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The place beyond the lines - efficient storage allocation in a spatially unbalanced power system with a high share of renewables

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Abstract

Increasing shares of wind and solar generation serve to decarbonize electricity generation; however, their temporal and spatial variability poses challenges in grid operation. While grid expansion is restricted in the medium term, storage technologies can potentially increase the power systems' efficiency by temporally aligning generation and demand and increasing network utilization. This paper uses a theoretical and a numerical model to evaluate the optimal allocation of battery storage. In a case study for Germany, we find that batteries can reduce system costs when placed behind the north-south grid bottleneck and near solar power. The supply costs in a setting with uniform prices and a random battery distribution are 9.3% higher than in the theoretical first-best benchmark with nodal prices. An optimal allocation of batteries can reduce this efficiency gap by 0.7 percentage points to 8.6%. This corresponds to almost a doubling of the supply cost savings per euro spent on battery installation. Due to a lack of spatially differentiated investment incentives under the German uniform pricing scheme, batteries have to be allocated by additional policies. Simple allocation rules such as tying battery siting to solar capacity or explicitly identifying a limited number of suitable sites and auctioning capacity can approximate an optimal allocation.

Keywords: Market Design, Electricity Markets, Nodal Pricing, Energy System Modeling, Renewable Energies, Storage, Flexibility, Batteries

JEL classification: D47, D61, C61, Q40

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1. Introduction

As countries strive for climate neutrality, they aim for high wind and solar power penetration rates. Wind and solar are intermittent, so temporal congruence with demand is not guaranteed. Additionally, resource quality varies across regions, which may lead to a spatial imbalance between supply and demand or extensive transmission requirements that exceed the capacity of existing grid infrastructure. Efficient coordination of investments in wind and solar, as well as in transmission grid expansion and power system flexibility, can mitigate these challenges and decrease system costs. Storage technologies, such as electric batteries, provide such power system flexibility. They can address temporal imbalances by shifting generation and load and reduce spatial imbalances by improving network utilization if allocated accordingly. Whether such an allocation is achieved ultimately depends on the market design. Under nodal pricing, allocation incentives are set by market prices. Such incentives do not exist in uniform pricing systems.

This paper analyzes investment in storage technologies in both a nodal and a uniform setting. We focus on a rapidly changing, spatially unbalanced power system, i.e., where solar and wind capacity expansion is fast, but grid expansion is slow. By applying a stylized, theoretical, and a numerical investment and dispatch model, we answer the following three research questions: Firstly, where in the transmission grid should batteries be allocated? Secondly, how important is storage allocation for the system's efficiency, and thirdly how could policy instruments be designed to approximate an optimal allocation under uniform pricing?

The importance of storage allocation is first illustrated using a theoretical two-node, two-time-step model that stylizes the characteristics of a spatially unbalanced power system. This model enables us to show fundamentally that storage capacity can increase line utilization depending on its location. We show that both an allocation before or behind a grid bottleneck can be efficient. Which allocation rule dominates crucially depends on the temporal relationship between the volatility pattern of renewable generation, the demand structure, and available transmission capacity. Naturally, the complexity of the allocation question increases as soon as more than two nodes and time steps are considered. Therefore, in the main part of the paper, we provide a comprehensive numerical model to investigate optimal storage allocation in a system with multiple technologies and a detailed grid representation. We use the German electricity system as a case study.

Already today, Germany exhibits characteristics of a spatially unbalanced electricity system. Under the single bidding zone, i.e., uniform pricing, wind generation is dominantly allocated in northern Germany on the shore of the North and Baltic Seas, while electricity demand is historically centered in the south and west of Germany, which is more densely populated and industrialized. As a result of this spatial mismatch, the volume and costs of network congestion measures have risen and are likely to increase further, given Germany's latest renewable capacity targets.

To investigate the optimal allocation of storage and identify policy design options for coordinating investments, we use a linear optimization market and grid model that endogenously determines the allocation of storage and renewable generation technologies. The storage technology is calibrated as short-term battery storage. The model computes a closed-form solution to the investment and dispatch optimization problem while considering a high spatial resolution. We use the results from modelling a nodal setup with consideration of transmission constraints as a theoretical first-best benchmark. This allows benchmarking battery allocation under a uniform setup without consideration of transmission constraints in the investment problem, similar to the current German market design.

The numeric simulation results confirm the significance of local demand, renewable feed-in volatility, and grid infrastructure availability for optimal battery allocation. Especially solar generation, which has a daily generation pattern that matches the batteries' short-term shifting abilities, is a key driver for an efficient allocation. Compared to the nodal first-best benchmark, we see that the uniform setting with randomly distributed batteries increases supply costs by 9.3%. An optimal allocation of batteries can reduce this efficiency gap by 0.7 percentage points to 8.6%. In relation to the cost of battery investments, this corresponds to almost a doubling of the supply cost savings per euro spent. The supply cost savings are realized in redispatch, where the location of batteries is crucial. In the current system in Germany, such an optimal allocation is not achieved, because spatially differentiated investment signals are not available under uniform pricing. However, with the help of an additional policy instrument, location-specific information could be made transparent to provide a reference point for allocating batteries in a system beneficial way. To get insights on how to design this policy instrument, we model different allocation rules and find that simple heuristics, such as tying battery allocation to solar generation or explicitly defining a limited number of nodes for capacity auctions, can closely approximate the optimal battery allocation.

The paper is organized as follows. Section 2 introduces literature on storage allocation, focusing on numerical studies of the German market. Section 3 explains the economic rationale of storage allocation using a two-node model. Section 4 presents the numerical model, describes our main assumptions, and the relevant input data. Additionally, the different model setups and allocation rules considered in our analysis are introduced. Section 5 presents the results, compares supply costs for each setup, and analyzes different policy instruments. Section 6 discusses the results and derives policy implications. We conclude our findings in section 7.

2. Literature review

Several publications have touched upon the role of storage in spatially unbalanced power systems. Newbery (2018) argues that storage can be used to increase grid utilization, thus decreasing system imbalances. However, literature is scarce regarding theoretical analyses of fundamental determinants of efficient storage allocation within transmission grids. Neetzow et al. (2018) analyze the interplay of storage facilities and grid expansion in an analytical setup and show that whether these two options are complements or substitutes depends critically on the characteristics of transmission congestion and the alignment of marginal generation costs between the regions or nodes. Weibelzahl and Märtz (2018) propose a simplified three-node model to examine the effect of storage on the optimal definition of price zones and highlight the additional complexity storage brings into the system. Predominantly, the current literature is based on more complex, numerical studies considering specific countries or regions.

Many of the studies focus on the short-term deployment of storage in uniform price systems (e.g. Zerrahn and Schill, 2017; Schill and Zerrahn, 2018; Bertsch et al., 2016; Abrell et al., 2019). These papers analyze the possibilities of using storage to balance the temporal volatility of renewables but do not include a grid representation. Thus, these papers cannot analyze questions of spatial allocation. In order to model spatial allocation and derive market design implications, a representation of grid constraints is crucial. Such an analysis is, for example, carried out by Schmidt and Zinke (2023) for the case of wind generation allocation. Comparing a nodal and a uniform market design in Germany in 2030, they show that the curtailment of wind energy in a nodal pricing system declines to one-third of its value under uniform pricing, and locations of wind power plants shift from the northwest coast to other areas in Germany. Hence, the authors find that grid utilization is improved due to a broader spatial allocation of wind power plants, and overall system efficiency increases. Similarly, vom Scheidt et al. (2022) investigate differences between a nodal and a uniform pricing system in Germany, focusing on the integration of hydrogen and system-optimal locations of electrolyzers in 2030. The authors find that under nodal pricing, locations shift from regions with high hydrogen consumption to regions with high electricity production, and prices for hydrogen are lower under nodal pricing. They further find that in 2030, under uniform pricing, electrolyzers impose additional congestion management costs of 11% compared to a scenario without electrolyzers which underpins the necessity for a spatially coordinated investment in the upcoming decade in Germany. Lindner et al. (2023) find that batteries, used as grid boosters or virtual power lines in the transmission grid, reduce grid congestion and curtailment volumes. For their analysis, they place batteries at two exemplary nodes in the north and south of Germany, respectively, but call for further research on optimal storage allocation.

Closest to our analysis is the following literature that integrates both grid modeling and storage or other comparable flexibility options: Ambrosius et al. (2018) investigate the effects of different market designs on investment incentives for flexible demand in the German industry. They construct a multi-stage equilibrium model for endogenous generation capacity investments and network expansion. Various outcomes under a nodal pricing scenario and uniform pricing are examined in different scenarios. The authors find that welfare increases and the expansion of conventional generation capacity decreases in the scenario with optimal locational investment, as fewer dispatchable power plants are needed to meet peak demands in certain regions. Göke et al. (2021) analyze the substitutability of grid expansion and a well-coordinated investment into generation and storage technologies in a (hypothetical) fully renewable German electricity system. The authors compare different market design options and find that a first-best solution can be well approximated if the current planning approach also considers storage for congestion management. They further show that shifting the location of renewables has no significant effect because the available area potentials have to be exploited almost entirely and there are hardly any optimization possibilities left. While both papers use a simplified transmission grid representation with 16 and 38 zones, respectively, Babrowski et al. (2016) apply a more detailed model to investigate the optimal storage amount and location in Germany. For 2040, their model implies a high amount of battery storage in the northwestern coastal region, mainly to balance the feed-in from offshore wind farms. In addition, a high storage capacity is found in the western region near transmission bottlenecks, relieving grid congestion.

Some publications focus on the longer term and analyze efficient power system configurations with (nearly) 100% renewable power generation. Schlachtberger et al. (2017) and Brancucci Martínez-Anido and de Vries (2013) confirm the analytical finding of Neetzow et al. (2018) that storage and grid expansion can be both complements and substitutes by applying numerical models of the European power system. Moreover, like Bussar et al. (2014), they find that batteries are suitable for smoothing solar power generation, while hydrogen storage capacities and grid expansion are suitable for integrating wind power generation.

Research gap and contribution

Reviewing current literature reveals a lack of systematic analysis of optimal storage allocation and market design implications. Consequently, our paper seeks to bridge the gap between existing publications that address storage, grid issues, or market design as individual issues in power systems with high shares of wind and solar. We contribute a fundamental analysis of storage allocation in a simplified model and verify and expand our findings by employing a numerical electricity market and detailed grid model with endogenous storage allocation. By doing so, we can evaluate the role of storage for temporal shifting against the backdrop of regionally differentiated demand and renewable generation time series and the electricity grid. Analyzing storage allocation in a uniform setting and a first-best nodal benchmark allows us to translate the insights from our integrated analysis into policy suggestions.

