Analyzing investments in the power system using optimization modeling

Marissa Moultak

Technische Universiteit Delft

TU Delft

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Marissa Moultak

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Student number:

4939735

Thesis committee:

First Supervisor	Dr. ir. R.A. Verzijlbergh	Section Energy and Industry
Second Supervisor	Dr. ir. J.H. Kwakkel	Section Policy Analysis
Advisor	Dr. ir. R.M. Stikkelman	Section Energy and Industry
External Supervisor	J. Peters MSc	Company Eneco

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Preface

This thesis is the final research project to conclude the two year Master in Complex Systems Engineering and Management at the Delft University of Technology.

I would like to express my gratitude to the Delft University of Technology for providing me a challenging and rewarding educational experience, as much in the classroom as outside of the classroom. Not only have I been exposed to countless new educational topics, but I believe a different way of thinking to address the complex problems our society faces. To be immersed in and exposed to Dutch culture provided a unique perceptive that often required me to step outside of what I deemed as normal and comfortable and reevaluate my base assumptions of the inner-workings of society. I believe this was particularly enhanced due to the nature of the Complex Engineering and Management study. As we globally currently are facing quite tumultuous times between Corona virus, climate change with its effects becoming ever more apparent and devastating, and political and social unrest, I believe that the cross-disciplinary, holistic study of the Faculty of Technology, Policy and Management is of extreme pertinence. I am eager and very much looking forward to taking the experiences and overall education I have received and applying it to my future endeavours, with the goal of helping us improve upon the problems we are currently facing, particularly in the energy and climate sectors.

First and foremost, I would like to thank my family and close friends for providing me with an endless amount of support over the past months and for listening to my constant ramble about energy system modeling. I would like to thank Remco, our weekly meetings and your guidance and input was essential - thank you for listening and helping me work through my idea, this was especially helpful given the circumstances. Thank you to Eneco and Jeroen for exposing me to the inner-workings of a large energy generation company (although for a much briefer time than anticipated), providing me with the general topic of the research, and for guidance. Laurens - thank you for first introducing me to electricity markets in your course, your captivating and interactive teaching method made me fascinated in the topic and provided me the basis I needed to perform this thesis. Finally, thank you to Jan for providing useful key insights during our meetings.

This thesis, given the nature of the research and the unforeseen circumstances of this year, has been a very difficult project. Through all the challenges, my utter fascination in the topic never varied, and I feel grateful to have found a project that has captivated and challenged me - solidifying the area I would like to focus my future work. I hope my fascination in this topic translates into an interesting and enjoyable reading experience.

Marissa Moultak

Executive summary

The European electricity system is rapidly changing. Over the next couple of decades, electricity demand is forecast to increase with the electrification of the heat and mobility sectors, and greenhouse emissions are required to decrease dramatically to meet emission reduction targets. The energy transition requires significant investments in new power generation, storage, and transmission technology. However, the complex, uncertain nature of the power system creates challenges for investors. The challenges continue to increase as the energy system transitions to a low carbon system, transitioning away from conventional sources to intermittent renewable energy sources. This transition changes the dynamics of the energy market and paired with unpredictable government climate change policies and regulation, can lead to highly uncertain investment outcomes for generators. Increasing the penetration of wind and solar power in the energy system changes the electricity market dynamics and therefore the resulting electricity prices. Investments in the power sector are long-term investments that require investors to analyze future profitability and risk to make investment decisions. Therefore, understanding and forecasting future market conditions is an essential component for investors to make investments in the system and for policy makers to understand the regulatory framework and market design changes that are necessary to meet emission reduction goals while maintaining a secure and stable power supply.

Under current market arrangements, decarbonization of the power sector will shift the investment environment. With the increasing penetration of VREs, the wholesale electricity price decreases in the short-term due to marginal pricing. The depression in market prices lead to lower revenue for all generators, the merit-order effect. Therefore, the penetration of VREs may drive down investments in the power sector. In an ideal, long-term, perfect market with sufficient CO2 pricing for a desired emissions reduction target, the revenue for VREs will always be enough to cover the total costs. The short-term effects, imperfections in the market, and policy choices can lead to situations where revenues drop below expenses for generators, causing investors to be unable to recoup their investment costs. Such a situation would lead to an under investment in the necessary generation capacity to maintain the security of supply.

Modeling and research is needed to forecast the profitability of investments given the evolving power system and to better understand how power system configurations affect profitability. The purpose of this research is to gain a better understanding into the economic feasibility behind investments in renewable energy generation and storage technologies as the energy system transitions to a low-carbon system. In particular, the research explores how energy optimization modeling paired with the uncertainty analysis, modeling-to-generate alternatives (MGA) can be used to provide insight into and aid in investment decision making. Therefore, the main research question is:

> *How can energy optimization modeling paired with the uncertainty technique, Modeling to Generate Alternatives be used to help make investment decisions considering the uncertainties in the future electricity system?*

The research takes a novel approach to utilizing energy system optimization models (ESOMs) and develops a methodological framework to use ESOMs from the perspective of an investor, to explore the economic feasibility of investments in the future power system in light of emission reduction targets. The method developed includes a partial-equilibrium, myopic, two-step energy system optimization model. The ESOM is paired with the MGA uncertainty analysis to show how optimization modeling can be used to provide a range of possible future power system designs and their resulting range of associated electricity prices and generator and storage dispatch. These results can then be used to determine the profitability of generation or storage technology over their respective lifetimes. From the perspective of a policy maker, the resulting business cases of the investments can be analyzed to shed light on the feasibility of investments in VREs and storage that are necessary to achieve a power system that meets emission reduction targets in a cost efficient manner. The analysis reveals insights into the inner-working of the real world electricity market and with the implementation of the uncertainty analysis MGA, how the imperfections in the market, that cause deviations from optimally, affect long-term profits for investors. As a proof of concept of the methodological framework, a model is developed and used to performed a case study on the Dutch power system. The model is validated with the conceptual, theoretical understanding of energy optimization modeling and verified against historical power system data to ensure it is used appropriately and to explore the limitations of the model. The investor perception of profitability and risk in generation and storage technology in the power system are essential to the energy transition and the realization of government targets. Therefore, the outcomes of this study and others that analyze the investment environment of the power sector are essential not only for investment but for policy makers.

The study develops a method for utilizing energy system optimization modeling from the perspective of an investor. Performing an uncertainty analysis, such as MGA, is imperative when using the energy system optimization modeling to forecast possible future energy systems. The case study performed utilizing the methodological framework developed in the research finds that there is a wide range of possible future near-optimal energy systems, but that profitability of technologies might lead to policy mechanisms or alternative market arrangements being required to achieve emission reduction targets within the near-optimal solution range.

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Nomenclature

Abbreviations

ESOM	Energy system optimization modeling
MV	Market value
VoLL	Value of Loss Load
VREs	Variable Renewable Energy Sources
LCOE	Levelized Cost of Electricity
VC	Variable Cost
FC	Fixed Cost
MGA	Modeling to Generate Alternatives
LMP	Locational marginal price

Mathematical terms

Sets & indices

Set	Index	Description
G	g	Generators
S	s	Storage units
L	l	Transmission lines
T	t	Dispatch time step
Y	y	Year
I	i	Investment period
N	n	Nodes

Decision variables

Primal variables

Symbol	Description	Units
$K_{n,g}$	Power capacity of generator g at node n	MW
$k_{n,g,t}$	Dispatch of generator g at node n at time t	MWh
$H_{n,s}$	Power capacity of storage unit s at node n	MW
$h^{+}_{n,s,t}$	Charge/storing of storage unit s at node n at time t	MWh
$h^{-}_{n,s,t}$	Discharge/dispatch of storage unit s at node n at time t	MWh
$soc_{n,s,t}$	State of charge of storage unit s at node n at time t	MWh
F_{l}	Power capacity of transmission at line l	MW
$f_{l,t}$	Flow of line l at node n at time t	MWh
$d_{n,b,t}$	Demand of consumer b at node n at time t	MWh

Dual variables

Symbol	Description	Units
$\lambda_{(n,t)}$	marginal price at node n at time t	Eur/MWh
μ_{CO_2}	CO_2 price	Eur/ton CO_2

Parameters

Symbol	Description	Unit
$c_{n,g/s}$	Annualized capital cost of generator g or storage unit s at node n	Eur/MW/year
c_l	Annualized capital cost of transmission line l	Eur/MW/year
$o_{n,g}$	Operating cost of generator g at node n	Eur/MWh
$\eta_{n,g}$	Efficiency of generator g at node n	MW_el/MW_th
$d_{n,t}$	Electric load at node n for time t	MWh
w_t	weight of each time step t	hours/year
$\alpha_{l,n,t}$	Direction of power flow of transmission line l at node n for time t	
CAP_{CO_2}	CO_2eq.emissions cap	tons CO_2eq.
$e_{n,g}$	Emissions for generator g at node n	ton CO_2eq./MWh
$r_{n,s}$	Time a storage unit can discharge at full output capacity	hours
$\eta_{n,s}^{+}$	Charging efficiency	%
$\eta_{n,s}^{-}$	Discharging efficiency	%
$U_{n,b,t}$	Utility of consumer b at node n at time t	EUR/h
$K_{n,g}^{min}$	Minimum installable capacity of generator g at node n	MW
$K_{n,g}^{max}$	Maximum installable capacity of generator g at node n	MW
$H_{n,s}^{min}$	Minimum installable capacity of storage unit s at node n	MW
$H_{n,s}^{max}$	Maximum installable capacity of storage unit s at node n	MW
F_l^{min}	Minimum installable capacity of transmission at line l	MW
F_l^{max}	Maximum installable capacity of transmission at line l	MW

1
Introduction

1.1. Problem background

1.1.1. Energy transition - Climate Agreement targets for the power system

European governments recently provided their 'National Energy and Climate Plan' for the period 2021-2030. The plans provide detailed outlines on how emission reduction targets will be met in each respective country to help achieve the global climate goals outlined in the 2015 Paris Agreement of limiting global warming to less than two degrees Celsius above pre-industrial levels. To achieve the long term decarbonization targets, the necessary changes to the entire energy system are substantial during the 2020-2050 period (Capros et al., 2018). The Dutch Climate Agreement details the plan to achieve the government's greenhouse gas emission reduction target of reducing greenhouse gases by 49% compared to 1990 levels (Netherlands Ministry of Economic Affairs (EZK), 2019). To transition to a sustainable energy system that has a high level of security and economic competitiveness, the share of the electricity generated from renewable energy sources must significantly grow (Child et al., 2019; Gioutsos et al., 2018). The target for the electricity sector is to reduce carbon emissions by at least 20.2 Mt by 2030, and in order to achieve these carbon reductions, the government plans for the electricity production from renewable energy sources to be at least 84 TWh in 2030 (Netherlands Ministry of Economic Affairs (EZK), 2019). According to the 2019 Netherlands Climate and Energy Outlook, the historical and forecasted values for total yearly greenhouse gas emissions from the electricity sector and the yearly amount of electricity produced from renewable sources are shown in Figure 1.1 below. In 2050, the government aims to achieve a 95% reduction in greenhouse gas emissions relative to the 1990 levels and for the electricity production to be carbon neutral (CBS, 2019). The amount of renewable energy sources will have to continue to increase well past the 2030 installed renewable targets to achieve the 2050 goals.

1.1.2. Necessity of cost modeling in the changing electricity system landscape

Due to the variable, distributed nature of VRE, integrating high shares of VRE into the grid makes the network more complex and presents unprecedented challenges in planning, regulating, and operating

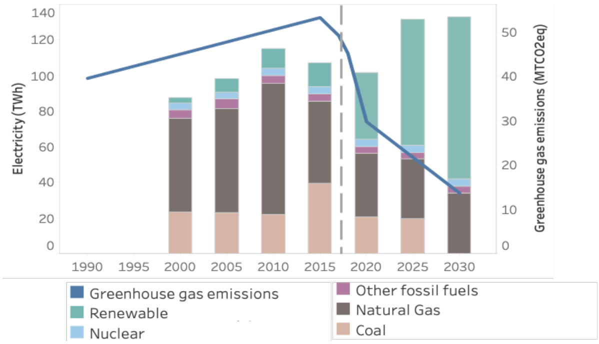

Figure 1.1: Historical and forecasted (2020-2030) yearly electricity production per source and total greenhouse gas emissions in the Netherlands (CBS, 2019).

the electricity system in a safe, stable, balanced, and financially feasible manner (Hörsch et al., 2018; Johnston et al., 2019; Kraan, Kramer, and Nikolic, 2018; Orgaz, Bello, and Reneses, 2018). Alongside the transition to VRE, the electricity system has been unbundled and liberalized (Hörsch et al., 2018). The liberalized, restructured power system introduces competition in the market and requires a balance between regulation and competition to provide cost efficiency and achieve emission reduction targets while maintaining security of supply (Botterud, 2003). The introduction of competition introduces decentralized decision making, competitive prices, profit maximization, partial information, and high levels of uncertainty compared to centralized decision-making, regulated tariffs, cost minimization, complete information, and limited levels of uncertainty with a heavily regulated system (Botterud, 2003). As the World Energy Council stated, it is "a time of unprecedented uncertainty for the energy sector" (World Energy Council, 2014). Due to the essential importance of electricity to our entire society, it is of the up-most importance that the entire electricity generation and delivery process is done reliably and cost-efficiently (Morales et al., 2014).

The changing energy system landscape increases the uncertainties in the system and therefore makes the associated investment decisions more difficult. Investments in the power system are subject to a number of factors, including technology advancements, government policy, the power market, and the national economy (Agency, 2007). The uncertain power market dynamics and unpredictable government climate change policy, make the investment cash flows increasingly more uncertain (Agency, 2007). The uncertainty, long time frame, and high cost regarding electricity generation and transmission assets make the associated investment decisions very challenging (Conejo et al., 2016). The high capital cost but low operating costs of renewable energy has and will continue to reduce the role of the market in guiding investments (Newbery et al., 2018). The integration of the highly variable renewable energies "will be challenging without substantial modification to the current '1st generation' market design" (Newbery et al., 2018). Liberalized electricity markets are designed based on merit order, where dispatchable electricity generation are ranked based on marginal cost. The market assumptions in such a market are undermined by large scale deployment of renewables, as renewables have zero marginal cost and cannot be dispatched (Kraan, Kramer, and Nikolic, 2018). With increasing penetration of low-carbon technologies, energy market revenues from the wholesale market price based on short-term marginal cost pricing under current market arrangements are not enough to stimulate the necessary amount of investments in new low-carbon generation capacity in a timely, low cost manner (Directorate-General for Economic and Financial Affairs, 2015; IEA, 2016).

To avoid the problems facing security of supply due to insufficient funding, 'the missing money problem', the market has to be redesigned to to support the high shares of renewables that are necessary to meet government targets (Newbery et al., 2018). Governments have to intervene by setting subsidy regimes and use capacity mechanisms to overcome market imperfections and internalize negative externalities (IEA, 2016; Newbery et al., 2018; Shahnazari et al., 2015; Winkler et al., 2016). The new market design needs to provide better price signals, incentives for investments, and greater system flexibility (Newbery et al., 2018). In the long run the goal is to create market arrangements that result in a sufficient amount of revenue for the necessary investments to take place without government intervention (Directorate-General for Economic and Financial Affairs, 2015). Regulatory regimes, market design, and system operation must be developed simultaneously with demand response, storage, and low carbon technology deployment to ensure electricity security in a cost-efficient manner while enabling the overall low-carbon transition (IEA, 2016).

Rigorous analysis, sophisticated models, and flexible simulations are required to help inform government policy and private company investments regarding new electricity generation, storage, and transmission in the increasingly complex future energy system (Conejo et al., 2016; Hilpert et al., 2018). Energy analytics are essential to make informed energy decisions regarding energy system design, implementation, and operation (Bazilian et al., 2012; Deng and Lv, 2020). Modeling the uncertainty in the energy system is crucial for the investment decision-making process for new power generation by generation companies (Conejo et al., 2016). In addition, dynamic and stochastic modeling can help governmental decision-making on a regulatory level by providing insight into the performance of the power system under different policies, regulations, and market designs (Botterud, 2003). Participants in the electricity system need to adapt to the changing regulatory environment and need to appropriately account for the increase in risk exposure. Planning methods need to be adjusted to account for the changes in the system and mathematical models need to be further developed to assist the decision making process in the new system landscape (Botterud, 2003). To help overcome these challenges, the research primarily focuses on determining the profitability of investment business cases in the range of near optimal energy system design solutions that achieve emission reduction targets. Investors can use this information to help in the decision making process in the evolving power system. In addition, the insights into how different power system configurations affect the favorability of investment business cases can provide useful guidance to policymakers regarding necessary policies to ensure the required investments needed to reach climate goals.

1.2. Problem statement

A significant amount of research has been dedicated to the advancement and development of energy optimization models. A number of sophisticated open source models have been developed and have been deemed mature enough in comparison to commercial/ proprietary tools to be used for serious use (Groissböck, 2019). Typically, energy system optimization models are used to determine a single cost-optimal energy system (the optimal installed generation, storage, and transmission capacities) given a set of constraints (e.g. CO2 emissions limits). The uncertainty pertaining to the future and the inability of mathematical models to accurately represent the complexity of the energy system cause optimal solutions to have limited significance, lack robustness and can even mislead decision makers by providing false precision in the future energy systems (DeCarolis et al., 2016; Voll et al., 2015; Yue et al., 2018). Accounting for uncertainty in energy system optimization models has been identified to be lacking and one of the major challenges of energy system optimization modeling. (Yue et al., 2018) identifies that uncertainties inherent in the model structure and input parameters in energy system optimization modeling are "at best underplayed and at worst ignored". Sub-optimal solutions may be favorable for reasons outside of purely cost, including public acceptance, land-use conflicts, ease of implementation (Neumann and Brown, 2019). The real-world energy system transition has been shown to not follow the cost-optimal solution but rather, fall within the range of near-optimal energy systems (Trutnevyte, 2016). To be able to account for this, an uncertainty technique, modeling-to-generate alternatives (MGA), has recently been applied to energy system optimization models (Neumann and Brown, 2019; DeCarolis et al., 2016; Price and Keppo, 2017). MGA explores the decision space to generate the maximally different near-optimal solutions within a defined cost slack from the optimal solution. Therefore, MGA provides a range of near optimal power system configurations. As the energy system has been shown to fall within the range of near optimal solutions, this research explores how energy system optimization modeling paired with MGA can be used by the investor. The investor in the system needs to understand the profitability of different investments in the range of possible future energy system configurations.

The recent advancements and sophistication of open source energy system optimization models paired with the uncertainty of investments sparks the question of how these advanced tools can be used from the perspective of an investor to explore the economic feasibility of investments, given the government emission reduction targets and whether the power systems solutions give by these ESOMs provide a feasible investment environment. This research looks to help contribute to two main areas currently lacking in energy system optimization modeling - accounting for uncertainty in energy system optimization modeling and identifying the profitability of of technologies in the range of various possible future power systems.

1.3. Research questions

How can energy optimization modeling paired with the uncertainty technique, Modeling to Generate Alternatives, be used to help make investment decisions?

1. How does energy optimization modeling work and how are electricity prices determined in energy system modeling?
2. How can the real electricity market be represented in energy optimization modeling?
3. How can modeling-to-generate-alternatives (MGA) be used to generate a range of electricity price and dispatch scenarios?
4. How can the range of near optimal solutions generated by modeling to generate alternatives provide economic profitability insights for investors in the power system?
5. Using the method developed in a case study, what insights can be provided for the economic feasibility of investments in the Dutch electricity system?

1.4. Research contributions

1. Develop a methodological framework for how energy system optimization paired with MGA can be used from the perspective of the investor, to generate insights into the profitability of investments.

2. Determine the profitability of investments in the range near optimal energy system solutions.
3. Contribute to the exploration of structural uncertainty in energy system optimization modeling.
4. Explore how the range of short-term realistic electricity system operation conditions can be accounted for in a long-term model.

The research develops a novel method for analyzing the economic feasibility of investments considering the long-term future power system. To the best of our knowledge, this research is the first to utilize energy system optimization modeling paired with the uncertainty analysis, MGA to examine the profitability of investments in the power system. The research builds upon existing energy system optimization modeling by uncovering a framework for how the rich and developed existing ESOMs can be used from the perspective of an investor in the system and how economically feasible investments are the in the range of near-optimal solutions that can be generated by ESOMs.

Typically, ESOMs are used to determine the cost optimal energy system or more preferably, using uncertainty analyzes, can determine the range of near-optimal energy systems, given a set of constraints. However, the cost optimal or near optimal solutions determined by energy system modeling does not necessarily ensure the economic feasibility of investments, as costs of technologies can outweigh benefits in the least-cost system (Ifzal, 1991). This can be problematic in determining the feasibility of achieving these future energy systems. In liberalized power systems, economic incentives must exist to achieve the adequate investment in generation and storage technologies. This is of particular importance as electricity demand increases due to the electrification of the heat and mobility sectors and as power systems are decarbonized to achieve climate targets. These two factors translate into a need of a significant amount of investments in the power system over the coming decades. Therefore, the method developed in this research provides insights not only for investors but insights for policy makers who need to understand the economic feasibility of the various near-optimal power system configurations. The understanding of profitability of investments in these various power systems is essential for policy makers to understand the necessary policy to help ensure the realization of an energy system within these near-optimal alternatives.

In addition, the research builds upon past research of utilizing the MGA analysis with energy system optimization modeling to explores the range of near-optimal power system designs. Price et. al identifies that the majority of energy-environment-economy models focus primarily on parametric uncertainty, largely neglecting structural uncertainties of the model (Price and Keppo, 2017). This research helps to contribute to the limited exploration of structural uncertainty in energy system models. In addition, the research examines how to incorporate detailed short-term variability in the power system in a study that examines the long-term, a main challenge that (Ringkjøb, Haugan, and Solbrekke, 2018) highlighted in their review of energy and electricity system modeling tools with high renewable penetrations. The research aims to help overcome this challenge and contribute to the representation of short-term variability in long-term studies by coupling of the investment optimization model with the operations (dispatch) optimization model.

This research purely focuses on the structural uncertainty, developing a modeling framework that uses modeling to generate alternatives to assess the profitability of investments in the future power system. The scope is limited to structural uncertainty due to time and computation constraints and due to the identified particular lack of research into structural uncertainty in energy system modeling Price and Keppo, 2017. However, assessments using energy system optimization models should carefully account for both the parametric and structural uncertainty (DeCarolis, 2011). Therefore to provide robust insights to decision makers, a parametric uncertainty analysis should be included in future research. The parametric uncertainty analysis can be done using various uncertainty techniques (i.e. Monte Carlo or stochastic optimization). These uncertainty techniques would need to be done to the set of input parameters used in the modeling framework, resulting in the developed framework being done for each iteration of the Monte Carlo or stochastic optimization runs.

1.5. Thesis outline

Chapter 2 provides the necessary background and theory into the electricity system, economics, energy optimization modeling, and uncertainty modeling to provide a basis for the remainder of the report. Chapter 3 introduces and provides a detailed description of the model developed in this research, including the mathematical formulation of the model components. In Chapter 4, the details of the case study that is performed using the developed modeling framework are introduced. Chapter 5 details the model verification and validation to ensure the usability of the model. In Chapter 6 the results and analysis of the case study are explored. In Chapter 7, the research, the research limitations, and further areas of research are discussed. Chapter 8, concludes the main body of the report with main findings and recommendations. Chapter 9 provides a personal reflection of the process of carrying out the thesis. Finally, the data used in the model can be found in the Appendices.

2

Background & Theory

2.1. Economic theory & the electricity market

Economic theory is needed to understand the foundation and working of the electricity market. In theory, competitive markets are the best structure to obtain economic efficiency. In other words, the law of supply and demand is identified to be the best mechanism to allocate production resources and determine the prices for goods and services (Ventosa, Linares, and Pérez-Arriaga, 2013). To progress towards a more economically efficient system design, since the 1990s, power systems in many countries have been liberalized and electricity markets have been instated to introduce competition in generation and retailing (Ventosa, Linares, and Pérez-Arriaga, 2013). Therefore, to reliably provide power at the lowest societal cost while mitigating market power and enabling transparency, electricity is bought, sold, and traded in a competitive, wholesale market (Milligan et al., 2017). In wholesale electricity markets, marginal-cost pricing is used to set the electricity price. Perfect competitive markets in long-term equilibrium follow the zero profit rule – all producers fully recover their costs through the market price set by marginal cost pricing (Ventosa, Linares, and Pérez-Arriaga, 2013; Milligan et al., 2017; Brown and Reichenberg, 2020). Under perfect markets, the optimal solution can be achieved by investors making investments based on profit (Brown, 2020).

In reality, due to imperfect markets and nonconvex costs, marginal-cost pricing alone does not ensure that generator revenues cover all capital expenses (Brown and Reichenberg, 2020; Milligan et al., 2017). The following six attributes make electricity markets deviate from being perfectly competitive (Milligan et al., 2017):

1. externalities (i.e. emissions)
2. inelasticity of demand
3. market power
4. network is a public good
5. price caps
6. time dependency of electricity (no large scale storage)

The imperfections in the real market affect the economic performance of markets and cause them to deviate from the economic efficiency expected from ideal markets. These imperfects lead to several market failures in electricity generation (Newbery et al., 2018). Regulatory intervention is required to help account for the imperfections in the real market and are needed to ensure:

1. fair competition
2. ensure all market players have adequate information
3. free entry for all market participates
4. all cost and benefits (including externalities) are accounted for

2.1.1. Marginal-cost pricing, merit-order, & merit-order effect

If the power market is structured to follow the merit-order, the marginal cost of the most expensive generator required to operate to satisfy demand at each point in time determines the marginal cost of electricity; this generator is called the ”marginal generator”.

Energy generation capacity bids into the market at the marginal cost of generation. As the marginal costs of VRE are close to zero, VRE bid into the electricity market at near zero marginal cost, the bottom of the merit order. As shown in 2.1, the introduction of VRE to the market shifts the merit-order curve to the right and can lead to a cheaper marginal generator, therefore decreasing the price the market clears. This is called the merit-order effect.

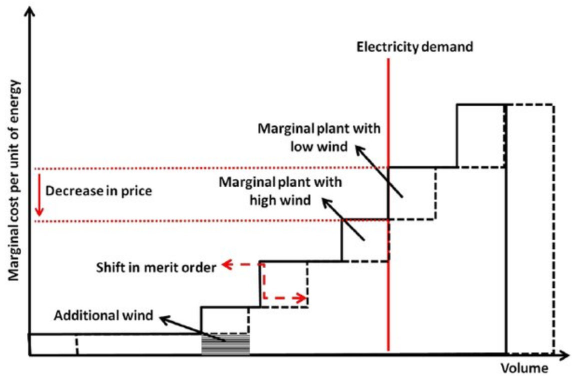

Figure 2.1: Merit-order effect. The solid black line denotes the supply curve without wind energy and the dashed line is the supply curve with the addition of wind energy to the merit-order. Source: (Bahar and Sauvage, 2013)

2.1.2. Market value

Market value of a particular generator is defined as the average revenue per unit of energy sold or in other words, the portion of the base-load price that the generator is able to capture. Market value differs per generator due to different generator availability and cost. Market value is calculated by the average market price weighted by the hourly production:

$$Market\ value = \frac{\sum_t \lambda_t K_{g,t}}{\sum_t K_{g,t}} \tag{2.1}$$

$$\lambda_t : market\ price\ at\ time\ t$$

$$K_{g,t} : Dispatch\ of\ generator\ at\ time\ t$$

Market value of VRE is crucial for both policy makers and renewable generators to perform economic assessments of VRE in the electricity system.

(Brown and Reichenberg, 2020) shows how under perfect competitive markets in long-term equilibrium, the market value of each generator equals (MV_g) the levelized cost of electricity ($LCOE_g$) (Brown and Reichenberg, 2020):

$$MV_g = LCOE_g \tag{2.2}$$

LCOE is the sum of all costs (investment, fuel, operation and maintenance costs) averaged over each unit of energy generated.

(Brown and Reichenberg, 2020) finds that if CO_2 price is the policy instrument used to incentive the increase share of wind and solar, VRE revenue will always be sufficient to cover their full costs under perfect competitive markets in long-term equilibrium. In the short-term, the integration of VRE impacts the electricity market price, due to the merit-order effect as described above. Without market interventions (i.e. CO2 prices) the average market price is reduced due to the lower marginal costs of VRE (Brown and Reichenberg, 2020). The lower electricity prices reduce the revenue of all generators but particularly those of wind and solar. Wind and solar depress the market prices at times they are producing and therefore cannibalize their own market values (Brown and Reichenberg, 2020). As a result, the market value of VRE can drop below their LCOE, leading to lower revenues than are necessary to recover capital cost investments. Policy interventions are needed to help overcome these challenges and ensure that investments are made into the required capacity to meet climate targets while maintaining system reliability. The transition to a clean power system require changes to the regulatory framework and the market design (Abrell et al., 2019). Policy makers need to provide a framework to enable industry to achieve climate targets at a reasonable cost while also ensuring security of supply (Newbery et al., 2018). To help determine the necessary policy interventions, sophisticated modeling tools are necessary. One of these modeling techniques, energy system optimization modeling, the modeling technique utilized in this research is described in the next section.

