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Predictive Power Dispatch for 100% Renewable Electricity Scenarios using Power Nodes Modeling Framework

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Abstract

In this thesis, a single-bus and a multi-bus representation of the German power system are investigated for high penetration levels of wind and solar energy. A technologically diverse portfolio of power system units consisting of dispatchable generators, storage facilities and a cluster of flexible electric water heaters is interfaced with the grid in order to compensate for the fluctuating renewable infeed. The power system units are modeled with the Power Nodes modeling framework, and their parameterization and technical constraints are implemented based on real performance figures derived from literature.

An extended case study with varying fluctuating renewable supply scenarios and different scalings of the power system units is presented. Each simulation covers a time span of one full year with a sampling time of 15 minutes. A model predictive control approach is applied to optimally dispatch the power system units. Thereby, the common concept of economic dispatch utilizing real monetary costs is extended by additional objectives enforced by heuristically chosen cost terms in order to gain a realistic dispatch behavior. Load shedding and curtailment of the intermittent renewable generators is considered as eligible control action. The simulation results are analyzed with the objective to determine the impacts of storages and flexible loads on the power system’s hosting capacity for fluctuating renewable infeed and the requirement for dispatchable generation units.
Acknowledgments

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Chapter 1

Introduction

In the light of climate change and the scarcity of fossil fuels, renewable energy sources (RES) will play a significant role in future power systems, as they are carbon free, abundant and sustainable. In this context, a lot of research efforts have been dedicated to the question whether it is possible to rely completely on RES. A recently published study has pointed out that the potential of wind, water, and solar energy is sufficient to meet the world’s electricity demand [1]. Another study has concluded that the shift towards a sustainable electricity supply is possible for Europe by the year 2050 [2].

However, the integration of RES imposes great challenges to grid management that is currently highly dependent on dispatchable, mostly fossil power plants. As most of the RES are intermittent (variable over time) by nature, system operators have to find a way to deal with their inconsistent and rather unpredictable generation output. Some publications have looked at the integration of RES and studied the feasibility to match demand on an hourly basis by combining different renewables with complementary intermittency [3, 4]. An enhanced view has been presented in [5] by incorporating a storage in the power system. The authors have intended to determine the necessary energy storage capacity and storage power for a full-supply scenario based on wind and solar power. A further transition towards a real power system operations has been accomplished in [6]. The authors have shown that an electricity supply in Germany entirely based on renewable generation is accomplishable. Thereby, a virtual power plant has been presented that comprises wind turbines, PV panels, dispatchable biogas generation units and a pumped hydro storage.

Further research has investigated control strategies to operate power systems with high penetration levels of fluctuating renewable resources. In [7] a control concept based on a multi-time-step optimization has been proposed to coordinate the dispatch of storage devices, intermittent energy sources and conventional generation units. Thereby, a multi-objective function has been considered with the overall goal to maximize renewable infeed and
minimize the usage of fast-ramping generation units. Another approach is presented in [8] that applies model predictive control to power systems with intermittent resources in order to minimize generation and environmental costs.

In this master’s thesis, a single-bus and multi-bus benchmark electricity grid is investigated under the assumption of very high shares of fluctuating renewable electricity infeeds. The main focus is to study the dispatch of controllable generation units, storage devices and flexible loads on a 15-min basis in order to account for the fluctuation of renewable infeeds. All power system units are modeled with the Power Node modeling framework presented in [9]. A predictive economic dispatch algorithm is utilized as optimization strategy that computes the dispatch schedules by minimizing marginal dispatch costs. The prediction of the available renewable infeeds is assumed to be perfect. Based on simulations over a time span of one full year, the impacts of storage units and controllable loads on the power system’s hosting capacity for fluctuating renewable energy are quantified.

1.1 Characteristics of renewable energy sources

Power system operation has to balance electricity generation and consumption at any time to guarantee grid stability and, hence, security of supply. In case of surplus generation, excess energy has to be stored or the output level of power plants needs to be lowered. However, reducing infeed from renewable energy sources (RES) like wind and photovoltaic (PV) means to curtail free energy. Contrary, in case the consumption is higher than the current generation output, either stored energy must be released or additional generation units have to be dispatched. The latter poses a problem for intermittent resources as their direct control is limited. In order to activate additional generation units, conventional power plants have to be operated in stand-by or in part-load. However, operating large fossil power plants not in full load conditions is economically unfavorable. Despite their long lead times for ramping, nuclear power plants are utilized to react on intraday load variations, e.g. in France. This commitment results in higher operation costs. As the power output of gas-powered units can be adjusted very quickly, they are appropriate to intraday balancing services. These power plants run either with natural gas or gas from renewable biomass plants.

As the penetration of RES is predicted to further increase in the future, power system operations have to cope with the nature of RES in order to reliably follow the demand side fluctuations. In general, RES can be grouped in three categories with respect to their dependency of generation on the weather/climate variability:

1. Not affected by weather conditions and season, e.g. geothermal and tidal energy.
2. Related to weather on the seasonal time scale, e.g. bioenergies and hydro power from water reservoirs.

3. Directly related to fluctuating weather conditions, e.g. wind power, photovoltaic, concentrating solar power systems, such as a parabolic trough power plant.

The more electricity generation from RES gets dependent on short-term changes in weather conditions, the more outstanding gets the fluctuating and intermittent nature of the power infeed. As power generation and demand have to be balanced at any time in a power system, the inherent fluctuating nature and the limited predictability of RES generation compromises the power system stability. Recently, the International Energy Agency stated that the increase in renewable electricity generation in the European Union between 2008 and 2035 is expected to be driven primarily by wind and solar PV, which will contribute 18% and 3% of the electricity generation in 2035, respectively [10].

In general, intermittent renewable units suffer from low load factors. Thus, a key challenge of accommodating high shares of renewables is to deal with the relatively high generation overcapacity and the associated high amounts of fluctuating power flows. Wind power production can vary significantly in longer time scales, such as 4–12 hours. In the past, several extreme ramp rates were recorded during storms [11]. In Northern Germany, the power system had to face a decrease of over 4000 MW (58% of the installed wind capacity) within 10 hours on 24th December 2004, with the extreme negative ramp rate of 16 MW/min. In Denmark wind generation decreased by 2000 MW (83% of the installed wind capacity) in 6 hours or 12 MW in a minute on 8th January 2005.

To be able to deal with that rapidly increasing share of fluctuating renewable electricity generation, several measures help to mitigate the effects of the variability and randomness of the renewable power availability and increase the value of RES to system operators:

1. Wind and solar energy are fluctuating resources and cannot be dispatched like conventional (fossil or nuclear) power plants. Thus, their infeed profiles vary independently from demand. However, the spatial aggregation of wind and solar units mitigates the variability of their power infeed. With increasing spatial scale of the power supply system, many local fluctuations are balanced by spatial smoothing effects. Consequently, the aggregation of distributed RES increases the predictability of their power infeed.

2. The full potential of spatial smoothing effects can only be exploited if sufficient transmission capacities between national and regional grid systems are available. The European Commission estimated that about
EUR 200 bn have to be invested in electricity transmission networks between today and 2020 [12]. Thereof EUR 40 bn need to be invested in the German grid. These huge investments are aimed at facilitating the integration of RES and the merging of European energy markets.

3. The predictability of energy supply and demand is crucial for grid management. In current power system practice the generation units are dispatched day-ahead based on demand forecasts. An increasing share of PV and wind generation calls for accurate and reliable forecasting techniques of the fluctuating and non-controllable renewable power infeed in order to schedule conventional power plants to meet the expected consumption. Currently, short-term wind power forecasting is much more developed than short-term forecasting of solar power (PV) as the installed capacities of PV are relatively small compared to installed wind power [1]. Nevertheless the need for solar forecasting techniques will increase in the following years as the potential for large-scale PV and concentrating solar power systems, such as a parabolic trough power plant, is tremendous. According to [13], over 90% of the world’s population could be supplied with clean solar power from deserts by using technologies that are available today.

4. In [4] the intermittency of wind and PV generation in Europe is analyzed for three dominant time scales. On the daily time scale wind power generation is about 2.7% lower during the day, while the average consumption during the day is about 8.2% higher than the daily average. On the other hand, PV generation peaks during the day and can be used to cut the peak in load during the day. The second time scale from 2–10 days is strongly connected to passing weather systems, which are characterized by anticyclones or cyclones with large kinetic energy. These crossing weather systems influence wind power to a greater extent than PV generation. On the seasonal time scale an analog pattern to the daily cycle can be observed. In the winter months the consumption is increased by 11% and wind power is increased by 32.2%, while PV is reduced by 34.1%. During summer the consumption is 9.1% below the average, wind power is decreased by 33.6% and PV generation is 28.2% higher than the average. Based on these results it can be concluded that wind and solar generation show a complementary pattern. Therefore, an optimal mix of complementary RES would reduce their intermittent generation in comparison with concentrating on only one source of renewable energy.

5. Energy storage technologies enable the power system to respond to short-, medium- and long-term variability and thus increase the hosting capacity for RES [14, 15]. Currently, major efforts in research are targeted at developing new storage technologies that incorporate very
6. Flexible and controllable loads are also seen as an enabler for renewable energy integration. Demand-side management (DSM) enables to influence the load shape in real-time to mitigate the imbalance between intermittent power and the demand. Therefore, the application of DSM further reduces the needs of new intermittent capacities \cite{10}.

7. Temporary curtailment of renewable generation can compensate for extreme infeed fluctuations and imbalances during periods of low demand and high renewable output. Moreover, grid bottlenecks during windy periods have necessitated curtailment actions of wind power in Northern Germany, where surplus production has occurred since mid 2003 in Schleswig-Holstein and since 2005 in Lower Saxony \cite{11}.

8. Even in supply scenarios with high shares of renewables the reliability and the quality of supply can be increased by a sufficient number of flexible and dispatchable generation units providing operational and capacity reserve.

This thesis investigates the impact of cross-border transmission capacities (2.), the complementary nature of wind and PV generation (4.), the deployment of storage facilities (5.), the incorporation of flexible loads (6.), the curtailment of intermittent generators (7.) and the necessity of flexible and dispatchable generation units (8.) on the integration of large shares of wind and PV in electric power systems.

1.2 Literature study of high-renewable-penetration scenarios

If different types of renewable energy sources (RES) are available, the very critical question arises: “What is the optimal mix between those different sources to serve the energy demand in the most reliable and economical way?”. Addressing this question, the European power system has been simulated with different penetration levels of photovoltaic (PV) and wind power for the years 2000–2007 in \cite{4}. Thereby, Europe was subdivided in 83 regions. To generate time series of wind and PV generation, real weather data was utilized. The study investigates imbalances between RES generation and consumption in a full energy supply scenario. The imbalance is also called residual load and is defined as intermittent generation minus consumption (load). Deviations from the predicted power output of the RES are not considered.

In case imbalances occur in the power system, either the dispatch of conventional power plants or the use of storage facilities to meet the consumption are required. In order to characterize the variability of imbalances
in the different simulation scenarios, the standard deviation of the time series of imbalance is calculated. Clearly, a low variability is favorable as little action for balancing is required and costs are reduced.

In [4], two different approaches to spatial aggregation are analyzed. In the first model all 83 regions are fully interconnected without considering line limits. Thus, the grid is regarded as a “copperplate”. The model enables to simulate one European control zone where unlimited and lossless cross-border power flows between the regions are possible (“European view”). Accordingly, regional imbalances will immediately be compensated by other regions. Consequently, there will be either a general excess or demand for energy, resulting in a time series of imbalance. In the second aggregation model no cross-border power flows between regions exist, i.e. deviations between generation and consumption have to be balanced on a regional level (“regional view”). In order to quantify the variance of imbalance for Europe, all regional results (standard deviations) are summed up. The temporal characteristics of RES generation in the power system are investigated by quantifying the dependency of the variability of the residual load on the shares of PV and wind infeed for different time scales, e.g. monthly, weekly, daily and hourly.

From the analysis of imbalance two main conclusions can be drawn. First, the optimal share of PV and wind depends on the spatial design of the power supply system (“European view” vs. “regional view”). On all investigated time scales the fluctuation of imbalances can be reduced by 50% in a common European control zone in comparison to the regional aggregation approach. In a Europe-wide grid the power flows smooth out spatial differences in PV and wind power infeed very effectively. Consequently, less energy from storage facilities is required to meet imbalances and storage losses are reduced.

Secondly, the optimal share of RES infeed is dependent to the greatest extent on the time scale, which affects the standard deviation of the imbalance profile. With decreasing time scale the share of PV in the system increases – while accordingly the share of wind power decreases – in order to obtain the lowest variability of imbalances. On the time scale of months, about 40% of the generated electricity should be based on PV, while the daily fluctuations are smallest when PV contributes around 60%. One can conclude that wind power introduces more fluctuations in the power system on shorter time scales (compared to PV). However, this does not apply when looking at the time scale of hours. The day/night cycle in PV generation introduces large imbalances. Results show that it is beneficial to have only 20–30% of PV infeed in the system.

At the end, the study reasons that the optimal mix between wind power and PV can only be determined when different time scales are investigated at the same time. Contrary to this statement, the author of this thesis believes that one has to consider the simulation results with the smallest time scale
(here hourly). This can be explained by the fact that the smaller the time scale gets, the more precisely the dynamic effects are taken into account. Thus, based on this study one can conclude that for a European power grid with no cross-border transmission congestions a full energy supply scenario with 80% wind energy and 20% PV energy minimizes the variability of imbalance and thus reduces the need for balancing action.

In comparison to the previous study, in [5] the authors aimed at determining the necessary total storage size and the maximum storage power for a full-supply scenario based on wind and solar power. Thereby, a European integrated network with a time resolution of one hour and weather data spanning 8 years was simulated. The power grid is modeled as a 1-bus network where power imbalances are immediately balanced without any losses. Accordingly, only one load time series and one RES generation time series exists for Europe. The residuum of both time series is the energy that is either demanded from the storage or that has to be stored. An iterative approach was used to determine the storage requirements. Only in case the storage is full, excess RES generation has to be shed. For the simulation the maximum input power and output power of the storage facility have not been restricted. The storage efficiency for feed-in and feed-out are 60% and 40%, respectively. Different storage technologies could be incorporated by varying these values.

The results of the analysis highlight that a maximum necessary storage size of 0.5%–8% of the European annual energy consumption, or in other words 16–260 TWh, is required to compensate for the fluctuating renewable infeed. In general, the results show a strong dependence of the storage size on the shares of PV and wind. Another outcome is the maximum storage power that has to be installed in order to meet the demand. In comparison to the results of the storage capacity, the optimal share of PV to minimize the power outflow from the storage is at lower levels. For a PV share between 10–20% the maximum required storage power varies between 30–40% of the peak load. Based on the simulation results the study concludes that even above a 100% share of renewables with respect to annual electricity consumption, a large power reserve is necessary to reliably meet the demand.

Section 1.1 highlights that several methods exist to reduce the intermittency of renewable energy sources, i.e. wind and solar. These methods include the utilization of the complementary intermittency effects between wind and PV, the spatial dispersion of generation units and the employment of energy storages. The first method is further extended in [3] by the integration of more than two RES technologies in the Californian power system. The main purpose of the analysis is to prove that despite the inherent intermittency of RES an optimized portfolio of renewable generation units can meet a statewide electricity demand in all hours of the year. Exemplarily, this is shown for a four-day period of a representative year by combining wind, solar, geothermal and hydroelectric power in optimal pro-
portions to meet up to 100% of the Californian future electricity demand in 2020. Geothermal plants deliver base load power, while hydro plants supply balancing power. The required wind and solar capacities are much larger than current installed capacities in California, but they are still within the reliable technical capacities for California.

The optimization was performed to construct a renewable peaking supply curve that matches or exceeds the consumption profile in each hour of the day. For selecting an optimal resource portfolio two different optimization conditions are considered. The first aims at reducing the monthly renewable supply surplus as much as possible. As the analysis does not consider storage units, electric vehicle charging or exporting excess electricity out of California, surplus renewable generation must be shedded and represents to some extent wasted cost in infrastructure. With the second condition, the demanded supply from hydro energy relative to the actual available hydro energy during the year in California is minimized. In scenarios with low capacities of wind and solar, this annual over-hydro percentage reaches up to 300%. As the optimizer is allowed to exceed the installed nameplate capacity of hydropower, a feasible generation portfolio is obtained by the requirement that hydropower stays fully within its limits; i.e. nameplate capacity and available energy over the year is never exceeded. Simulation results show that the first constraint is quite restrictive. By allowing hydro nameplate capacity to be exceeded in only four hours of the four-day representative year, the required solar capacity is reduced by nearly 4000 MW, or 1.3 million rooftop systems. This diminishment constitutes enormous cost and material savings, and highlights the importance of peak shaving measures in case of huge swings in demand over the day.

Although the study is based on real consumption and renewable generation data, it suffers from several simplifying assumptions. Therefore, the results do not represent a real-world design of a power grid with full renewable electricity supply. The main point of critique is that the analysis is performed only for the average day of the months January, April, July and October representing each season of the year. Consumption data was averaged over each month to obtain an hourly time series. Daily average supply profiles were calculated from modeled wind speeds and real insolation data, so that they represent wind turbines, photovoltaic and solar thermal generation units distributed all over the state. In doing so, the analysis does not address hour to hour or sub-hour fluctuations in wind or solar output. As supply and demand are averaged over the entire month, their profiles do not feature sharp peaks and large fluctuations. Therefore, by removing the fine variability, the simulation does not have much in common with real-world grid operations.

One step from simulations to actual implementation undertake the initiators of the study presented in [6]. The intention of the project is to show that a portfolio of decentralized renewable generation units in combination with
Table 1.1: Specifications of the virtual power plant presented in [6].

<table>
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<th>Annual generation [GWh/a]</th>
<th>Installed capacity [MW]</th>
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<tr>
<td>Wind</td>
<td>26.5</td>
<td>12.6</td>
</tr>
<tr>
<td>Solar</td>
<td>6.2</td>
<td>5.5</td>
</tr>
<tr>
<td>Biogas</td>
<td>10.8</td>
<td>4.0</td>
</tr>
<tr>
<td>Σ</td>
<td>43.5</td>
<td>22.1</td>
</tr>
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a storage device is fully able to meet Germany’s total electricity demand. Thereby, a centralized control unit aggregates the dispersed generation units to one virtual power plant. A 100% renewable supply scenario is considered with electricity generation based on wind, PV and biogas. Recent studies came to the conclusion that the potential of these renewable technologies in Germany sums up to 448 TWh/a. In contrast, the net electricity demand accounts for 411 TWh/a. Thus, one can infer that a full renewable supply of the German electricity demand is quantitatively feasible.

For the technical realization of the virtual power plant, a scale factor of 1/10,000 is determined, i.e. 1/10,000 of the current electricity demand is covered by the aggregation of renewable generation units. The virtual power plant is continuously in use since March 2007, and its dimensioning is optimized based on operating data of real facilities. The objective is to minimize power imports, that is to maximize security of supply. Additionally, the following constraints have to be fulfilled:

- The generation share of biogas must not exceed 25%.
- No curtailment of solar power infeed.
- Maximum storage capacity of 84.8 MWh.
- Limited electricity export of 1 MW.

The resulting specifications of the virtual power plant are summarized in Table 1.1. The wind turbines are located in the north of Germany whereas the PV panels are dispersed in the south. A pumped hydro facility with an energy capacity of 84.8 MWh and a power rating of 1060 kW serves as storage device. Accordingly, the storage features a discharge time of 80h. The energy capacity accounts for 0.21% of the total annual consumption, or 75.27% of the daily average.

The centralized control unit is the heart of the renewable combined power plant aggregating the dispersed generation units. In order to meet the demand and balance the fluctuating power infeed of wind and solar, the control unit constantly gathers data about operation status and weather. The functional principle breaks down in two phases. First, based on weather forecasts
in hourly resolution, the control algorithm derives power infeed predictions for the wind and solar generation units. Using these predictions and under consideration of current storage levels the algorithm compiles generation schedules spanning the next 24 hours for the pumped hydro and biomass plants. In the second phase, short term regulation to eliminate the power imbalance takes place based on measuring data of the actual wind and solar power infeed. Thereby, fast controllable biogas plants and the pumped hydro storage come into operation. The control algorithm dispatches the different units of the virtual power plant based on a hierarchical decision tree.

In addition to the technical implementation the authors present simulation results of their virtual power plant based on real data and infeed profiles. In three scenarios the influence of wind is investigated by comparing a year with strong, average and low wind infeed. Interestingly, the curtailed wind energy accounts for 35%, 30%, and 28%, respectively, of the available wind energy. The results show that in years with low wind infeed the share of curtailed energy is not considerably reduced in comparison to years with strong wind infeed. Thus, the authors highlight that minimizing the share of curtailed wind power is a great challenge in operating the virtual power plant. Sufficient cross-border transmission and storage capacities are necessary. The authors claim that storage units have to provide 20 GW in peak power in order to stay within export limits. In the year 2005, installed storage capacities accounted for 6.7 GW. One might raise the question whether such an extension in storage capacity is technically feasible and economically reasonable in the case of Germany.

1.3 Economic dispatch in power systems

An electric power system is considered, which is composed of generation, load and storage units. A generation unit can represent a conventional power plant, e.g. a coal-fired power station, or an intermittent generator, e.g. a wind turbine. The operation of the power system comprises the dispatch of generation and storage units to serve the electricity demand of the fluctuating loads.

In general, the dispatch routine should be carried out (1) reliably in order to guarantee a high quality of electricity supply, (2) such that carbon dioxide emissions are minimized and (3) in the most efficient and profitable way. The latter is achieved by minimizing an objective function, which considers commitment costs of generation and storage units. Therefore, this optimization procedure is termed economic dispatch. The result of the optimization is an optimal dispatch schedule, which constitutes the commitment of all generation and storage units interfaced with the power system.

Based on [8], the economic dispatch problem is formulated for a 1-bus
electric power system as follows:

Solve: \[
\min_{P_{G_i}(k), P_{S_j}(k)} \sum_{k=1}^{N} \left( \sum_{i \in \mathcal{G}} C_{G_i}(P_{G_i}(k)) + \sum_{j \in \mathcal{S}} C_{S_j}(P_{S_j}(k)) \right) \\
\text{s.t.} \quad (a) \quad \sum_{i \in \mathcal{G}} P_{G_i}(k) + \sum_{j \in \mathcal{S}} P_{S_j}(k) = \hat{L}(k) \\
(b) \quad E_{S_j}(k+1) = f_{S_j}(E_{S_j}(k), P_{S_j}(k)), \quad j \in \mathcal{S} \\
(c) \quad E_{S_j}^{\min} \leq E_{S_j}(k) \leq E_{S_j}^{\max}, \quad j \in \mathcal{S} \\
(d) \quad P_{G_i}^{\min} \leq P_{G_i}(k) \leq P_{G_i}^{\max}, \quad i \in \mathcal{G} \\
(e) \quad -P_{S_j}^{\max} \leq P_{S_j}(k) \leq P_{S_j}^{\max}, \quad j \in \mathcal{S} \\
(f) \quad |P_{G_i}(k+1) - P_{G_i}(k)| \leq R_{G_i}, \quad i \in \mathcal{G} \\
(g) \quad |P_{S_j}(k+1) - P_{S_j}(k)| \leq R_{S_j}, \quad j \in \mathcal{S} \\
(h) \quad P_{G_i}(k) \leq \hat{P}_{G_i}(k), \quad i \in \mathcal{G}, \\
(a-h) \quad \forall k = 1, \ldots, N \]

Given: \( \mathcal{G} \) set of all available generators \\
\( \mathcal{G_r} \) set of intermittent renewable generators \\
\( \mathcal{S} \) set of storages \\
\( P_{G_i}(k) \) power output of generator \( i \) at time step \( k \) \\
\( P_{S_j}(k) \) charge/discharge power rate of storage \( j \) at time step \( k \) \\
\( C_{G_i}(P_{G_i}) \) operating cost function of generator \( i \) \\
\( C_{S_j}(P_{S_j}) \) operating cost function of storage \( j \) \\
\( \hat{L}(k) \) forecast of total load demand at time step \( k \) \\
\( \hat{P}_{G_i}(k) \) predicted available output of generator \( i \) at time step \( k \) \\
\( E_{S_j}^{\max} \) upper boundary on storage level \( j \) \\
\( E_{S_j}^{\min} \) lower boundary on storage level \( j \) \\
\( P_{G_i}^{\max} \) maximum output level of generator \( i \) \\
\( P_{G_i}^{\min} \) minimum output level of generator \( i \) \\
\( P_{S_j}^{\max} \) power rating of storage \( j \) \\
\( R_{G_i} \) maximum ramp rate of generator \( i \) \\
\( R_{S_j} \) maximum ramp rate of storage \( j \) \\
\( N \) prediction horizon length

The constraints in the stated formulation express that (a) the power balance in the network has to be fulfilled, (b) the storage levels in the next
CHAPTER 1. INTRODUCTION

1.4 Economic dispatch algorithm based on model predictive control

In the previous section the economic dispatch concept has been formulated as a multi-stage optimization problem, which results in an optimal dispatch schedule of generation and storage units for a finite prediction horizon $N$ such that overall system costs are minimized. There are several reasons why the optimization problem is solved over a prediction horizon instead of just a single time step. By considering a time period it is possible to pay attention to ramp-rate constraints of generation units. Thus, power plants with a longer response time can be ramped up prior to possible supply shortfalls. Moreover, the look-ahead strategy enables to operate the storages in the most efficient way. In case excess infeed from intermittent generators is predicted, storage levels can be regulated beforehand in order to buffer the excess energy.

This section presents an algorithm based on Model Predictive Control (MPC) according to \cite{17}, which enables to implement the economic dispatch routine in power system operations. For this purpose, the electric power system composed of generation, load and storage units is modeled by a...
discrete-time linear time-invariant system

\[ x_{k+1} = Ax_k + Bu_k \quad , \tag{1.2} \]

subject to a set of equality and inequality constraints

\[
g(x_k, u_k, u_{k+1}, w_k) = 0 \quad , \tag{1.3} \]
\[
h(x_k, u_k, u_{k+1}, w_k) \leq 0 \quad . \tag{1.4} \]

The input vector \( u_k \) denotes the decision variables of the unit dispatch. The state vector \( x_k \) embodies the storage levels. External influences such as the forecasted load demand and the predicted output of the intermittent generators are denoted by the vector \( w_k \). The power balance and the operational constraints of the system units are represented by the constraint sets \( g \) and \( h \).

Based on this system description, the economic dispatch optimization can be formulated as a constrained finite time optimal control problem

\[
J_0^*(x(t)) = \min_{U_0} J_0(x(t), U_0) \tag{1.5}
\]

s.t. (a) \( x_{k+1} = Ax_k + Bu_k \)
(b) \( g(x_k, u_k, u_{k+1}, w_k) = 0 \)
(c) \( h(x_k, u_k, u_{k+1}, w_k) \leq 0 \)
(d) \( x_0 = x(t) \)

(a-c) \( \forall k = 0, \ldots, N - 1 \quad , \)

which is solved in an open-loop fashion at time \( t \). The objective function is denoted by \( J_0 \). Let \( U_0^* = \{ u_0^*, \ldots, u_{N-1}^* \} \) term the optimal input sequence. By applying the MPC strategy, the stated open-loop optimal control problem is solved at each sampling time. However, only the first element of \( U_0^* \) is applied to the system during the following sampling interval \([t, t+1]\). At the next time step \( t+1 \), the prediction horizon is shifted and a new optimal control problem based on new measurements of the state is solved. A state-feedback is thus established. The resulting controller is referred to as receding horizon controller.

The receding horizon control law is expressed by

\[
u(t) = f_0(x(t)) = u_0^*(x(t)) \quad . \tag{1.6}\]

Consequently, the closed loop system is described by

\[
x(k + 1) = A x(k) + B f_0(x(k)) = f_{cl}(x(k)), \quad k \geq 0 \quad . \tag{1.7}\]

In summary, the economic dispatch algorithm based on model predictive control is specified as follows:
1. **MEASURE** the system state $x(t)$ at time instance $t$.

2. **DETERMINE** $W_0 = \{w_0, \ldots, w_{N-1}\}$ by a forecast model, which predicts load demand and intermittent generation.

3. **OBTAIN** $U_0^*(x(t))$ by solving the optimization problem stated in Equation (1.5).

4. **APPLY** the first element $u_0^*$ of $U_0^*$ to the system.

5. **WAIT** for the new sampling time $t + 1$.

6. **GOTO** (1.).

### 1.5 DC power flow equation

This section aims at deriving the DC power flow equation, which enables to calculate the active power transferred by a lossless transmission line from node $m$ to node $n$. According to [18], the active power is calculated as a function of phase shift between the voltage phasors at the line ends. These voltage phasors can be written in polar representation as

$$
U_m = U_m e^{j\theta_m} \quad \text{and} \quad U_n = U_n e^{j\theta_n}.
$$

The transmission line is modeled as a purely inductive series impedance $jX_L = j\omega L$. As we neglect transmission losses, the active powers at both line ends are equal. Thus, the active power flow from node $m$ to node $n$ can be calculated according to

$$
P_{mn} = -P_{nm} = \text{Re}\{U_m L_m^*\} \quad . \quad (1.8)
$$

The current and its complex conjugate are derived from

$$
L_m = \frac{U_m - U_n}{jX_L} = \frac{U_m e^{j\theta_m} - U_n e^{j\theta_n}}{jX_L} \quad , \quad (1.9)
$$

$$
L_m^* = \frac{U_m e^{-j\theta_m} - U_n e^{-j\theta_n}}{-jX_L} = \frac{j}{X_L}(U_m e^{-j\theta_m} - U_n e^{-j\theta_n}) \quad . \quad (1.10)
$$

We assume the voltage amplitudes $U_m$ and $U_n$ at the line ends to be known and fixed. Moreover, we define one phase angle as reference value, e.g. at the end of the line: $\theta_n = 0$. Consequently, the active power transferred
between the two nodes is computed according to

\[ P_{mn} = \text{Re} \left\{ U_m I_n^* \right\} = \text{Re} \left\{ U_m e^{j\theta_m} \frac{1}{X_L} (U_m e^{-j\theta_m} - U_n) \right\} = \text{Re} \left\{ jU_m^2 \frac{1}{X_L} - jU_m U_n \frac{1}{X_L} e^{j\theta_m} \right\} = \text{Re} \left\{ jU_m^2 \frac{1}{X_L} - jU_m U_n \frac{1}{X_L} \cos \theta_m + U_m U_n \frac{1}{X_L} \sin \theta_m \right\} = U_m U_n \frac{1}{X_L} \sin \theta_m = U_m U_n \frac{1}{X_L} \sin(\delta_{mn}), \quad (1.11) \]

where \( \delta_{mn} = \theta_m - \theta_n \) denotes the angle difference between the voltage at the beginning and the end of the line. This difference is termed transmission angle and is during light load conditions very small. As a consequence, it is valid to approximate the node voltages to 1 p.u. Using

\[ \sin(\delta_{mn}) \approx \delta_{mn} \quad (1.12) \]
\[ U_m \approx U_m \approx 1 \text{ p.u.} \quad (1.13) \]

leads to the simplified expression of the active power flow

\[ P_{mn} = \frac{\delta_{mn}}{X_L}, \quad (1.14) \]

which is the called the DC power flow equation.