3. The economic rationale for storage allocation

This section introduces a model with two nodes and two time steps to analyze determinants of cost-optimal spatial allocation of storage in a spatially unbalanced transmission network. Generally, from a technical point of view, electrical storage technologies offer the possibility to shift the electricity supply between different points in time. In electricity markets, storage buys electricity when the market price is low and sells electricity when the market price is high. The arbitrage opportunities between different points in time, thus, determine the profitability of the storage technology.

Depending on their allocation in the grid, storage can use its temporal shifting potential to increase network utilization and thus reduce spatial imbalances in the grid. For illustration, consider the following:

Assume a weather-dependent, renewable generation technology in node R, for example, a wind or a solar generator g_{res}, with constant zero marginal costs $c_{res} = 0$. Renewable generation is stochastic and can take two possible states, 0 and 1. Demand d is allocated in node D and can also take two possible states d_{low} and d_{high}. For simplicity, demand and renewable availability are assumed not to be correlated. However, we assume a renewable generation capacity such that if availability is 1, generation equals the level of demand state d_{high}. From here on this state is called generation state res_{high}. Availability of 0 leads to no generation, from here on labeled state res_{low}. Further, we consider a peak-load technology g_{peak} at node D, with constant marginal costs $c_{peak} > 0$ and enough capacity to serve the demand in each time, i.e. $\overline{g}_{peak} > d_{high}$.

Both nodes are connected by a transmission line l with line capacity $d_{low} < \bar{l} < d_{high}$. So if demand is high and at the same time generation in node R is high, node D could still not be fully supplied by the low-cost renewable generation technology due to a grid bottleneck. The model is illustrated in Figure 1.

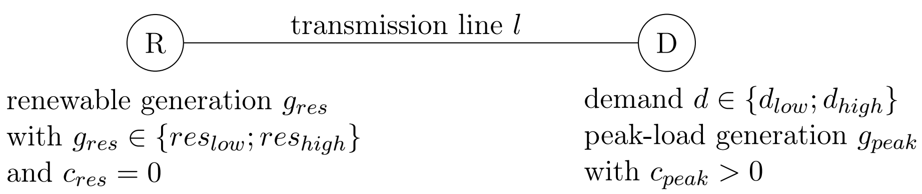


Figure 1: Two-node example

We consider two time steps t_1 and t_2. Combining renewable generation and demand in all its possible states yields eight different cases, shown in table 1.[1]

Table 1: Possible combinations of renewable generation and demand in both time steps

	Description	t_1	t_2	Allocation rationale
case 1	no volatility	res_{high}, d_{low}	res_{high}, d_{low}	no storage
case 2	no volatility	res_{high}, d_{high}	res_{high}, d_{high}	no storage
case 3	volatility in generation	res_{high}, d_{high}	res_{low}, d_{high}	storage in R
case 4	volatility in both	res_{high}, d_{low}	res_{low}, d_{high}	indifferent between R and D
case 5	volatility in generation	res_{high}, d_{low}	res_{low}, d_{low}	no storage
case 6	volatility in demand	res_{high}, d_{low}	res_{high}, d_{high}	storage in D
case 7	volatility in demand	res_{high}, d_{high}	res_{high}, d_{low}	no storage
case 8	volatility in both	res_{high}, d_{high}	res_{low}, d_{low}	no storage

Storage s can either be built in node R or D and comes without any investment costs. We further assume no storage losses or other variable costs in addition to charging costs, such that $c_s < c_{peak}$ when storage is charged with renewable energy For simplicity, we assume that storage power (charge and discharge) capacity equals supply and demand states res_{high} and d_{high} Furthermore, storage volume capacity $\overline{s}_{power}$ is sufficient to store at least one period of full charging, i.e., $\overline{s}_{volume} \geq \overline{s}_{power}$. By definition, storage is only useful if there are fluctuations in the system, either in renewable generation or demand. If renewable generation is high in both time steps and demand does not fluctuate either, the transmission line l is already used at capacity and peak generation is minimized. Hence, storage has no benefit to the system as a whole, which holds for cases 1 and 2.

If demand fluctuates and transmission line l is not utilized in t_1 or t_2, temporal shifting becomes useful. Consider the case that renewable supply is high in t_1 and low in t_2 and demand in node D is high in both time steps (case 3). Because there is a transmission bottleneck in t_1, storage could be used to store excess renewable generation $res_{high} - \bar{l}$. In t_2, the stored energy can be released and transmitted to node D, as transmission line l is not utilized because generation is otherwise low. Storage has to be allocated at the generation node R to do so, as l is fully utilized in t_1 when the storage is charged. A similar effect occurs, if demand is low in t_1 and high in t_2 (case 4). In this case, however, the location does not matter. Without storage, line l is not utilized at capacity in either time step. Thus, storage can charge regardless of whether it is allocated at node R or at

[1] We do not consider combinations in which renewable generation is low in t_1 as storage is per se useless in these cases.

node D. In case 5, where demand is low at both times, no storage is needed because both renewable generation and grid capacity are sufficient to meet demand at both times.

If the renewable generation is high at both times, the benefit of storage depends solely on the demand profile. In case 6, where demand is low in t_1 and high in t_2, storage capacity equal to $\overline{s}_{power} = \bar{l} - d_{low}$ is built in node D to use renewable generation in t_2 instead of the more expensive conventional generation. In cases 7 and 8, where res_{high} and d_{high} coincide, again, temporal shifting has no benefit.

Main findings and generalization

The simplified two-node, two-time-step model demonstrates that storage can indeed decrease supply costs by increasing line utilization, thus increasing system efficiency. The model further reveals that the location of storage is crucial to unlock said system benefits. The results suggest that storage can be optimal either before or behind a grid bottleneck. In the simple set-up, the optimal location depends on the volatility of the underlying demand and generation profiles. Thus, storage is allocated where volatility is higher. In practice, however, the underlying profiles are stochastic and exhibit more time steps, i.e., a sequence of the individual cases discussed above. When combining the cases into a sequence, the strict dominance of an allocation case ceases to exist, meaning that one of the cases could prevail or storage capacity could be split between the two nodes.[2]

Furthermore, the complexity of the model and the underlying relationships increases as soon as more than two nodes and technologies with different characteristics are considered. Even in the very simple model setup with only two nodes and two time steps, the storage allocation depends on the parametrization of generation and demand volatility. To decide where storage is allocated optimally, it is thus necessary to use a well-parametrized and numerical real-world model.

[2] With a longer sequence of time steps, also the assumption regarding the volume factor of storage $\frac{\overline{s}_{volume}}{\overline{s}_{power}}$ becomes more relevant than it is in the two-time-step example. The volume factor determines the maximum duration of temporal shifting. Different volume factors mean that different parts of a stochastic demand and supply pattern can be exploited, thus also potentially affecting efficient allocation.

4. Methodology and input data

4.1. Model framework

We employ an extended version of the investment and dispatch model SPIDER initially developed in Schmidt and Zinke (2023). SPIDER is a model of the European power sector that considers a detailed depiction of the German transmission grid.[3] The model invests in new power plants and dispatches generation capacities such that the net present value of the variable and fixed costs is minimized.

Demand, which means the structure, spatial distribution, and level, is assumed to be inelastic, i.e., not adjusting to prices. The model relies on the assumption of perfect markets and no transaction costs. Thus, the competition of profit-maximizing symmetric firms corresponds to the model's cost minimization of a central planner.

We set up a linear optimal power flow problem (LOPF) to approximate the inner-German transmission grid infrastructure. To keep the problem linear, DC power flow constraints are used to approximate non-linear AC power flow restrictions. Thereby, the model neglects grid losses and reactive power (c.f. van den Bergh et al., 2014). The implementation of DC power flows is based on the cycle-based Kirchhoff formulation, which has been proven to be an efficient formulation (c.f. Hörsch et al., 2018). Network investments are assumed to be exogenous, which is valid for the 2030 time horizon due to the long approval and construction times. European regulatory authorities usually review and approve grid expansion projects 10 to 15 years in advance (c.f. Bundesnetzagentur, 2019).

In addition to the initial model of Schmidt and Zinke (2023), in this paper, SPIDER is extended to allow for endogenous investments in storage as well as solar power capacities. The model optimizes the allocation of storage, but the ratio of maximal charging power (hereafter referred to as capacity) and stored energy (hereafter referred to as storage volume) is set exogenously. The key formulation of the cost minimization problem and the storage constraints are given in Appendix B.

Modeling a detailed representation of grid constraints and endogenous investments in generation and storage is a computational challenge. As in Schmidt and Zinke (2023), the model is therefore subject

[3] For a thorough description of the underlying model and its characteristics, the reader is referred to Schmidt and Zinke (2023).

to several limitations: As mentioned above, investments in transmission grid lines are exogenous assumptions. Ramping and minimum load constraints are approximated in order to avoid a mixed-integer optimization and the model does not include combined heat and power plants. Further, the model abstracts from uncertainty and assumes perfect foresight.

4.2. Assumptions and data

The regional focus of the model is Germany with a spatial resolution at transmission grid node level, i.e., 220 kV to 380 kV voltage levels. The depiction of the transmission grid is based on grid information from multiple sources, including Matke et al. (2016) and 50Hertz et al. (2019). Grid extensions follow the German 2030 grid development plan, which was reviewed and approved by the German grid regulator (c.f. Bundesnetzagentur, 2019).

While the German transmission grid is modeled for 2019 with 380 nodes and 606 lines, Germany's neighboring countries are depicted as singular nodes without intra-country grid restrictions. The model includes interconnectors to as well as between neighboring countries, which are approximated via net transfer capacities (NTC) based on ENTSO-E (2020a).

The regional scope and the depiction of the German transmission grid are visualized in Figure 2.

Our analysis covers the years 2019, 2025 and 2030. Each year is represented by 12 representative days at hourly resolution. We derive the representative days by using k-medoids clustering with respect to residual load (c.f. Kotzur et al., 2018).

For our case study, we parameterize the storage technology as large-scale electric batteries. Therefore, these batteries participate in the wholesale market and may be subject to redispatch measures (in the uniform setting).[4] Appendix C discloses further assumptions on technology parameters, demand development per country as well as fuel prices.

Existing power plant capacities and their distribution across Germany are derived from data provided by the German regulator Bundesnetzagentur.[5] Power plants are distributed via their post-codes to the nearest transmission grid node. The future distribution of offshore wind farms is based on 50Hertz et al. (2019).

[4]In practice, this does not apply to small storage systems such as photovoltaic systems or storage for electric vehicles designed to increase self-sufficiency.