2.2. Energy system modeling

Flexible, in-depth, sophisticated modeling tools are vital to help inform government policy and private company investments regarding new electricity generation plants and transmission lines in the increasingly complex future energy system (Conejo et al., 2016; Hilpert et al., 2018; Pereira, Ferreira, and Vaz, 2016). By providing in-depth analyses into the optimized future structure of the power system, models help to ensure the transition to a low carbon power system, aligned with the climate targets, is achieved reliably and cost effectively (Tash, Ahanchian, and Fahl, 2019). There are a wide range of energy system models.

Figure 2.2, provides an overview of the classification of energy system models and shows the further details of bottom-up models (Prina et al., 2020). From the diagram, it can be seen that energy system models can be divided into three types: top-down models, hybrid models, and bottom-up models. There are three types of bottom-up models: optimization models, simulation models, and accounting models (Fleiter, Worrell, and Eichhammer, 2011). Simulation models and optimization models have typically been used previously for investment analysis. As the focus of this research is to explore the use of energy system optimization modeling for the profitability of power system investments in the future energy system, the remainder of the section details the types and components of energy system optimization modeling. Energy system optimization models have been used widely to provide critical data driven insights into energy policy at the regional, national, and global scale (Yue et al., 2018).

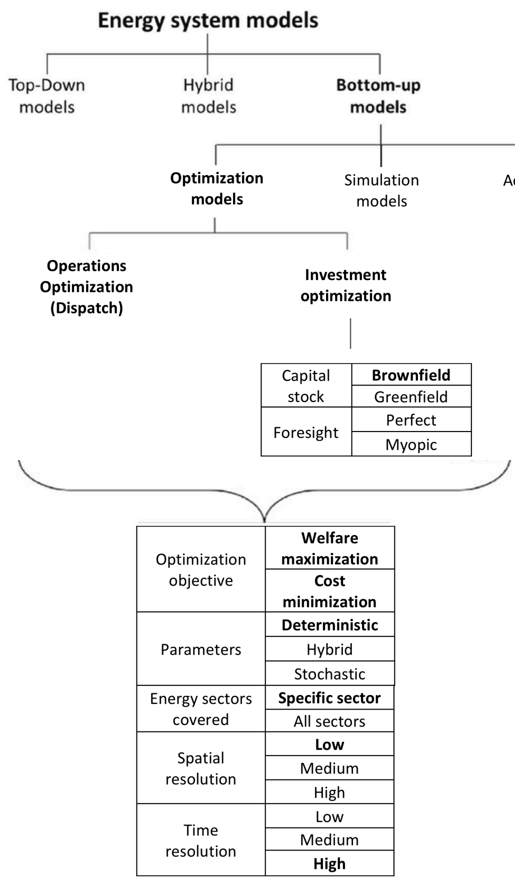

Figure 2.2: Classification of energy system models. Adapted from: (Prina et al., 2020)

2.2.1. Energy system optimization models

Focusing in on optimization models, they can be classified as either dispatch optimization or investment optimization. Dispatch optimization models are short-term models that optimize the dispatch of a given set of installed capital stock, determining how to best utilize the available technology (i.e. dispatch of the available generators). The decision variables for the short-term, operations optimization are the hourly generation, storage, and transmission. Investment optimization models determine the optimal system investments, and therefore the optimal generation portfolio to supply the demand under the given constraints (Brown, 2020). They can either optimize over the medium-term or the long-term. Medium-term optimization performs a brownfield optimization, it takes the existing infrastructure as a given and allows for endogenous investments and dis-investments. The medium-term optimization considers the existing infrastructure as sunk cost and therefore, the costs of existing infrastructure are disregarded from the optimization. A long-term optimization is a green-field optimization, it determines the optimal installed capacity assuming no capacity is installed in the system, it determines the optimal system from scratch. The decision variables for the investment (capacity expansion) planning optimization, are the installed capacities and hourly dispatch of generators, storage, and transmission. The investment optimization technically has an operations optimization embedded within the optimization, such that the optimization finds the optimal set of investments in generation capacity that, when operated optimally, leads to the minimum total system costs (Pérez-Arriaga, 2013), as is shown in Figure 2.3.

Perfect foresight models perform one optimization over the entire modeled time horizon and therefore assume that investment decisions take into account the entire modeled time horizon and have full information of all system parameters including future costs, prices, and constraints (Poncelet et al., 2016). Perfect foresight assumes that all data about the future is known from the start of the optimization and the optimization is simultaneously performed over the entire model time horizon. For the myopic case, the model is split into several time frames and each time period is optimized separately. Myopic models perform a sequence of optimizations, where decision makers are assumed to have perfect information for each period that is optimized and no information outside of the foresight window. Investors make decisions with limited knowledge of the future. The myopic approach can represent the short-time frames that occur in the real world decision making (Decarolis et al., 2017). In addition, the myopic approach can help to reveal the possible transition technologies.

An optimization model consists of an objective function, decision variables, model parameters, constraints, index sets, and input data sets (Dreier and Howells, 2019). Techno-economic optimization models can be designed to be deterministic, stochastic, or a hybrid between the two. Deterministic models have a fixed set of parameters, stochastic models have random parameter values, and therefore, a hybrid model would have a combination of random and fixed parameter values. The objective of an ESOM is either to maximize social welfare or minimize total system costs, given a set of technological, resource, environmental, and policy constraints (Berntsen and Trutnevyte, 2017). For the case of welfare maximization, the objective is to maximize total economic welfare, which is the sum of the consumers' and generators' surplus. The results of the optimization problem give the optimal set of generator, storage, and transmission capacities that when operated optimally result in the maximum total economic welfare for the energy system modeled. The objective function for a welfare maximization problem is:

$$Maximize\begin{pmatrix}\textit{Total economic}\\ \textit{welfare}\end{pmatrix} = \sum\begin{pmatrix}\textit{Consumer utility}\\ \textit{(value function)}\end{pmatrix} - \sum\begin{pmatrix}\textit{Generator costs}\\ \textit{(supply function)}\end{pmatrix} \tag{2.3}$$

In cases where the demand is assumed to be inelastic, the optimization objective can be cost minimization. Inelastic demand means that the consumer utility remains unchanged with changes to the electricity price. Therefore, since the consumer utility is constant, it does not affect the overall optimization and the overall optimization problem can be formulated as a cost minimization optimization with the objective to minimize the total annual system costs assuming inelastic demand. For the cost minimization optimization, the total annual system costs are minimized to find the long-term cost-optimal electricity system. To minimize the total annual system cost, the sum of the annualized investment costs (the annualized capital costs for generation, storage, and transmission capacities) and the annual operational costs for the snapshots of time identified in the model are minimized.

$$Minimize\begin{pmatrix}\textit{Total annual}\\ \textit{system cost}\end{pmatrix} = \sum\begin{pmatrix}\textit{Annualized}\\ \textit{capital cost}\end{pmatrix} + \sum\begin{pmatrix}\textit{Annual}\\ \textit{operating cost}\end{pmatrix} \tag{2.4}$$

The results of the optimization problem give the optimal set of generator, storage, and transmission capacities that when operated optimally result in the lowest overall costs for the annual demand data given to the model.

The objective function of both the welfare maximization and the cost minimization problems are subject to a number of constraints, including generator constraints, storage unit constraints, transmission constraints, emission constraint, and the nodal energy balance. The generator, storage unit, and transmission constraints ensure that the generators, storage units, and transmission lines operate in a technically feasible manner and fall within their minimum and maximum bounds. The emission constraint imposes a limit on the overall emissions in the system and the nodal energy balance ensures that the energy at each node is perfectly balanced at each point in time.

The electricity price results from the nodal energy balance as the marginal electricity price is the dual variable of the nodal energy balance. The dual variable represents the incremental change in the optimal solution value of the objective function as the right hand side of the constraint is relaxed by one unit. Dual variables are also referred to as shadow price and they signify the amount consumers are willing to pay for an additional unit of the given resource (electricity in this case). For utility based objective functions, the dual variable is the marginal utility of relaxing the constraint. For cost based objective functions, the dual variable is the marginal cost of relaxing the constraint. For the case of the cost minimization optimization problem, the optimal solution is the total system cost. For the nodal energy balance in the cost minimization optimization problem, the dual variable represents the amount the total system cost increases to generate one more unit of electricity, the marginal cost of electricity. For an investment cost minimization problem without load shedding, the marginal cost at the maximum demand would be the cost of installing another unit of generation capacity of the marginal generator. This results in a very large dual variable to the nodal energy balance or in other words, a very large marginal cost of electricity at the maximum demand over the modeled time period, much larger than is experienced in the real world electricity market. To be able to overcome this the demand can be modeled as elastic or in the case of inelastic demand, load shedding can be incorporated into the model. For the case of inelastic demand, where the demand does not change in response to changes in the price, the demand time series is a parameter provided to the model. The demand must be perfectly met at each time step throughout the model, except for at very high marginal utility. At very high marginal utility, the utility is the demand multiplied by the value of loss load, the maximum amount the average consumer is willing to pay to avoid loss of power. The load shedding can instead be represented by a dummy generator that has no fixed cost and very high variable costs, set at the value of loss load. In this work, to obtain more realistic electricity prices in the operations optimization, the demand is modeled to be elastic. In this work, the demand is modeled as elastic to more accurately represent the real world.

2.2.2. Optimization frameworks

The optimization problem can be performed under a short, medium, or long-term framework. Each framework refers to a different assumption regarding the capital stock (Hirth, 2017). In the short-term, the existing generation and transmission are given, there are no changes to the infrastructure. The short-term optimizes over only the operation of the system, the investments are not considered in the optimization problem, and therefore is a dispatch model. For the medium term case, the existing infrastructure is provided as a starting point to the model but endogenous investments and disinvestments are possible. Both the medium-term and the long-term require the addition of the investment in capacity. The medium-term optimizes over both the investments in new technology and the operation of the system. Since the existing infrastructure is sunk cost, it is disregarded from the optimization problem. The long-term is a green-field optimization, meaning that all existing infrastructure is disregarded and the system is built from scratch. It is important to distinguish between the different types of optimization. Table 2.1 describes the differences between the different types of optimization. As (Hirth, 2013) identifies, the market value of VRE is dependent on the modeling assumptions made regarding the existing installed capacities. Since the market value directly influences the profitability of VREs, the modeling assumptions greatly impact the profitability.

Table 2.1: Optimization frameworks adapted from (Hirth, 2013).

	Short-term (Dispatch)	Medium-term (Transition Brownfield)	Long-term (Greenfield)
Time frame optimized	Short	Medium	Long
Type of optimization	Operation	Hybrid	Investment
Optimizes	Operations VC	Operations VC & New capacity investment FC	Operations VC & All capacity investment FC
Existing capacity	Included	Included	Not included
Cost savings of VRE	VC (existing convl sources)	VC of existing convl sources FC (avoid new convl sources)	VC & FC (convl sources)
Long-term profits	+/-	0/-: existing capacity 0: new capacity	0

VC = variable cost; FC = fixed cost; convl = conventional[1]

2.2.3. Model features: time frame & modeling technique

In addition to the optimization frameworks specifying how the capital stock is dealt with in the optimization problem, The dispatch optimization and investment optimization align with the different timescales decisions are made in the energy system. These decision timescales are the operational, short-term and investment, long-term decisions. A main difficulty in an infrastructure planning model is the combination of different time scales. The planning of new infrastructure requires strategic decisions that have time horizons of many years, where as to gain insight into the the infrastructure's performance and profitability requires the modeling of the short-term operation of the system (Kaut et al., 2013). Both levels of time scales have associated uncertainty. As can be seen in Figure 2.3, the operational model is nested in the investment model. The sequence of decisions and the time-frame of the various decisions that can be made are very important to understand for power system development (Pérez-Arriaga, 2013).

ESOMs optimize the installed capacity given a representative year within each time period of demand and weather data. Many ESOMs consider a limited amount of time-steps to limit the computational power and time requirements. Limiting the number of time-steps can become problematic when high shares of VREs are considered in the model (Decarolis et al., 2017). An investment ESOM can be paired with a dispatch model to help overcome the limitations.

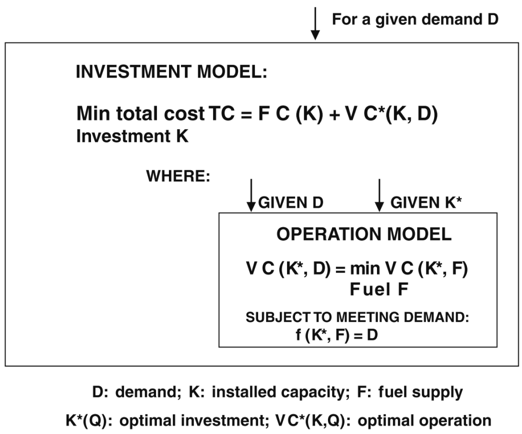

Figure 2.3: Relationship between investment and operation optimization models. Source: (Pérez-Arriaga, 2013)

2.2.4. Optimization modeling & the zero profit rule

As is discussed in Section 2.1, in perfectly competitive markets, the profit for all installed capacity, and therefore all investors, is exactly zero in the long-run. This results from the fact that in a perfectly competitive market if profit is being made new competition will enter the market and sell electricity at a lower price until the profit disappears. If the price is too low and investors are not recovery their costs, investors will leave the market until the price is high enough to recover costs (Pérez-Arriaga, 2013). The deviations of the electricity market in reality lead to deviations from the zero profit rule. A deterministic long-term ESOMs with perfect foresight follows the zero profit rule, with all investors making precisely enough to cover their costs. The long-term profits per optimization type are shown in Table 2.1.

2.3. Uncertainty in the electricity system

2.3.1. Deviation of real-world power system from energy optimization models

Many least-cost, bottom-up models of the electricity sector assume a perfectly competitive power market with perfect foresight (such as PyPSA-Eur, MARKAL) (Loulou, Goldstein, and Noble, 2004). In long-term equilibrium, the assumption and modeling of perfect competition and foresight lead to all system investors making precisely zero profit in the long run (Brown and Reichenberg, 2020). The economic theory perspective shows if investors are making a profit new actors will enter the market, driving profits to zero and if investors are losing money, market players will leave the market until losses no longer occur. Market equilibrium results in zero net profit for all participants, all participants receive a revenue that precisely covers all their costs. Often, demand is modeled as being inelastic until it reaches a threshold where the acquisition of electricity is more than the utility. This non-served energy or loss load is modeled in energy optimization models as another generation technology with very high variable costs and no fixed costs, this value is know as the value of loss load (VoLL). The inclusion of VoLL ensures that in an investment ESOM, that assume a perfectly competitive market with perfect foresight, will result in zero profit for all market investors. The VoLL is the amount the average customer is willing to pay to avoid in interruption in electricity supply (IEA, 2016). It is the loss in consumer surplus as a result of loss of load or in other words the loss of socio-economic activity or costs that results when electricity is not supplied to customers. In practice, power prices rarely reach the theoretical VoLL which can cause the market to provide insufficient revenues for investors leading to the ”missing money” problem (Petitet, Finon, and Janssen, 2017). This is due to a variety of reasons including operational price caps, political unacceptability of high prices, and system operator behavior at peak hours (Petitet, Finon, and Janssen, 2017). In addition, in practice VoLL is difficult to accurately estimate.

If the regulator is not seeking any specific objectives (such as security of supply, reliability, or environmental targets), the market price with sufficient scarcity pricing is sufficient to ensure adequate profits to generators. However this is often not the case. Adequate electricity supply is generally a very politically sensitive topic and therefore, regulators typically like to ensure generous security and reliability margins. Mandating energy capacity above optimal market determined values leads to situations that deviate from the economically efficient power system design (Pérez-Arriaga, 2013). Policies to achieve certain security, reliability, and environmental objectives include VRE installed capacity targets, minimum consumption of a certain fuel, emission caps, minimum installed capacity margin above peak. Achievement of these policy objectives, requires an additional form of payment must be supplied in addition to the market price. Failure of the regulator to adequately remunerate for these security, reliability, or environmental objectives can lead to a missing money problem for investors.

2.3.2. Uncertainty and energy optimization models

Following the classification used by DeCarolis2011, this paper classifies uncertainty into two distinct categories: structural uncertainty and parametric uncertainty. The structural uncertainty is defined as the uncertainty in the structure of the model due to the imperfect mathematical relationships and parametric uncertainty, the uncertainty in the model parameters (Decarolis et al., 2017). Structural uncertainty in the model stem from the fact that optimization models can not fully encompass the complexity of the real world, there will always be additional real world constraints and objectives that are not captured in the model (Decarolis et al., 2017).

Often a single optimal solution is generated for energy system optimization analyzes. As mathematical models never provide a perfect representation for the real world, modelers are frequently unaware or unable to model all practical constraints, and key future input parameters have a significant amount of uncertainty, singular cost optimal solutions provide merely an approximation for the real-world optimal solutions (Voll et al., 2015). The uncertainty pertaining to the future causes optimal solutions to have limited significance and can even mislead decision makers by providing false precision in the future energy systems (DeCarolis et al., 2016; Voll et al., 2015). Trutnevyte2016a performed a retrospective study and found that cost-optimal scenarios deviate significantly from the historical cumulative total system costs (Trutnevyte, 2016). The modeled cost optimal system did not approximate the developments that occurred in the real world (Trutnevyte, 2016). The cost optimal scenarios ignore the large amount of uncertainty arising from deviations from cost optimality. The large amount of parametric and structural uncertainty translates to an extremely low probability of selecting one scenario that will precisely represent the real-world transition (Trutnevyte, 2016). Therefore, a bounded analysis should be used to explore the possible future scenario space and analyze the extremes/ bounds. A large number near-optimal scenarios should be considered to provide an ”envelope of predictability” and capture the real-world transition (Trutnevyte, 2016).

Reviews of energy system optimization models find the uncertainty in the structure of energy system optimization models and the input parameter data to be under developed (Foley et al., 2010; Yue et al., 2018). Uncertainty is a vital component of energy system models to ensure that they provide results and insights that are robust and enable effective, well supported decision making (Yue et al., 2018). ESOMs should be used to explore alternative system configurations and suggest various alternatives to achieve policy goals under deep uncertainty. Decisions with deep uncertainty cannot be based on the most likely, optimal scenarios or forecasting of future developments (Papadelis, Flamos, and Psarras, 2013). Robust strategies, strategies that perform well compared to alternatives across a wide range of possible future scenarios, are key for evaluating alternative decisions under conditions of deep uncertainty (Davis, Bankes, and Egner, 2007; Lempert et al., 2006; Papadelis, Flamos, and Psarras, 2013; Walker, Lempert, and Kwakkel, 2013). Therefore, uncertainty analyses must be effectively communicated to decision makers to aid in robust decision making (Price and Keppo, 2017). The uncertainty inherent to the modeling process must be properly explored and accounted for (Price and Keppo, 2017).

One method for helping to account for the structural uncertainty in energy systems is Modeling to Generate Alternatives (MGA). By exploiting the near-optimal solution space, MGA provides a range of possible near-optimal solutions that helps facilitate robust decision-making, especially when considering other system constraints or variables that are not considered in the model. The MGA analysis provides decision makers with the required features, features that are common across all near-optimal solutions, the features that can be decided upon, features that are different between the near-optimal solutions, and the features that must be avoided, features that are not in present in any of the near-optimal solutions (Voll et al., 2015).

2.3.3. Effect of uncertainty on investments

The uncertainties in the electricity system cause the variability in profitability of investments. Krey2009 identifies that current investment decisions need to take into account the future risks of the uncertainties in the energy sector including basically the entire energy chain, energy demand, and future environmental policies. Investors in the capital-intensive energy system face not only market driven uncertainties but are particularly vulnerable to high degree of policy uncertainties (Fuss et al., 2008).

(Botterud, 2003) identifies that long-term uncertainties and their impact on optimal investment decisions are often underrepresented in long-term decision making. To fill this gap, dynamic models are created to provide a new framework for long-term investment analysis in new power generation capacity and price analysis given the restructured power systems. (Conejo et al., 2016) identities that investments in generation facilities require a long-term view, careful and comprehensive accounting of uncertainties, and large-scale optimization problems. The book goes on to further identify that comprehensive modeling and consideration of the uncertainty in the energy system is critical for investment decision-making. The large amount of uncertainty and risk in the electricity system results from its high sensitivity to sociocultural, geopolitical, economic, environmental, and technical parameters.

2.3.4. Necessity of uncertainty for forecasting possible energy system futures

To use energy optimization modeling to provide insight for investment decision making, the range of future possible outcomes for the design of the electricity system must be considered. Typically, energy system optimization models determine the cost optimal system of a set time period, given a set of constraints.

Policy makers are very unlikely to make policy decisions based purely on cost-optimality, other factors are considered in driving policy (Price and Keppo, 2017). The energy system has numerous stakeholders who do not have perfect foresight and each have their own objectives and non-cost related preferences(Price and Keppo, 2017). Although it is highly unlikely that the real-world energy transition will occur in precisely a cost optimal manner, it is expected to be driven by cost considerations (Price and Keppo, 2017). Therefore, the real-world energy system could be represented by a near-optimal cost solution.

The use of cost optimization for modeling the energy transition is based on the idea of a central planner, one centralized decision maker, whose goal is to maximize social welfare. Maximizing social welfare is achieved by maximizing both consumer and producer surplus with elastic demands. Equivalently maximizing social welfare can be transformed into minimizing total system cost, which is the negative of total surplus. Under inelastic demand this becomes purely minimizing producer total costs (Trutnevyte, 2016). However, in reality, there is not one centralized decision-maker. The energy system is composed of a variety of actors with various levels of decision power (Trutnevyte, 2016). In addition, cost optimization is used on the basis of partial equilibrium, that energy supply-demand equilibrium is met. Cost optimization models assume a perfect market with rational actors that behave in a cost optimal manner. Although costs are a key driver to the energy transition, the real world energy transition is very likely to not follow a cost-optimal pathway (Trutnevyte, 2016).

The real-world transition is suggested to follow the most investable path rather than the least cost path, since private energy companies are the ones who make the investments, not the government (Trutnevyte, 2016; Gross, Blyth, and Heptonstall, 2010). Investments in installed capacity are determined by expected return, which is based on risk regarding costs and returns (Gross, Blyth, and Heptonstall, 2010). Return risks are highly dependent on the electricity price fluctuations (Gross, Blyth, and Heptonstall, 2010). Policy makers currently mainly focus on the levelized cost of electricity per technology, considering only price risk (Trutnevyte, 2016; Gross, Blyth, and Heptonstall, 2010). However the real-world transition follows the most investable path suggests that policymakers should consider revenue risk to increase the effectiveness of policy making.

All of these reasons provide evidence as to why a range of near optimal solutions need to be used to provide insights into the future energy system. As the real-world transition is expected to deviate from the cost-optimal solution, in order to use energy optimization modeling to help support investment decision making, we must consider a range of near-optimal solutions and parametric uncertainty. This is supported by the ex-post study performed by (Trutnevyte, 2016) of near-optimal energy system modeling compared to the real-world energy transition in the UK from 1990-2014, that found that near-optimal systems can encapsulate the real-world energy transition and therefore should be used to gain general insights of the bounds of possible technology deployment. A method for generating the near-optimal systems is modeling to generate alternative (MGA), described in detail in the next section.

2.3.5. Modeling to generate alternatives

Due to the large uncertainty about the future, ESOMs should be used to identify patterns across many different model runs to produce insights rather than singular projections (Decarolis et al., 2017; Neumann and Brown, 2019). To address structural uncertainty, Modeling to Generate Alternatives (MGA) is a technique for determining near-optimal solutions by systematically exploring the decision space. MGA was first introduced by (Brill, Chang, and Hopkins, 1982) in water and management planning to determine a set of significantly different alternative solutions that are feasible and perform well with respect to the modeled objective. The ESOM formulation is modified to find a range of possible solutions that are maximally different in decision space but near the optimal solution in solution space (Decarolis et al., 2017). The optimal solution is used as a starting point and is relaxed by a certain cost increase to explore the near-optimal solution space (DeCarolis et al., 2016; Yue et al., 2018). MGA is a complement to methods that address the range of parametric uncertainty (Neumann and Brown, 2019). Near optimal solutions can help to account for unmodeled circumstances (i.e. unforeseen or unmodeled risks) (Yue et al., 2018).

MGA explores the range of technically diverse future electricity system configurations that meet model objectives within a set cost deviation from the cost optimal (least cost) system. The analysis can be used to provide a set of rules that must be satisfied to ensure the total system costs are within a set range of the cost optimal solution. Therefore, it can help guide policy by determining features that are required to keep the system costs within predefined ranges.

The can often be numerous solutions to a mathematical model of a problem that lead to very similar results with respect to the modeled variables but vary significantly in the decision space (Brill, Chang, and Hopkins, 1982). These alternative solutions can be better than other solutions with respect to unmodeled system components (Brill, Chang, and Hopkins, 1982). The methodology behind MGA analysis is further discussed in Chapter 3.

3

Modeling framework

3.1. Background on the developed modeling framework

This research looks to examine the profitability of investments in the actual power market and therefore requires analysis of realistic market conditions. Many ESOMs determine the optimal installed capacity of the power system over a certain time horizon under the assumptions that the market is perfect, competitive and deterministic. Under these assumptions, all of the capacity installed in the optimal system follows the zero profit rule, all investors receive precisely the necessary revenue to cover their expenses. In reality, as described in Section 2.1, there are many attributes of the electricity market that cause it to deviate from being a perfect, competitive market. The modeling framework presented utilizes the energy system optimization modeling technique paired with the MGA uncertainty technique over a long-term time frame, considering both long-term and short-term decision making. The use of the MGA uncertainty technique, the variation in weather and demand years used in the two step optimization process, the myopic optimization, and the elastic modeling of demand result in a deviation from the zero profit rule and aims to provide a more realistic representation of the real world. By providing a more realistic representation of the real world, the model is used to explore the profitabilty of investment decisions.

3.2. Description of the modeling framework

To account for these deviations from a perfect market and to represent the resulting variety of possible future business cases for each generation technologies, a medium-term, investment ESOM paired with the MGA analysis is developed and used to generate a variety of possible power system designs for a set of investment periods (i.e. 2030, 2040, 2050).

The investment medium-term optimizations are only calculated for each investment stage, where installation and decommissioning are assumed to only occur at the start of each investment stage. To be able to simulate a range of possible power system designs, the MGA technique is utilized to explore the decision space by minimizing and maximizing the installed capacities and allowing the system to be up to 10% more expensive than the optimal system. Then, the range of possible power system designs are used as the basis for a short-term, dispatch operations optimization for a variety of weather and demand years to represent the short-term variation that occurs in the power system. A two-step optimization is performed for each investment period to address the two main time frames of decision-making in the energy system, long-term decisions where investments are made and short-term operational decisions where dispatch is determined. The full model flow diagram is shown in Figure 3.1.