1.6 The Power Nodes modeling framework

Designing operation strategies for power systems, especially in the presence of non-dispatchable generation and rising storage capacities, is a challenging task. In traditional operation concepts, intermittent generation is regarded as a disturbance, which might cause significant imbalances in the power system. Power balance can only be restored either by controllable generators and loads, or by incorporating storage capacities. However, with an increasing variability in the grid, a paradigm shift has to take place from controllable generation and fluctuating, but more or less predictable, demand towards a holistic operation concept integrating intermittent generation, flexible demand and energy-constrained storages. The Power Nodes Modeling Framework presented in [9] aims at facilitating this shift. The framework is a novel concept which allows a system-level consideration of power grids composed of energy storages, dispatchable and non-dispatchable generators, and loads under consideration of grid-relevant aspects and physical properties.

A single Power Node can be regarded as a generic storage unit with energy storage capacity \( C \geq 0 \) and normalized energy storage level \( 0 \leq x \leq 1 \).
Figure 1.1 illustrates how the Power Node is embedded between the demand/supply process domain on the left side and the grid domain on the right side. The basic idea behind this approach is that any power source or sink connected to the electric power system requires the conversion of some form of energy into electric power, and vice versa. On the demand/supply side the provided and demanded energies are lumped into an external process termed $\xi$. A use of energy is denoted by $\xi < 0$, while a supply is indicated by $\xi > 0$. The power generation with an efficiency $\eta_{\text{gen}}$ is described by the term $u_{\text{gen}} \geq 0$, while $u_{\text{load}} \geq 0$ describes a conversion corresponding to a consumption with efficiency $\eta_{\text{load}}$. In case $\xi > 0$ holds true, a decoupling between the external process $\xi$ and the two grid-related exchanges $u_{\text{gen}}$ and $u_{\text{load}}$ takes place. Consequently, due to its storage capability the Power Node serves as a buffer between the two domains.

Figure 1.1: Notation of a single Power Node [9].

Curtailment of intermittent power infeed in areas with high RES penetration is sometimes the only countermeasure to preserve network security. Vice versa, in the case when sufficient generation capacities are not available to cover current demand, loads have to be disconnected from the grid to mitigate the imbalance. These enforced energy losses, e.g. curtailment/shedding of a supply/demand process, are denoted by the waste term $w$. A loss of provided energy is denoted by $w > 0$, an unserved demand process by $w < 0$. Internal energy losses associated with energy storage are modeled by the term $v \geq 0$.

The dynamics of the Power Node storage level $x$ can be mathematically expressed by accounting for all energy flows presented so far. Equation (1.15) describes the dynamics of an arbitrary power node $i \in \mathcal{N} = \{1, \ldots, N\}$ subjected to a generic set of constraints (a) - (f).
Chapter 1. Introduction

1.6.1 Characterization of unit types

The Power Node Modeling Framework enables to represent diverse units in the power system. In this context a “unit” is regarded as an arbitrary generation, load, or storage device with a specific set of unit and operational

\[ C_i \dot{x}_i = \eta_{\text{load},i} u_{\text{load},i} - \eta_{\text{gen},i}^{-1} u_{\text{gen},i} + \xi_i - w_i - a_i (x_i - x_{o,i}) \]  

(1.16)

Additionally, with a state-dependent physical loss term \( v_i(x_i) \) internal dependencies can be considered. In general, a heat storage suffers from heat losses due to a temperature gradient between the inside of the storage and the ambiance. In Equation (1.16) a linear dependence of \( v_i \) on the storage state \( x_i \) is modeled by the non-negative loss coefficient \( a_i \) and the steady-state storage level \( x_{o,i} \). In steady-state and in the absence of power inputs, the thermal storage is in equilibrium with the environment.
Table 1.2: Unit properties determined by Power Node equation constraints.

<table>
<thead>
<tr>
<th>Variable(s)</th>
<th>Constraint(s)</th>
<th>Implications</th>
</tr>
</thead>
</table>
| $u_{gen,i}$, $u_{load,i}$ | $u_{gen,i} = 0$  
$u_{load,i} = 0$  
$u_{gen,i} \cdot u_{load,i}$ | Load  
Generator  
One-conv.-unit storage  
Two-conv.-unit storage |
| $C_i$ | $C_i = 0$  
$C_i > 0$ | Non-buffered  
Buffered |
| $\xi_i$ | $\xi_i = 0$  
$\xi_i \geq 0$  
$\xi_i \leq 0$ | No external process  
Supply process  
Demand process |
| $\xi_i$, $w_i$ | $\xi_i = \xi_{drv,i}(t) \wedge w_i = 0$  
$\xi_i = \xi_{drv,i}(t)$  
$\xi_i$ arbitrary, $w_i = 0$ | Non-controllable  
Curtailable  
Controllable |
| $v_i$ | $v_i = 0$  
$v_i > 0$ | Lossless storage  
Lossy storage |
| $\dot{u}_{gen,i}$, $\dot{u}_{load,i}$ | $\dot{u}_{gen,i}^{\min} \leq \dot{u}_{gen,i} \leq \dot{u}_{gen,i}^{\max}$  
$\dot{u}_{load,i}^{\min} \leq \dot{u}_{load,i} \leq \dot{u}_{load,i}^{\max}$ | Ramp-rate-constr. gen.  
Ramp-rate-constr. load |

properties. In addition to the constraints (a) - (f) in Equation (1.15), further constraints can be imposed on the variables $u_{gen,i}$, $u_{load,i}$, $C_i$, $x_i$, $\xi_i$, $v_i$, and $w_i$ to represent these properties and distinct between unit types. Table 1.2 lists possible Power Node equation constraints and their implication on the unit properties. The selection of constraints is explained in the following:

- The grid infeed or output of a Power Node is determined by the variable $u_{gen,i}$ and $u_{load,i}$. In case of a generation unit the condition $u_{load,i} = 0$ holds true at all times, while a pure load is modeled by the constraint $u_{gen,i} = 0$. By contrast, energy storage systems can be considered as bi-directional conversion systems where not necessarily both variables have to be zero. Either both conversions happen at the same, e.g. a pumped hydro plant with independent pump and turbine, or one variable must always be zero, e.g. in an inverter connected battery storage.

- The storage capacity $C_i$ determines whether the Power Node features storage capability ($C_i > 0$) or not ($C_i = 0$).

- The nature of the external process is defined by the sign of $\xi_i$. The variable is positive for a supply process ($\xi_i > 0$), and negative for a demand process ($\xi_i < 0$). If no external process takes place, the condition ($\xi_i = 0$) holds.
The controllability of a unit is constituted by a set of constraints on the variables $\xi_i$ and $w_i$. In case $\xi_i$ is determined by an external signal $\xi_i = \xi_{\text{drv},i}(t)$, e.g. induced by an intermittent supply, two cases can be distinguished. The unit is either non-controllable and thus curtailment is not possible ($w_i = 0$), or excess supply can be curtailed (no further constraints on $w_i$). Contrary, a unit is controllable if $\xi_i$ is not externally driven. As the curtailment of controllable units is unnecessary, $w_i = 0$ is set.

In case the Power Node features storage capability ($C_i > 0$), the unit is lossless if $v_i = 0$, and lossy if $v_i > 0$.

A unit might be ramp-rate-constrained on the grid variables $u_{\text{gen},i}$ and $u_{\text{load},i}$. This property is reflected in continuous time by an upper and lower bound on the variables derivatives. Consequently, physical limitations on the rate of change of a power conversion process can be modeled.
Chapter 2

Modeling of power node portfolio

This chapter introduces the analyzed portfolio of Power Nodes, which represents conventional and flexible loads, dispatchable and intermittent renewable generation units, and diverse storage technologies. Each Power Node is modeled individually according to framework presented in Section 1.6. The parameterization and the technical constraints of the modeled units are based on real performance figures derived from literature.

The portfolio of Power Nodes consists of 7 units, \(i \in \mathcal{N} = \{1, \ldots, 7\}\), with the following characteristics:

1. A conventional load without buffer that can be curtailed if not enough electricity can be provided. The demand is driven by an external process \((C_1 = 0, \xi_1 = \xi_{\text{drv},1}(t) \leq 0)\),

2. A wind farm, implemented as non-buffered generation unit with curtailable supply \((C_2 = 0, \xi_2 = \xi_{\text{drv},2}(t) \geq 0)\),

3. An aggregation of PV panels, implemented as a non-buffered generation unit with curtailable supply \((C_3 = 0, \xi_3 = \xi_{\text{drv},3}(t) \geq 0)\),

4. A pumped hydro plant, implemented as a storage unit with capacity \(C_4\) and without external process \((\xi_4 = 0)\),

5. A sodium-sulfur (NaS) battery system, implemented as a storage unit with capacity \(C_5\) and without external process \((\xi_5 = 0)\),

6. A biomass power plant, implemented as a non-buffered generation unit with controllable supply \((C_6 = 0, \xi_6 \text{ controllable}, w_6 = 0)\),

7. An aggregation of electric water heaters with thermal energy storage capacity \(C_7\) and loss coefficient \(a_7\), implemented as a buffered load with non-controllable demand \((\xi_7 = \xi_{\text{drv},7}(t) \leq 0)\).
CHAPTER 2. MODELING OF POWER NODE PORTFOLIO

2.1 Conventional load

The entire electricity demand of the analyzed power system is lumped together in one Power Node. This conventional load is assumed to be non-buffered ($C_1 = 0$). The demand is driven by an external process ($\xi_1 = \xi_{\text{drv},1}(t) \leq 0$). In case not enough generation capacities are temporarily available, load demand can be shedded. Consequently, the Power Node equation is denoted by

$$\xi_1 - w_1 = -\eta_{\text{load},1} u_{\text{load},1}.$$  \hspace{1cm} (2.1)

There are two reasons why load shedding is incorporated. First, this measure is considered as eligible control action. However, it should be performed by the dispatch controller as a last resort. Secondly, an additional degree of freedom is added to the optimization, which enables the solver to always find a feasible solution.

The external demand process $\xi_{\text{drv},1}(t)$ is derived from the online data portal of ENTSO-E and represents the aggregated electricity consumption in Germany in the year 2009 [19]. The profile has a time resolution of 1 hour. The annual electricity demand amounts to 459.8 TWh. The maximum and minimum power demand are 73.0 GW and 29.0 GW, respectively. The average load demand amounts to 52.5 GW.

Figure 2.1 illustrates the graph of $\xi_{\text{drv},1}(t)$. A seasonal variation of demand is noticeable. In winter (November until March) electricity demand is considerably higher than in summer (May until September). Due to a higher need for lighting and heating devices, e.g. electric water heaters and electric heating, the consumption of electricity in Germany is about 15% higher in winter than in summer. In France, where many houses are heated electrically, this spread is even higher and amounts to about 30%. As in Spain many houses are cooled by air conditioning, the demand profile features a peak in summer and in winter.

Table 2.1 lists all constraints and parameters of the Power Node, which represents the total load demand in Germany.

2.2 Wind energy

The aggregation of wind turbines is modeled as non-buffered generation unit with curtailable supply ($C_2 = 0$, $\xi_2 = \xi_{\text{drv},2}(t) \geq 0$). Thus, the behavior of the Power Node $i = 2$ is described by

$$\xi_2 - w_2 = \eta_{\text{gen},2}^{-1} u_{\text{gen},2}.$$  \hspace{1cm} (2.2)

The intermittent generators are considered to be highly flexible with no limitation on control actions. Hence, ramp-rate constraints on $w_2$ and $u_{\text{gen},2}$ are not imposed.
CHAPTER 2. MODELING OF POWER NODE PORTFOLIO

Figure 2.1: External demand process $\xi_{\text{drv},1}(t)$ representing the load curve of the aggregated electricity consumption in Germany in the year 2009 [19].

Table 2.1: Constraints and parameters of the Power Node $i = 1$, which represents the total load demand in Germany.

<table>
<thead>
<tr>
<th>Constraints on a non-buffered load with curtable demand:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_{\text{gen},1} = 0$</td>
<td>$C_1 = 0$</td>
</tr>
<tr>
<td>$\xi_1 = \xi_{\text{drv},1}(t) \leq 0$</td>
<td>$w_1 \leq 0$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_{\text{max},\text{load},1} = 72.974$ GW</td>
<td>$u_{\text{min},\text{load},1} = 0$ MW</td>
</tr>
<tr>
<td>$u_{\text{max},\text{load},1} = 72.974$ GW</td>
<td>$w_{1\text{max}} = 72.974$ GW</td>
</tr>
<tr>
<td>$\eta_{\text{load},1} = 1$</td>
<td></td>
</tr>
</tbody>
</table>

Previous case studies utilized actual wind speed measurements in order to incorporate wind generation in their simulations. The advantage of this approach is that diverse spatial dispersion of generation units can be considered. The placement is arbitrary and can be chosen such that overall intermittency of wind generation is minimized. For instance, a wide-ranging installation of wind turbines reduces the correlations between their generation and smoothes the aggregated power infeed. However, this approach calls for weather data in high spatial resolution in order to gain reasonable results.

In this thesis a more straightforward approach is chosen by using an actual infeed time series of wind energy. The German high voltage transmission grid is divided into four control areas. Each of them is monitored by an independent transmission system operator, named 50Hertz, Amprion, EnBW TNG and TenneT. In their online databases, actual infeed profiles of wind generation are available for several years. In this thesis, the data set
of the TenneT control area is used as external supply processes ($\xi_{drv,2}(t)$) [20] [21]. The data set has a time resolution of 15 minutes and is a reasonable representation of a German portfolio of wind turbines as the TenneT control area ranges from Schleswig-Holstein, the northernmost German state, to Bavaria, the southernmost state.

The time series of the wind infeed profile is illustrated in Figure 2.2. The profile features a highly fluctuating behavior. Periods of days with low generation are followed by periods of high wind infeed. According to [22], the installed nameplate capacity of wind turbines in Germany increased between the years 2009-2010 from 25716 MW to 27204 MW. This results in a growth rate of 5.8%. Hence, the extension is negligible and does not necessitate a normalization of the profile $\xi_{drv,2}(t)$.

![Figure 2.2: External supply process $\xi_{drv,2}(t)$ of a wind farm dispersed over Germany [20] [21].](image)

In order to investigate the seasonal pattern of the wind energy, Figure 2.3 illustrates the monthly energy balance terms of the time series. The plot shows that wind energy is considerably lower during summer season.

As the aim of this thesis is to perform case studies with different renewable supply scenarios, the wind profile $\xi_{drv,2}(t)$ is scaled linearly by the dimensioning factor $\lambda_{2,1}$ in order to represent higher installed generation capacities. Clearly, with this approach it is assumed that new installed units are located right next to existing ones. In reality, system operators prefer to emphasize the decentralized character of their RES portfolio in order to benefit from smoothing effects of the aggregated infeed due to a spatial dispersion of generation units. In summary, Table 2.2 lists all constraints and parameters of the Power Node $i = 2$, which represents an aggregation of wind turbines distributed over Germany.
2.3 PV energy

Like the aggregated wind energy supply, the aggregation of PV panels is modeled as a non-buffered generation unit with curtailable supply \( C_3 = 0 \), \( \xi_3 = \xi_{\text{drv},3}(t) \geq 0 \). Hence, the Power Node equation is denoted as

\[
\xi_3 - w_3 = \eta_{\text{gen},3}^{-1} u_{\text{gen},3} \quad .
\] (2.3)

Unfortunately, available PV infeed profiles for Germany covering a time span of one full year are rare. Since July 2010 each transmission system operator is obliged to publish the infeed profiles of their renewable generation portfolio. Only the TenneT TSO GmbH has made data available since January 2010 [20, 21], which is illustrated in Figure 2.4.

With an appropriate zoom factor, the plot shows that the PV profile is affected by an intraday pattern with an infeed peak around 1 pm when incident solar radiation is the highest. An explicit seasonal pattern is observable with higher peaks during the summer season. However, the fact that a few peaks in October are higher than in July is not intuitive. This can only be
explained by large installations of additional PV capacities throughout the year.

The circumstance that the PV infeed profile peaks in October is investigated in the following. According to [22], the installed peak power of PV in Germany increased between the years 2009-2010 from 9914 MW to 17320 MW. This increase marks almost a doubling of the installed capacity. Based on monthly installation data of PV panels in the year 2010 [23], Figure 2.5 illustrates the increase of total PV capacity in Germany. The plot shows that additional PV panels have been installed mainly in the second half of the year.

In order to eliminate the extension effect, the actual PV infeed profile obtained from the TenneT database is normalized with the installation data.
from Figure 2.5. Thereby, a linear increase of additional installed capacity from month to month is assumed. The normalized infeed profile is plotted in Figure 2.6. The graph reveals that PV infeed peaks in October are still very high. This can only be explained with the assumptions that (1) before October not all installed PV panels have been considered in the dataset or (2) the extension of PV capacities in the TenneT control area is not correlated with the capacity extension in Germany. However, this profile is used in this thesis as external supply processes \( \xi_{\text{drv},3}(t) \) for PV energy.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure26.png}
\caption{External supply process \( \xi_{\text{drv},3}(t) \) for an aggregation of PV panels distributed over Germany.}
\end{figure}

Figure 2.7 plots the monthly energy balance terms of \( \xi_{\text{drv},3}(t) \). A typical seasonal pattern of solar energy is observable. Fortunately, the amount of supplied electricity by PV in October is considerably smaller than in the summer season months. Hence, \( \xi_{\text{drv},3}(t) \) is suitable for representing an aggregation of PV panels.

In summary, Table 2.3 lists all constraints and parameters of the Power Node \( i = 3 \), which represents an aggregation of PV panels distributed over Germany.

### 2.4 Pumped hydro plant

For several decades pumped hydro plants have been technically available and operated worldwide. Nowadays, they represent the most mature and economical technology to store electricity on the large scale. By pumping water from a lower to an upper reservoir, potential energy from height differences in water levels is stored. Electricity is generated by releasing water back into the lower reservoir through a turbine. This is the most common form of energy storage accounting for 97% of the worldwide installed stor-
Figure 2.7: Monthly energy balance terms of the external supply process \( \xi_{\text{drv},3}(t) \) representing PV energy.

Table 2.3: Constraints and parameters of the Power Node \( i = 3 \), which represents an aggregation of PV panels distributed over Germany.

<table>
<thead>
<tr>
<th>Constraint</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_{\text{load},3} = 0 )</td>
<td>( C_3 = 0 )</td>
</tr>
<tr>
<td>( \xi_3 = \lambda_{3,1} \cdot \xi_{\text{drv},3}(t) \geq 0 )</td>
<td>( w_3 \geq 0 )</td>
</tr>
</tbody>
</table>

Parameters:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_{\text{gen},3}^{\text{max}} = \max(\lambda_{3,1} \cdot \xi_{\text{drv},3}(t)) )</td>
<td>( u_{\text{gen},3}^{\text{min}} = 0 ) MW</td>
</tr>
<tr>
<td>( \dot{u}<em>{\text{gen},3}^{\text{max}} = \max(\lambda</em>{3,1} \cdot \xi_{\text{drv},3}(t)) )</td>
<td>( w_3^{\text{max}} = \max(\lambda_{3,1} \cdot \xi_{\text{drv},3}(t)) )</td>
</tr>
<tr>
<td>( \eta_{\text{gen},3} = 1 )</td>
<td></td>
</tr>
</tbody>
</table>

Currently, about 250 pumped hydro plants are in operation worldwide. Their cumulative generation capacity accounts for 120 GW. In recent years this capacity has grown by 5 GW.

Currently, in Germany the installed power of pumped hydro plants sums up to 6.7 GW. The installed capacity is equal to 40 GWh [24] and accounts for about 95% of the total storage capacity in Germany. The discharge time at rated power of the individual facilities varies between 4-8 h. Since the deployment of pumped hydro plants requires a topography with sufficient potential energy, most of the storage capacities are installed in Baden-Württemberg (2.0 GW), Thüringen (1.5 GW), and Sachsen (1.2 GW). By 2020, a storage capacity of 8.4 GW is assumed [25]. However, this figure does not consider the planned pumped hydro plant in Atdorf, which features a power rating of 1.4 GW. The storage facility is assumed to be put into operation by 2019. Further extensions in Germany are hardly possible as most of the sites are already occupied or new constructions are impeded due to environmental concerns.

The reasons why pumped hydro storages are a very popular solution to store electricity are manifold [26]. These units possess high cycle efficiencies...
Table 2.4: Constraints and parameters of the Power Node \( i = 4 \), which represents a pumped hydro plant.

<table>
<thead>
<tr>
<th>Constraints on a storage without external process:</th>
<th>Parameters:</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_{\text{gen},4} \cdot \xi_{\text{load},4} = 0 )</td>
<td>( u_{\text{max}, \text{gen},4} = \lambda_{4,1} \cdot 1060 \text{ MW} )</td>
</tr>
<tr>
<td>( \xi_{4} = 0 )</td>
<td>( u_{\text{max}, \text{load},4} = \lambda_{4,1} \cdot 1060 \text{ MW} )</td>
</tr>
<tr>
<td>( C_{4} &gt; 0 )</td>
<td>( u_{\text{min}, \text{gen},4} = 0 \text{ MW} )</td>
</tr>
<tr>
<td>( w_{4} = 0 )</td>
<td>( u_{\text{min}, \text{load},4} = 0 \text{ MW} )</td>
</tr>
</tbody>
</table>

(65-85%), large power ratings in the range of 100-1000 MW, high discharge times at rated power up to more than 24 h, and a long lifetime between 30-60 years. Capital cost per cycle are very low and vary between 0.1-1.4 \$/kWh/cycle. Due to their high ramp rates (0-1800 MW in 16s, Dinorwig pumping station), pumped hydro plants are able to level fluctuating renewable power generation. This is especially important at high penetration levels of wind generation.

The dimensioning of a pumped hydro plant is tied to the geographic circumstances. The pumped hydro plant Goldisthal is at the moment the largest one in Germany. It features a power rating of 1060 MW and an energy storage capacity of 8480 MWh. Hence, the turbines can be operated 8 h in full-load operations. The overall efficiencies of the pumps and turbines are 85% and 90%, respectively.

Based on the mentioned data, the Power Node representing a pumped hydro plant is modeled as a storage unit with capacity \( C_{4} \) and without external process \( \xi_{4} = 0 \). The storage is considered as bi-directional conversion system, but only one conversion can happen at the same time. Efficiencies for the charge/discharge process are denoted by \( \eta_{\text{load},4} \) and \( \eta_{\text{gen},4} \), respectively. As daily parasitic losses are negligible for bulk storage systems operated on a daily basis, the loss coefficient \( a_{i} \) is set to zero. Any losses are already included in the system efficiency. Thus, the Power Node equation is described by

\[
C_{4} \dot{x}_{4} = \eta_{\text{load},4} u_{\text{load},4} - \eta^{-1}_{\text{gen},4} u_{\text{gen},4} \quad .
\]  

In summary, Table 2.4 lists all constraints and parameters of the Power Node \( i = 4 \), which represents a pumped hydro plant. The dimensioning factor \( \lambda_{4,1} \) enables to scale the storage system. Please note that the discharge time at rated power, which is calculated by the division of \( C_{4} \) by \( u_{\text{max}, \text{gen},4} \), remains constant at 8 h.
2.5 NaS battery system

A sodium-sulfur (NaS) battery is a molten metal battery fabricated from sodium and sulfur. These materials are inexpensive, non-toxic and in the long-term future not affected by supply shortages. In the last decade, the installed capacity of NaS batteries has grown exponentially from 10 MW in 1998 to 305 MW at the end of the year 2008 [26]. According to a recent published life-cycle cost analysis [27], NaS batteries are the most economically mature battery storage option for energy management. Figure 2.8 lists further advantages of NaS batteries over other available battery technologies. It can be seen that NaS batteries ranks first in all evaluation criteria.

![Comparison between NaS battery and other, at the moment available battery technologies](image)

At the moment, NaS batteries are manufactured by only one company in Japan named NGK Insulators. A typical system features a rated input/output power of 2 MW and a rated capacity of 12 MWh. The system is composed of individual modules, each with a power rating of 50 kW and an energy capacity of 360 kWh. The largest NaS storage system installed by NGK features 34 MW/245 MWh and is sited in northern Japan for stabilizing a 51 MW wind farm. Apart from pumped hydro and compressed air energy storages, this installation is the largest energy storage system in the world. But even larger installations are possible due to the modular construction method.

For several reasons, NaS batteries are considered as attractive storage technology for managing intermittent renewable infeed [26]. They are very efficient (75-90%) and feature a high power density (150-240 W/kg). Moreover, they possess a 15-year service life and a high cycle life (2500 cycles at 100% depth-of-discharge, 4500 at 90%, 6500 at 65%). Additionally, the modular construction method enables to easily construct storage facilities with large energy capacities. A further advantage is that NaS battery sys-
Table 2.5: Constraints and parameters of the Power Node \( i = 5 \), which represents a NaS battery storage system.

<table>
<thead>
<tr>
<th>Constraints on a storage without external process:</th>
<th>Parameters:</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_{\text{gen},5} \cdot u_{\text{load},5} = 0 )</td>
<td>( u_{\text{min},5} = 0 ) MW</td>
</tr>
<tr>
<td>( \xi_5 = 0 )</td>
<td>( u_{\text{max},5} = 0 ) MW</td>
</tr>
<tr>
<td>( w_5 = 0 )</td>
<td>( u_{\text{min},5} = 0 ) MW</td>
</tr>
<tr>
<td>( u_{\text{max},5} = \lambda_{5,1} \cdot 50 ) kW</td>
<td>( u_{\text{max},5} = \lambda_{5,1} \cdot 50 ) kW</td>
</tr>
<tr>
<td>( u_{\text{gen},5} = \lambda_{5,1} \cdot 50 ) kW</td>
<td>( \eta_{\text{load},5} = 0.88 )</td>
</tr>
<tr>
<td>( \eta_{\text{gen},5} = 0.88 )</td>
<td>( \dot{u}<em>{\text{load},5} = \lambda</em>{5,1} \cdot 50 ) kW</td>
</tr>
<tr>
<td>( C_5 = \lambda_{5,1} \cdot 360 ) kWh</td>
<td>( \eta_{\text{gen},5} = 0.88 )</td>
</tr>
</tbody>
</table>

Systems can be sited at arbitrary locations. By contrast, a pumped hydro plant can only be sited at suitable geographical locations which enable to build high and low storage reservoirs.

Based on the mentioned data, the NaS battery is modeled as a storage unit with capacity \( C_5 \) and without external process \( \xi_5 = 0 \). The battery is considered as bi-directional conversion system, but only one conversion can happen at the same time. Efficiencies for the charge/discharge process are denoted by \( \eta_{\text{load},5} \) and \( \eta_{\text{gen},5} \), respectively. Thus, according to the Power Node framework, the dynamics of the Power Node are described by

\[
C_5 \dot{x}_5 = \eta_{\text{load},5} u_{\text{load},5} - \eta_{\text{gen},5}^{-1} u_{\text{gen},5} . \tag{2.5}
\]

In summary, Table 2.5 lists all constraints and parameters of the Power Node \( i = 5 \), which represents a NaS battery storage system. The dimensioning factor \( \lambda_{5,1} \) enables to scale the storage system. Please note that the discharge time at rated power, which is calculated by the division of \( C_5 \) by \( u_{\text{gen},5}^{\text{max}} \), remains constant at 7.2 h.

### 2.6 Biomass power plant

The potential for biomass-based electricity generation in Germany is enormous. With 17% of the usable agricultural area about 100 TWh/a of electricity could be generated [6]. Therefore, as dispatchable generation unit a biomass power plant is considered, which generates electricity with combined heat and power module (CHP) from biogas. The plant is modeled as a non-buffered generation unit with controllable supply. The Power Node equation of the generation unit is denoted by

\[
\xi_6 = \eta_{\text{gen},6}^{-1} u_{\text{gen},6} . \tag{2.6}
\]
Table 2.6: Constraints and parameters of the Power Node \( i = 6 \), which represents a biomass power plant.

| Constraints on a non-buffered generation unit with controllable supply: |
|-----------------------------|-----------------------------|
| \( u_{\text{load},6} = 0 \) | \( C_6 = 0 \) |
| \( \xi_6 \geq 0 \) | \( w_6 = 0 \) |

| Parameters: |
|-----------------------------|-----------------------------|
| \( u_{\text{max}}^{\text{gen},6} = \lambda_{6,1} \) | \( u_{\text{min}}^{\text{gen},6} = 0 \) |
| \( \dot{u}_{\text{max}}^{\text{gen},6} = \lambda_{6,1} \) | \( \eta_{\text{gen},6} = 0.42 \) |

The biogas is produced from biomass by a nearby sited fermentation plant. As such plants have a rather inflexible output rate, a sufficiently large gas tank is assumed as buffer in order to enable the CHP unit to react on fluctuating load demand and variation in the renewable infeed. Without the gas tank, the CHP unit could only provide baseload power. In general, the electric efficiency of large CHP units with a power rating of 2000 kW are in the range of 38-43\% \[29\].

In summary, Table 2.6 lists all constraints and parameters of the Power Node \( i = 6 \), which represents the biomass power plant. The installed power capacity can be scaled by the dimensioning factor \( \lambda_{6,1} \).

### 2.7 Aggregation of electric water heaters

In the light of demand side management, more attention is paid to the controllability of loads with inherent storage, such as plug-in electric vehicles and thermostat-controlled household appliances with thermal inertia \[30\], \[31\]. The potential of the latter to provide local load management (LLM) services has been investigated in \[32\]. Applications of LLM are peak shaving and load shifting, balance group optimization, provision of control reserves, wind ramp reduction and active network management. A technical and financial feasibility study shows that these applications can offer interesting business opportunities \[33\].

In general, LLM aims at including the end users and their loads into the control of the overall power system and contribute to its stability. In this context, appliances with thermal inertia, e.g. refrigerators, freezers, and electric water heaters, can be used as buffers. Due to the thermal storage capacity of these devices, their on/off state can be altered by an external toggle signal without any decrease of user comfort. As a consequence of the state alteration, the electrical power consumption increases or decreases. By aggregating a group of such appliances, considerable changes of the overall load curve can be achieved.

