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

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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).

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

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

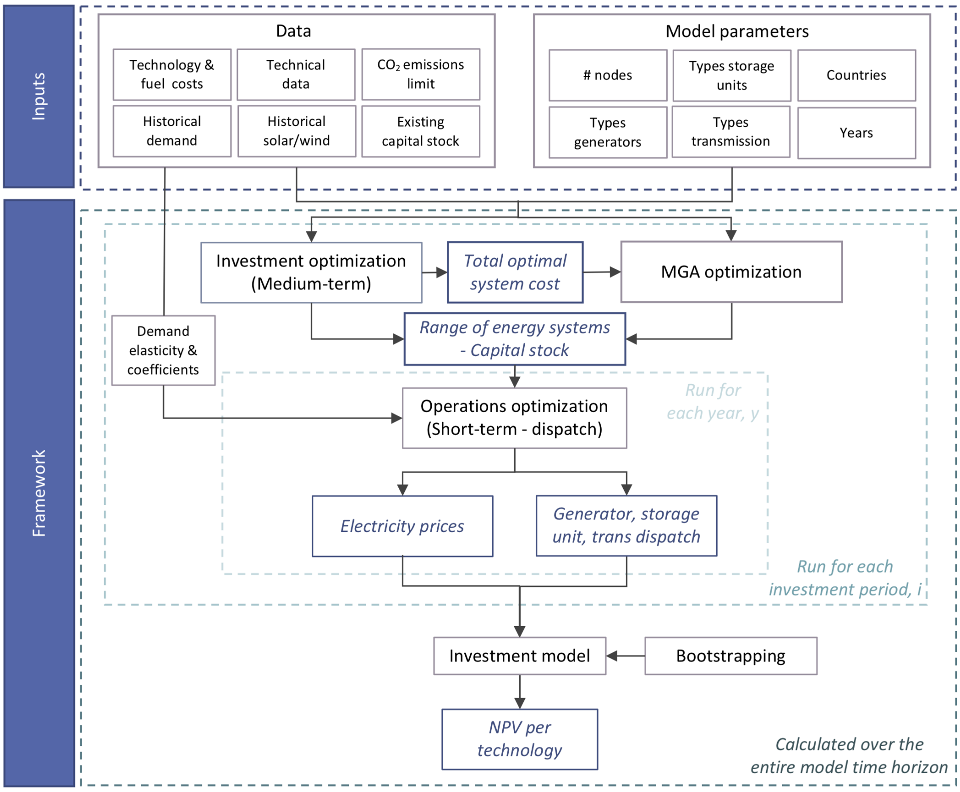

Figure 1: Modeling framework.

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.

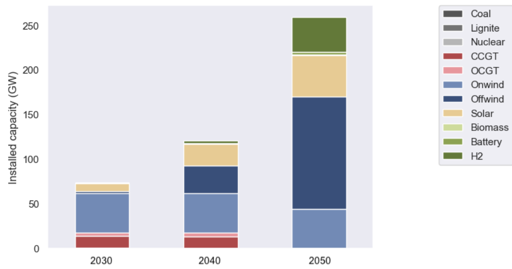

Figure 2: Bar chart comparing the total capacities the Netherlands for the optimal solution in 2030, 2040, and 2050.

