A methodology for storage allocation in large-scale integrated energy systems based on nodal prices

Kira Layer(1), Christian Perau(1), Moritz Fierke(1), Thorben Sandmeier(1), Wolf Fichtner(1)
(1) Karlsruhe Institute of Technology (KIT), Chair of Energy Economics, Hertzstraße 16, 76187 Karlsruhe, Germany
Tel.: +49 721 608 44583,
E-Mail: kira.layer@kit.edu,
Web: www.iip.kit.edu

Abstract:

Since electricity generation from wind and photovoltaics is volatile, storage units are needed for future energy systems to meet demand and reduce grid congestion and renewables (RES) curtailment. Due to grid constraints, the location of storage units is particularly important. Optimal storage allocation requires many computational resources. We propose a heuristic method for storage allocation in the transmission grid using nodal prices to indicate beneficial locations. The goal is to minimize system costs and reduce RES curtailment while mitigating computational effort. Due to the growing interconnectivity between the electricity and gas sectors, additionally, a heuristic method that allocates hydrogen storages to decommissioned natural gas storages as well as new additional storages, is presented. The results show that a well-parametrized nodal-based allocation outperforms the proposed benchmarks. We observe, that, from a system perspective, storage units with higher capacity rates are preferable due to their lower investments and operation and maintenance costs.

Keywords: Storage Allocation, Integrated Energy System Model, Flexibilities, Transmission System Optimization

1 Introduction

1.1 Motivation

To reach the targets of the European Green Deal, which means becoming climate-neutral until 2050, the European energy sector plays an important role [1]. It is necessary that the amount of fossil-fuelled power plants is reduced and the amount of renewable energy sources (RES) is increased. The most common RES are photovoltaics (PV) and wind power. Their share of energy production will rise further, so wind and PV will be the dominant technologies [2]. As RES are depending on weather, they are fluctuating and not always available. In times of very high or low wind and PV generation or demand this can lead to a mismatch of energy generation and demand, to grid congestion, and to RES curtailment as the energy system is not capable of transporting the energy. For this reason, the importance of flexibilities for the energy system, like electrical storage units, is growing. Storages can smooth the fluctuating character of the variable renewable energies and shift energy supply to times of high demand. If the storages are placed at beneficial locations within the grid, congestion, RES curtailment and thus the use of fossil-fuelled powerplants can be reduced leading to less emissions and overall system costs. If storage units are placed at nonbeneficial locations their advantages might be mitigated due to grid constraints. A wrong sizing of storage units has the same effect. For this reason, the allocation of electrical storage units in the energy system is of particular importance.

Apart from electric storage units, hydrogen storages are needed for the future energy system, as they are well suited for long-term and large-scale storage. To store hydrogen, old salt cavern natural gas storages can be repurposed [3]. Since the electrical and gas sectors will be more interconnected by electrolyzers and gas turbines [4], we do not only deal with electrical storage allocation but also with the allocation of hydrogen storages considering the repurposing of existing salt caverns as well as new overground storage.

1.2 Literature Review

The literature identifies four types of methods for electrical storage allocation.

First, analytical methods exist, which have the advantage of being flexible for various evaluation criteria. However, these methods take a long time to converge and tend to find only local minima [5]. In [6] an analytical method is used for optimizing the sizing and siting of energy battery storage systems (BESS) in distribution grids. Here, the variables to minimize are active and reactive power transferred through BESS and they are given as a function of place and size of solar power generation. For this optimization, a modified impedance matrix is used instead of a recursive load flow analysis. This method is tested for the IEEE 14-bus system.

The second type of method is mathematical optimization. These methods are seeking an optimal solution by using an approximated model. Their advantage is the ability to find an optimal solution and their disadvantage is the long computational time [8]. [9] deals with siting and sizing of BESS and the timing of distributed generation. The aim is to maximize the integration of RES. Therefore, a mixed integer linear optimization programming model is used. Here, the objective function minimizes the overall costs and the constraints of the optimization problem include active power balance and characteristics of BESS. This method is tested on the IEEE 119-bus test system.