[5]Conventional power plants are based on the power plant list (Bundesnetzagentur, 2020a) and renewables on data from the *Marktstammdatenregister* (Bundesnetzagentur, 2020b).

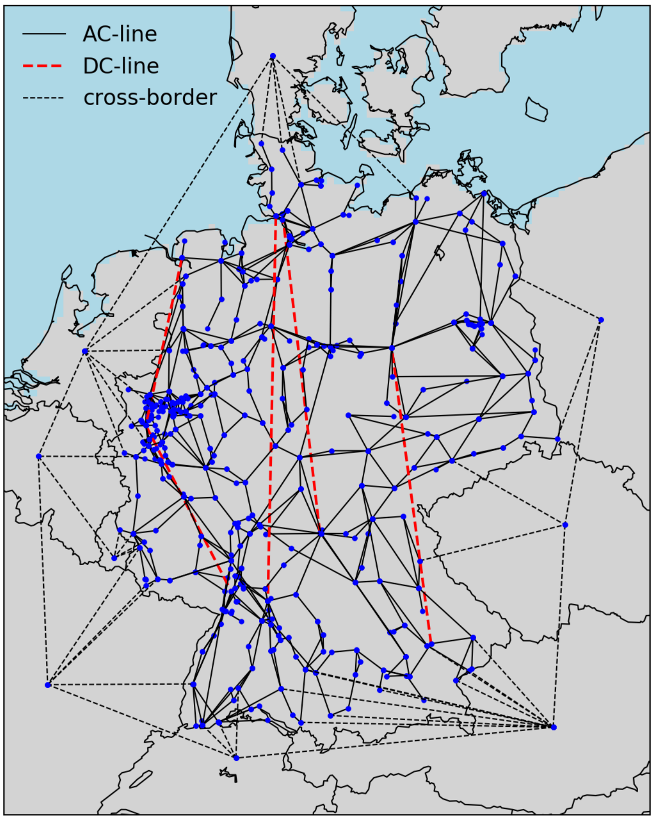


Figure 2: German transmission grid and NTC connections to neighboring countries

Capacity development at the national level is exogenous and follows the *National Trends* scenario in ENTSO-E (2020a) for all countries except Germany. For Germany, the assumed capacity development reflects the legal and political situation. Wind and solar expansion follow the current legal targets (EEG, 2023; WindSeeG, 2023). The legislation does not include a specific capacity target for batteries in 2030. Instead, aggregated battery capacity is an assumption based on *Scenario B* from the 2037/2045 grid development plan (50Hertz et al. (2022)).[6] Table 2 shows the assumed expansion of wind, solar, and battery capacities in Germany.

The phase-out of German nuclear, lignite, and coal power plants is implemented according to the path defined in the Act to Reduce and End Coal-Fired Power Generation (KAG, 2020). In addition, the announced phase-out of lignite-fired power generation by 2030 is considered for the

[6]In a sensitivity analysis, our results prove robust for deviating total battery capacities of 5, 10, and 20 GW, respectively Appendix D.2.

Table 2: Assumed development of installed wind, solar and battery capacities in Germany

[GW]	2019	2025	2030
Wind Onshore	53.4	65.4	115.0
Wind Offshore	7.5	14.3	30.0
Solar	49.2	105.2	215.0
Batteries	0.0	5	15.0

state of North Rhine-Westphalia (BMWK, 2022b). We assume that the electricity market triggers sufficient investments into backup power plants to meet demand at all times. The location of the required gas capacities is efficiently determined in the nodal setting and fixed for all model runs. The regional allocation of onshore wind, solar, and battery storage capacity is determined endogenously. Therefore, their regional allocation follows the economic rationale of the considered model setup (see 4.3) while taking into account distributions of determining factors such as demand and resource quality. Since the total installed capacities are the same in all settings examined, the efficiency of regional allocation alone determines the differences in electricity supply costs.
Demand time-series for neighboring countries are based on hourly national demand in 2014, according to ENTSO-E (2020b). The German demand is distributed to the nodes similar to the approach in 50Hertz et al. (2019): Based on sectoral demand shares on the federal state level (c.f. Länderarbeitskreis Energiebilanzen, 2020), household demand is distributed onto nodes proportionally to population shares. The distribution of industry and commercial demand reflects the regional distribution of gross value added for the respective sectors (c.f. EUROSTAT, 2020)). The demand time series are synthesized in a bottom-up approach using sector and application-specific standard load profiles, which reflect 2014 as a calendar and weather year.
The intermittency of renewable feed-in is modeled via weather-dependent hourly regional feed-in potential. The time series for onshore wind in Germany and solar generation are based on high-resolution reanalysis meteorological data from the COSMO-REA6 model. For onshore wind, the conversion of wind speeds to regional feed-in data is based on Henckes et al. (2017). For solar generation, solar radiation was converted to regional feed-in potential as described by Pfenninger and Staffell (2016a). Data for Germany's neighboring countries and German offshore wind power is provided by Pfenninger and Staffell (2016a) and Pfenninger and Staffell (2016b).

4.3. Nodal and uniform setting, allocation rules, and benchmarking

The model framework is applied to simulate investment and dispatch decisions under two different settings: nodal and uniform. In the nodal setting, each transmission grid node constitutes a market and grid constraints are considered within the price formation. When grid constraints are binding, prices differ between nodes. In the case of new investments, these spatially differentiated price signals and hence, transmission bottlenecks are considered in siting decisions. Without any frictions, the nodal setting represents the first-best configuration for an efficient coordination of power generation investments, dispatch, and the grid.

Germany employs a uniform pricing approach. The uniform pricing approach relies on larger market areas or zones, usually defined based on a country's national borders. Under uniform pricing, physical constraints concerning power flows within a market area are not considered in the market clearing. As a result, the scheduled dispatch after market clearing may violate physical grid restrictions. Hence, uniform pricing requires curative redispatch measures carried out by grid operators. As grid restrictions are not reflected in the market, prices within a market area are the same, i.e., uniform.

We model a uniform setting where transmission bottlenecks are neglected; thus, coordination between generation investment, dispatch, and the grid is missing. This setup represents the uniform pricing market design currently in place in Germany in a simplified way. We neglect additional factors that might impact siting decisions, such as additional policies or locational factors that relate to the preference of individual investors. Consequently, in the uniform setup, siting decisions for wind and solar are guided by resource quality so that new facilities are primarily built in areas where meteorological conditions allow a maximum yield. Other generators, including batteries, are indifferent to siting in the uniform setup.

Consequently, the two setups differ in terms of the amount of information available or, more specifically, in terms of the consideration of transmission constraints. While the grid constraints are part of the investment and dispatch optimization in the nodal setting, these constraints are neglected in the uniform setting. A subsequent dispatch run considering the DC power flow reveals whether the scheduled dispatch with given investment decisions obtained in the uniform setting violates grid constraints, i.e., whether a redispatch is required. The difference in supply costs between the initial dispatch and the subsequent redispatch run is considered the resulting redispatch cost. We model a perfectly efficient redispatch that includes all generation units in all modelled countries. Thus, the resulting total supply costs, i.e, dispatch plus redispatch costs, would be equal if capacity allocations in the nodal and uniform setting were the same. However, the allocation of new capacity is sub-optimal in the uniform case, resulting in higher total supply costs than in the nodal setup. We quantify efficiency losses of the uniform setting by comparing total supply costs with the nodal first-best benchmark. Capital costs can be neglected since total installed capacity is the same in each setting.

Assuming that the uniform pricing system is politically desired and will be maintained in Germany, location-specific information could be made transparent with the help of an additional policy instrument that provides a reference point for a system beneficial allocation of storage capacities. To get insights on how to design this policy instrument, we use the numerical model to analyze different allocation rules for storage investment in an otherwise uniform setting. Thereby, we focus on allocation rules that coordinate the storage allocation isolated from other technologies and employ our model to test these allocation rules. Specifically, we test for *heuristic* approaches and *explicit* allocation rules.

Heuristic approaches, on the one hand, allocate storage capacity based on a reference distribution. We select the heuristics under consideration based on an analysis of drivers for optimal storage allocation. A similar instrument to such a heuristic is used in the capacity auction for wind power generation. To achieve a broader capacity distribution over Germany, the merit order of capacity bids is altered to compensate for yield losses at sites with lower resource quality. The correction follows a non-linear heuristic based on the deviation from a reference wind generator. An additional example of a heuristic allocation approach can be found in Sweden, where generation network tariffs depend on latitude. The differentiation of network tariffs incentivizes generation investment at lower resource quality sites close to demand.

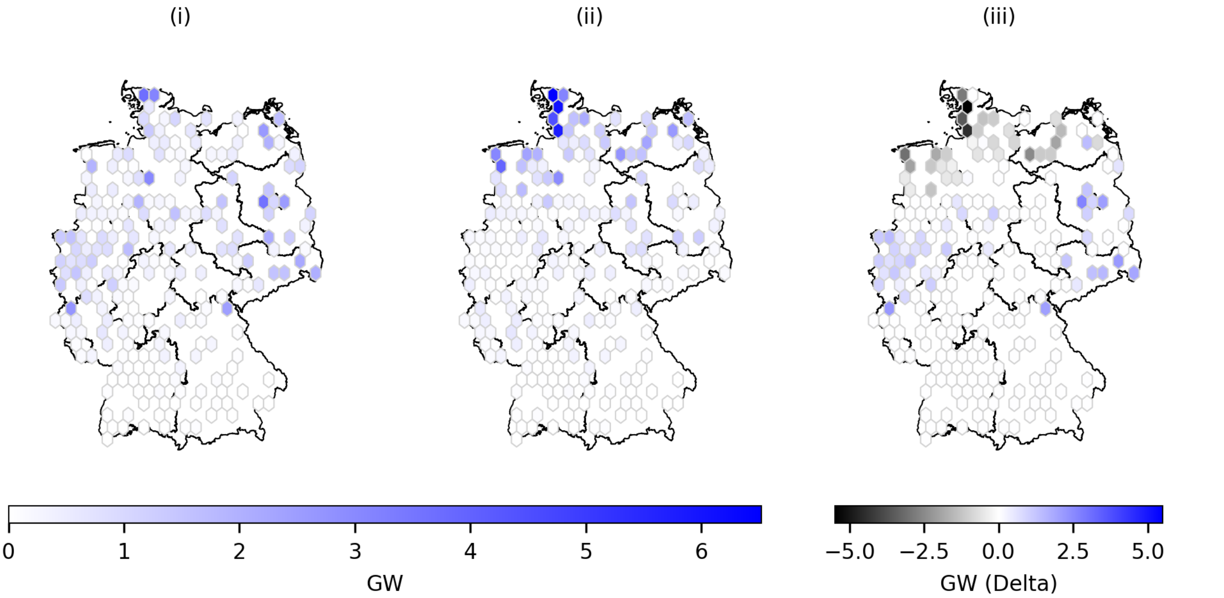
On the other hand, we test *explicit* approaches which allow storage investment at a limited number of candidate nodes identified as suitable in the optimal case. The capacity is then optimized across the candidate nodes. Hence, this approach requires detailed information about load flows. A similar policy is already implemented within the capacity auctions for wind generation, where a certain percentage of capacity is reserved for bids from the so-called south zone, a predefined area below the structural grid bottleneck. A different kind of location-specific capacity mechanism is used to procure the so-called grid reserve. The German grid regulator monitors the capacity demand for redispatchable power plants in the south of Germany. If available capacity is lower than capacity demand, grid operators can procure specific mothballed power plants or power plants scheduled for phaseout for grid reserve.