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

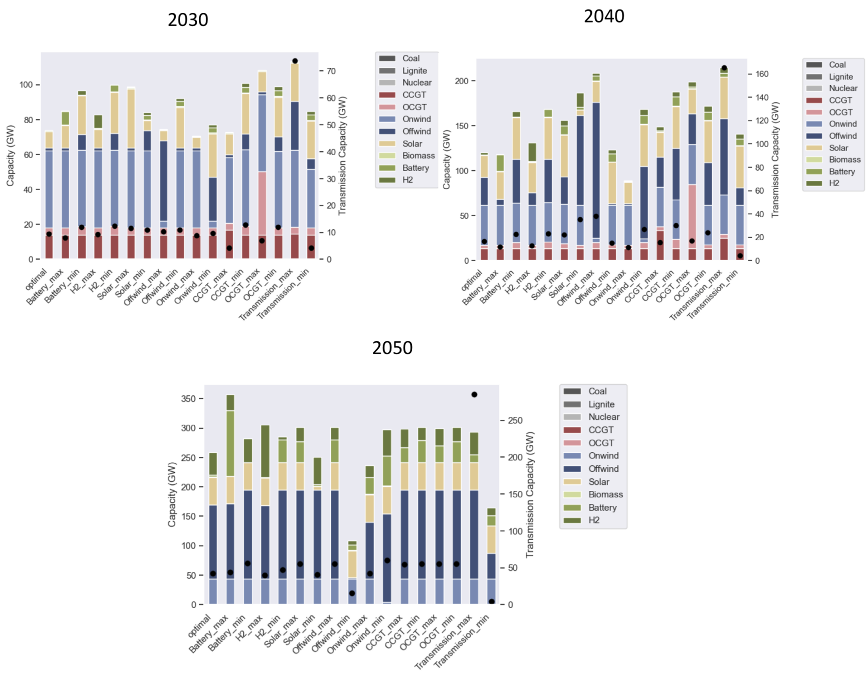

Figure 3: Bar chart comparing the built out capacities in the Netherlands for each alternative generated using MGA for 2030, 2040, and 2050.

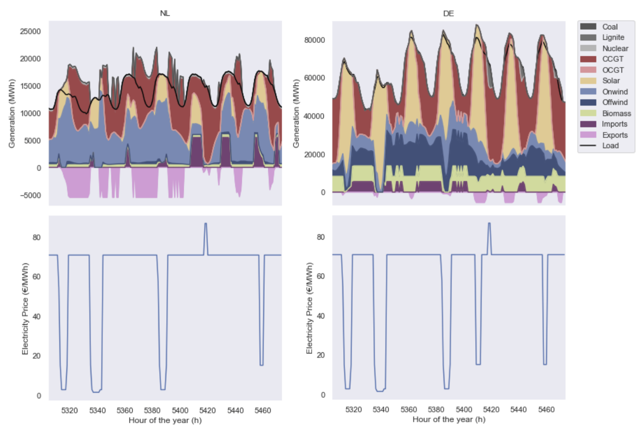

Figure 4: The top two graphs are stacked dispatch curves for all generation for a week in August from the 2030 model results. The bottom two graphs are the corresponding LMP curves over the same week in August. The graphs on the left are for the Netherlands and on the right are for Germany.

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

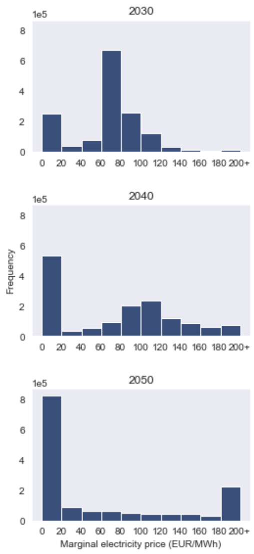

Figure 5: Histogram of all the LMP for all runs for each investment time period. Electricity prices greater than 200 EUR/MWh are all in the last bin. Shows distribution of electricity prices and how they differ between the different investment stages (2030-2039, 2040-2049, and 2050-2059).

