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IMPRESSUM

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A greenfield model to evaluate long-run power storage requirements for high shares of renewables*

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Abstract

We develop a dispatch and investment model to study the role of power storage and other flexibility options in a greenfield setting with high shares of renewables. The model captures multiple system values of power storage related to arbitrage, dispatchable capacity, and reserves. In a baseline scenario, we find that power storage requirements remain moderate up to a renewable share of around 80%, as other options on both the supply side and demand side also offer flexibility at low cost. Yet storage plays an important role in the provision of reserves. If the renewable share increases to 100%, the required capacities of power storage and other technologies increase strongly. As long-run parameter assumptions are highly uncertain, we carry out a range of sensitivity analyses, for example, with respect to the costs and availabilities of storage and renewables. A common finding of these sensitivities is that – under very high renewable shares – the storage requirement strongly depends on the costs and availability of other flexibility options, particularly on biomass availability. We conclude that power storage becomes an increasingly important element of a transition towards a fully renewable-based power system. Power storage gains further relevance if other potential sources of flexibility are less developed. Supporting the development of power storage should thus be considered a useful component of policies designed to safeguard the transition towards renewables.

Keywords: Power storage; flexibility options; renewable energy; energy transition;

JEL Codes: Q42; Q47; Q48

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1 Introduction

An increasing utilization of renewable energy sources is foreseen in many countries around the world, driven by tighter carbon constraints and growing concerns about security of supply. The power sector is often perceived as a particularly promising area for reaching high shares of renewables. In Germany, the shares of renewable sources in gross power demand have increased from around 3% in the early 1990s to 27% in 2014. In the context of an ambitious long-term *energy transition*, the German government aims for a share of at least 80% by 2050.[1] In the long run, comparable or even higher shares of renewables may also be required in many other countries, as greenhouse gas mitigation options outside the power sector appear to be comparatively expensive

In countries in which hydro, biomass or geothermal resources are limited, achieving such high shares of renewables requires a massive deployment of fluctuating wind and solar power generation. A cost-efficient power system that is largely based on such fluctuating renewables not only requires an appropriate mix of different generation technologies, but also the utilization of dedicated flexibility options such as power storage or demand-side management (DSM).

In this study, we set up a dispatch and investment model to explore the role of different power storage technologies in a long-term greenfield system with high shares of renewables between 60% and 100%. We do so by determining cost-minimizing combinations of generation, DSM, and power storage capacities and their respective dispatch. In addition, we explore the impact of alternative parameter assumptions and different modeling features by carrying out various sensitivity analyses, particularly on future costs and availabilities of different technology options. Whereas our greenfield analysis is parameterized to loosely reflect the German system, the simulation setup is rather general in nature, such that the findings are also relevant for other countries moving toward high shares of fluctuating renewables.

We contribute to the literature in several respects. First, we abstract from path dependencies by simultaneously optimizing the full power system with all capacities being endogenous variables. Next, the analysis not only focuses on the wholesale market, but also considers balancing reserves, the requirements of which are endogenously determined, depending on the deployment of fluctuating renewables. We further include a novel representation of DSM, building on a formulation presented by Zerrahn and Schill (2014), which is applied in a large-scale model for the first time. Aside from DSM and different power storage technologies, which can be freely optimized with respect to their energy to power (E/P) ratio[2], the model comprises further flexibility options such as flexible thermal plants, dispatchable biomass generators, and oversizing as well as curtailment of fluctuating renewables. Importantly, the model-based analysis considers three distinctive system values of storage and other flexibility options: an arbitrage value, a balancing value and a capacity value.[3] In contrast, other analyses often neglect balancing or capacity values by not considering reserve requirements or by not fully optimizing the capacity mix. Notwithstanding these various features, the model is set up as parsimonious as possible in order to remain traceable and to allow for numerous sensitivity analyses.

The remainder is structured as follows. Section 2 discusses the relevant literature. Section 3 introduces the analytical formulation of the numerical model, whereas 4 contains all relevant input data and scenarios. We present model results in section 5 and briefly discuss

[1]This target has been stated in numerous government documents and is also included in the 2014 Renewable Energy Sources Act.

[2]The E/P ratio is the relationship between the energy storage capacity (for example, in MWh) and the power rating (in MW) of a storage technology. Technologies with E/P ratios up to around 4 hours are referred to as short-term storage in the following; a ratio up to around 12 hours qualifies as mid-term storage, and larger ratios as long-term storage.

[3]Network-related values of flexibility options, such as the contribution to congestion management, are not considered here, as assumptions on network constraints would be rather arbitrary in our stylized, long-term, greenfield setting.

possible effects of model limitations in 6. The final section concludes.

2 Literature

The analysis of electricity or, more generally, energy systems with high shares of fluctuating renewables spawned a broad literature featuring a variety of modeling approaches. Naturally, power storage and other flexibility options are one important aspect of such exercises. Between the ends of traceability on the one hand and the degree of technical, economic or spatial detail on the other hand, there is always a trade-off depending on which features a particular focus is laid on. Power system models are suited to their application. In this section, we review some recent contributions related to our work. For a more comprehensive overview of large-scale models for long-term assessments of accommodating large renewable shares, together with a systematic classification, see Despres et al. (2014). While all discussed papers have their virtue and cover multiple aspects we abstract from, we highlight the dimensions our approach may raise complementary insights on.

Dispatch and investment models

Jägemann et al. (2013) apply a version of the electricity market model DIMENSION (Richter, 2011) to analyze different pathways of decarbonizing Europe's power sector. The model features cost-minimal investment and dispatch decisions for a comprehensive geographic coverage of Europe. Its temporal resolution is based on several type days. Consequentially, the intermittency of renewable energy sources (RES) impacts results based on a selected sample. The modeling of longer-term storages is rather vague. As well, demand-side flexibility options are not included.[4] A similar question – a future European electricity system with high shares of fluctuating renewables – is tackled in Nagl et al. (2013): their stochastic greenfield dispatch and investment model distinctly focuses on uncertainty, more precisely risk, concerning the realization of RES feed-in patterns. As central results, the authors put forward that fluctuating renewables are overvalued in a deterministic treatment, and total system costs are substantially higher. As their analysis is based on 30 days, however, the mitigating role of different storage options may be underestimated. Likewise, flexibility options on the demand side are not included.

Another stochastic dispatch and investment model for Europe (E2M2; Spiecker and Weber, 2014) explores different scenarios for long-term decarbonization. Based on a limited number of type hours, flexibility provision from demand-side management and the role of storage are, however, not pronounced.

Ludig et al. (2011) employ the dispatch and investment model LIMES to assess long-term decarbonization paths for a region within Germany. Introducing different storage technologies, the authors find a significantly higher deployment of wind power, along with decreased curtailment. The temporal resolution is based on 96 hours in different time slice configurations. This rather coarse approach may hamper assessing the role of power storage for mitigating RES variability. Flexibility options on the demand side are not included. Widening the geographical scope of the model to Europe and the MENA countries, Haller et al. (2012) aim to explore paths to decarbonize the region at moderate cost. The caveats concerning temporal resolution and demand-side flexibility, however, remain.[5]

Bussar et al. (2014) present a large-scale dispatch and investment model for Europe and the MENA region. Within a 100% renewables scenario, they isolate the different roles for three types of storage: short-term battery systems to accommodate fluctuating RES generation, mid-term pumped hydro storage, and long-term hydrogen storage for seasonal balancing. Beyond a rather opaque methodology, the authors neither incorporate compet-

[4]For a mathematical description of the model, see Fürsch et al. (2013).

[5]A detailed account of the LIMES model is given in Nahmmacher et al. (2014).

ing flexibility options such as DSM nor include the need for balancing reserves. Likewise, sensitivity analyses are not presented.

Hirth (2015) aims to determine the optimal share of variable renewables in Northwestern Europe with a stylized dispatch and investment model. Onshore wind and PV are assumed to incur specific investment costs of 1,300 and 1,600 EUR/kW, respectively, in the long run. These numbers are high compared to most other mentioned studies, particularly for PV. Under these assumptions, and with an assumed long-run CO_2 price of 20 EUR per tonne, Hirth (2015) determines optimal shares of only 2% for onshore wind power and 0% for PV. If cost reductions of 30% for wind and 60% for PV are assumed, long-run shares increase to 20% (wind) and 2% (PV). With a CO_2 price of 100 EUR per tonne, these shares are decreasing again because of assumed investment opportunities in low-cost nuclear and coal-fired plants with carbon capture and storage. Power storage – which is restricted to pumped hydro storage with a fixed E/P ratio of 8 hours – does not play a relevant role in this analysis, which is not surprising given the low renewable shares. To mention two other important shortcomings, the model neither includes power generation from biomass, nor offshore wind power.[6]

Henning and Palzer (2014) set up a comprehensive greenfield dispatch and investment model for analyzing German energy supply. While their approach also features the heat sector as an integral building block, their representation of the electricity system, yet broad, abstracts from aspects such as load flexibility outside the heating sector or control power. Based on one year with full hourly resolution, they present a cost-optimal configuration of the German energy system under 100% renewables in a companion paper (Palzer and Henning, 2014): large deployment of fluctuating wind and solar capacities entail extensive capacity of batteries and power-to-gas storage to ensure stable energy supply. It shall be noted that results are driven by heat demand, which is greater than demand for electricity in terms of energy, and are thus not directly comparable to our setting.

Dispatch models with exogenous capacity variations

Pleßmann et al. (2014) assess global storage deployment necessary for a world-wide transition to wind and solar: while batteries (lead-acid) play only a minor role in complementing fluctuating PV, thermal storage is found most important in accommodating short-term volatility, and power-to-gas serves longer-term mitigation purposes. Their dispatch and investment model covers a resolution of 8760 hours; the modeling details, however, remain rather vague. Likewise, sensitivity analyses are not provided.

De Boer et al. (2014) analyze the effect of storage deployment under high wind penetration. In a dispatch model they vary installed wind and storage facilities of different types on an exogenous scenario basis. The authors put forward that energy storage unfolds its beneficial impact on system costs under large installations of fluctuating wind power as it helps accommodating variability. Under their framework, pumped hydro storage proves most beneficial. Beyond exogenous capacities, their model, however, optimizes on restricted intervals of twelve hours; rendering longer-term benefits of storage difficult. Moreover, demand-side flexibility is neglected.

Jentsch et al. (2014) analyze the role of power-to-gas storage in Germany under a future renewables penetration of 85%. Exogenously varying the deployment of power-to-gas facilities in a dispatch model, they trade off system benefits against installation costs. The authors arrive at an optimal capacity between 6 and 12 GW, depending on whether competing power-to-heat facilities are deployed in parallel, together with an increased integration of fluctuating RES.

Denholm and Hand (2011) carry out an integration study for 80% fluctuating renewables in the Texan system, exogenously varying storage deployment in their dispatch model. The

[6]There is one sensitivity dealing with offshore wind power, but it only draws on historic offshore feed-in profiles without changing the assumed levelized cost of electricity.

authors find that already a moderate penetration – nearly 12 GW with around 138 GWh, compared to 60 GW peak load and 300 TWh annual energy demand – of mid-term (twelve hour) storage can substantially reduce RES curtailment. To address seasonal variability, longer term storage would be necessary, which is beyond the scope of their study.

Finally, Schill (2014) studies short- and long-term storage requirements in Germany under the hypothetical assumption that all renewable surpluses would have to be fully integrated by additional power storage facilities with a stylized dispatch model that allows for endogenous storage investments. In a 2050 scenario, 42 to 66 GW of power storage would be required if no other flexibility options, including temporary renewable curtailment, were available.

Theoretical approaches, time series and agent-based models

Steffen and Weber (2013) analyze storage investments in a high-RES system from a different methodological angle: within a theoretical peak-load pricing model, they carry out a dispatch and investment study for Germany. With low CO_2 prices, storage fulfills its classical role as arbitrageur between base and peak plants. For lower (clean) spreads between technologies, storage investments become efficient only for high RES shares. Beyond 60% renewable penetration, negative residual load triggers the additional role of storage to accommodate fluctuating renewable generation. As their analysis is based on residual load duration curves, information on cyclicality and according issues of storage energy are disregarded. Likewise, demand-side flexibility is only roughly approximated, and additional services as reserve provision are abstracted from.

Another modeling stream employs stylized theoretical time series models to analyze storage requirements to satisfy large shares of demand by fluctuating renewables. Assuming perfect flexibility for conventional power plants, stylized storage technologies serve to shift RES oversupply to periods with positive residual demand.

Weitemeyer et al. (2015) consider the German case. No storage is required to almost fully integrate wind and solar up to a renewable share of 50% in annual electricity demand. Between 50 and 80%, short-term storage is best suited to enhance integration, and for higher RES shares long-term storage is most adequate. For Europe, Heide et al. (2010) determine storage energy needs of 1.5 to 1.8 times the average monthly load. Finally, Rasmussen et al. (2012) identify a mix of efficient short-term storage and long-term hydrogen storage, with an energy capacity amounting to less than 1% of annual energy demand, as sufficient to almost completely integrate fluctuating RES and supply a large fraction of European energy demand by wind and solar. Beyond stylized representation of the generation side, precluding uses for storage other than integrating RES oversupply, Weitemeyer et al. (2015) and Heide et al. (2010) only consider one stylized storage technology defined by energy and efficiency, whereas Rasmussen et al. (2012) considers two stylized technologies. An efficient accommodation of short and long-term fluctuations, thus, cannot be fully captured. Demand-side measures, endogenous investment and an economic evaluation are disregarded, as well.

Genoese and Genoese (2014) pursue an agent-based approach to simulate annual investment decisions and an hourly dispatch for selected years. Taking an investor's perspective in a case study for Germany, they identify the potential for 5 GW of eight-hour pumped hydro storage (PHS) plants in a 58% RES system, where inertia of conventionals as well as a merit order-like effect drive results. In their model, investment in renewables and storage is implemented exogenously via scenarios. An optimization horizon of one day precludes the analysis of longer-term storage. Likewise, demand-side flexibility is neglected.

Gray literature

Several studies dealing with long-term power storage requirements in Germany have been published as gray literature. For example, VDE (2012b) study the requirement of two stylized short- and long-term storage options with a pure dispatch model. For a renewable share of 80%, 14 and 18 GW of short-term and long-term storage are considered economically advantageous. In a 100% renewable scenario, these values strongly increase to 36 and 68 GW short- and long-term storage, respectively. Yet the analysis abstracts from most other flexibility options, including DSM, and may thus overestimate storage requirements.

In the so-called "Roadmap Storage", Pape et al. (2014) determine German long-term storage requirements in a European context with a model that partially includes investment decisions.[7] For renewable shares under 70%, no additional storage investments are needed compared to assumed existing capacities. In a 88% case, additional short-term storage investments between 0 and around 20 GW are needed, depending on the availability of solar thermal power imports, DSM potentials, and other flexibility options. Among seven distinctive technologies, lead acid batteries are the dominant option. Results are largely driven by extensive power exchange with neighboring countries, which are assumed to have somewhat lower shares of renewables in all scenarios, and by the assumption of a very flexible demand side.

In a related study that draws on a pure dispatch model, Agora (2014) find that up to a renewable share of 60%, a moderate extension of existing German storage capacities would be beneficial only in case of optimistic assumptions on storage cost developments combined with pessimistic assumptions on system flexibility. For a share of 90%, additional installations of 7 and 16 GW short- and long-term storage would be preferable.

Synthesis

In a complete view, the literature does not provide coherent evidence, yet some broad common findings emerge. First, different types of storage are found be valuable to accommodate increasing generation of fluctuating RES. In this respect, up to around 50% to 70% RES penetration, only moderate storage deployment is necessary. Second, for higher shares, mostly short- and mid-term storage (roughly up to twelve hours) proves economical. The bulk of the literature identifies long-term storage entering optimal system configurations only for very high RES shares. The particular assessment, naturally, depends on the specific cost and efficiency projections.

In many models, the time resolution is rather coarse, for example based on aggregated type days, rendering a more in-depth assessment of longer-term storage deployment difficult. Likewise, competing flexibility options on the demand side are often disregarded; as is the potential value of storage for the balancing segment. Moreover, many complex and computationally demanding models tend to be silent about sensitivities towards parameter assumptions – of which many usually have to be made. With our approach, we aim to tackle these issues and thus complement previous research.