To rank the different instruments and their efficiency gains, we derive the optimal allocation of batteries for the uniform setup and use it for comparison. To obtain the optimal allocation, we perform a first model run calculating the distribution of wind and solar capacity without considering transmission constraints. Subsequently, in a second model run, we optimize the battery allocation considering transmission constraints and the given distribution of wind and solar. While the optimal allocation represents the upper bound for the efficiency achieved with a storage allocation mechanism, determining a lower bound is somewhat more complicated. In the uniform setting, there is no clear decision rule for storage because resource quality does not vary. Different factors such as demand typology, innovation drive or existing infrastructure could potentially influence storage allocation in the real world without spatially differentiated investment incentives. It is, however, unclear whether and how such factors influence the allocation and we therefore cannot include them in our model. Instead of a lower bound, we compute a demand-weighted random distribution of storage across Germany as a benchmark for the lack of coordination incentives. The random distribution is sampled 100 times and averaged to reflect an expected value.

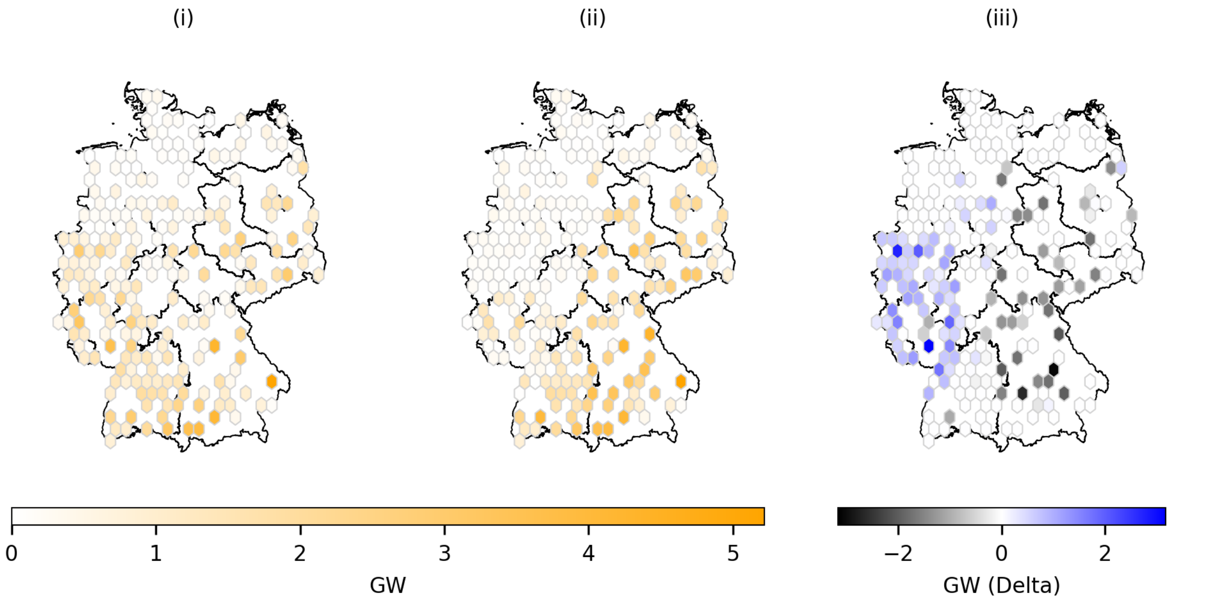
5. Numerical model results

5.1. Renewable allocation

Solar and wind power allocation is primarily driven by the consideration of transmission capacity. In the nodal setting, grid constraints are considered when siting new capacity. However, in the uniform case, investment decisions depend mainly on resource quality and, to a lesser extent, on feed-in patterns and resulting balancing effects. As a result, wind and solar capacity are distributed more broadly and closer to demand under the nodal setup. At the same time, it is concentrated at sites with high resource quality in the uniform setting. Figures 3a and 3b compare the spatial distribution of wind and solar capacity in both cases. Total capacity is exogenous for both settings and reflects Germany's 2030 capacity targets.



(a) Spatial distribution of wind capacity expansion in the (i) nodal and (ii) uniform setting and (iii) difference between both in 2030



(b) Spatial distribution of solar capacity expansion in the (i) nodal and (ii) uniform setting and (iii) difference between both in 2030

Figure 3: Spatial distribution of wind and solar capacity expansion in the nodal and uniform setting

In the nodal setting, wind capacity peaks in the very north of the country, where resource quality is high. The rest of the capacity is widely distributed above the 50th parallel. Solar capacity is relatively evenly distributed below the 52nd parallel, despite higher resource quality in the south of Germany. All in all, significant shares of wind and solar capacities are allocated close to the demand centers in western Germany.

In the uniform setting, investment in wind power concentrates above the 53rd parallel. Solar capacity concentrates in Germany's south and east, with the majority of capacity installed below the 50th parallel. The lack of coordination of renewable feed-in and grid bottlenecks under the uniform setup leads to high curtailment. This especially affects wind power, which is separated from demand by a structural north-south grid bottleneck. In total, 109 TWh of renewable electricity are curtailed under the uniform setup in 2030, compared to only 30 TWh under the nodal setup.

5.2. Battery allocation

In both settings, placing 15 GW battery capacity reduces supply cost, i.e., dispatch (and redispatch) costs.[7] In the nodal setting, supply costs decrease by 1.1% compared to a case without batteries in the system. In the uniform setting, batteries can reduce supply costs by 1.5%. The drivers for the efficiency gains differ between the two settings. Under the nodal setup, wind, solar, and batteries are allocated in an integrated optimization and under the consideration of grid constraints. This allows wind and solar generation to be shifted to locations with higher full-load hours that were subject to grid constraints without batteries. Thus, renewable power generation increases and higher-cost fossil generation is avoided compared to a case without batteries. In the uniform setting, supply cost reductions are split between cost savings in the initial market clearing and in redispatch. In the market clearing, batteries shift excess renewable energy to peak residual load periods, avoiding high-cost peak generation. The supply cost reductions are realized independent of the location and are equal in both battery allocation cases under the uniform setup. In redispatch, batteries create additional efficiency by avoiding high-cost generation behind grid bottlenecks. To

[7] Note that the amount of battery capacity is imposed exogenously in our setting. Thus, we do not investigate whether the savings in supply cost cover the capital cost of the batteries, and hence do not infer conclusions about the economic efficiency of the chosen amount of batteries installed. We discuss some rough estimates at the end of section 5.4.

achieve efficiency gains in redispatch, the allocation of batteries is relevant. This is illustrated by comparing a case of optimal battery allocation to a case of random battery allocation. On average, when allocated randomly, batteries can only decrease supply costs by 0.8% in comparison to a case without batteries. An optimal allocation sets the upper bound for supply cost reduction at 1.5%. Figure 4 compares the efficiency gains of placing 15 GW of battery capacity in the grid for the three cases.

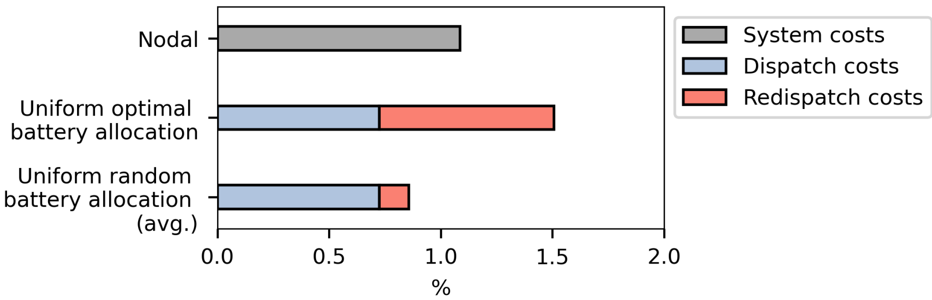
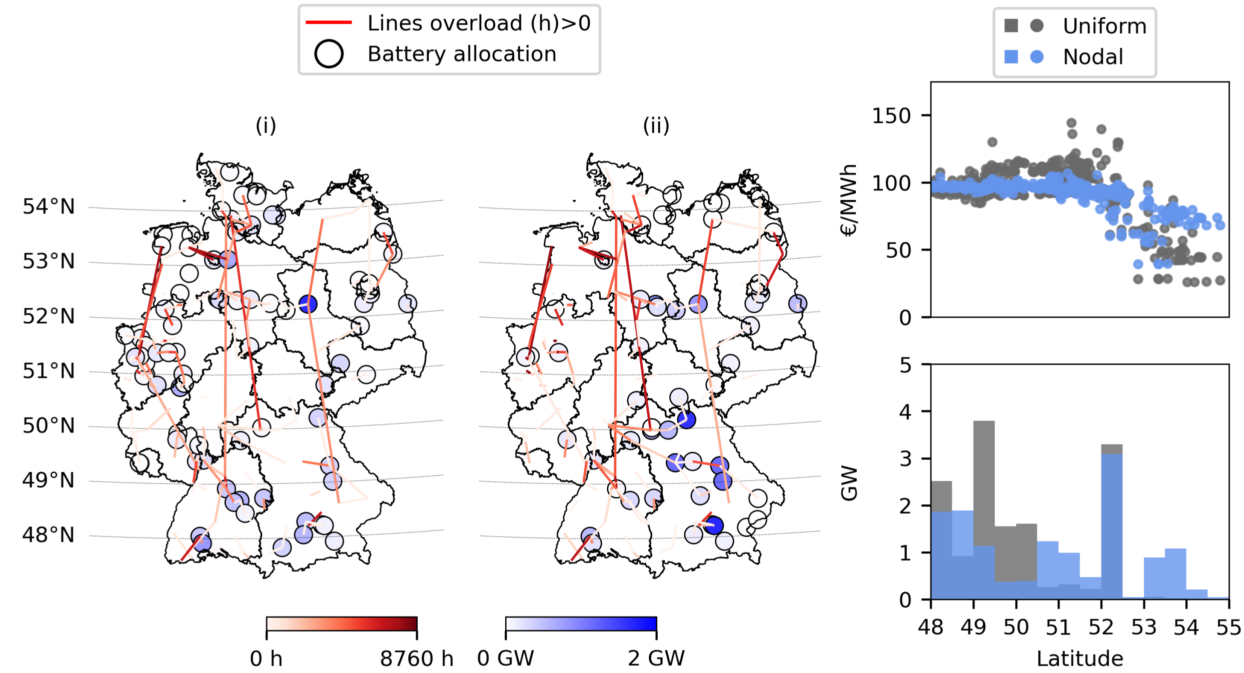


Figure 4: Relative reduction of supply costs due to batteries in the nodal and uniform setting compared to the case without batteries

When comparing the two settings, we find that the total supply costs are 8.6% higher in the uniform than in the nodal setting, even for optimal battery allocation. This cost difference is attributed solely to the sub-optimal distribution of renewable generation capacity.