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

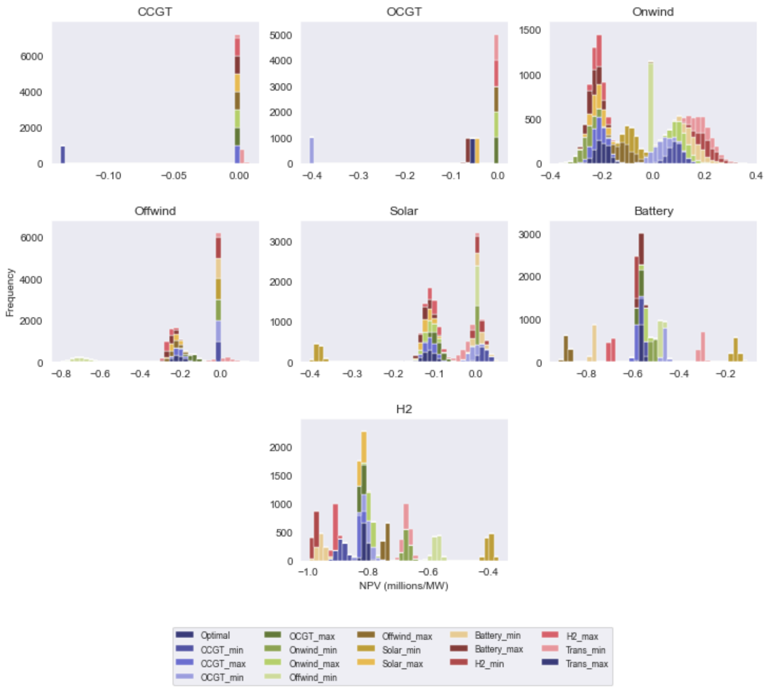

Figure 6: Histogram of NPV for technologies built in 2030 with bootstrapping 1,000 possible combination of NPVs within each 10-year investment period.

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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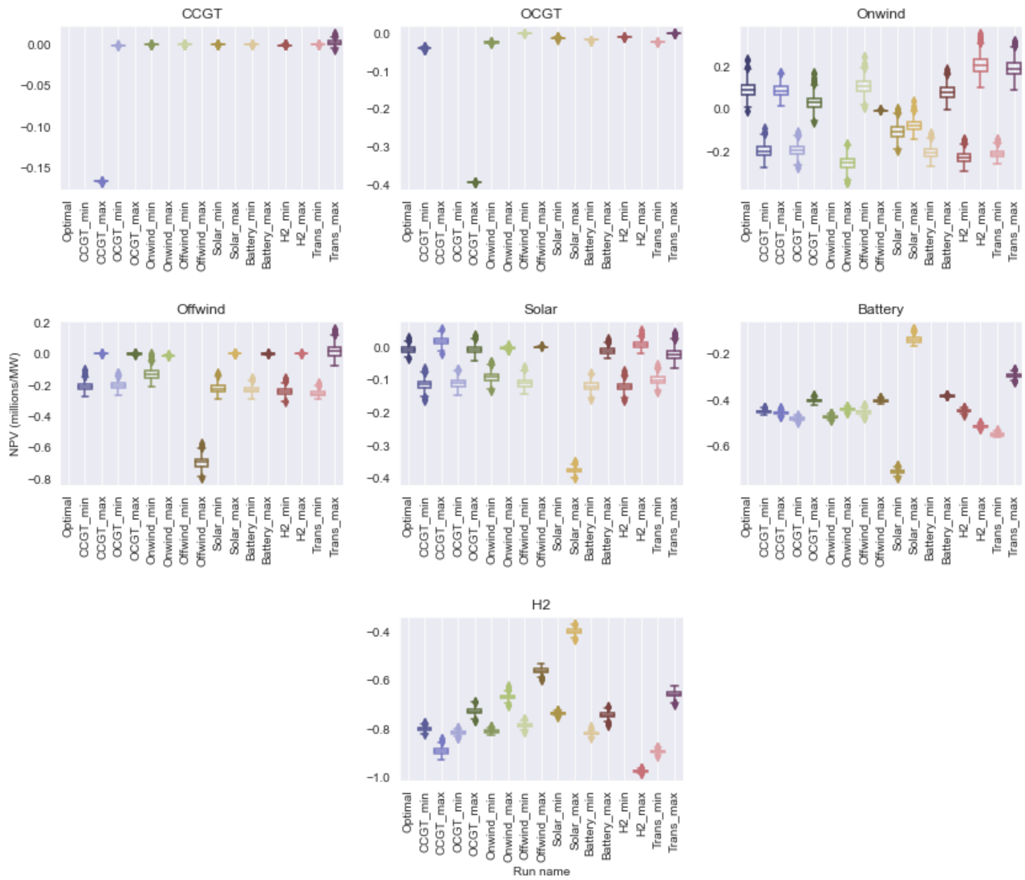

Figure 7: Boxplot for each run of NPV for technologies built in 2030 with bootstrapping 1,000 possible combination of NPVs within each 10-year investment period.

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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^{min}_l and F^{max}_l, 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 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	(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

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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)

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