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Integration of water electrolysis facilities in power grids: A case study in northern Germany

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ABSTRACT

This work presents a study of the effects that integration of electrolysis facilities for Power-to-X processes have on the power grid. The novel simulation setup combines a high-resolution grid optimization model and a detailed scheduling model for alkaline water electrolysis. The utilization and congestion of power lines in northern Germany is investigated by setting different installed capacities and production strategies of the electrolysis facility. For electrolysis capacities up to 300 MW (~50 ktH_2/a), local impacts on the grid are observed, while higher capacities cause supra-regional impacts. Thereby, impacts are defined as deviations from the average line utilization greater than 5%. In addition, the minimum line congestion is determined to coincide with the daily-constrained production strategy of the electrolysis facility. Our result show a good compromise for the integrated grid-facility operation with minimum production cost and reduced impact on the grid.

Introduction

As the German energy transition progresses, the integration of renewable energy sources (RES) in the power sector is increasing. However, RES integration in other sectors is still very limited and is facing many challenges. With 248.8 TWh of renewable electricity generation, Germany has reached a sector-specific renewable share of 50.7% in 2020 [1]. Wind energy accounts for the largest part with 60%, where the major wind energy potentials are located in the coastal areas of the northern federal states and offshore in the North Sea.

Although direct electrification is suitable in many domains and enables high efficiency, indirect electrification via so-called Power-to-X (PtX) processes is increasingly being considered for sectors that are difficult to defossilize. In this way, the amount of fossil carbon released is reduced or even substituted. Certain energy-intensive application fields are expected to rely on PtX for short- to medium-term greenhouse gas (GHG) emission reductions. This includes the aviation sector and the steel industry [2]. However, to produce relevant energy quantities, immense amounts of RES are required for the hydrogen-based direct reduction of steel as well as the electricity-based production of jet fuel.

According to the current state-of-the-art, particularly alkaline water electrolysis (AEL) is suitable to satisfy the demand of hydrogen. This is due to its technological maturity, large-scale availability, and recent developments to support flexible operations [3,4]. Flexible operation refers to wide load ranges, the high ramp-up and ramp-down rates, and short startup times of electrolyzers. Manufacturers report load ranges of 10–100%, a few seconds to reach changes in load set points, and 30–60 min to perform cold startups [5–8]. These features allow for enhancing the process performance by adjusting the operation in relation to electricity price, product demand, participation in grid services, renewable power generation or non-renewable content in the grid.

For the general case, electrolyzers operate with grid power while off-grid operations are less preferable due to the high volatility of RES. Load following operations can theoretically be supplemented by non-renewable power from the grid to compensate such volatility (i.e. grid compensation) [3]. However, such operations lead to a contradiction in the purpose of Power-to-X processes; higher flexibility leads to improved economic performance, as the process could benefit from periods of low electricity price, even with scarce renewable power, while hydrogen

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Nomenclature

b, m	Parameters of stack linear model, 19.3406 kg/MWh and 2.9634 kg/h, respectively
C_t^E	Electricity (day-ahead) cost in Germany 2018 [23] (Fig. 4)
C^{INV}	Investment cost, 2.3 M€/electrolyzer [32]
C^{ETS}	Penalty cost for the use of non-renewable energy, approximated with ETS price of 0.04 €/kg_{GHG}
C^{SU}	Cost of startup cycle, approximated to 50 €/cycle
$F_{n,t}$	Hydrogen production rate, in kg/h
F_t^{GHG}	GHG emissions factor in Germany 2018 [23] (Fig. 5)
F^{LT}	Lifecycle of electrolyzers, 7.5 a [32]
F^T	Annual demand of hydrogen, case study: 18 kt/a
$I_{n,t}$	Idle state, binary variable
$L_{n,t}$	Production state, binary variable
n	Electrolyzer index
N	Total number of electrolyzers
N^{PD}	Number of periodic demands
$S_{n,t}$	Standby state, binary variable
t	Time index, in h
τ	Time horizon, case study: 8760 h
$W_{n,t}$	Total power load, in MW
W_t^{NR}	Grid power load, continuous variable in MW
W_t^R	Renewable power load, continuous variable in MW
W_t^{RS}	Renewable power capacity, in MW (Fig. 3)
W^{LB}, W^{UB}, W^{PC}	Minimum, maximum, and peripheral load: 0.6 MW, 3.3 MW, and 0.3 MW, respectively
$Y_{n,t}$	Startup cycle, binary variable

cannot be considered renewable, as the grid has both conventional and renewable shares. Thus, optimal production schedules must be determined due to the fluctuating electricity prices, volatility of renewables, and current GHG content of the energy mix. Furthermore, the impact on the grid operation due to the variable load of PtX facilities must be assessed.

Given the relevance of electrolysis for the energy transition, extensive research is being conducted on modeling and simulation of AEL. Varela et al. [9] developed a scheduling model to account for changes in the operating states of AEL, allowing for realistic computation of renewable hydrogen production under variable loads. Further studies highlight the need for operational strategies e.g. demand-side management (DSM), to address the dynamics inherent in energy markets and promote participation in grid services [10–12].

There is a plethora of power grid models, each addressing specific research questions and representing the relevant interactions among generation, demand, grid operation, markets, and policy. These are often formulated as optimization models to minimize total system costs while considering physical grid constraints. However, the multiple interactions lead to high model complexity. Dealing with complexity or rather its reduction is therefore a major challenge for the modeling community. Currently, many studies address the question of how the complexity level affects the model results [13–15]. The reduction of the power grid spatial resolution is a promising option, since the deviation of total system costs remains below 20% with enhanced grid representations [16,17].

There are few recent studies about the effects of integration of electrolysis facilities on power grids. Bødal et al. [18] investigated the capacity sizing of the electrolyzer and hydrogen storage in Northern Norway, while considering the impacts of electrolysis in a quite simplified power grid representation with ten buses. The authors used a DC power flow simulation which allowed for wind power investments. The results show a high utilization rate of hydrogen storage which reduces grid congestions. However, a regional expansion of the grid has a negative effect as it increases the congestion level. Longoria et al. [19] explored the impacts of using hydrogen for residential heating on the power system with a focus on electricity prices and renewable generation curtailment. A linearized optimal power flow model was used to determine optimal investments in electrolyzers for three variants of the Irish 2030 target scenario (70% renewable electricity), whereby every electricity bus can be a potential location for electrolyzer investments. The authors show that the different scenarios have an impact on grid extension and that wind curtailment is dependent on the number of electrolysis used as they cause higher levels of congestion. The effects of regulation on grid congestion due to electrolysis integration in Germany are investigated by Scheidt et al. [20]. The approach used include three steps: a power system dispatch model for the extra-high voltage level of Germany provides the uniform and nodal electricity prices, which are then fed into a hydrogen model to determine the optimal spatial design of hydrogen supply chains, finally the resulting spatial electric loads of the electrolyzers are fed into the power system dispatch model. The authors found that the integration of hydrogen under the currently used uniform prices results in a substantial increase in congestion management costs of up to 18% (1.09 billion Euros) per year. Using nodal prices however results in a decrease of congestion management costs by 20% (1.249 billion Euros) per year.

