DOI: 10.1016/j.energy.2011.08.021

Fluctuating Renewables in a Long-term Climate Change Mitigation Strategy

Sylvie Ludig[a,*], Markus Haller[a], Eva Schmid[a], Nico Bauer[a]

[a] *Potsdam Institute for Climate Impact Research, PO Box 601203, 14412 Potsdam, Germany*

Abstract

Integrated Assessment models, widely applied in climate change mitigation research, show that renewable energy sources (RES)play an important role in the decarbonization of the electricity sector. However, the representation of relevant technologies in those models is highly stylized, thereby omitting important information about the variability of electricity demand and renewables supply. We present a power system model combining long timescales of climate change mitigation and power system investments with short-term fluctuations of RES. Investigating the influence of increasingly high temporal resolution on the optimal technology mix yields two major findings: the amount of flexible natural gas technologies for electricity generation rises while the share of wind energy only depends on climate policy constraints. Furthermore, overall power system costs increase as temporal resolution is refined in the model, while mitigation costs remain unaffected.

Keywords: Renewables, Variability, Power System Modeling, CO_2 price

*Tel.: +49 331 288 2427; Fax.: +49 331 288 2640
Email address: sylvie.ludig@pik-potsdam.de (Sylvie Ludig)

1. Introduction

Research in the field of climate change mitigation ([e.g. 1, 2]) has shown that on the road towards a low-carbon power system, several technology options play a role: RES, carbon capture and storage (CCS), biomass and nuclear energy. Among the options considered, RES prove to be especially important for the electricity sector where they take a major role in the decarbonization process. Increasingly large shares of fluctuating renewable energy sources (RES) for electricity generation in countries like Germany (see [3]) and RES targets for larger regions like Europe raise several general questions: How can a large share of fluctuating energy sources be handled by the power system? How does the uneven distribution of renewable potentials affect regional integration possibilities and, more specific, how do these problems influence power system and climate change mitigation costs?

Generally, two very different types of quantitative models are used to assess this kind of questions: Integrated Assessment Models (IAMs), with long time frames, allow for the analysis of different scenarios considering technology investments and climate targets. Dispatch models are applied for the assessment of power system operation given a certain technology mix and considering short time horizons.

Most IAMs can not give satisfactory answers to questions of RES integration due to a reduced temporal resolution or lack of technological details necessary to allow for the computation of long-term scenarios. Dispatch models fall short in the area of scenarios for power system adaption due to the limitation to short time frames. LIMES (Long-term Investment Model for the Electricity Sector) fills a gap by integrating long-term time scales of climate change mitigation and power system investments with the issue of short-term fluctuations of RES integrated in one model.

This study answers the following specific research questions: What are the integration costs when the amount of fluctuating RES within the power system is increased to attain decarbonization targets? Which time scales are relevant when analyzing how short-term fluctuations affect long-term investment paths and mitigation costs and which consequences arise for necessary model resolution?

The remainder of this article is structured as follows: Section 2 presents a literature review on the questions raised in this introduction, Section 3 outlines the methodology, Section 4 presents results and Section 5 concludes.

2. Literature Review

In the existing literature, the majority of modeling approaches that include RES as a climate change mitigation option in the power system adopt one of two extremes. Either they investigate long-term scenarios and treat fluctuations of RES in a very stylized manner or they perform short-term simulations that are not capable of considering structural capacity changes over time. Connolly et al. [4] provide a good overview on energy models that are used for the investigation of renewable energy integration, both on long-term and short-term time frames. Long-term IAMs like ReMIND [5], PERSEUS-CERT [6], MESSAGE-MACRO [7], DEMETER [8] or WITCH [9] represent the reduced availability of RES using highly aggregated parameterizations. Implementations include using load factors or secured capacities – see [10] for an example of fluctuation modeling. These generally use long time steps of five to ten years that do not allow for a more thorough investigation of fluctuation issues. On the other extreme, models with a focus on short-term power plant dispatch either neglect capacity extensions or only consider investments annuities. Lund [11] analyzes wind energy integration into the Danish power system using the EnergyPLAN model to perform technical and economical assessments under different regulatory assumptions. Benitez et al. [12] use a cost minimization model where hourly demand has to be met by existing generators. Maddaloni et al. [13] use a similar approach but include network constraints. DeCarolis and Keith [14] combine an hourly simulation of wind energy output with a minimization of remaining system costs over the time period of the simulation, which is five years only. Other models, such as GTMax [15] or MICOES [16] do not consider periods longer than one year.

To bridge the gap between short-term and long-term analyses, there is the need for models combining both timeframes. Furthermore, it is necessary to include a sufficient amount of technological detail to allow for the assessment of measures needed to balance RES fluctuations such as backup and storage technologies.

To date, there are very few models that aim at positioning themselves somewhere in the range spanned between the two approaches mentioned above by bringing both the long-term and short-term aspects together. Some models from the MARKAL/TIMES family [17] introduce a certain number of time slices to represent changes in yearly energy production. BALMOREL [18] allows for a flexible number of years and yearly subdivisions, depending on the study purpose. AEOLIUS is an extension to the PERSEUS model [19] using a 1-year simulation of the German power market including wind power time series derived from the ISI wind model [20]. Both models are solved iteratively. Due to the high computational costs (every single hour of a year is simulated) only a time-frame until 2020 is considered. The ReEDS model [21] uses a different approach by introducing several time slices to emulate variations of demand and RE supply during a year. It is solved sequentially by optimizing 2-year intervals for the time-frame 2006-2050. Neuhoff et al. [22] use an investment planning model with regional demand and wind output profiles for 20 load segments for 52 weeks but only consider a limited time horizon of 2005-2020. Table 1 shows a comparison of the relevant features of three of the aforementioned models. The modeling focus of most approaches lies on the representation of short to mid-term policy measures. However, technical power plant lifetimes of 40 to 50 years call for a long-term examination. This also holds for analyses of climate change mitigation options and their respective degree of utilization. LIMES fills this gap by combining long term and short term time scales and enables an analysis of the influence of temporal resolution on the technology mix in the electricity sector as well as on power system and climate change mitigation costs. Furthermore, the intertemporal optimization assures the refinancing of investments into generation technologies as the model optimizes capacity expansion under the constraint of short-term variability, leading to varying degrees of power plant utilization.

