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Early power to gas applications: Reducing wind farm forecast errors and providing secondary control reserve

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HIGHLIGHTS

- Reducing forecast errors and provision of secondary control reserve is simulated.
- Bidding strategies for secondary control reserve market participation are evaluated.
- Reducing wind farm forecast errors via fuel cell is not profitable.
- Both applications can be economically viable for electrolyzer operation.
- Both applications can be combined.

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ABSTRACT

The combination of wind turbines with fuel cells (FC) and electrolyzers (ELY) is an option for balancing fluctuating grid power injections from renewable energy sources. The conversion of electricity to hydrogen via ELY is often called "power to gas", while transforming hydrogen to electricity via FC is referred to as re-electrification. The application of these technologies currently faces high costs and finding a positive business case is challenging. This study quantifies the economic potential of marketing FC/ELY systems' flexibility. Their potential to reduce wind farm forecast errors as well as the system's ability to provide secondary control reserve (SCR) in Germany is investigated. For this purpose, data for the year 2013 is used. Different root mean squared errors and a probability density function (PDF) for forecast errors are considered. SCR dispatch power in high temporal resolution is approximated and different bidding strategies (SCR market) are taken into account. Results show that both applications can be economically viable, also when being combined. However, profitability is highly dependent on the system's configuration as well as its operating strategy.

1. Introduction

Electrolyzers (ELY) convert electricity to hydrogen, which can be stored and transformed back into electricity via fuel cells (FC) later. These processes are often called "power to gas" and "re-ele ctrification", respectively. Hydrogen originating from renewable energy sources (via electrolysis) can play a major role in decarbonizing the transport sector, since it can be used as a fuel. However, operating electrolysis profitably with renewable energy is challenging. But FC/ELY systems are capable of providing flexibility concerning the electrical generation and load, respectively. This can be valuable to the electricity sector, because fluctuating renewable energy generation has become a major contribution to electric energy systems worldwide. In Germany, 30.0% of gross electric energy generation in 2015 was produced by renewable energy sources [1]. Electric energy from wind turbines (13.3%) contributed the largest share. However, the fluctuating availability of wind energy raises the need for measures to adapt wind turbine output to the needs of customers and the electric grids in terms of consolidating the electric power output. Hydrogen-based storage systems are capable of compensating fluctuations directly at the wind farm as well as at a system level by providing control reserve energy. Compensating wind farm forecast errors and participation in the

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Nomenclature

Acronyms

ARMA	autoregressive moving average
CAPEX	capital expenditures
CMOL	merit order list based on capacity prices
EAC	equivalent annual cost
EEG	German renewable energy law
ELY	electrolyzer
EMOL	merit order list based on energy prices
FC	fuel cell
FE	forecast error
FLH	equivalent full-load hours
LHV	lower heating value
LRF	loan repayment factor
NPV	net present value
OPEX	operational expenditures
PCR	primary control reserve
PDF	probability distribution function
PEM	polymer electrolyte membrane
RMSE	root mean squared error
SCR	secondary control reserve
TCR	tertiary control reserve
TSO	transmission system operator
WFO	wind farm operator

secondary control reserve market (SCR) are possible approaches. To date, the economic potential of these operation modes as well as their technical implications have not been analyzed in detail, and it is unclear to potential power to gas system operators what can be expected, for example, in terms of profits, duration of operation per year or produced and consumed hydrogen mass. In particular, strategies for bidding on the SCR market have not been evaluated in depth. These research questions are addressed in this analysis.

1.1. Wind farms and forecast errors

In Germany, wind farm operators (WFO) are currently compensated for fed-in energy with a fixed tariff, which is defined in the renewable energy law (German: EEG) [2]. Additionally, it is possible for WFOs to participate in the existing energy markets, e.g. the day-ahead spot market. For day-ahead energy bidding, hourly slices of wind farm energy output have to be forecasted.

Wind forecasting is subject to error, leading to deviations of the fed-in energy from wind farm operators' market bids. Depending on the grid situation, energy deviations may result consequently in penalty payments or profits for the WFO. Payments and profits are quantified via an imbalance energy price, which can assume positive and negative values.

Fuel cells (FC) and electrolyzers (ELY) are among the technology options which are able to reduce the forecast error power by supplying electric energy (FC) or transforming surplus energy (ELY) into hydrogen, thereby reducing both negative forecast deviations (FC) and positive deviations (ELY), respectively.

1.2. Secondary control reserve

In Germany, transmission system operators (TSO) are responsible for balancing unforeseen deviations in both generation and consumption of electric energy. For this purpose, positive and negative control reserve is required. In order to provide positive control reserve, energy has to be fed into the grid or consumption has to be reduced while the provision of negative control reserve implies consuming surplus energy or reducing energy injection. Primary, secondary and tertiary control reserve (PCR, SCR and TCR) can be distinguished by activation order, response time and compensation system. Primary control reserve is activated automatically as soon as deviations in the grid frequency occur. If the activation of PCR is not sufficient to balance the frequency deviation, TSOs activate secondary and tertiary control reserve consecutively. Details on guaranteed activation time are shown in Fig. 1.

Table 1 gives an overview of how participation in primary, secondary and tertiary control reserve markets is organized. TSOs acquire control reserve via joint, weekly calls for tenders. Regarding SCR, each bid is defined by an energy price (€/MWh), a capacity price (€/MW) and the dedicated power (MW). Four products can be distinguished and offered separately: positive and negative control reserve during "peak time" (Mo. – Fr. 8 am till 8 pm, except holidays) and "off-peak time", respectively. The assumed demand for dedicated control reserve power is acquired by the TSOs according to a merit order list, which is based on the capacity prices (CMOL). The lowest bidder in capacity price is first on the CMOL, followed by the second lowest bidder and so on. Bids on the CMOL are accepted consecutively until the control reserve power demand

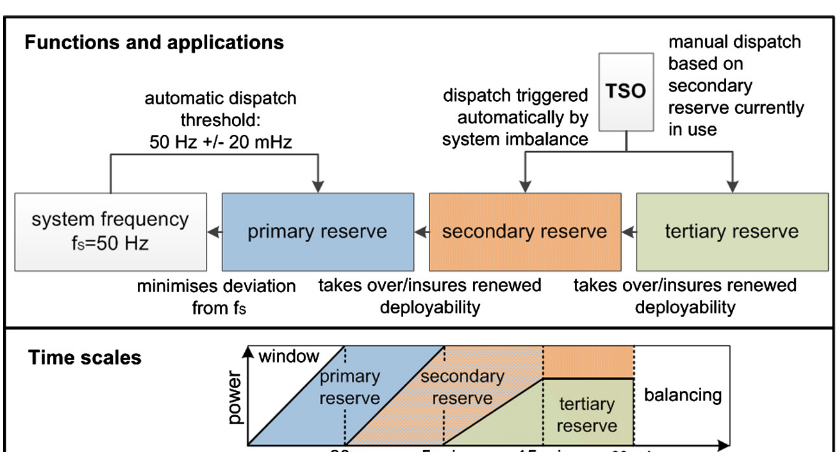

Fig. 1. Functions and time scales of primary, secondary and tertiary (minute) reserve [3–6].

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Table 1
Basic product characteristics of primary, secondary and tertiary control reserve. Based on [4,5,3].