3 The Model

The model minimizes total system costs over 8760 hours of a full year. System costs comprise annualized investment costs and fixed costs as well as variable costs of conventional generators, renewables, power storage, and DSM. As for storage, seperate investment decisions on power and energy capacities are made. The model ensures that power generation equals (price-inelastic) demand at all times, while also accounting for the provision and activation of balancing reserves. The full analytical formulation is provided in the following. Capital letters denote variables, and lowercase letters denote parameters. Tables 1, 2, and 3 provide an overview of the sets, variables, and parameters used.

[7] The study also contains an analysis of short- and mid-term storage requirements, which is carried out with a pure dispatch model.

Table 1: Sets

Set	Element	Description
$\mathfrak{C}$	$\ni con$	Conventional generation technologies
$\mathfrak{RE}$	$\ni res$	Renewable generation technologies
$\mathfrak{S}$	$\ni sto$	Storage technologies
$\mathfrak{LC}$	$\ni lc$	DSM load curtailment technologies
$\mathfrak{LS}$	$\ni ls$	DSM load shifting technologies
$\mathfrak{H}$	$\ni h$, hh	Hours
$\mathfrak{R}$	$\ni r$	Reserve energy qualities (PR, SR^{+}, SR^{-}, MR^{+}, MR^{-})

Table 2: Variables

Variables	Unit	Description
$\beta_{con,h}$	[MW]	*Balancing Correction Factor* conventional technology *con* in hour h
$CU_{res,h}$	[MW]	Curtailment renewable technology *res* in hour h
Δ_{r}	[MW]	Reserves demand of quality r
$DSM^{cu}_{lc,h}$	[MW]	Load curtailment curtailment technology lc in hour h
$DSM^{+}_{ls,h}$	[MW]	Net load increase shifting technology ls in hour h
$DSM^{-}_{ls,h,hh}$	[MW]	Net load decrease shifting technology ls in hour hh accounting for increases in hour h
$DSM^{d+}_{ls,h}$	[MW]	Load increase taking effect in the wholesale segment shifting technology ls in hour h
$DSM^{d-}_{ls,h}$	[MW]	Load decrease taking effect in the wholesale segment shifting technology ls in hour h
$G^{l}_{con,h}$	[MW]	Generation level conventional technology *con* in hour h
$G^{+}_{con,h}$	[MW]	Generation increase conventional technology *con* in hour h
$G^{-}_{con,h}$	[MW]	Generation decrease conventional technology *con* in hour h
$G_{res,h}$	[MW]	Generation renewable technology *res* in hour h
$P_{r,con,h}$	[MW]	Reserves provision quality r in hour h by conventional technology *con*; analogous for renewable, storage and DSM technologies
$S^{in}_{sto,h}$	[MW]	Storage inflow technology *sto* in hour h
$S^{out}_{sto,h}$	[MW]	Storage outflow technology *sto* in hour h
$S^{l}_{sto,h}$	[MWh]	Storage level technology *sto* in hour h
N_{con}	[MW]	Installed capacity conventionals
N_{res}	[MW]	Installed capacity renewables
N^{E}_{sto}	[MWh]	Installed capacity storage energy
N^{P}_{sto}	[MW]	Installed capacity storage power
N_{lc}	[MW]	Installed capacity DSM load curtailment
N_{ls}	[MW]	Installed capacity DSM load shifting

Table 3: Parameters

Parameters	Description
α	Hourly called fraction of provided reserves
$\bar{\alpha}_r$	Mean hourly activation of reserve type r
c^{cu}	Curtailment costs
c^{fix}	Annual fixed costs
c^i	Annualized specific investment costs
c^{iE}_{sto}	Annualized specific investments into storage energy
c^{iP}_{sto}	Annualized specific investments into storage power
c^m	Marginal costs
c^+	Load change costs for increases
c^-	Load change costs for decreases
d_h	Hourly wholesale demand
δ	Demand for primary reserves as fraction of demand for other reserves types
η_{ls}	DSM load shifting efficiency factor
η_{sto}	Storage roundtrip efficiency
γ^1	Fraction of secondary (minute) reserves among positive and negative reserves
γ^2	Intercept of reserve demand regression line
γ^3	Slope of reserve demand regression line
m^E_{bio}	Yearly energy cap for biomass
m_{lc}	Maximum installable DSM load curtailment capacity
m_{ls}	Maximum installable DSM shifting capacity
π	Maximum load change per minute
ϕ	Hourly delivered energy by renewables as fraction of installed capacity
ρ	Recovery time DSM
σ^{res}	Minimum fraction of annual total net load served by renewables
θ	Duration DSM
ζ	Initial storage level as fraction of storage energy installed

The objective function is given as

$$
\begin{aligned}
C = \sum_{h} \Bigg[& \sum_{con} \left(c^{m}_{con} G^{l}_{con,h} + c^{+}_{con} G^{+}_{con,h} + c^{-}_{con} G^{-}_{con,h} \right) + \sum_{res} c^{cu}_{res} CU_{res,h} \\
& + \frac{1}{2} \sum_{sto} c^{m}_{sto} \left(S^{out}_{sto,h} + S^{in}_{sto,h} \right) + \frac{1}{2} \sum_{ls} c^{m}_{ls} \left(DSM^{d+}_{ls,h} + DSM^{d-}_{ls,h} \right) + \sum_{lc} c^{m}_{lc} DSM^{cu}_{lc,h} \Bigg] \\
& + \sum_{con} \left[\left(c^{i}_{con} + c^{fix}_{con} \right) N_{con} \right] + \sum_{res} \left[\left(c^{i}_{res} + c^{fix}_{res} \right) N_{res} \right] \\
& + \sum_{sto} \left[\left(c^{iP}_{sto} + \frac{1}{2} c^{fix}_{sto} \right) N^{P}_{sto} + \left(c^{iE}_{sto} + \frac{1}{2} c^{fix}_{sto} \right) N^{E}_{sto} \right] \\
& + \sum_{lc} \left[\left(c^{i}_{lc} + c^{fix}_{lc} \right) N_{lc} \right] + \sum_{ls} \left[\left(c^{i}_{ls} + c^{fix}_{ls} \right) N_{ls} \right] \\
& + \frac{1}{2} \sum_{r} \sum_{h} \alpha_{r,h} \left[\sum_{sto} c^{m}_{sto} P_{r,sto,h} + \sum_{ls} c^{sh}_{ls} P_{r,ls,h} \right] \\
& + \sum_{lc} \sum_{h} c^{cu}_{lc} \left(P_{SR^{+},lc,h} \alpha_{SR^{+},h} + P_{MR^{+},lc,h} \alpha_{MR^{+},h} \right) \qquad (1)
\end{aligned}
$$

Specifically, capacity investments N occur per technology without addressing discrete units. Yet to account for different flexibility capabilities of conventional installations in following residual demand, we model the generation level of technology *con* in hour h, $G^{l}_{con,h}$, which can be altered by costly increases $G^{+}_{con,h}$ and $G^{-}_{con,h}$. The attached load change costs c^{+}_{con}, c^{-}_{con} vary by technology and reflect different levels of flexibility. The constraint for these generation dynamics is given by

$$
\begin{aligned}
G^{l}_{con,h} &= G^{l}_{con,h-1} + G^{+}_{con,h} - G^{-}_{con,h} && \forall con, h > 1 \qquad (2a) \\
G^{l}_{con,1} &= G^{+}_{con,1} && \forall con \qquad (2b)
\end{aligned}
$$

together with an initial condition for the first model period. Generation level $G^{l}_{con,h}$ and load changes $G^{+}_{con,h}$, $G^{-}_{con,h}$ are net in the sense that they comprise both energy actually delivered to the wholesale market and activated reserves. For the hourly energy balance 4, equalizing wholesale supply and demand, the generation level has to be corrected for the reserves share. To this end, we introduce the *Balancing Correction Factor* $\beta_{con,h}$.

$$
\begin{aligned}
\beta_{con,h} \equiv & -P_{SR^{+},con,h} \alpha_{SR^{+},h} - P_{MR^{+},con,h} \alpha_{MR^{+},h} \\
& + P_{SR^{-},con,h} \alpha_{SR^{-},h} + P_{MR^{-},con,h} \alpha_{MR^{-},h} \qquad \forall con, h \qquad (3)
\end{aligned}
$$

where for reserves type r, $P_{r,con,h}$ is the capacity provided by technology *con* in hour h. If a certain amount of secondary or minute reserve capacities is provided, fraction $\alpha_{r,h} \in [0, 1]$ will be called, following actual data from the base year. Primary reserves merely have to be provided without being called.[8] Wholesale gross supply by conventional generators is thus expressed as $G^{L}_{con,h} + \beta_{con,h}$. The (wholesale) energy balance reads

$$
d_h + \sum_{sto} S^{in}_{sto,h} + \sum_{ls} DSM^{d+}_{ls,h}
$$

[8]Note that for primary reserves, we also do not discriminate between positive and negative qualities. This choice reflects the actual market design in Germany and many other European countries.

$$= \sum_{con} \left(G^{l}_{con,h} + \beta_{con,h}\right) + \sum_{res} G_{res,h} + \sum_{sto} S^{out}_{sto,h} + \sum_{lc} DSM^{cu}_{lc,h} + \sum_{ls} DSM^{d-}_{ls,h} \quad \forall h \tag{4}$$

Equally for reserves of each type r, provision by conventional generators, storage, renewables, load curtailment, and load shifting, must equal demand Δ_r in each hour.

$$\sum_{con} P_{r,con,h} + \sum_{sto} P_{r,sto,h} + \sum_{res} P_{r,res,h} + \sum_{lc} P_{r,lc,h} + \sum_{ls} P_{r,ls,h} = \Delta_r \qquad \forall h \tag{5a}$$

where DSM is assumed not to be suited to satisfy primary reserves, and load curtailment cannot provide negative balancing power. Reserves demand is constant over all periods. It is determined endogenously in the model as a function of installed wind and solar capacities according – for secondary and minute reserves – to the following regression equation

$$\Delta_r \equiv 1000 * \gamma^1_r * \left(\gamma^2_r + \sum_{res} \gamma^3_{r,res} N_{res}/1000\right) \qquad \forall r \in \mathfrak{R} \setminus PR \tag{5b}$$

Parameter γ^1_r is the split between secondary and minute reserves, for positive and negative reserves separately.[9] Intercept and slope of the reserves regression line are rendered by γ^2_r, and $\gamma^3_{r,res}$ respectively. For the parameters we draw on Ziegenhagen (2013), who carried out a statistical convolution analysis determining reserves demand as a function of installed capacities of variable renewables. Demand for primary reserves is symmetric and rendered as fraction δ of overall demand for the other types of reserves, resembling the actual ratio for Germany.

$$\Delta_{PR} = \delta \sum_{r \in \mathfrak{R} \setminus PR} \Delta_r \tag{5c}$$

Moreover, we impose flexibility requirements on conventional generators for providing reserves, depending on the current load level of the technology.

$$P_{PR,con,h} \leq 0.5\pi_{con} \left(G^{l}_{con,h} + \beta_{con,h}\right) \qquad \forall con, h \tag{5d}$$
$$P_{SR^+,con,h} \leq 5\pi_{con} \left(G^{l}_{con,h} + \beta_{con,h}\right) \qquad \forall con, h \tag{5e}$$
$$P_{SR^-,con,h} \leq 5\pi_{con} \left(G^{l}_{con,h} + \beta_{con,h}\right) \qquad \forall con, h \tag{5f}$$
$$P_{MR^+,con,h} \leq 15\pi_{con} \left(G^{l}_{con,h} + \beta_{con,h}\right) \qquad \forall con, h \tag{5g}$$
$$P_{MR^-,con,h} \leq 15\pi_{con} \left(G^{l}_{con,h} + \beta_{con,h}\right) \qquad \forall con, h \tag{5h}$$

Equation 5e for instance restricts secondary reserves provision to the flexibility within five minutes where π_{con} is the maximum technically possible load change per minute.

The maximum production constraint on conventional generators requires gross wholesale generation plus positive reserves provision to be no larger than installed capacity.

$$G^{l}_{con,h} + \beta_{con,h} + P_{PR,con,h} + P_{SR^+,con,h} + P_{MR^+,con,h} \leq N_{con} \qquad \forall con, h \tag{6a}$$

Similarly, conventional generators may produce no less on the wholesale market than provided as negative reserves.

[9] Data follow the historical pattern of the years 2010-2012. Variations between years are negligible. We therefore refrain from adapting to the respective base year of the analysis. The dimensioning of the input data demands multiplication and division by the factor 1000.

$$P_{PR,con,h} + P_{SR^+,con,h} + P_{MR^+,con,h} \leq G^l_{con,h} + \beta_{con,h} \qquad \forall con, h \qquad (6b)$$

Constraints on renewables comprise the distribution of fed-in energy, 7a, between load serving $G_{res,h}$, costless curtailment $CU_{res,h}$, and positive reserve provision.[10] For each type of installed capacity N_{res}, $\phi_{res,h}$ describes the hourly availability factor based on exogenous actual time series from the respective base year.

Equation 7c is of central importance for our analysis: the share of conventional generation in the total yearly energy delivered may be no larger than $(1 - \sigma^{res})$. Put differently, σ^{res} prescribes the minimum renewable share in the electricity system.[11] Total yearly consumed energy, in this respect, comprises load minus load curtailment by DSM measures in the wholesale and reserves segments, as well as storage losses in both segments, corrected by actually activated reserves. For convenience, $\bar{\alpha}_r$ denotes the mean hourly activation of reserve type r. Finally, 7d caps the overall energy delivered by biomass at m^E_{bio}.

$$G_{res,h} + CU_{res,h} + P_{PR,res,h} + P_{SR^+,res,h} + P_{MR^+,res,h} = \phi_{res,h} N_{res} \qquad \forall res, h \qquad (7a)$$

$$P_{PR,res,h} + P_{SR^-,res,h} + P_{MR^-,res,h} \leq G_{res,h} \qquad \forall res, h \qquad (7b)$$

$$\begin{aligned}
\sum_{con \in \mathfrak{C} \setminus bio} \sum_h G^l_{con,h} \leq \\
(1 - \sigma^{res}) \sum_h \Bigg[& d_h + \sum_{sto} \left(S^{in}_{sto,h} - S^{out}_{sto,h} \right) - \sum_{lc} DSM^{cu}_{lc,h} \\
& + \bar{\alpha}_{SR^+} \Delta_{SR+^+} + \bar{\alpha}_{MR^+} \Delta_{MR^+} - \bar{\alpha}_{SR^-} \Delta_{SR^-} - \bar{\alpha}_{MR^-} \Delta_{MR^-} \\
& + \sum_{sto} \big[P_{SR^-,sto,h} \alpha_{SR^-,h} + P_{MR^-,sto,h} \alpha_{MR^-,h} \\
& \qquad - P_{SR^+,sto,h} \alpha_{SR^+,h} - P_{MR^+,sto,h} \alpha_{MR^+,h} \big] \\
& - \sum_{lc} \big[P_{SR^+,lc,h} \alpha_{SR^+,h} + P_{MR^+,lc,h} \alpha_{M^+,h} \big] \Bigg] \qquad (7c)
\end{aligned}$$

$$\sum_h G^l_{bio,h} \leq m^E_{bio} \qquad (7d)$$

The next set of constraints is related to storage technologies where efficiency losses in the storage dynamics equations 8a and 8b are attributed equally to loading and generation. Investments into energy and power are generally mutually independent – that is we do not impose a predetermined E/P ratio – and power investments are assumed to be symmetric between inflows and outflows; 8c - 8e. Equations 8f, 8g restrict provision of reserves to installed storage power. Two additional, more subtle restrictions concerning reserve provision are required: 8h constrains generation for satisfying wholesale demand plus positive reserve provision to last period's storage level, and 8i restricts storage inflow plus negative reserve provision to the wedge between energy capacity and last period's level. Otherwise, perverse patterns of storage behavior would be possible. For instance, an empty storage could provide reserves while anticipating never being called. Finally, to counteract model artifacts of excessive loading in the first periods, each technology starts with a fraction ζ of installed

[10] We set c^{cu}_{res} to zero in the numerical application.