Table 1: Comparison of modeling approaches for the evaluation of RES fluctuations and the relation to climate policy

Model	Method and Objective	Model Features		Research Issue	Policy Scenarios	
		Investment Time Horizon	Temporal Resolution		Climate Target	RES Target
BALMOREL [18]	Partial-equilibrium tool for the electricity sector	1-20 years	1h - 2 weeks	Bottom up investment and operation optimization	Emission tax	no
ReEDS [21]	Minimization of power system costs over 2-year-periods	2006-2050	16 time slices	Cost assessments of RES targets (Energy policy assessment)	no	yes
Investment planning model [22]	Least cost investment planning optimization	2005-2020	20 load segments for 52 weeks	Investment scenarios considering intermittent RES sources and transmission requirements	CO_2 price	yes
LIMES	Intertemporal ESM cost minimization	2005-**2100**	Variable number of time slices	Long-term assessment of integration of fluctuating RES into power sector under climate constraints	**yes**	**yes**

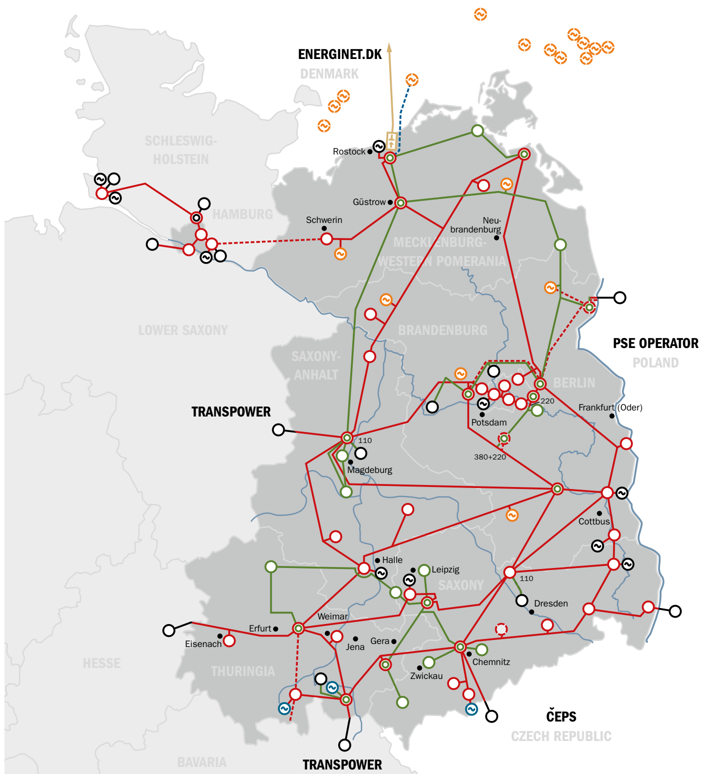


Figure 1: Map of the Area covered by 50Hz Transmission GmbH (Figure source: [23])

3. Methodology

LIMES constitutes a power system model minimizing total discounted power system costs for the time period 2005-2100 while meeting exogenously given demand paths. Investments into power generation capacities and their operation subject to the given variability of electricity demand and supply are decision variables to the model. Hence, the built-up of fluctuating RES implies that also investments into capacities balancing these fluctuations are necessary to ensure stable operation of the electricity system. Such capacities include conventional backup technologies or storage technologies. Long distance electricity transmission is not considered as an option to counterbalance RES variability in this study due to the small size of the model region. An overview of relevant model equations is given in AppendixB. The model introduces time slices to allow for the consideration of short time frames alongside long-term investment horizons. These are assessed in detail in Section 3.1. A broad range of electricity generation technologies are included as well as storage technologies (see Sections 4.2 and AppendixA). The model considers climate policy constraints in cost-effectiveness mode, operationalized by either emission trajectories, budgets or CO_2 prices[1] (Section 3.3).

LIMES is calibrated to the area of Germany that is covered by the company 50Hz Transmission GmbH (formerly Vattenfall Transmission, mainly eastern Germany and Hamburg, see Figure 1). A comparison of model results and and region data is conducted in Section 3.4.

The following sections detail the main methodology aspects of LIMES.

[1]Furthermore, it is possible to set goals for electricity generation from RES.

3.1. Modeling Temporal Variability

To represent variability of demand and RES supply within the model, we use a combination of two different approaches: subdivision of a year into different periods oriented at load differences and an assessment of fluctuations left uncovered by this parametrization.

Fluctuations are represented within LIMES by dividing a year into various characteristic periods, called time slices hereafter. The time slices differentiate variations between seasons, days of the week and phases of the day. Figure 2 shows the electricity demand for 16 time slices of the year 2007. Neighboring bars represent 6h intervals for the spring, summer, autumn and winter season. Other time slice configurations evaluated in this analysis distinguish more or less phases of the day, leading to the settings illustrated in Table 2. The time slices are generated using quarter-hourly data sets for demand, wind feed-in and solar energy feed-in for Eastern Germany, as well as the installed capacities for RES [24, 25, 26]. Following a subdivision into four seasons and different times of the day, the data is grouped into the respective time slices. The input values for electricity demand as well as wind and solar capacity factors are determined by calculating the mean values of the data points belonging to each time slice.

As mentioned above, the underlying data for the representation temporal variation in the model originates from actual time series for RES feed-in and electricity demand. Since time slices are derived through sorting and averaging of this data, no additional stochasticity is introduced. Although uncertainty about fluctuations, especially of wind energy, is an important driver for investments into backup capacities and other balancing options,

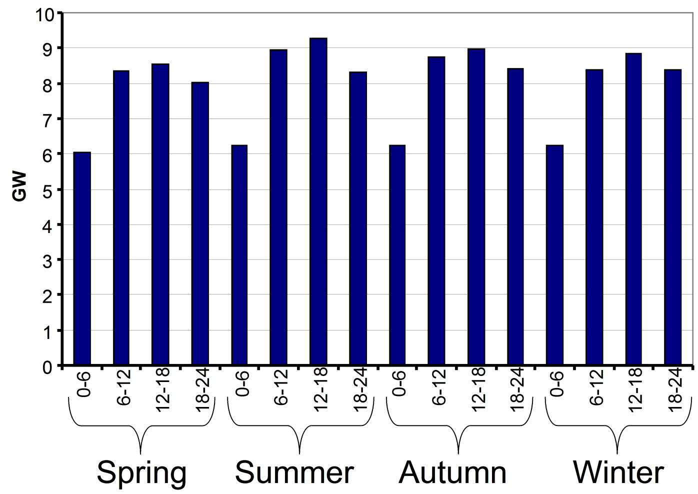


Figure 2: Mean electricity demand in time slices for the *6h* setup

wind forecasts have shown major improvements over the last years [27]. Their increasing accuracy for short time frames of two to four hours allow power system operators to take necessary actions for fluctuation balancing in due time. Since the time sales used in LIMES are similar to those relevant for system operation, the deterministic representation of fluctuations deems sufficient. Assessment of necessary backup and balancing capacities is conducted at the end of this section.