While the literature cited above investigates different aspects of hydrogen production via electrolysis, detailed investigations of the local impact of one large-scale electrolyzer and its operation strategy on the power grid operation and congestion rates analyzed via active power flows on the georeferenced power lines are not available. Especially a detailed grid representation including the high voltage level in Germany is necessary since on the one hand the electrolyzer is directly connected to this voltage level. On the other hand, a less detailed representation of the power grid underestimates the congestion events greatly. The case study presented in this work considers an integration in the region of Heide, which is located in Schleswig-Holstein, Germany. The region is of particular interest as it offers significant on-and offshore wind energy potential and strong efforts are being made to ramp-up the electrolysis capacity considerably. The anchor player is the Heide refinery, which aims to install 30 MW of electrolysis capacity in the short term and expand this to 700 MW by 2030 [21]. By fixing the annual target of hydrogen production, a suitable number of electrolysis stacks and four annual operation time series are determined in this work. For this purpose, the AEL model by Varela et al. [22] is employed and extended by novel cost terms for optimization of economic and environmental performance. Subsequently power flows in the regional and supra-regional power grid are analyzed for voltage levels of 110 kV and above. This enables the identification of grid congestion and bottlenecks in dependency of the scale of the electrolysis facility and production strategy. To the knowledge of the authors, the present study is the first to address the integration of electrolyzers into the power grid, and to investigate the facility-grid interaction for different operating modes at a regional level. The power grid model applied is an adapted version of the "eTraGo" transmission grid optimization package which is part of the "open_eGo" grid planning software [17]. It features a high spatial resolution at the grid-facility connection (federal state level) and simplifies distant regions with grid clustering to handle complexity issues with bearable information losses (at national level).

Methodology

This work combines a linear power flow optimization of the power grid (Section 2.1) and a scheduling algorithm of AEL (Section 2.2) to

compute the utilization and congestion of grid lines resulting from the integration of an electrolysis facility. Several simulation settings are investigated to account for the scale of the electrolysis facility and the production strategy over a full year of operation. Therefore, an optimization is performed in both models: while the power grid model minimizes the total system costs, the electrolysis facility model performs DSM to reduce the production cost of green hydrogen.

The data flow is shown in Fig. 1, where the inputs are defined by the case study: simulation time (8760 h), region of interest (northern Germany), hydrogen capacity (18 kt/a), and cost parameters (based on the data of Agorameter [23]). The outputs are the solution of the optimization model, which are the operation of the power grid, suitable number of electrolysis stacks and production schedule of the electrolysis facility. This information allows to compute regional line utilization and to identify line congestion due to the different scales and production strategies of the electrolysis facility.

Power system simulation

The linear power flow optimization is performed by the open-source software PyPSA [24] minimizing the total system costs. The required grid data is derived from the open_eGo project (more precisely the eTraGo model for the German power transmission grid). The power system relevant data of power generation (or supply) plants is taken from the Core Energy Market Data Register [25], whereas the electricity generation time series are based on Pfenninger et al. and Staffel et al. [26,27] and generation type costs are chosen according to Gerbaulet et al. [28]. The power demand is calculated according to the Federal States' Working Group on Energy Balances [29] with the load time series according to the data from the Federal Network Agency [30].

As mentioned in the introduction, one challenging aspect is the level of detail of power grid models. On the one hand the local power grid model should be as accurate as possible to perform and assess the electrolysis facility integration. On the other hand, detailed grid representation limits the computable system size due to increasing complexity and computational effort. To overcome this issue, we used the eTraGo grid data with 11,309 buses and simplified it to 501 buses (Fig. 2) using the k-means algorithm (also executable by eTraGo). The algorithm aggregates the power grid buses to a desired bus number and is applied to all federal states except Schleswig-Holstein as it is the region of interest in this study and should not be aggregated. Manual adaptions are required to combine the separated clusters to one computable grid network. The underlying assumption is to connect neighboring federal states by the bus pair with minimal distance (see Fig. 2).

The regional installed renewable capacity is primarily considered for the operation of electrolyzers at the facility (Fig. 3). Hereby, it is assumed that local wind onshore generators within approximately 10 km to the electrolysis facility contribute directly with their renewable capacity to the electrolysis operation. The wind time series used are obtained from the MERRA-2 [31] weather dataset for the year 2018. The appropriate time series is provided as input to the electrolysis model, and the actual load of the facility is considered as power demand. In such way, the electrolysis facility is simplified in the power system simulation as single load time series (Fig. 1).

Alkaline water electrolysis model

The AEL-scheduling model recently proposed in [9] is considered in this work. The model is presented in the Appendix with novel constraints that are implemented to account for the allowance of non-renewable power load from the grid (Equation (A.8)), the introduction of periodic hydrogen demands (Equation (A.9)), and the commitment of dedicated units to flexible operation (Equation (A.10)). The model is set to minimize the operation costs of the facility, allowing grid power to be used beyond the available renewable capacity to meet periodic hydrogen demands and/or minimize the production cost. A virtual cost term penalizes the use of non-renewable power to promote load-following operations based on the renewable power capacity (in Fig. 3). The penalty is based on the GHG emissions content in the grid (power generated from conventional sources) and Emissions Trading System (ETS) prices. The model parameters for the electricity cost and the GHG emissions content in the grid are the day-ahead price (Fig. 4) and the GHG emissions factor (Fig. 5) in Germany for the year 2018 [23], while the ETS price is set as 0.04 €/kg_{GHG} in this study.

To achieve the annual demand of hydrogen, the production can be distributed throughout the year. The optimization of the scheduling model is therefore performed with varying number of stacks (from 31 to 65) and production periods (from 1 to 8760). Those model parameters lead to different operation strategies of the electrolysis facility.