[11] Note that biomass, a renewable source, is from the model's point of view categorized as a conventional technology as we assume it dispatchable; biomass nonetheless adds to the renewable share of the system.

energy as initial level of energy stored 8a. Likewise, energy stored after the last period of the model horizon must equal that initial level according to 8j.

$$
\begin{aligned}
S^{l}_{sto,1} &= \zeta * N^{E}_{sto} + S^{in}_{sto,1}\tfrac{(1+\eta_{sto})}{2} - S^{out}_{sto,1}\tfrac{2}{(1+\eta_{sto})} && && \text{(8a)}\\
S^{l}_{sto,h} &= S^{l}_{sto,h-1} + S^{in}_{sto,h}\tfrac{(1+\eta_{sto})}{2} - S^{out}_{sto,h}\tfrac{2}{(1+\eta_{sto})} \\
&\quad + \left(P_{SR^-,sto,h}\alpha_{SR^-,h} + P_{MR^-,sto,h}\alpha_{MR^-,h}\right)\tfrac{(1+\eta_{sto})}{2} \\
&\quad - \left(P_{SR^+,sto,h}\alpha_{SR^+,h} + P_{MR^+,sto,h}\alpha_{MR^+,h}\right)\tfrac{2}{(1+\eta_{sto})} && \forall h > 1 && \text{(8b)}
\end{aligned}
$$

$$
\begin{aligned}
S^{l}_{sto,h} &\leq N^{E}_{sto} && \forall sto, h && \text{(8c)}\\
S^{in}_{sto,h} + P_{PR,sto,h} + P_{SR^-,sto,h} + P_{MR^-,sto,h} &\leq N^{P}_{sto} && \forall sto, h && \text{(8d)}\\
S^{out}_{sto,h} + P_{PR,sto,h} + P_{SR^+,sto,h} + P_{MR^+,sto,h} &\leq N^{P}_{sto} && \forall sto, h && \text{(8e)}\\
P_{PR,sto,h} + P_{SR^+,sto,h} + P_{MR^+,sto,h} &\leq S^{in}_{sto,h} + N^{P}_{sto} && \forall sto, h && \text{(8f)}\\
P_{PR,sto,h} + P_{SR^-,sto,h} + P_{MR^-,sto,h} &\leq S^{out}_{sto,h} + N^{P}_{sto} && \forall sto, h && \text{(8g)}\\
S^{out}_{sto,h} + P_{PR,sto,h} + P_{SR^+,sto,h} + P_{MR^+,sto,h} &\leq S^{l}_{sto,h-1} && \forall sto, h && \text{(8h)}\\
S^{in}_{sto,h} + P_{PR,sto,h} + P_{SR^-,sto,h} + P_{MR^-,sto,h} &\leq N^{E}_{sto} - S^{l}_{sto,h-1} && \forall sto, h && \text{(8i)}\\
S^{l}_{sto,h} &= \zeta * N^{E}_{sto} && \forall sto, h = |\mathfrak{H}| && \text{(8j)}
\end{aligned}
$$

Demand side management (DSM) measures are separated into load curtailment (lc) and load shifting (ls) measures. For load curtailment, demand is reduced in one period without recovery at a later point in time. Each installed facility N_{lc} may cut load once every ρ_{lc} hours, the recovery period, for a duration of maximally θ_{lc} hours. By reducing demand, load curtailment may also provide positive reserve energy.

$$
\begin{aligned}
\sum_{hh, h \leq hh < h+\rho_{lc}} & DSM^{cu}_{lc,hh} + P_{SR^+,lc,hh}\alpha_{SR^+,hh} \\
& + P_{MR^+,lc,hh}\alpha_{MR^+,hh} \leq N_{lc}\theta_{lc} && \forall lc, h && \text{(9a)}\\
DSM^{cu}_{lc,h} + P_{SR^+lc,h} &+ P_{MR^+lc,h} \leq N_{lc} && \forall lc, h && \text{(9b)}
\end{aligned}
$$

The implementation of DSM load shifting follows a granular interpretation: units which are shifted up in hour h, denoted by $DSM^{+}_{ls,h}$, must be shifted down again in the surrounding θ_{ls} hours, corrected by the efficiency factor η_{ls}.[12] In this respect, $DSM^{-}_{ls,h,hh}$ carries two time indices, representing downshifts in hour hh to account for upshifts in hour h. Equation 9c employs this double-indexation to ensure that each unit of load on hold is recovered within the specified duration period θ_{ls} of the DSM technology. Both DSM upshifts and downshifts may either take effect for the wholesale or the reserves segment.[13] Therefore, equation 9d distributes the respective net upshift $DSM^{+}_{ls,h}$ into a share $DSM^{d+}_{ls,h}$ entering the energy balance of supply and demand on the wholesale market, 4, and a share serving negative reserves activation. The analogous distribution equation for negative shifts is given by 9e, where the left-hand side simply represents all downshifts within period h, regardless for which hour's upshifts they account for. Interpreting each installed DSM load shifting unit N_{ls} as one granular unit which in each period can either shift up demand, shift down demand, provide reserves of one quality, or be inactive, then equation 9f ensures that no undue overuse takes place. Equation 9g specifies a recovery period ρ_{ls} for each DSM load shifting installation, and 9h, 9i restrict maximum investments. For a more in-depth treatment of the implemented DSM representation, see Zerrahn and Schill (2014).

[12] We set η_{ls} to zero in the numerical application.

[13] We assume DSM not to participate in primary reserves provision.

$$DSM^{+}_{ls,h}\eta_{ls} = \sum_{hh,h-\theta_{ls}\leq hh\leq h+\theta_{ls}} DSM^{-}_{ls,h,hh} \qquad \forall h \qquad (9c)$$

$$DSM^{+}_{ls,h} = DSM^{d+}_{ls,h} + P_{SR^{-},ls,h}\alpha_{SR^{-},h} + P_{MR^{-},ls,h}\alpha_{MR^{-},h} \qquad \forall ls,h \qquad (9d)$$

$$\sum_{hh,h-\theta_{ls}\leq hh\leq h+\theta_{ls}} DSM^{-}_{ls,hh,h} = DSM^{d-}_{ls,h} + P_{SR^{+},ls,h}\alpha_{SR^{+},h} + P_{MR^{+},ls,h}\alpha_{MR^{+},h} \qquad \forall ls,h \qquad (9e)$$

$$DSM^{d+}_{ls,h} + DSM^{d-}_{ls,h} + \sum_{r\in\Re\setminus PR} P_{r,ls,h} \leq N_{ls} \qquad \forall ls,h \qquad (9f)$$

$$\sum_{hh,h\leq hh<h+\rho_{ls}} DSM^{+}_{ls,h} \leq N_{ls}\theta_{ls} \qquad \forall ls,h \qquad (9g)$$

$$N_{lc} \leq m_{lc} \qquad \forall lc \qquad (9h)$$

$$N_{ls} \leq m_{ls} \qquad \forall ls \qquad (9i)$$

4 Data and Scenarios

The model is loosely calibrated to the German power system with regard to demand, hourly availabilities of fluctuating renewables, and constraints for offshore, wind power, biomass, pumped hydro storage, and DSM. Hourly load values are taken from ENTSO-E (2014) for the year 2013. For the fraction of reserves called, we divide the mean hourly actually activated reserves, provided by the German TSOs for 2013 (regelleistung.net, 2014a), by the contracted capacities at that point (regelleistung.net, 2014b).

Aside from such time-related input data, which is based on 2013 under baseline assumptions, all technology-specific input parameters reflect a 2050 perspective. Tables 5 to 9 in the Appendix contain a detailed representation of all technology-specific assumptions of the baseline, including respective units and data sources. Annualized fixed costs are generally calculated by drawing overnight investment costs, fixed costs not related to power generation (where applicable), specific technical lifetimes, and an assumed interest rate of 4%. Monetary values are generally stated in real prices of 2010.

Regarding thermal generation technologies, we include hard coal, combined cycle natural gas (CCGT) and two types of open cycle natural gas turbines (OCGT) – an “efficient” one with lower marginal but higher investment costs, and an “inefficient” type for which the opposite is true. By assumption, investments into nuclear, lignite, and run-of-river hydro power are not possible. In case of nuclear, this reflects the legal situation in Germany. Lignite plants, which have high specific CO_2 emissions, are assumed not to be compatible with a long-term, low-emission, renewable-based system.[14] Run-of-river is excluded because, on the one hand, potentials in Germany are small; on the other, it is a non-dispatchable low-cost technology, such that unlimited investment opportunities would render model results trivial.

The major source for cost parameters for conventional generators and biomass plants is the DIW Data Documentation (Schröder et al., 2013), of which medium projections for 2050 are used. Supplementary information stems from VGB PowerTech (2012), and from VDE (2012a) for load change flexibility. Marginal production costs of conventional plants are calculated based in the carbon content of the fuel (Umweltbundesamt, 2013), an assumed

[14] This assumption appears not to be critical. Additional model runs that include a lignite option parametrized according to Table show that no such investments take place under the assumed baseline CO_2 price of 100 Euro per tonne, as lignite plants incur both high investments and variable costs.

CO_2 price of 100 Euro per tonne, and specific efficiency and fuel costs. Fuel prices follow the “medium” price path within DLR et al. (2012), except for dena (2012) for lignite.

Regarding fluctuating renewable technologies, we include onshore and offshore wind power as well as solar photovoltaics. In addition, investments in dispatchable biomass generators – which are treated like conventional thermal plants in the model formulation – are possible. Cost data for renewables as well comes from Schröder et al. (2013). Under baseline assumptions, a cap on offshore wind power installations of 32 GW is assumed, leaning on DLR et al. (2012). We further assume a yearly biomass budget of 60 TWh in the baseline (BMU, 2012). We calculate hourly renewable availability factors by dividing the 2013 hourly in-feed of onshore wind (50Hertz Transmission, 2014b; Amprion, 2014b; TenneT TSO, 2014b; TransnetBW, 2014b), offshore wind (TenneT TSO, 2014b), or solar PV (50Hertz Transmission, 2014a; Amprion, 2014a; TenneT TSO, 2014a; TransnetBW, 2014a), provided by the German TSOs, by the installed capacity in the same year (BMWi, 2014).[15].

Building on Pape et al. (2014), we consider seven distinctive storage technologies which vary with respect to specific investments into power and energy as well as roundtrip efficiency. In most scenarios, investment choices are restricted to three of these technologies: lithium-ion batteries (Li-ion, as an example for a short-term storage technology), pumped hydro storage (PHS, mid-term), and power-to-gas (P2G, long-term).[16] The remaining four technologies are included only in a sensitivity as these are considered to be either risky with respect to environmental or security concerns, such as lead acid batteries and sodium-sulfur (NaS) batteries, or not to be cost-competitive with the other storage options like redox flow batteries and advanced adiabatic compressed air energy storage (AA-CAES). For DSM potentials and costs, we largely draw upon Frontier (2014) who assemble evidence from numerous academic and applied studies, as well as on Klobasa (2007), Gils (2014), and Agora (2013).

The model is implemented in the General Algebraic Modeling System (GAMS) and solved with the commercial solver CPLEX.[17] We apply the model to a baseline scenario and to numerous sensitivities, while always varying the requirement for the minimum renewable share between 60, 70, 80, 90, and 100%. In order to study the effect of deviating parameter assumptions and model, we carry out various sensitivity analyses (Table 4).

A first group of sensitivities deals with different assumptions on the costs and availabilities of power storage technologies: availability of additional storage technologies, deviations of specific investment costs, and a tighter energy cap for pumped hydro storage. Next, we consider two extreme variations of the assumed DSM potentials (zero or double compared to the baseline). Another group of sensitivities relates to costs and availabilities of renewables. This includes alternative assumptions on offshore wind power costs and potentials – a very important sensitivity for transferring results to other countries with higher or lower offshore wind potentials compared to Germany –, smoother onshore wind profiles[18], and alternative specific investments for PV. Moreover, we include a sensitivity on the availability of biomass and a worst case with respect to fluctuating renewable feed-in by assuming a week of “dark winter doldrums”, during which electricity demand is high, but no power generation from onshore wind, offshore wind, or PV is possible. We moreover vary the level of required reserves, which may be considered both as a sensitivity with respect to a distinctive model feature or a parameter assumption.

In Appendix A.2, we also provide capacity outcomes for sensitivity analyses with respect to the base year. While the patterns of renewable feed-in and load are based on German data of 2013 in all aforementioned model runs, we test the effect of alternatively drawing on 2011 or 2012 data. Yet the results are not fully comparable to 2013, as the offshore wind feed-in data is less reliable, being based on very few single wind turbines, such that results

[15]For convenience, we impose a linear expansion path on the installed capacities between the beginning and the end of 2013.

[16]Here, “power-to-gas” involves the use of electricity to generate hydrogen and later reconversion to electricity. A more precise, but rather lengthy term would be “power-to-hydrogen-to-power”.

[17]The source code and all input data is freely available from the authors upon request.

[18]Profiles are taken from Gerbaulet et al. (2014).

Table 4: Assumptions for sensitivities

Availability of storage technologies

	Li-ion	Lead acid	NaS	Redox flow	PHS	AA-CAES	P2G
Baseline	✓	-	-	-	✓	-	✓
Additional technologies	✓	✓	✓	✓	✓	✓	✓

Annualized specific investment costs of storage in EUR/kWh, EUR/kW

	Li-ion	Lead acid	NaS	Redox flow	PHS	AA-CAES	P2G
Baseline, c_{sto}^{iE}	14	-	-	-	< 1	-	< 1
Baseline, c_{sto}^{iP}	3	-	-	-	46	-	68
Double costs, c_{sto}^{iE}	28	-	-	-	1	-	< 1
Double costs, c_{sto}^{iP}	5	-	-	-	92	-	136
Half costs, c_{sto}^{iE}	7	-	-	-	< 1	-	< 1
Half costs, c_{sto}^{iP}	1	-	-	-	23	-	34

Storage energy restriction in GWh

	Li-ion	Lead acid	NaS	Redox flow	PHS	AA-CAES	P2G
Baseline	∞	-	-	-	300	-	∞
Tight restriction	∞	-	-	-	50	-	∞

DSM potentials in MW

	Load shifting					Load curtailment		
	1 h	2 h	3 h	4 h	12 h	cheap	medium	expensive
Baseline	793	2,535	1,385	1,451	1,050	3,300	1,600	5,400
No potential	0	0	0	0	0	0	0	0
Double potential	1,585	5,088	2,770	2,902	2,100	6,600	3,200	10,800

Offshore wind power costs and potentials

Baseline	32 GW
No offshore wind	0 GW
Offshore breakthrough	53 GW, and half specific investment costs

Onshore wind profiles

Baseline	Derived from German feed-in time series of 2013
Smooth	Smoothed pan-European pattern based on wind speed data of 2011

Specific annualized investment costs of PV in EUR/kW

Baseline	27
Double costs	54
Half costs	14

Dark winter doldrums

Baseline	Wind and PV availability according to German patterns of 2013
Dark winter doldrums	No wind and PV feed-in in week 45

Energy restriction on biomass in TWh

Baseline	60
No biomass	0

Reserve requirements

	γ_+^2	γ_+^3	γ_-^2	γ_-^3
Baseline, wind	1.912	0.031	3.242	0.026
Baseline, PV	1.912	0.005	3.242	0.018
No reserves, wind	0	0	0	0
No reserves, PV	0	0	0	0
Double reserves, wind	1.912	0.062	3.242	0.052
Double reserves, PV	1.912	0.010	3.242	0.036

Note: specific investment costs calculated using overnight investment costs and lifetime of the installation as provided in the appendix as well as an interest rate of 4%. Numbers generally rounded to integers, and to three decimals for reserve parameters. For reserve requirements, subscript $+$ indicates relevance for positive reserves, subscript $-$ for negative reserves.

may be distorted with respect to one decisive variable, i.e., offshore wind power deployment.

5 Results

5.1 Baseline scenario

Under baseline assumptions, we determine a renewable share of around 76.4% in the unrestricted case.[19] Photovoltaics and onshore wind power have the largest capacities installed (Figure 1). If the minimum renewable share approaches 100%, overall capacities increase strongly. Gas-fired power plants are substituted by a mix of other flexibility options in the 100% case. First, the capacity of dispatchable biomass increases strongly, while its energy limit stays constant. Biomass full-load hours accordingly decrease strongly. Second, the capacities of fluctuating renewables increase disproportionately. Offshore wind power reaches its installation limit already in the 90% case. At the same time, renewable curtailment increases from around 1.2% in the unrestricted case to more than 7% in the 100% case. Third, storage capacities are expanded.