	Primary control reserve	Secondary control reserve	Tertiary control reserve
Call for bids	Weekly Tuesday (previous week)	Weekly Wednesday (previous week)	Daily Mo-Fr
Products	One (whole week)	Peak-Time (Mo-Fr, 8 am–8 pm, no holidays) Off-Peak-Time	6 × 4-h-Slices
Product differentiation	None (symmetrical)	Positive and negative	Positive and negative
Number of products	1	4	12
Minimum bid	1 MW	5 MW	5 MW
Compensation	Pay-as-bid (capacity price)	Pay-as-bid (capacity and energy prices)	Pay-as-bid (capacity and energy prices)
Activation time	<30 s	<5 min	<15 min
Provision duration	Max. 15 min	Max. 52 h	Max. 4 h
Activation mechanism	Automatically, decentralized	Automatically, centralized control at TSO via control-signal	Automatically via interface

is met. All successful bidders are compensated according to their bid capacity price for dedicating the bid power. The TSOs then formulate a second merit order list based on the energy price of the successful bidders (EMOL). Whenever a demand for actual control reserve power arises, the lowest bidder (first on the EMOL) is called. For positive SCR, this means that the TSO requests this bidder to feed energy into the grid or reduce consumption, while for negative SCR this means that the bidder has to increase consumption or decrease energy provision. As soon as his contribution is no longer sufficient, the next bidder on the EMOL is called additionally and so on. The bidders are then compensated for the actual provided energy via their individual energy price. Therefore the reserve markets are pay-as-bid auctions (in contrast to uniform pricing, which implies one fixed price for all bidders). According to Swider (2007) [7], this leads to strategic bidding, which aims at exploiting market imperfections. FC and ELY operators can provide positive and negative SCR, respectively.

1.3. Literature review and goal of this analysis

A comprehensive review of power to gas technology and its components can be found in Schiebahn et al. (2015) [8]. Information on polymer electrolyte membrane (PEM) electrolysis is given in Carmo et al. (2013) [9], while a comparison of PEM and alkaline electrolysis is conducted in Mergel et al. (2013) [10]. Regarding PEM fuel cells, Wang et al. (2011) [11] give comprehensive insights into technology and applications.

Bolívar Jaramillo et al. (2016) [12] analyze a microgrid comprising a FC, an ELY and a photovoltaic generator. Its operation strategy is optimized, aiming to reduce purchased energy from the grid and operating costs by utilizing the system's flexibility. However, forecast errors and their costs are not considered. García Clúa et al. (2011) [13] consider a grid-assisted wind-hydrogen system and evaluate different operation modes. Forecast errors are disregarded and the focus of research is on power electronics. Prediction and statistical analysis of wind farm power has been extensively investigated in literature [14–16]. Segura et al. (2007) [17] analyze the minimum requirements on energy efficiency of a storage system based on the use of hydrogen to become economically competitive investigating different scenarios of wind farm and storage combination. As a conclusion, the necessity for an improvement of the efficiency of the subsystems that compose the hydrogen buffer is emphasized. However, the study does not focus on the participation in balancing energy markets for hybrid power plants and to investigate forecast error deviation compensation by FC/ELY. In Matevosyan et al. (2006) [18], the participation of wind power plants in short-term power markets is investigated. Bidding of wind farm energy is modified regarding minimal imbalance costs for expected forecast errors. A quantification of resulting forecast errors as in this analysis is not conducted. Furthermore, a combination of FC/ELY is not further considered.

In Korpås et al. (2006) [19], the authors describe a model of combined wind farm and FC/ELY operation within a day-ahead power market applying a receding horizon strategy. The authors conclude that an isolated hydrogen-based system with a backup generator could be an economically viable application. Deviations due to forecast errors are considered economically as being settled in a balancing energy market, different to a time-dependent deviation energy price as considered in this paper. Guandalini et al. (2015) [20] evaluate the combination of gas turbines with ELY for compensating wind farm forecast errors. The subject wind farm as well as forecast errors are scaled to nation-level and therefore results do not apply to the situation analyzed in this paper.

Participation in balancing service markets was analyzed for the French system in Guinot et al. (2015) [21]. PCR and a balancing mechanism, comparable to a combination of SCR and TCR, have been investigated under simultaneous day-ahead market participation. Prices and dedicated powers have been optimized in order to minimize hydrogen production costs. Results show that PCR market participation is not viable for FC/ELY operators under current conditions in France. Since balancing markets are organized differently in Germany, the results of Guinot et al. (2015) [21] are not transferable. Adding a hydrogen-based storage system to a wind farm in Germany was investigated in Kroniger et al. (2014) [22]. The system is assumed to participate in TCR and EPEX spot market. FC operation is determined to not be economic. SCR is not considered and probability distributions are used instead of actual time series. The latter is identified as a weakness that should be improved upon in future research. Other possibilities of using FC/ELY systems to complement fluctuating renewables have been considered in Paulus et al. (2011) [23] and Jorgensen et al. (2008) [24]. Paulus et al. (2011) [23] estimate the potential of ELY operation in industrial context for provision of demand side management services. The authors found a rather low potential, due to the necessity of high dedication of ELY capacity to industrial processes. Jorgensen et al. (2008) [24] investigated possible hydrogen production prices based on electrolysis and spot market participation in scenarios of high wind energy market penetration in Denmark. They conclude that ELY's flexibility can only be utilized economically if installation costs are low or energy price fluctuations are high.

This literature review shows that wind farm forecast error has been thoroughly researched in the past. A study of a direct-connected hybrid power plant containing a wind farm and FC/ELY components for reducing forecast error has not been sufficiently described yet and is the focus of this contribution. Furthermore, participation of FC/ELY systems in SCR market has not been analyzed in detail. Previous research especially lacks in quantifying the effect of different bidding strategies on FC/ELY operation, which the analysis at hand aims to evaluate.

This paper is organized as follows: In Section 2, the methodology for modeling of technical components, forecast error reduction and SCR market participation is described. In Section 3, simulation results for three operation strategies (reduction of forecast errors, SCR market participation and the combination of both) are presented and discussed. Section 4 gives conclusions, separately for the three operation strategies. Summary and recommendations on future research in the discussed field can be found in Section 5.

2. Methodology

2.1. Wind farm model, electrolyzer model and fuel cell model

For this application study, a 100 MW wind farm in the Brandenburg region, Germany, is modeled (ca. 52.5°N, 14°E). Both FC and ELY are considered to be operated by the WFO, assuming a single operator and a single balancing group for all components. Simulation is conducted with quarter-hourly time steps for one year (2013). The wind farm consists of 50 wind turbines of 2 MW rated power each (assumed wind turbine type: REpower MM82). Wind turbine power losses and wind farm power losses (e.g. through wind shadowing) of 5% respectively, are taken into account. Power output of a single wind turbine is modeled via a power curve (electric power output over wind speed). Wind speed values [25] have been adjusted to turbine hub height via application of wind shear law:

$$v(z) = v_r \frac{\ln(z/z_0)}{\ln(z_r/z_0)}$$

where:
z = hub height
z_r = hub height of measured wind speed
z_0 = roughness length
$v(z)$ = wind speed at hub height z
v_r = measured wind speed.

Assumed roughness length z_0 equals 0.1 m. Data of balance energy costs of 2013 for Germany is used. Source data is provided by German TSOs [26].