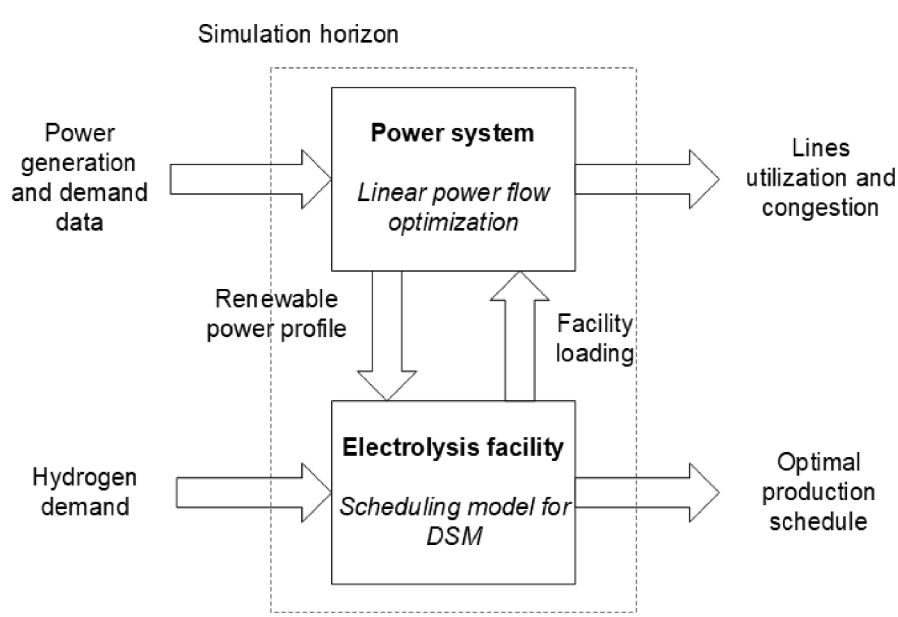

Fig. 1. Schematic workflow for the novel combined simulation of the power grid model and alkaline water electrolysis scheduling model.

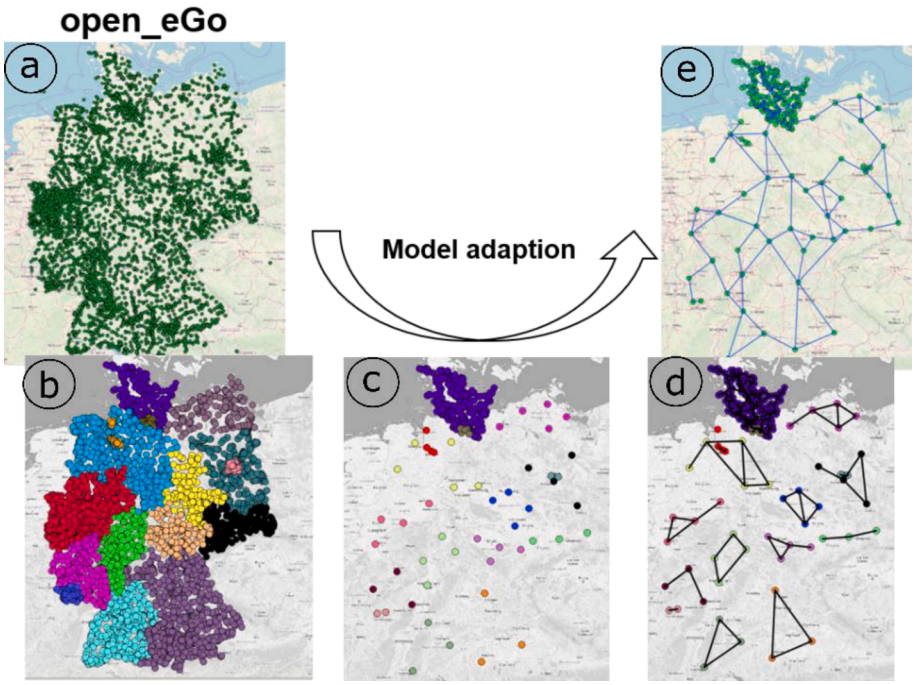

Fig. 2. Grid model adaption steps to simplify the open_eGo original data (a) with respect to federal states (b), by aggregating the grid in all German states (except Schleswig-Holstein) with k-means algorithm (as single bus representation (c) and including power line representations (d)) and to combine them to one computable grid structure (e).

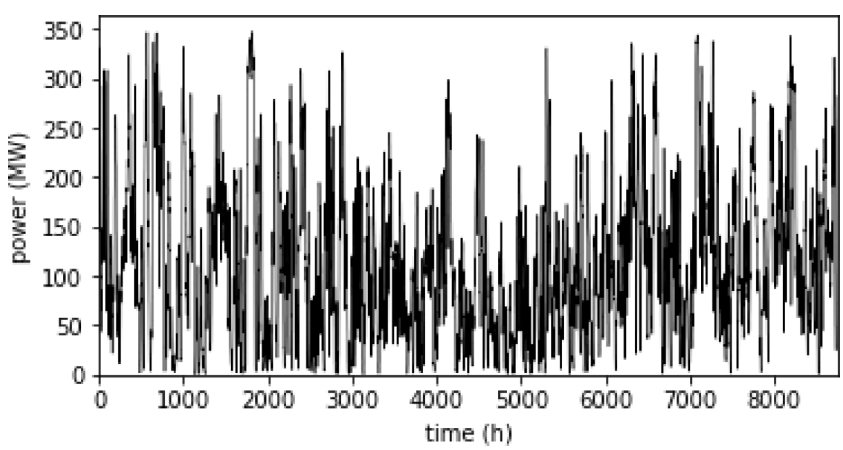

Fig. 3. Renewable power capacity in the neighborhood of the electrolysis facility.

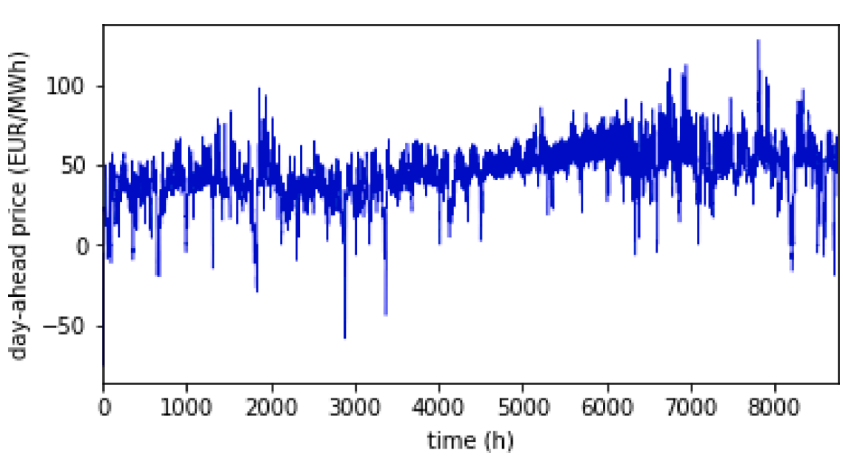

Fig. 4. Day-ahead electricity price in Germany for the year 2018.