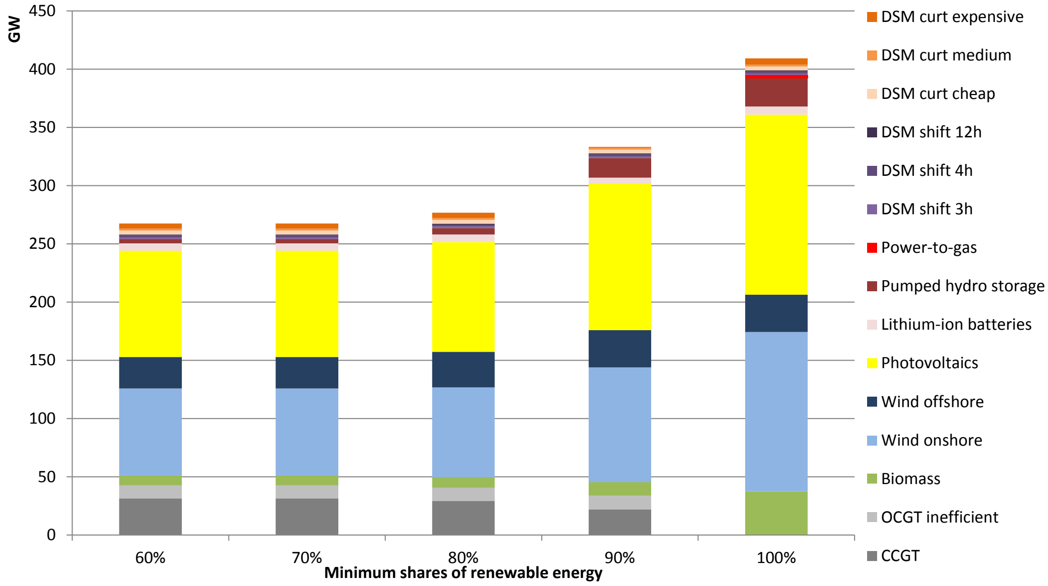

Figure 1: Baseline scenario: installed capacities

[19] As restriction 7c is not binding for minimum shares of both 60% and 70%, these can be interpreted as "unrestricted" cases. The same reasoning applies in the following. For the sake of consistency, we always show results for 60%, 70%, 80%, 90%, and 100%, respectively, even if the unrestricted renewable share is higher than 70%.

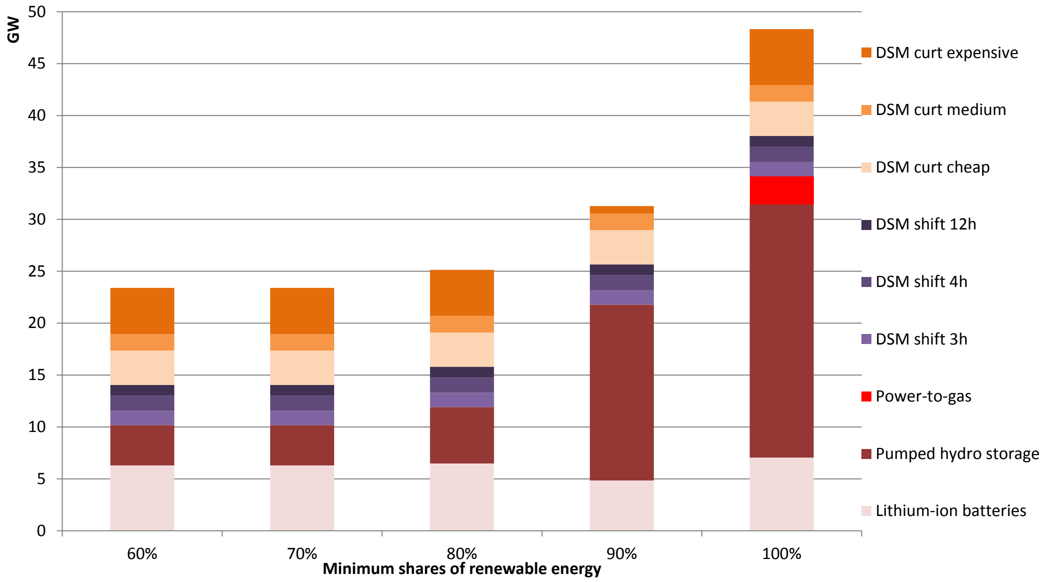

Figure 2: Baseline scenario: installed capacities of storage and DSM

Figure 2 shows more details with respect to installed capacities of power storage and DSM. It indicates that the requirements for short-term flexibility options (lithium-ion batteries and DSM) hardly change between the cases.[20] These technologies are already required in the unrestricted case. In contrast, pumped hydro storage increases strongly beyond a share of 80%. In a 100% renewable setting, pumped hydro reaches a capacity of around 24 GW, corresponding to 32% of the system peak load, and also reaches its energy cap. Long-term-storage is required only to a small extent and only in the 100% case under baseline assumptions (around 3 GW). Yet its E/P ratio is much larger compared to pumped hydro storage (42 compared to 12 hours for PHS and 3 for lithium-ion batteries). Overall, the storage requirement nearly triples from around 12 GW in the 80% renewables case to 34 GW in the fully renewable case.

As regards overall yearly energy provision, the shares of combined cycle gas turbines, biomass, and offshore wind power are larger compared to the respective shares of installed capacities (Figure 15 in Appendix A.1). This reflects the fact that these technologies achieve higher full-load hours compared to onshore wind power and PV. In contrast, open cycle gas turbines and load curtailment have disproportionately small energy shares, as these technologies have high variable costs and are thus hardly used.

Figure 3 shows the patterns of fluctuating renewable power generation and storage energy levels of all three baseline storage technologies for an exemplary week in spring time. Variations in renewable generation are dominated by daily PV patterns. The energy level of pumped hydro storage closely tracks these PV fluctuations. In this respect, pumped hydro storage may be referred to as "daily storage" or even as "PV storage". Lithium-ion batteries are operated in similar cycles, but have lower E/P ratios and thus reach their upper and lower capacity limit virtually every day. In contrast, power-to-gas storage follows a much longer-term cycle.

Compared to its shares in overall capacity or yearly energy, power storage plays a much larger role in the provision and activation of control reserves. This is particularly the case for short-term lithium-ion batteries. Figures 18-21 in Appendix A.3 show the shares of

[20]DSM shift 3h, DSM shift 4h, DSM shift 12h, DSM curt cheap, and DSM curt medium are always at their capacity limits. This is also true for most of the sensitivities.

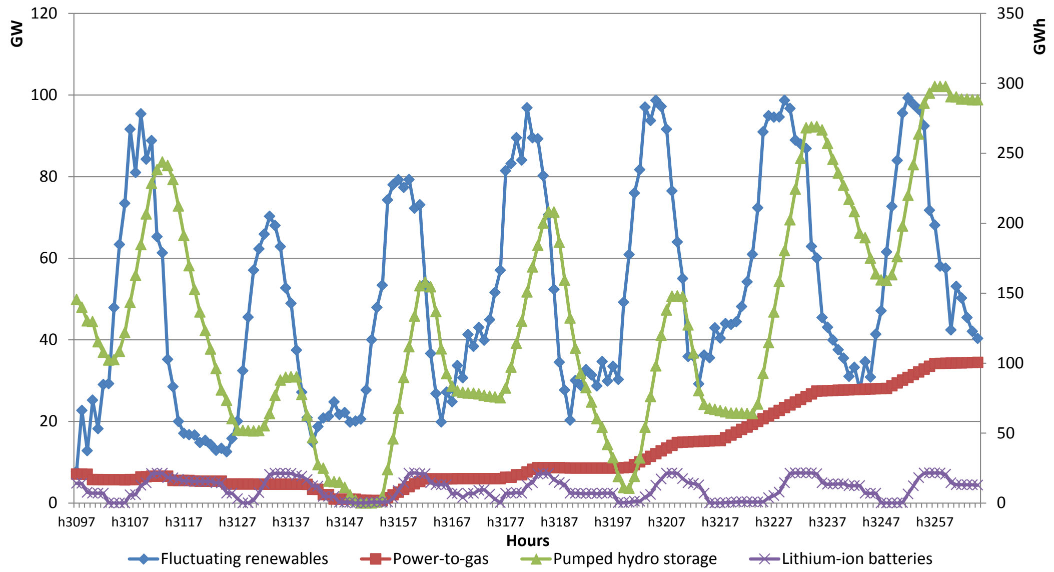

Figure 3: Baseline scenario: exemplary patterns of fluctuating renewable power generation and storage energy levels

technologies in both reserve provision and activation for overall renewable shares of 80% and 100%. It can be seen that power storage particularly contributes to PRL, and its relevance for the other reserve segments also increases in the 100% case.

5.2 Sensitivities on storage costs and availabilities

Availability of additional storage technologies

Under the assumption that additional storage technologies are available, parametrized according to Table 7, leaning on Pape et al. (2014), we observe a massive deployment of lead acid batteries which causes a full substitution of lithium-ion batteries as well as – in the 100% case – long-term storage. Moreover, pumped hydro storage capacities are partly replaced (Figure 4). Overall, storage capacity slightly increases compared to the baseline. Because of their favorable investment costs, lead acid batteries become the dominant short- and mid-term technology in this scenario with E/P ratios of 4 (unrestricted case) to nearly 6 (100% renewables). Pumped hydro, conversely, turns into some kind of long-term storage in the 100% case with an E/P ratio of 33 hours. Sodium-sulfur batteries are installed to a small extent with E/P ratios between 2 and 3. Overall system costs decrease by around 1% as a consequence of the assumed availability of the comparatively cheap lead acid technology. Redox flow batteries and adiabatic compressed air energy storage are never installed because of higher costs and lower round-trip efficiencies.[21]

[21] In an additional sensitivity run not shown here, we include all storage technologies except for lead acid batteries and find very similar but slightly less pronounced effects. In this case, lead acid capacities are almost entirely substituted by the slightly more expensive sodium-sulfur batteries which become the dominant short- and mid-term storage option. System costs savings compared to the baseline are accordingly less pronounced.

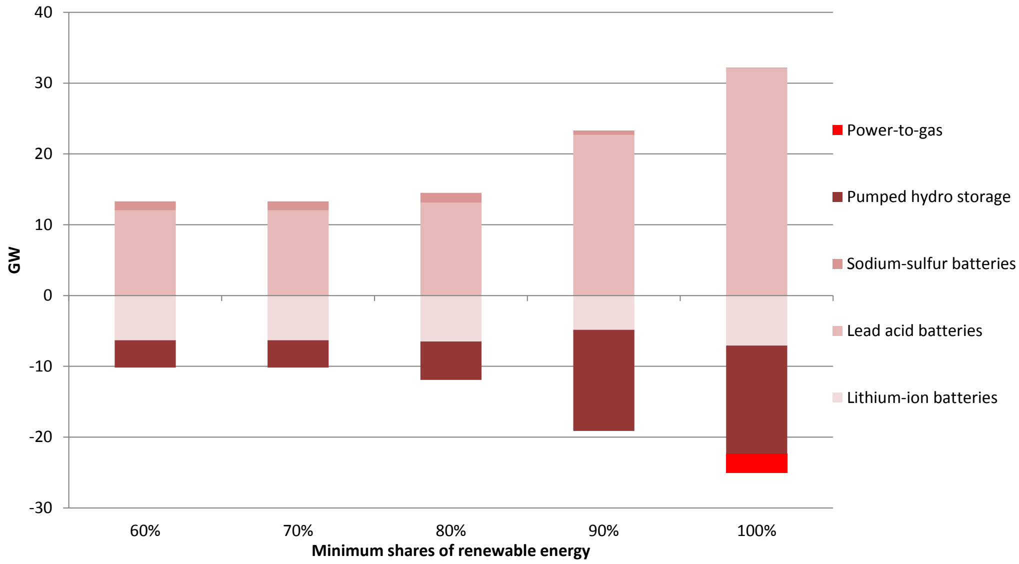

Figure 4: Availability of additional storage technologies: changes in installed storage power

Half or double specific investment costs of all storage technologies

If investment costs of the three storage options considered in the baseline are assumed to halve, for example because of technological breakthroughs, more short- and mid-term storage capacities are installed up to renewable shares of 90% (Figure 5). In the fully renewable case, lithium batteries increase by nearly 13 GW to a total level around 20 GW, corresponding to 26% of the system peak load. At the same time, both mid-term and long-term storage decrease slightly in the 100% case. Pumped hydro storage nonetheless reaches its energy cap, going along with a slightly increased E/P ratio. Overall, it appears that the assumed change in investment costs is relatively more favorable for lithium-ion batteries. These changes in the storage portfolio go along with slight deviations in the renewable mix: onshore and offshore wind power are used a little less, whereas PV generation slightly increases. System costs decrease by 2.2% due to cheaper storage options. Likewise, the renewable share in the unrestricted case increases from 76.4% to 78.1%.

Under the opposite assumption that investment costs of all storage technologies double compared to the baseline, for example because of lower research activities or a more challenging investment environment, we generally find opposite effects, but less pronounced. In particular, hardly any long-term storage is installed (around 1 GW). Instead, onshore wind power installations as well as renewable curtailment increase slightly. Installed PV capacity, which requires daily storage, also decreases. Overall costs increase by 3% in the fully renewable system.

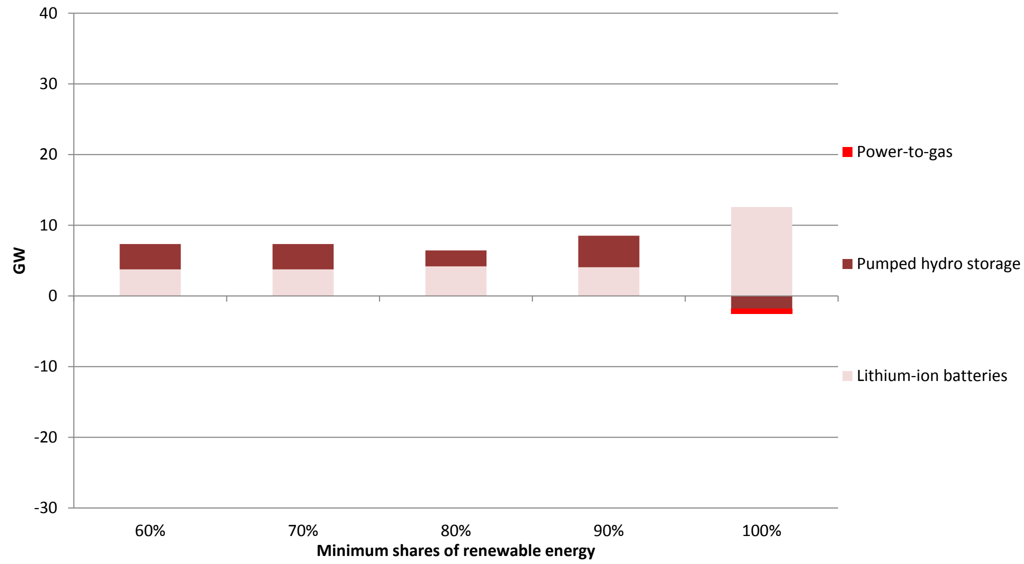

Figure 5: Half specific investment costs of all storage technologies: changes in installed storage power

Half specific investment costs of particular storage options

We now test the sensitivity of results with respect to cost breakthroughs of single storage technologies. In doing so, we focus on lithium-ion batteries and power-to-gas, as these are less developed than pumped hydro storage. As for the latter, it appears more reasonable to test the effect of tighter energy restrictions as compared to decreasing investment costs (see next section).

If specific investment costs of lithium-ion batteries decrease by 50%, we observe a major shift towards this technology (Figure 6). The E/P ratio of lithium-ion batteries increases to around 4 to 6 hours, depending on the required renewable share, such that they evolve into some kind of mid-term storage option. Pumped hydro requirements accordingly decrease. Yet pumped hydro still reaches its energy cap in the 100% because of an increased E/P ratio (nearly 33 hours). Overall costs decrease by 1.4%.

In contrast, a 50% cost reduction of long-term storage has smaller effects. Even under these optimistic cost assumptions, power-to-gas is never built except for the 100% case, and even there investments increase by merely 4 GW. Accordingly, cost breakthroughs in long-term storage appear not to be a game changer in the setting analyzed here. The sluggish uptake of the long-term storage option in the model is mainly caused by its comparatively low round-trip efficiency, which is way below the other options. If long-term storage is to become viable, cost reductions thus have to be accompanied by efficiency improvements.

Tighter energy restriction on pumped hydro storage

Under baseline assumptions, pumped hydro is the dominant mid-term storage option. We test the robustness of results with respect to a tighter cap on the maximum installable energy capacity, i.e., 75 GWh as compared to 300 GWh.[22] This is meant to reflect less optimistic

[22]We select 75 GWh, corresponding to 25% of the baseline value, as a sensitivity with 150 GWh (50%) does not result in noteworthy deviations from the baseline. 75 GWh are a little higher than the cumulative energy capacity of current pumped hydro storage facilities that are directly connected to the German transmission grid.