As calculated in \[30\], electric water heaters offer the largest storage ca-
capacity. Thus, in this section a model is derived which aims at representing the current number of installed electric water heaters in Germany.

2.7.1 Modeling approach

In the following, a mathematical model is derived to describe the dynamical behavior of an electric water heater’s energy storage content $E_{ewh}$. An illustration of a generic electric water heater and its energy in- and outflows is shown in Figure 2.9.

In general, water heating is a thermodynamic process using an energy source to heat water above its initial temperature. In case of an electric water heater, an electrical resistance heater is utilized as energy source which feeds energy into the system with the power rate $P_{load}$. The energy, which is extracted from the storage by drawing warm water, is accounted for by the enthalpy flow $\dot{E}_{water,warm}$. Analogously, the enthalpy flow $\dot{E}_{water,cold}$ considers the energy contained in the inflowing, unheated water. Due to a temperature gradient between the inside of the storage and the ambiance, heat losses occur. They are represented by the heat loss rate $\dot{Q}_{loss}$. Subsequently, the dynamics of the storage content $E_{ewh}$ can be expressed according to

$$\dot{E}_{ewh} = P_{load} - \dot{Q}_{loss} + \dot{E}_{water,cold} - \dot{E}_{water,warm}. \quad (2.7)$$

By heating up water from the inlet temperature $T_{water,cold}$ to the outlet temperature $T_{water,warm}$, the electric water heater increases its stored thermal energy. With the assumption that the average water temperature inside the water tank $T_{ewh}$ varies between these two boundaries, the available storage capacity of the electric water heater $C_{ewh}$ can be calculated according to Equation (2.8). The mass-specific heat capacity of water is considered by
the term $c_{m,\text{water}}$, the water’s density by $\rho_{\text{water}}$, and the volumetric capacity of the heater’s tank by $V_{\text{ewh}}$.

$$C_{\text{ewh}} = c_{m,\text{water}} \cdot \rho_{\text{water}} \cdot V_{\text{ewh}} \cdot (T_{\text{water,warm}} - T_{\text{water,cold}}) \quad (2.8)$$

The stored thermal energy inside the heater $E_{\text{ewh}}$ can be derived from the average water temperature $T_{\text{ewh}}$, which serves as a dynamic state variable of the device. The temperature is mapped to an interval of $[0,1]$ in relation to inlet and outlet temperatures. This mapping yields the storage level $x_{\text{ewh}}$. Hence, the energy content $E_{\text{ewh}}$ is derived by Equation (2.9).

$$E_{\text{ewh}} = C_{\text{ewh}} \cdot x_{\text{ewh}} = C_{\text{ewh}} \cdot \frac{T_{\text{ewh}} - T_{\text{water,cold}}}{T_{\text{water,warm}} - T_{\text{water,cold}}} \quad (2.9)$$

Heated-up water ascends from the bottom to the top of the water tank. Hence, in reality a temperature gradient inside the tank in vertical direction results. For the sake of simplicity this gradient and the resulting energy exchange processes between the horizontal water layers are neglected. For the presented model the assumption is made that the water column inside the tank is composed of two phases. The temperature of the upper phase is $T_{\text{water,warm}}$, the one of the lower $T_{\text{water,cold}}$. As long as $x_{\text{ewh}} > 0$ holds true, warm water is available to the household.

The heat losses $\dot{Q}_{\text{loss}}$ are modeled with the one-dimensional heat equation, which states that the flow rate of heat energy through a surface is proportional to the temperature gradient across the surface. In the case of electric water heaters, this yields to

$$\dot{Q}_{\text{loss}} = \lambda_{\text{ewh}} \cdot S_{\text{ewh}} \cdot \frac{T_{\text{ewh}} - T_{\text{amb}}}{t_{\text{ewh}}}$$

where $\lambda_{\text{ewh}}$ terms the heat conductivity of the tank’s insulation, $S_{\text{ewh}}$ the tank surface, $t_{\text{ewh}}$ the insulation thickness and $T_{\text{amb}}$ the ambient temperature.

According to Equation (2.11), the difference between the enthalpy flows $\dot{E}_{\text{water,cold}}$ and $\dot{E}_{\text{water,warm}}$ is determined by the households’s warm-water-draw profile $WWD(t)$ [l/h].

$$\dot{E}_{\text{water,cold}} - \dot{E}_{\text{water,warm}} = c_{m,\text{water}} \cdot \rho_{\text{water}} \cdot (T_{\text{water,cold}} - T_{\text{water,warm}}) \cdot WW\text{D}(t) \quad (2.11)$$

### 2.7.2 Aggregation size

Currently, the portion $p_{\text{ewh}}$ of German households serving their warm water demand with electric water heaters is approximately 32% [34]. In 2009, the total number of households $n_{\text{hh}}$ in Germany added up to 40,188,000 [35].
Table 2.7: Technical data of an electric water heater to cover a 2-person household’s warm water demand [39].

<table>
<thead>
<tr>
<th>Given:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Company</td>
<td>Domotec AG</td>
</tr>
<tr>
<td>Model</td>
<td>S200</td>
</tr>
<tr>
<td>Volumetric capacity $V_{\text{ewh}}$</td>
<td>200 liter</td>
</tr>
<tr>
<td>Rated power $P_{\text{ewh}}^{\text{rated}}$</td>
<td>2000 W</td>
</tr>
<tr>
<td>Tank height</td>
<td>1293 mm</td>
</tr>
<tr>
<td>Tank diameter</td>
<td>600 mm</td>
</tr>
<tr>
<td>Insulation thickness $t_{\text{ewh}}$</td>
<td>50 mm</td>
</tr>
<tr>
<td>Heat conductivity $\lambda_{\text{ewh}}$</td>
<td>0.025 W/(m K)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Calculated:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface $S_{\text{ewh}}$</td>
<td>3 m$^2$</td>
</tr>
</tbody>
</table>

According to Equation (2.12), the total number of electric water heaters in Germany $n_{\text{ewh}} = 12,860,160$ can be obtained:

$$n_{\text{ewh}} = p_{\text{ewh}} \cdot n_{\text{hh}}.$$  
(2.12)

At the same time, 81,802,257 people lived in Germany [35]. This results in an average household size $s_{\text{hh}}$ of about 2 persons. By taking industry standard practices into consideration and assuming high comfort claims, an electric water heater with a volumetric capacity $V_{\text{ewh}} = 200$ liter is selected to cover a 2-person household’s warm water demand [36, 37, 38]. Further technical data is listed in Table 2.7. The tank’s surface $S_{\text{ewh}}$ is calculated by considering the mantle, upper and lower shell.

After having determined the type of electric water heater, the core characteristics of one single appliance and the aggregation of all existing ones in Germany are listed in Table 2.8.

### 2.7.3 Warm water draw profile

Warm water is a matter of course and an essential good of our daily life. Where, when, and how much warm water is consumed depends on many influence factors, e.g. the standard of living, hygiene and health. According to individual habits, the daily warm water demand per person may range between 10-120 liter. Reference values for residential living are listed in Table 2.9.

In the following, a warm water draw profile is synthesized which represents the electricity consumption induced by the aggregation of all electric water heaters in Germany. As a basis for the warm water draw profile serves a data set presented in [40]. In five different field studies data was collected for 41 Californian households. The observation intervals ranged from 2 weeks
Table 2.8: Core characteristics of electric water heater(s) with technical specifications according to Table 2.7.

<table>
<thead>
<tr>
<th>Given:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Spec. heat capacity $c_{\text{m,water}}$</td>
<td>4183 J/(kg K)</td>
</tr>
<tr>
<td>Density $\rho_{\text{water}}$</td>
<td>1 kg/liter</td>
</tr>
<tr>
<td>Temperature $T_{\text{water,warm}}$</td>
<td>60 °C</td>
</tr>
<tr>
<td>Temperature $T_{\text{water,cold}}$</td>
<td>10 °C</td>
</tr>
<tr>
<td>Temperature $T_{\text{amb}}$</td>
<td>20 °C</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>One electric water heater:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{ewh}}$</td>
<td>11.6 kWh</td>
</tr>
<tr>
<td>$S_{\text{ewh}}$</td>
<td>3 m²</td>
</tr>
<tr>
<td>$P_{\text{rated,ewh}}$</td>
<td>2000 W</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Aggregation of 12,860,160 electric water heaters:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{agg,ewh}}$</td>
<td>149.4 GWh</td>
</tr>
<tr>
<td>$S_{\text{agg,ewh}}$</td>
<td>38.6 km²</td>
</tr>
<tr>
<td>$P_{\text{rated,agg,ewh}}$</td>
<td>25.7 GW</td>
</tr>
</tbody>
</table>

Table 2.9: Reference values of the daily warm water demand per person at temperature between 60-65 °C [36].

<table>
<thead>
<tr>
<th>Standard of living</th>
<th>Warm water demand [liter/day]</th>
<th>Minimum</th>
<th>Average</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td></td>
<td>30</td>
<td>35</td>
<td>40</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>35</td>
<td>40</td>
<td>50</td>
</tr>
<tr>
<td>High</td>
<td></td>
<td>40</td>
<td>50</td>
<td>60</td>
</tr>
</tbody>
</table>
to 27 months, resulting in a representative pattern. The averaged warm water demand per household $WWD_{\text{norm}}(t)$ in hourly resolution is illustrated in Figure 2.10. The profile is normalized on the daily total use. The usage peaks in the morning, when people wake up and take a shower, and in the 5–9 p.m. period, when dinner is prepared dishes are washed. Note here that inter-weekday and seasonal variations are smoothed out as the pattern represents an average day of the year.

Based on $WWD_{\text{norm}}(t)$, the warm water demand pattern of all electric heaters $WWD_{\text{agg,ewh}}(t)$ [liter/h] in Germany can be derived according to Equation (2.13). Assuming a maximum warm water demand and an average living standard, a daily warm water demand per person $wwd_{p,daily}$ equal to 50 liter is derived from Table 2.9. As already mentioned in the previous subsection, the portion of German households with an electric water heater $p_{\text{ewh}}$ is equal to 32%, and the number of person per household $s_{\text{hh}}$ is 2.

$$WWD_{\text{agg,ewh}}(t) = p_{\text{ewh}} \cdot n_{\text{hh}} \cdot s_{\text{hh}} \cdot wwd_{p,daily} \cdot WWD_{\text{norm}}(t)$$

Consequently, the aggregated electric power demand $P_{\text{agg,ewh}}(t)$ [MW] required to heat up the drawn water according to $WWD_{\text{agg,ewh}}(t)$ is obtained by Equation (2.14). Note that $-P_{\text{agg,ewh}}(t)$ corresponds to $\xi_i$ in the Power Node framework.

$$\xi_i(t) = -P_{\text{agg,ewh}}(t) = c_{m,\text{water}} \cdot \rho_{\text{water}} \cdot (T_{\text{water,cold}} - T_{\text{water,warm}}) \cdot WWD_{\text{agg,ewh}}(t)$$

The resulting profile of $P_{\text{agg,ewh}}(t)$ is illustrated in Figure 2.11. The pattern features two peaks. One peak with 5095 MW occurs at 7 a.m., the other with a power demand of 5058 MW at 8 p.m. The daily electricity demand is equal to 74.7 GWh, the annual is equal 27.3 TWh.
2.7.4 Model validation

The dynamic model of the electric water heater cluster in Germany and the synthesized electric power demand profile of the warm water supply $P_{agg,ewh}(t)$ have been validated in Simulink. Thereby, a time span of one full year was simulated. The initial storage level of the heaters was set to 0.5. Electric energy at constant power $P^o_{agg,ewh} = 3420.8$ MW is fed into the storage such that at the end of the simulation the storage level is back at its initial value. The timely integral of $P_{ss,ewh}$ represents the annual electricity demand of the aggregation. As a consequence, an average electricity demand for one electric water heater is derived by dividing the total demand by $n_{ewh}$. The simulation results in an electricity demand per heater equal to 2330 kWh. Literature values show a value of around 2000 kWh/a for 2-person households in Switzerland [41].

In a second simulation, the heating-up time has been validated. In [39], a warm-up time of 6 h/60°C is stated. In the Simulink simulation the heater needs 5h 53min to reach $x_{ewh} = 1$. Hence, one can conclude that the derived dynamic model and the synthesized warm water pattern reproduce reality with adequate accuracy.

2.7.5 Operational limits

The control algorithm, which aggregates a group of electric water heaters to follow a given load profile, has to take account of the cluster’s operational capability. Two operational constraints on the storage dynamics have to be considered.

The first constraint aims at bounding the energy storage functionality of the aggregation $E_{agg,ewh}$. Obvious limits to the storage capability are the upper and lower bound of the electrical energy content. Thus, the maximum usable interval is denoted by $E_{agg,ewh} \in [0, C_{agg,ewh}]$, or in a normalized form...
by \( x_{\text{agg,ewh}} \in [0, 1] \).

In order to prevent the aggregation of heaters from “chattering” around their upper or lower thermal energy content threshold, an operation close to the upper and lower absolute boundaries should be avoided. As suggested in [30], a reasonable range of operation is \( 0.1 \leq x_{\text{agg,ewh}} \leq 0.9 \). However, in our case \( T_{\text{ewh}} = T_{\text{amb}} = 20^\circ\text{C} \) marks the threshold when ambient heat losses change sign. Hence, we consider the lower bound \( x_{\text{agg,ewh}} \geq 0.2 \). Additionally, we aim at investigating the maximum potential and choose the upper bound to be 1. The resulting boundary constraint for the storage level is

\[
0.2 \leq x_{\text{agg,ewh}} \leq 1 \quad (2.15)
\]

The second constraint on the coordinated operation is related to the power consumption \( P_{\text{load}} \). In [30] the power input is restricted to a range between 20\% of the steady-state power consumption \( P_{\text{agg,ewh}}^{ss} \) and 80\% of the installed appliance capacity \( P_{\text{agg,ewh}}^{\text{rated}} \). However, we aim at exploiting the full potential and choose the limits according to

\[
0 \leq P_{\text{load}} \leq P_{\text{agg,ewh}}^{\text{rated}} \quad (2.16)
\]

### 2.7.6 Power Node representation

Based on the previous sections, the dynamic Equation (2.7) of the storage content \( E_{\text{ewh}} \) can be converted in the Power Node Framework according to

\[
\begin{align*}
\dot{E}_{\text{ewh}} &= P_{\text{load}} - \dot{Q}_{\text{loss}} + \dot{E}_{\text{water,cold}} - \dot{E}_{\text{water,warm}} \\
\frac{C_{\text{ewh}}}{c_i} \dot{x}_{\text{ewh}} &= \frac{P_{\text{load}}}{u_{\text{load},i}} - \frac{\lambda_{\text{ewh}} \cdot S_{\text{ewh}} \cdot (T_{\text{water,warm}} - T_{\text{water,cold}})}{t_{\text{ewh}} - \frac{\lambda_{\text{ewh}} \cdot S_{\text{ewh}} \cdot (T_{\text{water,warm}} - T_{\text{water,cold}})}{a_i} + \frac{T_{\text{amb}} - T_{\text{water,cold}}}{x_{\text{ewh}} - x_i} + \frac{T_{\text{water,warm}} - T_{\text{water,cold}}}{x_{\text{ewh}} - x_i} + \frac{c_{\text{m,water}} \cdot \rho_{\text{water}} \cdot (T_{\text{water,cold}} - T_{\text{water,warm}}) \cdot \text{WWD}(t)}{\xi}
\end{align*}
\]

Consulting the list of possible unit type definitions within the Power Node framework presented in [9], the aggregation of electric water heaters is defined as a buffered load with non-controllable demand.

As summary, Table 2.10 lists the important Power Node parameters and constraints. The assumption is made that the electric water heater has an efficiency \( \eta_{\text{ewh}} = 1 \). Thus, all electric energy is converted into heat. The size of cluster can be scaled by the dimensioning factor \( \lambda_{7,1} \). If the factor is chosen as 1, the cluster represents the full potential of electric water heaters in Germany.
Table 2.10: Constraints and parameters of the Power Node $i = 7$, which represents a cluster of electric water heaters in Germany.

<table>
<thead>
<tr>
<th>Constraints on a buffered load with non-controllable demand:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_{\text{gen},7} = 0$</td>
</tr>
<tr>
<td>$\xi_7 = \xi_{\text{drv},7}(t) \leq 0$</td>
</tr>
<tr>
<td>$C_7 &gt; 0$</td>
</tr>
<tr>
<td>$w_7 = 0$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters of a cluster of electric water heaters:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_{\text{load},7}^{\text{max}} = \lambda_7 \cdot 25720.3 \text{ MW}$</td>
</tr>
<tr>
<td>$u_{\text{load},7}^{\text{min}} = 0 \text{ MW}$</td>
</tr>
<tr>
<td>$\alpha_7 = \lambda_7 \cdot 965.4 \text{ MW}$</td>
</tr>
<tr>
<td>$x_7^{\text{max}} = 1$</td>
</tr>
<tr>
<td>$x_7^{\text{min}} = 0.2$</td>
</tr>
<tr>
<td>$\eta_{\text{load},7} = 1$</td>
</tr>
<tr>
<td>$\eta_{\text{load},7} = 1$</td>
</tr>
</tbody>
</table>

$C_7 = \lambda_7 \cdot 149.4 \text{ GWh}$

$\lambda_7 = 965.4 \text{ MW}$

$\lambda_7 = 25720.3 \text{ MW}$

$\lambda_7 = 149.4 \text{ GWh}$

Chapter 3

Marginal cost for economic dispatch

In this chapter, the marginal cost terms of the generation and storage units, which have been presented in the previous chapter, are derived. These cost terms will be used in the objective function of the economic dispatch optimization problem.

3.1 Wind turbine units

In the following, marginal generation costs for an onshore wind turbine are calculated. Unlike fossil fuel based power plants, a wind turbine do not make use of fuel. Hence, several studies assume wind generation costs to be zero. Here, it is proposed to determine costs based on maintenance efforts due to the dispatch of the wind turbine. This approach is based on the notion that the abrasion of a wind turbine rises with increasing electricity output.

For the calculation, 1 MW of installed wind capacity in Germany is considered. The investment costs for a wind turbine depend on the nominal power output and the hub height. Currently, costs for generators with less than 3 MW range between 800-1100 €/kW, while turbines with more than 3 MW cost 1400 €/kW and more [2, 42]. We choose a wind generator with a nominal power output of 2-3 MW and a hub height of 100 m, which costs 900 €/kW. For installation, planning and grid connection, expenses of about 300 €/kW have to be considered. Consequently, 1 MW installed wind capacity costs 1200 €/kW.

Maintenance on a regular basis is of great importance for the efficiency and safety of wind generators. Current estimations state fixed O&M cost of 23 €/kW/a [2], which is equal to 2% of the specific investment costs. The longer the unit is in operation, the higher the share of O&M gets. However, for this study a constant quota over the lifetime of 20 years is assumed.

In a next step the load factor \( Lf \) of a wind turbine in Germany is cal-
Table 3.1: Figures of wind energy in Germany \cite{43}, and the derived load factor and full load hours.

<table>
<thead>
<tr>
<th>Year</th>
<th>Inst. capacity [MW]</th>
<th>Annual infeed [GWh]</th>
<th>Load factor [%]</th>
<th>Full load hours [h]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>18415</td>
<td>27229</td>
<td>17.7</td>
<td>1554.0</td>
</tr>
<tr>
<td>2006</td>
<td>20622</td>
<td>30710</td>
<td>18.0</td>
<td>1573.4</td>
</tr>
<tr>
<td>2007</td>
<td>22247</td>
<td>39713</td>
<td>21.2</td>
<td>1852.8</td>
</tr>
<tr>
<td>2008</td>
<td>23897</td>
<td>40574</td>
<td>20.1</td>
<td>1758.6</td>
</tr>
<tr>
<td>2009</td>
<td>25730</td>
<td>38639</td>
<td>17.8</td>
<td>1557.2</td>
</tr>
</tbody>
</table>

The load factor is calculated in order to derive the annual energy infeed of 1 MW installed wind capacity. For this purpose, Table \ref{tab:wind-energy-inGermany} lists the installed capacity $Cap$ and electricity generation $Gen$ of wind energy in Germany between the years 2005-2009 \cite{43}. By assuming a linear increase of installed capacity during the year, the load factor $Lf_a$ in the year $a$ is calculated according to

\[
Lf_a = \frac{Gen_a}{8760 \cdot \frac{Cap_a + Cap_{a-1}}{2}} .
\]  

(3.1)

Consequently, the full load hours $Flh_a$ of a wind turbine in Germany in the year $a$ is derived by

\[
Flh_a = 8760 \cdot Lf_a .
\]  

(3.2)

The results of the calculation are comprised in Table \ref{tab:wind-energy-inGermany}. The figures show that the load factors of two consecutive years vary by up to 3 percentage points. This might be reasoned as follows: The derived load factor represents an average of all installed wind generators in Germany. This portfolio of units is distributed over the whole territory. Additional wind turbines are deployed such that the overall intermittency of the wind infeed is reduced due to spacial smoothing effects. This geographic placement changes the regional distribution of the units and results in varying load factors over the years. Moreover, strong and weak wind years result in different capacity utilizations of the portfolio. Therefore, the load factor is averaged over all listed years resulting in 18.9%.

Based on the averaged load factor, an annual electricity output of 1659.2 MWh for 1 MW of installed wind capacity is derived. Total expenses for O&M amount to 23,000 €. According to \cite{44}, only 26% of the O&M costs account for maintenance summing up to 5980 €. The remaining share of 74% takes into consideration expenses for insurance, tax and the plant site. If maintenance costs are broken down on the electricity output, marginal generation costs for onshore wind power in Germany of 3.6 €/MWh are derived. As summary, the main figures of this section are listed in Table \ref{tab:net-marginal-costs}.
CHAPTER 3. MARGINAL COST FOR ECONOMIC DISPATCH

Table 3.2: Marginal generation costs for onshore wind power.

<table>
<thead>
<tr>
<th>Assumptions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment costs [€/kW]</td>
<td>1200</td>
</tr>
<tr>
<td>Operation costs [€/kW/a]</td>
<td>17.02</td>
</tr>
<tr>
<td>Maintenance costs [€/kW/a]</td>
<td>5.98</td>
</tr>
<tr>
<td>Load factor [%]</td>
<td>18.9</td>
</tr>
<tr>
<td>Full load hours [h]</td>
<td>1659.2</td>
</tr>
</tbody>
</table>

Calculation:

Marginal generation costs [€/MWh] 3.6

Table 3.3: Operation and maintenance costs for a PV panel with 500 kW peak power operated in Switzerland [45].

<table>
<thead>
<tr>
<th>Cost terms</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Monitoring [Rp./kWh]</td>
<td>0.3</td>
</tr>
<tr>
<td>Replacement [Rp./kWh]</td>
<td>1.4</td>
</tr>
<tr>
<td>Repairing [Rp./kWh]</td>
<td>&lt; 0.1</td>
</tr>
<tr>
<td>Inspection [Rp./kWh]</td>
<td>0.2</td>
</tr>
<tr>
<td>Cleaning [Rp./kWh]</td>
<td>&lt; 0.1</td>
</tr>
<tr>
<td>Periodic expenses [Rp./kWh]</td>
<td>1.1</td>
</tr>
<tr>
<td>Administration [Rp./kWh]</td>
<td>0.7</td>
</tr>
<tr>
<td>Insurance [Rp./kWh]</td>
<td>0.9</td>
</tr>
<tr>
<td>Total [Rp./kWh]</td>
<td>4.7</td>
</tr>
</tbody>
</table>

3.2 PV units

Photovoltaic panels use free solar energy for electricity generation. Hence, no expenses incur for fuel. According to [2], typical investment costs for a panel are 3700 €/kW. In general, a photovoltaic system operates to the greatest possible extent maintenance-free. Small pollution like dust is removed by rain and snow. Greater pollutions like bird droppings and leaves have to be removed manually. In order to ensure that the panel operates technically as expected and to prevent faults, inspections should be performed by a specialist on a regular basis. System components are only replaced if they are broken. Overall, fixed costs for operation and maintenance of 22 €/kW/a have to be considered.

According to [45], Table 3.3 lists ordinary operation and maintenance costs for a PV panel with 500 kW peak power operated in Switzerland. Based on the assumption of 900 full load hours, the figures are presented for 1 generated kWh electricity. The table shows that the largest share is required for replacement, which mainly accounts for the converter. Its lifetime is stated with 10-15 years. Solar panels are designed to withstand
heat, cold, rain and hail for many years. Many manufacturers of silicon module offer a warranty that guarantees electrical production for 10 years at 90% of rated power output and 25 years at 80%. Hence, one can conclude that (1) the inverter and panel are replaced based on the total operating time rather than the actual energy output and (2) costs for operation and maintenance are fixed.

In the previous section it was argued that maintenance costs for wind turbines increase linear with the energy output, because the electricity generation involves moving mechanical parts. By contrast, a photovoltaic system is composed of an array of solar panels, an inverter, and interconnection wiring. There are no moving parts. Therefore, marginal generation costs for PV are set to 0 €/MWh.

There are two advantages of choosing marginal generation costs for PV equal to zero. First, PV energy is preferred over wind energy. This makes sense, as PV panels feature considerably higher investment costs than wind turbines. Hence, owners of PV panels are dependent on feeding-in as much electricity as possible in order to charge off their investment. Second, PV energy is preferred over stored energy. This is reasonable as buffered energy should only be returned to the grid when no intermittent energy is available.

### 3.3 Biomass units

In this section the marginal costs for electricity generation are derived for the presented biomass power plant in Section 2.6. The plant generates electricity from biogas with a combined heat and power module. The biogas is provided by a nearby sited fermentation plant, which utilizes renewable raw material such as corn.

In general, for a generation unit it can be distinguished between two cost types: fixed costs and variable costs. The former are expenses which are independent of the size of generation. They incur even in case no electricity is generated. The latter depend on the size of electricity output. Hence, only variable costs have to be considered for the calculation of the marginal generation costs.

Variable costs are mainly driven by fuel costs, which are dependent on the type of primary energy source. Additionally, variable maintenance costs might incur due to efforts directly related to the amount of electricity being produced. For instance, these costs account for the exchange of wearing parts and overhaul required after a specific number of operation hours.

In Table 3.4 variable cost terms are listed for a large combined heat and power unit, which features a power rating of 2000 kW and utilizes biogas. Specific maintenance costs for the generation module are obtained from [29]. Fuel costs for the biogas are derived from [46] and correspond to the levelized generation costs of a large fermentation plant, whose feedstock is composed of corn.
Table 3.4: Marginal generation costs of a biomass power plant, which utilizes biogas [29, 46].

<table>
<thead>
<tr>
<th>Assumptions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific maintenance costs [ct/kWh]</td>
<td>0.75</td>
</tr>
<tr>
<td>Fuel costs [ct/kWh(\text{th})]</td>
<td>5.8</td>
</tr>
<tr>
<td>Electric efficiency (\eta_{\text{gen}})</td>
<td>0.42</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Calculation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Marginal generation costs [€/MWh]</td>
<td>145.6</td>
</tr>
</tbody>
</table>

of 90% renewable raw material and 10% liquid manure.

As fuel costs are stated for a pure thermal use, the cost term is divided by the electric efficiency \(\eta_{\text{gen}} = 0.42\) of the combined heat and power module. Thus, the resultant fuel costs per generated kWh electricity are equal to 13.81 ct/kWh\(\text{th}\). If specific maintenance costs are added, total marginal generation costs of the biomass power plant amount to 145.6 €/MWh. As summary, the main figures of this section are listed in Table 3.4.

3.4 Pumped hydro units

Like all bulk energy storage technologies, a pumped hydro storage features high investment costs and rather small operation and maintenance costs. In general, these costs are fixed and stated independently of the annual operating time. According to [27], all cost terms of a pumped hydro plant are listed in Table 3.5. The table shows that no costs for replacement incur. This is reasonable as, unlike a battery system, a pumped hydro storage does not have to be replaced after a specific number of charge-discharge cycles. The lifetime of such a facility is stated between 30-60 years and regarded as independent from the cycle number. Hence, marginal dispatch costs of a pumped hydro storage cannot be derived at first view.

The webpage of a Pavilion Energy Resources [47], a company with plans to develop low environmental impact businesses in the renewable energy and sustainable mineral resources fields, states nominal operation and maintenance costs of a pumped hydro plant equal to 0.01 $/kWh. Assuming a currency exchange rate from Dollar to Euro of 0.75, this cost term is equal to 7.5 €/MWh and could be regarded as marginal dispatch costs.

Another approach to derive the marginal dispatch costs is based on the capital costs per cycle. According to [48], these costs vary between 0.1-1.4 $/kWh/cycle. The numbers have been derived without considering O&M costs. Hence, as an approximation it can be assumed that the ratio between capital costs per cycle and O&M costs per cycle is the same as the ratio between investment costs and annual O&M costs. In Table 3.5, the ratio
between power related investment costs and fixed O&M costs is 400. By considering 1.4 $/kWh/cycle as capital costs per cycle, the resultant O&M costs per cycle amount to 3.5 $/MWh/cycle, and accordingly 2.63 €/MWh/cycle.

So far, two values for the marginal dispatch cost term have been derived. The values differ by 65%. Thus, the average of both is taken, which is equal to 5.06 €/MWh and considered as marginal dispatch costs for a pumped hydro plant. As summary, the main figures of this section are listed in Table 3.6.

### 3.5 NaS battery units

In general, the lifetime of a battery is limited by the number of maximum possible charge-discharge cycles. If this number is reached, the battery has lost most of its functional capability and needs to be replaced. Consequently, it is possible to allocate investment costs of a battery system to the total energy cycled during the lifetime. These investment costs per charge-discharge cycle \( IC_{NaS, cycle} \) can be calculated according to

\[
IC_{NaS, cycle} = \frac{MP_{NaS}}{n_{cycle} \cdot C_{NaS} \cdot \eta_{NaS}}, \quad (3.3)
\]

where \( MP_{NaS} \) denotes the module price, \( n_{cycle} \) the cycle lifetime and \( \eta_{NaS} \) the efficiency of the NaS module.

According to [49], the module price of a recently installed NaS battery module amounted to 75,000 $. The module features a power rating of \( P_{NaS} = 50 \text{ kW} \) and an energy capacity equal to \( C_{NaS} = 360 \text{ kWh} \). The number of tolerated cycles \( n_{cycle} \) at a depth-of-discharge equal to 100% is denoted with 2500. The one-way efficiency is stated with 0.88.
Table 3.7: Marginal dispatch costs of a NaS battery module.