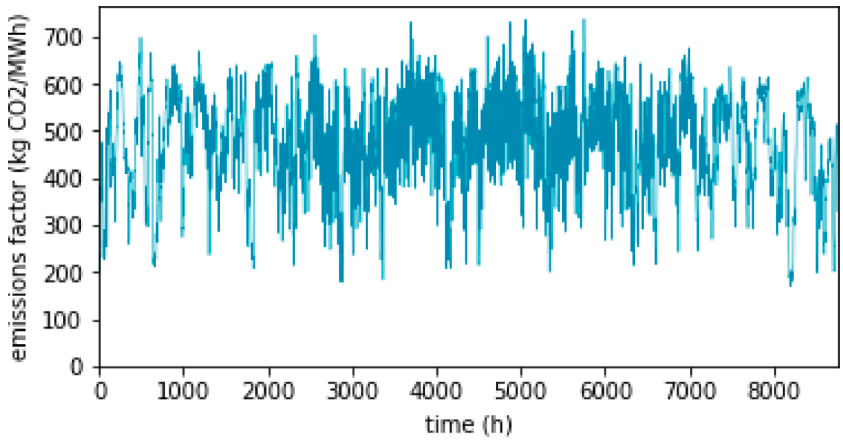

Fig. 5. GHG emissions factor Germany for the year 2018.

Results and discussion

Effects on the power grid due to the scale of electrolysis facilities

The challenge of integrating electrolysis facilities for green hydrogen in a desired location site is to guarantee the appropriate power supply with renewable energy through the regional and supraregional power grid. This may be difficult for a location-specific power demand utilized by the facility. To investigate the behavior of the power grid, a time-constant power demand with varying amplitude simulates the requirements of the electrolysis facility in a full-year operation. The amplitudes are chosen as percentages between 1% and 50% of the total annual power demand of the federal state of Schleswig-Holstein. Fig. 6 shows the impact of the electrolysis facility scale on the average power line utilization compared with a reference system without electrolysis facility.

The simulation results show a rather regional impact for a facility scale below or equal 225 MW. Starting with power demands of 300 MW,

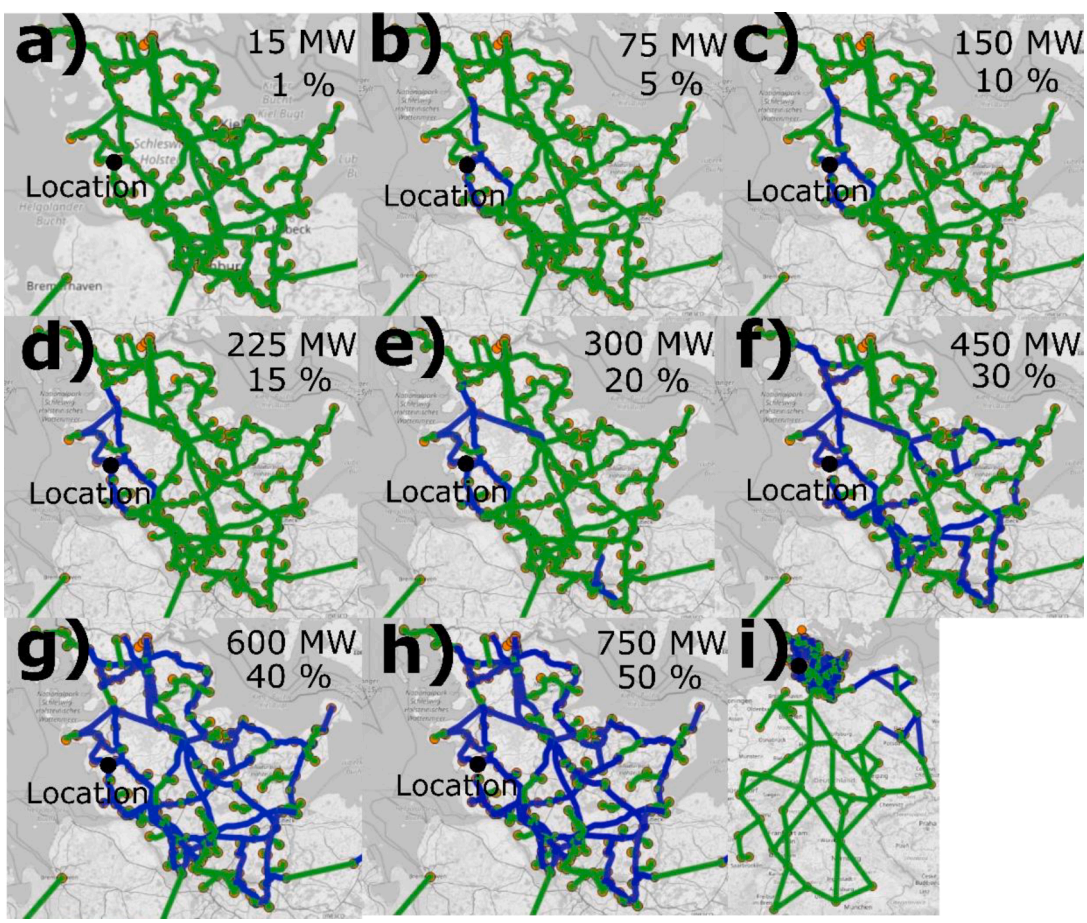

Fig. 6. Effects on the regional power grid due to various total power demands (a-h) between 15 MW and 750 MW of an electrolysis facility at the location site (black dot). Green lines indicate average line utilization deviations below 5% and blue lines above 5% with respect to a reference case without an electrolysis facility. The subplot (i) provides an overview of the national impacts of the electrolysis facility for the scenario (h). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

first the supraregional impacts on the area of Hamburg occur. Further increase of the demand leads to a broader distribution of these impacts across the entire federal state of Schleswig-Holstein. From demands of 450 MW, power lines in the federal states of Mecklenburg-Vorpommern and Brandenburg are also affected.