In both settings, nodal and uniform, the optimal battery allocation follows the allocation of wind and especially solar generation capacity. Thus, in the nodal case, batteries are allocated broadly across Germany, while in the uniform case, batteries concentrate in the south of Germany and especially below the 51st latitude. Moreover, under both settings, batteries are allocated close to congested transmission lines, i.e., lines that are frequently utilized at full capacity (depicted in red).



(a) Spatial distribution of battery capacity expansion and line utilization in the (i) nodal and (ii) uniform setting

(b) Nodal marginal supply costs and battery allocation by latitude

Figure 5: Spatial distribution of 15 GW battery capacity and marginal supply costs in 2030

Grid congestion is illustrated in the upper graph of Figure 5b, which shows marginal supply costs at each node over latitudes. In the nodal setting, marginal supply costs equal the nodal prices. In the uniform case, they reflect the supply costs in redispatch. Prices differ between nodes if transmission constraints are binding, i.e., if a bottleneck exists. This is especially the case between the 52nd and 53rd parallel, where price differences of up to 44 EUR/MWh in the nodal case and 70 EUR/MWh in the uniform case occur. The price difference in the uniform setting is higher because the grid bottleneck is more prevalent here. This can be attributed to the sub-optimal renewable allocation in this case. In both settings, placing most of the battery capacity below the grid bottleneck is optimal. It follows the distribution of solar generation capacity. Thus, it is distributed more uniformly across the west and east in the nodal setting, while it is concentrated in the southeast (the federal state of Bavaria) in the uniform setting. Close to solar generation, batteries can flatten the daily solar generation profile, mitigate local grid congestion and thus reduce local residual demand peaks.

Doing so, batteries help to avoid the high-cost (re-)dispatch of conventional power plants in this area.

Furthermore, in both settings, a significant battery capacity of about 3 GW is allocated right above the structural north-south transmission bottleneck. Under the nodal setup, this capacity is shifted closer to western demand centers, where substantial wind and solar generation capacity is allocated. Through temporal shifting, these batteries increase the utilization of connections to the north and the usage of local wind and solar generation. In the uniform setting, the battery capacity allocated at the structural grid bottleneck is concentrated in the middle and the east of Germany, making use of solar capacity allocated there while at the same time increasing utilization of the easternmost HVDC connection.

The north of Germany, i.e., above the 53rd parallel, attracts a battery capacity of 1.4 GW under the nodal setup. The allocation of this capacity is the result of the simultaneous optimization of battery and renewable capacity allocation. Batteries allocated in the far north increase the north-south transmission utilization at locations where HVDC lines are connected. Thus, they enable wind generation to increase its full load hours by moving further northwards. This rationale does not hold under the uniform setup, where the optimization of renewables and batteries is decoupled. Additionally, the structural north-south bottleneck is too prevalent to achieve a similar transmission. As a result, there are no batteries allocated in the far north.

The numerical model results confirm for the case study of the 2030 scenario of Germany what the two-node, two-time-step model revealed: Storage can reduce supply costs in transmission constraint power systems with high volatility, but allocation matters to unlock the efficiency gains. For the case of batteries, we show that efficiency gains can be made, especially in conjunction with solar generation, as batteries flatten the daily generation pattern. By locating them near solar generation and grid congestion, the batteries avoid high residual demand peaks, i.e., costly generation during dispatch and redispatch.

5.3. Policy instruments for battery allocation

The uniform pricing setting sets no spatial coordination incentives for batteries; thus, achieving optimal allocation is unlikely. Therefore, we investigate the supply costs of potential allocations that could be realized by regulatory mechanisms that impose additional price signals under uniform pricing. We test for two types of capacity distribution mechanisms: *heuristic* allocation rules that allocate battery capacities over all nodes according to a predefined distribution and *explicit* mechanisms that allow battery allocation only at specific candidate nodes.

5.3.1. Heuristic allocation rules

As shown in the two-node model and the numerical example, optimal storage allocation is driven by the volatility induced by renewable feed-in, demand, and transmission grid constraints. Therefore, the first two heuristics distribute battery capacity proportionally to solar generation capacity and demand, respectively. Even though wind generation allocation is not a driver for optimal battery allocation in the uniform setting, we test whether batteries could exploit the volatility of wind generation and decrease supply costs when distributed according to wind generation capacity in a third heuristic. Heuristic four reflects the allocation of both wind and solar, thus taking a combined approach to renewable volatility. Capturing the dynamic influence of transmission grid constraints in a heuristic approach is more difficult. We investigate whether heuristic five can address grid congestion, which distributes storage capacity proportionally to phased-out power plants. Phased-out plants were historically allocated close to demand and may thus address the north-south bottleneck.

To discuss the suitability of these heuristics, we assess them against the optimal battery allocation given the distribution of wind and solar in the uniform setting discussed in the previous section. The relative increase in total supply costs resulting from the heuristics compared to the hypothetical, optimal allocation of batteries lies between close to 0 and 1.1% (see table 3).

Table 3: Summary of relative cost increases and battery capacity factors for *heuristic* battery allocations

	opt. benchmark	random benchmark	solar	wind & solar	demand	phased-out power plants	wind
Supply cost delta [%]	-	0.66	0.27	0.38	0.61	0.90	1.07
Redispatch cost delta [%]	-	3.84	1.58	2.19	3.58	5.25	6.24
Battery capacity factor	0.15	0.15	0.16	0.15	0.16	0.13	0.08

As market efficiency gains are independent of the allocation, the differences in supply costs between the benchmark and the heuristic allocations correspond to the difference in redispatch costs, which are determined by the total redispatch volume and the power plants used in redispatch. The total redispatch volumes are similar in the benchmark case and for all heuristics. Redispatch is mainly caused by high wind power curtailment in the north of Germany. Situations of high wind feed-in and north-south transmission bottlenecks continue for long periods, and therefore the ability of batteries to reduce curtailment volumes is limited.

Hence, redispatch costs differ mainly due to the different types of power plants used for redispatch. Redispatch costs are lowest, if batteries can frequently shift low-cost electricity in time to avoid costly fossil-fired generation. In our scenario results, this is especially the case in the south and east of Germany, where high solar generation leads to high volatility in local marginal generation costs. Batteries can utilize this volatility by charging when solar power generation is high. They then use this energy to displace lignite power plants and gas turbines, which replace south German nuclear capacities, in redispatch. Conclusively, a heuristic, which distributes capacity according to solar generation capacity, is the most efficient, followed by a heuristic, which considers both wind and solar.

A demand-based heuristic is the third most efficient. Here, more battery capacity is located in the west of Germany, while solar power generation is concentrated in the east and south. Since marginal generation costs are higher in the west, battery charging is more expensive and replacement of fossil power plants in redispatch is less frequent. A similar effect occurs if the batteries are allocated accordingly to phased-out power plants since they are located near demand centers, too.

In contrast, if batteries are deployed close to wind generation, their contribution in redispatch is more limited. Even though batteries prevent more wind curtailment than in the other heuristics, they can only participate in redispatch above the structural grid bottleneck. There, marginal generation costs in redispatch are low, and so is volatility, making this allocation the least efficient. In fact, redispatch costs are even higher than in a case without batteries. This is because batteries increase the share of wind generation in the initial market outcome, which then has to be curtailed in redispatch due to grid constraints. However, market gains outweigh redispatch losses, resulting in lower total supply costs than without batteries. Moreover, the allocations according to wind or phased-out power plants are even less efficient than a random allocation of batteries. The random allocation leads to a broad distribution of batteries across Germany, meaning that at least some batteries are close to solar generation and demand.

The heuristics' supply cost differences are also reflected in battery utilization. In the wind-based heuristic, the battery capacity factor is less than half of the capacity factor of the solar-based heuristic, where a capacity factor of 0.16 is achieved. This corresponds to 345 battery cycles per year or an average of almost one charge cycle per day, i.e., a steady reduction of residual loads. The reason is the assumed capacity-to-volume ratio of 4h, which makes batteries better suited to buffer daily solar generation than wind generation profiles with their coarser volatility.

5.3.2. Explicit allocation rules

Secondly, we investigate *explicit* approaches that allow for an optimal battery allocation at pre-defined candidate nodes. We test the following variations: Starting from the 40 nodes with the highest capacity in the hypothetical benchmark case, we iteratively reduce the number of candidate nodes to 1. The resulting supply costs of these explicit allocation rules are between 0.00 and 0.85% higher than the optimal benchmark. The higher the number of candidate nodes, the lower are the supply costs. At 40 or more candidate nodes, supply costs are almost the same as in the optimal benchmark case. Even reducing the allocation to just two nodes leads to a cost increase of 0.37%, which is between the supply costs of the solar heuristic (0.27%) and the heuristic allocation according to solar and wind capacity (0.38%). If the number of candidate nodes is reduced to one, the supply cost delta more than doubles compared to the case with two nodes. With one endogenously chosen candidate node, all capacity is placed at a node in southern Germany. In this case, the battery cannot have its full effect because the installed battery capacity is higher than the sum of renewable and transmission capacity at that node. Consequently, the resulting capacity factor is much lower, and the total supply cost is higher than in the case of random distribution. Nevertheless, it is noteworthy that the single-node allocation is still more efficient than an allocation by wind capacity or phased-out power plants.