To assess which share of total variability contained in the initial data set is covered by the respective time slice setup, we calculate variances for the complete data set and those in the time slices (Equation 1).

$$vari\_cover = 1 - \frac{\sum_{ts} \sum_{j=1:n_{ts}} (x_j - \bar{x}_{ts})^2}{\sum_{i=1:n} (x_i - \bar{x}_{all})^2} \tag{1}$$

Table 2: Different time slice setups evaluated in this analysis

Time Slice Setup	Number of Time Slices	Time Slice Length
24h	4	24h
12h	8	day/night (12h each)
6h	16	6h
2h	48	2h
1h	96	1h

The variability covered in the respective time slice setup $vari\_cover$ is calculated by dividing time slice variability by data set variability: the sum of the n squared differences of all data points x_i in the complete data set to the mean value $\bar{x}_{all}$ is divided by the sum of the squared differences of all n_{ts} data points x_j belonging to one time slice ts to the mean value of this time slice $\bar{x}_{ts}$, summed over all time slices. Figure 3 shows the results of this calculation for different time slice setups: with increasing temporal resolution, more and more of the variability of demand and solar energy can be covered. Both display fairly regular daily and seasonal patterns that are caught well by time slices[2]. Wind, however, shows insufficient coverage of variability through time slices. Apart from seasonal variations, which follow regular patterns, wind fluctuations have strong stochastic properties that

[2]Small fluctuations beyond these patterns, e.g. cloud coverage for solar PV or electricity demand spikes can not be represented by time slices due to the averaging process used for their derivation. However, the above analysis shows good coverage of general daily and seasonal patterns for solar energy feed in and electricity demand.

are difficult to represent using average values for different periods of the year. As mentioned above, high quality wind forecasts ensure stable power system operation despite fluctuations. However, since the time slice method chosen for this model does not cover every aspect of wind energy fluctuations, additional parameterizations have been introduced to represent backup and balancing capacities necessary for system operation.

To approach this shortcoming, we consider variations happening on shorter time-scales by analyzing the change of wind electricity generation between different time intervals. Figure 4 shows the changes of wind power production sorted by magnitude for different time intervals, e.g. the largest drop of wind power production within 2h was 2645 MW and the largest increase was 2691 MW. From the analysis of these variations, we derive requirements for fast-ramping backup capacities needed within the system (the system has to provide sufficient backup capacities to encounter the largest drop) and supplementary electricity generation needed for fluctuation balancing. Backup and balancing capacity requirements are linked to the installed amount of variable RES to account for the increasing impact on power system operation when reaching higher shares of RES integration.

To account for periods with low electricity generation from wind and high demand, which typically occur during the winter time in the region considered, an additional time slice is introduced. This time slice combines the highest occurring electricity demand in the data set with the lowest observed wind output into a *superpeak*-slice. A length of 48 hours is assumed for the *superpeak* period. Hence reserve capacities need to be available and system reliability is ensured according to this constraint.

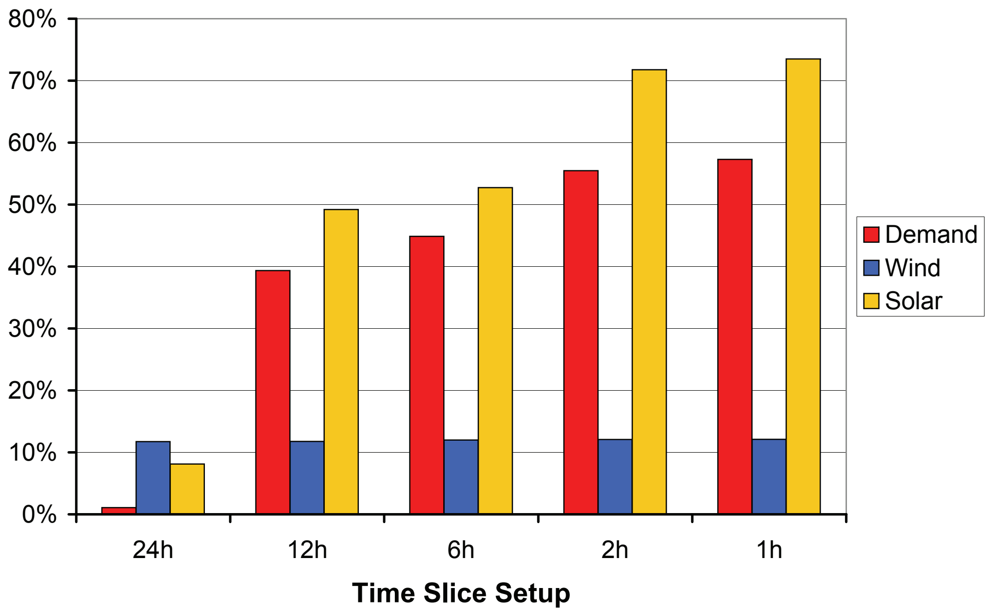


Figure 3: Share of variability covered by time slices of different lengths

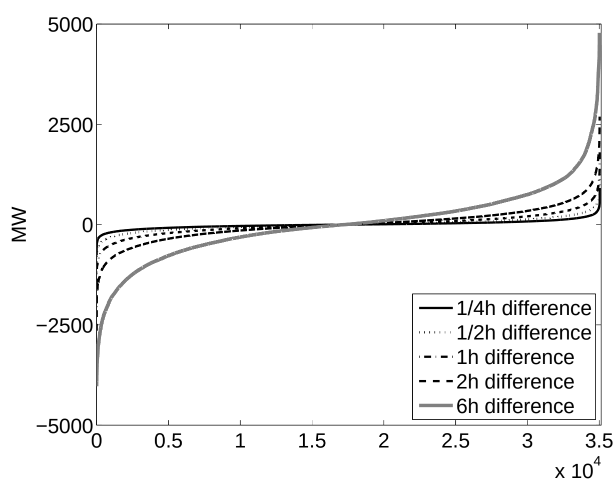


Figure 4: Load change curve of wind power (The x-axis displays the number of observations in the data set)

3.2. Introducing Technological Detail

The model includes a total of 14 different technologies for producing electricity and one storage technology. This choice is based on the power plant fleet currently installed in the area considered plus additional options such as carbon capture and sequestration (CCS). Electricity generation from nuclear power plants is phased out until 2030 and no investments into new nuclear capacities are possible for the model to represent German nuclear policy. Table A.3 in AppendixA displays the techno-economic parameters and the initially installed capacities for all electricity generation technologies considered. The maximum output of a power plant is constrained by the availability factor ν (cf. Equation B.2 in AppendixB) to represent scheduled outages for maintenance.

Electricity storage is modeled through the introduction of a generic storage technology, which allows for the subsequent assessment of different technologies by introducing the relevant sets of parameters. It consists of two distinct parts: Storage quantity and generation capacities. Both can be extended by investments. There is a constraint on maximum storage duration, allowing for storage only within one representative day. However, to allow for a thorough analysis of different options, storage is not available in the reference cases presented in Section 4.1. Section 4.2 shows an assessment of different storage options in LIMES.

3.3. Climate Policy Assessment

Climate policy constraints can be introduced using emission trajectories, emission budgets or CO_2 prices, mirroring different policy setups. The long model time horizon allows for an analysis of the impact of international climate agreements on the model region by prescribing emission budgets or CO_2 prices, while emission trajectories can be used to represent local climate policy laws. Because of the small model area, exogenously set CO_2 price paths are used for the assessment of policy impacts in Section 4.