With the proposed stack design (available in the Appendix), 15 MW-load indicates the allocation of five electrolysis stacks in the facility that would produce 2.67 kilotons of hydrogen per year. For the highest amplitude of 750 MW, 225 electrolysis stacks are required, and 132.91 kilotons of hydrogen per year would be supplied. It is observed that an annual capacity of up to 50 kilotons of hydrogen per year (300 MW-load) still avoids supraregional impacts on the power grid.

The case study of 18 kilotons of green hydrogen per year requires a power demand of at least 101.5 MW and 31 electrolysis stacks. However, such a setup has to operate constantly at full capacity, thus prohibiting to follow renewable energy peaks or to adjust the production according to the electricity market situation.

Effects on the power grid due to demand-side management of electrolysis facilities

Production strategy of the electrolysis facility

The electrolysis facilities can be optimized for their power consumption according to the electricity spot price or renewable share in the grid, yet the hydrogen demand must be satisfied. The surface plot in Fig. 7 has been generated with the optimization results of the AEL-scheduling model with the number of stacks and production periods as model parameters, while producing 18 kilotons of green hydrogen per year.

The solution space shows that the total costs can be minimized by allowing the electrolysis facility to operate with major flexibility over the year (i.e., few demand periods). In such way, the process benefits from periods with low electricity prices and low GHG content in the grid. With a low number of installed electrolyzers the facility is forced to load in non-beneficial periods to fulfill the production demands. On the other hand, with large numbers of installed electrolyzers, the investment cost has a major impact on the objective function. A balanced operation comprises 45 electrolyzers with total flexibility over the year in this case study.

For operations with strict demand period goals, as daily, weekly, or monthly demands, the cost is much higher because there are many periods where renewable power supply is scarce. This means that the facility regularly uses grid power to satisfy the demand, resulting in high grid compensation.

The facility load with the optimal number of stacks (N = 45) and annual, monthly, daily, and hourly demand constraints is shown in Fig. 8 (green curve), with the renewable capacity depicted in the background (black curve). For hourly-constrained production, the process has no flexibility and must load often with high grid compensation. Daily-constrained production increases the process flexibility; however, the load profile mismatches the renewable power generation which results in a non-renewable share of 21.6%. Monthly and annual constrained production allow to follow the renewable profile with low grid compensation. However, the total costs are slightly lower for the annual-constrained (49.28 M€/a) as compared to the monthly-constrained production (50.23 M€/a), with similar annual renewable content of 86.9% and 85.9%, respectively.

Lines utilization and congestion in the power grid

In addition to the scale of the electrolysis facilities, the production strategy is a relevant aspect to consider in their integration into power grids. The time series from Fig. 8 are passed to the power system grid simulation model to investigate the grid operation under different production strategies of the electrolysis facility. The following notation is provided:

- S1: annual-constrained operation (total flexibility).
- S2: monthly-constrained operation.
- S3: daily-constrained operation.
- S4: hourly-constrained operation (no flexibility).

In the aggregated representation shown in Fig. 9, the four operation strategies of the electrolysis facility (S1, S2, S3 and S4) show a similar effect in terms of grid congestion. Most power lines are rarely congested, i.e. less than one event per week. Noteworthy, congestion is rather frequent on some lines, from weekly to daily events. Potential bottlenecks of the power grid, defined as lines with at least one daily congestion event are located in the north of Schleswig-Holstein (one line) and around Hamburg (three lines).

As the visualization of the aggregated results for line congestion does not show any deviations between the considered hydrogen production strategies, detailed analyses have been included for sampled power

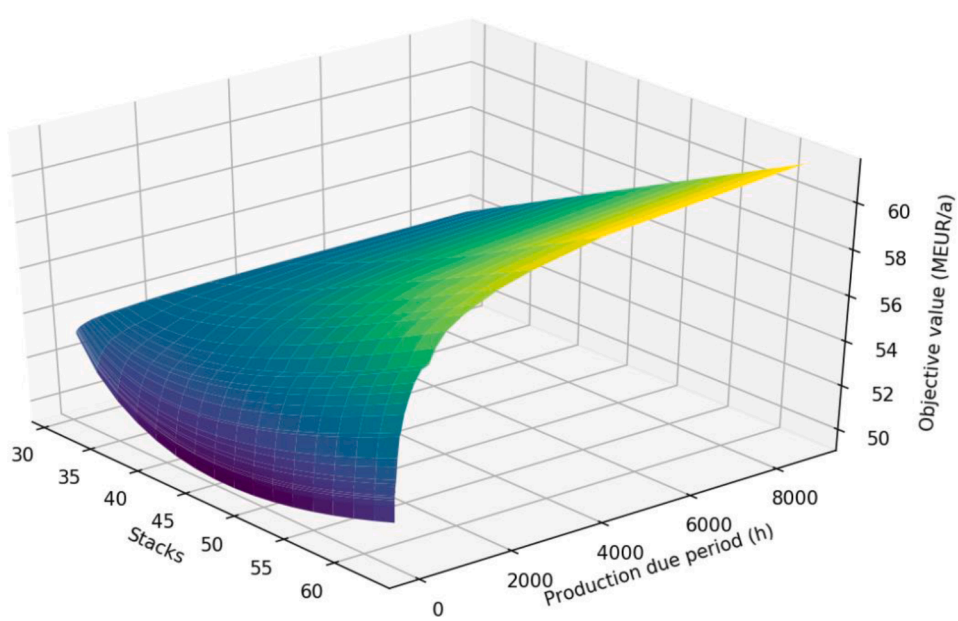

Fig. 7. Solution space with demand-side management of the electrolysis facility.