Another type of allocation method is meta-heuristics. Their benefit lies in being model-free and avoiding entrapment in local optima. Another advantage are the generally lower computation times. On the other side, these methods are less efficient in taking constraints into account. Meta-heuristics include genetic algorithm-based or particle swarm optimization-based methods [5]. An example of using the first one is [10], which deals with the siting and sizing of BESS in distribution grids with the goal of reducing voltage fluctuation. The genetic algorithm is used to solve the linear optimization problem and the method is tested on the IEEE 8500-Node test feeder. A particle swarm optimization-based method is proposed in [7]. The method is used for siting and sizing of energy storage systems and distributed generators in distribution grids at the same time and takes active as well as reactive power into account. Here the profit of the distribution company is maximized including also the approach of secure network operation. For this, a nonlinear mixed integer optimization problem is set up. This method is tested on a test system with 30 busbars. The results show that profit is the highest when planning both, energy storage systems and distributed generators and that network losses decreased.

The fourth type of method is artificial neural networks (ANN). They are fast, accurate and as they are flexible, ANNs are suitable for complex problems. Their disadvantage is the need for large amounts of historic training data. In [11] a complex-valued neural network (CVNN) is used to site BESS for contingency management and frequency control. The CVNN is suitable for systems with complex variables, such as power systems, and is used to predict voltage amplitudes and angles under different contingencies. Then sensitive busbars are determined as the busbars with the most variability of voltage amplitude and angle. The storages are sited at these sensitive busbars.

Moreover, there are hybrid methods, which combine two types of methods. In [12], mathematical optimization is combined with analytical methods. It deals with the siting and sizing of battery storages in low voltage grids with the goal of maximizing the utilization of PV and also minimization of battery degradation. This is done by minimizing investments and operation costs, where the grid constraints are included in the form of a linearized version of multi-period optimal power flow. The siting and sizing problem is difficult to solve with an infinite control horizon. As siting and sizing is a linear problem it can be decomposed by a Benders decomposition. This methodology is tested for the CIGRE test grid and has the benefit of reduced computational complexity compared to only using mathematical optimization. [11] also uses a combination of mathematical optimization and analytical approaches to be able to minimize two variables at the same time. The goal is to site and size ESS in a microgrid with demand response. A bi-objective optimization model is used which minimizes costs and loss of load expectation with separated objective functions. Therefore, the epsilon-constrained method is applied, which uses different upper bounds of the second objective function as a constraint for the minimizing problem for the first objective function. From the various resulting Pareto optimal solutions, a trade-off solution is chosen by the fuzzy satisfying method through evaluating the linear membership function for different solutions for both objective functions.

Regarding the allocation of hydrogen storages to decommissioned underground natural gas storages and new above-ground storages, we are not aware of any existing literature on this specific topic. [13] is dealing with optimal hydrogen storage allocation with the goal of reducing grid congestion even if installations of RES increase. This methodology is only tested on a 37-bus test grid. Other papers provide a multi-criteria decision-making method for selecting a site for a hydrogen storage, but do not incorporate the targets for hydrogen storages of the respective country. [14] identifies the best site of three alternatives with a case study for Turkey and [15] deals with wind power coupled hydrogen storages in China.

1.3 Contribution and Paper Organization

In this paper, we propose a heuristic allocation method for electrical storage units applicable to large-scale energy systems. The method uses nodal prices to indicate beneficial locations for storage units. The goal is to minimize system costs and reduce RES curtailment while mitigating computational effort. Moreover, a method for the allocation of hydrogen storages to decommissioned gas storages is presented. This method identifies the best combination of repurposed natural gas storages to meet the target capacities for hydrogen storages. The two methods are applied to a case study of the central European energy system.

The remainder of this paper is organized as follows. Section 2 explains the allocation methods for electrical and hydrogen storage units. The case study is described in Section 3. In Section

4 the results of the case study are presented. Finally, in Section 5 conclusions are drawn and an outlook is given.

2 Methodology

In the first part of this section, the methodology for the allocation of electrical storage units is explained. In the second part, the methodology for hydrogen storage allocation is described. The Nomenclature of all used variables can be seen in Table 1.