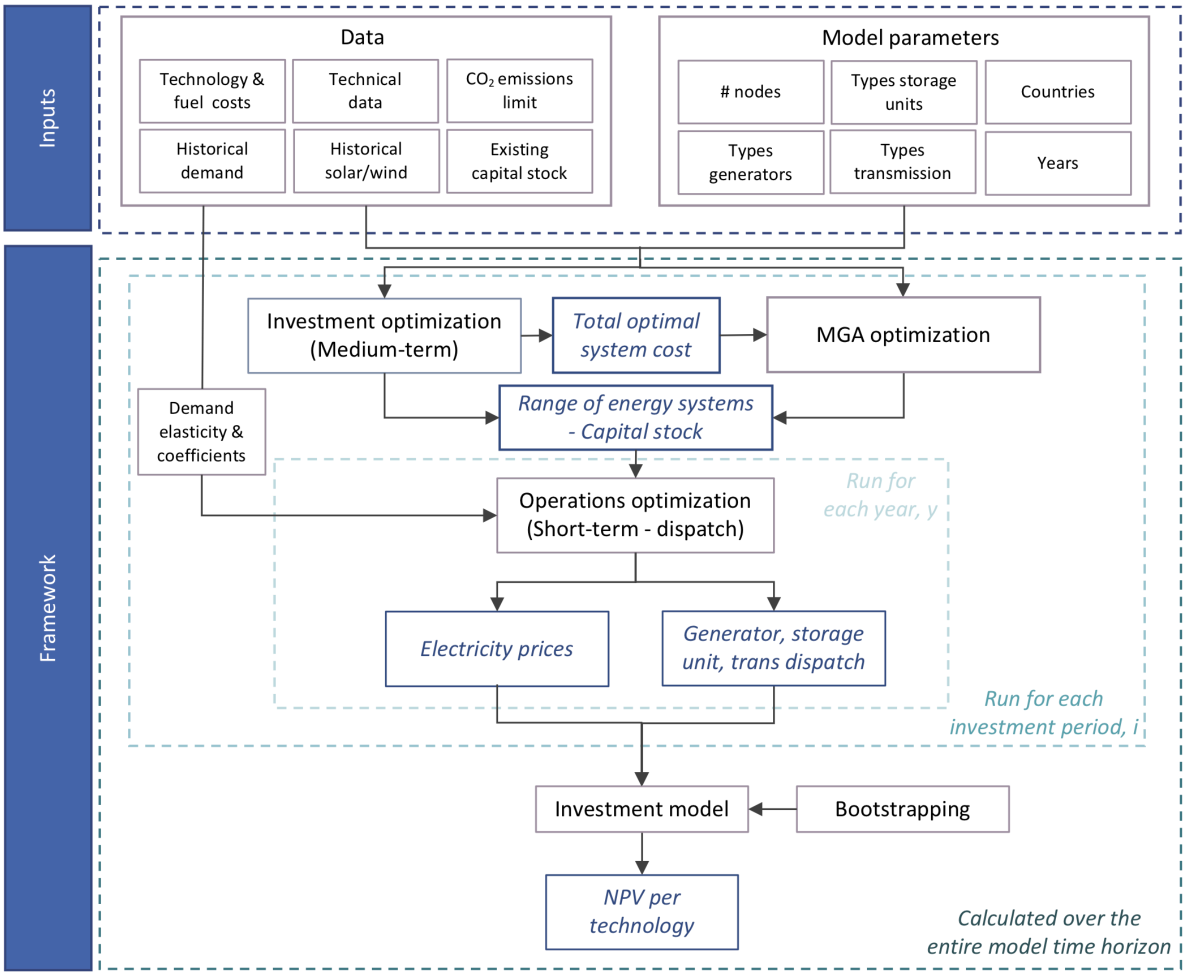

Figure 3.1: Modeling framework for determining profitability of generation and storage technologies using energy system optimization modeling and the MGA uncertainty technique.

Figure 3.2 provides a linear schematic for each full alternative run to show the relationship between investment periods and operation periods. The diagram provides a detailed representation of each of the dashed boxes in the modeling framework shown in Figure 3.1. Following the notation in (Kaut et al., 2013), circles denote investment decision stages (investment periods) and squares represent operational decision stages (operation periods). The model consist of three investment periods; investment decisions are assumed to only occur at these stages. The installed capacities are assumed to remain constant over the remainder of the time period. Using the installed capacity determined in the investment stage, a set of operation optimizations are performed given different historical demand and weather data. Each operations optimization is based on the capital stock determined in the respective investment stage, represented in the figure by the fact that investment nodes (grey circles) are the parent nodes of the set of operations optimizations. As can be seen, it is assumed that the operational decisions and their outcomes do not affect future investment or operational decisions. Therefore, the results from each investment stage feed directly into the consecutive investment stage, without considering the operational outcomes.

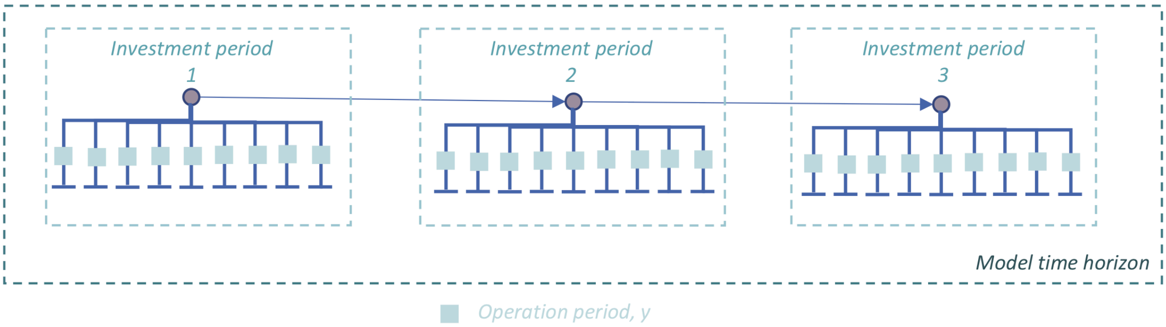

Figure 3.2: Schematic of each full scenario. This is performed for the investment optimization case (optimal case) and the various MGA cases.

A main challenge in formulating an optimization model over a long time horizon is the balance between adequately accounting for the complexities of the power system while being able to be solved within computational and time limitations. The developed modeling framework helps to overcome this challenge by assuming the investment decisions only occur at three points in time. Each optimization period is performed independently, making the model myopic - current investment decisions are assumed to be made under the assumption that no future knowledge of the system is known. This is done to help account for the non-deterministic nature of the the power system, investment decisions are made and capacities are installed without knowing the operational situations the system will encounter.

Given time and computation constraints, the demand is modeled to be inelastic in the investment optimization and is run as a cost minimization optimization. In addition, given the mathematical formulation of the optimization of the MGA optimization, the demand is modeled to be inelastic in the MGA analysis. The investment and MGA optimization are solving with the constraint of having to exactly satisfy the demand at each node for every point in time. To make the model more closely represent reality and generate more realistic electricity prices, the demand is assumed to be elastic in the operations optimization and therefore, the operations optimization is modeled as a welfare maximization optimization problem. The details of each component of the modeling framework are described in further detail in the following sections.

3.3. Investment optimization

The investment optimization model developed is a myopic partial-equilibrium cost minimization model, investors do not have perfect foresight, and therefore the market modeled deviates from a perfect competitive energy market. The modeled market is assumed to be competitive and follow marginal-cost pricing. The demand is modeled as being elastic, the demand changes in response to changes in the price. The demand is modeled to be elastic to provide a more accurate representation of the real electricity market. The investment optimization is formulated as a welfare maximization optimization, with the objective to maximize the total economic welfare.

Objective function

The optimization is formulate as a welfare maximization optimization. For the investment optimization, the total welfare is maximized to find the long-term cost-optimal electricity system. The welfare is determined by maximizing the customer utility subtracted by the total annual system cost. The total annual system costs is the sum of the annualized investment costs (the annualized capital costs for generation, storage, and transmission capacities) and the annual operational costs for the snapshots of time identified in the model are minimized. The results of the optimization problem give the optimal set of generator, storage, and transmission capacities that when operated optimally result in the lowest overall costs for the optimal demand determined by the model.

$$Maximize\begin{pmatrix}\text{Total economic}\\ \text{welfare}\end{pmatrix} = \sum\begin{pmatrix}\text{Consumer utility}\\ \text{(value function)}\end{pmatrix} - \sum\begin{pmatrix}\text{Generator costs}\\ \text{(supply function)}\end{pmatrix} \tag{3.1}$$

The optimization function maximizes the total economic welfare by maximizing the consumer utility subtracted by the generation costs. The optimization is run for one representative year with multiple time steps to represent the variety of weather and demand conditions that exist throughout the year. The detailed objective function is shown in 3.2 below. The objective function and constraints are adapted from (Neumann and Brown, 2019).

max f(d,K,H,F,k,h) =

$$\max_{K,H,F,k,h}\left[\sum_{n,t}(U_{n,t}d_{n,t}) - \sum_{n,g}(c_{n,g}K_{n,g}) + \sum_{n,s}(c_{n,s}H_{n,s}) + \sum_{l}(c_l F_l) + \sum_{n,g,t}(w_t o_{n,g}k_{n,g,t}) + \sum_{n,s,t}(w_t o_{n,s}(h^-_{n,s,t} + h^+_{n,s,t}))\right] \tag{3.2}$$

The objective function maximizes the utility of the consumer $U_{n,t}$ at each node n for each time t multiplied by demand at the respective node at time t, $d_{n,t}$ subtracted by the total system costs.The total system costs consist of the generator capacities $K_{n,g}$ at each node n for each generator technology g multiplied by their annualized capital cost $c_{n,g}$, the storage capacities $H_{n,s}$ at each node n for each storage technology s multiplied by their annualized capital cost $c_{n,s}$, transmission capacity F_l for each line l multiplied by their annualized capital cost c_l, dispatch of each generator technology $k_{n,g,t}$ at node n multiplied by their operating costs $o_{n,g}$ and the time step weight w_t, and dispatch of each storage technology $h^{-/+}_{n,s,t}$ at node n multiplied by their operating costs $o_{n,s}$ and the time step weight w_t. Each time period is given a weighting, w_t. The weightings are chosen such that the sum of the weights over the chosen time steps t equal 8,760, representing a full year of operation. The optimization function minimizes total system cost per year. For simplicity, start-up and shut-down costs of generators is not included in the objective function.

Only capital cost of generation, storage, and transmission capacities installed in the period being optimized are included in the objective function. Previously installed capacities are considered sunk cost and therefore, their capital cost is not included in the objective function.

Solving the investment optimization gives the optimal power system configuration. In addition, the objective function gives the optimal system cost, which is then used in the MGA optimization, described in the next section.

Elastic demand

In the case of the elastic demand, the consumer utility function can be determined using demand curves. Elastic demand is incorporated into ESOMs to align more closely with real world electricity market observations (Decarolis et al., 2017). Incorporating elastic demand in ESOMs, allows electricity demand to be responsive to price changes such that an increase in price leads to a decrease in demand and an decrease in price leads to an increase in demand. Linearized demand curves are used to represent how demand changes with a change in electricity price.

For the case where demand is assumed to be elastic, utility of the consumers needs to be calculated. To begin with, the coefficients for demand elasticity need to be determined. A reference demand D_{ref}, reference price P_{ref}, and the elasticity of demand b^{-1} are calibrated to historical price and demand values for the respective market being modeled. Using these values the necessary parameters can be determined to formulate the utility function for consumers, $U(d)$. The utility function or total benefits is given by the area under the demand curve bounded by the equilibrium price point (point that gives the demand and market price for a given time step), the point the supply and demand curves intersect as is shown in Figure 3.3.

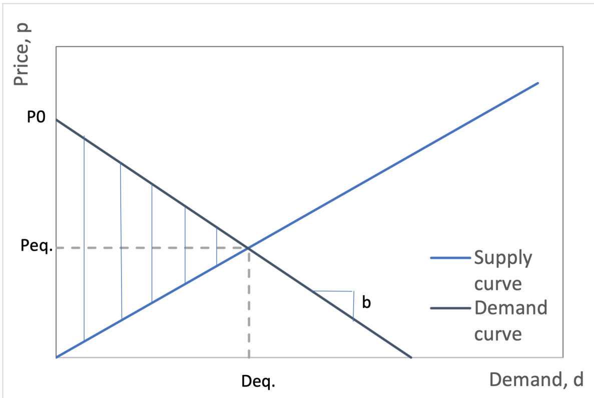

Figure 3.3: Supply and demand curves. The dashed triangle is the utility.

Therefore, to determine the utility, the demand function for each time step modeled must be formulated. The demand function is:

$$p = P_0 - bd \tag{3.3}$$

where p is the price, P_0 is the price when demand equals zero (the y-intercept of the demand curve), d is the quantity demanded, and b is the inverse of the price elasticity of demand (the slope of the demand curve). The price elasticity of demand is how much the quantity is demanded given a change in price or in other words, the ratio of the percentage change in demand to the percentage change in price.

The demand curve for each time step should be unique and it should be correlated with the demand hourly time series fed into the model. The elasticity of demand is assumed to remain constant from one time step to the next and thus, the slope of the demand curve remains constant. Given the original demand for the particular time step D_{org}, the elasticity of demand b^{-1} and the assumed reference price, P_{ref}, the y-intercept, P_0 is calculated for each time step with the demand equation:

$$P_0(t) = bD_{org}(t) + P_{ref} \tag{3.4}$$

These parameters and utility function given below are then used to determine the total benefits.

$$U_{n,b,t}(d_{n,b,t}) = (P_0 + 0.5bd_{n,b,t})d_{n,b,t} \qquad \forall(n,t) \tag{3.5}$$

where P_0 is the price when demand equals zero (the y-intercept of the demand curve), d is the demand, and b is the inverse of the price elasticity of demand. The price elasticity of demand is how much the quantity is demanded given a change in price or in other words, the ratio of the percentage change in demand to the percentage change in price.

3.3.1. Modeling to generate alternatives (MGA) optimization

The MGA analysis is used to determine the range of near-optimal solutions. The MGA methodology used in this research is modeled after (Neumann and Brown, 2019). The optimal system cost determined in the investment optimization is used to define a new constraint. The optimal solution value (f^*) plus an acceptable relative cost increase (ϵ) is then used to constrain the original feasible space as a new constraint in the optimization problems to explore the near-optimal feasible space.

$$min\ \ f(K,H,F,k,h) \leq (1+\epsilon) * f^* \tag{3.6}$$

The chosen epsilon value (slack value) is up to the discretion of the modeler. Several previous MGA studies use a range of epsilon values to examine the affect that epsilon has on the final output (Neumann and Brown, 2019; DeCarolis et al., 2016). in this study, an epsilon value of 10% is chosen. It is important to note that a medium-term optimization is used in this study and therefore, the investment optimization performed for the optimal solution minimizes the costs of additional capacity that is added to the system. The cost of existing technology is assumed to be sunk cost and is therefore not included in the total system costs. Since the optimal cost is used as the basis of the cost constraint for the MGA analysis, the MGA analysis is within epsilon of the cost of additional technology required in the system per investment period.

The new objective function becomes the minimization or maximization of the sums of subsets of generation, storage and transmission capacity expansion subject to the new allowable cost increase constraint.

$$min\ (x)\ or\ max\ (x) \tag{3.7}$$

Where x, the decision variable, is the subset of generation, storage, or transmission capacity.

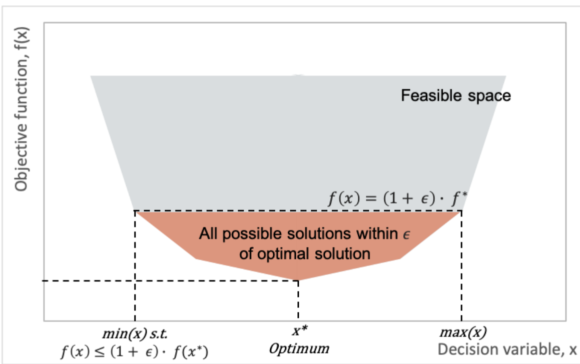

Figure 3.4: Example of how the minimum and maximum value for a decision variable are found using MGA. Decision space is multi-dimensional so this is repeated for each decision variable.

The set of new optimization problems are solved to determine the range of near optimal solutions. The resulting power system configurations generated by the investment optimization and MGA optimization are input into the operations optimization and are run for a range of weather and demand years. The next section details the operations optimization.

3.3.2. Operations optimization

Similar to the investment optimization, the operations optimization is modeled as a welfare maximization problem. For short-term equilibrium in the operations optimization, the objective function only maximizes over the short-term costs, which is the difference between the consumer utility and the producer operation costs. The capital costs (fixed costs) are excluded and the objective function is:

$$\max_{d_{n,t},k_{n,g,t},h_{n,s,t}} \left[\sum_{n,b,t} U_{n,t}(d_{n,t}) - \Big(\sum_{n,g,t} (w_t o_{n,g} k_{n,g,t}) + \sum_{n,s,t} o_{n,s,t}({h_{n,s,t}}^- + {h_{n,s,t}}^+) \Big) \right] \tag{3.8}$$

The objective function maximizes the utility of the consumer $U_{n,t}$ at each node n for each time t multiplied by demand at the respective node at time t, $d_{n,t}$ subtracted by the system operating costs. The system operating costs described in detail in the investment optimization section.

$$\max_{k_{n,g,t},h_{n,s,t}} \sum_{n,g,t} (w_t o_{n,g} k_{n,g,t}) + \sum_{n,s,t} o_{n,s,t}({h_{n,s,t}}^- + {h_{n,s,t}}^+)$$

3.4. Optimization model constraints

The following section provides the constraints for all optimization models used in the modeling framework.

3.4.1. Generator constraints

To solve the optimization function, the objective function is subjected to several constraints. The dispatch of generators $k_{n,g,t}$ are constrained by the generator capacity $K_{n,g}$ and the minimum and maximum time variable availability of the generator, $\tilde{k}_{n,g,t}$ and $\bar{k}_{n,g,t}$ respectively. The time variable availability of the generator is given per unit of installed capacity, $K_{n,g}$. The minimum time variable availability $\tilde{k}_{n,g,t}$ of the generator signifies the lower bound of the installed capacity that must be in operation for the given time. The maximum time variable availability $\bar{k}_{n,g,t}$ of the generator signifies the upper bound of the installed capacity that can be in operation for the given time.

$$\tilde{k}_{n,g,t} \leq k_{n,g,t} \leq \bar{k}_{n,g} K_{n,g} \qquad \forall n, g, t \tag{3.10}$$

Conventional generators (coal, gas, and nuclear) are assumed to be fully flexible - $\tilde{k}_{n,g,t}$ is 0 and $\bar{k}_{n,g,t}$ is based on a randomized parameter to model times when the generator unit is offline for maintenance or for other non planned reasons. Therefore, for conventional generators, 3.10 becomes:

$$0 \leq k_{n,g,t} \leq K_{n,g} \qquad \forall n, g, t \tag{3.11}$$

For VREs, 3.10 becomes:

$$0 \leq k_{n,g,t} \leq \bar{k}_{n,g,t} K_{n,g} \qquad \forall n, g, t \tag{3.12}$$

where $\bar{k}_{n,g,t}$ is the weather dependent power availability of the VRE.

For the investment optimization and the MGA, the installed capacity of generators are optimized within bounds of minimum and maximum installable potential values $K_{n,g}^{min}$ and $K_{n,g}^{max}$, respectively.

$$K_{n,g}^{min} \leq K_{n,g} \leq K_{n,g}^{max} \qquad \forall n, g \tag{3.13}$$

The capacity bounds are determined by existing/previously installed capacities, governmental phase-out decommissioning plans, or maximum renewable installation potential. For the first optimization period, 2030, currently existing installed capacities are used to define the minimum bounds $K_{n,g}^{min}$, $H_{n,s}^{min}$, and F_l^{min}. For the consecutive optimization periods, the minimum capacities are the optimal capacity from the previous optimization period. The maximum capacities for the conventional generators are determined from governmental decommissioning plans and the maximum capacities for VREs are the maximum renewable installation potentials, given in Table A.2.

3.4.2. Storage unit constraints

Similar to dispatch constraint for generators given in 3.10, the charging and discharging of storage units $h_{n,s,t}^{-}$ is constrained by the storage power capacity $H_{n,s}$:

$$0 \leq h_{n,s,t}^{+} \leq H_{n,s}^{+} \qquad \forall n, s, t \tag{3.14}$$

$$0 \leq h_{n,s,t}^{-} \leq H_{n,s}^{-} \qquad \forall n, s, t \tag{3.15}$$

In addition, the state of charge of the storage unit $soc_{n,s,t}$ is constrained by the nominal power, $H_{n,s}$ multiplied by the number of hours that are required to fill the storage unit to the maximum state of charge, $r_{n,s}$. In this research, the number of hours required to fill a storage unit to maximum charge are set to 6 hours for batteries and 168 hours for hydrogen storage.

$$0 \leq soc_{n,s,t} \leq H_{n,s} * r_{n,s} \qquad \forall n, s, t \tag{3.16}$$

The state of charge $soc_{n,s,t}$ has to be consistent from one time step to the next and therefore,

$$soc_{n,s,t} = soc_{n,s,t-1} + \eta_{n,s}^{+} h_{n,s,t}^{+} - \frac{1}{\eta_{n,s}^{-}} h_{n,s,t}^{-} \qquad \forall n, s, t \tag{3.17}$$

The state of charge must equal the state of charge at the previous time step $soc_{n,s,t-1}$ plus the amount of power charged to the batter (the efficiency of charging $\eta_{n,s}^{+}$ multiplied by the power charged $h_{n,s,t}^{+}$) minus the amount of power discharge from the battery (the amount of power discharged $h_{n,s,t}^{-}$ divided by the efficiency of discharging $\eta_{n,s}^{-}$. For simplification, it is assumed that the storage units have no standing losses (self-discharging leakage rate). For the investment optimization and the MGA, the installed capacity storage units are optimized within bounds of minimum and maximum installable potential values, $H_{n,s}^{min}$ and $H_{n,s}^{max}$, respectively.

$$H_{n,s}^{min} \leq H_{n,s} \leq H_{n,s}^{max} \qquad \forall n, s \tag{3.18}$$

For the first investment optimization period, 2030, the minimum bounds are the currently installed battery or hydrogen storage. The maximum bound is infinity. For the consecutive optimization periods, the minimum bound is the optimal storage unit capacity from the previous optimization period and the maximum bound remains infinity.

3.4.3. Transmission constraints

The flow in all transmission lines $f_{n,t}$ are constrained by their capacities F_l.

$$|f_{n,t}| \leq F_l \qquad \forall\ l, t \tag{3.19}$$

For the investment optimization and the MGA, the installed capacity of transmission are optimized within bounds of minimum and maximum installable potential values, F_l^{min} and F_l^{max}, respectively.

$$F_l^{min} \leq F_l \leq F_l^{max} \qquad \forall l \tag{3.20}$$

For the first investment optimization period, 2030, the minimum transmission capacity bound is the currently installed transmission. The maximum bound is infinity. For the consecutive optimization periods, the minimum bound is the optimal storage unit capacity from the previous optimization period and the maximum bound remains infinity. The transmission lines are modeled as lossless.

3.4.4. Nodal energy balance

For each point in time the demand at each node n must be exactly satisfied by the energy generated by the generators at node n $k_{n,g,t}$, the discharge of storage units at node n $h_{n,s,t}^{-}$, minus the charging of storage units at node n $h_{n,s,t}^{+}$, and the flow from the transmission lines to node n, $f_{l,t}$. This gives the nodal balance constraint detailed below.

$$\sum_g k_{n,g,t} + \sum_s (h_{n,s,t}^{-} - h_{n,s,t}^{+}) + \sum_l (\alpha_{l,n,t} f_{l,t}) = d_{n,t} \leftrightarrow \lambda_{n,t} \qquad \forall n, t \tag{3.21}$$

$$\alpha_{l,n,t} : -1\ if\ l\ starts\ at\ n,\ l\ withdraws\ power\ from\ i$$

$$\alpha_{l,n,t} : 1\ if\ l\ starts\ at\ n,\ l\ supplies\ power\ from\ i$$

The shadow price (i.e. dual variable) of the nodal energy balance gives $\lambda_{n,t}$, the marginal price at each bus for each period of time modeled.

3.4.5. Emission constraint

An emissions limit CAP_{CO_2} can be imposed on the system as a global constraint. The emissions can be constrained by calculating the sum of emissions for each generator over the course of the year modelled. The emissions per generator are calculated using the carbon intensities of the fuel used in the generator e_g and the efficiency of the generator $\eta_{n,g}$:

$$\sum_{n,g,t} w_t \frac{1}{\eta_{n,g}} e_g k_{n,g,t} \leq CAP_{CO_2} \leftrightarrow \mu_{CO_2} \tag{3.22}$$

μCO_2 is the shadow price of the CO2 emissions and therefore, identifies the CO2 price that is necessary to reach the carbon emission limit specified in the constraint.

3.4.6. Investment calculation

Given the electricity prices and the generator and storage unit dispatch determined in the operations optimization of all generated alternative power systems, the NPV is calculated for each technology. Net present value (NPV) is a basic financial calculation to assess the value of a project. The NPV is the sum of the discounted cash flows, costs and revenues, with a certain interest rate, r, over the assumed lifespan of the asset (Petitet, 2017).

Net present value (NPV) (Brown, 2020):

$$NPV = \sum_{y=0}^{Y} \frac{-C_y - O_y + R_y}{(1+r)^y} \tag{3.23}$$

$$C_y : capital\ expenditure\ in\ year\ y$$

$$O_y : operating\ \&\ maintenance\ expenditure\ in\ year\ y$$

$$R_y : revenue\ in\ year\ y$$

$$r : discount\ rate$$

If the NPV is positive, the investment is economically profitable and indicates that the investment is worthwhile. Whereas, a negative NPV indicates that the project should be rejected (Petitet, 2017). To account for the fact that t

Given that the NPV is calculated using a discount rate, the order of cash flow is significant; making earlier profits more desirable. To account for this and the randomness of weather and demand data for each operation year, bootstrapping, a statistical technique using random sampling with replacement, is performed over the operation optimization results. The set of dispatch and electricity price results from the operations optimization are randomly selected 1000 times and used to calculate 1000 different NPVs for each full model run. This provides a range of possible NPV outcomes.

4

Case Study

A simplified optimization model is built to practically show the modeling framework described in Chapter 3 for analyzing the business case of VREs and storage using ESOMS as the power system evolves to meet emission reduction targets. The case study explores the use of a simplified energy optimization model to analyze investments in the power system from the perspective of an energy generation company. The case study's objective is to provide a practical example of the modeling framework developed described in Chapter 4 and to gain insights into the profitability of generation and storage technologies installed in 2030 in the Netherlands.

4.1. Case study details

The model for the case study is built in Python with the open-source optimization package, Pyomo, and the CPLEX optimization solver. The case study considers a two-node, electricity only market. Following the methods described in Chapter 4, a multi-stage, medium-term optimization is performed, where each investment period is optimized independently. Following the investment optimization, an MGA analysis is performed on each of the investment periods. Using the optimal and MGA alternative power system configurations, 10 operations optimizations are performed. The model only considers the Netherlands and Germany in a two node system. A spatial resolution of two nodes was chosen as this allows for the simplest model while still being able to model all system components, including transmission. This allows for the case study to reveal how the developed modeling framework can be applied and to allow for a clearer understanding of the effect system components have on the overall model results. Germany was chosen as the second node, as it is the country the Netherlands shares the largest interconnection capacity with. The generation technologies modeled are solar, onshore wind, offshore wind, CCGT, OCGT, coal, lignite, biomass, and nuclear. The storage technologies included in the model are batteries and hydrogen storage. Minimum generation capacities in 2030 are assumed to be current installed capacities in each respective country (based on 2020 installed capacities). The time frame of the model is from 2030-2060, with investment years 2030, 2040, and 2050 (installation and decommissioning of capacities are assumed to only occur in these years). It is assumed that the demand and installed capacity remain constant throughout each 10 year investment segment (2030-

2039, 2040-2049, 2050-2059). The decommissioning of generation capacity is assumed to follow governmental decommissioning plans or plant lifetimes. The maximum VREs capacities are bounded by the potential renewable energy capacities for each respective country. Demand is modeled to follow historical data, scaled to represent increasing demand over time. The demand factor is consistent across each 10-year investment period and increases by 15% per ten-year period. It is assumed that installed capacity remains constant throughout each 10 year investment segment (2030-2039, 2040-2049, 2050-2059). A greenhouse gas emissions constraint is included in the model to follow governmental CO_2eq reduction targets. The greenhouse gas emission reduction targets outlined by the Dutch and German governments are assumed to be achieved.

The model assumes that conventional generators are fully flexible and therefore, their dispatch power is only limited by the capacity of the generator type. In addition, generators are assumed to have no startup or shutdown time. The operation costs for storage units is assumed to be zero. The capacity optimization is a medium-term optimization in terms of the capital stock. The optimization uses the existing installed capacities as a minimum for the initial investment period, 2030 and uses the previously determined capital stock as the minimum for the next investment optimization. All existing capacity is assumed to be sunk cost and is therefore excluded from the investment optimization calculation. The investments made in 2030 are assessed. Therefore, the NPVs calculated are for investments in 2030 and are normalized to 1 MW of capacity for each technology. The NPVs are calculated using a 7% discount rate.

4.2. Experimental setup

The experimental set up follows the modeling framework explained in Section 3.2 and the model flow diagram shown in Figure 3.1. A step by step explanation of the experimental setup is given below. See Figure 4.1 for a graphical representation of the experimental setup. This figure represents the setup for the optimal run and each MGA run (minimizing and maximizing each technology) and is therefore repeated 19 times.