<table>
<thead>
<tr>
<th>Assumptions:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power rating [kW]</td>
</tr>
<tr>
<td>Energy capacity [kWh]</td>
</tr>
<tr>
<td>Cycle life [cycles]</td>
</tr>
<tr>
<td>One-way efficiency [-]</td>
</tr>
<tr>
<td>Module price [$]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Calculation:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marginal dispatch costs [€/MWh]</td>
</tr>
</tbody>
</table>

Consequently, the investment costs per charge-discharge cycle $IC_{NaS, cycle}$ are equal to 94.7 $/MWh, or 71.0 €/MWh. These costs can be regarded as marginal costs of a NaS battery system for buffering one megawatt-hour of electric energy.

In order to validate the derived marginal cost term, another calculation possibility is presented in the following. In [27], specific replacement costs for a NaS battery system per installed storage capacity $RC_{NaS}$ are stated with 230 $/kWh. Thus, replacement costs per charge-discharge cycle $RC_{NaS, cycle}$ can be derived by

$$RC_{NaS, cycle} = \frac{RC_{NaS}}{n_{cycle} \cdot \eta_{NaS}},$$

and amount to 104.5 $/MWh, and accordingly 78.4 €/MWh. The values of $IC_{NaS, cycle}$ and $RC_{NaS, cycle}$ are almost equal, and therefore the derived marginal cost term is eligible. As summary, Table [3.7] lists the technical specifications and cost assumptions of the considered NaS module.
Chapter 4

The dispatch simulator

In this chapter, the software environment and the basic structure and functionality of the simulation tool are described. The core of the simulation tool is the dispatch simulator that enables to perform an economic dispatch optimization for a defined portfolio of Power Nodes with a set of marginal dispatch costs, and a specific supply scenario of wind and PV energy.

4.1 Description of the software environment

The dispatch simulator and the evaluation tools for the simulation results are implemented in MATLAB R2010b. As solver for the optimization problem serves the software tool CPLEX Optimization Studio 12.2 from IBM. The software provides a toolbox to call the solver within the MATLAB environment. The CPLEX solver enables to solve a variety of mathematical programming problems, such as linear programming problems (LP), quadratic programming problems (QP), and mixed integer programming problems (MIP). However, non-linear programming problems cannot be solved.

The big advantage of the CPLEX solver is that very large, real-world optimization problems can be solved with high performance in a robust and reliable way. For instance, it performs optimizations about 90–200 times faster than MATLAB’s own Quadprog solver. This performance increase enables to simulate large portfolios, which are composed of more than 20 Power Nodes, over a time span of one full year and a sampling time of 15 minutes in reasonable time of about 1 hour. A drawback of CPLEX is that it is a commercial solver and license fees are several thousand dollars. However, for academic purposes a free license can be acquired from the IBM Academic Initiative program [50].

The economic dispatch optimization problem is implemented in the MATLAB code with the modeling language YALMIP, which is provided as a free toolbox [51]. The language is consistent with the standard MATLAB syntax, and is therefore simple to use. The main benefit of YALMIP is the fact
that the optimization problem has to be coded only once in a standardized and high-level form. Based on the chosen external solver, YALMIP takes care of the low-level modeling and compiles the optimization problem in the most efficient and numerically sound way. Then, the compiled model can be solved with the external solver.

4.2 Structure and functionality of the simulation tool

In this section, the high-level structure of the software tool developed in the thesis is outlined. For the sake of brevity, not all subfunctions are listed here. But the full source code equipped with detailed comments can be found in the enclosed CD-Rom.

In Figure 4.1, the high-level structure of the simulation tool is illustrated. The main functions are framed black, and the main variables are highlighted in red. The script `loop_run.m` starts the simulation tool and calls the main function `run_dispatch_simulator.m` with the name of the Power Node portfolio that should be simulated.

At the beginning of the main function, the struct variable `RunParams` is defined, which contains all important simulation parameters, such as the prediction horizon length of the model predictive controller, the simulation start date $t_1$ and end date $t_2$, the name of the grid model, and the set of renewable supply scenarios. One scenario is characterized by the available shares of wind energy $s_{\text{Wind}}$ and PV energy $s_{\text{PV}}$.

The parametrization of the Power Node portfolio is defined in the cell variable `PowerNodeTopology`, which is loaded according to the defined portfolio name by the function `define_powernode_topology.m`. The cell contains for each Power Node the unit type definition, the upper and lower boundaries of the constraints, the cost terms for the objective function, the file name of the external demand/supply profile, and the grid bus number indicating where the Power Node is interfaced with the grid.

Then, the actual dispatch simulator is started. In a first step, the function `construct_powernodes.m` transforms the cell parametrization of the Power Node portfolio in the struct variable `PowerNodes` containing one field for each Power Node. Moreover, the external supply/demand process profiles $\xi_{\text{drv},i}(t)$ are imported and attached to the corresponding struct fields.

The aim of this thesis is to simulate a power system for various scenarios of fluctuating renewable infeed. For this reason a renewable supply scenario is characterized by the shares of wind energy $s_{\text{Wind}}$ and PV energy $s_{\text{PV}}$. Each share expresses how much renewable energy is available over the simulated time span $[t_1, t_2]$ relative to a selectable base value $\text{ScaleBase}$. For each Power Node it is possible to define the base value individually in the Power Node parametrization. The function `scale_xi_profile.m` scales
the imported profiles $\xi_{drv,i}(t)$ of all Power Nodes representing wind and PV energy with a factor $\lambda_i$ such that the energy-integral over the simulation interval $[t_1, t_2]$ is equal to the desired share multiplied by the base value. This is mathematically expressed by

$$\lambda_i \cdot \int_{t_1}^{t_2} \xi_{drv,i}(t) \, dt = s_i \cdot ScaleBase_i \quad , \quad i \in \{\text{Wind, PV}\} \quad . \quad (4.1)$$

The function build_dispatch_problem.m compiles the dynamic equations of the Power Node portfolio. In a next step, this set of continuous differential equations is discretized with a sampling time predefined in the RunParams struct. The output is a struct called DispatchProblem, which comprises all information about the economic dispatch optimization problem.

The function solve_dispatch_problem.m compiles the optimization model using YALMIP. Then, a routine calls CPLEX to solve the optimization model. At the end of the simulation, all settings and results are saved in a mat-file, which enables a convenient post-processing and evaluation.
Figure 4.1: Basic structure of the simulation tool.
Chapter 5

Economic dispatch optimization problem

This chapter presents the economic dispatch formulation as an optimization problem for the Power Node portfolio introduced in Chapter 2. For this case a simple 1-bus network is considered. As the obtained optimization problem is not linear, two implementation variants as mixed integer problem (MIP) and quadratic problem (QP) are introduced, which can be efficiently solved by CPLEX.

5.1 Formulation

In the following, a simple power grid composed of one single bus is considered. Energy flows are not afflicted with transmission losses, as no lines are modeled. This approach is equal to a copperplate model, where electricity flows are not limited by any line constraints. As already introduced in Chapter 2, the continuous dynamics of the Power Node portfolio are described by this set of algebraic and first-order differential equations:

\[ \xi_1 - w_1 = -\eta_{load,1} u_{load,1} \]  
\[ \xi_2 - w_2 = \eta_{gen,2} u_{gen,2} \]  
\[ \xi_3 - w_3 = \eta_{gen,3} u_{gen,3} \]  
\[ C_4 \dot{x}_4 = \eta_{load,4} u_{load,4} - \eta_{gen,4}^{-1} u_{gen,4} \]  
\[ C_5 \dot{x}_5 = \eta_{load,5} u_{load,5} - \eta_{gen,5}^{-1} u_{gen,5} \]  
\[ \xi_6 = \eta_{gen,6} u_{gen,6} \]  
\[ C_7 \dot{x}_7 = \eta_{load,7} u_{load,7} + \xi_7 - a_7 (x_7 - x_{0,7}) \]
CHAPTER 5. ECONOMIC DISPATCH OPTIMIZATION PROBLEM

This system of linear equations can be formulated as continuous-time state space model with input vector

\[
\begin{bmatrix}
u_{\text{load},1} & w_1 & u_{\text{gen},2} & w_2 & u_{\text{gen},3} & w_3 & u_{\text{gen},4} & u_{\text{load},4} & \cdots \\
u_{\text{gen},5} & u_{\text{load},5} & u_{\text{gen},6} & \xi_6 & u_{\text{load},7} & \xi_7 & \xi_1 & \xi_2 & \xi_3 & \xi_7
\end{bmatrix}^T \tag{5.8}
\]

and state vector

\[
x = [x_4, x_5, x_7]^T . \tag{5.9}
\]

For numerical computing, the continuous differential equations stated above are discretized with sampling time \( T \) resulting in a system of discrete difference equations in the form of

\[
x(k + 1) = A \cdot x(k) + B \cdot u(k) . \tag{5.10}
\]

The operational goal of an economic dispatch is to set up the schedules of the power system units such that the cost function is minimized while maintaining the power balance in the system and considering all operational and technical constraints. A model predictive control strategy with a prediction horizon of \( N \) time steps is implemented for choosing the optimal values for the controllable inputs. In time step \( k \), all inputs are expressed as vectors of the decision variables

\[
u = \begin{bmatrix}
u(l = k) & \ldots & u(l = k + N - 1) \\
u_{\text{load},1}(k) & \ldots & u_{\text{load},1}(k + N - 1) \\
w_1(k) & \ldots & w_1(k + N - 1) \\
\vdots & \ddots & \vdots \\
\xi_7(k) & \ldots & \xi_7(k + N - 1)
\end{bmatrix} . \tag{5.11}
\]

Accordingly, the dynamic state variables of the system are represented in vector notation

\[
x = \begin{bmatrix}
x(l = k) & \ldots & x(l = k + N - 1) \\
x_4(k) & \ldots & x_4(k + N - 1) \\
x_5(k) & \ldots & x_5(k + N - 1) \\
x_7(k) & \ldots & x_7(k + N - 1)
\end{bmatrix} . \tag{5.12}
\]

Hence, the economic dispatch optimization problem in time step \( k \) with
objective function $J(k)$ can be formulated as follows:

$$
\min J(k) = \sum_{l=k}^{l=k+N-1} \left( (x(l) - x_{\text{ref}})^T \cdot Q_x \cdot (x(l) - x_{\text{ref}}) + u(l)^T \cdot Q_u \cdot u(l) + R_u \cdot u(l) + \delta u(l)^T \cdot \delta Q_u \cdot \delta u(l) \right) + u(l)^T \cdot Q_u \cdot u(l) + R_u \cdot u(l) + \delta u(l)^T \cdot \delta Q_u \cdot \delta u(l) \\
\text{s.t.} \quad (a) \quad x(l+1) = A \cdot x(l) + B \cdot u(l) \\
(b) \quad 0 \leq x_{\text{min}} \leq x(l) \leq x_{\text{max}} \leq 1 \\
(c) \quad u_{\text{min}} \leq u(l) \leq u_{\text{max}} \\
(d) \quad \delta u_{\text{min}} \leq \delta u(l) \leq \delta u_{\text{max}} \\
(e) \quad \xi_1(l) = \xi_{\text{drv,1}}(l \cdot T) \\
(f) \quad \xi_2(l) = \xi_{\text{drv,2}}(l \cdot T) \\
(g) \quad \xi_3(l) = \xi_{\text{drv,3}}(l \cdot T) \\
(h) \quad \xi_7(l) = \xi_{\text{drv,7}}(l \cdot T) \\
(i) \quad u_{\text{gen,4}}(l) \cdot u_{\text{load,4}}(l) = 0 \\
(j) \quad u_{\text{gen,5}}(l) \cdot u_{\text{load,5}}(l) = 0 \\
(k) \quad \sum_{i=\{2,3,4,5,6\}} u_{\text{gen},i}(l) - \sum_{i=\{1,4,5,7\}} u_{\text{load},i}(l) = 0 \\
(a-k) \quad \forall l = \{k, \ldots, k + N - 1\}.
$$

In the objective function the diagonal weight matrices $Q_x$, $Q_u$, $R_u$, and $\delta Q_u$ aim at individually penalizing the input and state variables. At each time step $k$ all cost terms up to the prediction horizon $N$ are summed up. The constant vector $x_{\text{ref}}$ contains reference values for the state variables, i.e. these values represent the desired storage levels. The variable $\delta u(l)$ denotes the rate of change of the optimization variables, i.e. the difference of $u(l)$ between two time steps ($\delta u(l) = u(l) - u(l-1)$).

The constraints in Equation (5.13) are to express (a) the linear Power Node equations, (b) the state of charge is normalized and bounded, (c) the input variables are non-negative and bounded, (d) the input variables are rate-constrained, (e-h) the demand/supply processes of the Power Nodes $i \in \mathcal{N} = \{1, 2, 3, 7\}$ are externally driven, (i, j) the two storages do not possess two separate conversion systems and thus cannot feed-in and draw energy from the grid at the same time, and (k) the power balance of the single bus system has to be fulfilled.

### 5.2 Implementation

The optimization problem stated in the previous section features a quadratic objective function and a set of equality, inequality and bilinear constraints.
CHAPTER 5. ECONOMIC DISPATCH OPTIMIZATION PROBLEM

However, the bilinear constraints are not supported by the CPLEX solver. Hence, an alternative formulation for the constraints \((i, j)\) in Equation (5.13) has to be found in order to implement the optimization problem in the utilized software environment. In the following two possible solutions are introduced.

5.2.1 Mixed integer problem (MIP)

The first possibility is to restate the constraints \((i, j)\) in Equation (5.13) as logic constraints. As logic constraints lead to problems with binary variables, mixed integer programming is needed to solve the problem. As the CPLEX solver can deal with binary variables and constraints, this approach seems promising. The solver interface YALMIP provides a set of nonlinear operators to express logic constraints. Thus, the following restatement of the storage constraint \(u_{\text{gen},i} \cdot u_{\text{load},i} = 0\) in YALMIP is proposed

\[
\text{true}\left((\text{BoolA} \land \neg \text{BoolB}) \lor (\neg \text{BoolA} \land \text{BoolB})\right)
\]

\[
\text{implies}(\text{BoolA}, u_{\text{gen},i} \geq \epsilon)
\]

\[
\text{implies}(\text{BoolA}, u_{\text{load},i} < \epsilon)
\]

\[
\text{implies}(\text{BoolB}, u_{\text{gen},i} < \epsilon)
\]

\[
\text{implies}(\text{BoolB}, u_{\text{load},i} \geq \epsilon)
\].

The terms \(\text{BoolA}\) and \(\text{BoolB}\) are decision variables constrained to be binary \((0\ or\ 1)\). In order to implement a slack and facilitate the solving process, the non-negative constant \(\epsilon << 1\) is implemented. Furthermore, \(\land\) (and), \(\lor\) (or), \(\neg\) (not), \text{true}, \text{implies} denote logic operators. For a generic statement \text{true}(\text{BoolA})\,\text{true}\), the \text{true} operator returns the constraint \(\text{BoolA} \geq 1\).

Hence, in Equation (5.14) the operator ensures that the boolean expression enclosed in brackets is forced to be true. The operator \text{implies}(X,Y)\ aims at forcing \(Y\) to be true if \(X\) is true.

The proposed mixed-integer formulation seems a bit long-winded at first view. As \text{implies} is mainly intended for (binary -\(\rightarrow\) binary) or (binary -\(\rightarrow\) linear constraint) implications, the formulation has been carefully defined in order to reduce the numerical sensitivity.

Although the constraint set in Equation (5.14) is a valid formulation for a bilinear constraint, simulations with a long optimization horizon greater than 1 day resulted in unstable and slow computational performance. Hence, a second formulation for the MIP approach is suggested

\[
p_i \in \{0, 1\}
\]

\[
\frac{u_{\text{gen},i}}{u_{\text{max},\text{gen},i}} \leq p_i
\]

\[
\frac{u_{\text{load},i}}{u_{\text{max},\text{load},i}} \leq (1 - p_i)
\].
where $p_i$ is a bounded integer variable. The upper boundaries $u_{\text{gen},i}^{\text{max}}$ and $u_{\text{load},i}^{\text{max}}$ aim at normalizing their corresponding reference variables $u_{\text{gen},i}$ and $u_{\text{load},i}$, respectively. The proposed formulation ensures, that either $u_{\text{gen},i}$ or $u_{\text{load},i}$ is zero or both.

### 5.2.2 Quadratic problem (QP)

Without the constraints (i, j) in Equation (5.13), the optimization problem degenerates to a common quadratic problem (QP), which can be solved efficiently by using CPLEX. Hence, a second approach is to omit the constraints (i, j). However, the set of cost terms has to be carefully chosen in order to give the controller no incentives to store and supply electricity with one storage unit at the same time. For instance, such an incentive is given when curtailment of intermittent generators is more expensive than cycling the excess energy through a lossy storage. In this situation energy is withdrawn from the power system due to conversion losses. Such a dispatch of storage facilities does not represent common practice and has to be avoided.
Chapter 6

MPC controller

The economic dispatch optimization problem has been formulated in the previous chapter as mixed integer problem (MIP) and quadratic problem (QP). In this chapter, for both variants the cost terms of the objective function are derived. These penalty factors are termed controller parameters, as they significantly influence the dispatch behavior of the MPC controller.

6.1 Optimization strategy characterization

An optimization based on the concept of economic dispatch results in an optimal dispatch schedule of all units interfaced with the power system. Thereby, the control algorithm minimizes overall system costs within a specified prediction horizon. Consequently, the diagonal entries of the matrices $Q_x$, $Q_u$, $R_u$, and $\delta Q_u$ in the objective function constitute the controller parameters. They represent real monetary costs, e.g. incurred by electricity generation, generator ramping, or load curtailment.

So far, marginal costs for electricity generation and buffering energy in a storage have been derived in Chapter 3. These costs are affiliated with the decision variables $u_{\text{gen},t}$ and $u_{\text{load},t}$. Cost terms for ramping of generation, load shedding and curtailment of intermittent generation have not been chosen so far, as they are difficult to assign realistically. Thus, these values have to be determined heuristically. If they are not carefully chosen, the optimization result of the economic dispatch might not correspond to a realistic unit behavior. Hence, it is essential to characterize the optimization strategy first in order to validate the behavior of the implemented controller. For this reason the following four rules of conduct are formulated:

1. Load shedding is performed as a last resort in order to mitigate the system imbalance. In case of insufficient intermittent generation, electricity demand has to be served as long as stored energy and power reserves of dispatchable generation are available.
2. Curtailment of intermittent generators is forbidden as long as storage capacities are available to absorb the excess energy.

3. The incorporated storages are considered as bi-directional conversion systems, but the units can either store or supply electricity at once. As already discussed, this limitation is expressed by $u_{\text{gen},i} \cdot u_{\text{load},i} = 0$. This constraint has to be valid in every simulation step.

4. Erratic behavior of generation output and storage commitment has to be avoided. In order to reproduce power system practice and spare mechanical parts from unnecessary abrasion, unit dispatch should avoid sequences of excessive up- and down-ramping.

### 6.2 Controller parameters

The optimization problem stated in Equation (5.13) has been implemented in MATLAB both as MIP and QP. Because both versions might call for different controller parameters, this section presents the sets of chosen cost terms.

#### 6.2.1 Mixed integer problem (MIP)

Quadratic cost terms for the decision vector $u(l)$ are comprised in $Q_u$. As variable costs are considered to be linear dependent on unit commitment, the diagonal entries of $Q_u$ are set to zero:

$$Q_u^{\text{MIP}} = \text{diag}\left(\text{zeros}(1, 17)\right). \quad (6.1)$$

Linear cost terms of unit commitment are reflected by the diagonal entries of $R_u$. On the supply side, the decision variable $u_{\text{gen},i}$ of a Power Node representing a generation unit is penalized with the marginal costs of electricity generation. For wind, PV and biomass, these cost terms have been derived in Chapter 3. As no costs are involved with the consumption of electricity on the demand side, the amount of electric energy drawn from the grid by load units is not penalized.

The decision variable $\xi_i$ represents the demanded or provided energy on the demand/supply side within the Power Node framework and is therefore penalized with 0 €/MWh. For generation units, the primary energy consumption is already considered in the cost term of $u_{\text{gen},i}$. For load units no costs are involved in the use of demanded electricity.

A Power Node representing a storage features two decision variables, $u_{\text{gen},i}$ and $u_{\text{load},i}$. The former is penalized with the marginal costs for storages derived in Chapter 3. The latter is at no charge in order to initiate the controller to store excess renewable energy as long as storage capacity is available instead of curtailing generation.
Of great importance is how to penalize load shedding and curtailment of renewable power infeed. Unfortunately, costs involved in these control decisions are difficult to express in monetary values. While load shedding on household level results primarily in a loss of comfort, an uncovered load demand in the industry sector causes disruption of production and profit cuts.

In general, the MPC controller should reduce demand as a last resort. Therefore, $w_i$ of conventional loads is penalized with a high linear cost term of 500 €/MWh. Curtailment of intermittent RES should be avoided as it represents a waste of eco-friendly and free energy. In our case, arbitrary cost terms for wind and PV curtailment of 20 €/MWh are assumed. This choice is only based on the consideration that costs incurred by curtailment have to be higher than for generation. Otherwise excess renewable energy is curtailed instead of being stored. Consequently, the cost matrix $R_u$ is composed as follows:

$$
R_u^{MIP} = \text{diag}(0, -500, 3.6, 20, 0, 20, 5.06, 0, \ldots, 71, 0, 145.6, 0, 0, 0, 0, 0).
$$

The rate of change of the decision vector $\delta u(l)$ is penalized by the diagonal entries of $\delta Q_u$. For generation units these cost terms represent monetary costs incurred by ramping up or down the power output. Clearly, excessive ramping actions stress mechanical parts and results in higher deterioration. But in case of wind and PV units, adequate cost terms are difficult to define or obtain from literature. The same is valid for storages.

Simulations without penalizing the variable $\delta u(l)$ revealed an erratic behavior of load shedding and wind curtailment in periods of excess/missing renewable energy. This can be attributed to the storage commitment. In case more intermittent energy is within the prediction horizon available to fill up the deployed storages than necessary, the controller does not see a monetary difference in a sequence of ramping actions or a smooth charging behavior as long as both storage dispatches result in the same amount of energy drawn from the grid. Similarly, in case not sufficient intermittent energy is available to cover demand within the prediction horizon and simultaneously storages are not fully able to help out, load demand has to be shedded. The stored energy can be fed into the grid with a smooth or a volatile profile. Both options result in the same monetary costs.

In order to eliminate the erratic behavior, penalties on $\delta u(l)$ are introduced. The cost terms have been found heuristically and do not represent monetary value. They are set arbitrarily small such that the economic dispatch, mainly determined by $R_u$, is not distorted. The matrix $\delta Q_u$ is composed as follows:

$$
\delta Q_u^{MIP} = \text{diag}(0, 10^{-4}, 0, 10^{-4}, 0, 0, 10^{-4}, 10^{-4}, \ldots, 10^{-4}, 10^{-4}, 0, 0, 0, 0, 0, 0).
$$
The ramp-rate of load shedding is punished to prevent the controller from
transferring the variability of the load profile on the shedding time series.
Curtailment of wind energy is achieved by actuators which change the pitch
angle of the rotor blades. As erratic control actions stress mechanical parts
of wind generators, the ramp-rate of wind curtailment is penalized as well.
For PV panels this is not considered, as the power converter facilitates a
wearless curtailment. Additionally, the variables $\delta u_{\text{gen},i}$ and $\delta u_{\text{load},i}$ of the
pumped hydro plant and the NaS battery system are penalized in order to
smooth their ramping behavior. As no ramping costs are considered for the
biomass power plant, it provides control power to balance load variation on
the the scale of 15 minutes.

In the Power Node framework, energy storage levels are expressed in a
normalized fashion by the variable $x_i \in \{0, 1\}$. Deviations from the desired
level $x_{\text{ref},i}$ are penalized by the diagonal entries of $Q_x$. In general, it is
difficult to express level deviations in monetary costs such that these values
are in a reasonable relation to the marginal cost terms contained in $R_u$.
Hence, penalties on level deviations are chosen heuristically. However, the
choice has to be made carefully. If the entries of $Q_x$ are scaled too large,
storage filling at the expense of load shedding may result.

Regarding flexible loads, a full thermal energy storage of an electric water
heater is favorable as the maximum amount of warm water is available to
the household. Hence, $x_{\text{ref},i}$ is set to 1 and the corresponding entry of $Q_x$ is
chosen to be 10000. The penalty factor was selected such that the resulting
costs are about 2 orders of magnitude lower than linear costs of all individual
decision variables derived by $R_u$.

Referring storage facilities, the value selection of $x_{\text{ref},i}$ is connected to
the question how conservatively the power system should be operated. It
can be argued to set $x_{\text{ref},i} = 1$ in order to advocate filled storages. In case
intermittent renewable infeed is lower than predicted, the affiliated storages
could help out and mitigate the load imbalance. On the other hand, the
setting $x_{\text{ref},i} = 0$ facilitates to host larger amounts of excess renewable energy
in case of unpredicted extreme weather conditions.

As in this thesis perfect prediction is assumed, it is proposed not to
penalize level deviations of storages from a setpoint. The MPC controller
should dispatch the storage portfolio completely uncoupled from level set-
points and determine an optimal unit commitment solely on the penalization
of the input vector $u(l)$. In addition, during test simulations it became evi-
dent that the introduction of state penalties results in an abrupt and unde-
sirable storage dispatch. Further information about this topic are provided
in the Appendix A.1.

Taking all considerations into account, the following penalty matrix $Q_x$
results:

$$Q_x^{\text{MIP}} = \text{diag}(0, 0, 10000) .$$

(6.4)
6.2.2 Quadratic problem (QP)

In the QP version of the economic dispatch optimization problem the bilinear constraints, which ensure that storages do not draw and feed in electricity at the same time, are omitted. However, in case curtailment costs of an intermittent generator are higher than the sum of infeed costs of the intermittent generator and storage cycling costs the omitted constraint is essential to prevent the dispatch controller from withdrawing energy from the system due to storage conversion losses.

The first possibility to vanish the incentive of charging and discharging a storage at the same time is to set curtailment costs of wind and PV generation to zero. But marginal generation costs for wind are unequal zero. Thus, the implication of omitting curtailment costs is that excess energy from wind turbines is only absorbed to the extent it can be used within the prediction horizon and the dispatch controller experience a cost advantage by not dispatching biomass power plants. The other share of excess wind energy is curtailed even though storage capacities might be available. However, it is preferable to utilize available storage capacities to buffer the full amount of excess energy for a later point in time. Wind generation could not be penalized, but this notion macerates the concept of economic dispatch. Overall, rejecting curtailment cost is not an option.

The second possibility is to choose curtailment costs for intermittent generators such that the following condition is fulfilled:

\[
C_{w_i}(w_i) < C_{\text{u}_\text{gen},i}(u_{\text{gen},i}) + C_{\text{u}_\text{load},j}(u_{\text{load},j}) + C_{\text{u}_\text{gen},j}(u_{\text{gen},j}), \quad i \in G, j \in S,
\]

\[
(6.5)
\]

where \( C_{w_i}, C_{\text{u}_\text{gen},i}, C_{\text{u}_\text{load},j}, \) and \( C_{\text{u}_\text{gen},j} \) denote cost functions of the corresponding decision variable. The sets of intermittent generators and storages are denoted by \( G \) and \( S \), respectively.

At the same time, the condition

\[
C_{w_i}(w_i) > C_{\text{u}_\text{gen},i}(u_{\text{gen},i}) + C_{\text{u}_\text{load},j}(u_{\text{load},j}), \quad i \in G, j \in S,
\]

\[
(6.6)
\]

has to be fulfilled in order to incite the controller to absorb excess intermittent energy. Hence, the cost matrix \( R_u \) for the QP problem is composed as follows:

\[
R_u^{QP} = \text{diag}(0, -500, 3.6, 4, 0, 1, 5.06, 0, \ldots, 71, 0, 145.6, 0, 0, 0, 0, 0, 0, 0, \ldots)
\]

\[
(6.7)
\]

Like in the MIP implementation, erratic behavior of the decision variables is prevented by introducing penalties on \( \delta u(l) \). The penalty matrix \( Q_u \) is formed as follows:

\[
\delta Q_u^{QP} = \text{diag}(0, 10^{-4}, 0, 10^{-4}, 0, 0, 10^{-4}, 10^{-4}, \ldots, 10^{-4}, 10^{-4}, 0, 0, 0, 0, 0, 0, 0, 0)
\]

\[
(6.8)
\]
As for the MIP version, variable costs are considered to be linear dependent on unit commitment. Hence, \( Q_u \) is a zero matrix:

\[
Q_u^{QP} = \text{diag} \left( \text{zeros}(1,17) \right)
\]  

(6.9)

Level deviations from the setpoint \( x_{\text{ref},i} = 1 \) are penalized according to \( Q_x^{\text{MIP}} \):

\[
Q_x^{QP} = \text{diag}(0,0,10000)
\]  

(6.10)

6.3 Comparison of controller behavior

In the previous section different sets of controller parameters have been presented for the MIP and QP implementation variant of the economic dispatch optimization problem. This section compares the controller performances of both implementation variants and evaluates the dispatching behavior according to the rules of conduct defined in Section 6.1.

6.3.1 Setup

Both implementation variants have been simulated for the month of March with the same Power Node portfolio dimensioning. The renewable supply scenario is described by \( s_{\text{Wind}} = 70\% \) and \( s_{\text{PV}} = 30\% \). The sampling interval \( k \) has a duration of 15 min. The prediction horizon \( N \) is chosen as 288 (3 days) with the assumption of perfect prediction. The optimization frequency \( f \) is set to 4 intervals (1 hour).

Table 6.1 lists an overview of the important Power Nodes parameters, which are affected by the scaling of the Power Node portfolio. The power ratings of the pumped hydro plant and the NaS battery system are chosen such that they are both equal to 25\% of the average power demand specified in \( \xi_{\text{drv},1}(t) \). The discharge time at rated capacity of both units is chosen as 20 h. The installed output power of the biomass power plant \( u_{\text{gen},6}^{\max} \) is scaled to 25\% of the peak load demand of \( \xi_{\text{drv},1}(t) \). The power plant provides a constant baseload of 10\% of the peak load. Moreover, 50\% of the available electric water heaters in Germany are incorporated as flexible loads in the power systems.