3.4. Calibration and Scenario Definition

To assess the quality of the model calibration, results for the year 2010 are compared to electricity generation in the region according to the main power producer Vattenfall. According to [28], in 2009, 50 TWh electricity were generated from lignite while only 2.4 TWh were generated in nuclear power plants, due to long outages of the nuclear power plants Brunsbüttel and Krümmel. They both have been offline since mid-2007 after the occurrence of different incidents and have not returned to generating electricity until the end of 2010. LIMES model results for 2010 yield 40 TWh electricity from lignite and 13 TWh from nuclear energy. This is considered a reasonable result, since it can be expected that less electricity would have been generated from lignite, had the nuclear facilities not been offline.

A series of experiments are analyzed subsequently to assess the incremental effects of different setups for temporal resolution within the model on the technology mix in the electricity sector and on power system and climate change mitigation costs. Basically, the reference case distinguishes between a business-as-usual (BAU) scenario and a scenario with policy constraints (POL) where we impose a price path for CO_2 emissions. Based on [1], a price of 15 €/tCO_2 is set for 2005 and we assume an exponential increase of 5% per year in accordance with the model interest rate. The reference model version for these assessments is presented in Section 4.1. The storage availability on the electricity mix is discussed in Section 4.2. In section 4.3, we investigate the impact of feed-in priority for electricity from RES on the power sector composition.

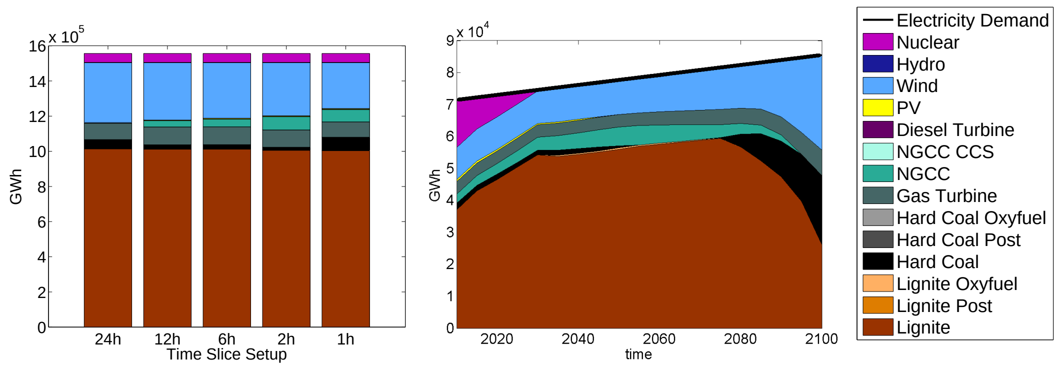
The insights gained from these experiments are combined in Section 4.4 to answer questions about the significance of variability for power system costs as well as climate change mitigation costs.

4. Results

4.1. Reference setup

Figure 5a displays cumulated electricity generation[3] for the BAU scenario in all five different time slice setups. Common to all is a considerable share of generation from lignite power plants together with a fairly substantial amount of wind energy. The difference between the various time slice setups lies in the amount of variability (of load and renewable energy supply) that can be represented. One would assume that more information about variability leads to less usage of RES as these show different load factors in each time slice. Together with ramping constraints on inflexible fossil fuel technologies, this entails that less wind energy would be used in the system. For the BAU scenario, this trend can clearly be seen in Figure 5a. The share of wind energy in electricity generation decreases from 22% to 17% as temporal resolution becomes finer. While the usage of natural gas turbines remains fairly constant at about 6%, the share of NGCC rises as mentioned above - wind energy is replaced by natural gas.

[3]Please note that the reference setup does not contain storage technologies.

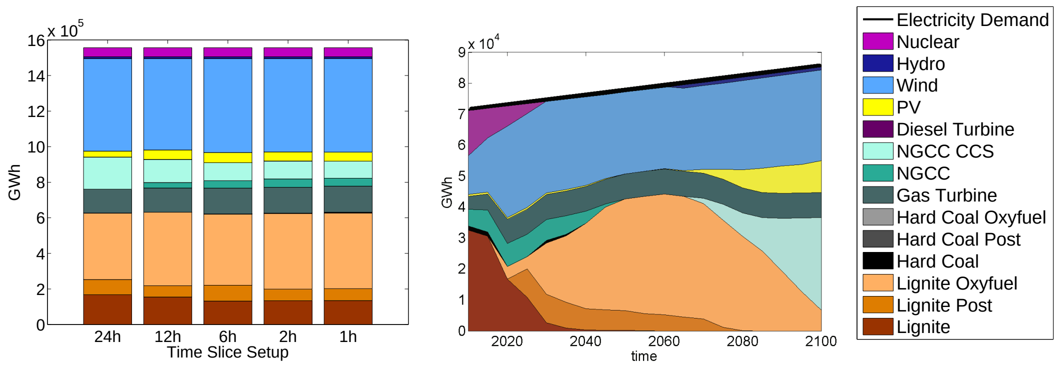


(a) Overview (b) *1h* setup

Figure 5: Reference scenario, BAU case, electricity generation

For the *1h* setup, Figure 5b shows evolution of the electricity generation mix over time. As noted in Section 3, the total amount of extractable lignite is constrained, which explains the decrease of lignite use at the end of the century. Also, hard coal plants replace NGCC as natural gas prices increase throughout the century. The amount of generation from gas turbines rises with the share of wind energy due to backup constraints.

As a next step, we investigate the impact of a CO_2 price path starting at 15 €/tCO_2 (about the current level in the EU ETS) in 2005 on the technology mix in the electricity sector using the same time slice setups as for the BAU scenario. The constraint on emissions leads to shifts in technology usage as can be seen from Figure 6b for the *1h* setup. While conventional lignite power plants are still used at the beginning of the century, no new capacities are installed and the existing plants are mothballed. Instead, a switch to facilities using CCS is performed. Lignite Oxyfuel and post-combustion plants are introduced and also NGCC generators in use at the beginning of the century



(a) Overview

(b) *1h* setup

Figure 6: Reference scenario, POL case, electricity generation

are substituted by their counterparts with CCS.

Figure 6a shows that the evaluation of different time slice choices draws a partly different picture than in the BAU scenario. The technology mix displays an overall share of about 33-34% wind energy in electricity generation for all time slice setups, which is more than 10 percentage points higher than for the BAU scenario. The amount of flexible natural gas turbines and NGCC increases with increasing resolution to balance fluctuations of demand and RES. Usage of NGCC with CCS, less flexible than its counterpart without capture, is reduced. The total amount of electricity production from lignite stays about constant while oxyfuel plants replace conventional capacities to make up for the lower deployment of NGCC with CCS as costs from CO_2 emissions underly the cost minimizing optimization.