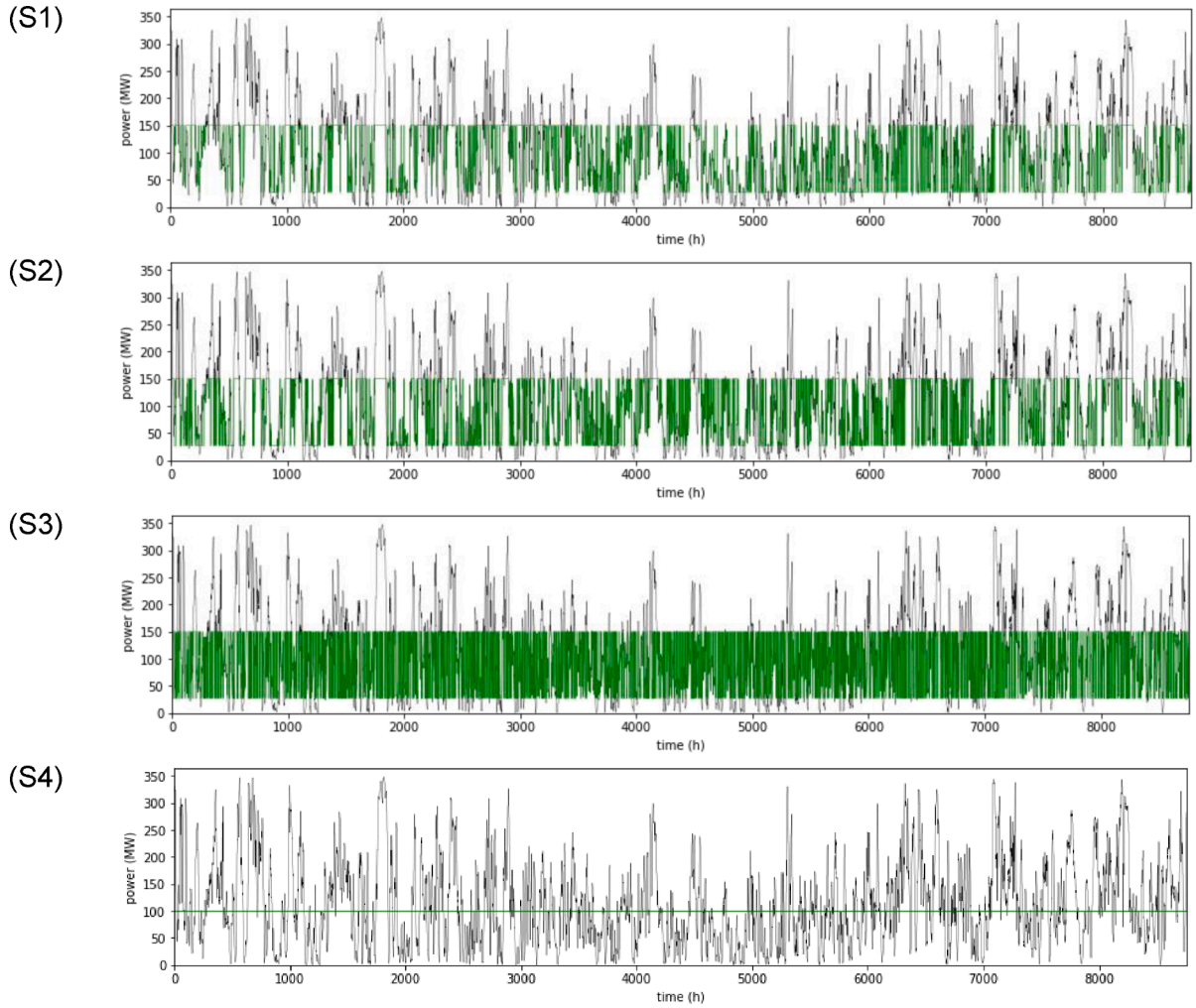

Fig. 8. Load of the electrolysis facility with 45 electrolyzers and (S1) annual, (S2) monthly, (S3) daily and (S4) hourly production constraint (for the year 2018) in green. The black curve depicts the renewable capacity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

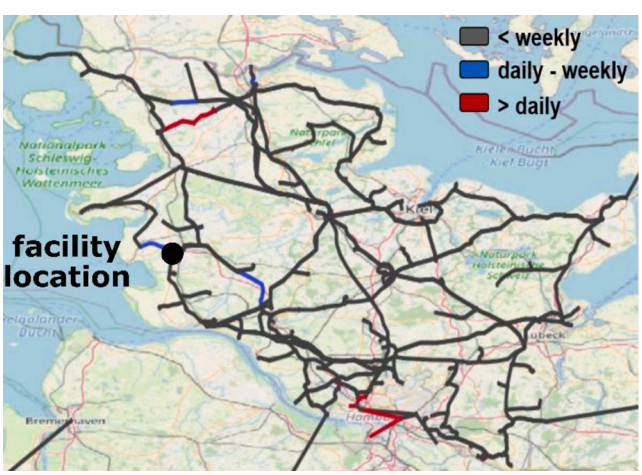

Fig. 9. Congestion rate of power lines during the year due to different operation strategies at electrolysis facility.

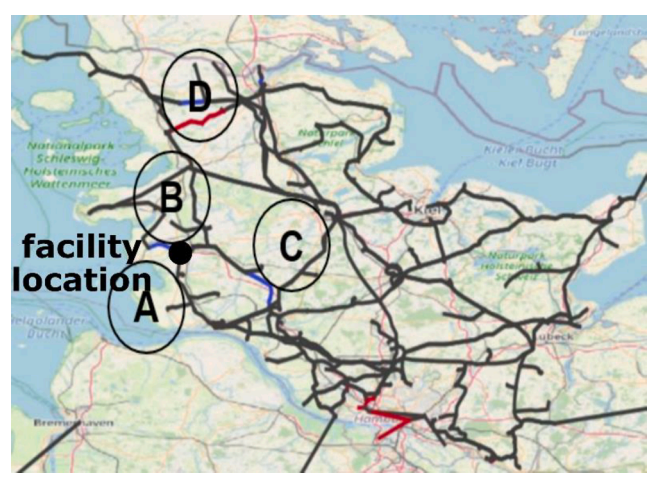

Fig. 10. Further investigated power lines for the grid congestion. Line cluster A denotes lines at the electrolysis facility, B and C are adjacent lines with frequent grid congestion. Cluster D consists of lines which are highly frequently congested during the simulated year.

lines. These lines are indicated in Fig. 10.

All lines starting or ending at the facility are denoted as line cluster "A". Lines with a pronounced congestion frequency between daily and weekly pattern are labeled line clusters "B" and "C", respectively. The

Table 2
Number of grid congestion events with respect to predefined line clusters and in total.

Congestion	Reference	S1	S2	S3	S4
A	0	2	2	0	1
B	71	88	86	77	70
C	288	256	254	279	293
D	901	1006	1018	948	980
Sum of clusters	**1260**	**1352 (7%)**	**1360 (8%)**	**1304 (3%)**	**1344 (7%)**
Total	**65,929**	**66,250 (0.5%)**	**66,345 (0.6%)**	**64,625 (−2%)**	**65,900 (0%)**

Table 3
Line utilization for the pre-defined operation strategies.