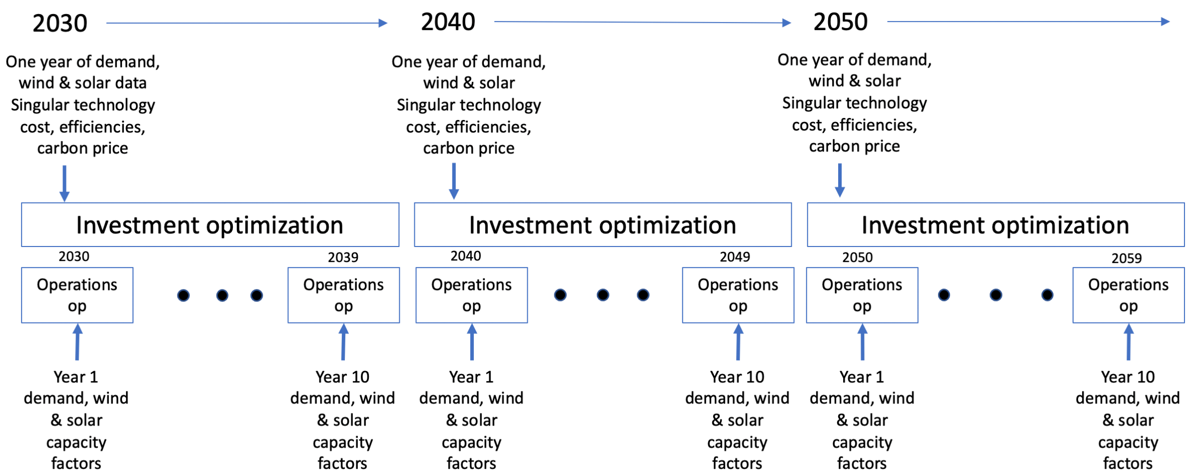

Figure 4.1: Graphical representation of the set-up for the optimal run and each MGA run.

1. A brownfield investment optimization for each investment period, 2030, 2040, 2050 is performed to determine the optimal installed capacity for each respective year. These optimizations are

based on historical weather and demand data from 2013. Existing capacity or capacity built in the previous optimization period is given. Existing capacities are considered sunk cost and therefore are disregarded in the optimization. The optimization determines endogenous investments in new capital stock.

2. MGA is performed using the optimal cost determined in step 1 for each of the investment optimization periods. The optimal cost plus a 10% cost deviation is encoded as a constraint. The objective function becomes the minimization or maximization of a certain technology. Alternatives are generated by minimizing and maximizing each technology (generators, storage units, transmission) one by one and determining the set of installed capacities while remaining within 10% of the cost optimal solution. 18 alternatives will be generated for each investment year (2030, 2040, 2050). Therefore, a total of 54 MGA optimizations will be performed. Similar to the optimal investment optimization, the MGA optimization is a multi-stage investment, where each investment year is optimized independently. The storage, generation, and transmission portfolios determined in the previous optimization period for the MGA run with the same objective will be used as minimum capacities for the the consecutive run.

3. A short-term optimization (dispatch optimization, only optimizing operations) is performed using the installed capacities determined in each of the MGA alternatives for each of the years in the investment periods (2030-2039, 2040-2049, 2050-2059). A set of 10 years of different historical demand, wind and solar capacity factor data (historical data from 2007-2017) are used to run 10 different short-term optimizations, each representing one year. The results give a range of future electricity prices and generator dispatch scenarios.

4. The resulting electricity prices and generator dispatch are used to determine the market value and NPV of each respective technology.

5. To account for the randomness of operation years, bootstrapping with replacement is performed over the operation optimization results. The dispatch and electricity price results from the operations optimization are randomly selected 1000 times and used to calculate 1000 different NPVs for each full model run. This provides a range of 1000 possible NPVs per full model run.

4.3. Model data

Techno-economic input data used in the model includes capital costs, variable and fixed operation costs, technology efficiency, technology lifetime, fuel carbon intensity, fuel price, greenhouse gas emissions, and potential renewable capacity. The majority of the data used in the model comes from the open source model, Python for Power System Analysis (PyPSA) (Brown, Hörsch, and Schlachtberger, 2018). The greenhouse gas emissions used to set the emission constraint in the model are from established government targets for the Netherlands and Germany of the allowable emissions from the power sector for the respective years. The VRE capacities for the Netherlands and Germany are the maximum installed capacity given geographical constraints. The historical installed generator capacity in the Netherlands and Germany are used as a basis for the model and to verify the model. For a complete table of all input parameters see Appendix A.

The demand is based on historical demand data from 2007-2017 for the Netherlands and Germany. To account for the anticipated increase in demand over the coming decades, the demand is increased by an additional 15% per investment stage relative to the reference year, 2020. In addition, the solar and wind capacity factors are based on historical capacity factors from the Netherlands and Germany for the years 2007-2017 (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016). All monetary values used in this study are in 2015 Euros.

4.4. Elastic demand parameters

The elastic demand parameters are calibrated using historical data. In this case study, the demand and weather data from 2015 is used to calibrate the elasticity demand parameters. The historical capital stock for the Netherlands and Germany are given as a parameter to the model. The installed generator capacities for the Netherlands, Germany, and total for both the Netherlands and Germany for 2015 are shown in Figure 4.2 below.

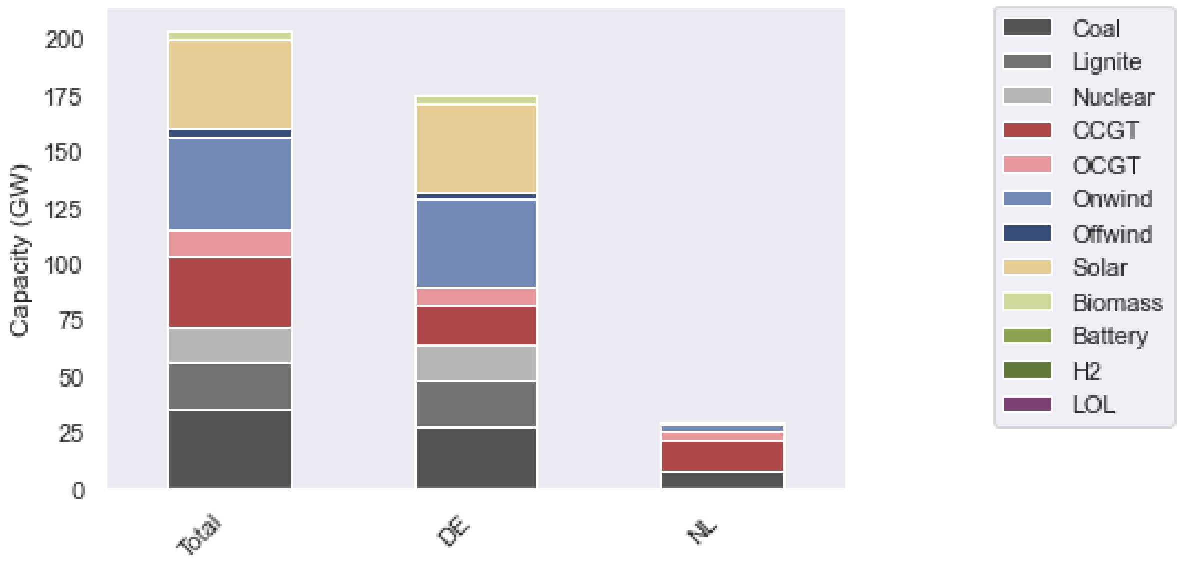

Figure 4.2: Bar chart of installed capacities by generator and storage types for both the Netherlands and Germany for 2015.

Many iterations of operations optimizations with varying elastic demand coefficients are then performed with the given historical capacities and weather and demand data to determine the elastic demand coefficients to be used in the model. The reference price (P_{ref}) is set at the average electricity price in 2015, 41€/MWh for the Netherlands and 37€/MWh for Germany. There are several model limitations that lead to the inability to accurately calibrate the elastic demand coefficients to historical values, including the exclusion of start-up and shut-down costs, ancillary services, must-run generators, strategic market bidding, or unique generators for each technology type (each technology is modeled as one generator with one set of marginal and capital costs). The average price and the price duration curves of the model are compared to historical values and the deviation of model prices from historical values are used to calibrate the elasticity coefficients. The slope of the demand curve, b, is calibrated to be approximately 0.01.

The price duration curve shows the electricity price over time, plotted in order of decreasing magnitude, revealing the number of hours in a year the electricity price is a given value. The load duration curves for the 2015 historical values and the 2015 model values are shown in Figure 4.3 below.

The most apparent difference between the historical prices and the model prices is the smoothness of the historical price duration curve compared to the model prices. This difference is primarily due to

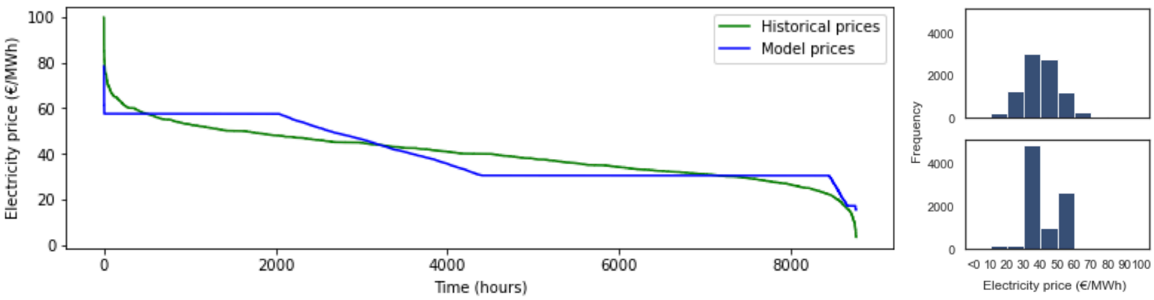

Figure 4.3: Price duration curve for the 2015 historical prices and the 2015 model prices.

modeling each generator technology as one unit, leading to the marginal cost to be the same for all electricity generation of the same technologies. As the marginal cost of the marginal generator sets the electricity price, this leads to the electricity price being the same price for many hours thorough out the year. The average electricity price in both the historical prices and the model prices is 40 €/MWh.

5

Model verification & validation

The model is verified and validated to ensure it can be used to adequately represent the profitability of investments in the power system, in other words, that the model is appropriate for the purpose it is designed for. Model verification and validation are the primary processes to provide evidence that the developed model can be used for its intended purposes (Thacker et al., 2004). Model verification is done to ensure that the computer programmed model correctly represents the conceptual mathematical model and accomplishes the conceptual goals outlined in Chapter 3 and 4. Model validation is the process of determining if the constructed model represents the real world to an acceptable degree. The model was consistently verified and validated during the development phase to ensure that each additional component added to the model was modeled correctly.

5.1. Model verification

Throughout the process of developing the model, there were numerous verification check points. The model was developed in a step by step manner, where in each step of the development a working model is built and each consecutive step, additional levels of complexity are added to the model, beginning with the most simplistic working model. A very simplistic one node model, only considering conventional generators, was built at the beginning. This base model could be easily verified against the graphical solution for the conceptual model. After this model was verified, additional more complex components were added and tested one by one to ensure that they were coded correctly in the model. These additional components include an additional node, renewable generators, storage units, the MGA optimization, minimum installed capacity for existing capital, governmental decommissioning targets, and constraints for maximum installable capacity for renewable generators.

5.1.1. MGA verification

The MGA optimization is verified by ensuring that for each MGA optimization, the total cost of the optimized alternative scenario (scenario minimizing or maximizing a certain technology) is within the epsilon value of the total optimal system cost. This analysis is performed to check whether or not the computer simulation model developed aligns with the conceptual definition of the MGA analysis, defined in Section 4.3.

5.2. Model validation

5.2.1. Capacity optimization validation

To validate the model, the final complete model is compared to real world historical data. To first test the capacity optimization, the optimal capacity optimization and MGA optimization are run for 2020 and the resulting capital stock is compared to the actual installed capacity in 2020 for the Netherlands and Germany. This validation is done to determine if the real installed capacity in 2020 are within the range of generated electricity systems using the methodology developed in Chapter 4.

This validation process supports the importance of performing an MGA analysis when performing energy system optimization modeling, as described in Section 2.2. The real power system has been shown to deviate from the optimal system due to the other, non-cost, factors (i.e social acceptance, risk of investments, imperfection of the market, irrational actors, decentralized decision making) that affect which energy system gets developed (Trutnevyte, 2016). The validation using the methodology developed in Chapters 3 and 4 and is run with precisely the same data input as the full working model. The demand and weather year is based on 2013 historical data, the same data year used in capacity optimization phase. Following the developed methodology, the capacity optimization is a medium-term optimization and therefore, all existing capacity is included. Per the methodology, the model assumes ten year investment periods, only allowing investments to occur in the first year of the investment period and takes the existing capacity to be the capacity installed 10-years earlier. Therefore, to test the year 2020, 2010 was used as the base year. All installed capacity from 2010, excluding decommissioned generators, are fed into the model as minimum capacities values per technology. Therefore, model includes the existing installed capacity and is able to optimize the system by adding additional capacity in addition to the existing installed capacity. Figure 5.1 compares the optimal and all MGA optimization solutions to the actual historical installed capacity in 2020. The figure reveals that the historical installed capacity values for each generation and storage type are within the range of installed capacities generated by the model, validating the models use to represent the real world. This validation process reveals that the range of solutions generated using the MGA methodology can encompasses the real world energy transition. This form of ex-post modeling can help reveal the necessity of uncertainty techniques when modeling the future energy system. As is revealed in Figure 5.1, the real world power system configuration deviates significantly from the optimal solution but the real world system falls within the range of MGA alternative system results.

It is also important to ensure that the build-out capacities from the capacity optimization in the model align with the historical values for each country. Due to the nature of the optimization model, capacity is built in the most cost-effective way, not considering individual country's policies or desire for energy independence. In the real world, a country's individual decision-making on power system developments can be a cause of deviation from the overall cost optimal solution. In addition, innate to the design of the model and due to the difficulty of associating emissions to each respective country, because of cross-boarder transmission, the CO_2e constraint in the model is the cumulative allowable emissions for the Netherlands and Germany. In reality, each country has their own emission reduction targets that they aim to achieve and therefore, the transition in each country might deviate from the model in

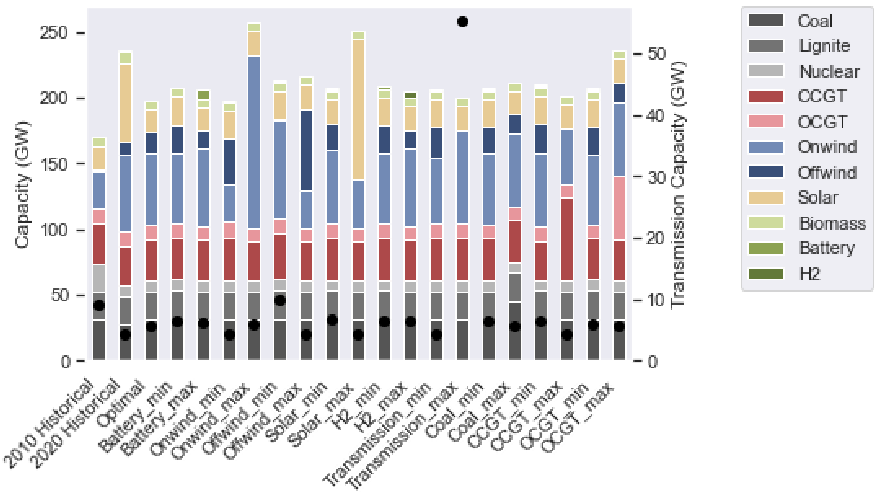

Figure 5.1: Bar chart of installed capacities by generator and storage types for both the Netherlands and Germany of the historical, optimal, and each MGA alternative.

this regard. The model does not consider that each countries power system will transition in light of achieving their emission reduction targets while maintaining a certain level of domestically produced power for energy security. The model determines the (near) cost-optimal without considering if that solution would achieve each respective countries power generation emission reduction targets and ensure each country retains a certain amount of domestically produced electricity. This could be a source of deviation of the model from reality. The EU as a whole has emission reduction targets (i.e. the European Green Deal's 55% emission reduction target by 2030 and net zero emissions by 2050). These generalized targets are inline with the way the model is currently programmed.

5.2.2. Insights from capacity optimization validation results

Insights can be drawn from the validation analysis to better understand how the model represents real world installed capacities. As can be seen from Figure 5.1, the actual cumulative installed generation capacities in 2020 are greater than the majority of the MGA alternatives and has approximately 29 GW (or 16%) more installed capacity than the cost optimal solution. It is important to acknowledge that the model is optimized on the basis of 2013 weather and demand data and therefore one of the sources of the deviation of the resulting optimal model from the actual cost optimal power system for 2020 is the difference between historical demand and weather data for that year and those of 2013. This is representative of a main source of uncertainty when optimizing the future energy system, the weather and demand data. The parametric uncertainty is outside the scope of this analysis but should be explored in further research, particularly how parametric uncertainty can be explore with the MGA uncertainty technique.

5.2.3. Operations optimization & electricity price validation

The full model is validated, the capacity optimization and the operations optimization, by performing an ex-post optimization of 2019. Similar to the capacity optimization validation performed in the previous section, 2010 is used as the base year. The operations optimization and electricity price validation is done for the year 2019, as historical electricity data for the whole year was available at the time of performing the analysis. Therefore the validation of the electricity prices is done assuming the base year is 2010 and the capacity and operations optimization is performed for 9 years later, the year 2019. This deviates from the actual model, as the actual model calculates the capacity optimization in 10 year segments, not 9 years. For this reason, the capacity optimization is validated for 2020 to account for a 10 year optimization segment.

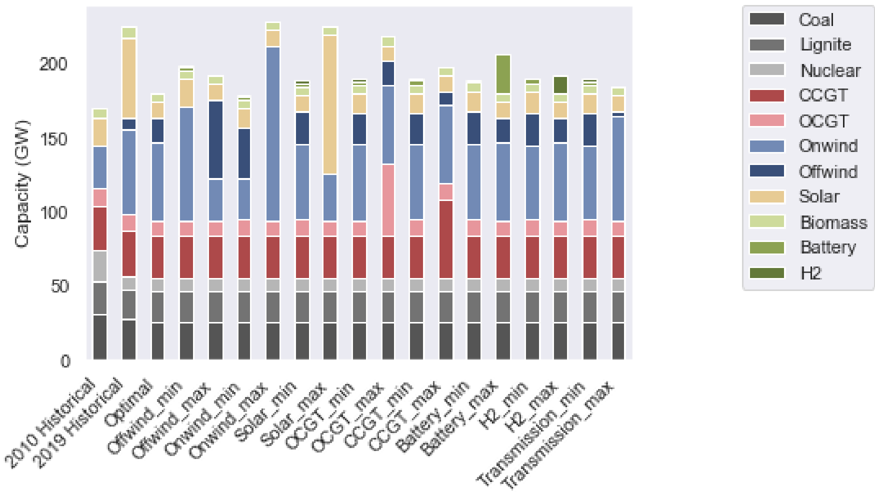

Figure 5.2: Bar chart of installed capacities by generator and storage types for both the Netherlands and Germany of the 2010 and 2019 historical values and the 2019 optimal values and values for each MGA run from the model.

The resulting electricity prices for each alternative is compared to historical values. These price duration comparison graphs are in Appendix C. The comparison of the model derived price duration curves with the historical values reveals that the model typically has higher electricity prices than occurred in reality. However, the average electricity prices are encompassed in the set of alternative runs. This provides verification that the set of near optimal solutions can be used to explore potential electricity prices. The higher electricity prices in the model can be due to a number of factors, primarily that the input parameters do not precisely align with real world values. These values include the cost data, technology data, and weather and demand data. This suggests that a parametric uncertainty analysis should be incorporated in future research to account for the uncertainty in these parameters.

5.2.4. Insights from operations optimization validation

There are larger variations in real world electricity prices compared to the model generated electricity price. This is a result of the model simplifications compared to the real world power system. First of all, each technology type is model as one larger unit, instead of several different unique unit for each type of technology as it is in the real world. The different units in reality cause differences in the marginal cost of each plant, leading to slightly different bid prices into the electricity market. These different bid prices leads to more variability in electricity price than is experienced in the model. In addition, the model does not consider shut-down or start-up costs, must-run generators, or market behavior of system actors. This leads to no negative prices in the model even though negative prices are possible and seen in the real power market. To obtain a model that more accurately represents the real power system, the additional components should be added to the model. The model only considers a two-node system, therefore, excluding the effects that the other interconnected countries have on the Dutch and Germany electricity systems and market. The Netherlands has additional direct electric transmission lines with Belgium, Great Britain, Norway, and Denmark. The interconnection between countries in Europe can have a large affect on individual countries electricity prices. Therefore, excluding these interconnection capacities in the model can be another cause of the deviation in the model electricity prices from historical values.

In addition, due to the simplifications of the model, demand elasticity parameters are difficult to model to historical values. A more complex model and proper calibration of demand parameters with historical prices, would lead to a more accurate representation of the real world electricity prices and should be performed in future work.

6

Case study: Results & analysis

6.1. Optimal results

In the first phase of the problem, the long-term investment optimization is performed to generate the optimal solution of installed capacities for 2030, 2040, and 2050. The optimal total installed capacities for the modeled 2-node system are given in Figure 6.1.

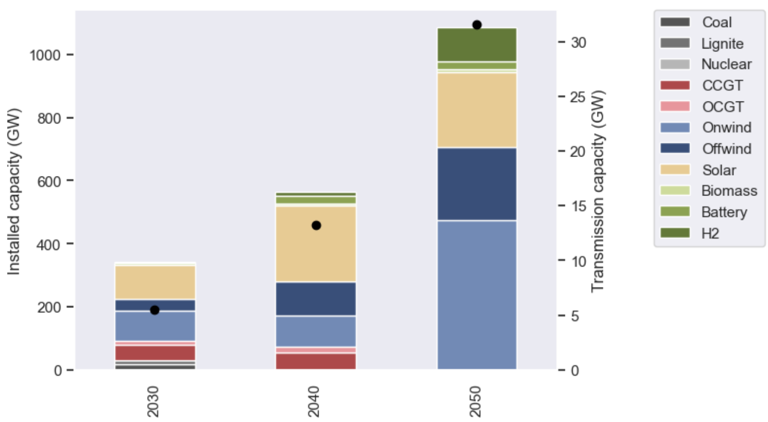

Figure 6.1: Bar chart comparing the installed total generator, storage, and transmission capacities for both the Netherlands and Germany for the optimal solution in 2030, 2040, and 2050. The generator and storage capacities are shown by the bars (left axis) and the transmission capacities are given with the points on the graph (right axis).

As can be seen from the figure, the necessary installed capacities increase over the 3 investment periods. This increase stems from a combination of the increase in demand that is assumed in the model and the increase in capacity that is required to account for the intermittency of VREs. In the 2050 time frame, wind dominates the system with solar providing the remainder of necessary generation capacity. The optimal transmission capacity is 32 GW, approximately 7 times the currently installed transmission between the Netherlands and Germany of 4.5 GW. In the zero emission scenario in 2050, the increased transmission capacity and the storage in the system help to smooth out the intermittency of the VREs. This is critical given that the only generation technologies in the system in 2050 are wind, solar, and a little bit of biomass. To achieve these optimal installed capacities, the model endogenously determines a CO2 price of 69 €/MWh in 2030 and 170 €/MWh in 2040. In 2050, there is no CO2 price as CO2 emission constraint is set to zero, aligning with emission reduction targets. The CO2 price is the dual variable of the CO2 limit constraint in the investment optimization.

The total generation for the optimal 2-node system modeled for each of the investment optimization runs (2030, 2040, and 2050) are given in Figure 6.2, this is assuming the average weather and demand year that is used in the investment optimization, year 2013. Comparing Figure 6.2 to Figure 6.1, it is clear that total installed capacity experiences a more significant increase over the model time horizon than the total generation. The total consumption is modeled to increase an additional 15% per investment period from the base year, 2020. The consumption is approximately equal to generation in the 2030 optimal system. This results from the fact that no transmission losses are modeled and the system has no storage and therefore, all power generated is consumed. In 2040 and 2050, generation is greater than consumption due to the inclusion of storage in these years. Storage experiences losses, losses from battery charging and discharging and the production of hydrogen from electricity through electrolysis and back to electricity with a fuel cell.

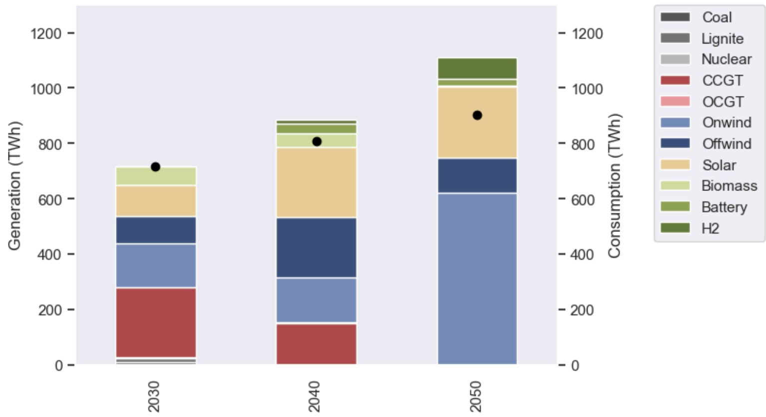

Figure 6.2: Bar chart comparing the total generation for the Netherlands and Germany per technology for the optimal solution in 2030, 2040, 2050 of a average operations year (year used in the investment optimization).

For each of the investment periods, a sequential operations optimization is run 10 times, for a range of 10-years of historical weather and demand data. The capacities determined in the investment optimization for each respective investment period are used as input. The results give a variety of ten year sets of generation and electricity prices for each investment period. The variation in the generation per technology over these 10 years for each investment period for the optimal optimization are shown in Figure 6.3.

The figure shows both the change in generation over each respective investment stage (2030-2039, 2040-49, 2050-59), as well as the variation in generation within each respective investment stage. The variation within the investment stages results from the variation in weather and demand data used for each of the short-term optimizations. Fossil production is nearly halved from 2030 to 2040, with no coal or lignite remaining in 2040, and further reduced to zero in the 2050 time frame. In the 2050-2059 time frame, the majority of the generation comes from the installed onshore wind.

Following the two step optimization of the optimal scenario, the MGA optimization is performed for each technology. The additional system costs of the optimal scenario plus a 10% cost increase are coded as a constraint. The optimization objective becomes the minimization or maximization of the

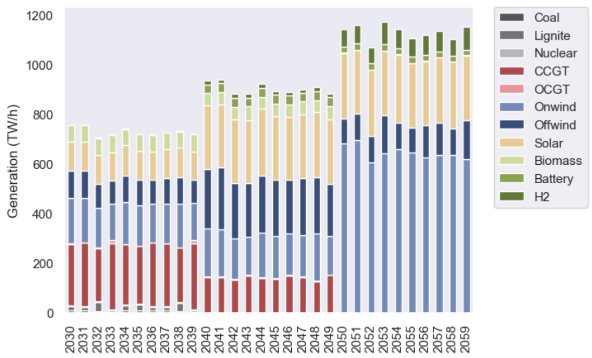

Figure 6.3: Bar chart comparing the total generation for both the Netherlands and Germany per technology for the optimal solution over the entire modeled time horizon: 2030-2059.

various generation, storage, and transmission technologies. The MGA optimization is run 16 times, minimizing and maximizing each technology. The resulting total installed capacities for the Netherlands and Germany for each MGA alternative as well as the optimal scenario are shown in Figure 6.4.