Table 1- Nomenclature

Sets		$\bar{V}$	Maximum storage Volume
$\mathcal{T}$	Time steps	$P_{NG,inj}^{exist}$, $P_{H2,inj}^{exist}$	Total existing injection capacities of natural gas and hydrogen storages
$\mathcal{S}_{ng}$	Natural gas storages	$P_{NG,wdw}^{exist}$, $P_{H2,wdw}^{exist}$	Total existing withdrawal capacities of natural gas and hydrogen storages
$\mathcal{S}_{ng,decommissioned}$	Decommissioned natural gas storages	$P_{NG,inj}^{target}$, $P_{H2,inj}^{target}$	Target for injection capacities for natural gas and hydrogen
Indices		$P_{NG,wdw}^{target}$, $P_{H2,wdw}^{target}$	Target for withdrawal capacities for natural gas and hydrogen
t	A time step	P_s^{inj}, P_s^{wdw}	Injection and withdrawal capacity of a storage
s	A storage	η_{in}, η_{out}	Charge and discharge efficiency
Parameters		**Variables**	
δ_t	Nodal price in Time step t	P_t^{in}, P_t^{out}	In and Outflow in time step
c_{var}	Variable operational costs	V_{start}, V_{end}	Storage volume at start and end
C_{fix}	Fix operational costs	V_t	Storage volume in time step
C_{invest}	Annualized investments	x_s	If storage is decommissioned
$\bar{P}$	Maximum output capacity	y_s	If storage is repurposed

2.1 Allocation of Electrical Storages

Except for pumped hydro storages, electrical storages such as batteries do not have restrictive geological requirements. Therefore, we assume that storage units can be built at and be connected to any busbar within the electrical grid. From the perspective of the system, the main purpose of electrical storage is to balance generation and demand. One example is storing energy generated at times with low production costs to use it at times when electricity production is expensive. Furthermore, storages might be able to supply control measures when there are congestions in the grid if said storages are placed at beneficial locations. In energy system models both problems become visible when considering the nodal prices. High nodal prices can indicate that additional generation at the corresponding node is beneficial to the system due to either of the effects. For the allocation of the electrical storage units, we use the nodal prices as an indication of the benefits a storage unit brings to the system when placed at that busbar. We use the integrated energy system model (IES) SYNERGINET to obtain the required nodal prices and other outputs such as RES curtailment [16]. To evaluate the potential benefits of different storage options which differ in their storage capacity and hence also in costs and investments, we use the model described by equations (1)-(6) for each of the busbars and storage options.

$$\max \sum_{t \in \mathcal{T}} -P_t^{in} \cdot \delta_t + P_t^{out} \cdot (\delta_t - c_{var}) - C_{fix} - C_{invest} \tag{1}$$

s.t.

$$V_{t+1} = V_t + P_t^{in} \cdot \eta_{in} - P_t^{out} \cdot \eta_{out} \qquad \forall\, t \in \mathcal{T} \tag{2}$$

$$V_{start} = V_{end} \tag{3}$$

$$0 \leq P_t^{in} \leq \overline{P} \qquad \forall\, t \in \mathcal{T} \tag{4}$$

$$0 \leq P_t^{out} \leq \overline{P} \qquad \forall\, t \in \mathcal{T} \tag{5}$$

$$0 \leq V_t \leq \overline{V} \qquad \forall\, t \in \mathcal{T} \tag{6}$$

The objective is to maximize the profit of a storage unit that consists of revenues from discharging electricity P_t^{out} minus costs from charging the storage unit P_t^{in}, variable operational costs c_{var}, fix operational costs C_{fix}, and the annualized investments in the current year C_{invest}. $\mathcal{T}$ denotes all time steps in the year whereas δ_t is the nodal price at the corresponding busbar in the time step t. We solve this model for each combination of busbar and storage investment option and compare the potential benefits that the storage options achieve. Sorting the potential benefits of the combinations of storage options and busbars in descending order provides a list of beneficial storage units.

In the next step, we must decide how many storages are placed at each beneficial site. For this sizing problem, we implement a greedy algorithm as presented in Figure 1. We initialize the output capacity limits for each busbar, $CapLim_b$, and set the total capacity installed, P_{inst}, to zero. Afterwards, we iterate through the sorted list of storage options and build as many storages as possible until we reach the defined capacity limit at the corresponding busbar. As storages are expected to mainly store electricity from RES, we choose the observed curtailed electricity at the corresponding busbar to serve as the capacity limit. Since these curtailments might have a few very high peaks, choosing the maximum curtailment could lead to oversizing. Therefore, the p^{th} quantile of curtailed RES at each busbar is chosen to serve as the capacity limit at the corresponding busbar. After the capacity limit at the corresponding busbar is reached, the next option is considered. When the total capacity installed is equal to or exceeds the target capacity specified in the respective scenario, the algorithm terminates.