6.3.2 Results

Simulation results of the MIP and QP variant are depicted in the Figures 6.1 and 6.2. In each figure, the upper plot shows the grid-related variables \( u_{\text{gen},i} \) and \( u_{\text{load},i} \). Grid infeeds are positive, while grid outputs are negative. The middle plot summarizes all enforced generation curtailment and load shedding, which are denoted by the variable \( w_i \). These control actions are performed in order to guarantee system balance in all time steps. The lower plot shows the developing of the storage levels \( x_i \).
Figure 6.1: Simulation results of the MIP variant of the economic dispatch optimization problem.
Figure 6.2: Simulation results of the QP variant of the economic dispatch optimization problem.
Table 6.1: Power Nodes parameters considered for the controller comparison.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Storage capacities</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_4$</td>
<td>262.5 GWh</td>
<td>$C_5$</td>
<td>262.5 GWh</td>
</tr>
<tr>
<td>$C_7$</td>
<td>74.7 GWh</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Power ratings</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P_{\text{rated},4}$</td>
<td>13.1 GW</td>
<td>$P_{\text{rated},5}$</td>
<td>13.1 GW</td>
</tr>
<tr>
<td>$P_{\text{rated},6}$</td>
<td>18.2 GW</td>
<td>$P_{\text{rated},7}$</td>
<td>12.9 GW</td>
</tr>
</tbody>
</table>

By comparing the plots one can observe that for both variants the dispatch behavior of the controller is the same. Hence, the stated observations in the following apply to the plots of both figures.

The first rule of conduct states that load shedding should be performed as a last resort. The middle plot reveals that load shedding is performed in several sequences between the days 7–11, indicated by the magenta areas. The biomass power plant operates with maximum power during these periods. However, it is conspicuous that at the instant of time load shedding occurs the two storage units do not discharge at their maximum power rating although their storage levels are not zero. This can be explained as follows: In case not enough generation capacities are available within a time frame equal or greater than the prediction horizon to cover demand, the stored energy is released not abrupt but rather constant over that time frame. At the end of the 11th day the storage levels are at their lower boundaries. Thus, one can conclude that load is shedded as a last resort.

According to the second rule of conduct, curtailment of intermittent generators is forbidden as long as storage capacities are available to absorb the excess energy. The middle plot reveals that only wind generation is curtailed. Between the days 12–15, a large amount of wind energy is not absorbed. The reason for this is that not enough energy storage capacities are available. The lower plot shows that both storages are charged smoothly. At the end of the curtailment sequence at day 15, both storages are completely charged. Between the days 18–31, smaller sequences of wind curtailment occur. The lower plot reveals that storage levels are low. Thus, curtailment can be attributed to insufficient power capacities of the storages. In the end, one can conclude that curtailment of intermittent generators only occurs when storages are not able to buffer the excess energy.

The third rule of conduct determines that storages should not be charged and discharged at the same time. The upper plot allows the conclusion that this condition is fulfilled. To be sure that the condition holds true in all time steps, Figure 6.3 plots the product $u_{\text{gen},i} \cdot u_{\text{load},i}$ for the pumped hydro plant. The red graph shows that the condition is always fulfilled in the MIP variant. The blue graph reveals that in the QP variant the condition is
not fulfilled. But the maximum of the product is less than 1.5. As values of $u_{\text{gen},i}$ and $u_{\text{load},i}$ are in the range of GW, this slight error is not severe. Thus, one can conclude that the third rule of conduct is only observed in the MIP variant. In the QP variant a small error is made.

![Figure 6.3: Product of $u_{\text{gen},i} \cdot u_{\text{load},i}$ for the pumped hydro plant.](image)

The last rule of conduct states that erratic behavior of unit commitment has to be avoided. The plot reveals that generation units are dispatched smoothly. Generation curtailment and load shedding occur in continuous sequences of hours. Hence, the last rule of conduct is observed.

Some additional remarks about the simulation results, illustrated in the Figures [6.1 and 6.2] can be made. Examining the upper plot, the interrupts of the green wind infeed profile by the turquoise PV infeed profile are striking. The reason for this is the preference of PV over wind energy due to the marginal generation costs of wind. However, such an abrupt down ramping of wind is rather unrealistic. An extreme example is observed on the first day. Around noon the controller inhibits wind infeed completely for a few hours resulting in severe down and up ramping. In reality, a system operator would not perform such a dispatch schedule and would preserve at least a modest wind infeed.

In order to suppress sequences of intensive wind ramping induced by the preference of PV, two options are possible. Either marginal costs of wind generation are set to zero or the ramping costs are increased as long as such ramping sequences are not beneficial in terms of money. The latter is not advisable as too high ramping costs result in a distortion of the economic dispatch determined by the penalty matrix $R_u$.

A consideration of the lower plot delivers a closer insight into the management of the energy storages. The thermal storages of the electric water heaters are charged in short time intervals of a few hours. By contrast, a charging interval of a storage unit can last up to several days. Moreover, one can observe that the controller favors charging of the pumped hydro plant.
Table 6.2: Balance terms of MIP and QP simulation run.

<table>
<thead>
<tr>
<th>Balance term</th>
<th>Value in MIP [TWh]</th>
<th>Value in QP [TWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity consumed by conv. load</td>
<td>39.148</td>
<td>39.148</td>
</tr>
<tr>
<td>Electricity consumed by flex. load</td>
<td>1.387</td>
<td>1.387</td>
</tr>
<tr>
<td></td>
<td>40.535</td>
<td>40.535</td>
</tr>
<tr>
<td>Electricity supplied by wind</td>
<td>21.812</td>
<td>21.815</td>
</tr>
<tr>
<td>Electricity supplied by PV</td>
<td>12.175</td>
<td>12.171</td>
</tr>
<tr>
<td></td>
<td>33.986</td>
<td>33.986</td>
</tr>
<tr>
<td>Electricity supplied by biomass</td>
<td>7.992</td>
<td>7.992</td>
</tr>
<tr>
<td>Electricity drawn by pumped hydro</td>
<td>3.284</td>
<td>3.283</td>
</tr>
<tr>
<td>Electricity drawn by NaS battery</td>
<td>2.294</td>
<td>2.294</td>
</tr>
<tr>
<td></td>
<td>5.578</td>
<td>5.577</td>
</tr>
<tr>
<td>Electricity supplied by pumped hydro</td>
<td>2.394</td>
<td>2.394</td>
</tr>
<tr>
<td>Electricity supplied by NaS battery</td>
<td>1.740</td>
<td>1.740</td>
</tr>
<tr>
<td></td>
<td>4.134</td>
<td>4.134</td>
</tr>
<tr>
<td>Wind energy curtailment</td>
<td>6.596</td>
<td>6.593</td>
</tr>
<tr>
<td>PV energy curtailment</td>
<td>0.000</td>
<td>0.003</td>
</tr>
<tr>
<td>Conv. load demand not served</td>
<td>-1.434</td>
<td>-1.434</td>
</tr>
<tr>
<td>Primary energy supplied by wind</td>
<td>28.408</td>
<td>28.408</td>
</tr>
<tr>
<td>Primary energy supplied by PV</td>
<td>12.175</td>
<td>12.175</td>
</tr>
<tr>
<td>Primary energy supplied by biomass</td>
<td>19.030</td>
<td>19.030</td>
</tr>
<tr>
<td>Use energy demanded by conv. load</td>
<td>-40.582</td>
<td>-40.582</td>
</tr>
<tr>
<td>Use energy demanded by flex. load</td>
<td>-1.158</td>
<td>-1.158</td>
</tr>
</tbody>
</table>

over the NaS battery system, as the storage level of the former is in general higher.

Table 6.2 lists the energy balance terms of the MIP and QP simulation run. Most of the figures are identical in the MIP and QP version. Only few balance terms differ, e.g. the one indicating the electricity supplied by wind. Of great importance is that the balance terms indicating storage commitment are the same. Thus, it can verified that the small error, which is made in the QP variant due to not fulfilling the condition $u_{gen,i} \cdot u_{load,i} = 0$ for storage units, is of no consequence.

6.3.3 Conclusions

Simulation results in the previous subsection have shown that the implementation of the optimization problem as MIP and QP results in the same dispatching behavior of the MPC controller. But the MIP variant is preferable, as it enables to arbitrarily choose curtailment costs for wind and PV in order to enforce the controller to host excess energy as long as storage...
capacities are available. This is not possible for the QP variant, where curtailment costs have to fulfill the conditions stated in the Equations (6.6) and (6.6) in order to prevent that energy is cycled through the storages. Moreover, it was highlighted that by omitting the bilinear constraints in the QP version a small numerical error occurs. Instead of $u_{\text{gen},i} \cdot u_{\text{load},i} = 0$ only $u_{\text{gen},i} \cdot u_{\text{load},i} \leq 1.5$ holds true.

Unfortunately, test runs with the MIP version revealed numerical difficulties and simulation breakups due to singularity problems. In order to eliminate the singularity problems, a CPLEX performance tuning for mixed integer programs was conducted by adjusting the solver parameters. The parameter `simplex.limits.singularity` restricts the number of times CPLEX attempts to repair the basis when singularities are encountered during the simplex algorithm. This value was set arbitrarily large. The numerical precision emphasis parameter `emphasis.numerical` controls the degree of numerical caution used during optimization of a model. This parameter was set such that CPLEX employs extreme caution in dealing with numerical properties. However, both settings did not eliminate the encountered numerical problems.

Singularity problems usually originate from a bad conditioning of the formulated optimization problem. Cost terms for $u(l)$ are several order of magnitudes higher than for $\delta u(l)$. Hence, a further approach is to recondition the problem by increasing the ramping costs in $\delta Q_u$ in the order of magnitude of the linear costs in $R_u$. Simulation test runs revealed a more stable solving behavior, but one optimization step took up to 2 minutes. As the aim of this thesis is to simulate a benchmark grid for a time span of one full year with different renewable supply scenarios and Power Nodes portfolio scalings, this value is by far too large. If ramping costs are further increased, the average optimization step time decreases. But in this case ramping costs surpass marginal costs defined in $R_u$.

In countless test runs it was not possible to find a set of cost terms for the MIP variant that led to a stable solver behavior without numerical problems and at the same time to a controller behavior according to the rules of conduct defined in Section 6.1.

A reliable case study can only be performed without numerical errors and simulation breakups. Based on the described circumstances above, the presented case studies in this thesis are performed with the QP implementation variant of the economic dispatch optimization problem in order to enable a sound solver performance.
6.4 Sensitivity of prediction horizon and optimization frequency

In the previous section it was highlighted that only the QP implementation variant of the economic dispatch optimization problem is eligible to perform an extensive case study. This section aims at investigating the impact of the prediction horizon length $N$ and optimization frequency $f$ on the optimal solution. Here, the optimal solution is expressed by the total dispatch costs, which are incurred by the penalty matrix $R_u$. The dimensioning of the Power Node portfolio and the renewable supply scenario are the same as described in Subsection 6.3.1. However, the simulated time span is chosen as 1 year instead of 1 month.

For a dispatch optimization the prediction horizon length $N$ indicates the time span in which weather and load demand forecast are available. The optimization frequency $f$ can be interpreted as the time interval in which new forecast data is available. Obviously, the larger $N$ and the shorter $f$ are chosen, the lower are overall dispatch costs.

In general, one might raise the question how the prediction horizon length $N$ impacts the dispatch costs. In the following, the main effects are highlighted. One benefit of a longer horizon length is that the deployed storage units can be optimally dispatched according to the prediction of renewable infeed. For instance, if a period of strong wind is predicted, the storage units should be discharged prior in order to host excess wind energy. How long it takes to fully discharge a storage is indicated by the discharge time at rated power. Thus, $N$ should be at least as long as this characteristic time in order to adequately adjust the charging levels prior the period of strong wind.

Additionally, a longer prediction horizon length enables to take account of the maximum power output and ramping constraints of generation units. For instance, a rather inflexible power plant can be ramped up smoothly in order to react on large load variations. Smooth ramping actions also reduce the deterioration of mechanical parts. For the case that not enough generation capacities are available to meet the load demand, the dispatch of storage units might be adjusted to close the supply gap and prevent load shedding.

Another advantage is given by the infeed of PV energy due to lower marginal generation and curtailment costs than for wind energy. A situation is illustrated in Figure 6.4, which explains in this context the benefit of a longer prediction horizon length $N$. It is assumed that one storage unit is deployed. At time $t_0$, its state of charge is almost maximal and only 2 extra MWh of electricity can be absorbed. At time $t_1$, excess wind energy is available. If $N$ is smaller than $t_2 - t_0$, the controller will dispatch wind energy and as consequence PV energy has to be curtailed at time $t_2$ and
However, in case $N$ is greater than $t_2 - t_0$, PV energy is preferred and dispatch costs can be reduced. The example shows that the longer $N$ the higher the savings potential. Clearly, the energy storage capacity has an influence too. The larger the capacity the more PV energy can be absorbed at time $t_2$ and $t_3$. As the energy storage capacity is determined by the discharge time at rated power, one can conclude that there might be a relationship between the prediction horizon length $N$ and the discharge time at rated power, which has to be fulfilled in order to guarantee minimal dispatch costs.

![Diagram](image.png)

Figure 6.4: Illustration of the benefit of a longer prediction horizon length $N$.

The intention of this thesis is to perform an economic dispatch close to reality. As weather forecasts get pretty inaccurate with increasing prediction horizon, a prediction horizon of longer than 1 week for the simulation is unrealistic. With the aid of satellites and the connection of weather stations via Internet, weather updates are available every second. Hence, a dispatch optimization can be performed every second in order to consider the altered weather situation. The time span between two consecutive optimizations is determined by the optimization frequency $f$. Because all utilized power profiles $\xi_{drv,i}(t)$ have a time resolution equal to 15 minutes, the lowest possible value of $f$ is equal to 15 minutes. But in this case, a simulation of 1 year and a sampling time of 15 minutes results in a sequence of 35040 simulation steps. Depending on the number of incorporated Power Nodes and the choice of the prediction horizon, a simulation step might take up to 5 seconds resulting in a total computation time of about 2 days. Therefore, the optimization frequency has to be chosen as high as possible to shorten simulation times without compromising the optimal solution.
First, a simulation is performed with an optimization frequency equal to 1 hour and a varying prediction horizon length between 1 hour and 7 days. Figure 6.5 illustrates the result normalized to the maximum by the blue graph. One can observe that costs decrease exponentially with increasing prediction horizon length. The decline stagnates at a prediction horizon length equal to 3 days, which is about three times the discharge time at rated power of the deployed storage units. In order to validate whether this finding holds always true, the simulation has been performed for various discharge times. The results are plotted for 10 h and 50 h by the red and magenta graph, respectively. The plots show that for a discharge time of 10 h the costs saturate at a horizon length of 1.5 days, and for 50 h at a horizon length equal to 6 days. From the results one can conclude that optimal dispatch costs for a power system with storages are obtained if the prediction horizon length is chosen at least three times larger than the storage discharge time at rated power.

![Figure 6.5: Linear costs of the decision vector u as a function of the prediction horizon length N for different storage discharge times at rated power.](image)

In a next step, the effect of the optimization frequency $f$ on the dispatch costs, which are incurred by the penalty matrix $R_u$, is illustrated in Figure 6.6. The discharge time at rated power of both storages is chosen as 20 h and the prediction horizon length $N$ is set to 3 days. The graph shows that the sensitivity of $f$ on the optimal costs is quite low. If $f$ is equal to 0.5 days, optimal costs increase only by 0.11 percentage points compared to the case when $f$ is equal 15 min. Hence, one can conclude that the optimization frequency $f$ can be set up to one sixth of the prediction horizon length $N$ without compromising the optimal solution.
Figure 6.6: Linear costs of the decision vector $u$ as a function of the optimization frequency $f$ for a constant prediction horizon length $N$ of 3 days.
Chapter 7

Case study descriptions

In this chapter, the two case studies are described, which have been performed about a single-bus and a multi-bus power system with high shares of fluctuating renewable infeed represented by wind and PV energy. The simulations have been carried out with the presented dispatch simulator and the QP variant of the economic dispatch optimization problem.

7.1 Single-bus all-renewable power system

In this case study, the impacts of storages and flexible loads on the power system’s hosting capacity for fluctuating renewable infeed and the requirement for dispatchable generation units are investigated. All simulations cover a time period of 1 year. The sampling interval \( k \) is set to 15 min. The prediction horizon length \( N \) is chosen as 384 steps (4 days) with the assumption of perfect prediction. One optimization is performed every 48 steps (12 hours).

A simple power system is considered where all Power Nodes are interfaced with one single grid bus. An illustration of the Power Node portfolio and how the individual parameters are scaled is provided in Figure 7.1. The modeling of the Power Nodes has been described in detail in Chapter 2.

Intermittent renewable generation is represented by wind turbines and PV panels. Their external supply process profiles \( \xi_{\text{drv},i}(t) \) are scaled according to the considered renewable supply scenario, which is described by the available share of wind energy \( s_{\text{Wind}} \) and PV energy \( s_{\text{PV}} \) relative to the total load demand. Here, the utilized demand process profile for the annual load demand amounts to 459.8 TWh. Thus, the renewable supply share is defined as

\[
s_i = \frac{\lambda_i \cdot \int_0^{8760h} \xi_{\text{drv},i}(t) \, dt}{459.8 \, \text{TWh}} , \quad i \in \{\text{Wind, PV}\} ,
\]

where \( \lambda_i \) denotes the scaling parameter for the original profile, which represents real infeed data from the German control area of TenneT [20].
In this case study, a renewable supply scenario is specified by the shares of wind and photovoltaic energy. Both shares are varied between 0–100%. Considering all possible combinations of pairs, the total number of renewable supply scenarios is equal to $11 \cdot 11 = 121$. In Table 7.1, the available annual energy and the resulting installed peak power are listed as a function of the renewable shares. In order to calculate the peak power, assumptions for the full load hours of wind and PV are 2000 h and 950 h, respectively [6].

Besides the variation of the renewable infeeds, the sizes of the interfaced storage unit and the cluster of flexible loads are varied. One specific sizing configuration constitutes one case, which is simulated for all 121 renewable supply scenarios. The ‘base case’ considers a power system without storage and flexible load units.

As a storage unit, a pumped hydro plant is considered. Its power rating is varied between 0–100% of the average load, which is equal to 52.5 GW. All scaling variations of the storage unit are listed in Table 7.2. The discharge time at rated power is chosen as 10 h. This is a typical value for a large pumped hydro storage. The largest one in Germany, which is currently being built in Atdorf, features a discharge time at rated power equal to 9.3 h [24].

Flexible loads are represented by the cluster of electric water heaters.
Table 7.1: Installed generation capacities of wind and PV.

<table>
<thead>
<tr>
<th>$s_{\text{Wind}}$, $s_{\text{PV}}$ [%]</th>
<th>Available energy [TWh]</th>
<th>Installed wind capacity [GW]</th>
<th>Installed PV capacity [GW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>46.0</td>
<td>23.0</td>
<td>48.4</td>
</tr>
<tr>
<td>20</td>
<td>92.0</td>
<td>46.0</td>
<td>96.8</td>
</tr>
<tr>
<td>30</td>
<td>138.0</td>
<td>69.0</td>
<td>145.2</td>
</tr>
<tr>
<td>40</td>
<td>183.9</td>
<td>92.0</td>
<td>193.6</td>
</tr>
<tr>
<td>50</td>
<td>229.9</td>
<td>115.0</td>
<td>242.0</td>
</tr>
<tr>
<td>60</td>
<td>275.9</td>
<td>137.9</td>
<td>290.4</td>
</tr>
<tr>
<td>70</td>
<td>321.9</td>
<td>160.9</td>
<td>338.8</td>
</tr>
<tr>
<td>80</td>
<td>367.9</td>
<td>183.9</td>
<td>387.2</td>
</tr>
<tr>
<td>90</td>
<td>413.8</td>
<td>206.3</td>
<td>435.6</td>
</tr>
<tr>
<td>100</td>
<td>459.8</td>
<td>229.9</td>
<td>484.4</td>
</tr>
</tbody>
</table>

Table 7.2: Dimensioning of the pumped hydro storage with a discharge time at rated power of 10 h.

<table>
<thead>
<tr>
<th>Case name</th>
<th>Power rating [% of average load]</th>
<th>Power rating [GW]</th>
<th>Storage capacity [GWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>S25%</td>
<td>25%</td>
<td>13.1</td>
<td>131.2</td>
</tr>
<tr>
<td>S50%</td>
<td>50%</td>
<td>26.2</td>
<td>262.5</td>
</tr>
<tr>
<td>S75%</td>
<td>75%</td>
<td>39.4</td>
<td>393.7</td>
</tr>
<tr>
<td>S100%</td>
<td>100%</td>
<td>52.5</td>
<td>524.9</td>
</tr>
</tbody>
</table>

The size of the cluster is varied such that it represents 25–100% of the total potential in Germany. The individual cluster variations are summarized in Table 7.3. If the cluster is scaled to 100%, its electric-equivalent warm-water demand corresponds to 6.3% of the conventional load demand.

In the base case, it is assumed that the electricity demand of the electric water heaters is included in the ENTSOE load profile, which serves as external demand process $\xi_{\text{drv},i}(t)$ for the Power Node representing the conventional load. Thus, in a case where the cluster of electric water heaters is added to the power system, its demand profile has to be subtracted from the one of the conventional load. This is done under the assumption that in an uncontrolled operation mode an electric water heater charges its thermal storage every night between 10 p.m. and 6 a.m.

As a dispatchable generation unit, a biomass power plant is considered. Its power rating amounts to 100% of the peak load, which is equal to 73.0 GW. Thus, the entire load demand could be served by biomass power and no load demand has to be shedded. In addition, the biomass unit provides a minimum baseload of 10% of the peak load.
Table 7.3: Dimensioning of the cluster of electric water heaters.

<table>
<thead>
<tr>
<th>Case name</th>
<th>Power rating [GW]</th>
<th>Thermal storage capacity [GWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>EWH25%</td>
<td>6.4</td>
<td>37.4</td>
</tr>
<tr>
<td>EWH50%</td>
<td>12.9</td>
<td>74.7</td>
</tr>
<tr>
<td>EWH75%</td>
<td>19.3</td>
<td>112.1</td>
</tr>
<tr>
<td>EWH100%</td>
<td>25.7</td>
<td>149.4</td>
</tr>
</tbody>
</table>

7.2 Multi-bus all-renewable power system

In this case study, a multi-bus power system is analyzed, which consists of 4 grid nodes. The transmission line flows are modeled with the DC power flow equation derived from Section 1.5. The investigated power system should represent Germany, which is subdivided in 4 areas: north, south, east, and west. Each area has an individual Power Node representing load demand, dispatchable generation from biomass, wind energy, and PV energy. In addition, a pumped hydro storage is added either to the northern or to the southern area. Thus, in total 17 Power Nodes are interfaced with the power system.

In Figure 7.2, an illustration is provided which shows how the electricity demand, generation and storage capacities are allocated to the individual areas. For Power Nodes with an external demand/supply profile \( \xi_{\text{drv},i}(t) \), e.g. wind energy, the percentage numbers indicate how the profile is split among the 4 areas. Like in the case study about the single-bus benchmark system, the supply profiles of wind and PV energy are scaled according to the figures listed in Table 7.2.

The electricity demand is distributed according to the current population figures of each federal state obtained from [35]. The figures show that the south/west region accounts for 64% of the demand, and the north/east region only for 36%.

The spreading of the PV generation capacities takes place according to the distribution figures of PV panels in the year 2007 [24]. From the figures one can infer that the largest share of energy from PV is generated in the south of Germany.

The dispersion of the wind generation capacities is also based on the figures from 2007, which state an installed peak power for onshore wind generators equal to 21.9 GW. Thereby, 78% is installed in the north/east region and only 22% in the south/west region. However, offshore wind energy will play a meaningful role for Germany in the future [24]. By 2030, onshore and offshore wind generation capacities equal to 35.9 GW and 23.8 GW are envisioned. Thereby, 22.1 GW of the offshore capacities will be installed in the North Sea. Overall, the north/east to south/west ratio will
change slightly to 86% vs. 14%.

The installed generation capacity of biomass is equal to 100% of the peak load. The capacities are more or less distributed according to the electricity demand in each area. However, a slight overcapacity in the south/west region exists. Consequently, electricity has to be exported from the south/west to the north/east region in case of insufficient infeed from renewable energy sources.

Referring to the storage deployment, 3 scenarios are considered. In the base case, no storage units are interfaced with the power system. In the case ‘S50%N’, a pumped hydro storage with a power rating equal to 50% of the power system’s average load is located in the northern area. In the case ‘S50%S’, the same storage is interfaced with the southern grid bus. As for the single-bus benchmark system, the storage units have a discharge time at rated power equal to 10 h.

The corresponding characteristics of the transmission lines are listed in Table 7.4. All values are given in per unit. The original base of the grid is 1000 MVA, but the resulting transmission line limits are too low for the expected power flows. Thus, the base has been heuristically set to 2300 MVA. For this setting, no load shedding occurs for the scenario $s_{\text{Wind}} =$
Table 7.4: Grid setup of the multi-bus all-renewable benchmark system.

<table>
<thead>
<tr>
<th>No.</th>
<th>From node</th>
<th>To node</th>
<th>X [p.u.]</th>
<th>Long term limit [p.u.]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>0.14</td>
<td>2.5</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>3</td>
<td>0.16</td>
<td>1.58</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>4</td>
<td>0.1</td>
<td>2.0</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>4</td>
<td>0.1</td>
<td>3.5</td>
</tr>
</tbody>
</table>

$s_{PV} = 0\%$ and the total load demand can be entirely served by biomass energy.

In general, the maximum power flow depends on the voltage level, the construction (tower height, etc.) and the length of the transmission line. Here, the same nominal voltage is assumed, but different line types and lengths. Typically, the power transfer capability of a transmission line is expressed in terms of the surge impedance loading (SIL). According to the St. Clair curve, the line loading decreases with the length of the line. In the presented case study, the line characteristics of the analyzed power system have been chosen such that the distances between the 4 areas are considered and congestions occur by transferring electricity from the north/east to the south/west region, such as it is the case for Germany.
Chapter 8

Results and discussion

8.1 Evaluation indices

The simulation runs of the single-bus and multi-bus power systems generate an enormous amount of data. For one simulation run the temporal evolutions of all input and state variables are available. In the following, evaluation indices are introduced, which are calculated based on the temporal evolutions of the variables. The indices enable to determine the power system’s hosting capacity for fluctuating renewable infeed and analyze the dispatch of the individual power system units.

8.1.1 Integrated Renewable Energy (IRE)

The examined power system is interfaced with a set of Power Nodes $\mathcal{R}$, which represents different variable renewable energy sources (VRES). The set of Power Nodes representing loads is denoted by $\mathcal{L}$. In order to evaluate how much renewable energy has been absorbed by the power system during the simulated time period $[t_1, t_2]$, the performance index Integrated Renewable Energy $IRE$ is introduced. $IRE$ is defined as follows:

\[
IRE = \frac{\int_{t_1}^{t_2} P_{\text{renewable}}^\text{gen}(t) \, dt}{\int_{t_1}^{t_2} \xi_{\text{total demand}}(t) \, dt},
\]

(8.1)

with

\[
P_{\text{gen}}^\text{renewable}(t) = \sum_{i \in \mathcal{R}} u_{\text{gen},i}(t),
\]

(8.2)

and

\[
\xi_{\text{total demand}}(t) = \sum_{i \in \mathcal{L}} \xi_i(t).
\]

(8.3)

In words, the index $IRE$ expresses how much fluctuating renewable energy has been absorbed by the grid relative to the total load demand. $IRE$ does not take into account dispatchable renewable energy sources,
e.g. biomass. Clearly, IRE should be close to 100%, as this implies a sustainable and eco-friendly electricity supply.

8.1.2 Curtailed Renewable Energy (CRE)

The examined power system is interfaced with a set of Power Nodes \( \mathcal{R} \), which represents different variable renewable energy sources (VRES). The performance index Curtailed Renewable Energy \( CRE \) expresses how much renewable energy has been curtailed relative to the available renewable energy during the simulated time period \([t_1, t_2]\). In general, curtailment of VRES means a waste of free energy, which could have been fed in the grid in order to generate profits for the operator of the renewable generator. Therefore, \( CRE \) should be as low as possible, because this results in high load factors of the renewable generators and maximizes profits. \( CRE \) is defined as follows:

\[
CRE = \frac{\int_{t_1}^{t_2} P_{\text{renewable}}(t) \, dt}{\int_{t_1}^{t_2} \xi_{\text{supply}}(t) \, dt},
\]

(8.4)

with

\[
P_{\text{cur}}(t) = \sum_{i \in \mathcal{R}} w_i(t),
\]

(8.5)

and

\[
\xi_{\text{supply}}(t) = \sum_{i \in \mathcal{R}} \xi_i(t).
\]

(8.6)

8.1.3 Relative Curtailment (RC)

In a power system, the electricity generation by one specific VRES, e.g. wind energy, is represented by a set of Power Nodes \( i \in \mathcal{R}_s \subseteq \mathcal{R} \). For this setup, the index Relative Curtailment \( RC_i \) expresses the share of curtailed energy of one Power Node \( i \in \mathcal{R}_s \) relative to the curtailed energy of all Power Nodes representing the same VRES. The index \( RC_i \) is defined as follows:

\[
RC_i = \frac{\int_{t_1}^{t_2} w_i(t) \, dt}{\int_{t_1}^{t_2} P_{\text{cur}}(t) \, dt}, \quad i \in \mathcal{R}_s,
\]

(8.7)

with

\[
P_{\text{cur}}(t) = \sum_{i \in \mathcal{R}_s} w_i(t).
\]

(8.8)

This index is valuable for multi-bus power systems, where a VRES is only represented by one Power Node per grid power. For this case, \( RC_i \) indicates in which area most of the renewable energy is curtailed.
8.1.4 Charge-Discharge Cycles (CDC)

The index \textit{CDC} expresses how many charge-discharge cycles per week a storage unit performs during the simulated time period \([t_1, t_2]\). A charge-discharge cycle is defined based on the temporal evolution of the storage level \(x_i\). If a storage charges, its state of charge increases and the derivative of \(x_i\) is positive. In case the storage supplies energy, the state of charge decreases and the derivative of \(x_i\) is negative. Hence, a charge-discharge cycle could be regarded as accomplished when the derivative of \(x_i\) changes sign from plus to minus, and again back to plus. An illustration of this definition is shown in Figure \ref{fig:8.1}. One can see that both storages perform two complete charge-discharge cycles, although the amount of cycled energy differs.

![Figure 8.1: Illustration of a charge-discharge cycle of a storage unit.](image)

The time series of \(x_i\) is discrete and sampled in intervals of 15 minutes. The derivative of the discrete signal is obtained by subtracting two consecutive sampling values. In order to suppress sequences of excessive ramping of the pumped hydro storage on the time scale of 15 minutes, quadratic penalties on the derivatives of the decision variables \(u_{\text{gen},i}\) and \(u_{\text{load},i}\) have been introduced in the objective function of the economic dispatch optimization problem. Thus, the time series of \(x_i\) is almost smooth and only little noise occurs. In order to eliminate marginal ups and downs of \(x_i\), a moving average filter with a window size of 1 h is applied prior the calculation of \textit{CDC}.