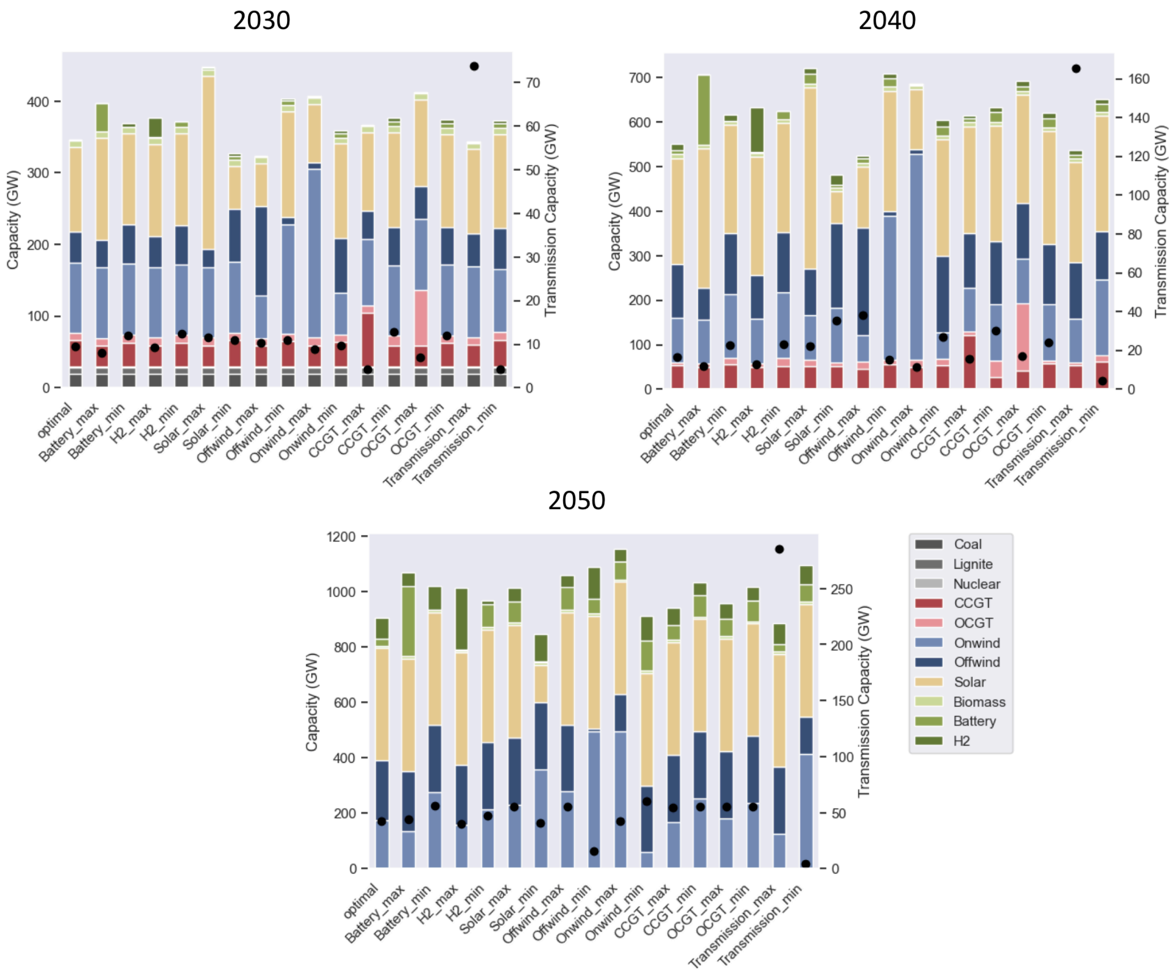

Figure 6.4: Bar chart comparing the capacities for both the Netherlands and Germany for each alternative generated using MGA for 2030, 2040, and 2050.

As a result of the MGA analysis, the figure reveals that within the 10% cost increase from the optimal solution there are a wide variety of possible near optimal power systems. This provides important insights for both investors looking to invest in the future power market, as well as regulators trying to implement policy to push the deployment of clean technologies and achieve their greenhouse gas emission targets. There are many different near-optimal pathways that allow for emission reduction targets to be met. This opens up the possibilities and can provide support and an increased degree of freedom in decisions both for investors and for policy makers. The exploration and acknowledgement of these various pathways are essential because there are factors other than cost that affect the development of the power system, as explained in Section 2.2.6. These alternative factors are often difficult to incorporate or anticipate, but they can play an important role in the the development of the power system. Relaxing the cost constraint allows for the model to help encompass the range of energy systems that can occur in the reality. Figure 6.5 shows the range of installed capacities per technology for each investment period from the generated alternative power systems that are within 10% of the cost optimal solution.

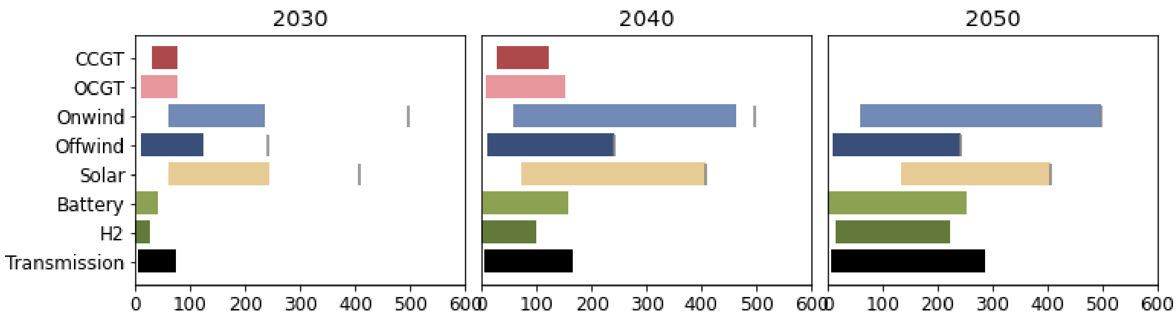

Figure 6.5: Bar chart comparing the capacities for both the Netherlands and Germany for each alternative generated using MGA for 2030, 2040, and 2050. The grey plotted line markers denote the total maximum potential renewable energy capacities in the Netherlands and Germany.

As can be seen in Figure 6.5, several technologies have a wide range of possible installed capacities in the range of near-optimal solutions. It is important to note that in 2050, an increased amount of onshore wind, solar, and hydrogen storage are all required to be in the power system to remain within 10% of the cost optimal solution. Each of these technologies is required at capacities greater than their currently installed capacities. The greatest flexibility is installed onshore wind. Several conclusions can be made from figure 6.4 and 6.5. By 2040, the offshore wind and solar maximum alternatives reach the maximum potential for each respective technology in at least one MGA solution. By 2050, onshore wind reaches its maximum installed capacity in two of the near optimal solutions, the MGA run maximizing onshore wind capacity and the run minimizing offshore wind capacity. Onshore wind reaches its maximum potential in 11 near optimal solution runs and solar in 16 runs, all but the MGA run minimizing installed solar capacity.

6.2. Results for the Netherlands

The results for the Netherlands are given in this section. It is important to note that there is a global emission constraint that constrains the total emissions for both the Netherlands and Germany in the model. This causes the location of VRE technology development to be based on weather data for each respective location, within the limits of the built transmission capacity.

Figure 6.6 shows the optimal installed capacities for 2030, 2040, and 2050 in the Netherlands. Offshore wind experiences a significant increase between 2040 and 2050, dominating the power system in the 2050 time frame. This large increase in offshore wind is due to the fact that onshore wind reaches its maximum capacity potential in the Netherlands in 2030 and wind capacity factors are more favorable in the Netherlands compared to Germany. As there is no constraint set on how much electricity can be imported in each country in the model, the Netherlands' favorable wind capacity factor lead to a large installed capacity of wind and therefore, a large generation of wind. Therefore, to provide for the increase in demand in both the Netherlands and Germany and the power production losses from the decommissioning of gas plants, offshore wind is maximized in the Netherlands in 2050.

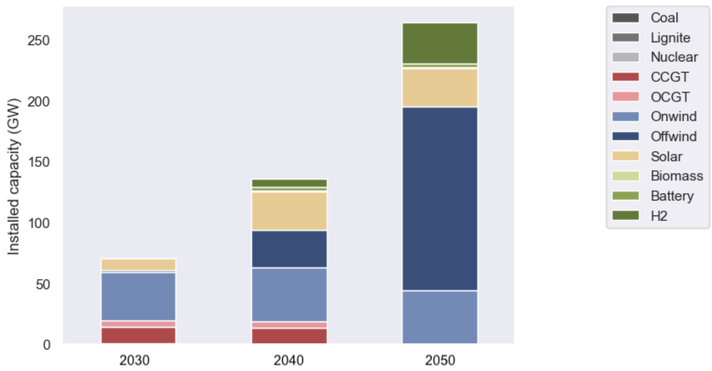

Figure 6.6: Bar chart comparing the total capacities the Netherlands for the optimal solution in 2030, 2040, and 2050.

Similar to Figure 6.4, Figure 6.7 shows the total installed capacities for the Netherlands for each MGA alternative and the optimal case for 2030, 2040, and 2050. As can be seen in the figure, there is a large amount of variation in the near-optimal solutions, particularly in the 2040 time frame. In 2040, offshore wind experiences the largest range of possible installed capacities, some alternatives experience no increase in offshore wind compared to the currently installed capacities, where as the offshore wind maximization scenario maximizes the possible installed capacity. By 2050, the majority of alternatives reach the maximum capacity potential for solar and wind. In 2050, offshore wind dominates the the Netherlands energy mix. These results suggest that there are many alternative transition pathways for the Netherlands, but many of the alternatives converge in order to reach full decarbonization in 2050, with much less variability of alternative solutions in the long-run. In most alternatives in 2040 and all but one alternative (minimizing onshore wind alternative) in 2050, onshore wind is maximized. Storage capacity in 2050 is comparably a larger portion of the overall installed capacity compared to storage in Germany.

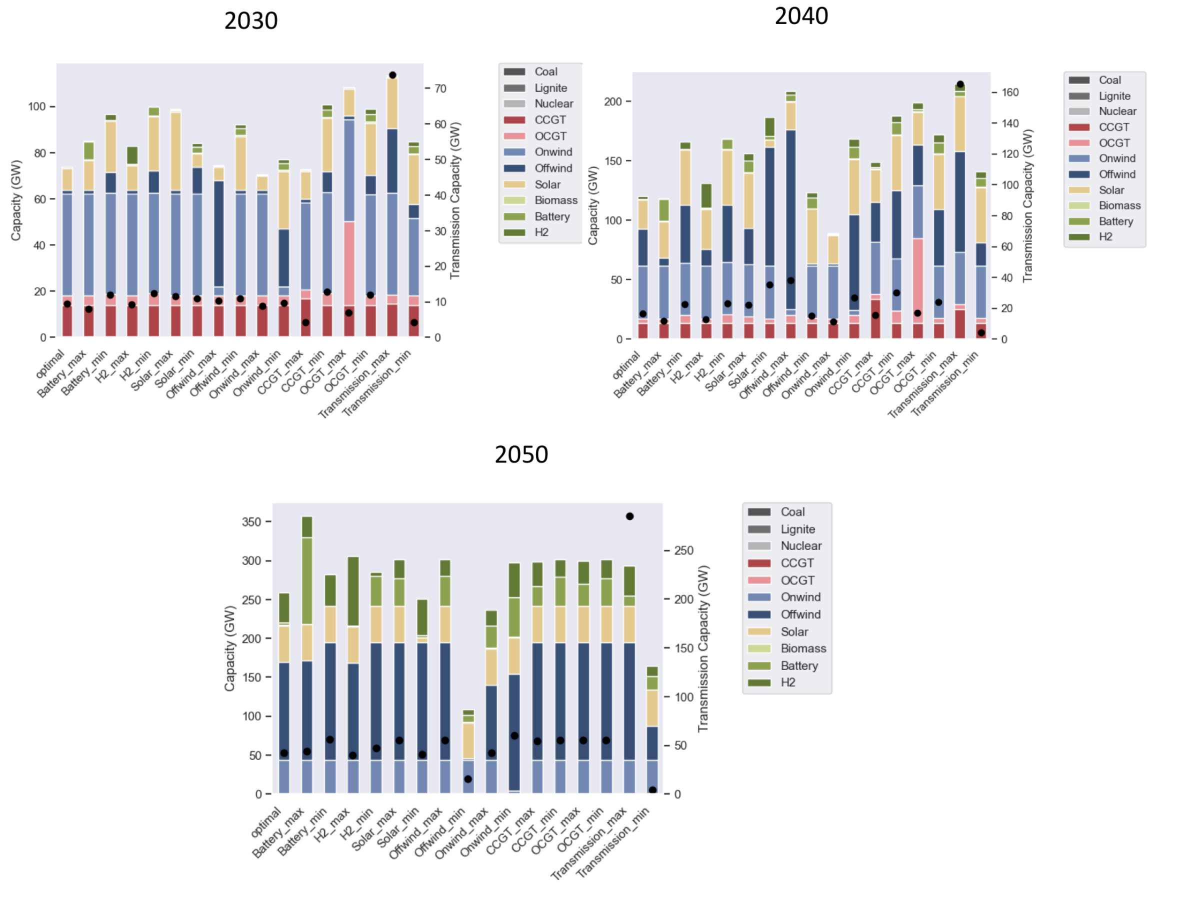

Figure 6.7: Bar chart comparing the built out capacities in the Netherlands for each alternative generated using MGA for 2030, 2040, and 2050.

Figure 6.8 shows the range of installed capacities per technology for each investment period from the generated alternative power systems that are within 10% of the cost optimal solution. In some alternatives, the onshore wind is at the maximum potential for the Netherlands and by 2050. In all alternatives but one, minimizing the onshore wind, have the maximum possible capacity of onshore wind installed. This suggest that all onshore wind should be invested in and developed in the Netherlands.

To stay within 10% of the cost optimal solution, the model finds there needs to be between 3.9-44 GW of onshore wind, 1.7-151 GW of offshore wind, 6-46 GW of solar, 0-111 GW of battery storage, and 5-89 GW of hydrogen storage in the Netherlands for a carbon neutral power system in 2050. This is approximately 1-11 times the onshore wind capacity, 1-88 times the offshore wind capacity, and 1-8 times the solar capacity currently installed in the Netherlands. Substantial investments are required in the power system over the next 30 years to reach emission reduction targets and satisfy demand.

For each of the 51 power systems shown in Figure 6.7, 10 different optimizations are performed for the ten various demand and weather years. The operation optimization determines the optimal dispatch of each technology to satisfy the demand at the least cost. The optimization gives the generation of each technology at each hour and determines the LMP for each node at each hour. As described in Section 3.6.4, the LMP is the shadow price of the nodal energy balance constraint. Figure 6.9 shows a sample week of dispatch and electricity prices for the Netherlands and Germany from the model for the year 2030. The electricity prices at each hour are determined through the dual variables of the objective

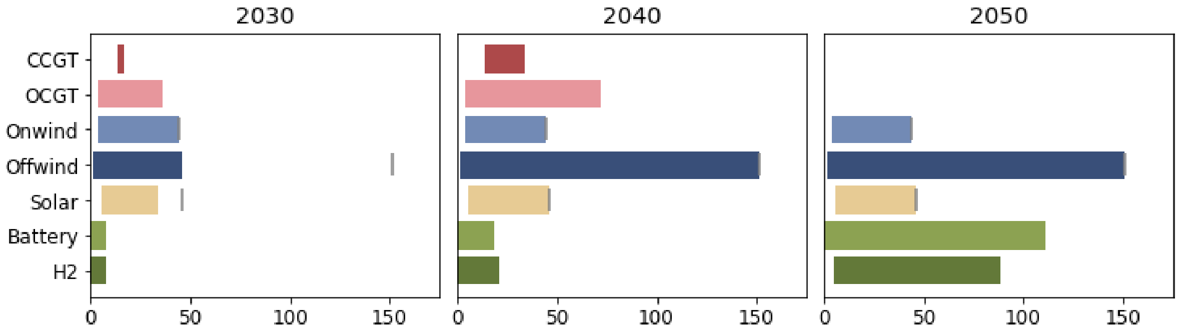

Figure 6.8: Bar chart comparing the built out capacities in the Netherlands for each alternative generated using MGA for 2030, 2040, and 2050. The grey plotted line markers denote the total maximum potential renewable energy capacities in the Netherlands.

function (see Section 2.1.1). As can be seen from the graphs, at times when only VRE supplies all of the demand, the electricity price is close to 0 €/MWh, as the marginal price of VRE is assumed to be close to 0 €/MWh. The graphs show the variation of electricity due to the variation of which generator is the marginal generator at each hour. It is important to note that conventional generators marginal price includes the CO_2 price. The peak electricity price around hour 5420 is a result of coal being the marginal generator and due to the high emissions from coal generation, the CO_2 causes coal to have a high marginal price.

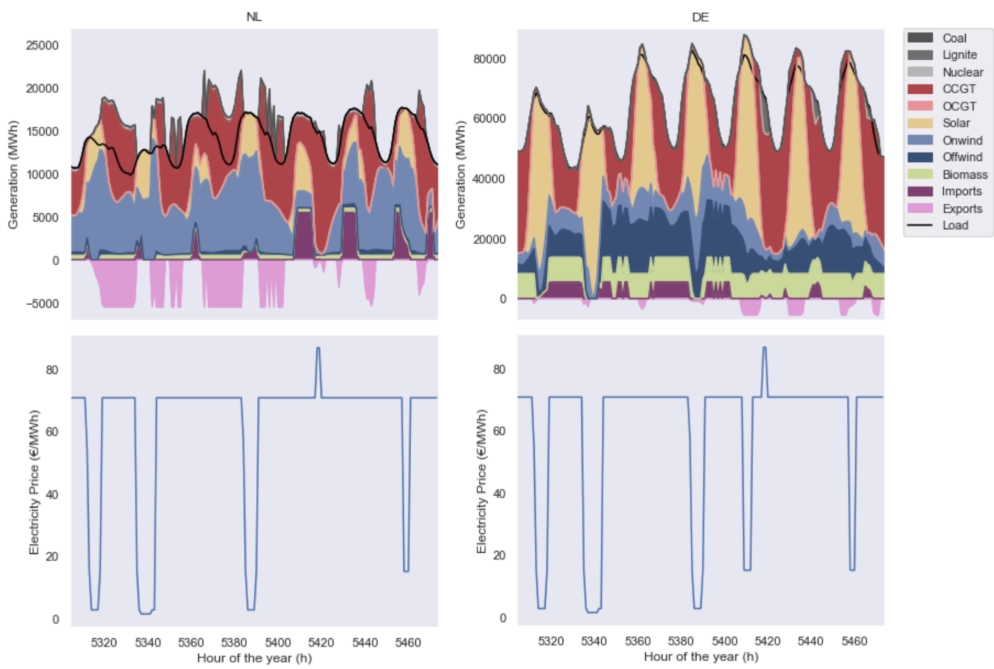

Figure 6.9: The top two graphs are stacked dispatch curves for all generation for a week in August from the 2030 model results. The bottom two graphs are the corresponding LMP curves over the same week in August. The graphs on the left are for the Netherlands and on the right are for Germany.

For each operations optimizations, a set of dispatch and marginal electricity prices for the Netherlands and Germany for every hour in a year are generated. In figure 6.10 histograms of the hourly electricity prices for each investment period are given. The electricity prices are clustered around certain prices.

In reality, electricity prices are more distributed and experience more variation. In the model, each generator type is modeled as one large generator rather than each individual generators that have their own distinctive marginal price, as is the case in reality. This deviation from reality causes the electricity prices to be less distributed. In addition, the fact that only the Netherlands and Germany are modeled eliminates the influence of other surrounding countries on the electricity prices.

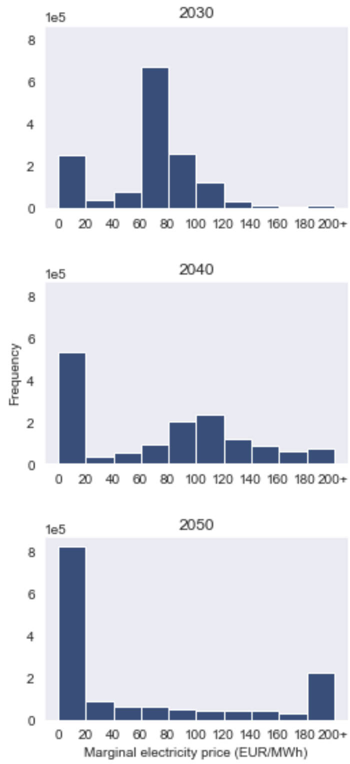

Figure 6.10: Histogram of all the LMP for all runs for each investment time period. Electricity prices greater than 200 EUR/MWh are all in the last bin.

For each investment period the electricity prices decease. In 2030, the average electricity price is €62/MWh, €66/MWh in 2040, and €64/MWh in 2050. Although the distribution of electricity prices changes through each of the investment periods modeled, the average electricity price remains around the same price. The increasing frequency of close to zero electricity prices over the time periods results from the increasing installed capacity of VRE sources in the system. With marginal based pricing, at times when there is enough VRE sources, the electricity price is set close to zero, as the marginal price of VREs is near zero. These lower electricity prices can lead to situations where the VREs cannibalize their own revenue. The absence of conventional generators means that CO2 pricing can not be used to ensure adequate electricity prices. However, the increase in storage capacity in the system can help to stabilize electricity prices through price arbitrage. Storage units can purchase electricity and charge or produce hydrogen at times when electricity is cheap and can sale electricity back to the grid (by discharging or producing electricity from hydrogen) at times when there is a shortage of renewable sources. This buying and selling of electricity by storage units helps to increase the variety of electricity prices rather than having a few instances throughout the year that have very high prices and the rest of the hours of the year have zero prices. The ability for storage to stable the electricity prices is limited by their storage capacities. In this optimization, the storage capacity of hydrogen and batteries is set to be that the batteries can discharge at full capacity for 6 hours and hydrogen for 168 hours.

The change in the distribution of electricity prices over the course of the year for each time period examined can be seen in Figure 6.11. The figure shows representative price duration curves for the optimal optimization solutions for one year in each of the investment periods (2030,2040, and 2050).

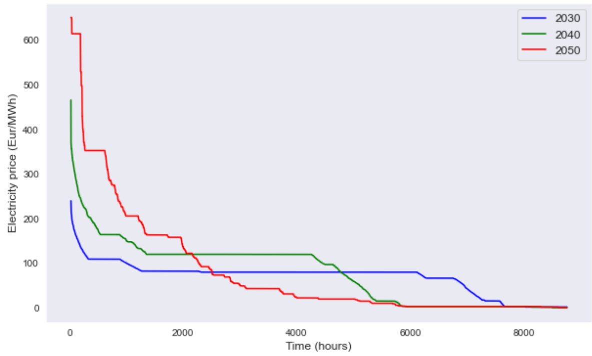

Figure 6.11: Price duration curves for 2030, 2040, and 2050 of the optimal scenario.

From the graph, it can be seen that with increasing investment periods, the number of hours that have close to zero electricity prices increases, correlated to increasing wind and solar generation. In addition, in the 2050 time frame, the increased capacity of storage in the system leads to a wide variety of electricity prices, as the storage units are able to buy and sell electricity. In future work, the electricity prices in a fully renewable system should be further explored. Allowing the storage unit capacity to be optimized could possibly lead to alternative electricity price behavior in the case of a fully renewable system. In addition, the energy system will progress to being more integrated; the future zero emission power system will be highly integrated with the rest of the energy system. Therefore, the other sectors of the energy system will influence the power system and the power system prices. Hydrogen is modeled as being exclusively used in the power system. However, hydrogen is used in other sectors and therefore has an associated commodity price. Hydrogen will likely be integrated through different energy systems and therefore will be sold at the set commodity price back into the power system. Future research should explore the integration of the power system with the entire energy system to get more accurate results.

The hourly electricity prices and dispatch of each respective technology are used to calculate the yearly revenue per technology. Bootstrapping is used to randomly select 10 years of revenue results within each investment period. This is done to help account for the uncertainty in future weather and demand, as each of the weather and demand years is equally as likely to occur in the future. Bootstrapping is performed 1,000 times and then the NPVs of each of the bootstrapping alternatives is calculated. The resulting NPVs for the Netherlands are shown in Figure 6.12. The NPVs are for capacity installed in 2030 and then run over the course of the next 30 years. The histogram provides the frequency of the NPVs For each installed technology. The color of the bars reveal the frequency and NPVs for each alternative optimization, the optimal and all MGA alternatives.

The majority of the NPVs for the generation technologies are clustered around 0, leading to no clearly favorable investments. Based on these results, investments in the Dutch power system in the 2030 time frame appear to have high risk. In a typical optimal result from a perfect foresight energy system optimization model, the NPVs of all generation and storage technologies in the system would have an NPV of zero, every generator and storage unit would follow the zero profit rule. However, the modeling framework developed in this model provide power systems with a range of NPVs for each

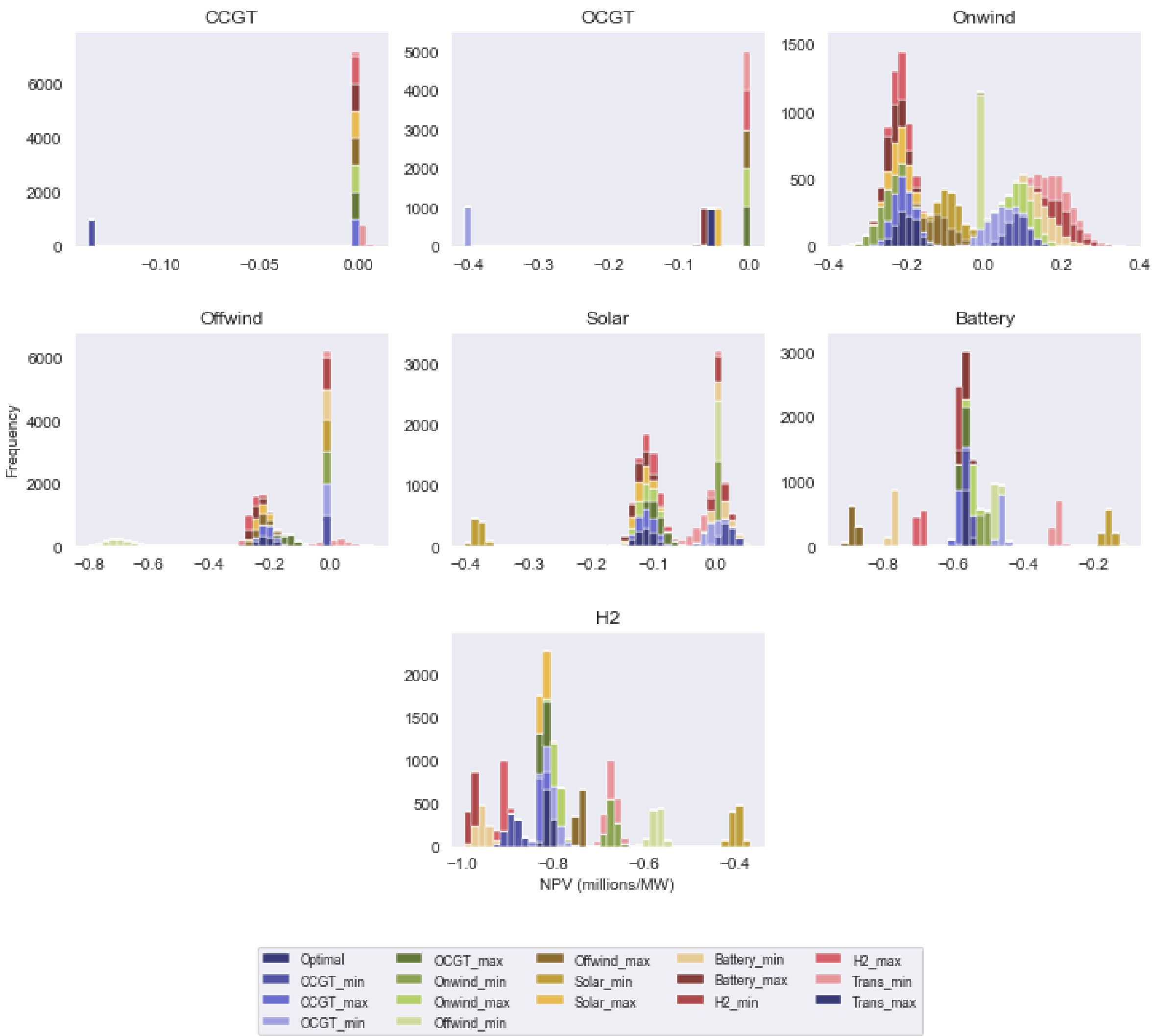

Figure 6.12: Histogram of NPV for technologies built in 2030 with bootstrapping 1,000 possible combination of NPVs within each 10-year investment period.

technology. This is due to the fact that the modeling framework considers a myopic, imperfect power system, intentionally deviating from a perfect competitive market to help account from the imperfections that occur in the real world power market. Storage technologies have the least favorable business case, with negative NPVs for all alternatives. In 2030, no storage technologies are built in the Dutch power system in the optimal case. However, batteries and/or hydrogen storage are built in some of the MGA alternatives. The results indicate that investments in storage technologies are unfavorable in the 2030 time frame in the Dutch power system.

Figure 6.13 visualizes the same data as Figure 6.12 as box-plots. This alternative graphical representation allows for the affect different MGA alternatives have on each technologies respective NPVs to be seen more clearly. The box plots show that the MGA alternatives that maximize a technology result in the amongst the lowest NPVs for the respective technology, particularly for CCGT, OCGT, offshore wind, solar, and hydrogen. This suggests that when more than the optimal amount of a technology is built, the technology cannibalizes its own revenue. For the case of onshore wind, additional flexibility options in the system, such as increased storage or transmission capacity, lead to higher NPVs. The increased flexibility that storage and transmission provide to the energy system help to mitigate the cannibalization effects that VREs face (Prol, Steininger, and Zilberman, 2020). The ability for storage technologies to arbitrage, purchase electricity and charge when electricity prices are low and discharge and sell electricity when price are high help to stabilize the electricity price and therefore damped the cannibalization effects experienced by VREs. Large distributions within an alternative indicates that the weather and demand year has a relatively larger effect on the revenue for the given technology.

