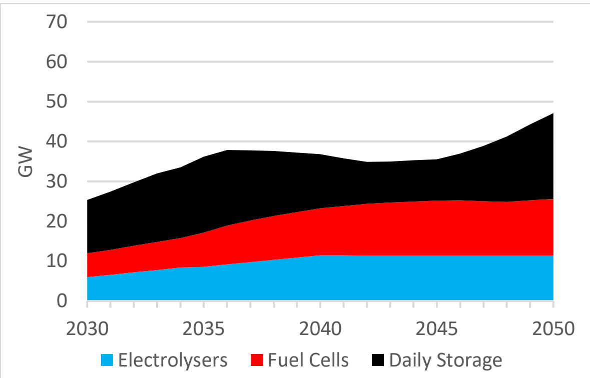


Figure 69: Installed Power Capacity Storage Assets - “x2” Experiment

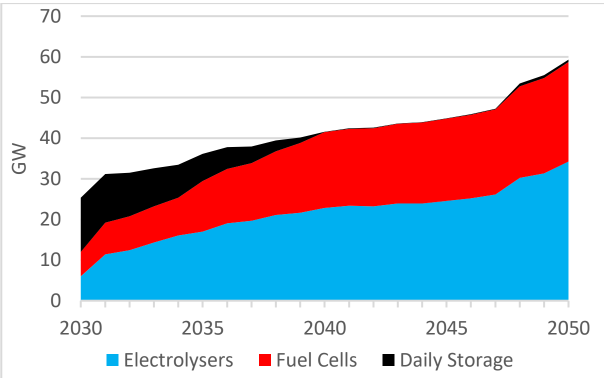


Figure 70: Installed Power Capacity Storage Assets - “1000” Experiment