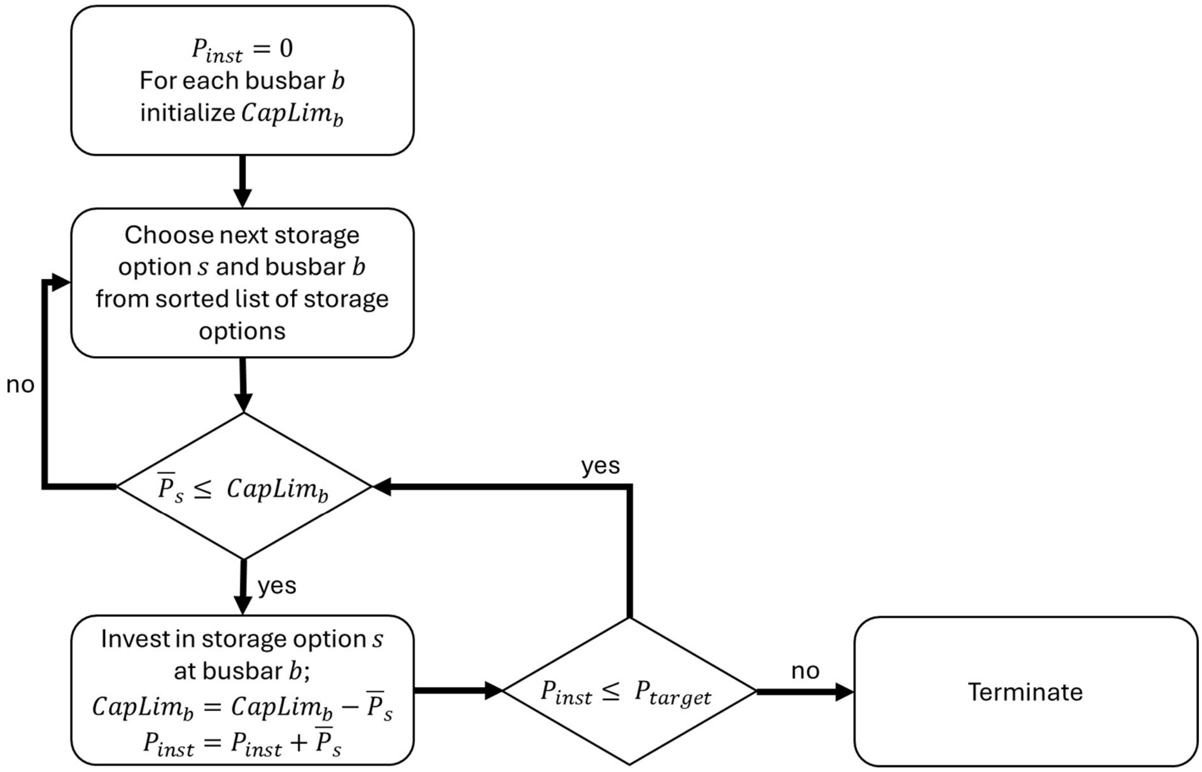

Figure 1 - Greedy algorithm used for sizing of storages

This procedure is repeated for each year and country considering the storage units that have been installed in previous years.

2.2 Allocation of Hydrogen Storages

The allocation of natural gas and hydrogen storages is different from the allocation of electrical storage units since most gaseous storages are underground storages that require certain geological properties. Furthermore, there is the possibility that existing natural gas storages can be repurposed to store hydrogen in the future. Therefore, we base the allocation of gaseous storages on a database of existing and projected natural gas and hydrogen storages that is based on data from the Gas Infrastructure Europe, H2 Infrastructure Map Europe and the Ten-Year Network Development Plan (TYNDP) 2022.

We assume a scenario where the total storage capacity of natural gas storages is either constant or decreasing in the future. In contrast, the total storage capacity of hydrogen storages is increasing. In a first step we identify those natural gas storages that will be decommissioned due to the scenario targets. To do so, we apply the model described by (7)-(8)

$$\min\left(\left|P_{NG,inj}^{exist} - P_{NG,inj}^{target} - \sum_{s\in S_{NG}} P_s^{inj} \cdot x_s\right| + \left|P_{NG,wdw}^{exist} - P_{NG,wdw}^{target} - \sum_{s\in S_{NG}} P_s^{wdw} \cdot x_s\right|\right) \quad (7)$$

s.t.

$$x_s \in \{0, 1\} \qquad \forall\, s \in S_{NG} \quad (8)$$

The objective is to find the combination of natural gas storages S_{NG} to decommission so that the remaining injection and withdrawal capacities are closest to the target capacities. $P_{NG,inj}^{exist}$ and $P_{NG,wdw}^{exist}$ represent the total existing injection and withdrawal capacities of the natural gas storages. $P_{NG,inj}^{target}$ and $P_{NG,wdw}^{target}$ are the target capacities for injection and withdrawal. The binary decision variables x_s describe whether a storage s with injection capacity P_s^{inj} and withdrawal capacity P_s^{inj} is decommissioned.