Line utilization	Reference	S1	S2	S3	S4
Average per line (%)	14.4	14.4	14.4	14.3	14.3
Average maximum value per line (%)	27.2	28.1	28.0	27.9	27.8
Average for lines at the facility (%)	22.7	25.2	25.2	25.1	25.1
Sum of differences (%)	**0**	**3.4**	**3.3**	**3.2**	**3.1**

potential bottleneck in the north of Schleswig-Holstein is labeled line cluster 'D'. Table 2 provides an overview of the number of grid congestion events with respect to the line clusters as well as in total. The reference case denotes the operation of the power grid without the electrolysis facility.

All operation strategies result in a slight increase in congestion events for all power line clusters. It is further noted that the line clusters "B" and "C" are correlated: a congestion increase in cluster "B" prevents further congestion in cluster "C", and vice versa, as the power flow follows another path through the power grid in those cases. Considering the clusters, the daily-constrained production strategy "S3" is the most convenient option since the slight increase for total congestion is not as high as for the other strategies. This is supported by the total congestion in the system. While the flexible annual and monthly strategies result in a slight increase, the rather restricted daily and hourly strategies decrease the number of congestions. Hereby, the rigid hourly-constrained strategy has a neglectable impact and the daily-constrained strategy decrease the congestion events by about 2%.

Besides the grid congestion, the average line utilization in the power grid is analyzed. The results are presented in Table 3 include the average line utilization for all power lines, the observed maximum of line utilization averaged for all power lines, and the average line utilization for lines directly connected to the location site.

While the average line utilization for all power lines, as well as for those lines that are directly connected to the facility, remains rather constant for all operation strategies, the average of maximum line utilization for all lines decreases with operational flexibility of the electrolysis facility. The computed differences suggest a positive trend for restricted operation strategies with low operation flexibility.

Conclusions

The novel simulation approach presented in this investigation allows for a high temporal (8760 time steps) and spatial (501 buses) resolution the assessment of the integration impact of electrolysis facilities in power grids. The assessment includes the evaluation of impacts on the grid due to the flexible operation of electrolyzers to minimize hydrogen production cost while efficiently integrating locally generated renewable energy. The findings are of special interest for the development of PtX projects using volatile renewable energy through the grid.

This study focuses on Northern Germany with its rich wind energy potential. The results show local effects on the grid for facilities capacity below 225 MW (40 kilotons of hydrogen per year), while anticipated demands greater than 300 MW signify a supraregional impact. Moreover, the production strategy of the electrolysis facility follows the regional renewable capacity and uses grid compensation when required, while achieving the goal of 18 kilotons of hydrogen per year. Through DSM, the facility operates cost-optimized with total flexibility i.e. without periodic demands of hydrogen. This implies more congestion events in the grid as compared to the reference case, while a daily-constrained production reduces them by about 2%.

This work provides first insights on the integration of water electrolysis for PtX facilities in power grids, with a parallel optimization of both systems, yet the findings are subject to the inherent uncertainties of the models. The results have to be validated and compared with future research, which could also expand the region of interest, include several electrolysis facilities of different scales, and optimize the facility-grid system simultaneously. Additionally, other regions and further planned grid extension can influence the results as well as compensation schemes (market designs) and policy. Those effects have to be further analyzed, but it is expected that the system grid-facility can improve its performance by including grid services during periods of high congestion. Moreover, the grid compensation should be minimized by including storage of green hydrogen into the assessments, allowing for better matches between the facility demand and renewable power time series.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. AEL-Scheduling model, modified version of Varela et al. [9].

Objective function.

$$\mathrm{Obj} = \min_{x}\left(\sum_{t=1}^{\tau} C_t^{E}\sum_{n=1}^{N} W_{n,t} + N\frac{C^{INV}}{F^{LT}} + C^{SU}\sum_{t=1}^{\tau}\sum_{n=1}^{N} Y_{n,t} + C^{ETS}\sum_{t=1}^{\tau} F_t^{GHG}\sum_{n=1}^{N} W_t^{NR}\right) \tag{A.1}$$

Decision variables.

$$x = \left[W_t^{R}, W_t^{NR}, S_{n,t}, L_{n,t}, I_{n,t}, Y_{n,t}\right]$$

Constraints.

State exclusivity:

$$L_{n,t} + S_{n,t} + I_{n,t} = 1, \forall n \in \{1, \cdots, N\}, \forall t \in \{1, \cdots, \tau\} \tag{A.2}$$

Cycles count:

$$I_{n,t-1} - I_{n,t} \leq Y_{n,t}, \forall n \in \{1, \cdots, N\}, \forall t \in \{2, \cdots, \tau\} \tag{A.3}$$

Minimum down time:

$$I_{n,t-2} - I_{n,t-1} + I_{n,t} \geq 0, \forall n \in \{1, \cdots, N\}, \forall t \in \{2, \cdots, \tau\} \tag{A.4}$$

Renewable load capacity:

$$\sum_{n=1}^{N} W_{n,t}^{R} \leq W_{t}^{RS}, \forall t \in \{1, \cdots, \tau\} \tag{A.5}$$

Total load capacity:

$$\left(W^{LB} + W^{PC}\right)L_{n,t} + W^{PC}S_{n,t} \leq W_{n,t} \leq \left(W^{UB} + W^{PC}\right)L_{n,t} + W^{PC}S_{n,t},$$

$$\forall n \in \{1, \cdots, N\}, \forall t \in \{1, \cdots, \tau\} \tag{A.6}$$

Production rate:

$$F_{n,t} = m\left(W_{n,t} - W^{PC}\left(1 - I_{n,t}\right)\right) + bL_{n,t}, \forall n \in \{1, \cdots, N\}, \forall t \in \{1, \cdots, \tau\} \tag{A.7}$$

Load balance:

$$W_{n,t} = W_{n,t}^{R} + W_{n,t}^{NR}, \forall n \in \{1, \cdots, N\}, \forall t \in \{1, \cdots, \tau\} \tag{A.8}$$

Product demand with "N^{PD}" periods:

$$\sum_{t=1+(j-1)\frac{\tau}{N^{PD}}}^{j\frac{\tau}{N^{PD}}} \sum_{n=1}^{N} F_{n,t} = \frac{F^{T}}{N^{PD}}, \forall j \in \{1, \cdots, N^{PD}\} \tag{A.9}$$

Unit commitment.

$$W_{n,t} \leq W_{n+1,t}, \forall n \in \{1, \cdots, N-1\}, \forall t \in \{1, \cdots, \tau\} \tag{A.10}$$

References

[1] Fraunhofer ISE. Annual renewable shares of electricity production in Germany. Energy Charts 2021.