8.1.5 Full Load Hours (FLH)

An important performance index of generation units is the number of full load hours. According to the Power Node notation, the Full Load Hours index \textit{FLH} is calculated from

\[
FLH_i = \frac{\int_{t_1}^{t_2} u_{\text{gen},i}(t) \, dt}{u_{\text{max},i}} , \quad i \in \mathcal{G} ,
\]  

(8.9)
where $\mathcal{G}$ is the set of Power Nodes representing controllable generation units, $u_{\text{gen},i}^{\text{max}}$ denotes the unit’s power rating, and $[t_1, t_2]$ the considered simulation period.

For the incorporated wind turbines and PV panels a different approach is needed, because they are modeled as Power Nodes with an externally driven supply process $\xi_i = \xi_{\text{drv},i}(t)$. As the Power Nodes should provide as much energy as possible from the supply-side to the grid-side, the upper boundary $u_{\text{gen},i}^{\text{max}}$ on the grid variable $u_{\text{gen},i}$ is not defined.

The utilized time series $\xi_{\text{drv},i}(t)$ are published on the TSO’s webpage without information about the installed peak power of wind and PV energy [20]. Hence, the number is calculated first according to

$$PP_i = \frac{\int_{t_1}^{t_2} \xi_i(t) \, dt}{FLH_{\text{std},i}} , \quad i \in \mathcal{R} ,$$  \hspace{1cm} (8.10)

where $FLH_{\text{std},i}$ indicates a standard value for the number of full load hours. For wind turbines in Germany a standard value of 2000 h is assumed, for PV panels 950 h [6]. Consequently, the index $FLH$ for the renewable energy sources are derived from

$$FLH_i = \frac{\int_{t_1}^{t_2} u_{\text{gen},i}(t) \, dt \cdot FLH_{\text{std},i}}{\int_{t_1}^{t_2} \xi_i(t) \, dt} , \quad i \in \mathcal{R} .$$  \hspace{1cm} (8.11)

### 8.1.6 Normalized Conversion Losses (NCL)

As the incorporated pumped hydro storage is considered to be lossy, energy conversion losses occur every time the storage is dispatched. Thus, this energy balance term can be utilized to evaluate how often the storage unit is utilized as a function of the renewable supply scenario. Clearly, total losses increase with storage capacity. In order to enable a comparison between different storage scalings, the index Normalized Conversion Losses (NCL) is introduced. $NCL$ is defined as

$$NCL_i = \frac{\int_{t_1}^{t_2} P_{\text{loss},i}(t) \, dt}{C_i} , \quad i \in \mathcal{S} ,$$  \hspace{1cm} (8.12)

with

$$P_{\text{loss},i}(t) = \left( \frac{1 - \eta_{\text{gen},i}}{\eta_{\text{gen},i}} u_{\text{gen},i}(t) + (1 - \eta_{\text{load},i}) u_{\text{load},i}(t) \right) , \quad i \in \mathcal{S} ,$$  \hspace{1cm} (8.13)

where $\mathcal{S}$ is the set of Power Nodes representing storages, $C_i$ denotes the storage capacity, and the interval $[t_1, t_2]$ is the simulation period.
CHAPTER 8. RESULTS AND DISCUSSION

8.1.7 Transmission Line Utilization (TLU)

In case the simulated power system is modeled as a multi-bus grid, the index Transmission Line Utilization $TLU$ indicates for a transmission line between node $m$ and node $n$ the mean power flow normalized to the maximum transmission capacity of the line. $TLU$ is defined as

$$TLU_{mn} = \frac{\int_{t_1}^{t_2} |P_{line,mn}(t)| \, dt}{(t_2 - t_1) \cdot C_{line,mn}},$$

(8.14)

where $P_{line,mn}$ denotes the power flow of the line and $C_{line,mn}$ considers the maximum transmission capacity.

8.2 Single-bus all-renewable power system

8.2.1 Integrated renewable energy

In this subsection, the impact of the pumped hydro storage and the cluster of flexible loads on the share of integrated renewable energy relative to the annual load demand, which is expressed by the index $IRE$, is evaluated. The results are graphically illustrated by colored surface plots and contour plots, which display the isolines. An isoline is a curve along which the plotted evaluation index has a constant value. In order to facilitate the viewer’s perception, two thicker black lines are added in the surface plots. The lines indicate a wind share ($s_{\text{Wind}}$) and PV share ($s_{\text{PV}}$) of 50%. If a renewable share is lower than 50%, the penetration level of the corresponding renewable energy source is considered to be 'low' (↓). If the share is higher than 50%, it is referred to a 'high' (↑) penetration level.

In Figure 8.2, $IRE$ is illustrated as a function of the renewable supply scenario for the base case where no storages and flexible loads are deployed. The corresponding contour plot is shown in the top left corner of Figure 8.3.

The surface plot shows that $IRE$ rises with increasing levels of $s_{\text{Wind}}$ and $s_{\text{PV}}$. However, the sensitivity of both parameters on $IRE$ is not the same. For low renewable penetration levels, the growth of $IRE$ is considerably larger for an increase in $s_{\text{Wind}}$ compared with an increase in $s_{\text{PV}}$. In case $s_{\text{PV}}$ is further increased, the value of $IRE$ grows only marginally by less than 1.6 percentage points per additional 10 percentage points of $s_{\text{PV}}$. Contrary, if $s_{\text{Wind}}$ is increased in the range of 50–100%, the value of $IRE$ rises by maximal 4.7 percentage points (pp) per additional 10 percentage points of $s_{\text{Wind}}$. The higher sensitivity of $s_{\text{Wind}}$ on $IRE$ is explained as follows: PV generation features an inherent diurnal cycle. By installing additional PV panels, the characteristic infeed peak around noon increases. Already at very low PV shares this peak exceeds the load demand. As a consequence, the excess PV energy has to be curtailed. By contrast, available wind energy is not concentrated at noon but rather distributed in sequences of several
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Figure 8.2: 3D plot of the integrated renewable energy share for the base case.

Figure 8.3: Contour plot of the integrated renewable energy share for different storage scalings.
CHAPTER 8. RESULTS AND DISCUSSION

Table 8.1: Average value of the integrated renewable energy share.

<table>
<thead>
<tr>
<th>Case</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>37.8%</td>
<td>48.1%</td>
<td>61.2%</td>
<td>67.1%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
<td>53.0%</td>
</tr>
<tr>
<td>S25%</td>
<td>41.1%</td>
<td>55.0%</td>
<td>65.5%</td>
<td>73.1%</td>
<td>58.0%</td>
<td>58.0%</td>
<td>58.0%</td>
<td>58.0%</td>
<td>58.0%</td>
<td>58.0%</td>
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<td>58.0%</td>
<td>58.0%</td>
<td>58.0%</td>
</tr>
<tr>
<td>S50%</td>
<td>43.4%</td>
<td>60.8%</td>
<td>68.5%</td>
<td>77.3%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
<td>61.7%</td>
</tr>
<tr>
<td>S75%</td>
<td>45.0%</td>
<td>65.1%</td>
<td>70.5%</td>
<td>79.9%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
<td>64.3%</td>
</tr>
<tr>
<td>S100%</td>
<td>46.0%</td>
<td>67.9%</td>
<td>71.8%</td>
<td>81.3%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
<td>65.9%</td>
</tr>
</tbody>
</table>

Table 8.2: Average change of the integrated renewable energy share compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
<th>$s_{\text{Wind}}$</th>
<th>$s_{\text{PV}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S25%</td>
<td>+3.3 pp</td>
<td>+6.9 pp</td>
<td>+4.3 pp</td>
<td>+6.0 pp</td>
<td>+5.0 pp</td>
<td>+5.0 pp</td>
<td>+5.0 pp</td>
<td>+5.0 pp</td>
<td>+5.0 pp</td>
<td>+5.0 pp</td>
</tr>
<tr>
<td>S50%</td>
<td>+5.6 pp</td>
<td>+12.6 pp</td>
<td>+7.3 pp</td>
<td>+10.2 pp</td>
<td>+8.7 pp</td>
<td>+8.7 pp</td>
<td>+8.7 pp</td>
<td>+8.7 pp</td>
<td>+8.7 pp</td>
<td>+8.7 pp</td>
</tr>
<tr>
<td>S75%</td>
<td>+7.2 pp</td>
<td>+17.0 pp</td>
<td>+9.3 pp</td>
<td>+12.7 pp</td>
<td>+11.3 pp</td>
<td>+11.3 pp</td>
<td>+11.3 pp</td>
<td>+11.3 pp</td>
<td>+11.3 pp</td>
<td>+11.3 pp</td>
</tr>
<tr>
<td>S100%</td>
<td>+8.2 pp</td>
<td>+19.7 pp</td>
<td>+10.7 pp</td>
<td>+14.2 pp</td>
<td>+12.9 pp</td>
<td>+12.9 pp</td>
<td>+12.9 pp</td>
<td>+12.9 pp</td>
<td>+12.9 pp</td>
<td>+12.9 pp</td>
</tr>
</tbody>
</table>

days resulting in a lower imbalance even at higher wind shares. From the results one can conclude that power systems without storages are able to host wind energy to a greater extent than PV energy. Moreover, it is not reasonable to install PV capacities which can supply more than 50% of the annual load demand in the absence of storage units.

In Figure 8.4 the influence of $s_{\text{Wind}}$ and $s_{\text{PV}}$ on $IRE$ for the case 'S50%' is graphically illustrated by the semi-transparent plane. As reference the results from the base case are added, which are represented by the nontransparent plane. In general, an increase of $IRE$ is observable for all renewable supply scenarios. According to Table 8.1 the average value of $IRE$ rose from 53% to 61.7%. However, according to Table 8.2 the upward shift of the plane is not the same in all scenarios. The gain is the greatest in scenarios with high $s_{\text{PV}}$ and low $s_{\text{Wind}}$. Moreover, the surface plot shows that compared to the base case the value of $IRE$ rises more if $s_{\text{PV}}$ is increased in the range of 50–100%. In the corresponding contour plot, shown in the bottom left corner of Figure 8.3, this is indicated by the fact that the isolines are not parallel to the y-axis for high penetration levels of PV.

Additionally, the contour plot reveals that the rise of $IRE$ stagnates and increases by maximal 10 percentage points if both renewable shares are chosen greater than 50%. From the plots one can conclude that the tendency towards a better integrability of wind energy in power systems
with deployed storage capacity equal to 50% of the average load persists. Moreover, it is not reasonable to install additional wind and PV capacities if for both renewable energy sources the energy penetration level is greater than 50%, as almost no further gain in $IRE$ is achieved.

In Figure 8.5, $IRE$ is graphically illustrated by the semi-transparent plane as a function of $s_{\text{Wind}}$ and $s_{\text{PV}}$ for the case 'S100%'. Again, the results from the base case are depicted by the nontransparent plane. The results show a considerable increase of $IRE$ compared to the base case. According to Table 8.2, the value rose by almost 20 percentage points for low penetration levels of wind and high levels of PV. The shape of the plane has changed such that it is almost symmetric to the line defined by $s_{\text{Wind}} = s_{\text{PV}}$. This indicates that the sensitivities of $IRE$ on $s_{\text{Wind}}$ and $s_{\text{PV}}$ are almost the same. The corresponding contour plot in Figure 8.3 indicates that the value of $IRE$ is greater than 80% if both renewable shares are greater than 70%. From the results one can conclude that a power system with a storage power capacity equal to 100% of the average load still favors wind generation. However, the transformation of the plane shape indicates that the larger the power rating of the deployed storage is chosen the smaller gets the inherent drawback of PV generation induced by the diurnal cycle of the sun. Additionally, the results show that an integrated renewable energy share equal to 100% is not reached even with very large storage capacities.

In order to graphically illustrate in which renewable supply scenarios the value of $IRE$ increases the most, Figure 8.6 shows the deviation of $IRE$ be-
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Figure 8.5: 3D plot of the integrated renewable energy share for the case 'S100%' (semi-transparent) and for the base case (nontransparent).

Figure 8.6: Increase of the integrated renewable energy share compared to the base case for the cases 'S50%' (nontransparent) and 'S100%' (semi-transparent).
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tween the base case and the two cases ‘S50%’ (nontransparent) and ‘S100%’ (semi-transparent). Both planes show that the increase of IRE is greater for scenarios with large $s_{PV}$ and small $s_{Wind}$ than vice versa. This may be explained as follows: The diurnal cycle of PV generation facilitates an optimal storage dispatch where excess PV energy is buffered at noontime and fed back to the grid throughout the rest of the day. Thus, the charge/discharge cycle of the storage is time-delayed with respect to the PV generation cycle. By contrast, the rather stochastic and more complex pattern of wind generation does not enable periodic storage operations. As a period of high wind generation might last up to several days, excess wind energy is absorbed until the storage is full. The longer the phase of strong wind, the more wind energy has to be curtailed.

Scenarios of particular interest are defined by $s_{PV} + s_{Wind} = 100\%$, as the available renewable energy equals the annual load demand. If sufficient lossless storage facilities were deployed, load demand could be fully served by renewable infeed. Hence, these scenarios are termed full supply scenarios.

In Figure 8.7, the influence of the full supply scenarios on IRE is plotted for a pumped hydro storage with a power rating varying between 0–200% of the average load. The plots show that by increasing the installed storage power the value of IRE increases more for full supply scenarios with high penetration levels of PV. In the base case, IRE is maximized for $s_{Wind} = 80\%$. This finding verifies the result in [4]. The study investigates the variance of the residual load for power systems without storage facilities and full supply scenarios with wind and PV. However, with increasing power rating of the storage, the maximum shifts to higher penetration levels of PV. For a storage power equal to 200% of the average load, the value of IRE is maximized for $s_{Wind} = 60\%$. Additionally, the graphs reveal that the increase of IRE gets smaller the more storage capacities are deployed. From the results one can conclude that an integrated renewable energy share of 100% would only be reached with unrealistically high storage power ratings several times higher than the average load demand.

In Figure 8.8, IRE is graphically illustrated as a function of the renewable supply scenario for the case ‘EWH100%’, where all electric water heaters in Germany are incorporated into the power system as a cluster of flexible loads. The depicted plane features the same shape as the one in the base case, which is shown in Figure 8.2. According to Table 8.3, the average value of IRE rose to 56.7%, resulting in an increase by 3.7 percentage points compared to the base case. From Table 8.4 one can infer that the value of IRE increases the most in scenarios with low shares of wind and high shares of PV. This finding has already been discovered for the deployment of the pumped hydro storage. From the results one can conclude that the cluster of electric water heaters, which accounts for 6.3% of the total load demand in the simulation, increases the share of integrated renewable energy on average by 3.7 percentage points. This impact is quite large, if
Figure 8.7: Integrated renewable energy as a function of the full supply scenario ($s_{PV} + s_{Wind} = 100\%$) for different storage power ratings varying between 0–200\% of the average load.

Figure 8.8: 3D plot of the integrated renewable energy share for the case 'EWH100\%'.

one considers that a pumped hydro storage with a power rating equal to 25% of the average load increases the share by 5.0 percentage points.

In order to evaluate in which scenarios the value of $IRE$ is increased the most, Figure 8.10 illustrates the deviation of $IRE$ between the base case and the cases where 50% (nontransparent) and 100% (semi-transparent) of the electric water heaters are considered as flexible loads. If 50% of the potential is exploited, the gain of $IRE$ is on average about 2 percentage points. The plane is almost even and features a slight elevation for high $s_{PV}$ and low $s_{Wind}$ with a maximum value equal to 2.8 percentage points. Considering the case where the full potential is used, the elevation develops further. A preference for renewable supply scenarios with high $s_{PV}$ and low $s_{Wind}$ is clearly observable. This can be explained by: The volume of the electric water heaters is dimensioned such that the daily warm-water demand can be served. The thermal storages are charged at noontime when PV generation peaks. Until the next day the warm water is used up and the cluster of electric water heaters is ready again to absorb energy from PV generation. Thus, the diurnal cycle of PV generation enables an optimal utilization of the thermal storage. From the results one can conclude that the impact of the electric water heater cluster on the share of integrated renewable

Figure 8.9: Contour plot of the integrated renewable energy share for different scalings of the electric water heater cluster.
Table 8.3: Average value of the integrated renewable energy share.

<table>
<thead>
<tr>
<th>Case</th>
<th>( s_{Wind} )</th>
<th>( s_{PV} )</th>
<th>( s_{Wind} )</th>
<th>( s_{PV} )</th>
<th>( s_{Wind} )</th>
<th>( s_{PV} )</th>
<th>( \emptyset )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>37.8%</td>
<td>48.1%</td>
<td>61.2%</td>
<td>67.1%</td>
<td>53.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EWH25%</td>
<td>38.6%</td>
<td>49.5%</td>
<td>62.1%</td>
<td>68.2%</td>
<td>54.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EWH50%</td>
<td>39.4%</td>
<td>50.8%</td>
<td>62.9%</td>
<td>69.3%</td>
<td>55.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EWH75%</td>
<td>40.0%</td>
<td>52.1%</td>
<td>63.6%</td>
<td>70.2%</td>
<td>55.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EWH100%</td>
<td>40.7%</td>
<td>53.3%</td>
<td>64.3%</td>
<td>71.2%</td>
<td>56.7%</td>
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<td></td>
</tr>
</tbody>
</table>

Table 8.4: Average change of the integrated renewable energy share compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>( s_{Wind} )</th>
<th>( s_{PV} )</th>
<th>( s_{Wind} )</th>
<th>( s_{PV} )</th>
<th>( s_{Wind} )</th>
<th>( s_{PV} )</th>
<th>( \emptyset )</th>
</tr>
</thead>
<tbody>
<tr>
<td>EWH25%</td>
<td>+0.8 pp</td>
<td>+1.4 pp</td>
<td>+0.9 pp</td>
<td>+1.1 pp</td>
<td>+1.0 pp</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EWH50%</td>
<td>+1.5 pp</td>
<td>+2.7 pp</td>
<td>+1.7 pp</td>
<td>+2.1 pp</td>
<td>+2.0 pp</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EWH75%</td>
<td>+2.2 pp</td>
<td>+3.9 pp</td>
<td>+2.4 pp</td>
<td>+3.1 pp</td>
<td>+2.9 pp</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EWH100%</td>
<td>+2.8 pp</td>
<td>+5.1 pp</td>
<td>+3.1 pp</td>
<td>+4.0 pp</td>
<td>+3.7 pp</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

energy is the greatest in scenarios with few wind and high PV generation capacities. However, the power system’s preference for wind energy over PV energy persists.

In Figure 8.11, \( IRE \) is plotted as a function of the full supply scenario for different shares of incorporated electric water heaters as flexible loads varying between 0–100% of the full potential in Germany. The graphs show that \( IRE \) is maximized for all incorporation levels with \( s_{Wind} \) in the range of 70–80%. Additionally, the graphs reveal that the increase in \( IRE \) stays constant the more electric water heaters are considered as flexible loads. Thus, one can conclude that it is beneficial to incorporate as many electric water heaters as flexible loads as possible.

In a next step, a power system has been simulated which is interfaced with the pumped hydro storage and the cluster of flexible loads in combination. As before, the power rating of the storage is varied between 25–100% of the average load. The cluster’s size is kept constant at 100% of the potential. The results for the share of integrated renewable energy \( IRE \) are listed in the Tables 8.5 and 8.6. By comparing the listed numbers with the results of the simulations, which considered the storage unit and the cluster of flexible loads separately, the following interesting observation can be made: Compared to the base case, the value of \( IRE \) is increased by 5.0 percentage points (pp) for the case 'S25%', and by 3.7 pp for the case 'EWH100%'.
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Figure 8.10: Increase of the integrated renewable energy share compared to the base case for the cases 'EWH50%' (nontransparent) and 'EWH100%' (semi-transparent).

Figure 8.11: Integrated renewable energy as a function of the full supply scenario ($s_{PV} + s_{Wind} = 100\%$) for different shares of incorporated electric water heaters as flexible loads.
Table 8.5: Average value of the integrated renewable energy share.

<table>
<thead>
<tr>
<th>Case</th>
<th>↓ s_{Wind}</th>
<th>↓ s_{PV}</th>
<th>↑ s_{Wind}</th>
<th>↑ s_{PV}</th>
<th>(\emptyset)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>37.8%</td>
<td>48.1%</td>
<td>61.2%</td>
<td>67.1%</td>
<td>53.0%</td>
</tr>
<tr>
<td>S25%+E100%</td>
<td>43.3%</td>
<td>59.7%</td>
<td>68.1%</td>
<td>76.4%</td>
<td>61.1%</td>
</tr>
<tr>
<td>S50%+E100%</td>
<td>45.1%</td>
<td>64.7%</td>
<td>70.5%</td>
<td>79.7%</td>
<td>64.2%</td>
</tr>
<tr>
<td>S75%+E100%</td>
<td>46.1%</td>
<td>67.9%</td>
<td>72.0%</td>
<td>81.5%</td>
<td>66.0%</td>
</tr>
<tr>
<td>S100%+E100%</td>
<td>46.7%</td>
<td>69.6%</td>
<td>73.1%</td>
<td>82.5%</td>
<td>67.2%</td>
</tr>
</tbody>
</table>

Table 8.6: Average change of the integrated renewable energy share compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>↓ s_{Wind}</th>
<th>↓ s_{PV}</th>
<th>↑ s_{Wind}</th>
<th>↑ s_{PV}</th>
<th>(\emptyset)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S25%+E100%</td>
<td>+5.5 pp</td>
<td>+11.6 pp</td>
<td>+6.9 pp</td>
<td>+9.2 pp</td>
<td>+8.1 pp</td>
</tr>
<tr>
<td>S50%+E100%</td>
<td>+7.2 pp</td>
<td>+16.5 pp</td>
<td>+9.3 pp</td>
<td>+12.5 pp</td>
<td>+11.2 pp</td>
</tr>
<tr>
<td>S75%+E100%</td>
<td>+8.3 pp</td>
<td>+19.8 pp</td>
<td>+10.8 pp</td>
<td>+14.4 pp</td>
<td>+13.1 pp</td>
</tr>
<tr>
<td>S100%+E100%</td>
<td>+8.9 pp</td>
<td>+21.5 pp</td>
<td>+11.9 pp</td>
<td>+15.4 pp</td>
<td>+14.2 pp</td>
</tr>
</tbody>
</table>

However, if the storage and the flexible load cluster are simulated together, \(IRE\) rises only by 8.1 pp. This is 0.6 pp less than the sum of the individual results. If this analysis is made for a storage size equal to 100%, the deviation accounts for 2.4 pp. Hence, one can conclude that the larger the storage size is chosen, the lower gets the additional benefit of incorporating the cluster of electric water heaters as flexible loads.

### 8.2.2 Curtailed renewable energy

In Figure 8.12, the share of curtailed renewable energy relative to the available renewable energy \(CRE\) is plotted as a function of the renewable supply scenario for the base case where no storages and flexible loads are deployed. The corresponding contour plot is shown in the top left corner of Figure 8.13.

The plots show that \(CRE\) is highly dependent on \(s_{PV}\). According to Table 8.7, the value of \(CRE\) is on average above 50% in scenarios with high shares of PV energy. Following a line of constant \(s_{Wind}\) in the surface plot shown in Figure 8.12, \(CRE\) is always minimized for \(s_{PV} = 0\%). By contrast, if \(s_{PV}\) is kept constant above 40%, the value of \(IRE\) is minimized for \(s_{Wind}\) in the range of 30–50%. From the results one can infer that if the load demand of a power system without storages and flexible loads should be served solely with wind and PV energy, renewable supply scenarios with
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Figure 8.12: 3D plot of the curtailed renewable energy share for the base case.

Figure 8.13: Contour plot of the curtailed renewable energy share for different storage scalings.
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high $s_{\text{Wind}}$ and low $s_{\text{PV}}$ are favorable in order to reduce curtailment and increase the utilization factor of the renewable generators.

The impact of a storage with a power rating equal to 50% of the average load on $CRE$ is shown as a function of the renewable supply scenario in Figure 8.14. Compared to the base case, the plane has lowered considerably in the region with low $s_{\text{Wind}}$ and high $s_{\text{PV}}$. According to Table 8.8, the value of $CRE$ decreased in that region on average by 13.2 pp. Following a line of constant $s_{\text{PV}}$ in the surface plot, the value of $CRE$ is now minimized for $s_{\text{Wind}}$ in the range of 0–30%. The corresponding contour plot in Figure 8.13 shows that the isolines begin to transform into semi-circles with central points in the origin. This indicates that the predominant influence of $s_{\text{PV}}$ on $CRE$ decreases. However, the gradient in the direction of $s_{\text{PV}}$ is still steeper than in $s_{\text{Wind}}$-direction. Thus, one can conclude that a power system with a deployed storage power equal to 50% of the average load still favors renewable supply scenarios with high $s_{\text{Wind}}$ and low $s_{\text{PV}}$ as curtailment is reduced.

Figure 8.14: 3D plot of the curtailed renewable energy share for the case ‘S50%’.

In Figure 8.15, $CRE$ is illustrated as a function of the renewable supply scenario for the case ‘S100%’. Compared to the base case, the shape of the plane has changed considerably and is now almost symmetric to the line defined by $s_{\text{Wind}} = s_{\text{PV}}$. Thus, the gradients in $s_{\text{Wind}}$- and $s_{\text{PV}}$-direction are nearly the same. In the contour plot shown in Figure 8.13 this is indicated by the circular alignment of the isolines. According to Table 8.8, curtailment is reduced on average by 13.6 pp. From the results one can conclude that
with increasing storage size the predominant dependency of the installed PV capacity on the share of curtailed renewable energy is diminished. Regarding the utilization factor of a renewable generation portfolio, it is still beneficial to install large wind and rather small PV generation capacities if the deployed storage power is equal to 100% of the average load.

Figure 8.15: 3D plot of the curtailed renewable energy share for the case 'S100%'.

In the Appendix B.1, the individual shares of the curtailed wind and PV energy are shown in the Figures B.1 and B.2 for all storage scalings. The graphs make clear that the pumped hydro storage mainly buffers PV energy, as curtailment of PV energy is reduced the more storage capacities are installed. By contrast, curtailment of wind turbines is hardly observable. Additionally, one can see that the plane of PV curtailment declines the most for low shares of wind energy.

### 8.2.3 Requirement of dispatchable generation

Power generation has to match the load demand at every instant. In general, three different types of power plants are used for this purpose: base power plants, load-following power plants, and peak power plants. For power systems with high shares of fluctuating renewable infeed it is interesting to evaluate how these different unit types are operated and how this changes when the shares of renewable energy are varied, and in addition storage units are deployed.

In the performed case study, dispatchable generation is incorporated
CHAPTER 8. RESULTS AND DISCUSSION

Table 8.7: Average value of the curtailed renewable energy share.

<table>
<thead>
<tr>
<th>Case</th>
<th>CRE ↓ sWind</th>
<th>CRE ↓ sPV</th>
<th>CRE ↑ sWind</th>
<th>CRE ↑ sPV</th>
<th>CRE ↑ sWind</th>
<th>CRE ↓ sPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>19.5%</td>
<td>50.9%</td>
<td>36.6%</td>
<td>54.4%</td>
<td>40.5%</td>
<td>35.2%</td>
</tr>
<tr>
<td>S25%</td>
<td>13.7%</td>
<td>43.7%</td>
<td>32.2%</td>
<td>50.2%</td>
<td>31.4%</td>
<td>28.7%</td>
</tr>
<tr>
<td>S50%</td>
<td>9.9%</td>
<td>37.7%</td>
<td>29.2%</td>
<td>47.3%</td>
<td>31.4%</td>
<td>28.7%</td>
</tr>
<tr>
<td>S75%</td>
<td>7.2%</td>
<td>33.0%</td>
<td>27.2%</td>
<td>45.5%</td>
<td>28.7%</td>
<td>26.9%</td>
</tr>
<tr>
<td>S100%</td>
<td>5.5%</td>
<td>30.0%</td>
<td>25.7%</td>
<td>44.5%</td>
<td>26.9%</td>
<td>26.9%</td>
</tr>
</tbody>
</table>

Table 8.8: Average change of the curtailed renewable energy share compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>∆CRE ↓ sWind</th>
<th>∆CRE ↓ sPV</th>
<th>∆CRE ↑ sWind</th>
<th>∆CRE ↑ sPV</th>
<th>∆CRE ↑ sWind</th>
<th>∆CRE ↓ sPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>S25%</td>
<td>-5.8 pp</td>
<td>-7.2 pp</td>
<td>-4.1 pp</td>
<td>-5.2 pp</td>
<td>-5.2 pp</td>
<td></td>
</tr>
<tr>
<td>S50%</td>
<td>-9.7 pp</td>
<td>-13.2 pp</td>
<td>-7.0 pp</td>
<td>-9.1 pp</td>
<td>-9.1 pp</td>
<td></td>
</tr>
<tr>
<td>S75%</td>
<td>-12.3 pp</td>
<td>-17.9 pp</td>
<td>-8.8 pp</td>
<td>-11.8 pp</td>
<td>-11.8 pp</td>
<td></td>
</tr>
<tr>
<td>S100%</td>
<td>-14.0 pp</td>
<td>-20.9 pp</td>
<td>-9.8 pp</td>
<td>-13.6 pp</td>
<td>-13.6 pp</td>
<td></td>
</tr>
</tbody>
</table>

by one Power Node, which represents a biomass power plant. The unit’s power rating is equal to 100% of the peak load. Hence, the single Power Node demonstrates the requirement for a portfolio of dispatchable generation units, which is necessary to reliably meet the load demand.

In a first step, it is analyzed in which bandwidth of the available capacity the biomass power plant is dispatched as a function of the renewable supply scenario. For this purpose, Figure 8.16 illustrates the duration curves of the biomass power plant by blue graphs for the base case, where no storages are deployed, and different renewable penetration levels. The graphs are derived by plotting the sorted time series of $u_{gen,i}$ in descending order normalized to the peak load. In addition, the load duration curve is illustrated by the red graph. This curve indicates the requirement for dispatchable generation in case both renewable shares $s_{Wind}$ and $s_{PV}$ are equal to zero. Please note that the value of $u_{gen,i}$ is never smaller than 10%, because must-run generation has been considered by choosing a minimum power output equals 10% of peak load.

From the figure one can observe that if both renewable shares are less than 50% ("low"), the duration curves are distributed over a broad band, especially in the power bandwidth of 10–50%. In low wind and high PV scenarios, the curves are bundled in 6 strings. One string equates to a constant wind share. From this follows that for high PV shares an installation
of additional PV capacities does not release dispatchable power capacities. In case of high wind and low PV shares, one can observe that the array of curves lies almost completely to the left of the array gained if both renewable shares are less than 50%. If both shares are greater than 50%, the graphs are closer aligned to each other. From the results one can conclude that (1) the higher both renewable energy shares are the more the duration curve shifts to the left. As a consequence, dispatchable generation capacities are released. And (2), wind energy provides the largest savings potential.