Concerning FC and ELY, simplified models are used. Alkaline ELY technology is assumed, because of its maturity and moderate costs compared to PEM technology [10]. Regarding FC, PEM technology is chosen, since it is a common technology for stationary fuel cells [11]. It is assumed that these components behave ideally with respect to short-term dynamic effects, which therefore are considered to be negligible. Thermal behavior is neglected as well. Intermittent operation is not penalized during simulation and degradation is not considered, although this can lead to reduced lifetime. This assumption was made in order to investigate operation isolated from other effects like degradation. Efficiencies are chosen to be 50% (FC) for hydrogen to electricity conversion and 65% (ELY) for electricity to hydrogen conversion based on the lower heating value of hydrogen. The efficiencies are assumed to be constant and independent of the components' load. FC and ELY are assumed to not be connected directly, so there are no storage units, storage costs or storage capacity limitations. Nevertheless, the mass balance of hydrogen production and consumption is considered on a yearly basis in each analyzed scenario. Compressors as well as further hydrogen handling components are disregarded. Table 2 gives an overview of assumptions regarding FC's and ELY's economics.

Table 2
Model parameters of fuel cell and electrolyzer.

	Fuel cell (FC)	Electrolyzer (ELY)
Technology	PEM	Alkaline
Efficiency (LHV)	50%	65%
Specific capital expenditures (CAPEX)	1,000,000 €/MW	
Specific operational expenditures (OPEX)	4% * CAPEX/a	
Life time	20 a	
Interest rate	5%/a	

In order to compare different scenarios and to calculate specific costs of hydrogen production or usage, the method of Equivalent Annual Cost (EAC) is used. The net present value (NPV) is multiplied by the loan repayment factor (LRF) to obtain the EAC

$$EAC = NPV * LRF$$
$$LRF = \frac{r * (1+r)^t}{(1+r)^t - 1}$$

with r being the interest rate and t the system's lifespan. Annual earnings due to forecast error reduction or SCR market participation are taken into account via NPV. Hydrogen production costs are calculated by dividing the ELY's EAC by the produced hydrogen mass. Hydrogen usage costs are calculated by dividing the FC's EAC by the consumed hydrogen mass. Keep in mind that calculated hydrogen costs include neither taxes and apportionment, nor costs for further components like compressors or storage units. Calculated costs and profits are therefore optimistic estimates, useful primarily for comparison of different scenarios.

2.2. Balancing forecast error

The wind farm operator is assumed to participate in day-ahead market based on forecasts. Positive and negative forecast errors can be mitigated by ELY and FC, respectively (Fig. 2).

In order to examine the forecast errors of the wind farm, an appropriate modeling approach has to be determined. Forecast errors of a single wind turbine can show a high stochastic uncertainty, whereas forecast errors of several wind farms on state or national level are "smoothed" and more predictable via appropriate probability density functions (PDF) according to the law of large numbers [27].

For the investigation of forecast errors, a Gaussian probability distribution is frequently assumed. However, in the paper at hand, the forecast error distribution has a main influence on technical and economic results. Therefore, an appropriate approach for modeling the forecast errors has to be applied. The prediction of output power of wind turbines is thoroughly researched [28–31]. Regarding forecast errors, the literature is sparse. In [32], market integration of wind power in Spain was examined. For wind power forecast errors, the authors use published data of the Spanish transmission system operator. In [33], a similar approach for investigating the influence of wind forecast errors on gas infrastructure in Ireland is applied. However, as explained above, this approach neglects possible stochastic uncertainties of a single wind farm, which we investigate in this paper. In [18], bidding strategies of a WFO are researched, taking forecast errors into account. For generating the forecast error time series, the authors apply an autoregressive moving average (ARMA) model. However, the algorithm is trained to fit given forecast errors from a certain site. In our work, no forecast error timeseries is given beforehand, as a fictive wind farm is under investigation. In [16], wind power forecast errors are statistically analyzed, taking measured time series from two different wind farms into account. The authors conclude that wind power forecast errors are not Gaussian distributed and propose a new approximation function based on Beta probability distribution function (PDF). In [34], a penalty analysis for wind farm forecast errors is conducted. The authors investigate a persistence approach and formulate a novel, mixed normal distribution-based function for the distribution of forecast errors.

For modeling forecast errors, a mixed weighted normal Laplace probability distribution function (PDF) based on Wu et al. [35] is used. In [35], forecast errors of an existing wind farm were examined and a mixed weighted normal Laplace PDF resulted in the best fit out of the examined PDFs. Compared to forecast errors for the

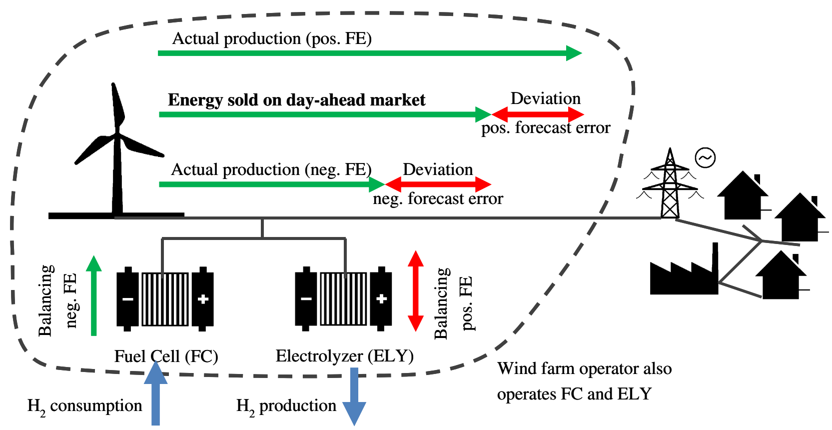

Fig. 2. Depiction of the modeled system. The wind farm operator also operates fuel cell (FC) and electrolyzer (ELY) in order to compensate positive and negative forecast errors (FE), respectively.

German 50Hertz control area, the forecast error distribution of hourly data (2013) of the output power of all wind turbines within the control area is similar, whereas a different root-mean-squared error (RMSE) applies (Fig. 3). Despite the different regional resolution and due to the similarity of the compared forecast error distributions, we use the approach of [35] here.

Three cases for different RMSEs of 5%, 10% and 15% are modeled. To reduce improbable deviations, forecast errors exceeding the limit of three times the RMSE are redistributed into the function area (e.g. see Fig. 3). Resulting forecast error percentages are converted into the quantity of desired time steps, i.e. 35,040 for a year in quarter-hourly resolution, and distributed on the simulated wind farm power. The distribution of forecast errors is conducted randomly with the constraint that the wind farm power with forecast error must not exceed the nominal power of the wind farm. The forecast error power of the wind farm can induce a utilization of an ELY (in case of positive forecast errors) or a FC (in case of negative forecast errors). The electric energy intake leads to hydrogen production (ELY) and hydrogen consumption (FC) of the components, respectively.

For FC and ELY application, scenarios with different rated electric power capacities of ELY (0.5 to 1.5 MW) and FC (0.1 to 0.75 MW) are considered. Resulting forecast error energy, remaining forecast error energy (which cannot be met by ELY and FC), hydrogen production/consumption and cash flows are calculated. Profits or payments for reducing forecast errors are applied on resulting hydrogen consumption or production, leading to hydrogen production/consumption profits/costs.

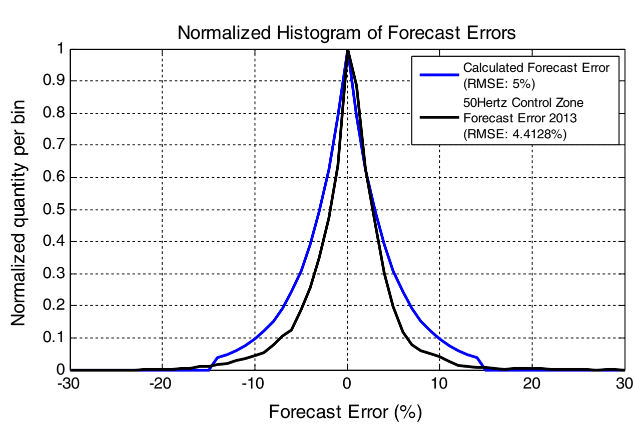

Fig. 3. Comparison of forecast error distributions.