4.2. Assessment of Storage Technologies

To assess the impact of different storage technologies on the usage of natural gas and lignite technologies, we subsequently introduced the following storage technologies into the model: Pumped Hydro Storage, Compressed Air Storage, Lead Acid batteries, Hydrogen Fuel Cells (in combination with electrolysis), Vanadium Redox Flow Batteries and Lithium Ion Batteries. Table A.4 in AppendixA shows the parameterizations chosen for the different storage technologies. The analysis showed that even under optimistic assumptions for investment costs and efficiency of the different technologies, pumped hydro storage was the only technology used before the end of the century. We will thus focus on the results obtained with pumped hydro storage in the following.

The introduction of pumped hydro storage into the model shows interesting impacts on cumulated yearly electricity generation. For the BAU as well as POL model settings (*2h* time slice setup), the presence of storage reduces the necessity for flexible NGCC plants to almost zero (Figure 7). The BAU scenario shows an increased amount of hard coal usage as the lower flexibility of this technology can be balanced by the use of storage. Similarly, the change for the policy setting consists in a higher usage of NGCC plants with carbon capture and lignite, mainly with oxyfuel capture. There is only litte change between different time slice setups for experiments with storage availability. Increasing the number of time slices leads to more information about system variability and thus knowledge about the need for flexible generation technologies; storage, however, provides additional power generation flexibility and allows for high usage of slow-ramping power plants. Technology choice is thus influenced only slightly by increasing temporal resolution when storage is available. The same is true for emissions: though the trajectories differ between the cases with and without storage, the same residual

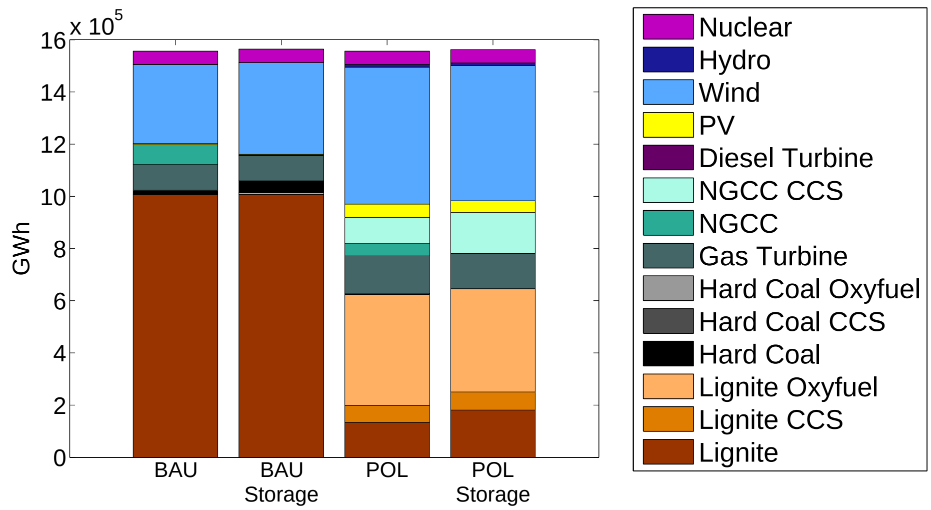


Figure 7: Electricity generation for scenarios with and without storage (*2h* setup)

emissions threshold of about 50 $MtCO_2$ is observed for POL scenarios with storage.

There is, however, another impact that can be seen when analyzing curtailment of wind power plants as displayed in Figure 8: in the presence of storage, the installed capacity of wind shows a strongly increased utilization level and curtailments are reduced to less than 5% over the time horizon considered. For the scenario without storage, this picture is largely different as up to 17% of wind power plants switched off due to system constraints.

Figure 9 displays electricity generation for 2040 over all 48 time slices (*2h* setup). It becomes apparent that wind production during lower demand periods at night is stored to be used for peak electricity demand during the day. This leads to a higher utilization of wind power over the year,

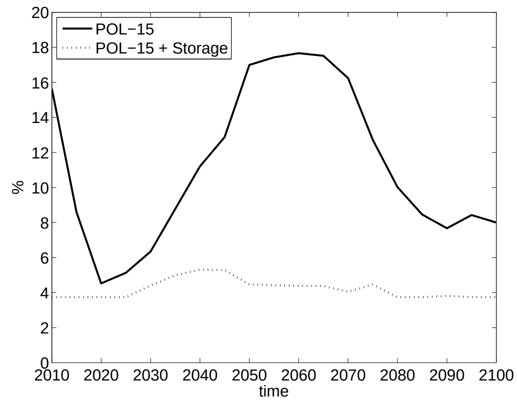


Figure 8: Wind Curtailment with and without storage (POL, *2h* setup)

thus reducing the need for curtailments. A constraint on maximum storage duration only allows for daily storage but storage accounting shows that even in model runs without this constraint, the technology is mostly used for daily balancing.

4.3. Feed-in priority for RES

In several countries, e.g. Germany, electricity from RES is given a priority when it comes to grid feed-in. Curtailments are only possible for strictly technical reasons in case of imminent danger for power grid operation [29]. While this preference is a reasonable measure to support RES development and force necessary grid extensions, an assessment of impacts on the operation of conventional power plants and electricity network operation seems reasonable. However, most studies (see e.g.[30, 31]) concerning the (mostly financial) repercussions of RES development in Germany treat the feed-in priority as given and do not analyze scenarios where curtailment is possible. One of the few sources analyzing welfare losses induced by priority feed-in

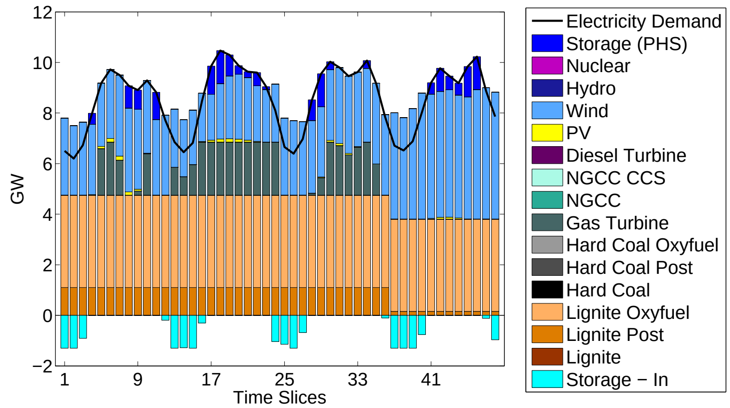


Figure 9: Electricity generation in 2040 with 24h storage over time slices (POL, *2h* setup)

are Andor et al. [32] who suggest a revision of RES policies to allow for curtailments to increase social welfare[4].

For the following analysis, it has to be kept in mind that the present model takes the perspective of a central social planner, optimizing the system as a whole instead of considering the decentral decisions of different players in the market. Furthermore, no technical aspects of electricity grid bottlenecks or power plant wear from frequent ramping of output are taken into account[5].

[4]Social welfare is to be understood as overall benefits to the system from minimized energy system costs. This means in the present situation that plant operators who forego their market opportunity to sell their electricity to customers could be in principle compensated by those plant operators who sell their output to customers at a positive price. In the present example the compensation might be organized via an implementation across time slices. Research about the market design of efficient curtailment is - however - yet in its infancy.