From the graphs shown in Figure 8.16, a quantitative conclusion cannot be drawn as the families of curves are widely distributed. Another way to illustrate the family of duration curves for different renewable penetration levels is to calculate the average duration curve. This is done by taking the average in y-direction of all curves, which belong to one family. As the result is a single curve, it is possible to derive quantitative conclusions, e.g. the number of operating hours per year of a dispatchable power plant as a function of the renewable penetration level.

In Figure 8.17, the average load curves are illustrated for the base case by the blue solid lines. The two dotted lines enclose a band defined by the mean value plus/minus the standard deviation. Again, the load duration
curve is shown by the red solid line. The operating hours per year of a power plant, which is operated at a specific level of the load bandwidth, can be derived from the plot as follows: Draw an additional horizontal line with the desired level as ordinate value. Determine the abscissa of the intercept point between the horizontal line and the duration curve, which represents the number of operating hours per year. This has been exemplarily done for levels of the load bandwidth equal to 25%, 50%, 75%, and 90% of the peak load. The results are stated in Table 8.9. Enclosed in brackets are the standard deviations, which serve as an indicator of how broad the band of the original family of curves is at that level.

![Graph](image)

**Figure 8.17:** Averaged duration curves of the biomass power plant (blue) and the load duration curve (red) for the base case and different renewable penetration levels.

From Table 8.9 one can infer that in the base case and for low penetration levels of wind and PV energy the number of operating hours for a load bandwidth level equal to 25% decreases on average from 8760 h to 6435 h, or expressed relatively by 26.5%. However, for a load bandwidth level equal to 75%, the number of load hours decreases from 3895 h to 944 h, constituting a reduction by 75.8%.

In Table 8.10, the relative reduction of operating hours per year compared to the scenario without wind and PV energy are listed. In general, one can observe that the higher the load bandwidth level the larger the relative
reduction. This statement holds true for all renewable penetration levels. As a reduction of operating hours implies a release of dispatchable generation capacities, one can conclude that the integration of wind and PV energy reduces to the greatest extent the requirements of generation capacities for peak power, then for load-following power, and finally for base load power. The figures also prove that the reduction of operating hours is greater in scenarios with high shares of wind energy and low shares of PV energy than vice versa.

In a next step, the impact of storage deployment on dispatchable generation requirements are investigated. For this purpose, Figure 8.18 shows the average duration curves of the biomass power plant for different renewable penetration levels and varying storage power ratings between 25–100% of the average load. The turquoise graphs represent the base case. The graphs from light blue to pink represent the cases with increasing storage sizing.

Figure 8.18: Averaged duration curves of the biomass power plant for the base case (turquoise) and varying storage power ratings between 25–100% of the average load.

In scenarios with low shares of wind and PV energy, one can observe that by the deployment of storages only little generation capacities are released in the load bandwidth of 20–50%. In the remaining spectrum the duration curves coincide. This result was expected as for low renewable shares in the base case the amount of excess intermittent energy is small. Consequently,
Table 8.9: Operating hours per year of a dispatchable generator as a function of the load bandwidth level, the renewable penetration levels and the storage size.

<table>
<thead>
<tr>
<th>Load bandwidth level</th>
<th>( s_{\text{Wind}}=0% )</th>
<th>( s_{\text{PV}}=0% )</th>
<th>( \downarrow s_{\text{Wind}} )</th>
<th>( \downarrow s_{\text{PV}} )</th>
<th>( \uparrow s_{\text{Wind}} )</th>
<th>( \uparrow s_{\text{PV}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>891 h</td>
<td>141 h</td>
<td>106 h</td>
<td>14 h</td>
<td>(±190 h)</td>
<td>(±122 h)</td>
</tr>
<tr>
<td></td>
<td>(±190 h)</td>
<td>(±190 h)</td>
<td>(±190 h)</td>
<td>(±190 h)</td>
<td>(±190 h)</td>
<td>(±190 h)</td>
</tr>
<tr>
<td>75%</td>
<td>3895 h</td>
<td>944 h</td>
<td>637 h</td>
<td>280 h</td>
<td>180 h</td>
<td>180 h</td>
</tr>
<tr>
<td></td>
<td>(±780 h)</td>
<td>(±780 h)</td>
<td>(±780 h)</td>
<td>(±780 h)</td>
<td>(±780 h)</td>
<td>(±780 h)</td>
</tr>
<tr>
<td>50%</td>
<td>8383 h</td>
<td>4069 h</td>
<td>3152 h</td>
<td>1658 h</td>
<td>1180 h</td>
<td>1180 h</td>
</tr>
<tr>
<td></td>
<td>(±1756 h)</td>
<td>(±1756 h)</td>
<td>(±1756 h)</td>
<td>(±1756 h)</td>
<td>(±1756 h)</td>
<td>(±1756 h)</td>
</tr>
<tr>
<td>25%</td>
<td>8760 h</td>
<td>6435 h</td>
<td>5187 h</td>
<td>3801 h</td>
<td>2985 h</td>
<td>2985 h</td>
</tr>
<tr>
<td></td>
<td>(±1348 h)</td>
<td>(±1348 h)</td>
<td>(±1348 h)</td>
<td>(±1348 h)</td>
<td>(±1348 h)</td>
<td>(±1348 h)</td>
</tr>
<tr>
<td><strong>50%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>890 h</td>
<td>129 h</td>
<td>80 h</td>
<td>3 h</td>
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<td>(±4 h)</td>
</tr>
<tr>
<td></td>
<td>(±190 h)</td>
<td>(±190 h)</td>
<td>(±190 h)</td>
<td>(±190 h)</td>
<td>(±190 h)</td>
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<td>75%</td>
<td>3893 h</td>
<td>860 h</td>
<td>473 h</td>
<td>174 h</td>
<td>92 h</td>
<td>92 h</td>
</tr>
<tr>
<td></td>
<td>(±791 h)</td>
<td>(±791 h)</td>
<td>(±791 h)</td>
<td>(±791 h)</td>
<td>(±791 h)</td>
<td>(±791 h)</td>
</tr>
<tr>
<td>50%</td>
<td>8383 h</td>
<td>3527 h</td>
<td>2033 h</td>
<td>1197 h</td>
<td>637 h</td>
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</tr>
<tr>
<td></td>
<td>(±1925 h)</td>
<td>(±1925 h)</td>
<td>(±1925 h)</td>
<td>(±1925 h)</td>
<td>(±1925 h)</td>
<td>(±1925 h)</td>
</tr>
<tr>
<td>25%</td>
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<td>5975 h</td>
<td>4026 h</td>
<td>3014 h</td>
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</tr>
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<td>(±1767 h)</td>
<td>(±1767 h)</td>
<td>(±1767 h)</td>
<td>(±1767 h)</td>
</tr>
<tr>
<td><strong>100%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>889 h</td>
<td>125 h</td>
<td>73 h</td>
<td>1 h</td>
<td>(±95 h)</td>
<td>(±2 h)</td>
</tr>
<tr>
<td></td>
<td>(±191 h)</td>
<td>(±191 h)</td>
<td>(±191 h)</td>
<td>(±191 h)</td>
<td>(±191 h)</td>
<td>(±191 h)</td>
</tr>
<tr>
<td>75%</td>
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<td>424 h</td>
<td>127 h</td>
<td>61 h</td>
<td>61 h</td>
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<tr>
<td></td>
<td>(±799 h)</td>
<td>(±799 h)</td>
<td>(±799 h)</td>
<td>(±799 h)</td>
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<tr>
<td>50%</td>
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<td>3371 h</td>
<td>1734 h</td>
<td>1004 h</td>
<td>475 h</td>
<td>475 h</td>
</tr>
<tr>
<td>25%</td>
<td>8760 h</td>
<td>5669 h</td>
<td>3130 h</td>
<td>2646 h</td>
<td>1282 h</td>
<td>1282 h</td>
</tr>
</tbody>
</table>
Table 8.10: Relative reduction of the number of operating hours per year of a dispatchable generator compared to the scenario $s_{\text{Wind}} = 0\%$ and $s_{\text{PV}} = 0\%$ as a function of the load bandwidth level, the renewable penetration levels and the storage size.

<table>
<thead>
<tr>
<th>Load bandwidth level</th>
<th>$s_{\text{Wind}}=0%$</th>
<th>$s_{\text{PV}}=0%$</th>
<th>↓ $s_{\text{Wind}}$</th>
<th>↓ $s_{\text{PV}}$</th>
<th>↑ $s_{\text{Wind}}$</th>
<th>↑ $s_{\text{PV}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>981 h</td>
<td>-84.2%</td>
<td>-88.1%</td>
<td>-98.4%</td>
<td>-98.5%</td>
<td></td>
</tr>
<tr>
<td>75%</td>
<td>3895 h</td>
<td>-75.8%</td>
<td>-83.6%</td>
<td>-92.8%</td>
<td>-95.4%</td>
<td></td>
</tr>
<tr>
<td>50%</td>
<td>8383 h</td>
<td>-51.5%</td>
<td>-62.4%</td>
<td>-80.2%</td>
<td>-85.9%</td>
<td></td>
</tr>
<tr>
<td>25%</td>
<td>8760 h</td>
<td>-26.5%</td>
<td>-40.8%</td>
<td>-56.6%</td>
<td>-65.9%</td>
<td></td>
</tr>
<tr>
<td><strong>S50%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>890 h</td>
<td>-85.5%</td>
<td>-91.0%</td>
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<td>-99.8%</td>
<td></td>
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<td>75%</td>
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<td>-87.9%</td>
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<td>-97.6%</td>
<td></td>
</tr>
<tr>
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<td>-57.9%</td>
<td>-75.7%</td>
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<td>-92.4%</td>
<td></td>
</tr>
<tr>
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<td>-31.8%</td>
<td>-54.0%</td>
<td>-65.6%</td>
<td>-79.8%</td>
<td></td>
</tr>
<tr>
<td><strong>S100%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>889 h</td>
<td>-85.9%</td>
<td>-91.8%</td>
<td>-99.9%</td>
<td>-99.9%</td>
<td></td>
</tr>
<tr>
<td>75%</td>
<td>3892 h</td>
<td>-78.6%</td>
<td>-89.1%</td>
<td>-96.7%</td>
<td>-98.4%</td>
<td></td>
</tr>
<tr>
<td>50%</td>
<td>8382 h</td>
<td>-59.8%</td>
<td>-79.3%</td>
<td>-88.0%</td>
<td>-94.3%</td>
<td></td>
</tr>
<tr>
<td>25%</td>
<td>8760 h</td>
<td>-35.3%</td>
<td>-64.3%</td>
<td>-69.8%</td>
<td>-85.4%</td>
<td></td>
</tr>
</tbody>
</table>
only small storage capacities are required to buffer the surplus.

If a power system features high shares of wind energy and low shares of
PV energy, one can see that the duration curve noticeably shifts to the left
by increasing the storage capacity. However, the number of operating hours
is more reduced in the load bandwidth of 10–40% than for higher levels. This
indicates that base load power and load-following power is replaced by the
combination of the pumped hydro storage, wind and PV power. Moreover,
the plots reveal that in the load bandwidth of 70–100% almost no generation
capacities are released by increasing the storage capacity. This is explained
as follows: The utilized profile for wind features periods in winter, which last
up to several days, with few generation potentials. These periods coincide
with annual high electricity demand. The storage is not able to bridge the
gaps, no matter how large its size is chosen. As a result, the biomass plant
is dispatched to serve the load demand.

In case of scenarios with low shares of wind energy and high shares of PV
energy, the plots reveal that by increasing the storage capacity the biomass
power plant is considerably fewer dispatched in the load bandwidth of 10–
70%, where the reduction is the greatest for the level equal to 40%. Above
70% only few generation capacities are released. This might be explained
by the fact that PV infeed is inherently low in spring and winter and as
result the filling levels of the pumped hydro storages are low. In these
periods the load demand reaches its annual high. Consequently, generation
from biomass has to be dispatched in order to meet the demand.

In scenarios with high shares of wind and PV energy, a considerable shift
of the duration curve is observable. The lower the load bandwidth level is
chosen, the more the number of operating hours is reduced.

From the results the following conclusion can be drawn: Base load and
load-following power plants in the bandwidth of 10–70% of the peak load are
considerably fewer dispatched the larger the storage is scaled. The reduction
is the greatest in scenarios with high shares of PV energy. In addition,
the necessity of peak power plants persists despite the combination of high
penetration levels of wind and PV and the deployment of storage facilities.

8.2.4 Evaluation of storage operations

In Figure 8.19 the number of charge-discharge cycles per week CDC is
illustrated as a function of the renewable supply scenario for the case ‘S50%’.
The corresponding contour plot is shown in the upper right corner of Figure
8.20. The plots show that the number of storage cycles is highly dependent
on the share of PV energy. Following a line of constant $s_{\text{Wind}}$, the value of
$CDC$ considerably rises if $s_{\text{PV}}$ is increased in the range of 0–50%. If $s_{\text{PV}}$ is
further increased, the number of cycles per week saturates between 5.5–7.
This was expected, as PV generation features a diurnal cycle. Additionally,
one can observe that if the PV share is kept below 30%, the value of $CDC$
Table 8.11: Average value of the number of charge-discharge cycles per week of a pumped hydro storage.

<table>
<thead>
<tr>
<th>Case</th>
<th>( \downarrow ) s\text{Wind}</th>
<th>( \downarrow ) s\text{PV}</th>
<th>( \uparrow ) s\text{Wind}</th>
<th>( \uparrow ) s\text{PV}</th>
<th>( \varnothing )</th>
</tr>
</thead>
<tbody>
<tr>
<td>S25%</td>
<td>3.8</td>
<td>5.9</td>
<td>5.1</td>
<td>6.1</td>
<td>5.1</td>
</tr>
<tr>
<td>S50%</td>
<td>3.7</td>
<td>5.9</td>
<td>5.1</td>
<td>6.0</td>
<td>5.1</td>
</tr>
<tr>
<td>S75%</td>
<td>3.7</td>
<td>5.9</td>
<td>5.0</td>
<td>6.0</td>
<td>5.1</td>
</tr>
<tr>
<td>S100%</td>
<td>3.7</td>
<td>5.9</td>
<td>5.0</td>
<td>6.0</td>
<td>5.1</td>
</tr>
</tbody>
</table>

is maximized for high wind shares. Above a PV share of 30\%, CDC peaks for a wind share equal to 50\%. According to Table 8.11, CDC is on average above 5, if one renewable share is greater than 50\%. From the results one can conclude that for a pumped hydro storage the number of 6 charge-discharge cycles per week is only reached if the share of PV energy is greater or equal than 50\%.

Figure 8.19: 3D plot of the number of charge-discharge cycles for the case 'S50\%'.

From Table 8.11 and the contour plots in Figure 8.20, one can infer that the evaluation of the index CDC for the remaining cases 'S25\%', 'S75\%', and 'S100\%' yields almost the same results as for the presented case 'S50\%'. Considering a single scenario where \( s_{\text{Wind}} \) and \( s_{\text{PV}} \) are kept constant, the value of CDC decreases by less than 0.25 cycles per week if the storage
capacity is increased from 25% to 100% of the peak load. Hence, one can conclude that with an economic dispatch the number of charge-discharge cycles is independent of the deployed storage capacity.

In a next step, it is investigated how the dispatch of the pumped hydro storage is influenced by its technical specifications. In general, a storage unit possesses two factors which might limit its operation: (1) the storage capacity and (2) the power rating.

In Figure 8.21 the histogram of the energy storage level $x_i$ is shown for the case ‘S50%’ and different renewable penetration levels. In the top left plot a scenario with low shares of wind and PV energy is considered. From the plot one can infer that the state of charge is mainly below 25%. The diagram in the top right corner shows the results for low $s_{\text{Wind}}$ and high $s_{\text{PV}}$. One can observe that $x_i$ features a higher probability for lower charging levels. In the lower left plot a scenario with high $s_{\text{Wind}}$ and low $s_{\text{PV}}$ is considered. Here, the probability is the highest at the lower and upper boundary. The diagram in the lower right corner considers a scenario with high shares of wind and PV energy. One can see that the state of charge is almost uniformly distributed and features a slightly higher probability in the range of 50%. From the results one can conclude that in scenarios where PV energy is predominant the deployed pumped hydro storage utilizes mainly
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Figure 8.21: Distribution of the energy storage level \( x_i \) for the case 'S50\%' and different renewable penetration levels.

the lower bandwidth of its energy capacity. Hence, one could assume that a reduction of storage capacities diminishes the share of integrated renewable energy slightly. By contrast, in scenarios with high penetration levels of wind energy a reduction of storage capacities might have larger impact on the share of integrated renewable energy as the probability of the state of charge peaks at the upper boundary.

In Figure 8.22, the histogram of the energy storage level \( x_i \) is graphically illustrated for the case 'S100\%'. Compared to the previously analyzed case 'S50\%', some minor differences can be observed. In scenarios where \( s_{PV} \) is predominant, the distribution features now a slight peak for a SOC-value of 50\%. For scenarios with high shares of wind and low shares of PV energy, the peak at the upper boundary vanished and \( x_i \) is now almost uniformly distributed. In scenarios where both renewable shares are high, one can clearly see that the state of charge is most of the time above 50\%.

In general, from the illustrated histograms of the state of charge one can conclude that in scenarios with high penetration levels of wind energy the full storage capacity is approximately uniformly utilized. However, a tendency towards the upper and lower boundary exists. By contrast, in scenarios where PV energy prevails, the state of charge is mainly below 50\%.

In order to evaluate how storage operations are influenced by the power rating, Figure 8.23 illustrates the histogram of the pumped hydro plant’s
decision variable $u_{\text{load}}$ for the case ‘S50%’. Note, that the shown histograms only consider values of $u_{\text{load}}$ greater than 0.01 MW. One can observe that all histograms feature a sharp peak at the upper constraint. This can be explained by the absorption of excess PV energy at noontime. In scenarios with low wind shares, $u_{\text{load}}$ is approximately uniformly distributed below the upper constraint. By contrast, for scenarios with high wind shares the distribution of $u_{\text{load}}$ is exponentially decreasing. The storage charges mainly with a power below one half of its power rating. Hence, from the results one can conclude that the more the penetration of PV energy increases, the more the deployed storages are operated at their power rating. Based on this conclusion, one can infer that the power rating of the deployed storages is the limiting factor for integrating fluctuating energy in scenarios with high shares of PV energy.

In Figure 8.24, the histogram of the pumped hydro plant’s decision variable $u_{\text{load}}$ is shown for the case ‘S100%’. Compared to the case ‘S50%’, the pumped hydro plant is now operated more often in the lower power bandwidth for scenarios with low shares of PV energy. As the peak at the upper constraint is considerably reduced in scenarios with high wind shares, one can infer that the power rating is chosen too high.

Figure 8.22: Distribution of the energy storage level $x_i$ for the case ’S100%’ and different renewable penetration levels.
Figure 8.23: Distribution of the storage variable $u_{\text{load}}$ for the case 'S50\%' and different renewable penetration levels.

8.2.5 Energy conversion losses

In Figure 8.25, the energy conversion losses normalized to the energy storage capacity $NCL$ of the pumped hydro storage are graphically illustrated as a function of the renewable supply scenario for the cases 'S25\%' (semi-transparent) and 'S100\%' (non-transparent).

In general, one can see that $NCL$ is highly dependent on $s_{\text{PV}}$. Both planes show that the value of $NCL$ is maximized for $s_{\text{Wind}} = 100\%$ as long as $s_{\text{PV}}$ is kept below 20\%. If $s_{\text{PV}}$ is above 50\%, $NCL$ peaks for $s_{\text{Wind}}$ in the range of 0–40\%. By comparing the two graphs, one can observe that for the large storage the normalized energy conversion losses are smaller in all scenarios. Consequently, one can infer that for larger storages less energy is cycled through the storage relative to its energy storage capacity.

From the results one can conclude that energy conversion losses are maximized in scenarios with high PV and low wind shares. If a power system should feature high penetration levels of wind or PV energy, it is favorable to install large wind generation capacities because energy conversion losses are reduced.
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Figure 8.24: Distribution of the storage variable $u_{load}$ for the case 'S100%' and different renewable penetration levels.

Figure 8.25: Normalized storage conversion losses for the cases 'S25%' (semi-transparent) and 'S100%' (nontransparent).
8.2.6 Full load hours of intermittent generators

In situations where the available energy from an intermittent renewable energy source cannot be absorbed by the grid to the full extent, the power output $u_{\text{gen},i}$ of the intermittent generator has to be curtailed. As a consequence, the share of curtailed renewable energy $\text{CRE}$ is increased, and consequently the share of integrated renewable energy $\text{IRE}$ is decreased. Moreover, the curtailment reduces the number of full load hours $\text{FLH}$ of the intermittent generator. $\text{FLH}$ is calculated by dividing the annual electricity output by the installed generation capacity.

In Figure 8.26, the number of full load hours $\text{FLH}$ of a wind turbine is plotted as a function of the renewable supply scenario for the base case. The corresponding contour plot is shown in Figure 8.28. The 3D plot shows that the value of $\text{FLH}$ considerably decreases already in scenarios with low renewable shares, and the maximum of 2000 h is only reached if both renewable shares are lower than 10%. Following a line of constant $s_{\text{PV}}$, the value of $\text{FLH}$ decreases linearly even at high wind shares. By contrast, if $s_{\text{Wind}}$ is kept constant, the value of $\text{FLH}$ diminishes disproportionately high until $s_{\text{PV}}$ reaches 50%. If the share of PV is further increased, the value of $\text{FLH}$ saturates. This can be explained as follows: Contrary to wind energy, no marginal generation costs are considered for PV energy. Thus, the higher the share of PV is chosen, the more wind energy is curtailed. However, at medium levels of $s_{\text{PV}}$ the peaks of the supply profile $\xi_{\text{drv},i}(t)$ of the PV panels exceed the demanded electricity. As a consequence, no more solar energy can be fed in the grid and the replacement of wind energy by solar energy ends. The listed figures in Table 8.12 indicate that for low penetration levels of wind and PV energy the number of full load hours of a wind turbine amounts to 1647.3 h, which is 82% of the maximum. In general, one can conclude that, for wind turbine operators, low penetration levels of wind and PV energy are beneficial as the number of full load hours of their units is maximized.

In Figure 8.27, the influence of the pumped hydro storage on the number of full load hours of the wind turbines is plotted. One can see that all planes feature the same shape as for the base case. Interesting is the fact that even for the largest storage scaling the maximum of 2000 h is only reached if both shares are less than 20%. The numbers in the result tables show that on average $\text{FLH}$ is larger for all storage scalings in scenarios with low $s_{\text{Wind}}$ and high $s_{\text{PV}}$ than vice versa. The largest gain of $\text{FLH}$ is achieved in scenarios with low renewable penetration. As a result, one can conclude that despite the deployment of a pumped hydro storage wind turbines operators prefer low penetration levels of wind and PV energy.

The number of full load hours $\text{FLH}$ of a PV panel as a function of the renewable supply scenario for the base case is illustrated in Figure 8.29. The graph shows that $\text{FLH}$ is independent of $s_{\text{Wind}}$. This was expected as PV
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Figure 8.26: 3D plot of the number of full load hours of a wind turbine for the base case.

Figure 8.27: 3D plot of the number of full load hours of a wind turbine for different storage scalings.
Figure 8.28: Contour plot of the number of full load hours of a wind turbine for different storage scalings.

Figure 8.29: 3D plot of the number of full load hours of a PV panel for the base case.
energy is always preferred to wind energy due to zero marginal generation costs. Following a line of constant $s_{\text{Wind}}$, $FLH$ decreases disproportionately high. The maximum value of 950 h is only reached in scenarios with $s_{\text{PV}} = 10\%$. From the results one can conclude that without a storage the owner’s of PV panels only have to fear the installation of additional PV panels as this reduces the number of full load hours of their own units and thus downsizes profits.

In Figure 8.30 the number of full load hours $FLH$ of a PV panel as a function of the renewable supply scenario is plotted for the cases where a pumped hydro storage is deployed. The corresponding contour plots are shown in Figure 8.31. For all cases the maximum value of 950 h is only reached if $s_{\text{PV}} \leq 20\%$. From Table 8.15 one can infer that the value of $FLH$ increases less in scenarios with high $s_{\text{Wind}}$. This might be explained as follows: The larger the storage size is chosen, the more wind energy is buffered during nighttime and periods of strong wind, which might last up to several days. As a consequence, less PV energy can be buffered during daytime as storage capacities are already occupied. From the results one can conclude that with the deployment of the pumped hydro storage the owners of PV panels prefer scenarios with low $s_{\text{Wind}}$ and $s_{\text{PV}}$, as the number of full load hours is maximized. For these scenarios and a storage power rating equals 100\% of the average load, a mean value of 912.7 h is, which is 96\% of the possible maximum.
Table 8.12: Average value of the number of full load hours of wind turbines.

<table>
<thead>
<tr>
<th>Case</th>
<th>↓ s_{Wind}</th>
<th>↓ s_{PV}</th>
<th>↑ s_{Wind}</th>
<th>↑ s_{PV}</th>
<th>∅</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>1647.3 h</td>
<td>1345.2 h</td>
<td>1188.5 h</td>
<td>969.8 h</td>
<td>1271.3 h</td>
</tr>
<tr>
<td>S25%</td>
<td>1730.8 h</td>
<td>1408.1 h</td>
<td>1256.3 h</td>
<td>1002.6 h</td>
<td>1331.0 h</td>
</tr>
<tr>
<td>S50%</td>
<td>1786.7 h</td>
<td>1456.3 h</td>
<td>1303.6 h</td>
<td>1024.2 h</td>
<td>1372.8 h</td>
</tr>
<tr>
<td>S75%</td>
<td>1824.9 h</td>
<td>1488.0 h</td>
<td>1338.1 h</td>
<td>1039.2 h</td>
<td>1401.9 h</td>
</tr>
<tr>
<td>S100%</td>
<td>1851.1 h</td>
<td>1505.3 h</td>
<td>1366.0 h</td>
<td>1051.5 h</td>
<td>1422.4 h</td>
</tr>
</tbody>
</table>

Figure 8.31: Contour plot of the number of full load hours of a PV panel for different storage scalings.
Table 8.13: Average change of the number of full load hours of wind turbines compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\downarrow s_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S25%</td>
<td>+83.5 h</td>
<td>+63 h</td>
<td>+67.8 h</td>
<td>+32.8 h</td>
<td>+59.7 h</td>
</tr>
<tr>
<td>S50%</td>
<td>+139.4 h</td>
<td>+111.2 h</td>
<td>+115.1 h</td>
<td>+54.4 h</td>
<td>+101.4 h</td>
</tr>
<tr>
<td>S75%</td>
<td>+177.6 h</td>
<td>+142.8 h</td>
<td>+149.6 h</td>
<td>+69.4 h</td>
<td>+130.6 h</td>
</tr>
<tr>
<td>S100%</td>
<td>+203.8 h</td>
<td>+160.1 h</td>
<td>+177.5 h</td>
<td>+81.7 h</td>
<td>+151.1 h</td>
</tr>
</tbody>
</table>

Table 8.14: Average value of the number of full load hours of PV panels.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\downarrow s_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>754.9 h</td>
<td>422.4 h</td>
<td>750.9 h</td>
<td>420.5 h</td>
<td>574.4 h</td>
</tr>
<tr>
<td>S25%</td>
<td>821.0 h</td>
<td>502.3 h</td>
<td>811.8 h</td>
<td>483.5 h</td>
<td>640.1 h</td>
</tr>
<tr>
<td>S50%</td>
<td>865.5 h</td>
<td>569.9 h</td>
<td>848.7 h</td>
<td>528.6 h</td>
<td>687.5 h</td>
</tr>
<tr>
<td>S75%</td>
<td>894.9 h</td>
<td>622.3 h</td>
<td>869.6 h</td>
<td>555.6 h</td>
<td>719.2 h</td>
</tr>
<tr>
<td>S100%</td>
<td>912.7 h</td>
<td>655.7 h</td>
<td>879.9 h</td>
<td>568.9 h</td>
<td>737.6 h</td>
</tr>
</tbody>
</table>

Table 8.15: Average change of the number of full load hours of PV panels compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\downarrow s_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S25%</td>
<td>+66.1 h</td>
<td>+79.9 h</td>
<td>+60.9 h</td>
<td>+63.0 h</td>
<td>+65.8 h</td>
</tr>
<tr>
<td>S50%</td>
<td>+110.7 h</td>
<td>+147.5 h</td>
<td>+97.8 h</td>
<td>+108.1 h</td>
<td>+113.2 h</td>
</tr>
<tr>
<td>S75%</td>
<td>+140.1 h</td>
<td>+199.9 h</td>
<td>+118.8 h</td>
<td>+135.1 h</td>
<td>+144.9 h</td>
</tr>
<tr>
<td>S100%</td>
<td>+157.9 h</td>
<td>+233.3 h</td>
<td>+129.0 h</td>
<td>+148.5 h</td>
<td>+163.2 h</td>
</tr>
</tbody>
</table>
CHAPTER 8. RESULTS AND DISCUSSION

8.3 Multi-bus all-renewable power system

In this section, the simulation results of the multi-bus all-renewable power system are presented. Three different cases have been considered: (1) the base case where no storage capacities are deployed, (2) the case ‘S50%N’ where a pumped hydro storage with a power rating equal to 50% of the average load is located in the north of Germany, and (3) the case ‘S50%S’ where the same pumped hydro storage is interfaced with the power system in the southern area. The results can be compared with the results of the base case and the case ‘S50%’ from the single-bus system, because the load demand, generation and storage capacities are equal.

8.3.1 Integrated renewable energy

In Figure 8.32, the share of integrated renewable energy $IRE$ is shown as a function of the renewable supply scenario for all three cases. The corresponding contour plots are illustrated in Figure 8.33. For the base case, the surface plot indicates a preference for scenarios with high penetration levels of wind energy. This was not expected, because transmission constraints between the wind-generation-intensive north/east region and the load-intensive south/west region have been introduced. Thus, one might raise the question whether the limits are chosen too high. However on the whole, the line constraints made an impact. According to Table 8.16, the mean value of $IRE$ amounts to 50%. That is 3% less than in the base case of the single-bus power system. Hence, one can conclude that the modeling of transmission constraints reduced the share of integrated renewable energy. Still, the preference for wind energy persists.