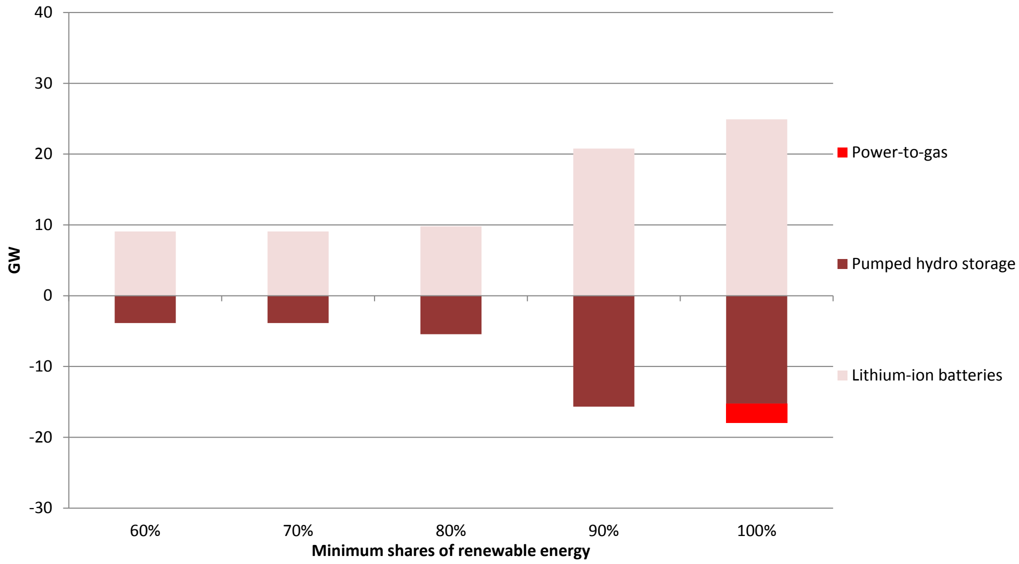

Figure 6: Half specific investment costs of lithium-ion batteries: changes in installed storage power

prospects for constructing upper and/or lower reservoirs, for example because of limited topographic potentials, public resistance or environmental restrictions.

Due to the tighter energy cap, the E/P ratio of pumped hydro storage remains around 8 hours for all renewable shares, compared to up to 12 hours in the baseline. Accordingly, the installed power of pumped hydro facilities changes less dramatically than its energy cap. Investments into storage power change compared to the baseline only in the 90% and 100% cases. Pumped hydro storage now reaches its energy cap already in the 90% case, such that capacity is around 8 GW lower. Yet this decrease is partly compensated by a 6 GW increase in lithium-ion batteries. In the 100 % case, pumped hydro decreases by nearly 16 GW, but is substituted by the more expensive short-term (+10 GW) and long-term (+6 GW) storage options. Overall system costs therefore increase by 1.7% in the fully renewable case.

5.3 Sensitivities on DSM potentials

Under the assumption that demand-side options cannot be developed, required power storage capacities increase (Figure 7). In particular, DSM is substituted by lithium-ion batteries. In case of double DSM potentials, we find corresponding effects in the opposite direction, but less pronounced. For example, double DSM potentials decrease overall storage requirements by less than 4 GW compared to the baseline in the 80% case, whereas the corresponding opposite effect of zero DSM shown in Figure 7 is much larger. Accordingly, the marginal rate of substitution between DSM and storage decreases strongly. This may be due to time-related restrictions of load shifting and comparatively high costs of several DSM segments.

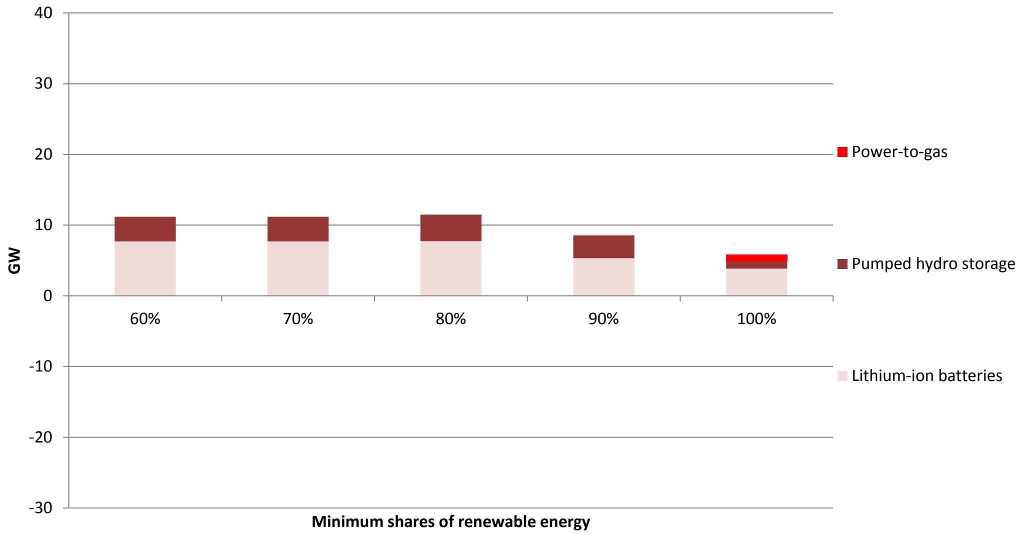

Figure 7: No DSM potential: changes in installed storage power

5.4 Sensitivities on renewable costs and availabilities

Alternative costs and potentials of offshore wind power

Given the parameter assumptions used in this study, offshore wind power is a very cost-efficient renewable energy source. Under an alternative assumption that offshore wind power potentials cannot be developed, model results drastically change. The share of renewables in the unrestricted case decreases to 65.6%, compared to 76.4% in the baseline. In order to reach minimum shares of 70% and more, substantial capacity additions of onshore wind power and PV are necessary (Figure 8). Because of comparatively lower full-load hours of onshore wind and PV, overall installed capacity of all technologies increases by nearly 130 GW compared to the baseline, and reaches an absolute level of 538 GW in the 100% case, which is more than seven times higher than the system peak load. At the same time, renewable curtailment increases to 14% in the 100% renewable scenario (7% in the baseline). In such an environment, power storage requirements also increase. In the 80% and 90% cases, around 14 to 17 GW additional pumped hydro storage capacity is needed, whereas in the 100% case additional 10 GW of power-to-gas are installed compared to the baseline. System costs are accordingly 13.7% higher than in the baseline in the fully renewable setting.

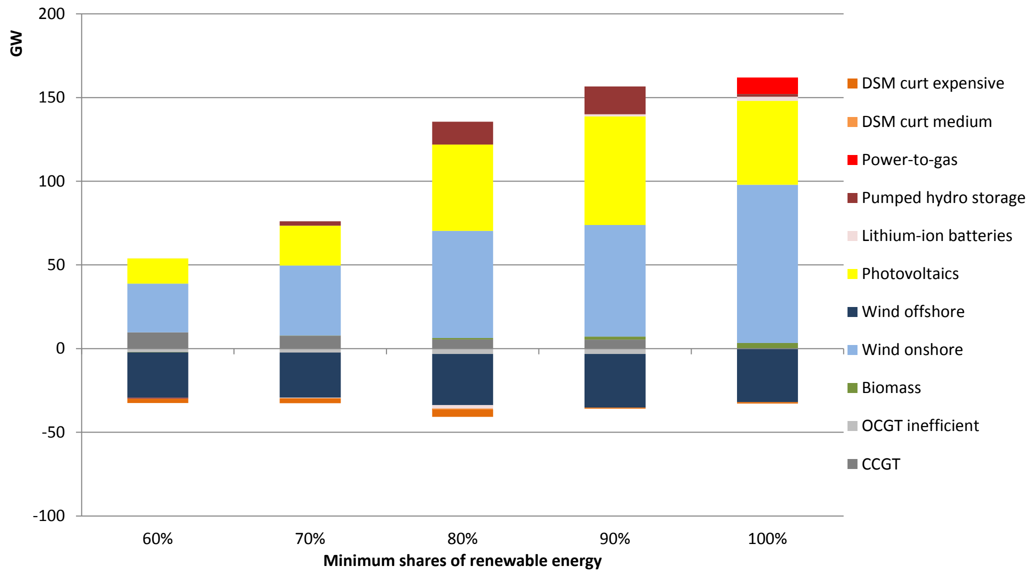

Figure 8: No offshore wind power: changes in installed capacities

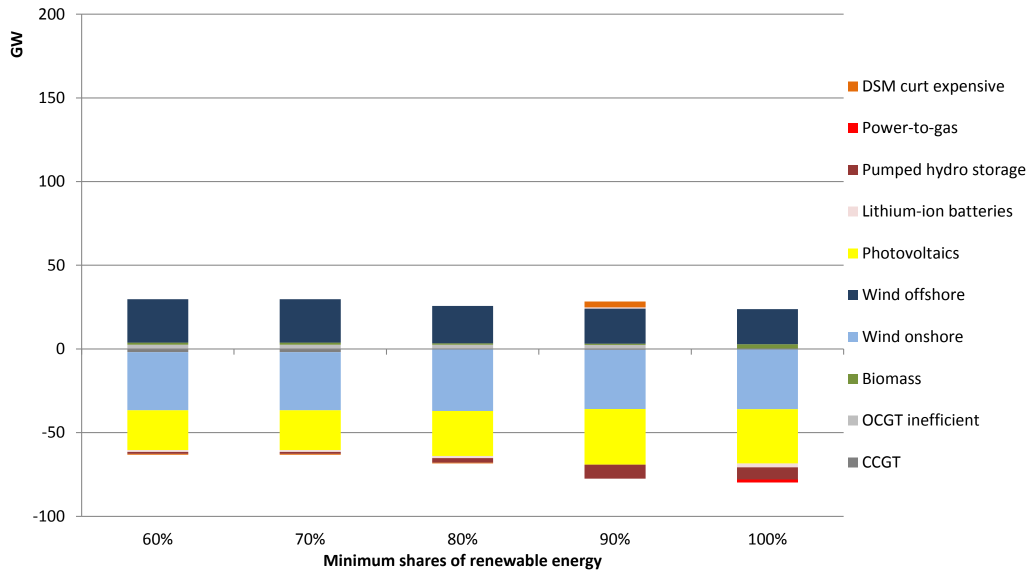

Figure 9: Offshore wind power breakthrough: changes in installed capacities

Figure 9 indicates the effect of deviating assumptions in the opposite direction, i.e., an offshore wind power breakthrough. Extending the installation cap for offshore wind power to 53 GW and at the same time halving specific investment costs increases the renewable share to 81.3% in the unrestricted case. Lower capacities of onshore wind power and PV are required in all cases. As offshore wind power fluctuates less than onshore wind and PV, the overall storage requirement also decreases by around 11 GW (largely pumped hydro) in the fully renewable setting. System costs substantially decrease by 11.4% in the 100% case compared to the baseline. Accordingly, the availability and the costs of offshore wind power play an important role for future power systems with high shares of renewables, and also have a strong impact on the requirement of mid- and long-term storage technologies.

Alternative projections for onshore wind profiles

Figure 10 indicates the effect of alternative projections of onshore wind profiles. Here, we aim to capture the effects of both widespread geographical[23] balancing, which makes the profiles smoother, and future changes in generator configuration, which increases full-load hours. Under these assumptions, onshore wind power gains ground in the competition with other renewable technologies. We accordingly observe a massive shift towards onshore wind power, which substitutes both offshore wind and PV capacity. At the same time, storage requirements hardly change compared to the baseline. In the 100% case, there is a minor shift from pumped hydro (-4 GW) to lithium-ion batteries (+1 GW) and power-to-gas (+3 GW). This may be due to the fact that onshore wind substitutes technologies which fluctuate both more (PV) and less heavily (offshore wind), such that the net effect on storage largely cancels out.

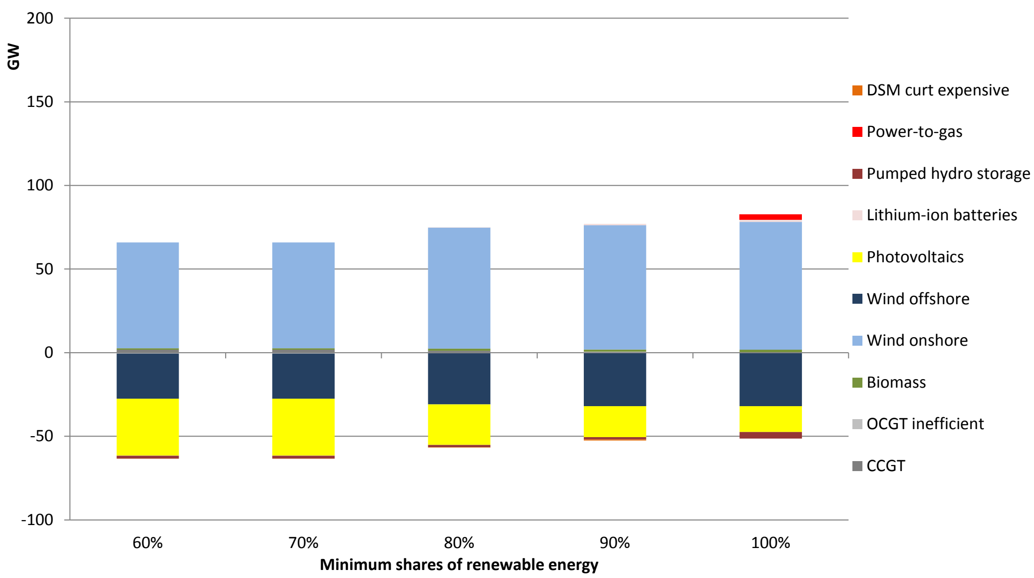

Figure 10: Smoother onshore wind profiles: changes in installed capacities

Half or double specific investment costs of photovoltaics

We have examined the effects of variations in the costs and availabilities of offshore wind power as well as smoother generation profiles of onshore wind power. As regards PV, we carry out model runs with respect to different developments of specific investment costs, as these appear to be the most relevant sensitivities, given the wide range of long-term cost projections (Schröder et al., 2013). Under the assumption that specific PV investment costs halve compared to the baseline, PV capacity increases by around 40 GW in all cases examined here, substituting either offshore or onshore wind power (Figure 11).[24] At the

[23] The profiles are based on interpolated European wind-time series data of the year 2011. From these, hourly availabilities for many wind farm locations over Europe are derived. For further detail, see Gerbaulet et al. (2014)

[24] Note that the y-axes of Figures 11 and 12 have a different scale compared to previous Figures in order to improve readability.

same time, pumped hydro storage requirements increase in the order of 5 to 6 GW.

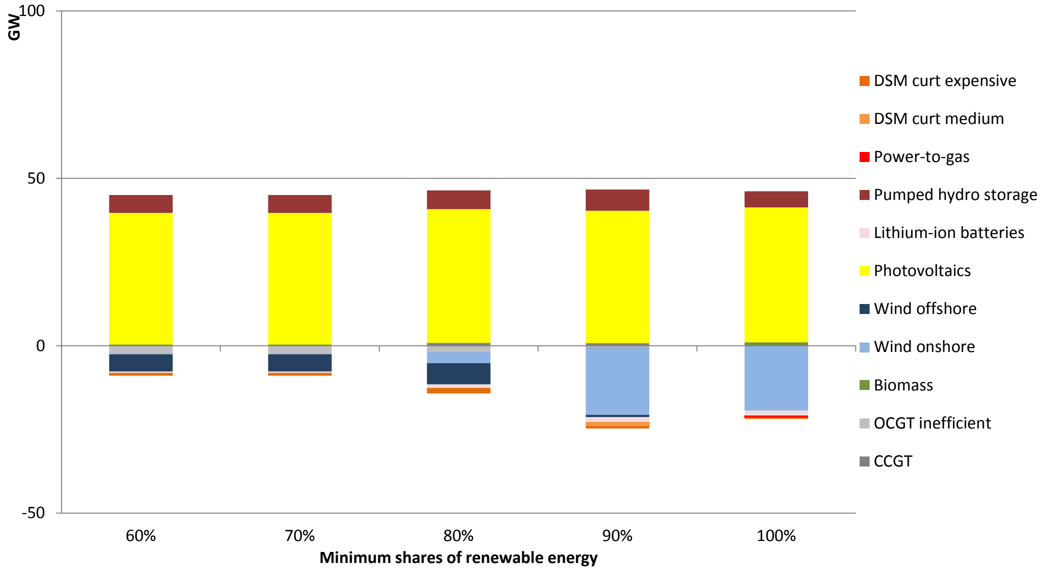

Figure 11: Half specific PV investment costs: changes in installed capacities

Under the assumption that specific PV investment costs are twice as high as in the baseline, we find corresponding effects in the opposite direction. Lower PV capacities go along with decreases in pumped hydro storage requirements between 3 and 8 GW, depending on the renewable share. These outcomes thus support the previously discussed finding that pumped hydro may be interpreted as "PV storage" in this setting.