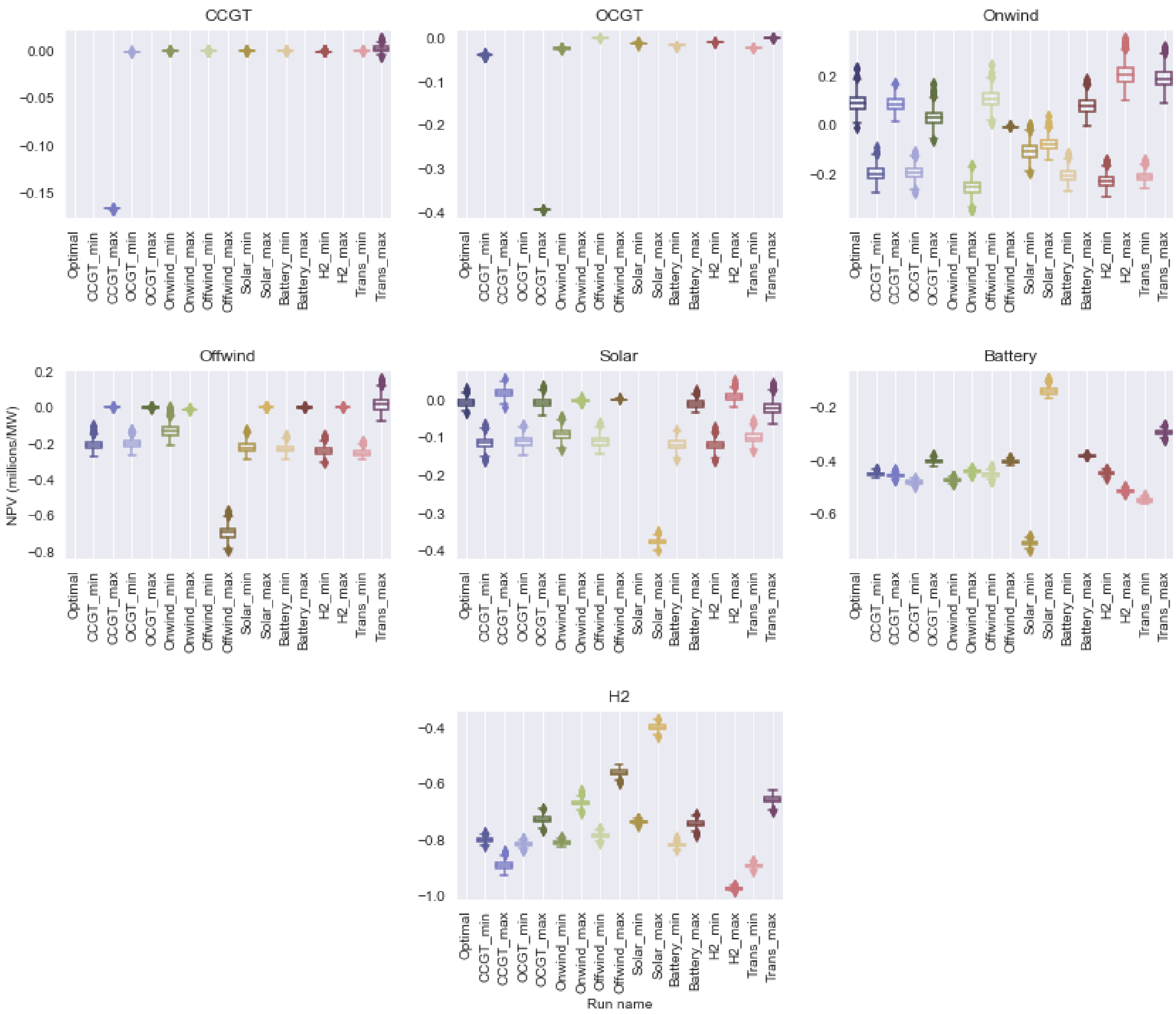

Figure 6.13: Boxplot for each run of NPV for technologies built in 2030 with bootstrapping 1,000 possible combination of NPVs within each 10-year investment period.

7

Discussion, research limitations & further research

In this thesis, the goal was to investigate if ESOMs could be used to help aid in energy investment decisions. The modeling framework developed in this research and the case study proof of the concept revealed how energy system optimization modeling can be used for investment decisions. The combination of the range of near-optimal solution for the installed capacities for 2030, 2040, and 2050 paired with the results from the investment analysis provide useful insights into the power system and the power market. Investors can use the combination of these results to help support investment decisions as the energy system evolves to achieve emission reduction targets.

Throughout the research, the necessity and importance of appropriate uncertainty analyzes was very apparent. To be able to account for the variability and uncertainty in the power system and provide useful insights for energy system developments, extensive uncertainty analyzes must be performed. To adequately use ESOMs for energy investment decisions requires a full scale uncertainty analysis. Due to the limitations of the study, only the structural uncertainty was considered and modeled. The analysis focuses on Modeling-to-Generate Alternatives and does not consider parametric uncertainty. To perform a complete assessment of the profitability of the future energy system and gain further insights into investment decisions, a full uncertainty analysis should be performed including a robust uncertainty analysis over the parametric uncertainty. Particularly, the demand and weather year used to perform the capacity optimization should be explored. The affects of various years on the profitability of investments is explored by using various historical weather and demand data in the operations optimization portion of the modeling framework. In the operations optimization, the demand and weather data from 2007-2017 is used to help represent the variability of weather and demand data that exists from year to year and to reveal how, based on a power system configuration, the profitability of different generator and storage units changes with various weather and demand data. However, the determination of the capacity in the model is currently performed over one year - the capacity optimization is performed using one, average weather year, the year 2013. In addition, the demand is modeled to be elastic but correlated to and based on reference values from 2013. Therefore, the optimization determines the optimal installed capacity for 2030, 2040, and 2050 assuming that the weather and demand (scaled to account for expected growth in electricity demand) for each of the future years is equivalent to 2013. However, in reality, the demand and weather data varies significantly from year to year. The model should be further developed to account for the parametric uncertainty in the demand and weather. The need for the incorporation of uncertainty in the demand can be particularly seen in the drastic reduction in power demand that occurred in the spring of 2021 due to Covid-19. The high levels of renewable generated electricity combined with reduced power demand from Covid-19, led to record levels of negative electricity prices (Halbrügge et al., 2021). Models used to forecast the future should be able to account for instances as unforeseen as Covid-19 or for periods of extremely low wind and solar production, such as the Dunkelflaute. In addition, modeling the uncertainty in weather data is becoming increasing important as climate change is leading to more extreme weather conditions across our global, having significant impacts on both the generation of solar and wind generators and on the power demand (particularly the heating and cooling of buildings). Increased storage capacities will be needed to account for extreme weather conditions.

Another essential input parameter to consider the uncertainty of is the technology cost inputs. Singular cost projects are currently considered for all fuel prices and technologies. In reality, there are a large amount of uncertainty in the future fuel and technology prices in the 2030-2050 time frames due to uncertainty in the learning curves of technologies, technology uptake, and the cost of raw materials used to make the generators, storage units, or transmission lines.

In addition, the carbon emission constraint should be explored. The current study is performed under the assumption that government outlined emission reduction targets are achieved. The power system configurations generated all met carbon emission reduction targets. However, in reality this is likely to not exactly be the case. To get a full view of investments in the future power system, the carbon emission constraints should be explored. In addition, although the MGA uncertainty analysis is performed, identifying a range of near optimal solutions that can help account for the development of systems that fall outside of the cost optimal solution, scenarios that cover for redundancy in the system for situations that compromise the security of supply (e.g. irregular weather events, unusual disruptions in supply) or for political/strategic reasons (e.g. energy independence, power reserves) are not explicitly explored. Additional constraints and/or relaxed constraints can be added to the model to help account for these factors (e.g. constraints that ensure a country produces a certain percentage of their consumed electricity can ensure a certain level of energy security). Within the uncertainty analysis performed, MGA, additional slack values that bound the feasible space can be explored to see how the model results differ under different cost deviations from the optimal cost solution. Relaxing the cost slack values leads to a wider range of possible system configurations, accounting for a wider range of factors, outside of cost, that influence the system. Tightening the cost slack value leads to a less diverse set of alternative power systems, and therefore leads to a range of near cost optimal solutions that are closer to the cost optimal solution.

The case study is a very simplified 2 node system to show the methodology developed in practice. To be able to drawn more accurate and deeper insights into the investments for the Dutch grid, a more expansive and detailed model would need to be developed or an already developed model could be used. The modeling of only two countries, the Netherlands and Germany, under-represents the flexibility provided by surrounding countries and underplays the possible flexibility provided by interconnection with other countries. In reality, the Netherlands' interconnection with other surrounding countries (i.e. Norway, Belgium, Denmark, the UK) and the potential for increased interconnection allows for additional flexibility options in the system. The interconnection with the other surrounding countries can play an important role on the Dutch grid and therefore, the power systems of surrounding countries should be modeled as well, with the most ideal scenario being modeling the entire European power system.

In addition to a spatial resolution of 2 nodes (one node per country), and a temporal resolution of 1 hour over the course of a full year are modeled in the case study. The model uses an hourly temporal resolution to help account for time dependent nature of VREs. The 2-node system was chosen for simplicity and computational limitations. There are significant trade-offs between spatial and temporal resolution and computation time. Energy system optimization modeling is computationally intensive (Hörsch and Calitz, 2017). Increasing the number of nodes (i.e. spatial resolution) helps expose transmission bottlenecks and variation in renewable resources but requires more computation time (Hörsch and Calitz, 2017). Low spatial resolution underestimates total cost by ignoring transmission bottlenecks that either require transmission upgrades or restrict welfare-enhancing transfers and lowers average capacity factors by average renewable resources over a large area (Hörsch and Calitz, 2017). Clustering the spatial resolution to one node per country smooths the variability in VRE production to appear less variable than is the case in the real power system with many nodes. In high spatial resolution models, sites with high renewable resource capacities can be fully exploited (Hörsch and Calitz, 2017). Therefore, to help overcome these limitations, higher spatial and temporal resolution can be used. Further research should be done into reducing necessary computation power needed to solve the problem or ways to use more computation power, such as high distributed optimization methods. This is essential when considering modeling a larger spatial area and performing complete uncertainty analyses.

The model considers 10-year investment periods and new capacities can only be built at the being of each 10-year segment. In reality, investment can occur at any point in time. To improve upon the model and the analysis, further research should look to decrease the length of the investment period to more accurately represent the real power system. In addition, the operations model could be more detailed and advanced. To do so, a key element that should be considered in further research is the inclusion of must-run generators in the model and allowing negative electricity prices. As has been shown, particularly over the past couple of years, the increasing share of VREs and must-run conventional generators have lead to increasingly more instances of negative electricity prices in the Netherlands and Germany. In addition, to more accurately represent the real electricity system, the start-up and shut-down of generators and randomly causing generators to go offline, inline with the probability of unexpected shutdowns in the actual power system should be incorporated. Ancillary services are not considered in this analysis. The incorporation of these service could lead to higher revenues for investors than is shown.

In terms of the modeling the elasticity of demand, there are several data related challenges associated with the demand elasticity factors used in ESOMs. As (Decarolis et al., 2017) identifies that these factors can significantly influence the results and therefore the high uncertainty regarding these factors must be taken into consideration. Considering variations in the demand elasticity factors is outside the scope of this study but should be taken into consideration in future research to determine the effect these factors have on model results. Various historic demand data can be used to help do so. Adjusting these factors would help to make the electricity price more accurately represent real world electricity prices and therefore provide more accurate NPVs forecasts.

Power system optimization models are becoming expanded to incorporate cross-sector integration. The analysis only considers the electricity sector. To enhance the research, the coupling of energy sectors (i.e. electricity, heat, transport) should be examined, particularly due to the added flexibility coupling various sectors can have to help overcome electricity grid balancing problems. A model that combines both cross-boarder and cross-sector integration would provide a better representation for the market, especially as the transition is made to integrate power and heat and increase the penetration of electricity and hydrogen vehicles. This type of modeling is currently being done with models such as PyPSA-Eur-Se-30, which is cross-sector integrated model that builds on the PyPSA-Eur power sector only model.

The complexity, uncertainty, and rapidly evolving nature of the power system demands continuous research and development. All further research and development topics listed above increase the complexity of the optimization problem and therefore, increase the required computation time and power. The balance between creating a model that encompasses the complexity of the real world to give useful, accurate insights and a model that requires a reasonable amount of computation time and can provide a solution in a reasonable amount of time, needs to be considered in all future development. Smart techniques need to be developed to incorporate the topics listed above while still creating a feasible, usable model.

8

Conclusion & recommendations

Energy system optimization modeling is a widely used bottom-up modeling technique to help in the transition to sustainable energy systems. Open source energy optimization tools (such as PyPSA, OSeMOSYS, TEMOA) have become increasingly more advanced and have been cited to be mature enough to be used for decision making capabilities (Groissböck, 2019). The wide availability of open source energy optimization tools leads to the question of how these tools can be utilized from the perspective of the investor to analyze the profitability of different technologies. Therefore, to answer this question and fill the gap, this study explores using optimization modeling from the perspective of an investor in the power system. The modeling framework developed in this study utilizes energy system optimization modeling paired with the uncertainty technique, Modeling-to-Generate Alternatives and a financial model to analyze the profitability of investments in the power system. The modeling framework addresses the need to account for both the long-term investment decisions in the power system and the short-term detailed dispatch decisions. Based on the framework, a model is developed. The model is used as a proof of the method developed and is utilized in a case study to see the practical application of the method for the Dutch power system in the 2030 time frame. The research shows that energy system optimization modeling can aid in investment decisions by providing a range of possible future energy systems and therefore the range of technologies that will be required to achieve emission reduction targets and by performing as an electricity price generator. By producing possible future electricity prices and dispatch of generator and storage units, the models can be used to determine the profitability of different technologies. Applying the developed method to a Netherlands case study provides important insights into investments in the Dutch electricity system.

Main findings:

Energy optimization modeling is an important tool for investors in the power system and can be utilized to help aid in investment decision making. With the increasingly advanced ESOMs available, these modeling tools can be a useful addition to an investors set of tools to aid in the decision-making process. The modeling framework developed in this research can help do so.

By providing a range of near optimal energy system solutions, the uncertainty technique, MGA can provide valuable insight into the possible future power systems. Energy system optimization models determine the cost optimal or maximum society welfare system given a set of input parameters. However, in reality cost optimal systems are not achieved due to the imperfections in the market, market failures, policy failures, and uncertainty. To gain insight into the range of possible future energy systems, the MGA technique can be used to generate a range of near-optimal solutions.

There are a wide range of possible near optimal future power systems. This research reveals that small deviations in overall cost of an energy systems can lead to significantly different energy infrastructure designs. This is crucial to understand for energy modelers, energy investors, and policy makers, as small cost assumptions (deviations) can lead to vastly different energy system designs, business cases and adequate policy to achieve governmental targets. The range of possible energy systems provides flexibility and opportunity for both investors and policy makers. Knowing and examining these possible ranges allow policy makers to incorporate and consider other factors that effect the power system aside from cost.

Near-optimal solutions generated by energy system optimization modeling do not necessarily ensure the economic feasibility of investments required to achieve the respective energy system. The economic feasibility of investments in the range of near optimal electricity systems are not ensured. The economic feasibility of investments in such systems should be studied in parallel with energy system optimization models.

Main findings of case study: These findings should be interpreted with the understanding of the limitations of the model developed in the study. The model developed is a simplified model whose main purpose is to explore and provide a proof of concept of the modeling framework developed in this research. The main findings listed below show the findings that can be derived from the utilization of the modeling framework.

Significant investments in the power market are required to meet government set emission reduction targets. A minimum of approximately 4 times the currently installed capacity is required for a carbon neutral power system. Large changes to the power system and substantial capital investments are required to achieve the outlined goals, making the investment perspective on the power system essential to achieving the emission reduction goals.

Investments in storage technologies in the 2030 time frame are unfavorable. Although some near-optimal power systems include storage technologies, the business case for such technologies is unfavorable across all scenarios. However, these dynamics could change if governments introduce policy mechanisms to increase the penetration of storage. Governments might implement these type of policies to help drive down storage costs, as they will be needed in the long run to achieve government emission reduction targets.

Storage technologies can help improve the business case for VRE technologies. The presence of storage technologies in the power system in 2030 is shown to potentially increase the NPVs of onshore wind and solar. Storage allows the transfer of load from period of low prices to high prices, flattening the hourly electricity prices and reducing the cannibalization effect experienced by VREs. However, the business case for storage technologies are shown to be poor and therefore, are unlikely to be heavily invested in without governmental support.

Recommendations:

ESOMs should not be used to give exact results, rather a range of possible near-optimal solutions should be reported. ESOM like all other modeling should be used to give insights, not exact results or even numerical outputs. Giving exact, optimal results like in the case of a basic ESOM, gives a false sense of certainty about the future and the capability of modeling the future. The uncertainty analysis, MGA can be a very useful technique to enrich the results of an ESOM and provide more robust data based support for decision makers.

Policy makers need to consider how favorable investments are to investors, and therefore how likely the investments are to occur, to ensure adequate investments are made to reach emission reduction targets and ensure security of supply. The case study results reveal that the investment environment for VRE and storage technologies in the 2030 time frame in the Netherlands is not particularly appealing. Therefore, to reach government climate targets while ensuring security of supply might require government intervention.

Caution should be taken to not over-invest in VRE or storage technologies. The case study analysis reveals that the MGA alternative generated by maximizing a particular technology, leads to the among the lowest NPVs for the respective technology. Therefore, overcapacity of a technology cannibalizes its own revenue.

Recommendations for further research:

Complexity should be added to the overall model. The model should incorporate all interconnected countries to capture the impact of transmission. The operation model should be more advance. Must run generators, hydro-power, start-up and shut-down of generators, generators outages,and ancillary services should be incorporated in the operation model.

Cross-sector integration should be incorporated into the model. To enhance the research, the coupling of energy sectors (i.e. electricity, heat, transport) should be examined, particularly due to the added flexibility coupling various sectors can have to help overcome electricity grid balancing problems. A model that combines both crossboarder and crosssector integration would provide a better representation for the market, especially as the transition is made to integrate power and heat and increase the penetration of electricity and hydrogen vehicles.

Demand elasticity should be further explored. There are several data related challenges associated with the demand elasticity factors used in ESOMs. The demand elasticity factors can significantly influence the results and therefore the high uncertainty regarding these factors should be explored and taken into consideration in future work.

Parametric uncertainty should be performed on the model. The current framework only considers structural uncertainty; the MGA analysis changes the underlying structure of the mathematical model to find the near-optimal power system portfolios. To be able to provide robust decision making support, a parametric uncertainty analysis should be performed.

Methods to reduce computation time should be explored. In the modeling the energy system, it is essential to find a balance between the required computational power and the accuracy of the model. Given the long time periods and extensive model and parametric uncertainty, energy system optimization modeling quickly encounters computational power and time constraints. Therefore, techniques to reduce computation time should be explored in parallel with the above mentioned recommendations to allow for feasible computation power and time requirements.

9 Reflection

Throughout the course of the research, I often struggled with the idea of how best to utilize an optimization model for a purpose that deviates from its objective function. ESOM's objective are to either maximize social economic welfare or minimize total system costs. The goal of this research was to determine how an investor can utilize ESOMs. An investors objective is to maximize profit which, given the imperfections in the market, do not necessarily correlate to maximizing social economic welfare or total system cost minimization. Under perfect competitive market conditions, producers and consumers behaving in a fashion to maximize their surplus would result in a system that maximizes social welfare and results in a zero net profit for producers. However, due to market imperfections, this is often not the case.

Several times, I ran into difficulties with the difference between theory and reality in the energy system, both conceptually and how to use a modeling technique, that is typically rooted in how the energy system should theoretically operate, to adequately forecast the range of possible realistic futures of the energy system. The uncertainties and complexities of the power system cause modeling the future system to be a very challenging task. As DeCarolis et. al stated:

> Given the complexity of the modeled system and the inability to validate model results, energy modeling requires a significant amount of modeler judgment that – depending on one's perspective – makes energy modeling a blend of art and science or a craft that is neither art nor science (Decarolis et al., 2017).

After the months spent trying to understand, develop, and utilize energy system modeling, this quote resonated with me and I believe is an accurate statement, exemplifying the complexity and challenges of energy system modeling and the importance of the modeler and their fundamental understanding of both the energy system and the models used. The necessity of having a very firm and solid fundamental understanding in the energy system and optimization modeling became very apparent to me during the first months of the project. This need led to a longer project timeline than originally plan, but I feel fortunate to have been able to invest the time and effort to learn and explore the power system and optimization modeling. This understanding allowed me to be more confident in the 'modeler judgement' that I had to use during the course of the research. It should be stated however, that the need for modeler's judgement does not undermine the importance and necessity of energy system modeling and their results, it rather amplifies the need of modelers who are well versed in the topic and in the continue development and advancement of energy system modeling to help as we transition to a sustainable energy system.

On a more personal level, being a novice to python and energy optimization modeling prior to starting this project lead to a very steep learning curve to overcome. In addition, the location and state of the world in which I carried out this thesis differed greatly from what I anticipate. I began this thesis with the intention of performing my research and day to day at the Eneco office. In light of Covid-19 and the associated uncertainty and global lock-down, I decided it was best to be with my family in California. I feel very fortunate to have had the opportunity to be with my direct family and close to my family and friends in California during these tumultuous times, but it also lead to some difficulties being very removed from the Netherlands and being 9-hours behind while carrying out my thesis.

I believe that the individual nature of thesis projects is often a difficult component. The innate difficulties of an individual project, paired with the isolation of Covid-19 certainly led to a testing period of time. The limitation of not being able to meet in person made me greatly appreciative and realize the necessity of in person interaction with colleagues when performing researching projects or general work, but it also led me to understand the necessity of being flexible and adaptive, and I hope strengthened my ability to be adaptive in future circumstances.

The past year has been a very stressful, uncertain, and trying year between a global pandemic and social and political unrest. I believe performing my thesis in this context has pushed me and taught me far more than I could have imagined. I greatly enjoyed expanding my knowledge in the technical components of the project: power systems, energy optimization modeling, electricity markets, and programming. In addition, I believe I have grown to learn how to better structure a research project from start to end, how to most effectively self-teach myself topics or skills I had little or no prior experience with, and to become better at being comfortable with and knowing how and when to ask for help or guidance. I look forward to utilizing these skills in my future work.

A
Data

Table A.1: Greenhouse gas emissions from electricity generation for the Netherlands and Germany for 2015, 2020, 2030, 2040, 2050 (United Nations, 2020; Federal Ministry for the Environment and Safety, 2020; CBS, 2019; Umweltbundesamt, 2020).

Year	Greenhouse gas emissions ($MTCO_2$)		
	Germany	Netherlands	Total
1990	366	39.6	406
2010	313	52.0	365
2015	304	53.3	357
2020	200	29.8	230
2030	139	14.1	153
2040	69.5	7.05	76.6
2050	0	0	0

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Table A.2: Potential renewable energy capacities for Germany and the Netherlands used in model (Brown, Hörsch, and Schlachtberger, 2018)

	Potential Renewable Capacity per Country (MW)		
	Solar	Onshore wind	Offshore wind
Netherlands	46,300	44,100	151,000
Germany	360,000	452,000	90,400

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Table A.3: Techno-economic data used in model

	Year 2030	2040	2050	Source
Lifetime (years)				
Coal	40	40	40	(IEA, 2020)
CCGT	30	30	30	(IEA, 2020)
OCGT	30	30	30	(IEA, 2020)
Nuclear	45	45	45	(Schröder et al., 2013)
Onshore wind	30	30	30	(*Technology Data,* 2020)
Offshore wind	30	30	30	(*Technology Data,* 2020)
Solar	25	25	25	(IEA, 2020)
Battery	15	15	15	(Cole and Frazier, 2019)
Battery inverter	15	15	15	(Budischak et al., 2013)
Fuel cell	20	20	20	(Budischak et al., 2013)
Electrolysis	25	27	28	(Smolinka et al., 2018)
Transmission (HVAC overhead)	40	40	40	(Zappa et al., 2019)
Investment (EUR/kWel)				
Coal	1400	1400	1400	(Schröder et al., 2013)
CCGT	820	820	820	(Schröder et al., 2013)
OCGT	410	410	410	(Schröder et al., 2013)
Nuclear	6450	6450	6450	(Schröder et al., 2013)
Onshore wind	1040	980	960	(*Technology Data,* 2020)
Offshore wind	1570	1450	1420	(*Technology Data,* 2020)
Solar	650	510	460	(Schröder et al., 2013)
Battery	200	170	150	(Cole and Frazier, 2019)
Battery inverter	380	310	280	(Cole and Frazier, 2019)
Fuel cell	340	310	290	(Budischak et al., 2013)
Electrolysis	600	540	490	(Smolinka et al., 2018)
Transmission (HVAC overhead)	1000	1000	1000	(Hagspiel et al., 2014)
Fixed operating & maintenance (FOM) (%/year)				
Coal	1.9	1.9	1.9	(Schröder et al., 2013)
CCGT	2.5	2.5	2.5	(Schröder et al., 2013)
OCGT	3.8	3.8	3.8	(Schröder et al., 2013)
Onshore wind	1.2	1.2	1.2	(*Technology Data,* 2020)
Offshore wind	1.9	1.8	1.8	(*Technology Data,* 2020)
Solar	2.0	2.0	2.0	(Ioannis Tsiropoulos, Dalius Tarvydas, and Andreas Zucker
Battery inverter	3	3	3	(Cole and Frazier, 2019)
Fuel cell	3	3	3	(Budischak et al., 2013; Steward, 2009)
Electrolysis	3.3	3.6	3.9	(Smolinka et al., 2018)
Transmission (HVAC overhead)	2	2	2	(Hagspiel et al., 2014)
Variable operating & maintenance (VOM) (EUR/MWel)				
Coal	6.0	6.0	6.0	(Schröder et al., 2013)
CCGT	4.0	4.0	4.0	(Schröder et al., 2013)
OCGT	3.0	3.0	3.0	(Schröder et al., 2013)
Nuclear	8.0	8.0	8.0	(Schröder et al., 2013)
Onshore wind	1.4	1.2	1.2	(*Technology Data,* 2020)
Offshore wind	2.7	2.5	2.4	(*Technology Data,* 2020)
Solar	0.01	0.01	0.01	(Ioannis Tsiropoulos, Dalius Tarvydas, and Andreas Zucker
Efficiency (%)				
Coal	0.46	0.47	0.47	(Schröder et al., 2013)
CCGT	0.5	0.5	0.5	(Schröder et al., 2013)
OCGT	0.39	0.40	0.40	(Schröder et al., 2013)
Nuclear	0.34	0.34	0.34	(Schröder et al., 2013)
Battery inverter	0.81	0.81	0.81	(Budischak et al., 2013)
Fuel cell	0.58	0.62	0.62	(Budischak et al., 2013; Steward, 2009)
Electrolysis	0.65	0.66	0.69	(Smolinka et al., 2018)

3

Table A.4: Fuel price, carbon intensity, and value of loss load forecasts for 2030, 2040, and 2050 in Europe.

	Year			Source
	2030	2040	2050	
Fuel price (EUR/MWh_{th})				
Coal	10.35	10.60	10.85	(International Energy Agency, 2018)
Gas	24.33	26.70	29.08	(International Energy Agency, 2018)
Nuclear fuel (uranium)	3.02	3.02	3.02	(Schröder et al., 2013)
Carbon intensity (tCO_2/MWh_{th})				
Coal	0.51	0.51	0.51	(Skone et al., 2016)
Gas	0.31	0.31	0.31	(Skone et al., 2016)
Value of loss load (EUR/MWh)				
VOLL	5,000	5,000	5,000	Brown2018a

Table A.5: Historical installed generator capacities in the Netherlands and Germany for 2010, 2015, and 2020.

	Year			Source
	2010	2015	2020	
Netherlands (NL)				
Hard coal	2943	7270	4662	(Gotzens et al., 2019)
Lignite	0	0	0	(Gotzens et al., 2019)
CCGT	12271	13582	13582	(Gotzens et al., 2019)
OCGT	3991	3991	3991	(Gotzens et al., 2019)
Nuclear	492	492	492	(Gotzens et al., 2019; ENTSO-E, 2020)
Biomass	1205	400	490	(Rijksoverheid, 2010; ENTSO-E, 2020)
Onshore wind	2009	2646	3973	(Rijksoverheid, 2010; ENTSO-E, 2020)
Offshore wind	228	228	1709	(Rijksoverheid, 2010; ENTSO-E, 2020)
Solar	88	1000	5710	(Rijksoverheid, 2010; ENTSO-E, 2020)
Germany (DE)				
Hard coal	28390	28650	22630	(Gotzens et al., 2019; Fraunhofer ISE, 2020)
Lignite	21340	21420	20860	(Gotzens et al., 2019; Fraunhofer ISE, 2020)
CCGT	18121	18121	17256	(Gotzens et al., 2019)
OCGT	7801	7588	6628	(Gotzens et al., 2019)
Nuclear	20500	10800	8110	(Gotzens et al., 2019; Fraunhofer ISE, 2020)
Biomass	6130	7170	8240	(Fraunhofer ISE, 2020)
Onshore wind	26820	41300	54640	(Fraunhofer ISE, 2020)
Offshore wind	80	3280	7740	(IRENA, 2013; ENTSO-E, 2020; Fraunhofer ISE, 2020)
Solar	18000	39220	53580	(Fraunhofer ISE, 2020)

B

Research flow chart

Below is a flow chart that details each step of the research.