2.3. Provision of secondary control reserve

The FC/ELY operator is considered separate from the WFO and TSO in this application. In this analysis, it provides positive (via FC) and negative (via ELY) secondary control reserve to the TSO (Fig. 4). The respective preceding, weekly auction process is taken into account and calls for actual provision of secondary control energy are approximated. Since FC and ELY are controlled by the TSO and their capacity is dedicated to providing SCR, a direct combination with a wind farm is not possible. Nevertheless, when virtually splitting the FC's and ELY's capacity and dedicating only one part to providing SCR, the other part could be used for different purposes. In this analysis, the devices' capacities are fully dedicated to one operation mode at a time.

2.3.1. Input data and data preparation

Historical data for one year (2013) is used for bids, their dedicated power and their capacity and energy prices. These data are publicly available [36]. CMOL and EMOL are derived from the bid data. For each week of the considered year, four bids concerning the capacity price are taken into account for further investigation (referred to as "basic scenarios" in the following):

- Lowest price ("min"): The FC/ELY operator is the lowest bidder. Its bid capacity price is identical to the lowest bid in each week.
- Highest price ("max"): The FC/ELY operator is the highest bidder among the successful bids.
- Median price ("median"): The FC/ELY operator's bid is as high as the median of all successful bids.
- Average price ("average"): The FC/ELY operator's bid is as high as the weighted average of all successful bids.

This methodology implies the operator's bids are successful in every week. It serves to quantify the theoretical potential of SCR market participation. Such a bidding strategy is not possible in reality, though, since all bids would have to be known in advance. In order to investigate realistic bidding strategies as well, scenarios are defined where all bids are based on the previous week's CMOL ("advanced scenarios"). By applying these strategies, especially the "max" strategy, it is not guaranteed that the FC/ELY operator's bids are successful. For all mentioned strategies the CMOL is updated considering the additional bid of the FC/ELY operator.

With respect to the energy price, three strategies are implemented:

- Lowest price ("min"): The FC/ELY operator is the lowest bidder. His bid energy price is identical to the lowest bid in each week.

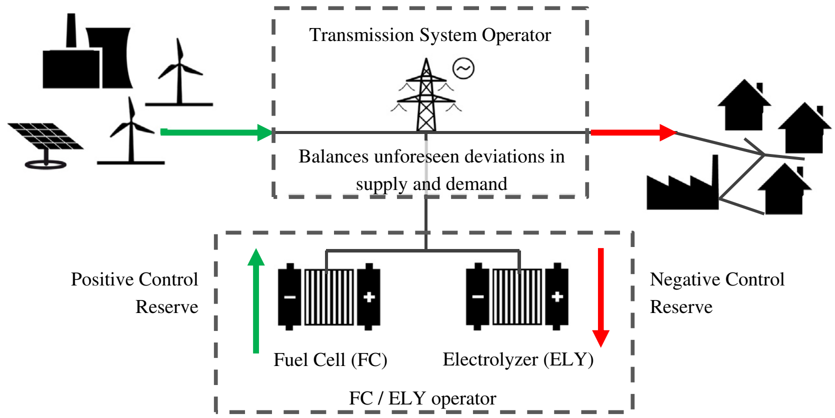

Fig. 4. Depiction of the modeled system. The fuel cell (FC) and electrolyzer (ELY) operator provides positive (via FC) and negative (via ELY) secondary control reserve to the transmission system operator.

– Median price ("median"): The FC/ELY operator's bid is as high as the median of all successful bids.
– Average price ("average"): The FC/ELY operator's bid is as high as the weighted average of all successful bids.

A "max" strategy is not included, because this strategy necessarily leads to very few calls - if any. Derived earning projections from energy price would not be reliable but misleading. In analogy to the above-mentioned strategy regarding capacity prices, bidding strategies based on the previous week are taken into account as well. As for the CMOL, the EMOL is updated for all strategies by considering the additional bid. Furthermore, it is determined for all strategies at which amount of SCR power the TSO will call the FC/ELY operator (threshold power), which depends on the position of the bid on the EMOL and the dedicated power of all lower bids.

Data on the requested secondary balancing energy in high temporal resolution is not publicly available. In order to obtain an approximation, available data on the actual secondary balancing energy in 15 min resolution (*SBE900*) is used separately for positive and negative SCR [37]. Furthermore, the theoretical secondary balancing power demand is available in 4 s resolution (*SBP4*) [38]. The TSOs convert the *SBP4* signal into actual SCR calls. In order to compare the *SBP4* signal to the *SBE900* signal, *SBP4* is averaged over 225 values, corresponding to 15 min (*SBP900_av*). Fig. 5a) compares |*SBE900*| to *SBP900_av*. Ideally, all values in the left diagram should be on a line through origin with a slope of 1 or on a line through origin with a slope of -1. The right diagram shows that for |*SBE900*| $\leqslant$ 50 MW, a high deviation of more than 100% on average can be observed. In order to improve the approximation, a moving average function is applied on *SBP4*. Window size is optimized using a multi-objective evolutionary algorithm [39] with absolute and relative squared errors of SCR energy as optimization targets to be minimized. Values where |*SBE900*| $\leqslant$ 50 MW are not taken into account during optimization. Based on this optimization, 69 is chosen as moving average window size, corresponding to 276 s. Afterwards, positive values are limited to 2500 MW and negative values are limited to -2500 MW. These values were chosen because they are realistic with respect to the maximum amount of positive and negative SCR power acquired by the TSOs (2473 MW and -2418 MW respectively). The result of this limiting and applying a moving average function is depicted in Fig. 5b). It is apparent that the deviation is significantly reduced.

SBP4 is then further adjusted to match *SBE900*. Three cases are considered for each value in *SBE900*, separately for positive and negative values of *SBE900* and *SBP900_av*:

Case 1: $SBE900 = 0 \wedge SBP900\_av \neq 0$
All values in *SBP4* within the respective 15 min interval are set to 0.
Case 2: $SBE900 \neq 0 \wedge SBP900\_av = 0$
SBP4 cannot be adjusted. The deviation remains.
Case 3: $SBE900 \neq 0 \wedge SBP900\_av \neq 0$
All values in *SBP4* within the respective 15 min interval are multiplied by a factor (*sf*) to fulfill $SBE900 = SBP900\_av * sf$. For values in *SBE900* where the necessary scaling factor *sf* is greater than 10, the approximation via *SBP4* is considered insufficient and *sf* is limited to 10 in order to avoid extreme scaling. The resulting difference between *SBP900_av* and *SBE900* remains.

The result of applying these three cases on the *SBP4* signal can be seen in Fig. 5c). The remaining deviation occurs mainly for values in |*SBE900*| < 50 MW. This clearly leads to an underestimation of the actual called SCR power. This means that the estimation of earnings from energy price, which are to be derived in the following, will be slightly pessimistic.