Dark winter doldrums

All model calculations presented so far have drawn on hourly renewable availability factors derived from historic time series. Under baseline assumptions (based on feed-in data of 2013), the sum of hourly availabilities of PV, onshore wind power, and offshore wind power drops to very low levels only during a few subsequent hours. We now examine a kind of worst case scenario with respect to security of supply by assuming that PV, onshore wind power and offshore wind power are completely unavailable over a full winter week in which power demand is high ("dark winter doldrums"). Figure 12 shows that up to a renewable share of 90%, some 11 to 13 GW of additional gas-fired power plants (largely open cycle gas turbines) are sufficient to serve power demand during the dark winter week. These partly substitute installations of the expensive load curtailment category, as gas turbines have comparatively lower variable costs and thus displace load curtailment in both the reserve and wholesale markets. Only in the 100% renewable case, in which no gas-fired generators can be built, we observe substantial capacity additions of biomass as well as moderate increases in all three power storage technologies (nearly 2 GW lithium-ion batteries, 3 GW pumped hydro, and 1 GW power-to-gas). It is thus biomass, and not power storage, that serves as the main source of flexibility in this setting. Note that the energy cap on biomass does not change, such that full-load hours of biomass decrease substantially.[25] In order to offset lower power

[25]We implicitly assume that it is possible to shift a substantial fraction of the yearly biomass energy budget to one particular winter week. In practice, this would require additional storage capacity of either biomass or biogas.

generation from biomass in the remaining hours of the year, additional PV installations are required in the 100% case, which also contribute to increased storage requirements.

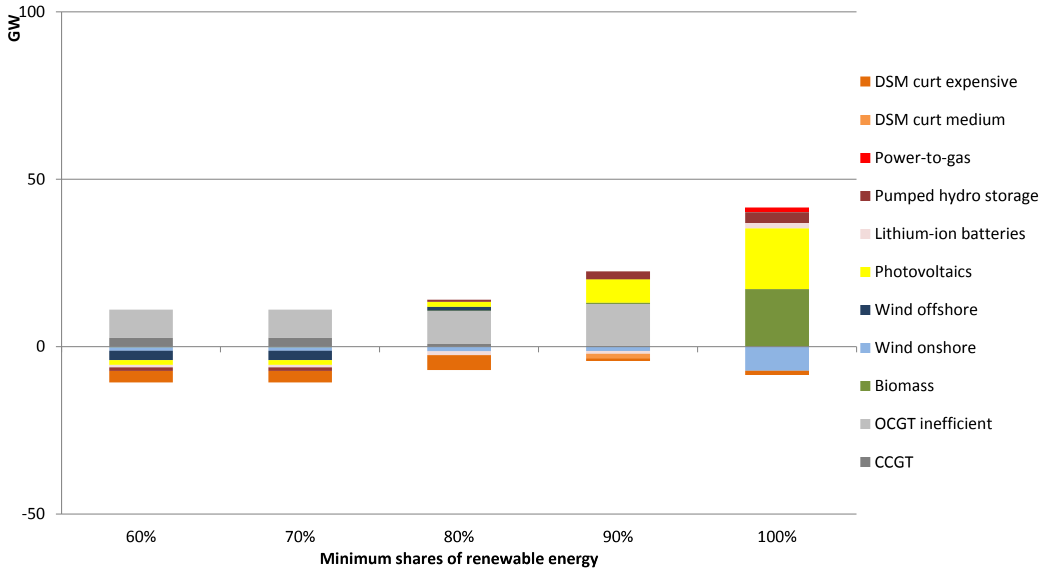

Figure 12: Dark winter doldrums: changes in installed capacities

No biomass

Not only in the dark winter doldrums setting, but also under baseline assumptions, flexible power generation from biomass plays an important role. Under the alternative assumption that no biomass is available for power generation, model results substantially change. In the cases with renewable shares of 80 and 90%, substantial capacity additions of onshore wind power and PV are required – offshore wind power is already at the assumed capacity limit. As a consequence of increased supply-side fluctuations, storage requirements (largely pumped hydro) also rise (Figure 13). At the same time, renewable curtailment increases to 4.7% (80%) and 8.3% (90%), compared to 1.6% and 3.7% in the baseline, respectively. In the 100% case, however, the picture changes. Here, excessive additional onshore wind power capacity is deployed combined with power-to-gas storage (additional 27 GW compared to the baseline) in order to achieve full renewable supply without flexible biomass. At the same time, both renewable curtailment and system costs drastically increase. In other words, substantial capacity of seasonal storage is required only under the assumption of both very high renewable shares and restricted availability of biomass in our model setup.

In an additional model run, we combine the assumptions of "dark winter doldrums" and complete non-availability of biomass. In such a setting, power-to-gas is used as seasonal storage and becomes a main source of flexibility in the 100% renewable case with an absolute power rating of 59 GW, and an energy capacity of nearly 17 TWh. The corresponding E/P ratio is 286 hours, i.e., around 12 days. The case for seasonal storage discussed above thus increases further, if high RES shares and non-availability of biomass are combined with simultaneous non-availabilities of fluctuating renewables for longer periods.

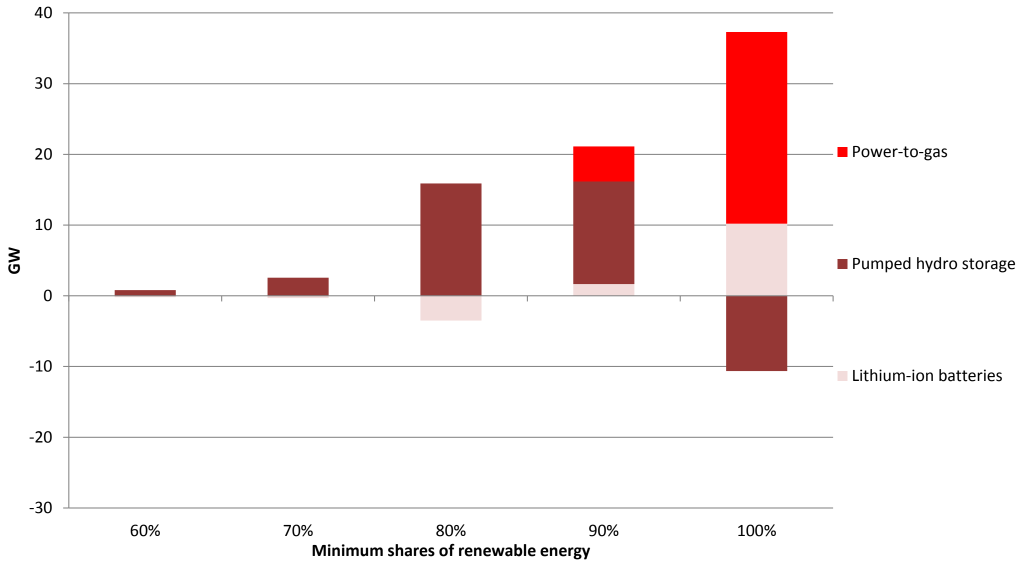

Figure 13: No biomass: changes in installed capacities

5.5 Sensitivities on reserve requirements

The future demand for reserves is generally uncertain, as it depends, among other factors, on the size of the balancing area, tender and delivery periods, and the technical prequalification of various technologies. We carry out two sensitivities with zero and – compared to the baseline – double reserve requirements. The sensitivity without any reserves also serves as a test of the importance of including reserves at all in the model.

If reserve requirements are set to zero, the capacities of both short-term storage and DSM decrease in all runs compared to the baseline, irrespective of the minimum renewable share. In particular, the expensive load curtailment technology is not deployed any longer. Likewise, lithium-ion battery capacity is 2 to 3 GW lower than in the baseline. Neglecting reserves in power system models may thus lead to a systematic underestimation of short-term storage and DSM capacities.

If, on the contrary, reserve requirements are twice as high as in the baseline, we find an corresponding effect in the opposite direction. Yet the impact on short-term storage is much stronger with a capacity increase of some 6 to 7 GW compared to the baseline. Load curtailment capacity also increases, but less pronounced, as many DSM segments are already at their capacity limit in the baseline. Overall, our findings thus suggest that considering reserves in power system modeling is particularly important for a proper assessment of short-term power storage requirements.

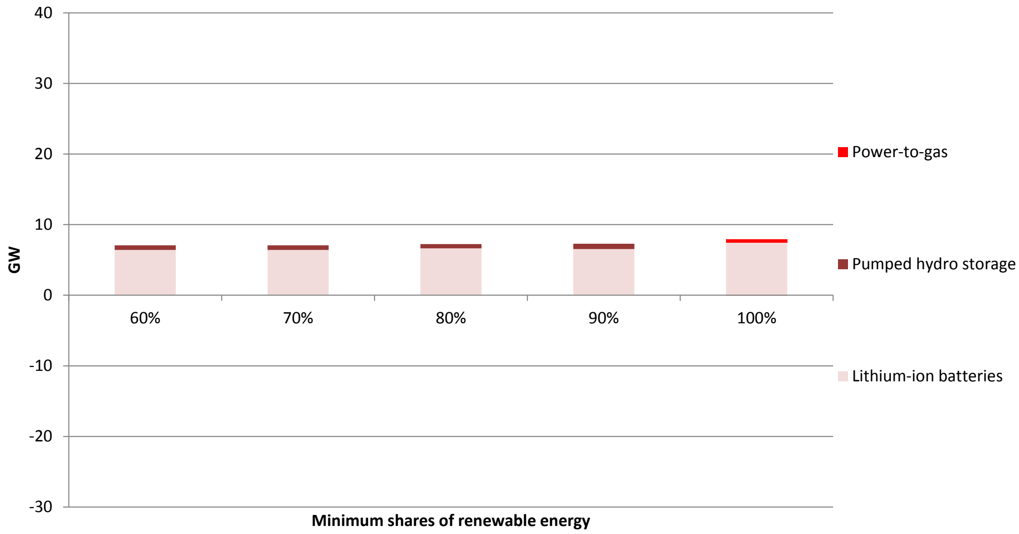

Figure 14: Double reserve requirements: changes in installed storage power

6 Discussion of Limitations

In the following, we briefly discuss important limitations of our model and how these may affect results.

To begin with, we deliberately abstract from a real power system and instead adopt a long-term, greenfield perspective. This necessarily restricts the potential to draw policy conclusions that are immediately relevant for today's power systems. Rather, we aim to provide on the one hand long-run benchmarks for power storage in an optimized future power system, and, on the other, qualitative insights into interdependencies of power storage and various other flexibility options. Our analysis may thus not be used to draw conclusions on today's power systems, but rather to guide longer-term research and development policy on power storage and other technologies as well as the regulatory framework. Because of the greenfield perspective, we also do not address questions of path-dependency or intermediate development stages of the power system on the way towards high renewable shares. Results should accordingly not be interpreted as a forecast, but rather as a benchmark for an optimized future system.

Despite adopting a greenfield perspective, it is necessary to loosely calibrate the model to a specific power system. For example, the capacities of dispatchable renewables such as hydro power or biomass have to be restricted in order not to generate meaningless results. Our choice of Germany is obvious because of the legally binding long-term renewable targets; yet it involves a range of issues. For example, we abstract from power exchange with neighboring countries and thus neglect the possibilities of smoothing both renewable fluctuations and power demand by balancing over larger geographical areas.[26]. This may result in exaggerated fluctuations of renewable generators, which in turn leads to an overestimation of the need for flexibility and, ultimately, power storage. Another limitation that may distort results in a similar direction is the linear scaling of historic renewable feed-in time series. This approach neglects future changes in generator design as well as changes in the geographical distribution (even within Germany), which would lead to smoother feed-in profiles. Likewise,

[26]One exception to this approach is the sensitivity with smoother onshore wind power profiles derived from historic European wind speed data.

the demand profile may become smoother in the future because of demand-side innovations and behavioral changes. Our analysis, however, already includes such developments at least to some degree, as we assume substantial DSM capacities of both load shifting and load curtailment.

Next, the model analysis focuses on the power system and neglects interactions with the heating or mobility sectors. While this simplification appears to be largely justified for current real-world power systems, it may constitute an increasingly strong assumption in the context of future power systems with very high shares of renewables. It can be expected that interactions with the heat and mobility sectors gain importance in high-RES systems, for example, by means of power-to-heat applications which may partly take up temporary renewable surpluses, or by flexibly using electricity for mobility purposes. If such additional "power-to-X" flexibility options were considered, power storage requirements should tend to decrease. Yet including such cross-sector interactions would require extending the analytical framework from a partial equilibrium power sector model towards a larger-scale energy system model. This appears to be both challenging and a promising avenue for future research.

Finally, investment models generally require simplifications with respect to technical details of thermal generators as compared to pure dispatch models. Otherwise, investment models as large as the one used for this analysis would be very hard to solve numerically. For example, our linear model setup does not allow to accommodate a unit-commitment formulation with start-up restrictions and costs of single thermal blocks, minimum on-time or off-time, or minimum generation levels. Instead, we aim to approximate such constraints with linearized ramping costs of aggregated technologies. This may tend to underestimate flexibility restrictions of thermal generators and thus lead to an undervaluation of flexibility. Yet in a future system with strongly growing renewable shares this might be of decreasing importance. Further, we keep the model solvable by abstracting from network issues and by assuming perfect foresight. These simplifications render possible a parsimonious model formulation that allows traceability of results. Even more important, this provides scope for multiple sensitivities, which are at the heart of our analysis, as long-run parameter assumptions in the power system are subject to very high uncertainties.

7 Conclusions

We develop a dispatch and investment model to study the role of power storage and other flexibility options in a greenfield setting with high shares of renewables. In contrast to many other analyses, our model not only captures the arbitrage value of power storage, but also system values related to the provision of dispatchable capacity and reserves. In a baseline scenario, we find that power storage requirements remain moderate up to a renewable share of around 80%, as other options on both the supply side and demand side also offer flexibility at low cost. These findings connect to other model-based studies cited in section 2. If the renewable share increases to 100%, the required capacities of power storage – and other technologies – increase strongly and nearly triple compared to the 80% case. Yet even in a completely renewable-based system, not much long-term storage is needed under baseline assumptions. Compared to the wholesale market, power storage generally plays a larger role in the provision and activation of control reserves.

As long-run parameter assumptions are highly uncertain, we carry out a range of sensitivity analyses with respect to the costs and availabilities of storage and renewables. We also vary assumptions on DSM potentials and reserve requirements. A common finding of these sensitivities is that – under very high renewable shares – the storage requirement strongly depends on the costs and availability of other flexibility options. Aside from demand-side options, the availability of dispatchable biomass generators appears to be a key determinant for the power storage requirement. Further, storage needs strongly depend on the costs and the potentials of offshore wind power, which has relatively smooth generation profiles compared to onshore wind power and PV. Low-cost demand-side measures, both load shifting and curtailment, turn out to be dominant options. In particular, load shifting potentials with 3, 4, and 12 hours are installed up to their assumed capacity limits in most scenarios; the same is true for the cheap and the medium load curtailment technologies.

As regards single storage technologies, we conclude that pumped hydro storage will continue to play a dominant role under the cost assumptions made here. Pumped hydro is deployed with such energy to power ratios that it serves as daily storage for balancing out PV-related fluctuations. Lithium-ion (and other) batteries may increasingly contribute not only to reserve provision, but also to wholesale balancing, in particular if their costs decrease further. In contrast, long-term storage plays a major role only in rather extreme scenarios of model analysis – for example, if no biomass is available in a 100% renewable setting, and even more so if this assumption is combined with a winter week without any fluctuating renewable feed-in.

While our model is loosely parameterized to the German power system, many of the findings are also relevant for other countries moving toward high shares of fluctuating renewables. In particular, the sensitivities may be of interest to international readers, as other countries may, for example, have higher or lower offshore wind power potentials or lower biomass availability compared to Germany.

Based on our model results, we conclude that power storage becomes an increasingly important element of a transition towards a fully renewable-based power system. Power storage gains further relevance if other potential sources of flexibility are less developed. Supporting the development of power storage should thus be considered a useful component of policies designed to safeguard the transition towards renewables. Policy-makers should aim for technological progress and cost reduction in different power storage technologies, primarily by means of broad-based support for research and development. At the same time, politics should enable a level playing field for competition among flexibility options in the various areas of application.