In a second step, the repurposing of decommissioned natural gas storages to store hydrogen is considered. Since salt caverns are the most likely type of natural gas storage to be repurposed, we only allow repurposing of decommissioned salt caverns [17], [18]. The model given by (9)-(10) identifies the best combination of repurposed natural gas storages to meet the target capacities for hydrogen storages.

$$\min\left(\left|P_{H2,inj}^{target} - P_{H2,inj}^{exist} - \sum_{s\in S_{NG,decommissioned}} P_s^{inj} \cdot y_s\right| + \left|P_{H2,wdw}^{target} - P_{H2,wdw}^{exist} - \sum_{s\in S_{NG,decommissioned}} P_s^{wdw} \cdot y_s\right|\right) \qquad (9)$$

s.t.

$$y_s \in \{0,1\} \qquad \forall\, s \in S_{NG,decommissioned} \qquad (10)$$

Where y_s is the binary decision variable representing the repurposing of a decommissioned salt cavern.

If the target capacities for hydrogen are not met, overground hydrogen tanks will be constructed at other nodes where natural gas storages are located until the target capacities are met. The assumption is that these locations will also be important in the hydrogen system since some of the pipeline infrastructure might be repurposed in the future.

3 Case Study

We apply the methodology described in section 2 to a scenario based on the TYNDP 2022 [19]. We consider the following countries with their respective electricity and natural gas grids in 2030: Germany, the Netherlands, Belgium, Luxembourg, France, Switzerland, Austria, Czech Republic, and Poland. Since there is still a lot of uncertainty regarding hydrogen infrastructure, we only consider hydrogen on a national level. For the storage options in the electricity grid, we consider three sizes of lithium-ion energy storage units with ratios of 2, 4, and 6 regarding their storage capacity and output capacity. The techno-economic data, including investment and operation and management (O&M) costs, are presented in Table 2 and based on [20].

Table 2 - Techno-economic data for storage options based on [16]

Option	1	2	3
Output capacity [MW]	200	200	200
Storage capacity [MWh]	400	800	1200
Specific investment output capacity [€/kW]	160	160	160
Specific investment storage capacity [€/kWh]	142	142	142
Fixed O&M cost [€/(MW*a)]	540	540	540
Variable O&M cost [€/MWh]	1.8	1.8	1.8
Charge efficiency	98.5	98.5	98.5
Discharge efficiency	97.5	97.5	97.5

For the p^{th} percentile of RES curtailments, we choose to compare the following values: 0.5, 0.6, 0.7, 0.8, 0.9, 0.95, 1.0. The scenario of choosing the 1.0 percentile is equal to choosing the maximum RES curtailment.

We benchmark our approach to an allocation of storages where only the maximum RES curtailments multiplied by the value p and one storage option is considered. Since wind offshore is much more centralized than other RES technologies, we also calculate benchmark scenarios excluding offshore wind capacities. Furthermore, we also include a scenario where we only allow investments in storage option 1 since we experienced a tendency of the methodology to choose storages with a bigger storage capacity.

Scenarios named “Nodal_p” are scenarios where the nodal prices are considered choosing the p^{th} percentile whereas “Nodal400_p” indicates a scenario with nodal price-based allocation with only storage option 1 available. Benchmark scenarios are named “BenchX_p” or “BenchXwo_p” where X is the storage capacity and “wo” indicates that wind offshore capacities are considered. E.g., Bench400wo_0.5 is the benchmark scenario where we allocate storage units with a size of 400 MWh to all RES capacities multiplied by 0.5 including wind offshore.

In the initial run that provides the nodal prices, existing storages, such as pumped hydro, are considered. After the allocation of the additional storages, we optimize the model again and compare the different scenarios.

4 Results

The run times for the allocation of either electrical or gas storages is within the span of minutes. The optimization, on the other hand, takes between ten to twelve hours. An endogenous allocation within the optimization would lead to significantly more additional run time than the proposed heuristic.