2.3.2. Assumptions

It is assumed that the participation of the FC/ELY operator in the control reserve market influences neither the market nor the auction results. The operator's bid is considered to be successful if its capacity price does not exceed the highest successful bid. Furthermore, the minimum lot size of 5 MW is neglected. The bids of all other bidders are assumed to be known a priori except for "advanced" scenarios. The bids of the last week in 2012 are assumed to be the same as those of the first week in 2013. The operator is assumed to dedicate the FC's and ELY's rated powers fully to positive and negative SCR, respectively. All four products are offered in every week. In cases of non-successful bids, it is assumed that the respective component is not used for other purposes and remains shut-off for the corresponding period of time. Taxes as well as EEG apportionment are not taken into account.

2.3.3. Simulation

Simulation is performed for different rated power capacities of ELY (0.3 MW to 0.5 MW) and FC (0.15 MW to 0.25 MW) with time step width of 4 s. In each time step, it is determined whether the FC/ELY operator's bid was successful in the respective week and product and whether and to what extent the FC/ELY operator is called for provision of SCR. This depends on whether the actual amount of power of the TSO's call exceeds the threshold power of the FC/ELY operator's bid. In addition, a dead-band of +/−50 MW is introduced, since the approximation of the TSOs' calls is insufficient for low call power requests. This means that no call is

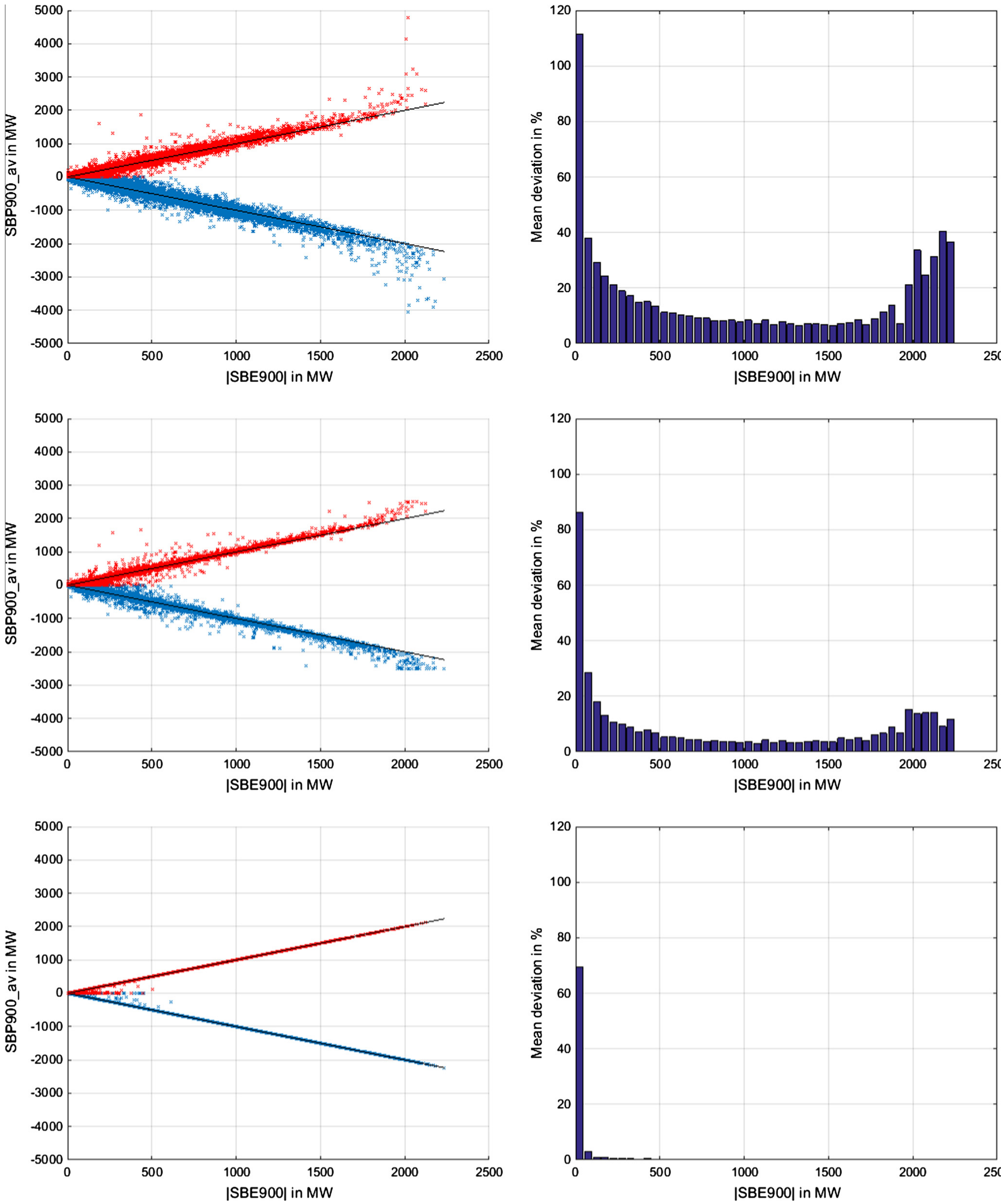

Fig. 5. Positive (red) and negative (blue) secondary control reserve call power of 15 min data (SBE900) and approximated 4 s data (averaged over 15 min, SBP900_av). Top (a): original data. Middle (b): after limiting and applying moving average. Bottom (c): after (b) and additional scaling. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

assumed if the TSO's called power is between −50 MW and 50 MW regardless of the determined threshold power. This leads to an underestimation of the actual provided SCR energy by the FC/ELY operator and therefore of the earnings from energy price. Based on the simulation results, equivalent full-load hours, produced or consumed hydrogen, as well as annuities and hydrogen costs are determined. Equivalent full-load hours are referred to as full-load hours (FLH) in the following.

2.4. Combination of operation strategies

The combination of an ELY providing SCR and a FC reducing forecast errors is analyzed as well. Both operation strategies are simulated separately for different rated powers. It is assumed that FC and ELY are fully dedicated to one of the operation strategies, respectively. The necessary storage is disregarded. Hydrogen is considered to be available for the FC at all times. Suitable configurations regarding hydrogen balance are identified and evaluated afterwards.

3. Results

3.1. Balancing forecast errors

In the given PDF, there is a high peak of forecast errors near the expectation value (Fig. 6 shows this exemplarily for RMSE = 10%), leading to low forecast errors for most time steps. This results in high reductions of forecast error energy even at low installed-power capacities of FC and ELY. For example, given a forecast RMSE of 10%, results indicate that using a 0.7 MW ELY and a 0.2 MW FC (which amounts to 0.7% and 0.2% of the wind farm's rated power, respectively), a total reduction of the forecast error energy by 17.8% can be achieved.

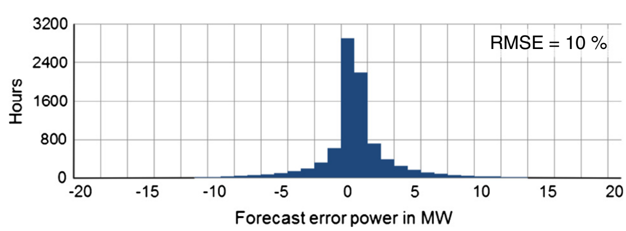

Fig. 6. Histogram of forecast error power (root mean squared error = 10%) of the regarded wind farm.

Fig. 7 emphasizes this observation. The black bars represent sorted forecast error powers, positive on the left, negative on the right. The ordinate has been limited to +/−12 MW for better readability. The red line on the left shows which amount of positive forecast error power can be reduced by the ELY, while the red line on the right depicts the amount of negative forecast error power which can be reduced by the FC. For 1800 h per year the positive forecast error can be completely compensated, while for 800 h the negative forecast error can be fully compensated. A comparison of different rated powers for RMSE = 10% with respect to FLH is depicted in Fig. 8. As expected, utilization shrinks with rising rated powers. Furthermore, FLH of ELY and FC are higher if RMSE rises.