[5]While we consider constraints on ramping abilities of power plants, we do not include reductions of efficiency in part-load situations so far.

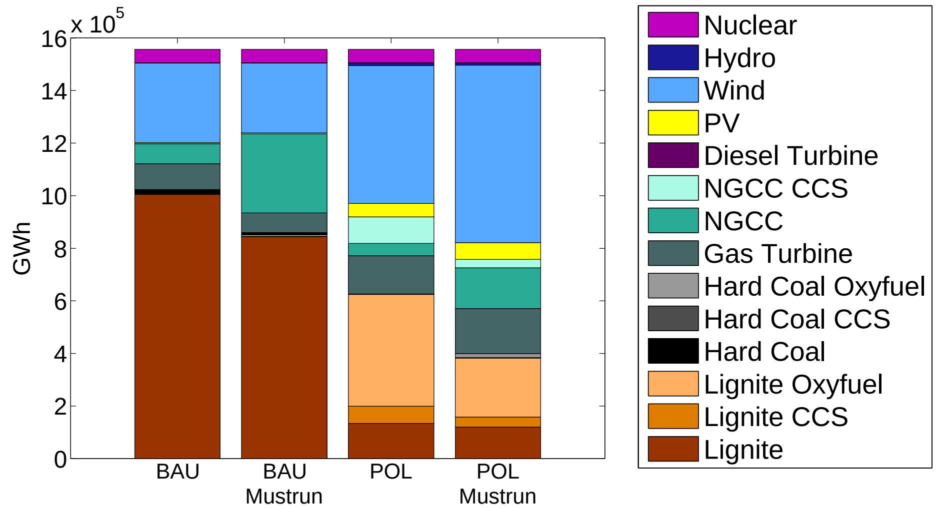


Figure 10: Cumulated electricity generation for scenarios with and without RES priority feed-in (*2h* setup)

Figure 10 displays cumulated electricity generation for the BAU and POL scenarios, with the first and third bars showing the standard situation where output from all power plants can be reduced (with the curtailment velocity being only limited by ramping abilities of different technologies) and the second and fourth bar presenting model runs where of wind and solar energy must not be curtailed. For the BAU scenarios, the model chooses to reduce investment in wind energy capacities (the share of wind in total energy production drops from 22.5% to 17.1%) and, more substantially, in lignite capacities (64.7% to 54.7% of electricity generation) to build up flexible natural gas CC plants instead.

The reduction in wind power production, however, is not observed in the POL scenarios. On the contrary, electricity generation from wind energy increases from 33.7% to 43.3% of total power generated. Inflexible lignite power plants are replaced by mainly gas fueled generation: NGCC, gas turbines and NGCC+CCS to reduce costs from CO_2 emissions. The overall electricity price is lowered through the forced feed-in of mostly wind, reducing refinancing possibilities of inflexible lignite base load plants. The missing flexibility of RES thus leads to a decrease of lignite oxyfuel usage. Since curtailments are not possible in this case to balance demand fluctuations, additional investments into natural gas technologies are undertaken, thus limiting the amount of lignite oxyfuel plants in the technology mix. An assessment of power system costs for cases with and without feed-in constraints is conducted in Section 4.4.

These results show that the possibility of curtailments of renewable energy technologies is of importance for system operation as this can provide some of the flexibility necessary for balancing of demand variations. This analysis, however, keeps a strict social planner perspective and does not comprise assessments of political support systems that have grid parity of RES as their aim. As the reduction of investment costs for wind and solar energy is an exogenous assumption in this model, it is not possible to assess the impact of learning curve progression through capacity extensions.

4.4. Cost Assessment

In this section, we assess power system and mitigation costs for the different scenarios presented in the previous sections to assess the effect of different temporal resolutions on cost estimations for the electricity sector.

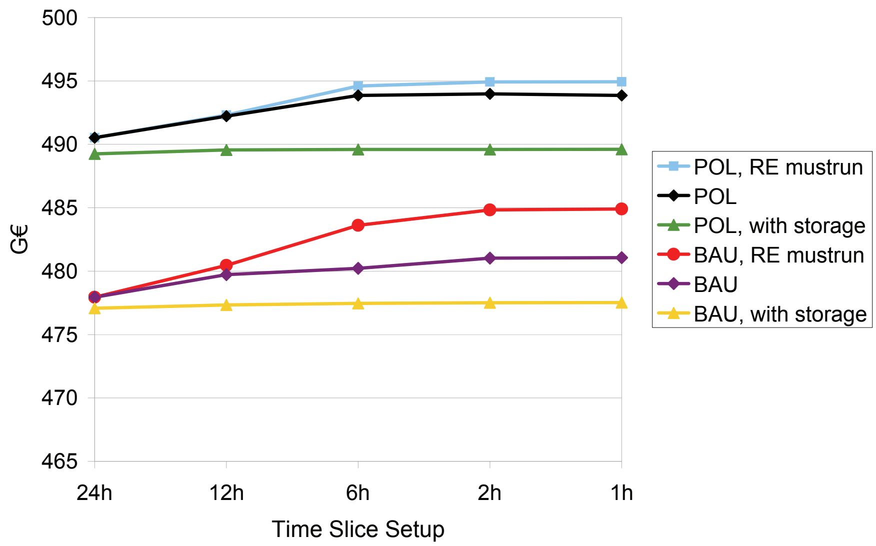


Figure 11: Comparison of total discounted power system cost for all time slice setups and scenarios

Figure 11 shows the total discounted power system costs[6] for BAU and POL scenarios over all time slice setups including model runs with storage availability and RE feed-in priority for different scenarios and time slice setups. Costs increase if more variability is considered in the model, mostly due to the increased use of natural gas technologies where fuel costs rise significantly throughout the century. This trend holds for power system costs of both BAU and policy scenarios, thus leading to the conclusion that models that use an aggregated representation for variability underestimate power system costs.

[6]Power system costs consist of investment costs, O&M costs, fuel costs and costs for CO_2 emissions.

Figure 11 also shows that the increase in power system costs level out with increasing temporal resolution. Experiments with a temporal resolution of 1h for time slices shows only minor cost increases compared to the *2h* setup, pointing to an information threshold after which additional information about variability does not lead to substantial changes in results.

A comparison of different scenarios shows that the most important factor for the level of power system costs is natural gas consumption. Experiments in which storage is available display lower costs while scenarios with RES feed-in constraints, where additional balancing is required, show higher costs.

The difference between total discounted power system costs in BAU and POL scenarios, i.e. mitigation costs, changes only slightly between 2% and 3% for the different setups as can be seen from Figure 11 by comparing the respective BAU and POL cost trajectories. As the need for flexible technologies in the presence of fluctuation causes higher power system costs already in the BAU scenarios, the difference between BAU and POL costs diminishes leading to similar results for all different time slice setups. While disregarding variability within models can lead to underestimation of power system costs, it does not have a clear effect on mitigation costs.