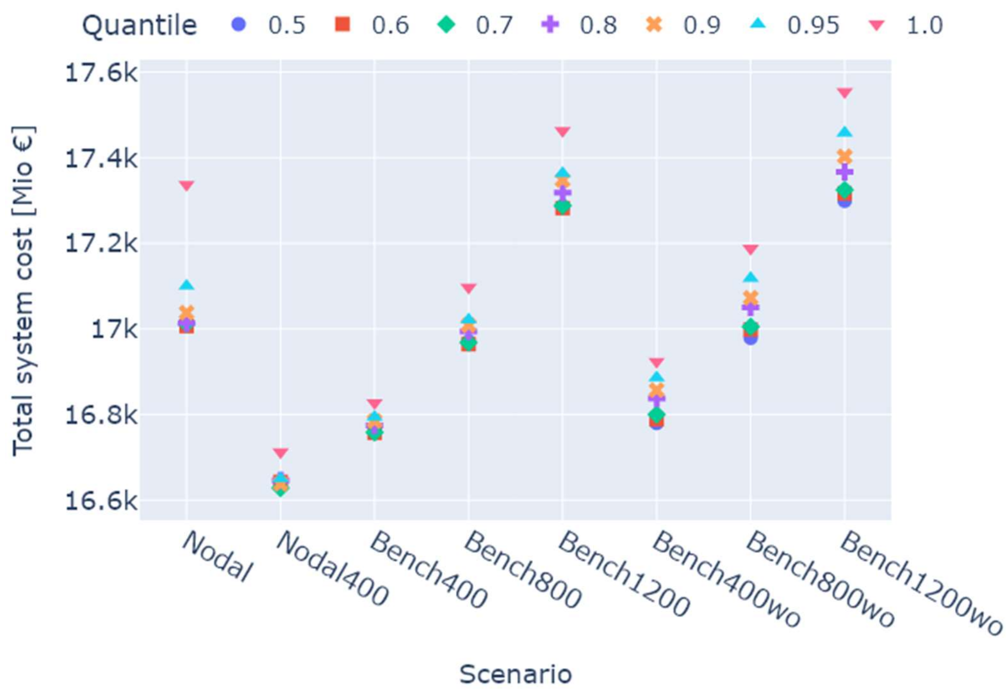

Figure 2 - Total system cost of the different scenarios

Figure 2 presents the annual costs of the storages as well as the total system cost including the costs of the operational optimization as described in [16]. We observe that the scenarios with lower storage sizes perform generally better. The allocation based on nodal prices where we only allow for the small storage option performs best. Furthermore, we see that a lower quantile p chosen leads generally to lower system cost. Regarding the allocation at wind offshore generation, we observe only a marginal decrease in costs when the storage units are not allocated at sites of wind offshore capacities. However, the marginal effect is higher the higher the quantile is. Figure 3 further details the respective costs with the distinction between optimization costs and storage costs. Optimization cost refers to the value of the objective function of the SYNERGINET model – costs due to consumption of energy carriers, CO_2-emissions, and variable O&M costs. The storage costs include the annualized investment and the fix O&M costs. We observe that the allocation based on nodal prices reduces the costs within the optimization compared to all other benchmarks. However, since the storage capacities are generally higher the cost of the storages exceeds the savings in optimization costs.