The *explicit* approaches that distribute battery capacity to five or more nodes outperform all *heuristic* approaches. When comparing the results, it, however, has to be noted that the installed capacity per node is optimized endogenously in the *explicit* cases. In contrast, capacity distribution is determined exogenously in the *heuristic* cases.

Table 4 compares resulting capacity factors and supply costs relative to the hypothetical benchmark for each of the *explicit* options.

Table 4: Summary of relative cost increases and battery capacity factors for *explicit* battery allocations

	opt. benchmark	random benchmark	40	20	10	5	3	2	1
Supply cost delta [%]	-	0.66	0.00	0.02	0.10	0.16	0.29	0.37	0.85
Redispatch cost delta [%]	-	3.84	0.00	0.12	0.57	0.94	1.70	2.14	4.97
Battery capacity factor	0.15	0.15	0.15	0.15	0.15	0.15	0.14	0.13	0.10

5.4. Summary

We quantify the efficiency gains of placing 15 GW of batteries in the German transmission grid by comparing supply costs for two settings, nodal and uniform, to equivalent cases without any batteries. The results show that batteries reduce supply costs in both cases. In the uniform setting, the efficiency gains are composed of supply costs reduction in the electricity market, which are independent of battery allocation, and in redispatch, which depend on battery location. To compare different allocation rules under the uniform setup, a hypothetical, optimal allocation for a given distribution of renewable capacity is used as an upper benchmark. Furthermore, a random distribution of batteries is used as a benchmark for missing local investment incentives. The analysis shows for our scenario that *explicit* approaches with endogenous battery investment allowed at a limited number of pre-determined nodes can approximate the optimal distribution well and already from five nodes it outperforms all *heuristic* approaches with a fixed distribution. Among the fixed *heuristic* approaches, an allocation that mimics the distribution of solar generation capacity performs best. Solar generation is a crucial driver for optimal allocation since batteries can exploit the daily solar generation pattern to reduce gas-fired redispatch. Other *heuristic* approaches prove to be less suitable. An allocation proportional to phased-out power plants or wind generation capacity is less efficient than a random distribution. The wind-based heuristic leads to even higher redispatch costs than the case without any batteries.

The performance of the different allocation rules is compared to the theoretical first-best nodal benchmark. Figure 6 shows the relative increase in supply costs compared to this benchmark for the allocation variations ordered by efficiency. It highlights the efficiency gains that can be made by introducing and coordinating batteries. The most efficient allocation rule is the *explicit* allocation to 40 nodes, leading to 8.6% higher supply costs than the nodal benchmark. Least efficient is the *heuristic* allocation by wind capacity (+9.7%). Hence, the range of total supply costs between the best and the worst performing allocation amounts to 1.1% of the nodal supply costs.

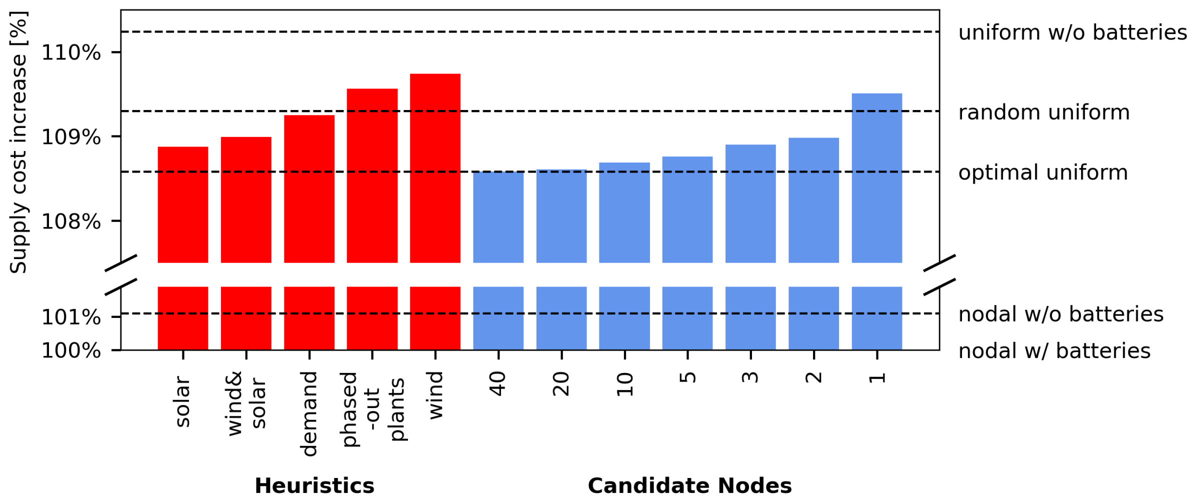


Figure 6: Supply cost differences between allocation rules and the first-best nodal benchmark in 2030

The relevance of appropriate coordination can be further illustrated by relating the supply cost savings achieved by batteries to the capital cost incurred. The supply cost saving of each battery allocation is the difference in total supply costs compared to the uniform setting without any batteries. To calculate the capital costs of batteries, we assume investment costs of 600 EUR/kW, a lifetime of 16 years, and an interest rate of 8% (c.f. EWI, 2021). The ratio of savings to annualized capital cost depends strongly on battery allocation. Batteries can yield 1.08 EUR in savings per euro spent if allocated optimally in the uniform setting. A random allocation reduces the savings by 47 ct per euro spent. With an explicit allocation at 5 or more candidate nodes, the battery-induced savings come close to the savings under an optimal allocation (0.96 - 1.08 EUR saved per euro spent, depending on the number of nodes). In the best heuristic allocation (solar), the ratio of savings to expenditures is 19 ct lower than with an optimal allocation. In the worst case (wind) examined, the savings drop to just 33 ct per euro spent. Under the assumed capital costs, 15 GW of battery capacity is in the money if allocated optimally. With the help of the allocation rules, savings are higher than the annualized capital costs for explicit approaches at 10 or more nodes. With all other rules, savings are below expenditures. However, batteries can generate additional value not considered in the present analysis through system services, e.g., balancing power provision or avoiding grid expansion in the long run and thus savings can be higher. Further, these results are highly dependent on the (assumed) capital costs.

6. Discussion

6.1. Policy implications

The stylized model with two nodes and two time steps indicates the significance of storage allocation, which is confirmed and quantified in our numerical analysis using Germany as a case study.

The largest efficiency difference occurs between the nodal and uniform setting. Supply costs are at least 8.6% higher in the uniform case than under the nodal setup. This is primarily because in the nodal setting also wind and solar generators are allocated optimally and shows that the leverage of a simultaneous allocation and coordination of wind and solar expansion exceeds the leverage of allocating batteries. However, the results in the nodal setting rely on several assumptions that tend not to hold in practice (see 6.3), and switching from uniform to nodal pricing may not be politically feasible in practice as it involves transformation costs and leads to distributional effects (c.f. Schmidt and Zinke, 2023).

In practice, there is no allocation coordination under uniform pricing; thus, the optimal battery allocation that minimizes the efficiency gap to the nodal benchmark is not achieved. Our analysis reveals that with a random battery allocation, the efficiency gap relative to the first-best nodal case lies 0.7 percentage points higher than with an optimal allocation. The least efficient allocation that was tested even increases the efficiency gap by 1.1 percentage points. It is therefore worth discussing how coordination can be achieved and local incentives can be set even in a system with uniform pricing. In Germany, this question is currently being asked as part of the government initiative *Climate Neutral Electricity System Platform* - a dialogue platform that aims to prepare for an upcoming electricity market reform. Our model results show that several allocation rules are conceivable to approximate an optimal allocation of batteries in the uniform setting. For example, a heuristic approach that allocates batteries close to solar capacity or explicit approaches that rely on grid analyses to determine a limited number of locations for a capacity auction can reduce supply costs in the uniform setting. In addition, the implementation of such an allocation rule would ensure that inefficient distributions, like an allocation close to installed wind power capacity, are not realized.

Policy makers designing regulatory instruments based on these findings should weigh the reduction in supply costs resulting from improved allocation against the implementation costs. In case of the heuristic approaches, the difficulty lies in identifying a mechanism that yields the desired distribution of batteries. Costs could also be incurred if the chosen mechanism leads to a high number of transactions, e.g., if batteries were subsidized via feed-in tariffs. For the explicit approaches that allow the installation of batteries at limited locations in the grid, the allocation could be managed via a limited number of auctions. Here, transaction costs arise from the information asymmetries of the regulator in determining optimal locations and capacities. Further, our results benefit from the assumption of perfect foresight. In practice, it may be more complicated to determine optimal candidate notes ex ante, in particular if only a few nodes are chosen and in a dynamic setting the optimality of nodes may change over time. Choosing a heuristic approach that is directly connected to the distribution of solar power may be more robust to the deviations from a modeled scenario.

Policies that coordinate wind, solar, and storage capacity in an integrated way could come even closer to the first-best benchmark. However, the analysis of such an integrated approach is beyond the scope of this paper. It would likely lead to additional efficiency gains but would be a more complex endeavor with higher implementation costs.

We conclude that it is possible to design a policy instrument that is suitable to approximate an optimal storage allocation under uniform pricing. Any potential policy should either be simple and low-cost to implement or be part of a comprehensive mechanism that coordinates all types of generation and flexibility with the grid.

6.2. Generalization

Although the numerical model results are specific to the chosen setting, they can be generalized for several aspects. First, the finding of the two-node model that optimal storage allocation is driven mainly by volatility is valid and applicable for all time horizons and countries. In our case study, solar power is the dominating renewable capacity driving volatility and, thus, battery allocation. Divergent renewable energy shares may lead to different optimal battery allocations, e.g., previous analyses assuming higher shares of wind power conclude that higher shares of battery capacity should be allocated near wind energy.

Secondly, the numerical analysis at hand focuses on batteries, i.e., a storage technology with a relatively small storage volume compared to installed charging capacity, which complements the daily fluctuations of solar power generation. Therefore, we perform a sensitivity analysis regarding the storage type and show that the optimal allocation depends on the specific technology. In particular, storage with a larger power-volume ratio is favorable at locations with high shares of wind power (see Appendix D.2).

Thirdly, we show that storage can generate value in a uniform setting in both the initial market clearing and in redispatch. The latter can only be exploited if the market design allows for the participation of storage in redispatch. If this is not the case, a substantial part of the potential benefits of storage technologies - in our numerical analysis, about 50% - cannot materialize.

Fourthly, the findings for the transmission level can be used to get insights for the distribution grid. Distribution grid operators could use the batteries' flexibility to lower curtailment volumes and required grid expansion if the batteries' allocation matches flexibility demands and technical and regulatory properties allow. However, on the distribution grid level, storage is usually used to increase the self-consumption of solar generation, e.g., home-storage systems. Therefore, these systems are neither dispatched by market signals nor used in redispatch.