With the 2013 imbalance energy price data provided, specific hydrogen costs are compared for ELY and FC in the case of 10% RMSE. Fig. 9 shows hydrogen mass produced in t/a on the abscissa. Negative values refer to hydrogen consumption by FC. The ordinate depicts costs in €/kg. Negative values represent earnings per kg of hydrogen consumed. Despite only minor differences in FLH, earnings from balancing negative forecast errors via FC differ significantly for different rated power capacities. Rated power of 100 kW induces relatively high earnings of 2.5 €/kg. Regarding ELY operation, earnings from forecast error compensation do not exceed costs, leading to costs per kg hydrogen produced. Production costs vary between 2 and 3 €/kg. For balance of produced and consumed hydrogen mass, a 0.7 MW ELY can be complemented with a 0.2 MW FC.

3.2. Provision of secondary control reserve

FLH are nearly independent of the respective component's rated power capacity. Only if the called power exceeds the threshold derived from the EMOL but does not fully exploit the dedicated power capacity do differences among various rated power capacities occur. Therefore, results depending on FLH are not discussed for different rated power capacities. The results show that FLH are highly dependent on the bidding strategy regarding energy

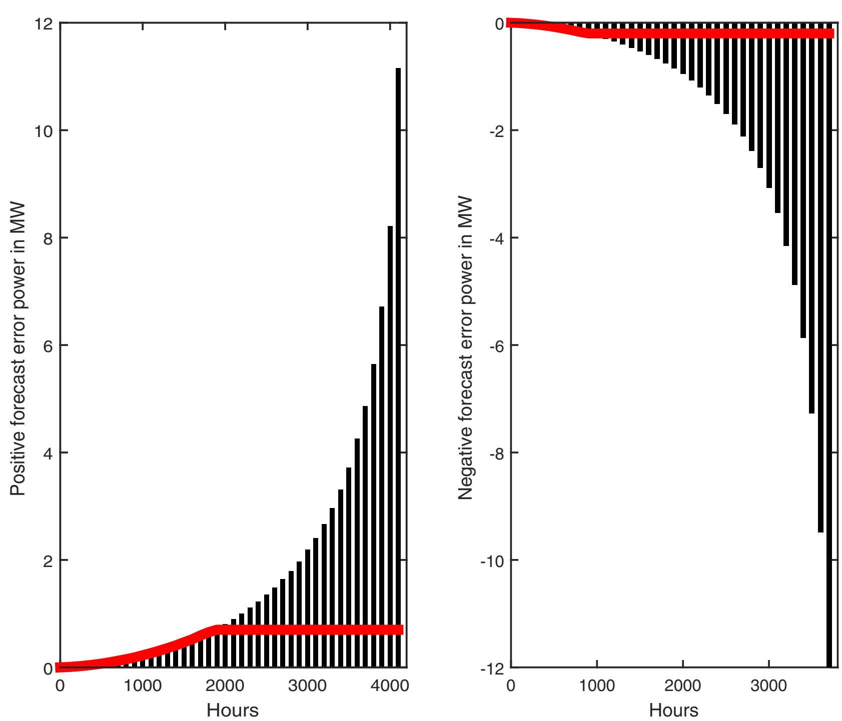

Fig. 7. Sorted forecast error powers (black bars) and sorted powers of electrolyzer (left, red line) and fuel cell (right, red line) for root mean squared error = 10%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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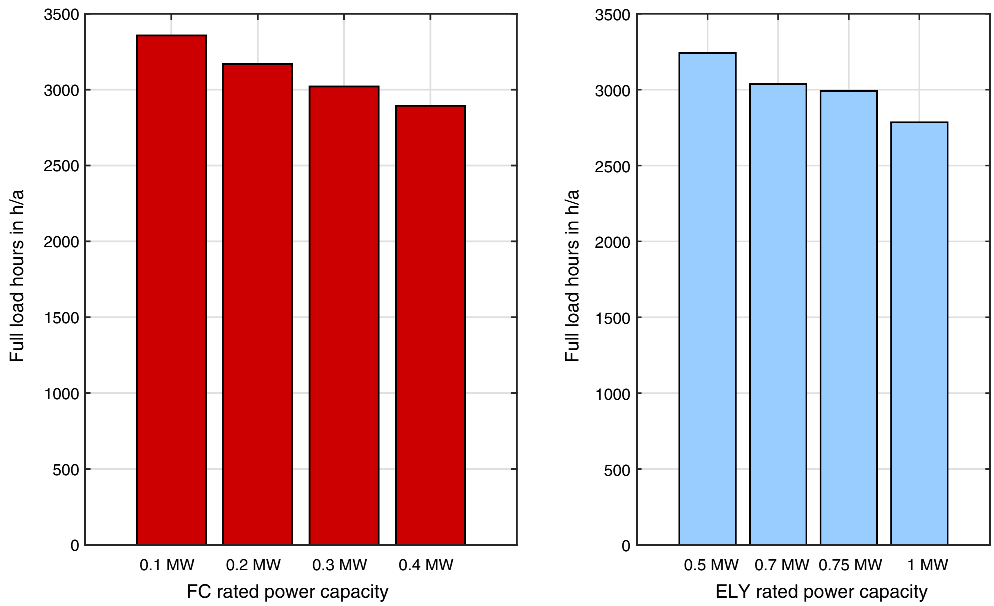

Fig. 8. Comparison of different rated powers of fuel cell (FC) and electrolyzer (ELY) for root mean squared error = 10% in regard of full-load hours.

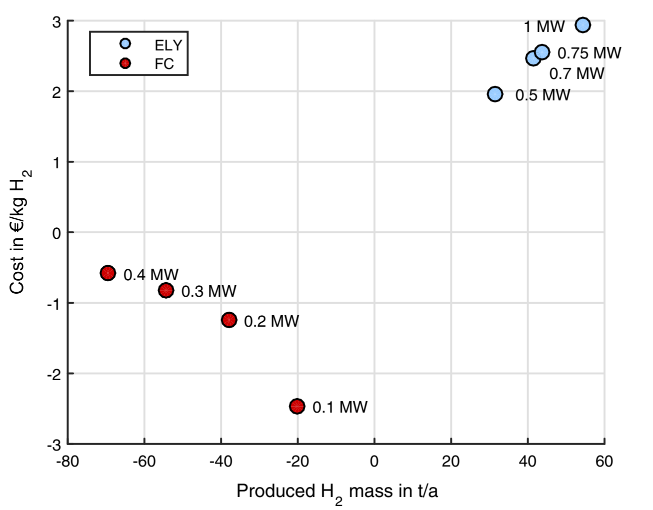

Fig. 9. Produced hydrogen mass (abscissa, negative values indicate consumption) and specific costs (ordinate, negative values indicate earnings) of different rated power capacities for fuel cell (FC) and electrolyzer (ELY).