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A Appendix

A.1 Shares of energy provision in the baseline

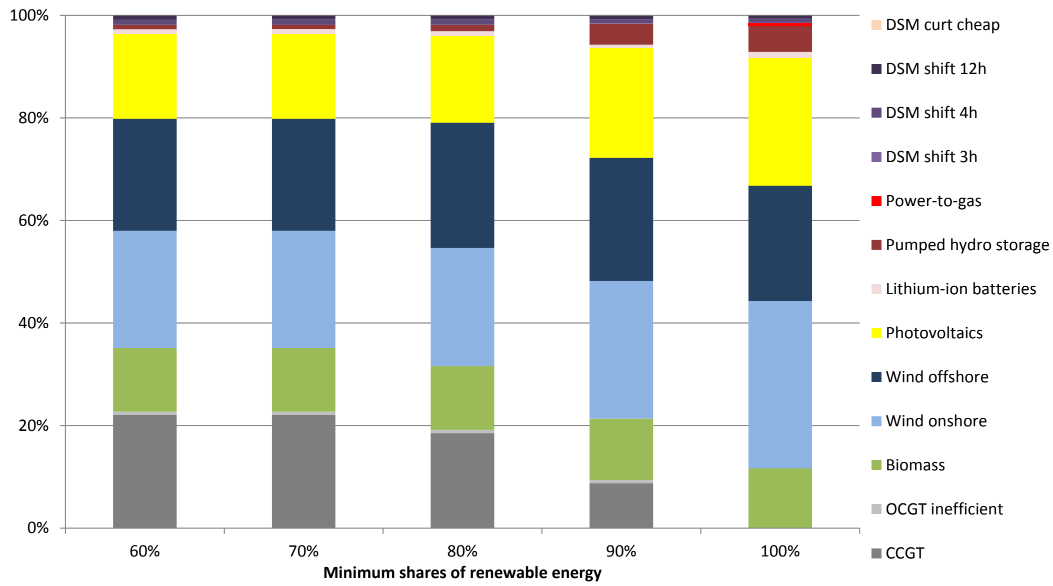

Figure 15: Baseline scenario: energy shares

A.2 Sensitivities with respect to alternative base years

The baseline draws on 2013 data with respect to load, renewable feed-in, and control reserves. It would be desirable to test the robustness of results with respect to different base years. We alternatively choose 2011 or 2012. Yet results are not fully comparable, as offshore wind power feed-in time series of the years 2011 and 2012 are based on very few single wind turbines, the feed-in of which is very synchronous, and which were also simultaneously maintained at times. Results may thus be distorted with respect to offshore wind power deployment, which proves to be a decisive variable (compare section 5.4).

Because of these distortions, offshore wind power capacities are lower for all renewable shares in both the 2011 and the 2012 sensitivities, whereas PV and – except for the 100% case in the 2011 sensitivity – onshore wind power capacities are higher. Because of increased renewable fluctuations, storage requirements also increase. In the 100% case based on 2012 data (Figure 16), overall storage capacity increases by 20 GW compared to the baseline, of which 10 GW are short-term storage. Drawing on 2011 data, the storage requirement increases even further in the 100% case – by 31 GW compared to the baseline, of which the largest share (21 GW) is again short-term storage (Figure 17). This is driven by large capacity additions of solar PV, as 2012 was a relatively good PV year in Germany. Note that pumped hydro, which turns out to be the prime option for PV storage in other model runs, already reaches its energy cap in the 90% cases of both the 2011 and the 2012 sensitivities. Instead, mainly additional short-term storage is applied in the fully renewable setting.

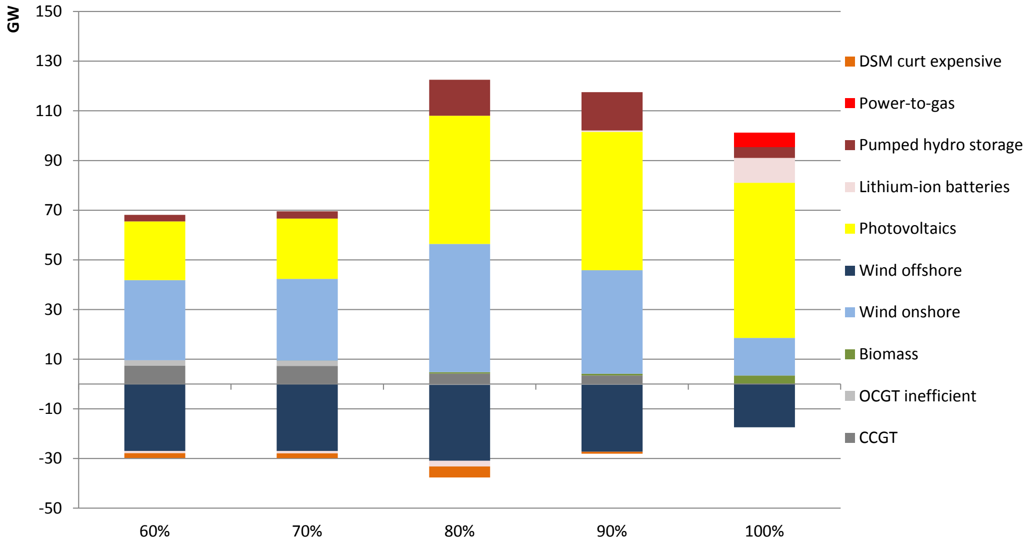

Figure 16: Base year 2012: energy shares

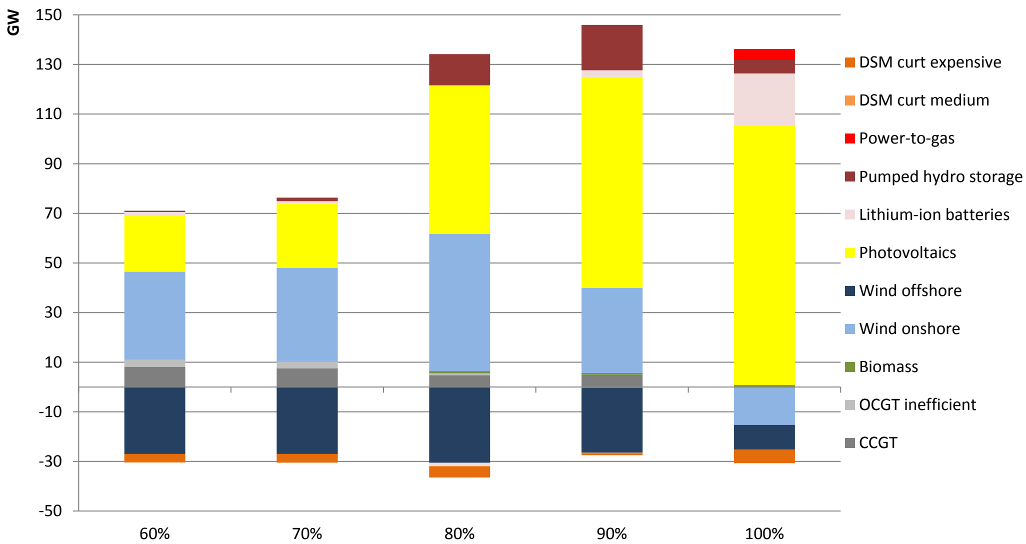

Figure 17: Base year 2011: energy shares

A.3 Reserve provision and activation

Model outcomes on reserves differ between reserve provision (capacity) and activation (energy). Figure 18 shows how different technologies contribute to reserve provision over the whole year for a renewable share of 80%. Short-term and mid-term power storage substantially contribute to primary reserve provision, and, less pronounced, to secondary and minute reserve provision. These large shares are caused by storage's high flexibility, high availability, and low variable costs. CCGT plants have disproportionately high shares compared to overall energy provision because of their dispatchability. CCGT shares are particularly high for negative SR and MR provision, as a respective activation incurs relatively high savings of variable costs in the objective function. In addition, the demand side is a relevant provider of short-term flexibility.

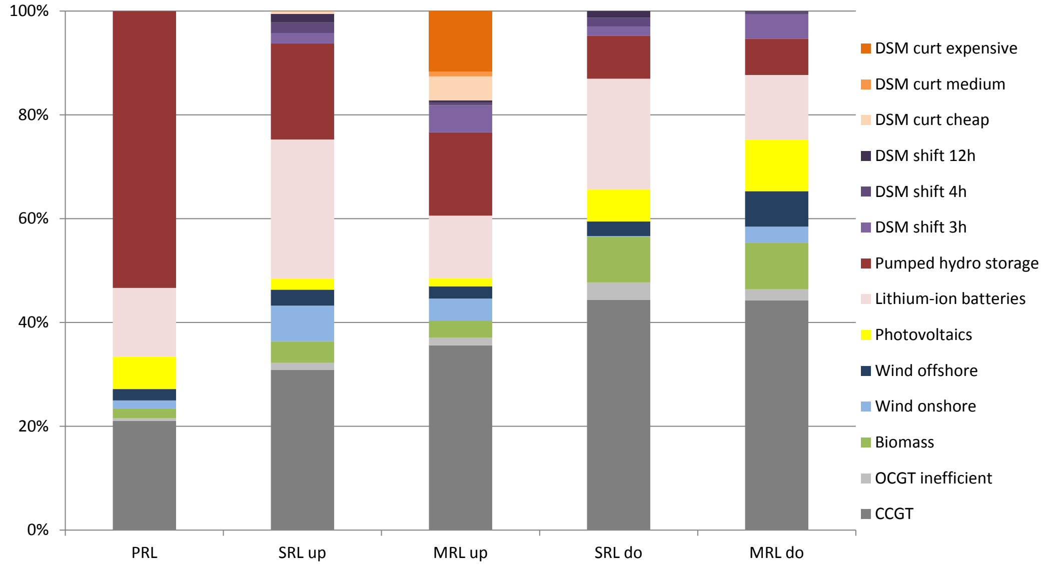

Figure 18: Baseline scenario: shares of reserve provision for a renewable share of 80%

The respective energy shares (Figure 19) show a similar picture. Here, primary reserve shares are not provided as the model abstracts from PR activation and only considers PR provision.

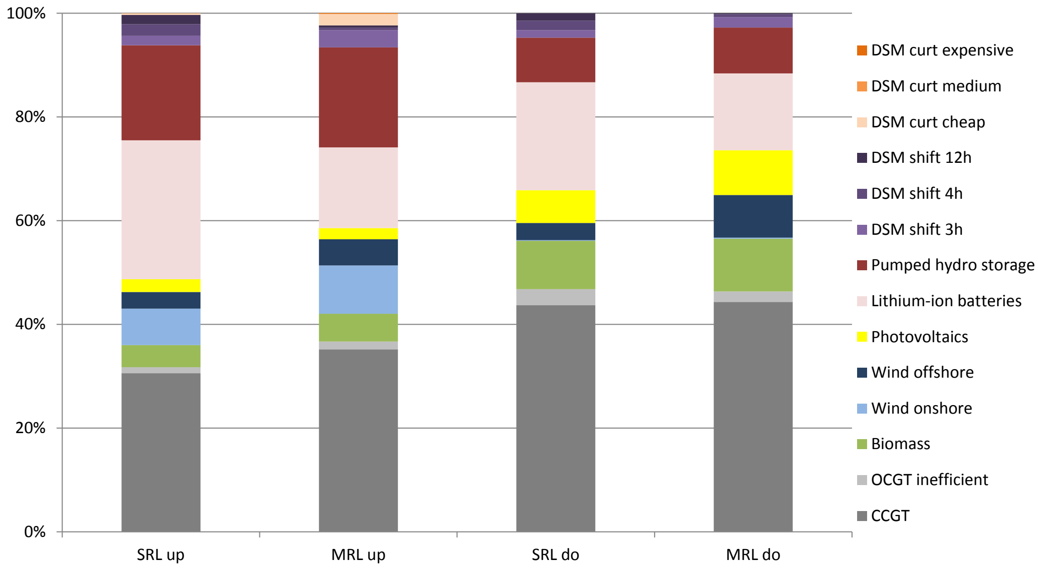

Figure 19: Baseline scenario: shares of reserve activation for a renewable share of 80%

Corresponding figures on the shares of reserve provision and activation for a renewable share of 100% are provided in Figures 20 and 21. It can be seen that power storage technologies gain further importance with respect to reserves in a fully renewable scenario. An even more pronounced effect can be observed for biomass, which largely substitutes dispatchable gas-fired plants. Accordingly, both storage and flexible biomass are not only vital for residual load balancing, but also for reserve provision in a 100% renewable setting.

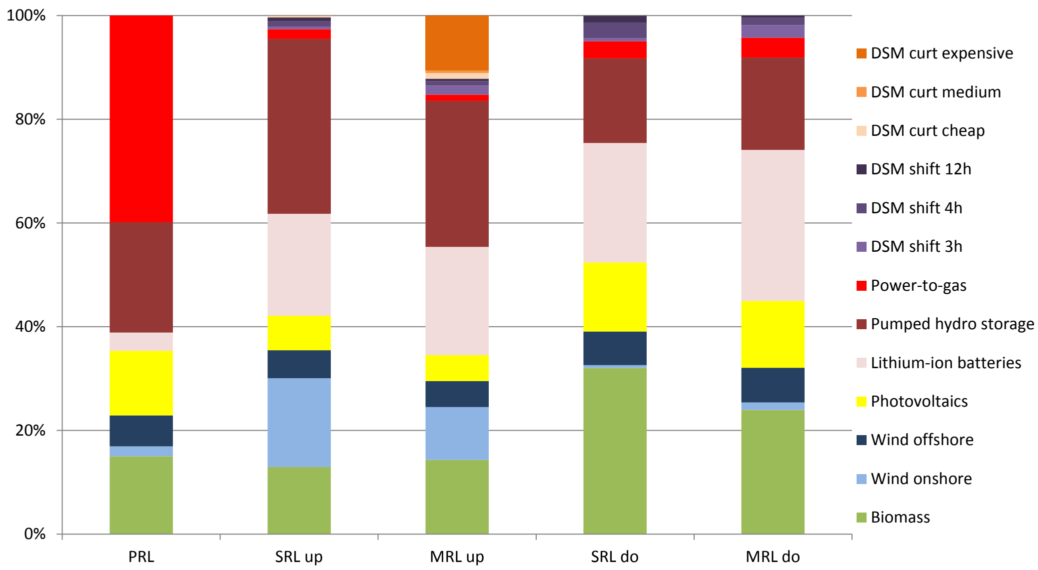

Figure 20: Baseline scenario: shares of reserve provision for a renewable share of 100%

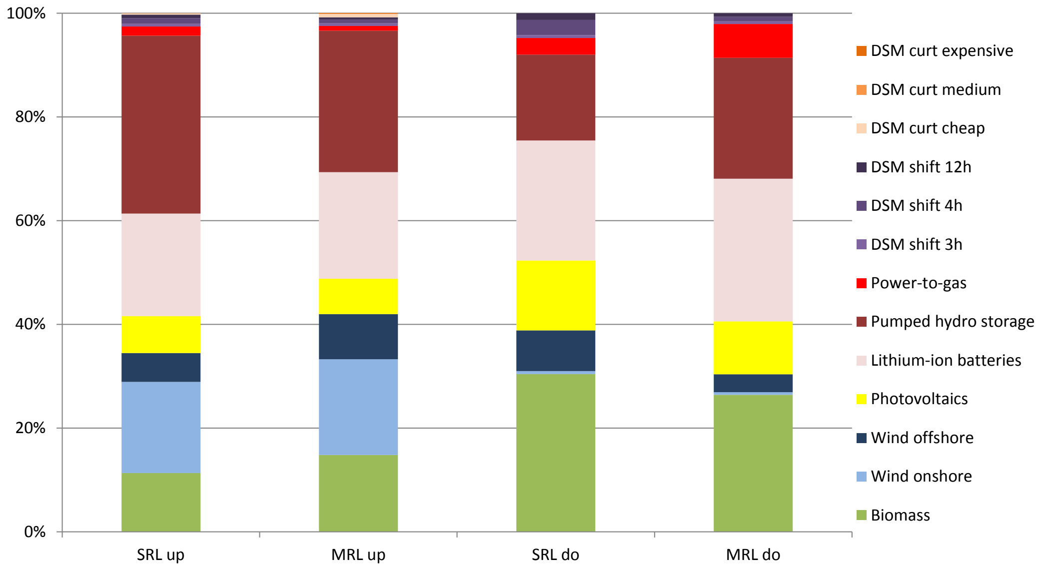

Figure 21: Baseline scenario: shares of reserve activation for a renewable share of 100%