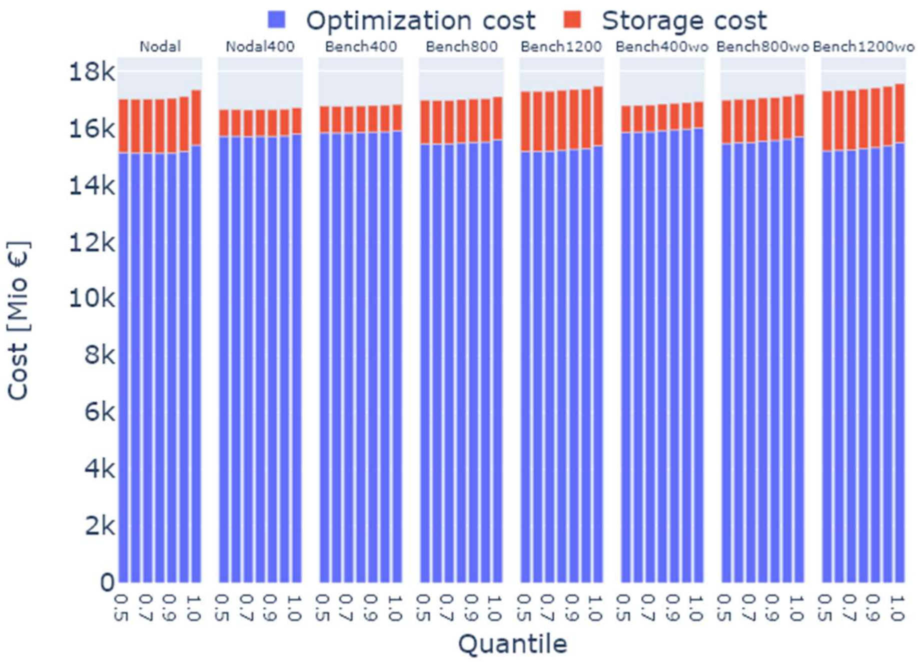

Figure 3 - Comparison of costs of optimization and storages between the different scenarios

Figure 4 presents the remaining RES curtailments in the different scenarios. We observe a clear trend that the RES curtailments decrease with higher storage capacities. The allocation based on nodal prices results in similar curtailments as the benchmarks with storage sizes of 800 MWh. Generally, we can also see a trend that the lower the value p is chosen the lower the curtailments are. There are, however, a few exceptions, especially considering the allocation based on nodal prices.