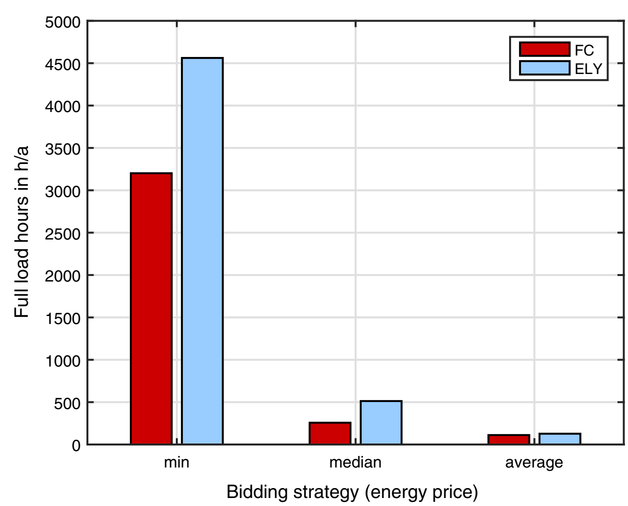

Fig. 10. Comparison of different energy price bidding strategies in terms of full-load hours of fuel cell (FC) and electrolyzer (ELY).

prices (Fig. 10). Average energy prices induce very low FLH (<150 h/a), median prices can cause up to 250 h/a (FC) and 500 h/a (ELY), while low prices can allow for more than 3.200 h/a (FC) and 4.500 h/a (ELY), respectively.

Earnings from energy price, however, depend on the dedicated rated power. Fig. 11 shows the effect of different bidding strategies. The ordinate depicts earnings per rated power and year in order to make scenarios of different rated powers comparable. It is remarkable that bidding low prices leads to relatively high earnings of 200,000 €/(MW∗a) for FC, but to negative earnings of −75,000 €/(MW∗a) for ELY. The market for negative SCR accepts negative energy prices since the provision of negative SCR means that the provider either reduces its production of electricity or increases its demand for electricity. Marginal costs for negative SCR market participation of ELY operation can be negative when taking the value of the produced hydrogen into account. For FC, higher energy prices (average and median) cannot compensate low full-load hours in terms of earnings. ELY operation on the other hand benefits (in terms of earnings from energy price) from higher prices and achieves positive earnings with bidding strategies "median" and "average". However, earnings from energy price are not a sufficient criterion for evaluating bidding strategies, because the value of consumed (FC) or produced (ELY) hydrogen is not taken into account.

Bidding strategies for capacity price influence the operation as well, by accounting for whether the bidder is accepted or not. The previously defined "basic scenarios" imply that all bids are always accepted. So bidding strategies in the "basic scenarios" for capacity price only differ in earnings from capacity price and have no influence on operation. Earnings from positive SCR market participation vary between 50,000 €/(MW∗a) and 80,000 €/(MW∗a) for FC and between 75,000 €/(MW∗a) and 200,000 €/(MW∗a) for ELY (Fig. 12). The respective upper value represents the theoretical maximum that can be obtained when always bidding perfectly.

A good understanding of the bidding strategies' importance can be gained by evaluating hydrogen production cost in €/kg and the specific earnings from consuming hydrogen via FC operation in

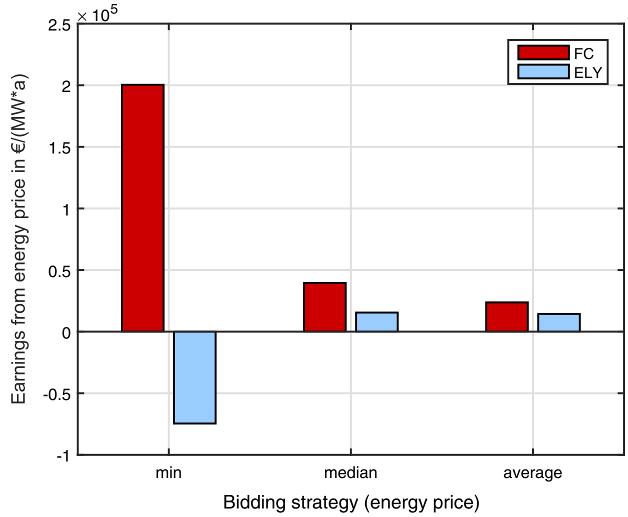

Fig. 11. Comparison of different energy price bidding strategies in terms of earnings due to fuel cell (FC) and electrolyzer (ELY) operation.

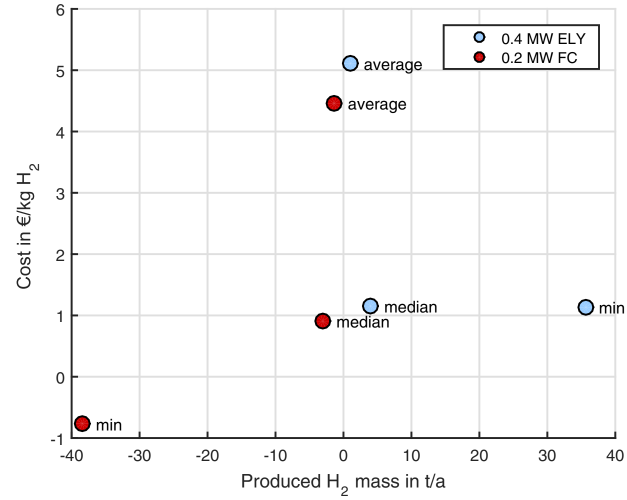

Fig. 13. Produced hydrogen mass (abscissa, negative values indicate consumption) and specific costs (ordinate, negative values indicate earnings) for different energy price bidding strategies for fuel cell (FC) and electrolyzer (ELY).

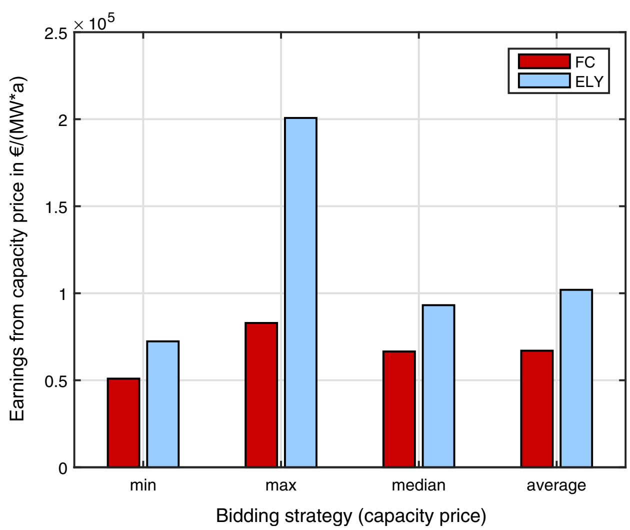

Fig. 12. Comparison of different capacity price bidding strategies in terms of earnings for fuel cell (FC) and electrolyzer (ELY).

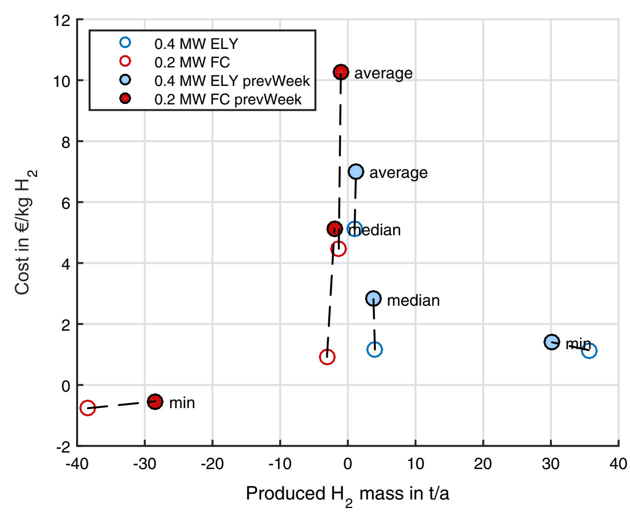

Fig. 14. Produced hydrogen mass (abscissa, negative values indicate consumption) and specific costs (ordinate, negative values indicate earnings) for different energy price bidding strategies for fuel cell (FC) and electrolyzer (ELY). Filled circles represent strategies whose bids are based on the previous week.