6.3. Limitations

Several limitations should be noted when considering the results and analysis presented. First, the numeric modeling results are based on several strong assumptions, e.g., perfect foresight, no transaction costs, perfect markets, and the exogenous distribution of inelastic exogenous demand.

The mathematical duality between a central planer and a profit-maximization of symmetric firms holds only if these assumptions are all met. In practice, this is rather not to be expected. In particular, the first-best nodal benchmark is a rather theoretical benchmark as in reality frictional losses can distort optimality, e.g., reduced liquidity, lack of transparency, market power issues, and increased transaction costs (c.f. Antonopoulos et al., 2020).

Furthermore, modeling the market setup of uniform pricing, as it is currently in place in Germany, comes along with some simplifying assumptions. We abstract from additional policy instruments for the expansion of wind and solar power. In particular, the reference yield model should affect wind power expansion compared to our modelled distribution. The cost-based redispatch mechanisms applied in practice are less efficient than those modeled in our numerical analyses. In our model, power plants outside Germany and all technologies including storage can be used for redispatch without any restrictions, which is not necessarily the case in practice. In particular, redispatch of hydro-pumped storage in the Alps can be fully exploited in the model which might cannibalize the value of batteries in Southern Germany. Additionally, further efficiency gains of storage deployment are possible, which were not part of the numerical analyses, e.g., avoided grid expansion or increased security of supply.

In addition to these model properties, the results have to be interpreted in light of the specific scenario chosen for the analysis. To demonstrate the robustness of our results, we perform a sensitivity analysis regarding the total installed battery capacity in Appendix D.2. Additionally, the scenario-specific renewable energy allocation largely determines the magnitude of the identified efficiency gap between the first best nodal and the uniform setting. Besides resource quality, further aspects, such as land availability and residents' opposition, play into renewable investors' decision process. Hence, the resulting renewable energy distribution for 2030 is likely to be less concentrated in reality, which also impacts the optimal storage allocation and system efficiency.

7. Conclusion

This paper investigates the allocation of battery storage in spatially unbalanced power systems in the transition to climate neutrality, i.e., with rapidly increasing shares of wind and solar power generation. Specifically, we seek to answer three questions: Firstly, where in the transmission grid should batteries be allocated, secondly, how important is storage allocation for the system's efficiency, and thirdly how could policy instruments be designed to approximate an optimal allocation? To investigate the drivers of optimal storage allocation, we develop a theoretical two-node, two-time-step model that simplifies the dynamics of spatially unbalanced power systems. Employing this model, we show that an allocation close to volatile renewables or close to demand can be optimal. We find that optimal allocation depends on the volatility and location of demand and generation relative to grid bottlenecks.

The importance of volatility and grid constraints as critical factors for efficient storage allocation is verified in a numerical case study using the example of a spatially unbalanced power system in Germany. The benefits of batteries are split between market-based dispatch and subsequent redispatch. In our case study, half of the potential efficiency gains arise only in redispatch. Comparing different allocation rules, we find that simple heuristics, such as tying battery allocation to solar generation or defining a limited number of nodes for capacity auctions, can come close to an optimal allocation of batteries in terms of efficiency. Inefficient battery allocation, e.g., according to wind power capacity, may increase the supply cost compared to random distribution. Overall, the range of efficiency gains or losses due to battery allocation is limited compared to the impact of renewable energy allocation. We conclude that any potential policy should either be simple and low-cost to implement or be part of a comprehensive mechanism that coordinates all types of generation and flexibility with the grid.

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Appendix A. Notation

Throughout the paper at hand, the notation presented in table A.5 is used. To distinguish (exogenous) parameters and optimization variables, the latter are written in capital letters.

Table A.5: Sets, parameters and variables

Sets		
$i \in I$		Electricity generation and storage technologies
$m, n \in M$		Markets
$l \in L$		Transmission Grid Lines
$c \in C$		Linear independent cycles of modelled grid
$y, y1 \in Y$		Years
$d \in D$		Representative Days
$h \in H$		Hours
Parameters		
$demand(y, d, h, m)$	[MWh]	Electricity demand
$avail(y, d, h, m, i)$	[-]	Availability of technology
$eff(i, m)$	[-]	Efficiency of technology
$linecap(y, m, n)$	[MW]	Available transmission capacity
$\beta(y)$	[-]	Discount factor
$\delta(y, i)$	[EUR/MW]	Annualized investment cost
$\sigma(i)$	[EUR/MW]	Fixed operation and maintenance cost
$\gamma(y, i)$	[EUR/MWh]	Variable generation cost
$cap_{add,min}(y, m, i)$	[MW]	Capacities under construction
$cap_{sub,min}(y, m, i)$	[MW]	Decommissioning of capacity due to lifetime or policy bans
$l(m, n)$	[-]	Relative transmission Losses
$\kappa(m, l)$	[-]	Incidence matrix
$\phi(l, c)$	[-]	Cycle matrix
Variables		
$CAP(y, m, i)$	[MW]	Electricity generation capacity
$GEN(y, d, h, m, i)$	[MWh]	Electricity generation
$CAP_{add}(y, m, i)$	[MW]	Investments in electricity generation capacity
$CAP_{sub}(y, m, i)$	[MW]	Decommissioning of electricity generation capacity
$TRADE(y, d, h, m, n)$	[MWh]	Electricity trade from m to n
$TRADE\_BAL(y, d, h, m)$	[MWh]	Net trade balance of m
$FLOW(y, d, h, l)$	[MWh]	Power flow along line l
TC	[EUR]	Total costs
$FC(y)$ / $VC(y)$	[EUR]	Yearly fixed or variable costs

Appendix B. Power market model

Appendix B.1. Basic model

The central planner invests into new power plants and dispatches generation capacities such that the net present value of the variable (VC) and fixed costs (FC) is minimized, where β represents the discount factor.

The objective is hence:

$$min!\ TC = \sum_{y \in Y} \beta(y) \cdot [VC(y) + FC(y)].$$

Installed electricity generation capacities (CAP) are modeled endogenously: The model invests in new generation capacities (CAP_{add}) and decommissions capacities (CAP_{sub}), which are not profitable. For a realistic depiction of European energy markets, existing as well as under construction capacities ($cap_{add,min}$) and decommissioning due to end-of-lifetime or technology bans ($cap_{sub,min}$) are given exogenously. These parameters serve as lower bounds for building or decommissioning capacities, respectively. The fixed costs per year comprise the annualized investment costs (δ) plus fixed operation and maintenance costs (σ) per installed capacity. The following equations describe these interrelations.

$$CAP(y,m,i) = CAP(y-1,m,i) + CAP_{add}(y,m,i) - CAP_{sub}(y,m,i)$$

$$CAP_{add}(y,m,i) \geq cap_{add,min}(y,m,i)$$

$$CAP_{sub}(y,m,i) \geq cap_{sub,min}(y,m,i)$$

$$\forall y \in Y, \forall m \in M, \forall i \in I$$

$$FC(y) = \sum_{m \in M, i \in I} CAP(y,m,i) \cdot \sigma(i) + \sum_{y1: y-y1 < econ\_lifetime(i)} CAP_{add}(y1,m,i) \cdot \delta(y,i)$$

Electricity generation (GEN) in each market, day (d) and hour (h) has to level the (inelastic) *demand* minus the trade balance ($TRADE\_BAL$), which depicts the net imports of trade flows ($TRADE$) from other markets. Availability of power plants ($avail \cdot CAP$), which, e.g., considers maintenance shutdowns limit their generation. Trade flows between markets are limited by interconnection capacities (*linecap*). Yearly total variable costs (VC) result from the generation per technology times the technology-specific variable operation costs (γ), which mainly comprise costs for burnt fuel and required CO_2 allowances.

$$\sum_{i \in I} GEN(y,d,h,m,i) = demand(y,d,h,m) - TRADE\_BAL(y,d,h,m)$$

$$GEN(y,d,h,m,i) \leq avail(y,d,h,i) \cdot CAP(y,m,i)$$

$$TRADE\_BAL(y,d,h,m) = \sum_{n} (1 - l(n,m)) \cdot TRADE(y,d,h,n,m) - TRADE(y,d,h,m,n)$$

$$TRADE(y,d,h,m,n) \leq linecap(y,m,n)$$

$$\forall y \in Y, \forall m,n \in M \;\; \& \;\; m \neq n, \forall i \in I$$

$$VC(y) = \sum_{m \in M, i \in I, d \in D, h \in H} GEN(y,d,h,m,i) \cdot \gamma(y,i)$$

Appendix B.2. Storage equations

The charging level of storage ($STORLEVEL$) is determined by the level in the previous time step and the net-balance of electricity charged and withdrawn. The level cannot exceed the storage volume which is given by the installed capacity and an exogenous ratio of capacity and volume (vol_factor).

$$
\begin{aligned}
STOR\_LEVEL(y,d,h,m,i) &= STOR\_LEVEL(y,t-1,m,i) \\
&\quad - eff(m,i) \cdot GEN(y,d,h,m,i) + eff(i,m) \cdot GEN(y,d,h,i,m) \\
STOR\_LEVEL(y,d,h,m,i) &\leq STOR\_VOL \\
STOR\_VOL &= avail(y,d,h,i) \cdot vol\_factor(i) \cdot CAP(y,m,i) \\
&\forall y \in Y, \forall d \in D, h \in H, \forall m \in M, \forall i \in I_{Storage}
\end{aligned}
$$

The amount of energy which can be shifted between typedays (DAY_SALDO) is limited according to the number of days that a typeday represents (d_rep). The total of the energy shifted by storage must add up to zero.

$$
\begin{aligned}
DAY\_SALDO(y,d,m,i) &= \sum_{h \in H} (GEN(y,d,h,i,m) - GEN(y,d,h,m,i)) \\
DAY\_SALDO(y,d,m,i) \cdot d\_rep(d) &\leq STOR\_VOL(y,m,i) \\
DAY\_SALDO(y,d,m,i) \cdot d\_rep(t) &\geq -STOR\_VOL(y,m,i) \\
\sum_{d \in D} DAY\_SALDO(y,d,m,i) &= 0 \\
&\forall y \in Y, \forall d \in D, \forall m \in M, \forall i \in I_{Storage}
\end{aligned}
$$

Appendix C. Assumptions on technologies, demand and fuel prices

Table C.6: Considered technologies and their generation efficiency, assumptions based on scenario *Stated Policies* in World Energy Outlook 2021 (IEA, 2021) and Knaut et al. (2016)