5. Conclusions and Outlook

This analysis investigates impacts on the technology mix for electricity generation and on power system costs using different setups for temporal resolution and varying emission constraints. Increased temporal resolution, representing more of the fluctuations in RES and load, leads to a decrease of the share of inflexible technologies while more flexible power plants are employed to cover electricity demand. The dominant technologies remain wind power and lignite power plants (with or without CCS). As flexible natural gas technologies display higher fuel costs than base load lignite plants, this leads to higher power system costs regardless of whether CO_2 prices are considered or not. However, the increase shows a stabilization, leading to the conclusion that further increases in temporal resolution might not lead to more accurate results. While power system costs increase under parameterizations of time with increasing resolution, climate change mitigation costs display little change.

The availability of storage strongly reduces the need for curtailments of wind energy and displaces NGCC plants almost completely. As the potential for pumped hydro storage is limited in most regions, further research will include several types of storage with differing properties and costs. The interdiction of renewables curtailment in a system without storage leads to significant increases in natural gas usage and, for the BAU scenario, a reduction in wind energy deployment. Our analysis takes a social planner perspective and suggests that decentral explorations including multiple players and policy assessments should take a deeper look into the impacts of RES feed-in priority.

Further research will take a closer look at the temporal resolution based on time slices. The model results gained so far point to the importance of higher temporal resolution. Since time slices designed around electricity demand show limitations for wind variability representation as discussed in Section 3.1, other methods should be investigated for time slice generation. Different clustering methods should help to find time slices that constitute an adequate representation of variability of RES and electricity demand while not overly increasing model complexity and thus numerical cost.

A planned European multi-region version of LIMES as presented conceptually in [33] will allow for investigation of the importance of electricity transmission for the integration of substantial amounts of RES into the electricity mix. Considering a larger geographical area also enables the analysis of pooling effects of regional resources of RES. As a further option for RES integration, demand side management measures will be investigated. This includes price elastic demand and load-shifting measures. Combined heat and power plants with electricity-controlled operation and CCS plants with flexibility for post-combustion measures will complete the technology options.

The combination of these options within one model will allow us to determine the optimal combination of measures to balance variability of RES sources in the electricity sector while providing a cost-optimal solution. Emission targets will add climate protection measures to the picture to provide the necessary long-term scenarios for the energy sector with a sufficiently high temporal resolution to account the effect of fluctuations of RES.

AppendixA. Model Data

AppendixA.1. Technologies

The model includes a total of 14 different technologies for producing electricity and one storage technology. This choice is based on the power plant fleet currently installed in the area considered plus additional options such as carbon capture and sequestration (CCS). Table A.3 AppendixA displays the techno-economic parameters and the initially installed capacities for all electricity generation technologies considered.

Fixed O&M costs contain labor costs and yearly overhead maintenance, while variable O&M include all costs related to auxiliary material as well as wear and tear maintenance. Please note that variable O&M Costs do not include fuel costs. Fuel costs are treated below the table in Section AppendixA.2.

Wind and solar photovoltaics are technologies characterized by decreasing investment costs over time due to learning effects. As these are overwhelmingly determined by global capacity increases we do not include learning curves for our model, but introduce an exogenous cost degression deduced from the model ReMIND-D [38]. Figure A.12 shows the investment cost curves implemented within LIMES.

The technical potential for onshore wind energy in Germany is estimated to be 71 $^{TWh}/_{a}$ by Kaltschmitt and Streicher [41]. Using the European Wind Atlas [42], the assumption is made that one third of this potential is situated in the region considered. For photovoltaic energy, we combine data from [43] and [44] to obtain a technical potential of 37 $^{TWh}/_{a}$. Average yearly capacity factors are at about 21% for wind and 8% for PV. To emulate current RES deployment, it is not possible to reduce capacities for wind energy below once installed numbers. Biomass fueled technologies are not considered in the current model setup due to major political insecurity about their projected role and, furthermore, to allow for a better determination of main model trends by limiting the number of technologies considered.

Table A.4 shows the parametrization used in Section 4.2.

Table A.3: Techno-economic parameters (See sources indicated in the table for mapping to technology)

Technology[a]	Investment Costs [€/kW][b]	Fixed O&M Costs [% Inv. Cost]	Variable O&M Costs [€/GJ]	Initial Capacity [GW]	Technical Life-time [a]
PC [34, 35, 36, 37]	1100	2	2.11	0.5	50
PC+Post [34, 35, 36]	1800	2	3.52	–	50
PC+Oxy [34, 35, 36]	1900	2	4.23	–	50
Lignite [34, 35, 37]	1300	2	2.82	9.3	50
Lignite+Post [34, 35]	2100	1	4.58	–	50
Lignite+Oxy [34, 35]	2200	2	5.28	–	50
DOT [38, 37]	322	3	0.28	–	35
NGT [39, 37]	300	3	0.57	1	30
NGCC [39, 37]	500	6	0.16	–	40
NGCC+CCS [39]	850	4	0.58	–	40
Wind (onshore) [38]	1000	3	0	9.5	40
PV [38]	4000	1	0	0.3	30
Hydro [38]	5000	2	0	0.009	80
TNR [40]	-	3	0.87	2.1	60

[a]Abbreviations: PC - Pulverized Coal Power Plant (Hard Coal), Post - Post-combustion capture, Oxy - Oxyfuel Capture, Lignite - Lignite Power Plant, DOT - Diesel Oil Turbine, NGT - Open Cycle Gas Turbine, NGCC - Natural Gas Combined Cycle, Wind - Wind Turbine, PV - Solar Photovoltaics, Hydro - Hydroelectric Power Plant, TNR - Thermonuclear Reactor, PHS - Pumped Storage

[b]All investment costs are overnight costs. All €-values in this paper are 2005 values.

Table A.4: Parametrization of storage technologies

	Inv. costs generator [€/kW]	Inv. costs storage vol. [€/kWh]	Efficiency [%]	O&M fix [%inco/year]	O&M var [€/kW]	Technical lifetime [a]
PHS[a] [45, 46]	1500.00	16.10	80	0.5	21.43	80
CAES[b] [47, 45, 46]	482.94	40.25	60	1.0	15.23	30
Lead Acid [48, 47]	300.00	375.00	70	1.0	56.41	8
H2 FC[c] [45]	800.00	12.07	45	1.0	0.00	15
VRB[d] [45, 48]	2500.00	300.00	70	1.0	0.00	10
LiIon[e] [49, 46, 48]	1.00	500.00	95	1.0	0.00	10

[a]Pumped Hydro Storage
[b]Compressed Air Energy Storage
[c]Electrolysis and Hydrogen Fuel Cell
[d]Vanadium Redox Flow Battery
[e]Lithium Ion Battery

AppendixA.2. Fossil Resources and CCS Potential

The 50Hz Transmission region is assumed to act as a price taker for several fossil fuel types, fuel prices are thus unaffected by demand for fossil energy. Prices for internationally traded hard coal, oil and natural gas are derived from [50][7] for the period of 2005 to 2050, and a constant increase of 2% over 5 years is assumed for the second half of the century. For the price of domestic lignite, we assume a growth rate of 5% p.a. starting from [51]. Furthermore, to represent the lignite open cast mine situation in the 50Hz Transmission region, we introduce a cap on cumulative lignite extraction following [52] for economically extractable resources in approved mines (2.5 Gt). Hence intertemporal optimization implies a scarcity rent that is added to the cost of fuel for lignite.