€/kg. Results are discussed on the basis of 0.2 MW and 0.4 MW rated power capacities of FC and ELY, respectively. "Median" is chosen as bidding strategy for capacity price and only the bidding strategy for energy price is varied. Fig. 13 shows produced hydrogen mass in t/a on the abscissa. Negative values refer to hydrogen consumption by FC. The ordinate depicts costs in €/kg. Negative values represent earnings per kg of hydrogen consumed. For the FC, only bidding strategy "min" (energy price) leads to earnings (below 1 €/kg). All other strategies lead to costs and are thus not viable. For ELY operation, bidding strategies "median" and "min" induce nearly identical costs of 1.1 €/kg, but strategy "min" is capable of producing more than 35 t hydrogen per year – nearly ten times the amount of strategy "median". Strategy "average" leads to relatively high hydrogen production costs of more than 5 €/kg. The discussed case provides an acceptable balance of hydrogen production and consumption for the "min" strategy. Hydrogen consumption exceeds production by ca. 8%.

When applying realistic strategies ("advanced scenarios"), where bids are based on the previous week's auction, not all bids are necessarily successful. During times of unsuccessful bids, FC and ELY are not utilized, subsequently FLH are lower and earnings from capacity as well as energy price are absent. Furthermore, the respective changes in energy price bids can lead to a different position on the EMOL which also affects FLH and earnings. While the position of "min" bids cannot further improve, "median" and "average" bids can shift the position on the EMOL both ways. Fig. 14 illustrates the effect on hydrogen cost. Filled circles represent "advanced scenarios", while ring-shapes refer to "basic scenarios". All results deteriorate with respect to cost as well as hydrogen mass produced (ELY) or consumed (FC) – except for the "average" strategy for ELY, where realistic strategies induce a minor increase of hydrogen production. Remarkably, "min" strategies show only a slight cost increase and earning reduction, respectively. Hydrogen balance is also affected, as production exceeds consumption by ca. 6% for the "min" strategy.

3.3. Combination of operation strategies

If both applications are combined, it is reasonable to use the FC to reduce forecast errors and the ELY to produce hydrogen using electric energy from the SCR market. The FC's rated power should amount to 0.2 MW to complement a 0.4 MW ELY in hydrogen production and consumption. Furthermore, low production cost of 1.1 €/kg (SCR) and relatively high earnings from hydrogen usage of 1.25 €/kg (forecast error reduction regarding 10% RMSE) are achieved with this setup.

4. Conclusions

This analysis, based on data for the year 2013, indicates that FC/ELY systems are able to reduce forecast errors of wind farms by a significant amount. Low installed capacities of 0.2 MW FC and 0.7 MW ELY can reduce the forecast error energy of a 100 MW wind farm by more than 17% assuming a forecast RMSE of 10%. FC operation requires hydrogen prices of less than 1.25 €/kg (0.2 MW FC) to be profitable, though. ELY operation costs between 2 €/kg and 3 €/kg. Therefore, the combination of FC and ELY to reduce wind farm forecast errors is not economically sensible. Using ELY for hydrogen production in order to supply fueling stations can be a viable option when comparing production costs to the (fixed) price at refueling stations of 9.5 €/kg [40].

This kind of system also is capable of participating in the SCR market (when being pooled in order to match the minimum required capacity). Accepting low energy prices is necessary to obtain high FLH and low hydrogen production costs of 1.1 €/kg. Earnings of FC are below 1 €/kg, which is significantly below market prices for hydrogen (∼6 €/kg [22]). Participating in SCR market with a FC is therefore not economically beneficial. On the other hand, ELY operation can be profitable, especially when delivering hydrogen to refueling stations where it is sold at 9.5 €/kg [40].

Combining these operating modes by reducing forecast errors with a FC and providing negative SCR with an ELY can be advantageous. The installed capacity of the ELY should be twice the FC's installed capacity in order to balance hydrogen production and consumption.

These calculated costs and profits are optimistic estimates, however. More detailed investigation is required for applications identified as promising within this analysis. This applies to using ELY for reducing wind farm forecast errors as well as for SCR market participation and combining FC (forecast error reduction) with ELY (SCR market participation). These might have the potential to be viable early applications of power to gas technology.

5. Summary and outlook

In order to evaluate the capabilities and economic viability of fuel cell (FC)/electrolyzer (ELY) systems to reduce wind farm forecast errors, forecast error data was generated by applying a mixed weighted normal Laplace probability distribution function (PDF) to an actual wind farm production profile of the year 2013. The corresponding wind farm has a rated power of 100 MW. Different rated power capacities of FC (0.1–0.4 MW) and ELY (0.5–1 MW) and forecast root mean squared errors (RMSE) have been simulated. Results show that relatively low installed capacities of 0.2 MW (FC) and 0.7 MW (ELY) are capable of reducing forecast errors by more than 17% (at 10% RMSE). FC operation is not profitable, though. The ELY can produce hydrogen at costs of between 2 €/kg and 3 €/kg (depending on the installed capacity).

Secondary control reserve (SCR) call data was approximated based on the actual secondary balancing energy in 15 min resolution and data of the theoretical secondary balancing power demand in 4 s resolution. The approximation was achieved by applying limits as well as a moving average with optimized window-size, followed by scaling. The approximated call data was combined with SCR market data for the year 2013. A simulation was conducted for different rated power capacities of ELY (0.3 MW to 0.5 MW) and FC (0.15 MW to 0.25 MW). Several bidding strategies for capacity and energy prices were analyzed. Realistic bidding strategies, using auction data of the respective previous week, were also taken into account. The results indicate that low energy prices are essential for sensible FC and ELY operation. FC market participation requires hydrogen cost below 1 €/kg, however, and cannot be considered viable. However, ELY operation can obtain high FLH (>4500 h/a) and low hydrogen production costs of 1.1 €/kg. While these values represent the theoretical potential, realistic bidding strategies lead to slight increases in cost and decreases in hydrogen production.

When combining both applications, FC should be used to reduce forecast errors and ELY should participate in the SCR market. FC rated power of 0.2 MW can be complemented by 0.4 MW ELY in terms of hydrogen balance and lead to a hydrogen production cost of 1.1 €/kg at earnings of 1.25 €/kg due to FC operation. Using ELY for reducing wind farm forecast errors as well as using ELY for SCR market participation are two strategies which have been identified as promising applications of power to gas technology.

The results and findings of this analysis are therefore an important basis for short term application of hydrogen technology. This work provides insights into the marketability of electrolyzers' flexibility, which is especially important for hydrogen production for transportation. Short-term hydrogen infrastructure roll-out is necessary, but high costs of hydrogen are still a major obstacle. By operating electrolyzers as indicated in this analysis, this hurdle can be reduced and infrastructure build up can be accelerated.

This work opens up avenues for further research. Future investigations could include hydrogen storage and compression, improve modeling of FC and ELY, examine technical aspects of operation, use more recent SCR market data and evaluate the impact of taxation and EEG legislation. Bidding strategies might be refined by letting the bids depend on the actual available storage capacity. Baseload operation of ELY would allow provision of positive SCR via ELY. There is also the possibility of wind farm forecast error compensation via intraday trading. Besides re-electrification via FC, additional hydrogen usage paths could be considered.

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