A.4 Numerical assumptions on input parameters

Table 5: Technical assumptions on conventional power plants

	Parameter	Value	Unit	Source
Lignite				
Efficiency		0.466	-	Schröder et al. (2013)
Carbon content		0.364	$tons/MWh_{th}$	Umweltbundesamt (2013)
Fuel price		4.90	EUR/MWh_{th}	dena (2012)
Marginal generation costs	c^m_{con}	88.54	EUR/MWh	
Overnight investment costs		1,500	EUR/kW	Schröder et al. (2013)
Technical lifetime		35	$years$	Schröder et al. (2013)
Annualized investment costs	c^i_{con}	80	EUR/kW	
Annual fixed costs	c^{fix}_{con}	30	EUR/kW	Schröder et al. (2013)
Load change costs up and down	c^+/c^-	30	EUR/MW	Own assumption
Maximum load change for reserves	π	4	$\%\, of\, capacity\, per\, minute$	VDE (2012a)
Hard Coal				
Efficiency		0.467	-	Schröder et al. (2013)
Carbon content		0.354	$tons/MWh_{th}$	Umweltbundesamt (2013)
Fuel price		23.04	EUR/MWh_{th}	DLR et al. (2012)[a]
Marginal generation costs	c^m_{con}	125.12	EUR/MWh	
Overnight investment costs		1,300	EUR/kW	Schröder et al. (2013)
Technical lifetime		35	$years$	Schröder et al. (2013)
Annualized investment costs	c^i_{con}	70	EUR/kW	
Annual fixed costs	$c^{fix_{con}}$	30	EUR/kW	Schröder et al. (2013)
Load change costs up and down	c^+/c^-	30	EUR/MW	Own assumption
Maximum load change for reserves	π	6	$\%\, of\, capacity\, per\, minute$	VDE (2012a)
CCGT				
Efficiency		0.619	-	Schröder et al. (2013)
Carbon content		0.202	$tons/MWh_{th}$	Umweltbundesamt (2013)
Fuel price		38.16	EUR/MWh_{th}	DLR et al. (2012)[a]
Marginal generation costs	c^m_{con}	94.28	EUR/MWh	
Overnight investment costs		800	EUR/kW	Schröder et al. (2013)
Technical lifetime		25	$years$	Schröder et al. (2013)
Annualized investment costs	c^i_{con}	51	EUR/kW	
Annual fixed costs	c^{fix}_{con}	20	EUR/kW	Schröder et al. (2013)
Load change costs up and down	c^+/c^-	20	EUR/MW	Own assumption
Maximum load change for reserves	π	8	$\%\, of\, capacity\, per\, minute$	VDE (2012a)
OCGT inefficient				
Efficiency		0.396	-	VGB PowerTech (2012)
Carbon content		0.202	$tons/MWh_{th}$	Umweltbundesamt (2013)
Fuel price		38.16	EUR/MWh_{th}	DLR et al. (2012)[a]
Marginal generation costs	c^m_{con}	147.37	EUR/MWh	
Overnight investment costs		400	EUR/kW	Schröder et al. (2013)
Technical lifetime		25	$years$	Schröder et al. (2013)
Annualized investment costs	c^i_{con}	26	EUR/kW	
Annual fixed costs	c^{fix}_{con}	15	EUR/kW	Schröder et al. (2013)
Load change costs up and down	c^+/c^-	15	EUR/MW	Own assumption
Maximum load change for reserves	π	15	$\%\, of\, capacity\, per\, minute$	VDE (2012a)
OCGT efficient				
Efficiency		0.457	-	Schröder et al. (2013)
Carbon content		0.202	$tons/MWh_{th}$	Umweltbundesamt (2013)
Fuel price		38.16	EUR/MWh_{th}	DLR et al. (2012)[a]
Marginal generation costs	c^m_{con}	127.72	EUR/MWh	
Overnight investment costs		650	EUR/kW	Schröder et al. (2013)
Technical lifetime		25	$years$	Schröder et al. (2013)
Annualized investment costs	c^i_{con}	42	EUR/kW	
Annual fixed costs	c^{fix}_{con}	15	EUR/kW	Schröder et al. (2013)
Load change costs up and down	c^+/c^-	15	EUR/MW	Own assumption
Maximum load change for reserves	π	15	$\%\, of\, capacity\, per\, minute$	VDE (2012a)

[a] Medium price path

Table 6: Technical assumptions on renewable power plants (baseline)

	Parameter	Value	Unit	Source
Wind onshore				
Overnight investment costs		1,075	EUR/kW	Schröder et al. (2013)
Technical lifetime		25	$years$	Schröder et al. (2013)
Annualized investment costs	c^{i}_{res}	69	EUR/kW	Schröder et al. (2013)
Annual fixed costs	c^{fix}_{res}	35	EUR/kW	Schröder et al. (2013)
Maximum capacity or energy		-	-	
Wind offshore				
Overnight investment costs		3,522[a]	EUR/kW	Schröder et al. (2013)
Technical lifetime		25	$years$	Schröder et al. (2013)
Annualized investment costs	c^{i}_{res}	225	EUR/kW	Schröder et al. (2013)
Annual fixed costs	c^{fix}_{res}	80	EUR/kW	Schröder et al. (2013)
Maximum capacity or energy		32	GW	DLR et al. (2012)
Photovoltaics				
Overnight investment costs		425	EUR/kW	Schröder et al. (2013)
Technical lifetime		25	$years$	Schröder et al. (2013)
Annualized investment costs	c^{i}_{res}	27	EUR/kW	Schröder et al. (2013)
Annual fixed costs	c^{fix}_{res}	25	EUR/kW	Schröder et al. (2013)
Maximum capacity or energy		-	-	
Biomass				
Efficiency		0.487	-	Schröder et al. (2013)
Carbon content		0.00	$tons/MWh_{th}$	Umweltbundesamt (2013)
Fuel price		23.04	EUR/MWh_{th}	Own assumption
Marginal generation costs	c^{m}_{con}	47.31	EUR/MWh	
Overnight investment costs		1,951	EUR/kW	Schröder et al. (2013)
Technical lifetime		30	$years$	Schröder et al. (2013)
Annualized investment costs	c^{i}_{con}	113	EUR/kW	
Annual fixed costs	c^{fix}_{con}	100	EUR/kW	Schröder et al. (2013)
Load change costs up and down	c^{+}/c^{-}	25	EUR/MW	Own assumption
Maximum load change for reserves	π	15	$\%\ of\ capacity\ per\ minute$	VDE (2012a)
Maximum capacity or energy	m^{E}_{bio}	60	TWh/a	DLR et al. (2012)

[a] The number includes additional investments for offshore grids.
These are 1,429 EUR/kW according to calculations based on O-NEP (2014).

Table 7: Technical assumptions on power storage (baseline)

	Parameter	Assumption	Unit	Source
Lithium-ion batteries				
Efficiency	η_{sto}	0.92	-	Pape et al. (2014)
Marginal costs of storage operation		1	EUR/MWh	Own assumption
Overnight investment costs power		35	EUR/kW	Pape et al. (2014)
Overnight investment costs in energy		187	EUR/kWh	Pape et al. (2014)
Technical lifetime		20	$years$	Agora (2014)
Annualized investment costs capacity	c^{iP}_{sto}	3	EUR/kW	
Annualized investment costs energy	c^{iE}_{sto}	14	EUR/kWh	
Annual fixed costs	c^{fix}_{sto}	10	$EUR/kW(h)$	Own assumption
Maximum power or energy capacity		-	-	
Lead acid batteries				
Efficiency	η_{sto}	0.84	-	Pape et al. (2014)
Marginal costs of storage operation		1	EUR/MWh	Own assumption
Overnight investment costs power		35	EUR/kW	Pape et al. (2014)
Overnight investment costs in energy		67	EUR/kWh	Pape et al. (2014)
Technical lifetime		15	$years$	Pape et al. (2014)
Annualized investment costs power	c^{iP}_{sto}	3	EUR/kW	
Annualized investment costs energy	c^{iE}_{sto}	6	EUR/kWh	
Annual fixed costs	c^{fix}_{sto}	10	$EUR/kW(h)$	Own assumption
Maximum power or energy capacity		0	MW	
Sodium-sulfur batteries				
Efficiency	η_{sto}	0.88	-	Pape et al. (2014)
Marginal costs of storage operation		1	EUR/MWh	Own assumption
Overnight investment costs power		35	EUR/kW	Pape et al. (2014)
Overnight investment costs in energy		89	EUR/kWh	Pape et al. (2014)
Technical lifetime		15	$years$	Pape et al. (2014)
Annualized investment costs power	c^{iP}_{sto}	3	EUR/kW	
Annualized investment costs energy	c^{iE}_{sto}	8	EUR/kWh	
Annual fixed costs	c^{fix}_{sto}	10	$EUR/kW(h)$	Own assumption
Maximum power or energy capacity		0	MW	
Redox flow batteries				
Efficiency	η_{sto}	0.8	-	Pape et al. (2014)
Marginal costs of storage operation		1	EUR/MWh	Own assumption
Overnight investment costs power		600	EUR/kW	Pape et al. (2014)
Overnight investment costs in energy		70	EUR/kWh	Pape et al. (2014)
Technical lifetime		25	$years$	Pape et al. (2014)
Annualized investment costs power	c^{iP}_{sto}	38	EUR/kW	
Annualized investment costs energy	c^{iE}_{sto}	4	EUR/kWh	
Annual fixed costs	c^{fix}_{sto}	10	$EUR/MW(h)$	Own assumption
Maximum power or energy capacity		0	MW	
Pumped hydro storage				
Efficiency	η_{sto}	0.8	-	Pape et al. (2014)
Marginal costs of storage operation		1	EUR/MWh	Own assumption
Overnight investment costs power		1,100	EUR/kW	Pape et al. (2014)
Overnight investment costs in energy		10	EUR/kWh	Pape et al. (2014)
Technical lifetime		80	$years$	Pape et al. (2014)
Annualized investment costs power	c^{iP}_{sto}	46	EUR/kW	
Annualized investment costs energy	c^{iE}_{sto}	< 1	EUR/kWh	
Annual fixed costs	c^{fix}_{sto}	10	$EUR/kW(h)$	Own assumption
Maximum power or energy capacity		300	GWh	Various sources[a]

	Parameter	Assumption	Unit	Source
Adiabatic compressed air energy storage				
Efficiency	η_{sto}	0.73	-	Pape et al. (2014)
Marginal costs of storage operation		1	EUR/MWh	Own assumption
Overnight investment costs power		750	EUR/kW	Pape et al. (2014)
Overnight investment costs in energy		40	EUR/kWh	Pape et al. (2014)
Technical lifetime		30	$years$	Pape et al. (2014)
Annualized investment costs power	c^{iP}_{sto}	43	EUR/kW	
Annualized investment costs energy	c^{iE}_{sto}	2	EUR/kWh	
Annual fixed costs	c^{fix}_{sto}	10	$EUR/kW(h)$	Own assumption
Maximum power or energy capacity		0	MW	
Power-to-gas				
Efficiency	η_{sto}	0.46	-	Pape et al. (2014)
Marginal costs of storage operation		1	EUR/MWh	Own assumption
Overnight investment costs power		1,000	EUR/kW	Agora (2014)
Overnight investment costs in energy		0.2	EUR/kWh	Pape et al. (2014)
Technical lifetime		22.5[b]	$years$	Pape et al. (2014)
Annualized investment costs power	c^{iP}_{sto}	68	EUR/kW	
Annualized investment costs energy	c^{iE}_{sto}	< 1	EUR/kWh	
Annual fixed costs	c^{fix}_{sto}	10	$EUR/kW(h)$	Own assumption
Maximum power or energy capacity		-	-	

[a] Based on EnBW (2012), LfU (2014) TMWAT (2011), Fichtner (2014).
[b] Average for electrolysis and reconversion.

Table 8: Technical assumptions on load curtailment (baseline)

	Parameter	Assumption	Unit	Source
DSM curt cheap (industry)				
Load curtailment costs	c^m_{lc}	500	EUR/MWh	Frontier (2014)
Overnight investment costs		10	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c^i_{lc}	1	EUR/kW	
Annual fixed costs	c^{fix}_{lc}	1	EUR/kW	Frontier (2014)
Maximum duration DSM	θ	4	h	Klobasa (2007)
Recovery time DSM	ρ	24	h	
Maximum installable capacity	m_{lc}	3,300	MW	Frontier (2014)
DSM curt medium (industry)				
Load curtailment costs	c^m_{lc}	1,500	EUR/MWh	Frontier (2014)
Overnight investment costs		10	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c^i_{lc}	1	EUR/kW	Frontier (2014)
Annual fixed costs	c^{fix}_{lc}	1	EUR/kW	Frontier (2014)
Maximum duration DSM	θ	4	h	Klobasa (2007)
Recovery time DSM	ρ	24	h	Own assumption
Maximum installable capacity	m_{lc}	1,600	MW	Frontier (2014)
DSM curt expensive (industry)				
Load curtailment costs	c^m_{lc}	8,000	EUR/MWh	Frontier (2014)
Overnight investment costs		10	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c^i_{lc}	1	EUR/kW	Frontier (2014)
Annual fixed costs	c^{fix}_{lc}	1	EUR/kW	Frontier (2014)
Maximum duration DSM	θ	4	h	Klobasa (2007)
Recovery time DSM	ρ	24	h	Own assumption
Maximum installable capacity	m_{lc}	5,400	MW	Frontier (2014)

Table 9: Technical assumptions on load shifting (baseline)

	Parameter	Assumption	Unit	Source
DSM shift 1h (climatization, process heat/cold)				
Load shifting costs	c_{ls}^{m}	1	EUR/MWh	Frontier (2014)
Overnight investment costs		745	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c_{ls}^{i}	92	EUR/kW	Frontier (2014)
Annual fixed costs	c_{ls}^{fix}	-	EUR/kW	
Maximum duration DSM	θ	1	h	Agora (2013)
Recovery time DSM	ρ	1[a]	h	Own assumption
Maximum installable capacity	m_{ls}	793	MW	Frontier (2014)
DSM shift 2h (circulation pumps, heat pumps, ventilation)				
Load shifting costs	c_{ls}^{m}	1	EUR/MWh	Frontier (2014)
Overnight investment costs		1,517	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c_{ls}^{i}	187	EUR/kW	Frontier (2014)
Annual fixed costs	c_{ls}^{fix}	-	EUR/kW	
Maximum duration DSM	θ	2	h	Stadler and Bukvić-Schäfer (2003), Agora (2013)
Recovery time DSM	ρ	1[a]	h	Own assumption
Maximum installable capacity	m_{ls}	2,535	MW	Frontier (2014)
DSM shift 3h (industry)				
Load shifting costs	c_{ls}^{m}	100	EUR/MWh	Own assumption
Overnight investment costs		10	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c_{ls}^{i}	1	EUR/kW	Own assumption (as curtailment)
Annual fixed costs	c_{ls}^{fix}	-	EUR/kW	
Maximum duration DSM	θ	3	h	Gils (2014)
Recovery time DSM	ρ	1[a]	h	Own assumption
Maximum installable capacity	m_{ls}	1,385	MW	Gils (2014)
DSM shift 4h (white goods, ventilation)				
Load shifting costs	c_{ls}^{m}	1	EUR/MWh	Frontier (2014)
Overnight investment costs		835	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c_{ls}^{i}	103	EUR/kW	Frontier (2014)
Annual fixed costs	c_{ls}^{fix}	-	EUR/kW	
Maximum duration DSM	θ	4	h	Own assumption
Recovery time DSM	ρ	1[a]	h	Own assumption
Maximum installable capacity	m_{ls}	1,451	MW	Frontier (2014)
DSM shift 12h (storage heaters)				
Load shifting costs	c_{ls}^{m}	1	EUR/MWh	Frontier (2014)
Overnight investment costs		30	EUR/kW	Frontier (2014)
Technical lifetime		10	$years$	Own assumption
Annualized investment costs	c_{ls}^{i}	4	EUR/kW	Frontier (2014)
Annual fixed costs	c_{ls}^{fix}	-	EUR/kW	
Maximum duration DSM	θ	12	h	Agora (2013)
Recovery time DSM	ρ	1[a]	h	Own assumption
Maximum installable capacity	m_{ls}	1,050	MW	Frontier (2014)

[a] This means that recovery time is not restricted for shifting processes.