In case the pumped hydro storage is deployed in the north, the upper right graph shows that the value of $IRE$ is the highest in scenario where wind energy is predominant. The figures from Table 8.16 confirm this observation, which was expected as the pumped hydro storage is located in the region with the majority of wind turbines. On average the value of $IRE$ rose to 54.9%, which indicates an increase by 4.9 pp compared to the base case.

The bottom left graph shows the value of $IRE$ for the case where the pumped hydro storage is deployed in the southern area. One can observe
that the plane experienced a clear upward shift for scenarios with high $s_{PV}$ and low $s_{Wind}$. The average value of $IRE$ for these scenarios amounts to 59.7%. This is only slightly lower than 61.9% for scenarios with low $s_{PV}$ and high $s_{Wind}$. As a result, the plane is now almost symmetric to the line defined by $s_{Wind} = s_{PV}$. This indicates that the power system is indifferent whether wind or PV energy is installed. Interesting is the fact that this condition was not reached for the single-bus power system until a storage power rating equal to 100% of the average load, i.e. for the double-installed capacity.

From Table 8.16, one can infer that the mean value of $IRE$ and all individual mean values of $IRE$ for different renewable penetration levels are larger for the case with the storage located in the south. Hence, one can conclude that intermittent renewable energy is absorbed to a larger extent when the storage is located in the south even for scenario with high penetration levels of wind energy. This finding is quite unexpected, because only 14% of the wind generation capacities are installed in the south/west region.

In Table 8.17, the average change of $IRE$ compared to the base case is listed. One interesting observation can be made. For the case 'S50%N', the value of $IRE$ increased more in scenarios with low $s_{Wind}$ and high $s_{PV}$ than...
vice versa. This trend was also observed in the base case for the single-bus power system. But for the multi-bus power system one had expected that the increase of $\textit{IRE}$ for high penetration levels of wind energy is greater than for high levels of PV energy, because the pumped hydro storage is directly located next to the majority of wind farms. Why this is not the case might be explained as follows: In the north/east region only 16% of the PV generation capacities are installed. Apparently, for high penetration levels of PV energy ($s_{\text{PV}} > 50\%$) these capacities are already enough to optimally utilize the storage unit and yield a higher share of integrated renewable energy than high penetration levels of wind energy.

Table 8.17: Average change of the integrated renewable energy share compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\downarrow s_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S50%N</td>
<td>+3.3 pp</td>
<td>+6.9 pp</td>
<td>+4.5 pp</td>
<td>+5.1 pp</td>
<td>+4.9 pp</td>
<td>+4.9 pp</td>
<td></td>
</tr>
<tr>
<td>S50%S</td>
<td>+5.0 pp</td>
<td>+12.8 pp</td>
<td>+5.8 pp</td>
<td>+11.5 pp</td>
<td>+8.5 pp</td>
<td>+8.5 pp</td>
<td></td>
</tr>
</tbody>
</table>
Table 8.18: Average value of the curtailed wind energy share.

<table>
<thead>
<tr>
<th>Case</th>
<th>CRE&lt;sub&gt;Wind&lt;/sub&gt; ↓s&lt;sub&gt;Wind&lt;/sub&gt;</th>
<th>CRE&lt;sub&gt;Wind&lt;/sub&gt; ↑s&lt;sub&gt;Wind&lt;/sub&gt;</th>
<th>CRE&lt;sub&gt;Wind&lt;/sub&gt; ↓s&lt;sub&gt;PV&lt;/sub&gt;</th>
<th>CRE&lt;sub&gt;Wind&lt;/sub&gt; ↑s&lt;sub&gt;PV&lt;/sub&gt;</th>
<th>CRE&lt;sub&gt;Wind&lt;/sub&gt;</th>
<th>∅</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>21.7%</td>
<td>35.6%</td>
<td>47.5%</td>
<td>57.1%</td>
<td>41.3%</td>
<td></td>
</tr>
<tr>
<td>S50%N</td>
<td>12.4%</td>
<td>25.3%</td>
<td>42.3%</td>
<td>54.2%</td>
<td>34.7%</td>
<td></td>
</tr>
<tr>
<td>S50%S</td>
<td>18.2%</td>
<td>32.7%</td>
<td>45.0%</td>
<td>55.9%</td>
<td>38.8%</td>
<td></td>
</tr>
</tbody>
</table>

The presented results in this section have shown that the transition from a single-bus to a multi-bus power system and the consideration of line constraints decreases the share of integrated renewable energy in all renewable supply scenarios. Hence, one can conclude that transmission system operators should pay attention to the enhancement of existing grid infrastructures and aim for reducing line congestions.

Furthermore, power system engineers have to carefully evaluate where to install additional storage capacities. The results have shown that for the presented grid it is more beneficial to install the pumped hydro storage in the region with high load demand and PV generation capacities, no matter how high the overall penetration level of wind energy is.

Additionally, it became obvious that the presented power system, which features an unequal distribution of wind generation and load demand among the north/east and south/west regions, only prefers wind energy over PV energy if the pumped hydro storage is deployed in the northern area. If the storage is deployed in the south, the power system is indifferent whether wind or PV generation capacities are installed.

8.3.2 Curtailed renewable energy

In order to clarify why it is beneficial to install the pumped hydro storage in the south independent of the renewable supply scenario, the shares of curtailed wind and PV energy in the multi-bus power system are investigated in the following. In Figure 8.34, the index CRE for wind and PV energy is plotted for the three simulated cases.

For the base case, the two planes show the same characteristics as already described for the single-bus power system in Subsection 8.2.2. What stands out is how the shape of the planes transforms when a storage is either deployed in the northern or the southern area. The numbers in the Tables 8.18, 8.19, 8.20, and 8.21 quantify the trends.

In case the storage is deployed in the north, the average value of CRE<sub>Wind</sub> decreases from 41.3% down to 34.7%. Surprisingly, the value diminishes the most in scenarios with low s<sub>Wind</sub> and high s<sub>PV</sub>. This might be explained as follows: PV energy is preferred in scenarios with low renewable shares
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Table 8.19: Average change of the curtailed wind energy share compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\Delta CRE_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S50%N</td>
<td>-9.3 pp</td>
<td>-10.3 pp</td>
<td>-5.3 pp</td>
<td>-2.9 pp</td>
<td>-6.6 pp</td>
<td></td>
</tr>
<tr>
<td>S50%S</td>
<td>-3.5 pp</td>
<td>-3.0 pp</td>
<td>-2.6 pp</td>
<td>-1.2 pp</td>
<td>-2.4 pp</td>
<td></td>
</tr>
</tbody>
</table>

Table 8.20: Average value of the curtailed PV energy share.

<table>
<thead>
<tr>
<th>Case</th>
<th>$CRE_{\text{PV}}$</th>
<th>$\downarrow s_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>21.8%</td>
<td>56.1%</td>
<td>21.8%</td>
<td>56.1%</td>
<td>40.3%</td>
<td></td>
</tr>
<tr>
<td>S50%N</td>
<td>18.9%</td>
<td>49.8%</td>
<td>19.3%</td>
<td>52.0%</td>
<td>36.3%</td>
<td></td>
</tr>
<tr>
<td>S50%S</td>
<td>8.8%</td>
<td>39.7%</td>
<td>9.3%</td>
<td>41.7%</td>
<td>26.5%</td>
<td></td>
</tr>
</tbody>
</table>

Table 8.21: Average change of the curtailed PV energy share compared to the base case.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\Delta CRE_{\text{PV}}$</th>
<th>$\downarrow s_{\text{Wind}}$</th>
<th>$\downarrow s_{\text{PV}}$</th>
<th>$\uparrow s_{\text{Wind}}$</th>
<th>$\uparrow s_{\text{PV}}$</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S50%N</td>
<td>-2.9 pp</td>
<td>-6.4 pp</td>
<td>-2.5 pp</td>
<td>-4.2 pp</td>
<td>-4.0 pp</td>
<td></td>
</tr>
<tr>
<td>S50%S</td>
<td>-13.0 pp</td>
<td>-16.5 pp</td>
<td>-12.5 pp</td>
<td>-14.5 pp</td>
<td>-13.8 pp</td>
<td></td>
</tr>
</tbody>
</table>
because of zero marginal generation costs. But at higher PV shares, not enough transmission or energy storage capacities are available to host excess PV energy. Hence, wind energy is dispatched and less curtailed. If the storage is located in the south, $CRE_{\text{Wind}}$ diminishes only to 38.8%. This time, the reduction is the greatest if both renewable shares are low.

Referring to the curtailment of PV energy, the mean value of $CRE_{\text{PV}}$ decreases already by 4.0 pp, from 40.3% to 36.3%, if the storage is located in the northern area. Thereby, the reduction is the largest in scenarios with low $s_{\text{Wind}}$ and high $s_{\text{PV}}$. In case the storage is deployed in the south, a considerable reduction on average by 13.8 pp is gained. This was expected as in the south/west region the majority of load demand and PV generation capacities are located.

From the results one can conclude that by deploying the pumped hydro
storage, wind curtailment is always reduced the most in scenarios with low shares of wind energy. Referring to PV energy, curtailment is minimized in scenarios with high PV shares. The intersection of both sets are scenarios with low wind and high PV shares. This explains why according to the previous subsection the share of integrated renewable energy rises the most in these scenarios.

The results also made clear why it is beneficial to install the pumped hydro storage in the southern area: On average the value of $CRE_{\text{Wind}}$ is decreased by 4.2 pp more, if the storage is located in the northern area next to the majority of wind turbines. However, the value of $CRE_{\text{PV}}$ is reduced on average by 9.8 pp more, if the storage is located in the southern area. As the reduction of PV curtailment exceeds the reduction of wind curtailment, it is always beneficial for the presented power system to locate the pumped hydro storage in the southern area.

### 8.3.3 Transmission line utilization

In Figure 8.35, the transmission line utilization ratios $TLU$ of all 4 lines are graphically illustrated for the base case. In general, one can observe that the utilization for the north-east and south-west lines are quite low, and according to Table 8.22 on average below 31%. By contrast, the north-west and the south-east lines are operated closer to their transmission capacities. This was expected and can be explained by the fact that the north/east region imports free of charge electricity from PV panels and exports electricity from wind turbines. The value of $TLU$ for both lines peaks for high penetration levels of wind energy. Thus, one can infer that the export of wind energy is higher than the import of PV energy.

In Figure 8.36, the transmission line utilization ratios $TLU$ are plotted for the case ‘S50%N’, where the pumped hydro storage is located in the north of Germany. The graphs show that compared to the base case the north-east and north-west lines are considerably closer operated to their capacity limits. According to Table 8.23 the utilization of the these lines is still the highest in scenarios with high $s_{\text{Wind}}$ and low $s_{\text{PV}}$. However, one can infer that the increase of $TLU$ is the greatest in scenarios with low $s_{\text{Wind}}$ and high $s_{\text{PV}}$. This indicates that mainly PV energy is buffered in the storage.

In Figure 8.37, the transmission line utilization ratios $TLU$ are shown for the case ‘S50%S’, where the pumped hydro storage is located in the south of Germany. From the plots one can observe that the planes did not experience major transformations compared to the base case. According to Table 8.24 the value of $TLU$ increased on average the most for the south-west line, i.e. from 27.7% to 34.2%. The gain is mainly achieved in scenarios with low $s_{\text{Wind}}$ and high $s_{\text{PV}}$. Thus, one can infer that the transmission of electricity from PV panels is responsible for the increase of the utilization ratio of the line.
Table 8.22: Average value of transmission line utilization ratios for the base case.

<table>
<thead>
<tr>
<th>Line</th>
<th>$\downarrow$ s_{Wind}</th>
<th>$\downarrow$ s_{PV}</th>
<th>$\uparrow$ s_{Wind}</th>
<th>$\uparrow$ s_{PV}</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>N↔E</td>
<td>24.3%</td>
<td>21.7%</td>
<td>41.4%</td>
<td>35.3%</td>
<td>30.4%</td>
</tr>
<tr>
<td>N↔W</td>
<td>45.8%</td>
<td>40.4%</td>
<td>64.8%</td>
<td>56.6%</td>
<td>51.7%</td>
</tr>
<tr>
<td>S↔E</td>
<td>46.1%</td>
<td>47.0%</td>
<td>64.6%</td>
<td>62.6%</td>
<td>54.7%</td>
</tr>
<tr>
<td>S↔W</td>
<td>23.9%</td>
<td>21.5%</td>
<td>36.0%</td>
<td>30.6%</td>
<td>27.7%</td>
</tr>
</tbody>
</table>

Table 8.23: Average value of transmission line utilization ratios for the case 'S50%N'.

<table>
<thead>
<tr>
<th>Line</th>
<th>$\downarrow$ s_{Wind}</th>
<th>$\downarrow$ s_{PV}</th>
<th>$\uparrow$ s_{Wind}</th>
<th>$\uparrow$ s_{PV}</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>N↔E</td>
<td>39.8%</td>
<td>56.3%</td>
<td>60.9%</td>
<td>58.2%</td>
<td>53.0%</td>
</tr>
<tr>
<td>N↔W</td>
<td>58.6%</td>
<td>71.4%</td>
<td>80.5%</td>
<td>80.1%</td>
<td>72.0%</td>
</tr>
<tr>
<td>S↔E</td>
<td>48.4%</td>
<td>54.8%</td>
<td>67.9%</td>
<td>69.7%</td>
<td>59.6%</td>
</tr>
<tr>
<td>S↔W</td>
<td>31.0%</td>
<td>38.9%</td>
<td>44.6%</td>
<td>42.3%</td>
<td>38.6%</td>
</tr>
</tbody>
</table>

Table 8.24: Average value of transmission line utilization ratios for the case 'S50%S'.

<table>
<thead>
<tr>
<th>Line</th>
<th>$\downarrow$ s_{Wind}</th>
<th>$\downarrow$ s_{PV}</th>
<th>$\uparrow$ s_{Wind}</th>
<th>$\uparrow$ s_{PV}</th>
<th>$\emptyset$</th>
</tr>
</thead>
<tbody>
<tr>
<td>N↔E</td>
<td>25.5%</td>
<td>23.2%</td>
<td>40.2%</td>
<td>29.2%</td>
<td>29.4%</td>
</tr>
<tr>
<td>N↔W</td>
<td>48.1%</td>
<td>42.0%</td>
<td>68.4%</td>
<td>60.0%</td>
<td>54.3%</td>
</tr>
<tr>
<td>S↔E</td>
<td>49.1%</td>
<td>55.5%</td>
<td>66.3%</td>
<td>63.4%</td>
<td>58.3%</td>
</tr>
<tr>
<td>S↔W</td>
<td>28.0%</td>
<td>34.1%</td>
<td>38.0%</td>
<td>37.8%</td>
<td>34.2%</td>
</tr>
</tbody>
</table>
Figure 8.35: 3D plot of the transmission line utilization ratios for the base case of the multi-bus power system.

Figure 8.36: 3D plot of the transmission line utilization ratios for the case 'S50%N'.
Figure 8.37: 3D plot of the transmission line utilization ratios for the case ‘S50%S’. 
Chapter 9

Conclusions and outlook

This chapter summarizes the most important findings and achievements of this thesis and concludes with an outlook for further research.

9.1 Conclusions

In this thesis a dispatch, sizing and feasibility evaluation of power systems with 100% renewable electricity has been performed. Generation, load and storage units have been modeled with the Power Node framework, and their marginal dispatch costs have been derived from realistic and empirical data. A single-bus and a multi-bus power system with high penetration levels of intermittent renewable generation from wind turbines and PV panels have been simulated over a time span of 1 year. The dispatch schedules of the power system units have been obtained by a predictive economic dispatch optimization routine. Thereby, load shedding and curtailment of intermittent renewable generation units have been considered as eligible control action. The simulation results have been analyzed with the objective to determine the impacts of storages and flexible loads on the power system’s hosting capacity for fluctuating renewable infeed and the requirement for dispatchable generation units. The most important conclusions are briefly listed below.

Power Node modeling framework: An excellent tool to represent the various power system units is the Power Node modeling framework. The generic Power Node equation provides the possibility to account for the state of charge and all energy flows, such as shedded load demand and curtailed intermittent generation. The corresponding variables can be penalized in the objective function of the optimization problem. This enables to implement a holistic operation concept that considers intermittent generation, flexible loads and energy-constrained storages.

Modeling of electric water heaters as flexible loads: A cluster has been parameterized that represents the full potential of all electric water heaters in Germany as flexible loads. The power rating is equal to 25.7 GW
and the thermal storage capacity amounts to 149.4 GWh. In order to calculate the thermal storage capability, 60°C and 10°C have been considered as upper and lower temperature boundaries. Heat losses have been modeled with the one-dimensional heat equation. As an external demand process, a representative warm-water demand profile, scaled to the total number of households in Germany, has been utilized.

**Marginal dispatch costs:** A challenge was the derivation of reasonable marginal dispatch costs for wind energy, PV energy and a pumped hydro storage. In literature only levelized costs of energy (LCOE) are mentioned, which consider also capital cost. However, capital costs are not incorporated in an economic dispatch. In general, renewable generation and bulk energy storage units feature high capital costs and low operation and maintenance costs. These expenses are usually stated as fixed costs, which are incurred each year. With several assumptions it was possible to derive reasonable marginal dispatch costs for all units. At this point one should mention that also different assumptions are possible, e.g. variable dispatch costs for operation and maintenance. In the end, one has to pay attention to the condition that marginal dispatch costs for a storage unit are higher than for intermittent generators. This is crucial, because otherwise storage commitment is preferred over infeed from intermittent generators.

**Dispatch simulator:** Initially, the dispatch simulator has been developed by Stephan Koch. During this thesis, the software tool has been further enhanced. Especially the integration of the CPLEX solver increased the performance considerably. It is now possible to reliably simulate a portfolio of more than 20 Power Nodes over a time span of 1 year and a sample time of 15 minutes with a computation time of less than 1 hour. Thereby, a prediction horizon length of more than 7 days is selectable. The incorporation of the optimal power flow concept enables to simulate multi-bus power systems.

**Implementation of the predictive economic dispatch optimization problem:** A tough and time-consuming task was the implementation of the bilinear constraint \( u_{gen,i} \cdot u_{load,i} = 0 \) for a storage unit. The constraint ensures that the unit either charges or discharges at the same time. Two implementation variants of the economic dispatch optimization problem have been presented: as mixed integer problem (MIP) and as quadratic program (QP). The former variant is preferable, because the dissipation of energy due to cycling of electricity with a lossy storage is always prevented. However, a stable and sound solver performance could not be accomplished. As a consequence, the QP variant was utilized to perform the simulations. Thereby, restrictions on the choice of cost terms for the objective function had to be accepted. Another drawback is the fact that one of the two variables is never exactly zero, but rather in the interval \([10^{-12}, 10^{-1}]\). As a consequence, the evaluation process of the simulation results was impeded, e.g. for the computation of the number of charge-discharge cycles.
Impacts of storage deployment on the power system’s hosting capacity for fluctuating renewable infeed: In the performed case studies a pumped hydro storage with a discharge time at rated power equal to 10 h and a power rating varying between 25–100% of the average load has been considered. The results show that, depending on the storage size, on average the share of integrated renewable energy is increased from 53% to 58-65.9%. Thereby, the largest increase is gained in scenarios with high penetration levels of PV energy and low levels of wind energy.

Impacts of the electric water heater cluster on the power system’s hosting capacity for fluctuating renewable infeed: If the full potential of electric water heaters in Germany is utilized as a cluster of flexible loads, the share of integrated renewable energy is increased on average from 53% to 56.7%. The impact is quite large if one consider the fact that a pumped hydro storage with a power rating equal to 25% of the average load increases the share only by 1.3 percentage points more.

Requirement of dispatchable generation: The integration of wind and PV energy releases dispatchable generation capacities to the greatest extent for peak power, then for load-following power, and to the lowest extent for base load power. In general, the reduction of operating hours is greater in scenarios with high shares of wind energy and low shares of PV energy than vice versa. In case pumped hydro plants are deployed, base load and load-following power plants operating in the bandwidth of 10-70% of the peak load are considerably fewer dispatched the larger the storage is scaled. However, despite the combination of high penetration levels of wind and PV and the deployment of storage facilities the necessity of peak power plants persists.

Storage operations: The number of charge-discharge cycles per week of the pumped hydro plant is mainly influenced by the penetration level of PV energy. In scenarios with high shares of PV energy and low shares of wind energy, the storage performs 5.9 cycles per week. By contrast, in case wind energy is predominant the number of cycles per week decreases to 5.1.

Predominance of wind energy: The performed case studies have clearly shown that wind energy can be better absorbed by power systems than PV energy. This predominance prevails even for the deployment of large storage power ratings equal to 100% of the average load. However, large shares of PV energy enable an optimal storage dispatch with one charge-discharge cycle per day.

9.2 Outlook

Based on the presented results and findings, this thesis offers many interesting research opportunities for future projects. The most interesting suggestions are briefly listed below.
**Power Node Modeling:** One topic is the extension of the presented Power Node portfolio by different types of flexible loads and storage units. Especially the benefit of seasonal storages, such as hydrogen, could be interesting to look into. At the moment, it is claimed that hydrogen storage may be unacceptable due to its very low cycle efficiency in the range of 30–40% and high capital costs. But due to the high seasonality and increasing penetration levels of fluctuating renewable energy sources, this drawback may become subordinate. Another idea is the explicit modeling of base load, load-following and peak load power plants with corresponding ramp-rate constraints and cost terms. On this basis, a study could be performed as to how many generation units of each type are necessary to reliably meet the load demand and balance fluctuating renewable infeed.

**Stochastic MPC and prediction errors:** A highly interesting research topic offers the extension of the predictive economic dispatch optimization problem by stochastic MPC and the modeling of prediction errors of fluctuating renewable infeed. This extension should have impacts on the dispatch of the deployed storage units and the requirement for power reserves. For instance, if a period of 5 days with strong wind is predicted, without prediction errors the controller charges the storage uniformly as it knows that the predicted amount of wind energy is available for sure. However, in case of prediction errors the controller should follow the objective to charge the storage as soon as possible.

**Transmission and distribution grid:** The enhanced dispatch simulator offers the possibility to simulate multi-bus power systems interfaced with a large set of Power Nodes. An interesting task is the modeling of a grid on the medium-voltage level in order to consider the decentralized character of renewable energy sources. In case of bottlenecks and line congestions, the share of integrated renewable energy may be considerably reduced without a selective positioning of storage units.
Appendix A

MPC controller

A.1 Controller parameterization for utilizing excess renewable energy

During this thesis, it was investigated how the MPC-controller for an economic dispatch could be initiated to host excess renewable energy. In Chapter 3 marginal generation costs for wind and PV have been calculated. The cost term for PV panels amounts to 0 €/MWh, whereas for wind turbines costs equal to 3.6 €/MWh are incurred. The dispatch schedules of the renewable generation units are obtained by a predictive economic dispatch optimization, which minimizes total generation costs. As marginal generation costs for wind are nonzero, a way has to be found to initiate the controller to host excess wind energy as long as storage capacities are available. This is necessary because without an appropriate incentive the MPC-controller only dispatches wind energy to the extent high priced electricity from conventional generation can be substituted within the prediction horizon.

In the following, a portfolio of Power Nodes is considered, which consists of a conventional load, a wind farm, an aggregation of PV panels, a biomass power plant and a pumped hydro storage. In order to initiate the controller to host excess wind energy as long as storage capacities are available, two sets of cost terms for the objective function are regarded:

In the first set, the cost terms are chosen as described in Subsection 6.2.2. Thereby, curtailment costs for wind energy are considered. For the second set, a cost term on storage level deviations from the reference level $x_{ref} = 1$ equal to 50,000 is introduced for the pumped hydro plant. In addition, the marginal generation and curtailment costs for wind energy are set to zero. As a consequence, wind energy is always preferred over energy stored in the pumped hydro plant. The Tables A.1 and A.2 summarize the choice of cost terms.
Table A.1: First set of cost terms.

<table>
<thead>
<tr>
<th>Power Node</th>
<th>Cost term $u_{\text{gen},i}$</th>
<th>Cost term $u_{\text{load},i}$</th>
<th>Cost term $w_i$</th>
<th>$(1 - x_i)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load</td>
<td>-</td>
<td>0</td>
<td>-500</td>
<td>-</td>
</tr>
<tr>
<td>Wind</td>
<td>3.6</td>
<td>-</td>
<td>4</td>
<td>-</td>
</tr>
<tr>
<td>PV</td>
<td>0</td>
<td>-</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>Biomass</td>
<td>145.6</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PumpedHydro</td>
<td>5.06</td>
<td>0</td>
<td>-</td>
<td>0</td>
</tr>
</tbody>
</table>

Table A.2: Second set of cost terms.

<table>
<thead>
<tr>
<th>Power Node</th>
<th>Cost term $u_{\text{gen},i}$</th>
<th>Cost term $u_{\text{load},i}$</th>
<th>Cost term $w_i$</th>
<th>$(1 - x_i)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load</td>
<td>-</td>
<td>0</td>
<td>-500</td>
<td>-</td>
</tr>
<tr>
<td>Wind</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>PV</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Biomass</td>
<td>145.6</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PumpedHydro</td>
<td>5.06</td>
<td>0</td>
<td>-</td>
<td>$5 \times 10^4$</td>
</tr>
</tbody>
</table>

The described portfolio has been simulated with the two sets of cost terms for a time span of 1 year. The resulting energy balance terms are listed in Table A.3. By comparing the figures, one can see that in the case with state costs more wind energy and less PV energy is absorbed than in the case with wind curtailment costs. The reason for this is that wind generation costs are set to zero in the case with state costs. As a consequence, PV energy is not anymore preferred over wind energy. However, in total the same amount of renewable energy is absorbed. The two balance terms differ only by less than 0.01%. This might be explained by small numerical differences during the optimization process.

In addition, the numbers in the table show that the pumped hydro storage cycles in both cases the same amount of energy. However, by examining the times series of the state of charge it becomes obvious that the dispatch schedules of the storage unit considerably differ for both cost sets. In the following, this is investigated in detail.

In Figure A.1 for the first 20 days the evolution of the grid variables (top), curtailment variables (middle) and the storage level (bottom) are illustrated for the set of cost terms, which considers curtailment and generation costs. A period of weak wind is identifiable in the first 8 days, as infeed from wind is low and no curtailment occurs. Afterwards, a period of strong wind occurs. From the upper plot one can see that within the time frame of weak wind the load demand is mainly served by the biomass power plant. The pumped hydro storage is discharged uniformly and operates like a baseload power plant. At the transition from weak to strong wind, the lower plot...
Table A.3: Energy balance terms for the analysis to incite the controller to host excess renewable energy.

<table>
<thead>
<tr>
<th>Balance term</th>
<th>With curtailment and generation cost for wind [TWh]</th>
<th>With state cost and without generation cost for wind [TWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elec. consumed by conv. load</td>
<td>459.831</td>
<td>459.831</td>
</tr>
<tr>
<td>Elec. supplied by wind</td>
<td>284.215</td>
<td>303.188</td>
</tr>
<tr>
<td>Elec. supplied by PV</td>
<td>91.763</td>
<td>72.846</td>
</tr>
<tr>
<td></td>
<td>375.977</td>
<td>376.034</td>
</tr>
<tr>
<td>Wind energy curtailment</td>
<td>83.657</td>
<td>64.684</td>
</tr>
<tr>
<td>PV energy curtailment</td>
<td>0.203</td>
<td>19.120</td>
</tr>
<tr>
<td></td>
<td>83.861</td>
<td>83.804</td>
</tr>
<tr>
<td>Elec. supplied by biomass</td>
<td>102.286</td>
<td>102.233</td>
</tr>
<tr>
<td>Elec. drawn by pumped hydro</td>
<td>81.672</td>
<td>81.728</td>
</tr>
<tr>
<td>Elec. supplied by pumped hydro</td>
<td>63.239</td>
<td>63.293</td>
</tr>
<tr>
<td>Prim. energy supplied by wind</td>
<td>367.872</td>
<td>367.872</td>
</tr>
<tr>
<td>Prim. energy supplied by PV</td>
<td>91.966</td>
<td>91.966</td>
</tr>
<tr>
<td>Prim. energy supplied by biomass</td>
<td>243.539</td>
<td>243.539</td>
</tr>
<tr>
<td>Energy demanded by conv. load</td>
<td>-459.831</td>
<td>-459.831</td>
</tr>
</tbody>
</table>

reveals that the state of charge is close to zero. Thus, the storage is ready to host as much excess wind energy as possible.

In Figure A.2, the simulation results are plotted for the cost set, which considers costs on storage level deviations. The lower plot reveals that within the period of weak wind the pumped hydro storage does not supply electricity, as its state of charge is not decreasing. This is unexpected because marginal generation costs for biomass are higher than for storage commitment and consequently electricity should be supplied first from the storage. However, the storage is discharged abruptly right before the occurrence of the period with strong wind. The reason why in a phase of weak wind the storage is not discharged can be stated as follows: Quadratic costs on deviations from the reference storage level $x_{ref} = 1$ cause the dispatch controller to maintain the state of charge as long as possible. In case insufficient wind energy is available within the prediction horizon, a dispatch schedule from the MPC-algorithm is obtained which enables to discharge the storage in the last period of the prediction horizon. Because the optimization is performed in every time step, only the first step is implemented and consequently the storage is never discharged until a transition from weak to strong wind occurs.

As a result, one can conclude that curtailment costs for wind energy as well as the introduction of costs on storage level deviations result in the same
amount of integrated renewable energy. However, two major drawbacks are involved with the introduction of state costs: (1) marginal generation costs for wind have to be set equal to zero and (2) the storage is discharged abruptly right before a transition from weak to strong wind. In periods of weak wind the state of charge is kept constant. By contrast, without state costs a uniformly discharging behavior was observed. This strategy is preferable as it might offer potentials to cut down on dispatchable generation capacities.
Figure A.1: Evolution of the grid variables (top), curtailment variables (middle) and the storage levels (bottom) for the case with curtailment and generation cost for wind energy.
Figure A.2: Evolution of the grid variables (top), curtailment variables (middle) and the storage levels (bottom) for the case with cost on storage level deviations and without generation cost for wind energy.
Appendix B

Results

B.1 Single-bus all-renewable power system

In Figure B.1, the individual shares of curtailed renewable energy CRE of the wind turbines and PV panels for the single-bus power system are plotted as a function of the renewable supply scenario and for different storage scalings. The corresponding contour plots are illustrated in Figure B.2.
Figure B.1: 3D plots of the curtailed renewable energy share of wind and PV for the single-bus power system and different storage scalings.
Figure B.2: Contour plots of the curtailed renewable energy share of wind and PV for the single-bus power system and different storage scalings.
Bibliography


[20] TenneT TSO GmbH. Network figure: Actual and forecasted energy infeed by wind and photovoltaic for the entire Tennet control area,