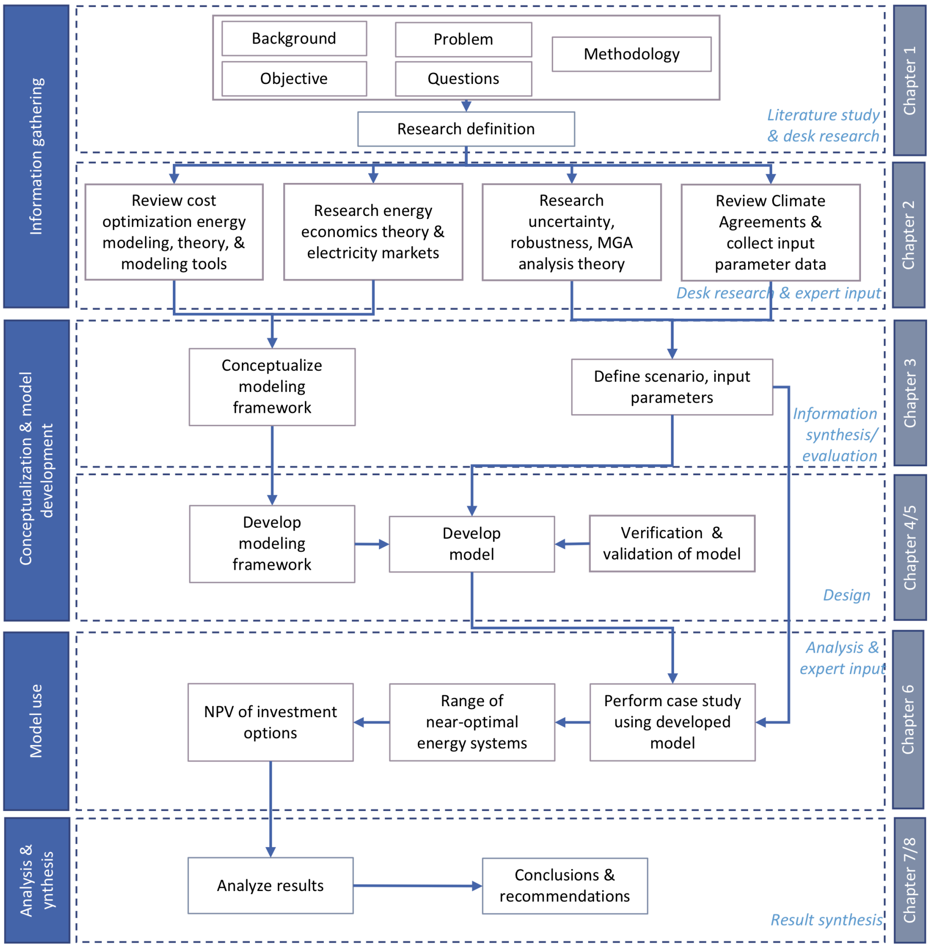

Figure B.1

C

Validation dispatch curves

Below are the price duration curves for each of the various years for each alternative is plotted against the historical values.

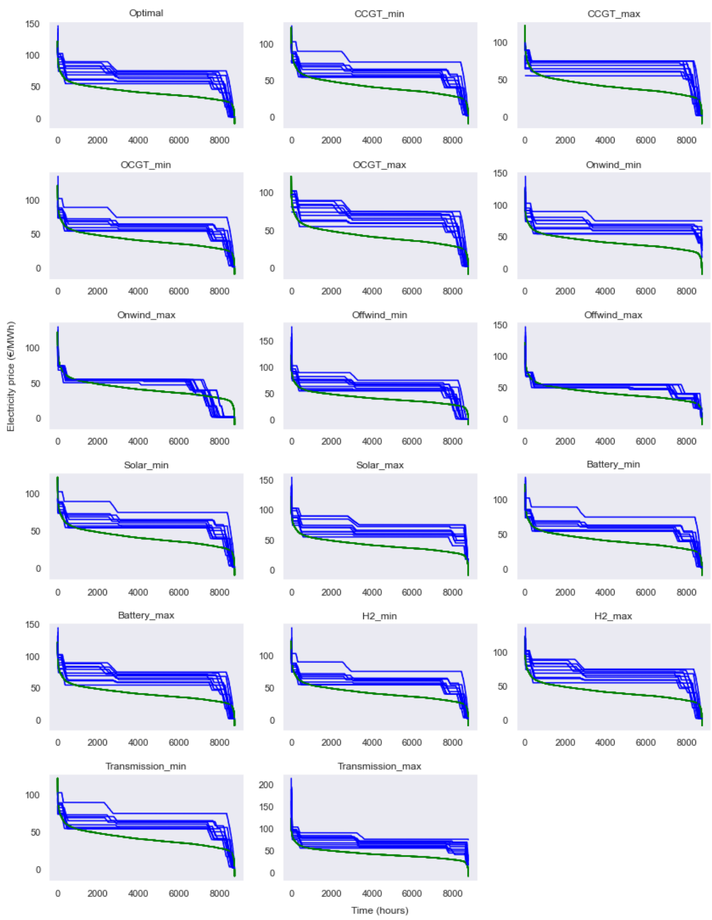

Figure C.1: Price duration curves for each 10-years (one year for each operations optimization run with a different demand and weather year) of alternative MGA runs (blue curves) plotted against the historical price duration curve for 2019 (green curve).

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Utilizing energy system optimization modeling and modeling to generate alternatives to explore the economic feasibility of investments in the future electricity system

Marissa Moultak
TU Delft, The Netherlands

Abstract The energy transition requires significant investments in new power generation, storage, and transmission technology to achieve emission reduction targets while ensuring a stable supply of electricity. However, the increasingly complex, uncertain nature of the power system creates challenges for investors and requires advanced research and modeling. An exploratory analysis is preformed to determine if and how energy system optimization modeling can be used to explore the long-term economic feasibility of investments in the power sector in light of the energy transition. A modeling framework is developed utilizing energy system optimization modeling paired with the uncertainty analysis, modeling to generate alternatives, to explore and provide insights into the profitability of investments in the range of possible near-optimal power system configurations that meet government emission reduction targets. We apply the modeling framework in a case study of the Dutch power system, focusing on investments in the 2030 time frame. The case study is used as a proof of concept of the developed methodological. The case study finds that the developed modeling framework can provide insight into the range of near-optimal power system configurations that meet emission reduction targets and, through an economic analysis, can shed light on the economic feasibility of different technologies. In the particular case of the Netherlands, the case study finds a wide range of possible future near-optimal energy systems exist to meet emission reduction targets, but a lack of profitability of investments indicate policy mechanisms or alternative market arrangements are needed to ensure economic incentives exist for the necessary investments. Further research should include a parametric uncertainty analysis to provide a complete and comprehensive overview, including all types of uncertainty in the system and to identify the affects different types of uncertainty have on the profitability of investments.

1 Introduction

The European electricity system is rapidly changing. Over the next couple of decades, electricity demand is forecast to increase with the electrification of the heat and mobility sectors, and greenhouse gas emissions are required to decrease dramatically to meet emission reduction targets. The energy transition requires significant investments in new power generation, storage, and transmission technology. However, the increasingly complex, uncertain nature of the power system creates challenges for investors. The challenges continue to increase as the energy system transitions to a low carbon system, transitioning away from conventional sources to intermittent renewable energy sources. This transition changes the dynamics of the energy market and, paired with unpredictable government climate change policies and regulation, can lead to increasingly risky investment outcomes for generators.

Increasing the penetration of wind and solar power in the energy system changes the electricity market dynamics and therefore the resulting electricity prices and the dispatch of respective generators. Investments in the power sector are long-term investments that require investors to analyze long-term future profitability and risk to make investment decisions. Therefore, understanding and forecasting future market conditions is an essential component for investors to make investments in the system and for policy makers to understand the regulatory framework and market design changes that are necessary to meet emission reduction goals while maintaining a secure and stable power supply.

Flexible, in-depth, sophisticated modeling tools are vital to help inform private company investments regarding new electricity generation plants, storage units, and transmission lines in the increasingly complex future power system (Conejo et al., 2016; Hilpert et al., 2018; Pereira et al., 2016). Energy system optimization models, one type of modeling tool, have become increasingly developed and several open source energy system optimization models have been deemed sophisticated enough for serious use (Groissböck, 2019).

Typically, energy system optimization models are used to determine a single cost-optimal energy system given a set of constraints. The uncertainty pertaining to the future and the inability of mathematical models to accurately represent the complexity of the energy system cause optimal solutions to have limited significance and can even mislead decision makers by providing false precision in the future energy systems (DeCarolis et al., 2016; Voll et al., 2015). Sub-optimal solutions may be favorable for reasons outside of purely cost, including public acceptance, land-use conflicts, ease of implementation (Neumann and Brown, 2019). The real-world energy system transition has been shown to not follow the cost-optimal solution but rather, fall within the range of near-optimal energy systems (Trutnevyte, 2016). To be able to account for this, an uncertainty technique, modeling-to-generate alternatives (MGA), has recently been applied to energy system optimization models ((Neumann and Brown, 2019; DeCarolis et al., 2016; Price and Keppo, 2017)). MGA explores the decision space to generate the maximally different near-optimal solutions within a defined cost slack from the optimal solution. Therefore, MGA provides a range of near optimal power system configurations. As the energy system has been shown to fall within the range of near optimal solutions, this research explores how energy system optimization modeling paired with MGA can be used by the investor. The investor in the system needs to understand the profitability of different investments in the range of possible future energy system configurations.

In addition, as the power system is determined by the decisions of electricity generation companies. Regulators need to monitor and provide policy to ensure that a stable supply of electricity is provided while emission reduction targets are met; the economic feasibility of investments is of importance to regulators. By using energy optimization modeling to explore the economic feasibility of investments, the results also contribute and give insights to policy makers to understand the investment landscape of different alternative future electricity system configurations.

The purpose of this study is to conceptually explore and develop a modeling framework for how the increasingly advanced energy system optimization models can be utilized by investors in the system. The main contribution is the modeling framework developed in the study. To the best of our knowledge, this is the first research to utilize energy system optimization modeling, paired with the uncertainty analysis, MGA to examine the profitability of investments in the energy system. The research builds upon published literature studies that explore the utilization of modeling to generate alternatives for energy system optimization modeling.

The research focuses purely on how modeling to generate alternatives in energy system optimization modeling can be used from the perspective of an investor in the system and therefore, considers the structural model uncertainties (uncertainty pertaining to the inability of the model to provide a perfect representation of the real world). To gain a complete understanding of the uncertainties in the system and the affects the uncertainties have on the profitability, a full parametric uncertainty analysis should be performed in addition to the structural uncertainty analysis conducted in this study. A parametric uncertainty analysis (i.e. Monte Carlo simulation, stochastic programming) could be done over the set of input parameters provided to the modeling framework. This would require significantly more required runs, computation power and time.

The remainder of the paper is structured as follows. Section 2 gives background on modeling to generate alternatives and energy system optimization modeling. Section 3 provides an overview of the developed modeling framework and the mathematical formulation for each component of the model. Section 4 introduces the case study that is performed using the developed modeling framework. The results are given and discussed in Section 5 and the conclusion is in Section 6.

2 Energy system optimization modeling and modeling to generate alternatives

By providing in-depth analyses into the optimized future structure of the power system, energy system optimization models help to ensure the transition to a low carbon power system, aligned with the climate targets, is achieved reliably and cost effectively (Tash et al., 2019). Due to the large uncertainty about the future, ESOMs should be used to identify patterns across many different model runs to produce insights rather than singular projections (Decarolis et al., 2017; Neumann and Brown, 2019). When paired with the uncertainty analysis, modeling to generate alternatives, ESOMs can provide a range of near-optimal solutions and the bounded analysis can be used to explore the possible future scenario space. The range of near-optimal systems are founded to be able to encapsulate the real-world energy transition and provide an ”envelope of predictability” (Trutnevyte, 2016). Therefore, to utilize energy optimization modeling to help support investment decision making, we must consider a range of near-optimal solutions. In addition, as the range of near-optimal solutions has been shown to encapsulate the real-world energy transition, the configuration of the near-optimal solutions can reveal to investors the necessary investments needed over the coming decades to align with government targets.

3 Modeling framework

As identified in the introduction, in the rapidly evolving power sector, in-depth modeling tools are required to provide insights for investors and policy makers. To analyze investments in generation and storage technologies, these modeling tools must consider a multi-timescale framework, considering both the short-term and long-term time frames that exist in the power system (Abrell et al., 2019). In addition, they must also consider the range of possible future outcomes and provide a realistic representation of the real world. As the range of near-optimal power system solutions can capture the real world energy transition, these generated near-optimal power system configurations can be used to calculate the economic feasibility of investments in the future power system. Considering these factors, a modeling framework that utilizes different timescales, energy optimization modeling, and modeling to generate alternatives is formulate.

To account for the deviations from a perfect market and to represent the resulting variety of possible future business cases for each generation technologies, a medium-term, investment ESOM paired with MGA is developed and used to generate a variety of possible power system designs for a set of investment periods over the entire timeframe. To be able to account for the profitability of different investments over the lifetime of the technology, the power system must be modeled over the whole time frame.

For optimization models of economic markets, the primal variables are the production and consumption levels and the dual variables are the costs of goods and services (Freund, 2004). For electricity markets, the primal variables are the capacity and dispatch of the generators, storage units, and transmission lines. The dual variables are the marginal electricity price and the CO_2 price. Therefore, the primal variables of the investment optimization can be used to determine the installed capacities of generators, storage units, and transmission lines. The primal variables of the operations optimization can determine the dispatch and the dual variables can be used to find the marginal electricity prices.

The investment medium-term optimizations are only calculated for each investment stage, where installation and decommissioning are assumed to only occur at the start of each investment stage. To be able to simulate a range of possible power system designs, MGA is utilized to explore the decision space by minimizing and maximizing the installed capacities and allowing the system to be up to 10% more expensive than the optimal system. Then, the range of possible power system designs are used as the basis for a short-term, dispatch operations optimization for a variety of weather and demand years to represent the short-term variation that occurs in the power system. A two-step optimization is performed for each investment period to address the two main time frames of decision-making in the energy system, long-term decisions where investments are made and short-term operational decisions where dispatch is determined. Two types of optimization models are utilized. The full model flow diagram is shown in Figure 1.

In the next sections each of the modeling techniques utilized in the developed methodology are explained.

3.1 Investment optimization

The investment optimization model developed is a myopic partial-equilibrium cost minimization model, investors do not have perfect foresight, and therefore the market modeled deviates from a perfect competitive energy market. The modeled market is assumed to be competitive and follow marginal-cost pricing. The demand is modeled as being elastic, the demand changes in response to changes in the price. The demand is modeled to be elastic to provide a more accurate representation of the real electricity market. The investment optimization is formulated as a welfare maximization optimization, with the object to optimize the total economic societal welfare.

The optimization is run for one representative year with hourly time steps to represent the variety of weather and demand conditions that exist throughout the year. The detailed objective function is shown in 1 below. The objective function and constraints are adapted from (Neumann and Brown, 2019).

$$\begin{aligned} \mathit{min\ f(d,K,H,F,k,h)} = \max_{d,K,H,F,k,h} \Bigg[\sum_{n,t}(U_{n,t} d_{n,t}) - (\sum_{n,g}(c_{n,g} K_{n,g}) \\ + \sum_{n,s}(c_{n,s} H_{n,s}) + \sum_{l}(c_l F_l) + \sum_{n,g,t}(w_t o_{n,g} k_{n,g,t}) \\ + \sum_{n,s,t}(w_t o_{n,s}(h^-_{n,s,t} + h^+_{n,s,t}))) \end{aligned} \tag{1}$$

The objective function maximizes the utility of the consumer $U_{n,t}$ at each node n for each time t multiplied by demand at the respective node at time t, $d_{n,t}$ subtracted by the total system costs.The total system costs consist of the generator capacities $K_{n,g}$ at each node n for each generator technology g multiplied by their annualized capital cost $c_{n,g}$, the storage capacities $H_{n,s}$ at each node n for each storage technology s multiplied by their annualized capital cost $c_{n,s}$, transmission capacity

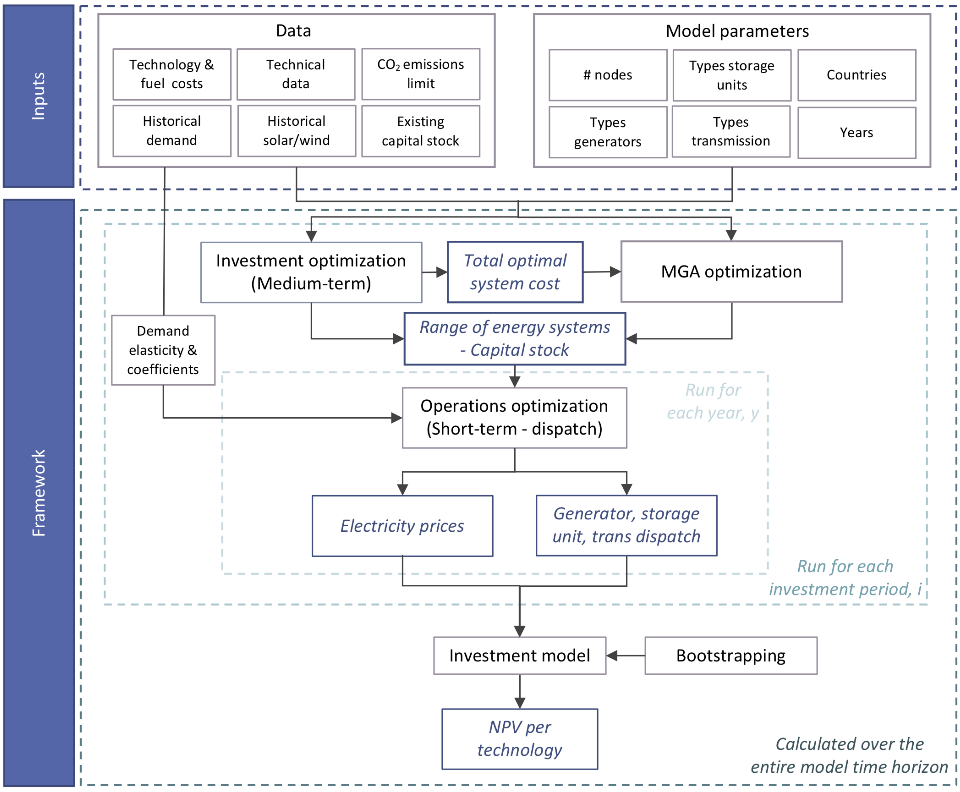

Figure 1: Modeling framework.

F_l for each line l multiplied by their annualized capital cost c_l, dispatch of each generator technology $k_{n,g,t}$ at node n multiplied by their operating costs $o_{n,g}$ and the time step weight w_t, and dispatch of each storage technology $h^{-/+}_{n,s,t}$ at node n multiplied by their operating costs $o_{n,s}$ and the time step weight w_t. Each time period is given a weighting, w_t. The weightings are chosen such that the sum of the weights over the chosen time steps t equal 8,760, representing a full year of operation. The optimization function minimizes total system cost per year. For simplicity, start-up and shut-down costs of generators is not included in the objective function.

Only capital cost of generation, storage, and transmission capacities installed in the period being optimized are included in the objective function. Previously installed capacities are considered sunk cost and therefore, their capital cost is not included in the objective function.

Solving the investment optimization gives the optimal power system configuration. In addition, the objective function gives the optimal system cost, which is then used in the MGA optimization, described in the next section.

3.2 Modeling to generate alternatives (MGA) optimization

The MGA analysis is used to determine the range of near-optimal solutions. The MGA methodology used in this research is modeled after (Neumann and Brown, 2019). The optimal system cost determined in the investment optimization is used to define a new constraint. The optimal solution value (f^*) plus an acceptable relative cost increase (ϵ) is then used to constrain the original feasible space as a new constraint in the optimization problems to explore the near-optimal feasible space.

$$min \;\; f(K,H,F,k,h) \leq (1+\epsilon) * f^* \tag{2}$$

The new objective function becomes the minimization or maximization of the sums of subsets of generation, storage and transmission capacity expansion subject to the new allowable cost increase constraint.

$$min\ (x)\ or\ max\ (x) \tag{3}$$

Where x, the decision variable, is the subset of generation, storage, or transmission capacity. The set of new optimization problems are solved to determine the range of near optimal solutions. The resulting power system configurations generated by the investment optimization and MGA optimization are input into the operations optimization and are run for a range of weather and demand years. The next section details the operations optimization.

3.3 Operations optimization

Similar to the investment optimization, the operations optimization is modeled as a welfare maximization problem. For short-term equilibrium in the operations optimization, the objective function only maximizes over the short-term costs, which is the difference between the consumer utility and the producer operation costs. The capital costs (fixed costs) are excluded and the objective function is:

$$\max_{d_{n,t},k_{n,g,t},h_{n,s,t}} \left[\sum_{n,t} U_{n,t}(d_{n,t}) - \left(\sum_{n,g,t} (w_t o_{n,g} k_{n,g,t}) + \sum_{n,s,t} o_{n,s,t}(h_{n,s,t}{}^{-} + h_{n,s,t}{}^{+}) \right) \right] \tag{4}$$

The objective function maximizes the utility of the consumer $U_{n,t}$ at each node n for each time t multiplied by demand at the respective node at time t, $d_{n,t}$ subtracted by the system operating costs. The system operating costs are described in detail in the investment optimization section.

The electricity prices in the operations optimization are the shadow price, optimal dual variable, of the nodal energy balance. The nodal energy balance is a constraint given to the optimization problem. For each point in time the demand each node n must be satisfied by the energy generated by the generators at node n, the discharge of storage units at point n, or the flow from the transmission line to node n. This gives the nodal balance constraint detailed below.

$$\sum_g k_{n,g,t} + \sum_s (h^{-}_{n,s,t} - h^{+}_{n,s,t}) + \sum_l (\alpha_{l,n,t} f_{l,t}) = d_{n,t} \leftrightarrow \lambda_{n,t} \qquad \forall n,t \tag{5}$$

$$\alpha_{l,n,t} : -1 \; if \; l \; starts \; at \; n, \; l \; withdraws \; power \; from \; i$$

$$\alpha_{l,n,t} : 1 \; if \; l \; starts \; at \; n, \; l \; supplies \; power \; from \; i$$

The shadow price of the nodal energy balance gives $\lambda_{n,t}$, the marginal price at each bus for each period of time modeled. All other detailed constraints for all of the optimization problems are given in Appendix A.

Investment model

Given the electricity prices and the generator and storage unit dispatch determined in the operations optimization of all generated alternative power systems, the NPV is calculated for each technology. Net present value (NPV) is a basic financial calculation to assess the value of a project. The NPV is the sum of the discounted cash flows, costs and revenues, with a certain interest rate, r, over the assumed lifespan of the asset (Petitet, 2017).

Net present value (NPV) (Brown, 2020):

$$NPV = \sum_{y=0}^{Y} \frac{-C_y - O_y + R_y}{(1+r)^y} \tag{6}$$

$$C_y : capital \; expenditure \; in \; year \; y$$

$$O_y : operating \; \& \; maintenance \; expenditure \; in \; year \; y$$

$$R_y : revenue \; in \; year \; y$$

$$r : discount \; rate$$

If the NPV is positive, the investment is economically profitable and indicates that the investment is worthwhile. Whereas, a negative NPV indicates that the project should be rejected (Petitet, 2017).

Given that the NPV is calculated using a discount rate, the order of cash flow is significant; making earlier profits more desirable. To account for this and the randomness of weather and demand data for each operation year, bootstrapping, a statistical technique using random sampling with replacement, is performed over the operation optimization results. The set of dispatch and electricity price results from the operations optimization are randomly selected 1000 times and used to calculate 1000 different NPVs for each full model run. This provides a range of possible NPV outcomes.

4 Case study

Using the development modeling framework, a case study is performed on the Netherlands.

4.1 Experimental setup

The case study considers a two-node, electricity only market. Following the methods described in Section 2, a multi-stage, medium-term optimization is performed, where each investment period is optimized independently. Following the investment optimization, an MGA analysis is performed on each of the investment periods. For each of the optimal and MGA alternative power system configurations, 10 operations optimizations are performed. The model only considers the Netherlands and Germany in a two node system. A spatial resolution of two nodes was chosen as this allows for the simplest model while still being able to model all system components, including transmission. This allows for the case study to reveal how the developed modeling framework can be applied and to allow for a clearer understanding of the effect system components have on the overall model results. Germany was chosen as the second node, as it is the country the Netherlands shares the largest interconnection capacity with. The generation technologies modeled are solar, onshore wind, offshore wind, CCGT, OCGT, coal, lignite, biomass, and nuclear. The storage technologies included in the model are batteries and hydrogen storage. Minimum generation capacities in 2030 are assumed to be current installed capacities in each respective country (based on 2020 installed capacities). The time frame of the model is from 2030-2060, with investment years 2030, 2040, and 2050 (installation and decommissioning of capacities are assumed to only occur in these years). It is assumed that the demand and installed capacity remain constant throughout each 10 year investment segment (2030-2039, 2040-2049, 2050-2059). The decommissioning of generation capacity is assumed to follow governmental decommissioning plans or plant lifetimes. The maximum VREs capacities are bounded by the potential renewable energy capacities for each respective country. Demand is modeled to follow historical data, scaled to represent increasing demand over time. The demand factor is consistent across each 10-year investment period and increases by 15% per ten-year period. It is assumed that installed capacity remains constant throughout each 10 year investment segment (2030-2039, 2040-2049, 2050-2059). A greenhouse gas emissions constraint is included in the model to follow governmental CO_2eq reduction targets.

4.2 Data and inputs

All model parameters can be found in Appendix B.

5 Results & Discussion

5.1 Optimal results

In the first phase of the problem, the long-term investment optimization is performed to generate the optimal solution of installed capacities for 2030, 2040, and 2050. Figure 2 shows the optimal installed capacities for 2030, 2040, and 2050 in the Netherlands. In the 2050 time frame, offshore wind dominates the system with onshore wind and solar providing the remainder of necessary generation capacity. Offshore wind experiences a significant increase between 2040 and 2050, dominating the power system in the 2050 time frame. This large increase in offshore wind is due to the fact that onshore wind reaches its maximum capacity potential in the Netherlands in 2040 and wind capacity factors are more favorable in the Netherlands compared to Germany. Therefore, to provide for the increase in demand and the power production losses from the decommissioning of gas plants, offshore wind is maximized in the Netherlands in 2050. The optimal transmission capacity between the Netherlands and Germany is 33 GW, approximately 8 times the currently installed transmission between the Netherlands and Germany of 4.5 GW. In the zero emission scenario in 2050, the increased transmission capacity and the storage in the system help to smooth out the intermittency of the VREs. This is critical given that the only generation technologies in the system in 2050 are wind and solar.

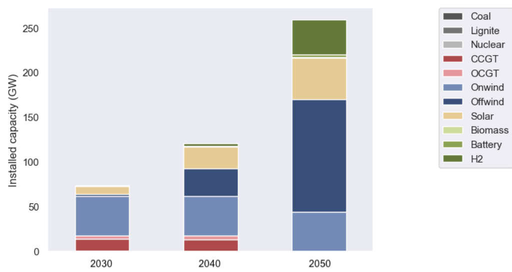

Figure 2: Bar chart comparing the total capacities the Netherlands for the optimal solution in 2030, 2040, and 2050.

Figure 3 shows the total installed capacities for the Netherlands for each MGA alternative and the optimal case for 2030, 2040, and 2050. As can be seen in the figure, there is a large amount of variation in the near-optimal solutions, particularly in the 2040 time frame. In 2040, offshore wind experiences the largest range of possible installed capacities, some alternatives have no offshore wind where as the offshore wind maximization scenario maximizes the possible installed capacity. By 2050, the majority of alternatives reach the maximum capacity potential for solar and wind. In 2050, offshore wind dominates the the Netherlands energy mix. These results suggest that there are many alternative transition pathways for the Netherlands but the alternatives converge in order to reach full decarbonization in 2050, with much less variability of alternative solutions in the long-run. In most alternatives in 2040 and all alternatives in 2050, onshore wind is maximized.