In line with [53], a total potential of about 10 Gt CO_2 for carbon sequestration is presumed for Germany. We assume that one third of this potential is available for our model region. Power plants equipped with Post-Combustion CCS (PC+CCS, Lignite+CCS, NGCC+CCS) have a capture rate of 90% while Oxyfuel plants are assumed to capture 95% of emissions.

Electricity demand is given exogenously. Starting with 2007 values obtained from [26], an increase of 0.2% p.a. is assumed as this region is expected to experience a moderate development of energy demand. The interest rate is set to 5% p.a.

[7] We use fuel cost path B with a moderate increase.

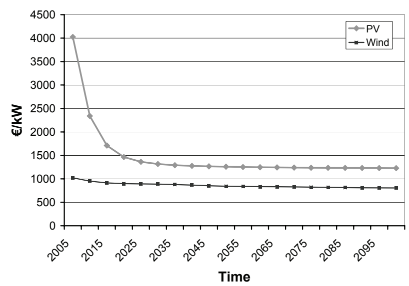


Figure A.12: Wind and PV investment costs

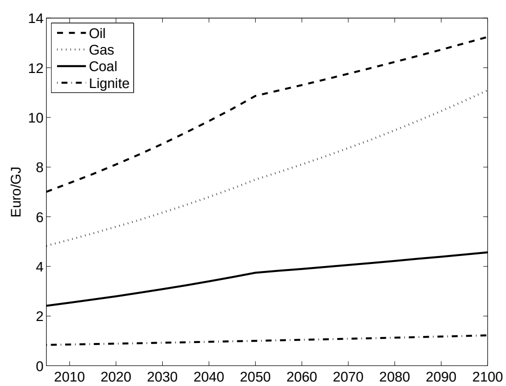


Figure A.13: Fuel price and cost paths (source: [50, 51])

AppendixB. Model equations

This Section provides an overview on the equations used in the model. A nomenclature containing all variables can be found in Table B.5. The model objective (Eq. B.1) consists of a minimization of total discounted power system costs over the model time frame from 2005 to 2100. Power system costs are the sum of investment costs C_I in technologies i in each time step t and operation and maintenance costs $C_{O\&M}$ and fuel costs C_{Fuel} for each technology in each time slice τ and time step t. Furthermore, costs from the applied CO_2 price C_{Emi} are added to power system costs.

$$\min \sum_t \left(\sum_i C_I(t,i) + \sum_{\tau,i} C_{O\&M}(t,\tau,i) + \sum_{\tau,i} C_{Fuel}(t,\tau,i) + \sum_{\tau} C_{Emi}(t,\tau) \right) e^{-\rho t} \quad \text{(B.1)}$$

Electricity generation P_i is constrained by capacities K_i for each technology i and their availability rate ν_i (Eq. B.2). For renewable energy sources, ν_i depends on grades that distinguish differences in resource potential.

$$P_i(t,\tau) \leqslant \nu_i K_i(t) \quad \forall t,\tau \quad \text{(B.2)}$$

Demand for electricity D and production by the different technologies P_i and storage input P^j_{in} and output P^j_{out} have to be balanced within each time slice τ and each time step t (Eq. B.3).

$$\sum_i P_i(t,\tau) + \sum_j P^j_{out}(t,\tau) = \sum_j P^j_{in}(t,\tau) + D(t,\tau) \quad \forall t,\tau \quad \text{(B.3)}$$

From analyses of power drops in the system (as shown in Figure 4), we derive the maximum backup capacity that needs to be present within the

Table B.5: Nomenclature

i	Technology
t	Time step
τ	Time slice
ρ	Interest rate
η_i	Transformation efficiency
ℓ_τ	length of time slice
$C_I(t, i)$	Investment costs
$C_{O\&M}(t, \tau, i)$	O&M Costs
$C_{Fuel}(t, \tau, i)$	Fuel Costs
$C_{Emi}(t, \tau)$	Costs from CO_2 prices
P_i	Electricity generation by technology i
K_i	Capacity of technology i
ν_i	Availability rate
D	Electricity demand
P_{in}^j	storage input
P_{out}^j	storage output

system (relative to the amount of wind and solar power installed). This is introduced into the model as a constraint on necessary backup capacity as shown in Equation B.4. TE_{BACK} describes the group of technologies providing backup (Gas and Oil Turbines, NGCC, Hydropower and storage) and TE_{REN} contains wind power and photovoltaics.

$$\sum_{i \in \mathrm{TE}_{BACK}} K_i(t) \geqslant \mathrm{maxdropfrac} \cdot K_k(t) \quad \forall t, k \in \mathrm{TE}_{REN} \tag{B.4}$$

The same analyses also show how much electricity generation from backup technologies was necessary because of drops in output from renewables. The variable backupprodfrac designates this production relative to the installed capacity of wind power and photovoltaics in Equation B.5, which shows the constraint on output $P_i(t, \tau)$ of backup facilities.

$$\sum_{\tau} \sum_{i \in \mathrm{TE}_{BACK}} P_i(t, \tau) \geqslant \mathrm{backupprodfrac} \cdot K_k(t) \quad \forall t, k \in \mathrm{TE}_{REN} \tag{B.5}$$

The storage implemented into the model consists of two parts: the turbine/pump facility, determining how much power can be produced/stored within each time slices and the storage volume limiting the amount of energy storage in the reservoir. Equation B.6 shows the connection between storage in- and output and storage volume (with η_j being the transfomation efficiency of the storage technology and ℓ_τ the length of a time slice) while Equations B.7 describe the additional capacity constraints for storage.

$$\begin{aligned} P^k_{stor}(t, \tau) = {} & P^k_{stor}(t, \tau - 1) \\ & + \left(\eta_j * P^j_{in}(t, \tau) - P^j_{out}(t, \tau)\right) * \ell_\tau \quad \forall t, \tau \end{aligned} \tag{B.6}$$

$$
\begin{aligned}
&P^j_{in}(t,\tau) && \leq \nu^j(\tau)K^j(t) \quad \forall\tau && \text{Storage input} && \text{(B.7)}\\
&P^j_{out}(t,\tau) && \leq \nu^j(\tau)K^j(t) \quad \forall\tau && \text{Storage output} && \text{(B.8)}\\
&P^k stor(t,\tau) && \leq \nu^k(\tau)K^k(t) \quad \forall\tau && \text{Storage quantity} && \text{(B.9)}
\end{aligned}
$$

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