[2] BMWi, Die Nationale Wasserstoffstrategie, Berlin, 2020.

[3] Moseley PT, Garche J. Electrochemical energy storage for renewable sources and grid balancing. Elsevier; 2015.

[4] Carmo M, Stolten D. *Energy storage using hydrogen produced from excess renewable electricity*. Elsevier Inc.; 2019.

[5] Seibel C, Kuhlmann JW. Dynamic water electrolysis in cross-sectoral processes. Chem-Ing-Tech 2018;90(10):1430–6. https://doi.org/10.1002/cite.201800114.

[6] Godula-jopek A. Hydrogen Science and Electrochemical Science and Technology – Fundamentals Electrochemical Technologies for Energy Storage and Fuel Cell Science and High Energy Density Lithium; 2015.

[7] Lüke L, Zschocke A. Alkaline water electrolysis: efficient bridge to CO2-emission-free economy. Chem-Ing-Tech 2020;92(1-2):70–3. https://doi.org/10.1002/cite.201900110.

[8] Ulleberg Ø, Nakken T, Eté A. The wind/hydrogen demonstration system at Utsira in Norway: evaluation of system performance using operational data and updated hydrogen energy system modeling tools. Int J Hydrogen Energy 2010;35(5): 1841–52. https://doi.org/10.1016/j.ijhydene.2009.10.077.

[9] Varela C, Mostafa M, Zondervan E. Modeling alkaline water electrolysis for power-to-x applications: a scheduling approach. Int J Hydrogen Energy 2021;46(14): 9303–13. https://doi.org/10.1016/j.ijhydene.2020.12.111.

[10] Burre J, Bongartz D, Brée L, Roh K, Mitsos A. Power-to-X: between electricity storage, e-production, and demand side management. Chemie Ing Tech 2020;92(1-2):74–84. https://doi.org/10.1002/cite.201900102.

[11] Kiaee M, Cruden A, Infield D, Chladek P. Utilisation of alkaline electrolysers to improve power system frequency stability with a high penetration of wind power. IET Renew Power Gener 2014;8(5):529–36. https://doi.org/10.1049/iet-rpg.2012.0190.

[12] Troncoso E, Newborough M. Electrolysers as a load management mechanism for power systems with wind power and zero-carbon thermal power plant. Appl Energy 2010;87(1):1–15. https://doi.org/10.1016/j.apenergy.2009.04.006.

[13] Priesmann J, Nolting L, Praktiknjo A. Are complex energy system models more accurate? an intra-model comparison of power system optimization models. Appl Energy 2019;255:113783. https://doi.org/10.1016/j.apenergy.2019.113783.

[14] Cao K-K, von Krbek K, Wetzel M, Cebulla F, Schreck S. Classification and evaluation of concepts for improving the performance of applied energy system optimization models. Energies 2019;12(24):4656. https://doi.org/10.3390/en12244656.

[15] Kotzur L *et al.*, A modeler's guide to handle complexity in energy system optimization, Sep. 2020, doi: https://arxiv.org/abs/2009.07216.

[16] Horsch J, Brown T. The role of spatial scale in joint optimisations of generation and transmission for European highly renewable scenarios. In: *2017 14th International Conference on the European Energy Market (EEM)*; 2017. p. 1–7. https://doi.org/10.1109/EEM.2017.7982024.

[17] Müller UP, Schachler B, Scharf M, Bunke W-D, Günther S, Bartels J, et al. Integrated techno-economic power system planning of transmission and distribution grids. Energies 2019;12(11):2091. https://doi.org/10.3390/en12112091.

[18] Bodal EF, Korpas M. Regional effects of hydrogen production in congested transmission grids with wind and hydro power. In: *2017 14th International Conference on the European Energy Market (EEM)*; 2017. p. 1–6. https://doi.org/10.1109/EEM.2017.7982013.

[19] Longoria G, Lynch M, Curtis J. Green hydrogen for heating and its impact on the power system. Int J Hydrogen Energy 2021;46(53):26725–40. https://doi.org/10.1016/j.ijhydene.2021.05.171.

[20] vom Scheidt F, Qu J, Staudt P, Mallapragada DS, Weinhardt C. Integrating Hydrogen in Single-Price Electricity Systems: The Effects of Spatial Economic Signals; 2021.

[21] Niebler S, Wollschläger J. Für die Raffinerie der Zukunft. Nachr Chem 2021;69(3): 24–6. https://doi.org/10.1002/nadc.v69.310.1002/nadc.20214105518.

[22] Varela C, Mostafa M, Zondervan E. Modeling alkaline water electrolysis for power-to-x applications: A scheduling approach. Int J Hydrogen Energy Feb. 2021;46(14): 9303–13. https://doi.org/10.1016/j.ijhydene.2020.12.111.

[23] Agora Energiewende, Agorameter, 2020.

[24] T. Brown, J. Hörsch, and D. Schlachtberger, PyPSA: Python for Power System Analysis, Jul. 2017, doi: 10.5334/jors.188.

[25] "Marktstammdatenregister." [Online]. Available: https://www.marktstammdatenregister.de/MaStR. [Accessed: 05-Feb-2020].

[26] Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 2016;114:1251–65. https://doi.org/10.1016/j.energy.2016.08.060.

[27] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:1224–39. https://doi.org/10.1016/j.energy.2016.08.068.
[28] Gerbaulet C, Lorenz C. dynELMOD: A Dynamic Investment and Dispatch Model for the Future European Electricity Market, *Dtsch. Inst. für Wirtschaftsforsch.*, no. 88, 2017.
[29] Länderarbeitskreis Energiebilanzen. [Online]. Available: https://www.lak-energiebilanzen.de/eingabe-dynamisch/?a=e900. [Accessed: 27-Feb-2020].
[30] Bundesnetzagentur, "Smard-Daten." [Online]. Available: https://www.smard.de/home. [Accessed: 05-Mar-2020].
[31] Gelaro R, McCarty W, Suárez MJ, Todling R, Molod A, Takacs L, et al. The modern-era retrospective analysis for research and applications, Version 2 (MERRA-2). J Clim 2017;30(14):5419–54. https://doi.org/10.1175/JCLI-D-16-0758.1.
[32] NOW GmbH, Studie IndWEDe Industrialisierung der Wasserelektrolyse, 2018.