For each of the 51 power systems shown in Figure 3, 10 different optimization optimizations are performed for the ten various demand and weather years. The operation optimization determines the optimal dispatch of each technology to satisfy the demand at the least cost. The optimization gives the generation of each technology at each hour and determines the LMP for each node at each hour. As described in Section 3.3, the LMP is the shadow price of the nodal energy balance constraint. Figure 4 shows a sample week of dispatch and electricity prices for the Netherlands and Germany from the model for the year 2030.

The electricity prices at each hour are determined through marginal-cost pricing (see Section 2.1.1). As

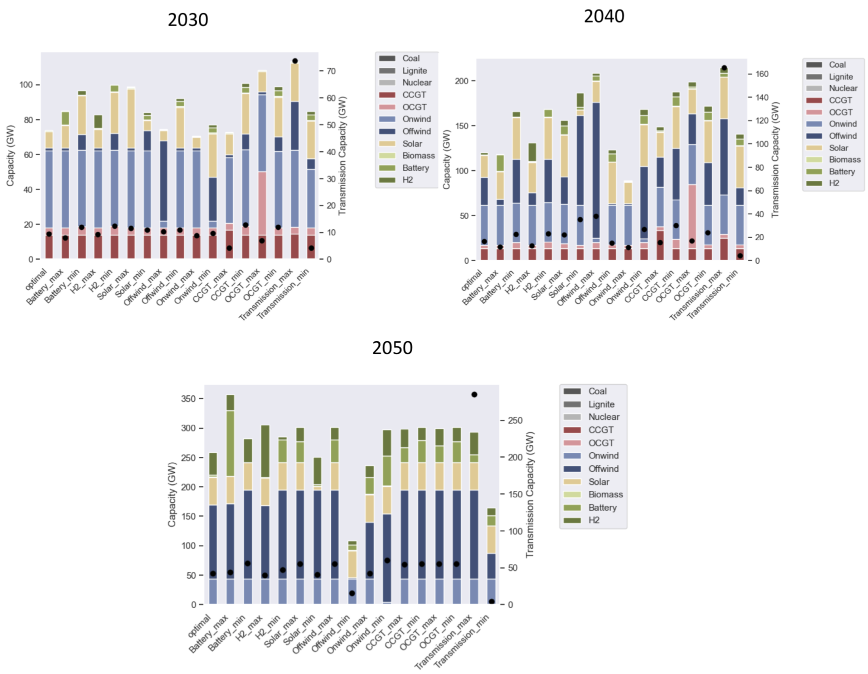

Figure 3: Bar chart comparing the built out capacities in the Netherlands for each alternative generated using MGA for 2030, 2040, and 2050.

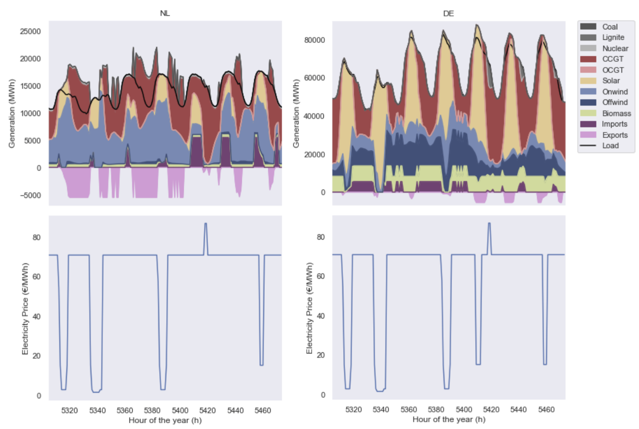

Figure 4: The top two graphs are stacked dispatch curves for all generation for a week in August from the 2030 model results. The bottom two graphs are the corresponding LMP curves over the same week in August. The graphs on the left are for the Netherlands and on the right are for Germany.

can be seen from the graphs, at times when only VRE supplies all of the demand, the electricity price is close to 0 €/MWh, as the marginal price of VRE is close to 0 €/MWh. The graphs show the variation of electricity due to the variation of which generator is the marginal generator at each hour. It is important to note that conventional generators marginal price includes the CO_2 price. The peak electricity price around hour 5420 is a result of coal being the marginal generator and due to the high emission from coal generation, the CO_2 causes coal to have a high marginal price.

For each operations optimizations, a year set of dispatch and marginal electricity prices for the Netherlands and Germany are generated. In Figure 5 histograms of the hourly electricity prices for each investment period are given. The electricity prices are heavily segmented around certain prices. In reality, electricity prices are more distributed and experience more variation. In the model, each generator type is modeled as one large generator rather than each individual generators that have their own distinctive marginal price, as is the case in reality. This deviation from reality causes the electricity prices to be less distributed.

The hourly electricity prices and dispatch of each respective technology are used to calculate the yearly revenue per technology. The resulting NPVs for the Netherlands are shown in Figure 6. The NPVs are for capacity installed in 2030 and then run over the course of the next 30 years. The histogram provides the frequency of the NPVs For each installed technology. The color of the bars reveal the NPVs for each alternative optimization, the optimal and all MGA alternatives.

The majority of the NPVs for the generation technologies are clustered around 0, leading to no clearly favorable investments. Based on these results, investments in the Dutch power system in the 2030 time

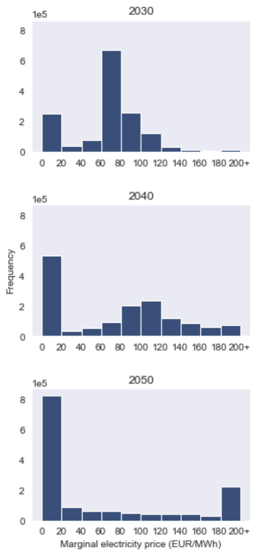

Figure 5: Histogram of all the LMP for all runs for each investment time period. Electricity prices greater than 200 EUR/MWh are all in the last bin. Shows distribution of electricity prices and how they differ between the different investment stages (2030-2039, 2040-2049, and 2050-2059).

frame appear to have high risk. Storage technology has the least favorable business case, with negative NPVs for all alternatives.

Figure 7 visualizes the same data as Figure 6 as box-plots. This alternative graphical representation allows for the affect different MGA alternatives have on each technologies respective NPVs to be seen more clearly. The box plots show that the case of transmission maximization, leads to relatively higher NPVs for the generation technologies, particularly CCGT, OCGT, Offwind. In addition, the MGA alternatives that maximize a technology result in the among the lowest NPV for the respective technology. This suggests that when more than the optimal amount of a technology is built, the technology cannibalizes its own revenue. For the case of solar and onshore wind, additional flexibility options in the system, such as increased storage or transmission capacity, lead to higher NPVs. The increased flexibility that storage and transmission provide to the energy system help to mitigate the cannibalization effects that VRE face (Prol et al., 2020). The ability for storage technologies to arbitrage, purchase electricity and charge when electricity prices are low and discharge and sell electricity when price are high help to stabilize the electricity price and therefore damped the cannibalization effects experienced by VREs. If the transmission capacity is maximized within 10% of the cost optimal solution, the investment environment across all generation technologies is favorable. Large distributions within an alternative indicates that the weather and demand year has a relatively larger effect on the revenue for the given technology.

6 Further research

Further research should explore the demand elasticity. As (Decarolis et al., 2017) identifies that these factors can significantly influence the results and therefore the high uncertainty regarding these factors must be taken into consideration. Considering variations in the demand elasticity factors is outside the scope of this study but should be taken into consideration in future research to determine the effect these factors have on model results. Various historic demand data can be used to help do so. Adjusting these factors would help to make the electricity price more accurately represent real world electricity prices and therefore provide more accurate NPV forecasts. In addition, complexity should be added to the overall model used in the case study or an already developed energy system optimization model should be adapted to the modeling framework. A large geographic area should be modeled to account for the overall affects of transmission. Finally, a parametric uncertainty analysis should be performed on the entire model to be able to provide robust decision making support to investors and policy makers. Incorporating a parametric uncertainty analysis would require significantly more computation power and therefore, techniques to reduce the necessary computation time should be researched.

7 Conclusion

The research explores how energy system optimization modeling can be used to help make investment decisions in the evolving power system. The main insights of the study are two fold.

First, the study uncovers how energy system optimization modeling can be used to help make investment decisions in the evolving electricity system given emission reduction targets. The modeling framework outlined in this study provides a method for how investors in the electricity system can use the increasingly more advanced and developed energy system optimization models to contribute to investment decision making. Pairing an ESOM with the MGA uncertainty analysis provides a wide range of possible future electricity system configurations. In addition, the consideration of the short-term effects on the operation of the electricity market while considering long-term decisions helps understand how the long-term investment decisions will fair in the electricity market. The case study finds that there are a wide range of

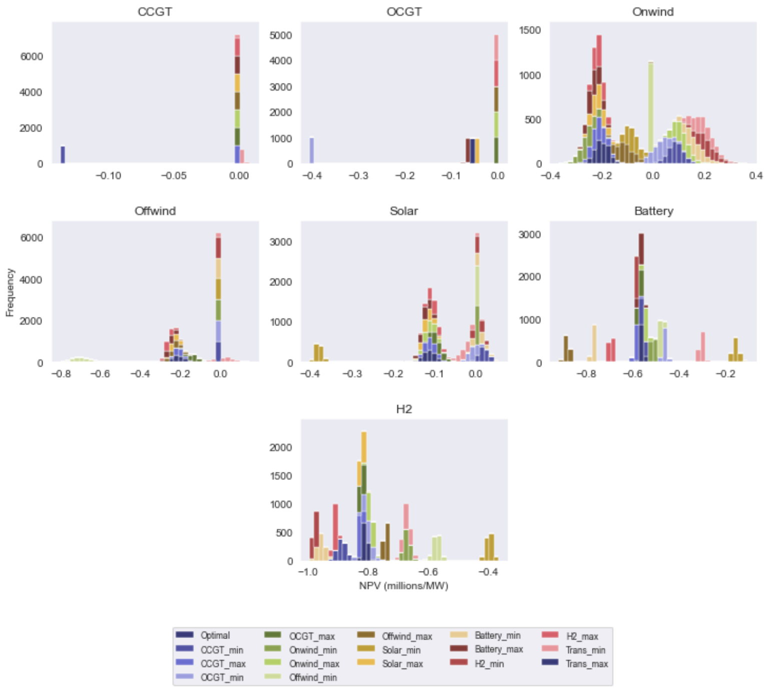

Figure 6: Histogram of NPV for technologies built in 2030 with bootstrapping 1,000 possible combination of NPVs within each 10-year investment period.

near-optimal electricity system configurations that allow emission reduction targets to be achieved, but that the lack of economic incentives in the alternatives indicate that regulatory intervention or electricity market reform might be necessary to ensure the necessary investments occur to maintain a stable supply of electricity while reaching climate targets.

Secondly, the study reveals how economic feasible the range of cost near-optimal solutions generated by ESOMs are from the perspective of an investor. Typically, energy system optimization modeling is used to determine the cost optimal or near optimal power systems. These models tend to neglect the economic feasibility of the cost optimal or near optimal solutions from the perspective of the investor, an important component given that in free liberalized, competitive market, the installed capacity is determined by investors. Therefore, the modeling framework developed in this study can be used from the perspective of regulators to gain insights into how the investment landscape looks for different near-optimal solutions.

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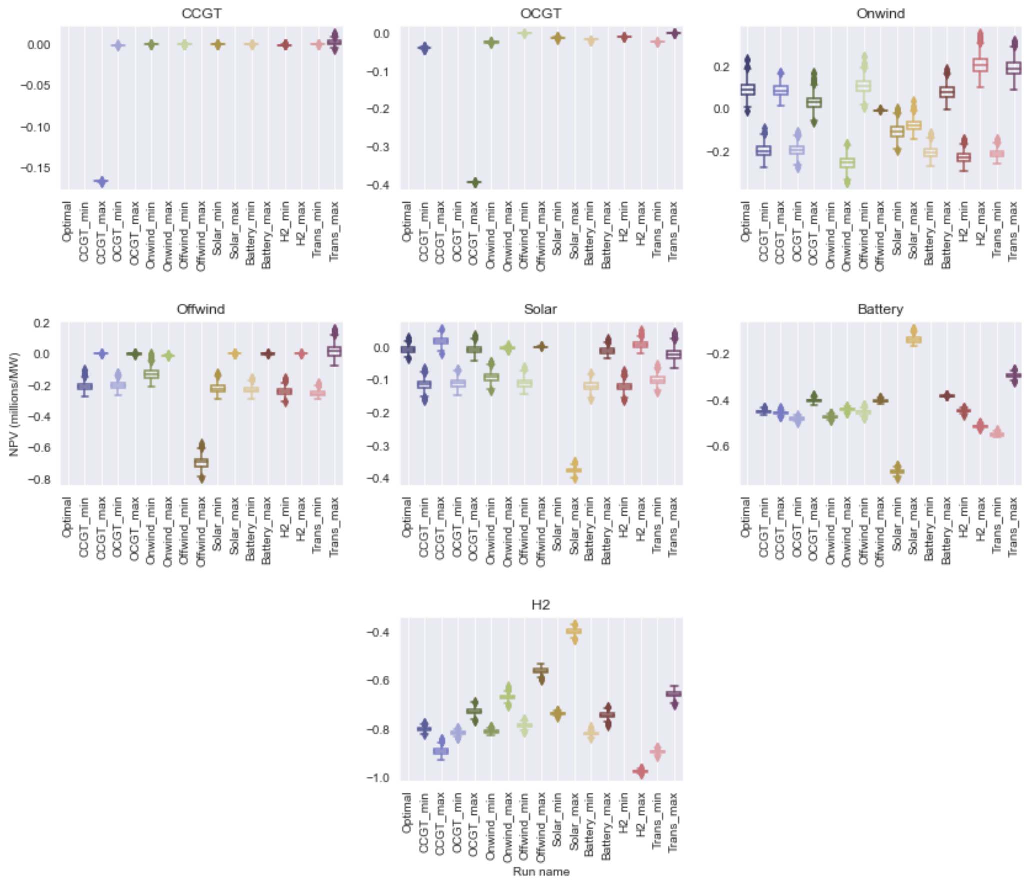

Figure 7: Boxplot for each run of NPV for technologies built in 2030 with bootstrapping 1,000 possible combination of NPVs within each 10-year investment period.

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A Constraints for optimization problems

The following constraints are for all optimization problems used in the modeling framework.

A.0.1 Generation constraints

To solve the optimization function, the objective function is subjected to several constraints. The dispatch of generators $k_{n,g,t}$ are constrained by the generator capacity $K_{n,g}$ and the minimum and maximum time variable availability of the generator, $\tilde{k}_{n,g,t}$ and $\bar{k}_{n,g,t}$ respectively. The time variable availability of the generator is given per unit of installed capacity, $K_{n,g}$. The minimum time variable availability $\tilde{k}_{n,g,t}$ of the generator signifies the lower bound of the installed capacity that must be in operation for the given time. The maximum time variable availability $\bar{k}_{n,g,t}$ of the generator signifies the upper bound of the installed capacity that can be in operation for the given time.

$$\tilde{k}_{n,g,t} \leq k_{n,g,t} \leq \bar{k}_{n,g} K_{n,g} \qquad \forall n, g, t \tag{7}$$

Conventional generators (coal, gas, and nuclear) are assumed to be fully flexible - $\tilde{k}_{n,g,t}$ is 0 and $\bar{k}_{n,g,t}$ is 1. Therefore, for conventional generators, 7 becomes:

$$0 \leq k_{n,g,t} \leq K_{n,g} \qquad \forall n, g, t \tag{8}$$

For VREs, 7 becomes:

$$0 \leq k_{n,g,t} \leq \bar{k}_{n,g,t} K_{n,g} \qquad \forall n, g, t \tag{9}$$

where $\bar{k}_{n,g,t}$ is the weather dependent power availability of the VRE.

A.1 Storage constraints

Similar to dispatch constraint for generators given in 7, the charging and discharging of storage units $h^{-}_{n,s,t}$ is constrained by the storage power capacity $H_{n,s}$:

$$0 \leq h^{+}_{n,s,t} \leq H^{+}_{n,s} \qquad \forall n, s, t \tag{10}$$

$$0 \leq h^{-}_{n,s,t} \leq H^{-}_{n,s} \qquad \forall n, s, t \tag{11}$$

In addition, the state of charge of the storage unit $soc_{n,s,t}$ is constrained by the nominal power, $H_{n,s}$ multiplied by the number of hours that are required to fill the storage unit to the maximum state of charge, $r_{n,s}$.

$$0 \leq soc_{n,s,t} \leq H_{n,s} * r_{n,s} \qquad \forall n, s, t \tag{12}$$

The state of charge $soc_{n,s,t}$ has to be consistent from one time step to the next and therefore,

$$soc_{n,s,t} = soc_{n,s,t-1} + \eta^{+}_{n,s} h^{+}_{n,s,t} - \frac{1}{\eta^{-}_{n,s}} h^{-}_{n,s,t} \qquad \forall n, s, t \tag{13}$$

The state of charge must equal the state of charge at the previous time step $soc_{n,s,t-1}$ plus the amount of power charged to the batter (the efficiency of charging $\eta^{+}_{n,s}$ multiplied by the power charged $h^{+}_{n,s,t}$) minus the amount of power discharge from the battery (the amount of power discharged $h^{-}_{n,s,t}$ divided by the efficiency of discharging $\eta^{-}_{n,s}$.

For simplification, it is assumed that the storage units have no standing losses (self-discharging leakage rate).

A.2 Transmission constraints

The flow in all transmission lines $f_{n,t}$ are constrained by their capacities F_l.

$$|f_{n,t}| \leq F_l \qquad \forall\, l, t \tag{14}$$

The installed capacity of transmission are optimized within bounds of minimum and maximum installable potential values, F_l^{min} and F_l^{max}, respectively.

A.3 Nodal energy balance

or each point in time the demand at each node n must be exactly satisfied by the energy generated by the generators at node n $k_{n,g,t}$, the discharge of storage units at node n $h^{-}_{n,s,t}$, minus the charging of storage units at node n $h^{+}_{n,s,t}$, and the flow from the transmission lines to node n, $f_{l,t}$. This gives the nodal balance constraint detailed below.

$$\sum_g k_{n,g,t} + \sum_s (h^{-}_{n,s,t} - h^{+}_{n,s,t}) + \sum_l (\alpha_{l,n,t} f_{l,t}) = d_{n,t} \leftrightarrow \lambda_{n,t} \qquad \forall n, t \tag{15}$$

$$\alpha_{l,n,t} : -1 \; if \; l \; starts \; at \; n, \; l \; withdraws \; power \; from \; i$$

$$\alpha_{l,n,t} : 1 \; if \; l \; starts \; at \; n, \; l \; supplies \; power \; from \; i$$

The shadow price of the nodal energy balance gives $\lambda_{n,t}$, the marginal price at each bus for each period of time modeled.

A.3.1 Emission constraint

An emissions limit CAP_{CO_2} can be imposed on the system as a global constraint. The emissions can be constrained by calculating the sum of emissions for each generator over the course of the year modelled. The emissions per generator are calculated using the carbon intensities of the fuel used in the generator e_g and the efficiency of the generator $\eta_{n,g}$:

$$\sum_{n,g,t} w_t \frac{1}{\eta_{n,g}} e_g k_{n,g,t} \leq CAP_{CO_2} \leftrightarrow \mu_{CO_2} \tag{16}$$

μCO_2 is the shadow price of the CO2 emissions and therefore, identifies the CO2 price that is necessary to reach the carbon emission limit specified in the constraint.

A.3.2 Generator capacity constraints

The installed capacity of generators are optimized within bounds of minimum and maximum installable potential values $K^{min}_{n,g}$ and $K^{max}_{n,g}$, respectively.

$$K^{min}_{n,g} \leq K_{n,g} \leq K^{max}_{n,g} \qquad \forall n, g \tag{17}$$

The capacity bounds are determined by existing/previously installed capacities, governmental phase-out decommissioning plans, or maximum renewable installation potential. For the first optimization period, 2030, currently existing installed capacities are used to define the minimum bounds $K^{min}_{n,g}$, $H^{min}_{n,s}$, and F^{min}_l. For the consecutive optimization periods, the minimum capacities are the optimal capacity from the previous optimization period. The maximum capacities for the conventional generators are determined from governmental decommissioning plans and the maximum capacities for VREs are the maximum renewable installation potentials, given in Table 2.

A.3.3 Storage unit capacity constraints

The installed capacity storage units are optimized within bounds of minimum and maximum installable potential values, $H_{n,s}^{min}$ and $H_{n,s}^{max}$, respectively.

$$H_{n,s}^{min} \leq H_{n,s} \leq H_{n,s}^{max} \qquad \forall n, s \tag{18}$$

For the first investment optimization period, 2030, the minimum bounds are the currently installed battery or hydrogen storage. The maximum bound is infinity. For the consecutive optimization periods, the minimum bound is the optimal storage unit capacity from the previous optimization period and the maximum bound remains infinity.

A.3.4 Transmission capacity constraints

The installed capacity of transmission are optimized within bounds of minimum and maximum installable potential values.

$$F_l^{min} \leq F_l \leq F_l^{max} \qquad \forall l \tag{19}$$

For the first investment optimization period, 2030, the minimum transmission capacity bound is the currently installed transmission. The maximum bound is infinity. For the consecutive optimization periods, the minimum bound is the optimal storage unit capacity from the previous optimization period and the maximum bound remains infinity.

B Data

Table 1: Greenhouse gas emissions from electricity generation for the Netherlands and Germany for 2015, 2020, 2030, 2040, 2050 (United Nations, 2020; Federal Ministry for the Environment and Safety, 2020; CBS, 2019; Umweltbundesamt, 2020).

Year	Greenhouse gas emissions ($MTCO_2$)		
	Germany	Netherlands	Total
1990	366	39.6	406
2010	313	52.0	365
2015	304	53.3	357
2020	200	29.8	230
2030	139	14.1	153
2040	69.5	7.05	76.6
2050	0	0	0

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Table 2: Potential renewable energy capacities for Germany and the Netherlands used in model (Brown et al., 2018)

	Potential Renewable Capacity per Country (MW)		
	Solar	Onshore wind	Offshore wind
Netherlands	46,300	44,100	151,000
Germany	360,000	452,000	90,400

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Table 3: Techno-economic data used in model

	Year			Source
	2030	2040	2050	
Lifetime (years)				
Coal	40	40	40	(IEA, 2020)
CCGT	30	30	30	(IEA, 2020)
OCGT	30	30	30	(IEA, 2020)
Nuclear	45	45	45	(Schröder et al., 2013)
Onshore wind	30	30	30	(DEA, Danish Energy Agency (DEA)
Offshore wind	30	30	30	(DEA, Danish Energy Agency (DEA)
Solar	25	25	25	(IEA, 2020)
Battery	15	15	15	(Cole and Frazier, 2019)
Battery inverter	15	15	15	(Budischak et al., 2013)
Fuel cell	20	20	20	(Budischak et al., 2013)
Electrolysis	25	27	28	(Smolinka et al., 2018)
Transmission (HVAC overhead)	40	40	40	(Zappa et al., 2019)
Investment (EUR/kWel)				
Coal	1400	1400	1400	(Schröder et al., 2013)
CCGT	820	820	820	(Schröder et al., 2013)
OCGT	410	410	410	(Schröder et al., 2013)
Nuclear	6450	6450	6450	(Schröder et al., 2013)
Onshore wind	1040	980	960	(DEA, Danish Energy Agency (DEA)
Offshore wind	1570	1450	1420	(DEA, Danish Energy Agency (DEA)
Solar	650	510	460	(Schröder et al., 2013)
Battery	200	170	150	(Cole and Frazier, 2019)
Battery inverter	380	310	280	(Cole and Frazier, 2019)
Fuel cell	340	310	290	(Budischak et al., 2013)
Electrolysis	600	540	490	(Smolinka et al., 2018)
Transmission (HVAC overhead)	1000	1000	1000	(Hagspiel et al., 2014)
Fixed operating & maintenance (FOM) (%/year)				
Coal	1.9	1.9	1.9	(Schröder et al., 2013)
CCGT	2.5	2.5	2.5	(Schröder et al., 2013)
OCGT	3.8	3.8	3.8	(Schröder et al., 2013)
Onshore wind	1.2	1.2	1.2	(DEA, Danish Energy Agency (DEA)
Offshore wind	1.9	1.8	1.8	(DEA, Danish Energy Agency (DEA)
Solar	2.0	2.0	2.0	(Ioannis Tsiropoulos et al., 2018)
Battery inverter	3	3	3	(Cole and Frazier, 2019)
Fuel cell	3	3	3	(Budischak et al., 2013; Steward, 2009)
Electrolysis	3.3	3.6	3.9	(Smolinka et al., 2018)
Transmission (HVAC overhead)	2	2	2	(Hagspiel et al., 2014)
Variable operating & maintenance (VOM) (EUR/MWel)				
Coal	6.0	6.0	6.0	(Schröder et al., 2013)
CCGT	4.0	4.0	4.0	(Schröder et al., 2013)
OCGT	3.0	3.0	3.0	(Schröder et al., 2013)
Nuclear	8.0	8.0	8.0	(Schröder et al., 2013)
Onshore wind	1.4	1.2	1.2	(DEA, Danish Energy Agency (DEA)
Offshore wind	2.7	2.5	2.4	(DEA, Danish Energy Agency (DEA)
Solar	0.01	0.01	0.01	(Ioannis Tsiropoulos et al., 2018)
Efficiency (%)				
Coal	0.46	0.47	0.47	(Schröder et al., 2013)
CCGT	0.5	0.5	0.5	(Schröder et al., 2013)
OCGT	0.39	0.40	0.40	(Schröder et al., 2013)
Nuclear	0.34	0.34	0.34	(Schröder et al., 2013)
Battery inverter	0.81	0.81	0.81	(Budischak et al., 2013)
Fuel cell	0.58	0.62	0.62	(Budischak et al., 2013; Steward, 2009)
Electrolysis	0.65	0.66	0.69	(Smolinka et al., 2018)

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Table 4: Fuel price, carbon intensity, and value of loss load forecasts for 2030, 2040, and 2050 in Europe.

	Year			Source
	2030	2040	2050	
Fuel price (EUR/MWh_{th})				
Coal	10.35	10.60	10.85	(International Energy Agency, 2018)
Gas	24.33	26.70	29.08	(International Energy Agency, 2018)
Nuclear fuel (uranium)	3.02	3.02	3.02	(Schröder et al., 2013)
Carbon intensity (tCO_2/MWh_{th})				
Coal	0.51	0.51	0.51	(Skone et al., 2016)
Gas	0.31	0.31	0.31	(Skone et al., 2016)
Value of loss load (EUR/MWh)				
VOLL	5,000	5,000	5,000	Brown2018a

Table 5: Historical installed generator capacities in the Netherlands and Germany for 2010, 2015, and 2020.

	Year			Source
	2010	2015	2020	
Netherlands (NL)				
Hard coal	2943	7270	4662	(Gotzens et al., 2019)
Lignite	0	0	0	(Gotzens et al., 2019)
CCGT	12271	13582	13582	(Gotzens et al., 2019)
OCGT	3991	3991	3991	(Gotzens et al., 2019)
Nuclear	492	492	492	(Gotzens et al., 2019; ENTSO-E, 2020)
Biomass	1205	400	490	(Rijksoverheid, 2010; ENTSO-E, 2020)
Onshore wind	2009	2646	3973	(Rijksoverheid, 2010; ENTSO-E, 2020)
Offshore wind	228	228	1709	(Rijksoverheid, 2010; ENTSO-E, 2020)
Solar	88	1000	5710	(Rijksoverheid, 2010; ENTSO-E, 2020)
Germany (DE)				
Hard coal	28390	28650	22630	(Gotzens et al., 2019; Fraunhofer ISE, 2020)
Lignite	21340	21420	20860	(Gotzens et al., 2019; Fraunhofer ISE, 2020)
CCGT	18121	18121	17256	(Gotzens et al., 2019)
OCGT	7801	7588	6628	(Gotzens et al., 2019)
Nuclear	20500	10800	8110	(Gotzens et al., 2019; Fraunhofer ISE, 2020)
Biomass	6130	7170	8240	(Fraunhofer ISE, 2020)
Onshore wind	26820	41300	54640	(Fraunhofer ISE, 2020)
Offshore wind	80	3280	7740	(IRENA, 2013; ENTSO-E, 2020; Fraunhofer ISE, 2020)
Solar	18000	39220	53580	(Fraunhofer ISE, 2020)