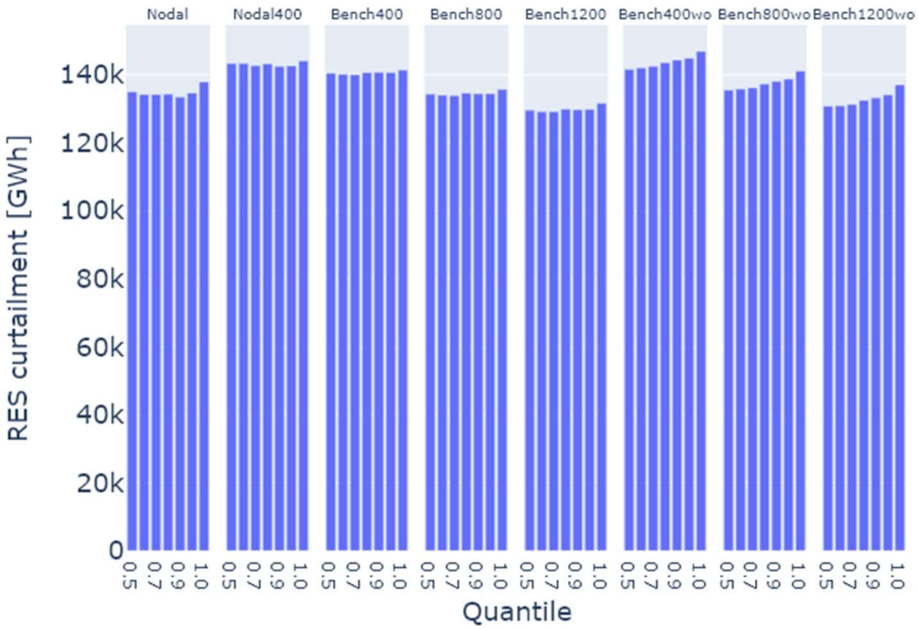

Figure 4 - RES curtailments in the different scenarios

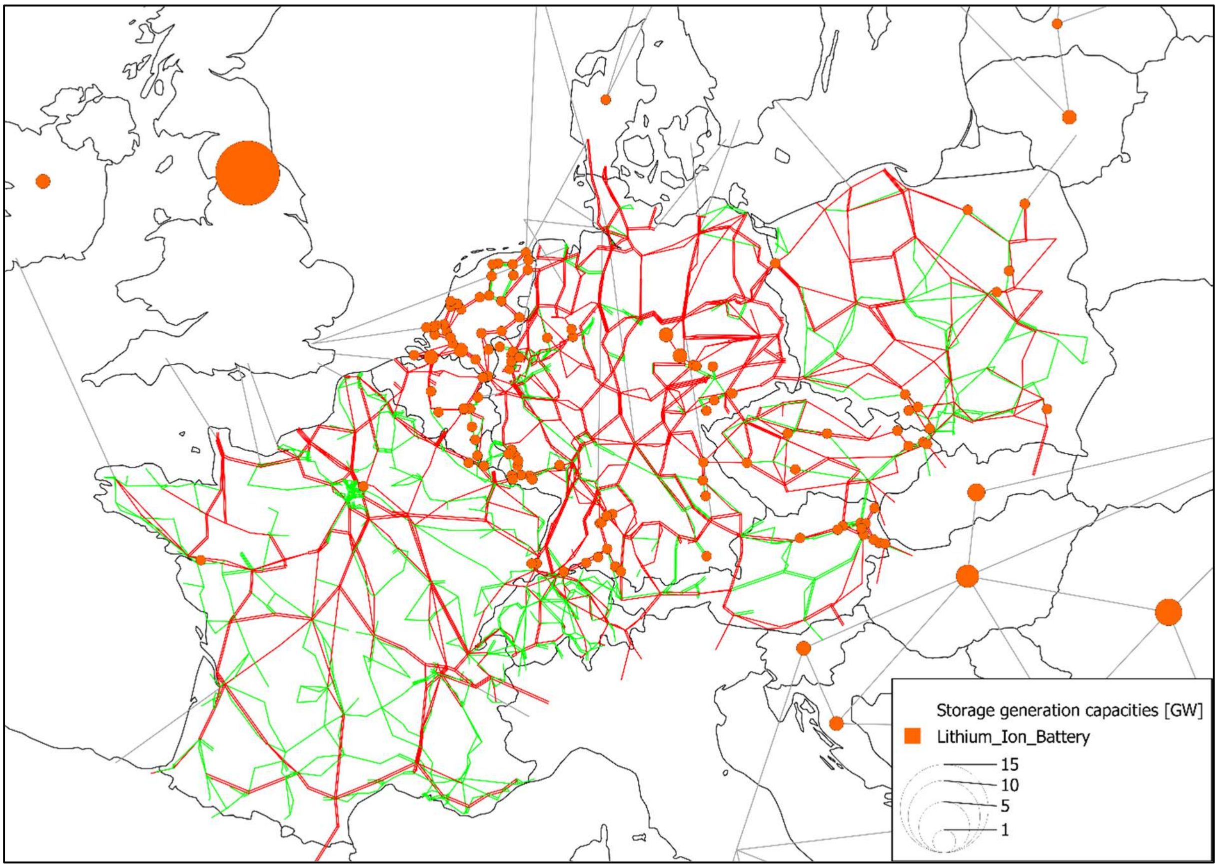

Figure 5 - Allocation of storages in the case Nodal400_0.7

Figure 5 presents the allocation of the storage units in the best-performing allocation scenario, Nodal400_0.7. We observe that the allocation of storages is decentralized, i.e. there are a lot of locations with low storage output capacity. Due to the scenario targets some countries contain rather high amounts of storage units for their respective size, e.g. the Netherlands and Belgium, whereas France has rather few storage units. If we look at Germany, we observe that storage units are rather located at sites of high electrical demand, e.g. the Rhine-Ruhr area. Furthermore, we see that a lot of storage units are built in the South of Germany where one might expect missing generation or transmission capacities in the future. We observe fewer storage units in the north of Germany which is characterized by high wind capacities.

Regarding the hydrogen storages, we notice that the projected storage capacities are not sufficient to meet the targets and additional overground storage tanks must be built in most of the considered countries. In total 8.2 GW of storage output capacity must be constructed as overground storages until 2030.

5 Conclusions

In this paper, we introduced a novel methodology for the allocation of electrical storages in the transmission grid as well as an approach for the decommissioning and repurposing of existing natural gas storages for the use of hydrogen. We observed that the run times of the proposed approach are very short and therefore well applicable to large-scale systems. Our proposed allocation methodology outperforms our proposed benchmarks when well-parametrized. We noticed that from a system perspective, storages should be chosen with comparably low storage sizes compared to their maximum power output to reduce the costs of said storages. Furthermore, we find that one should use a quantile between 0.5 and 0.7 for the maximum RES curtailment at a given busbar to prevent oversizing.

The proposed methodology results in higher overall system cost if storage options with high storage capacities are available. This is most likely due to the neglected price-maker effect since the storage itself influences the nodal prices at its corresponding busbar. One way to overcome this issue might be to limit the amount of energy in the allocation method that a storage unit can feed into or withdraw from the grid so that bigger storage capacities are not as profitable.

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