Technologies	Efficiency
Nuclear	0.33
Lignite	0.4
Coal	0.45
Combined Cycle Gas Turbines (CCGT)	0.5
Open Cycle Gas Turbines (OCGT)	0.38
Oil	0.4
Biomass	0.3
PV	1
Wind Onshore	1
Wind Offshore	1
Hydro	1
Pumped Storage	0.78
Battery Storage	0.95

Table C.7: Development of fuel and carbon prices $[EUR/MWh_{th}]$, based on scenario *Net Zero Emissions* in World Energy Outlook 2022 (IEA, 2022)

Fuel	2019	2030
Uranium	3.0	3.0
Lignite	3.9	4.0
Coal	7.9	7.7
Natural Gas	13.6	25.9
Oil	33.1	44.9
Biomass	21.0	23.0
Carbon [EUR/tCO2]	24.9	95.0

Table C.8: Development of demand [TWh], for Germany based on BMWK (2022a) and for all other countries on scenario *National Trends* in ENTSO-E (2020a)

Country	2019	2025	2030
AT	67	77	79
BE	85	87	91
CH	62	62	61
CZ	63	73	78
DE	524	600	715
DK	35	52	46
FR	456	496	486
NL	114	114	119
PL	156	181	182

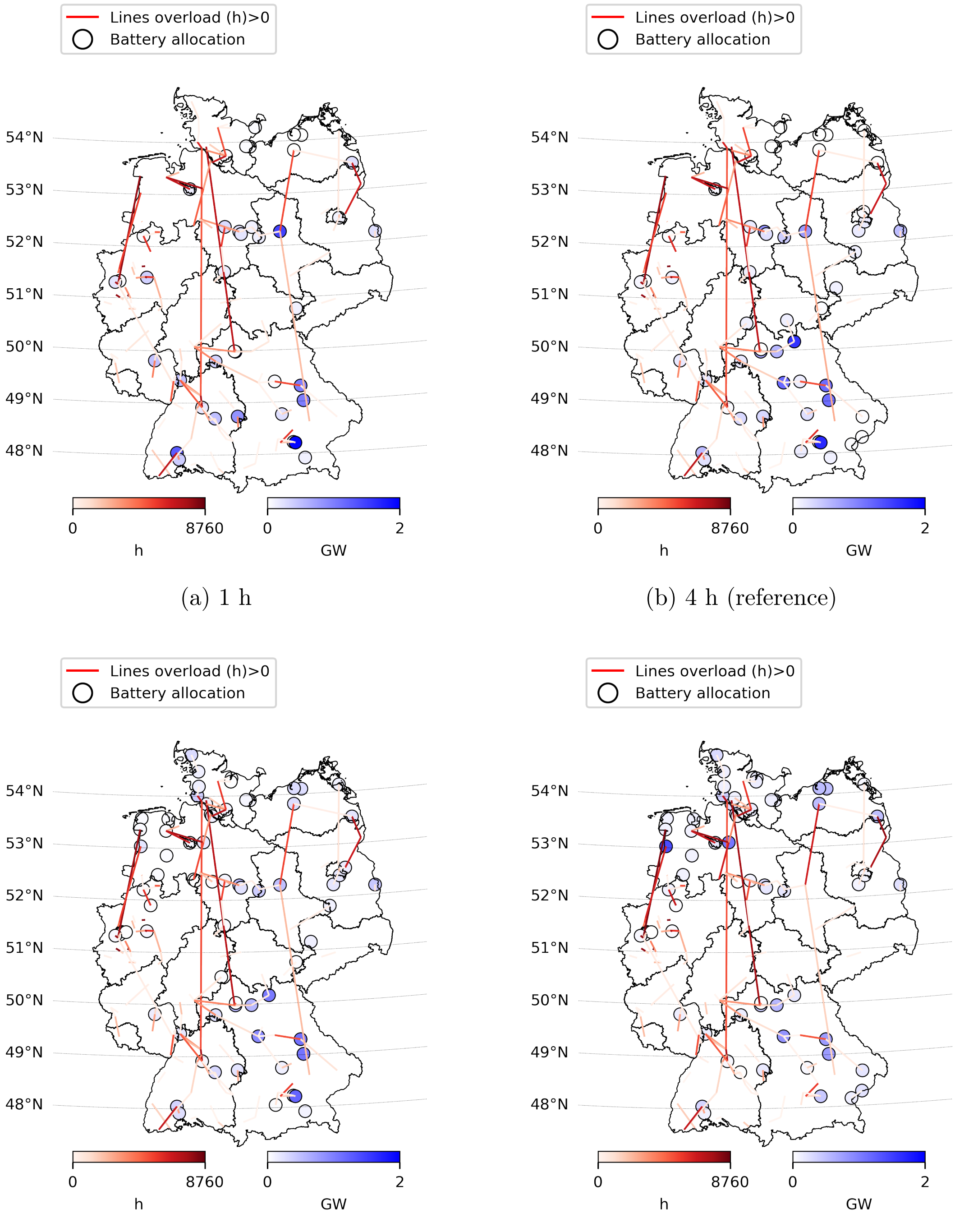
Appendix D. Additional results and sensitivity analyses

Appendix D.1. Volume factor

Figure D.7 shows variations of the volume factor, i.e., the ratio between connected power (GW) and the energy volume (GWh) of a storage technology. Low volume factors correspond to battery storage, while higher factors can be seen for technologies using a different energy carrier for storage, e.g,. hydrogen. Storage allocation depends significantly on the volume factor. For higher volume factors (>4h), storage moves northwards and closer to wind generation. Here, they buffer volatile wind generation and increase utilization of the congested lines along the structural grid bottleneck. However, even for higher volume factors, significant capacities are allocated in the south of Germany. Even when volume factors are above 100h and the majority of storage is located above the 52nd parallel, storage is needed to buffer volatile PV infeed in the south.

Appendix D.2. Battery capacity

Figure D.8 shows sensitivity analyses for the total installed capacity of batteries for a given distribution of wind and solar generation according to the nodal setting. The allocation of batteries close to grid bottlenecks along the 53rd parallel as well as in the south of Germany is robust. In the case of 15 and more GW of batteries, saturation in those areas leads to an allocation in the north, close to wind generation centers. The sensitivity analyses, therefore, highlights again the role of batteries in balancing short-term volatility from demand and solar feed-in time series as opposed to wind generation that requires longer storage of electricity.



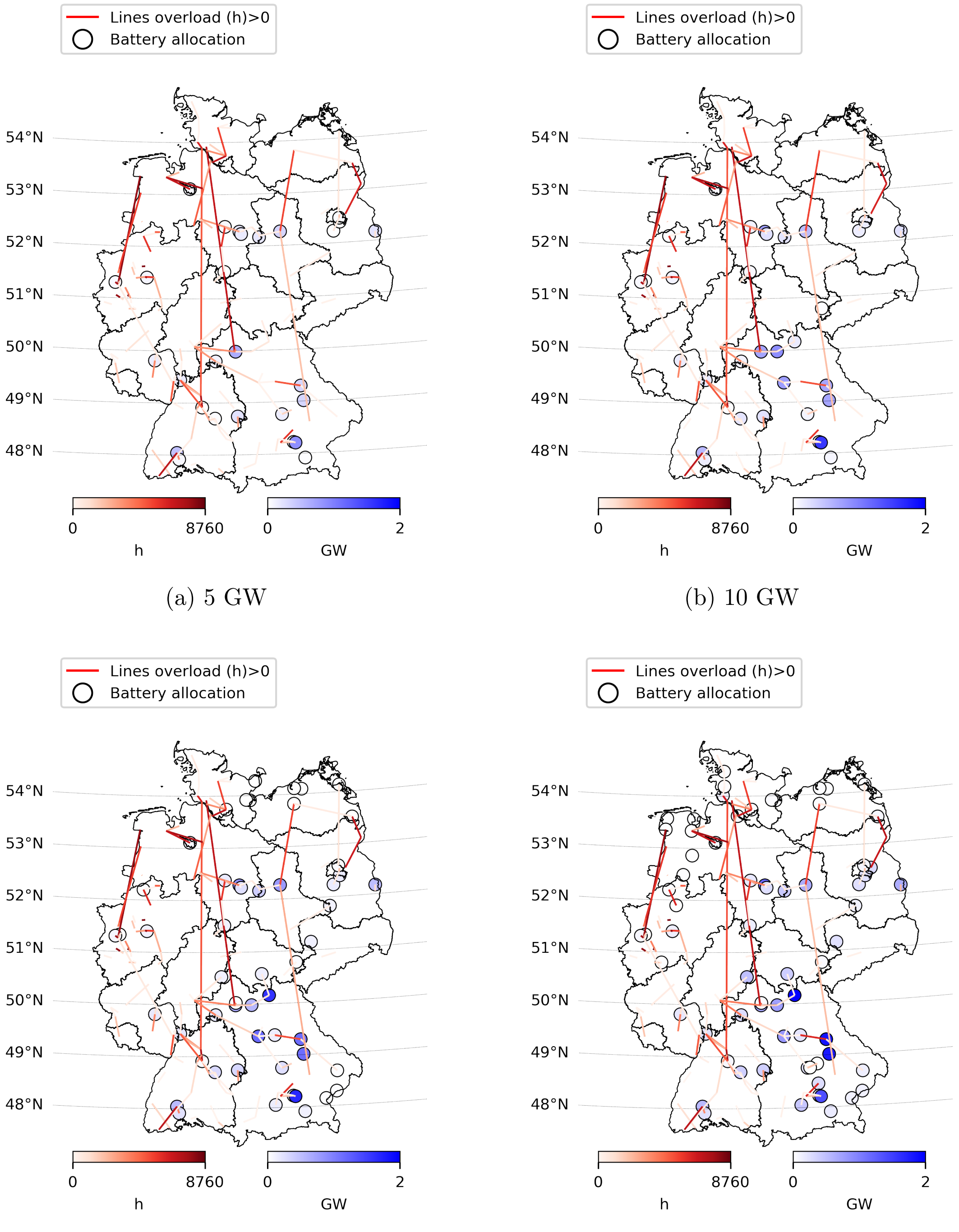
(a) 1 h

(b) 4 h (reference)

(c) 50 h

(d) 200 h

Figure D.7: Optimal battery allocation based on the distribution of wind and solar in the uniform setting for different battery volume factors



(a) 5 GW

(b) 10 GW

(c) 15 GW (reference)

(d) 20 GW

Figure D.8: Optimal battery allocation based on the distribution of wind and solar in the uniform setting for different battery capacities