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Optimized electrolyzer operation: Employing forecasts of wind energy availability, hydrogen demand, and electricity prices

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ABSTRACT

One of the main advantages of fuel cell based mobility over other sustainable mobility concepts is the flexible production of hydrogen via electrolysis. To date, it is unclear how electrolysis at hydrogen refueling stations should be operated in order to achieve the lowest possible costs despite the constraints of hydrogen demand. This study proposes and evaluates an intelligent operating strategy for electrolysis capable of exploiting times of low electricity prices while participating in the spot market and maximizing wind energy utilization when combined with a wind farm. This strategy is based on a simulation model considering imperfect forecasts (e.g. of wind availability or energy prices) and non-linear electrolyzer behavior. Results show that this approach reduces hydrogen production costs by up to 9.2% and increases wind energy utilization by up to 19%, respectively.

Introduction

The transport sector has to achieve a significant reduction of CO_2 emissions in order to contribute to the overall goals of mitigating global warming. In Germany, this sector relies heavily on fossil fuels [1,2] and its emissions have been reduced by only 2% from 1990 to 2015 [3] by far the lowest value among all sectors. Battery electric vehicles (BEV) and fuel cell electric vehicles (FCEV) are two promising options to reduce emissions if renewables are used as the energy source.

BEV-based mobility has higher overall efficiency compared to FCEV [4] but implicates a long duration of charge and a temporally rigid demand for electrical energy, if flexibility measures like vehicle-to-grid technology are not deployed at large scale in the future [5]. This aggravates grid and supply related problems arising from increasingly fluctuating energy production due to growing shares of renewables. FCEV on the other hand, offer low refueling durations. Their fuel, hydrogen (H_2), can be produced flexibly via electrolysis at hydrogen refueling stations (HRS) whenever electrical energy from renewables is available. Hydrogen can then be stored in gas

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vessels and transported via pipelines or trucks [6] at a lower cost than the cost of (transforming and) storing electrical energy by other means [7]. This relevance to the overall energy system is often referred to when discussing hydrogen as a fuel [8–12].

The electrolyzer's operator, however, intends not only to optimize operation in terms of compatibility to the energy system, but also needs to achieve lowest hydrogen production cost and meet hydrogen demand at any time. This means, flexibility is not unlimited. Thus, forecasts of wind energy availability, spot market price and hydrogen demand have to be taken into account. To date, an applicable, practice-oriented strategy for electrolyzer operation at an HRS is missing.

Therefore, this study proposes and evaluates an intelligent operating strategy for electrolysis at HRS, using energy from near-site wind turbines as well as spot market energy. The operating strategy is incorporated within an optimization and simulation framework, minimizing hydrogen production costs and increasing renewable energy utilization. The remaining part of this introduction focuses on electrolysis and technical as well as regulatory boundary conditions for spot market participation and direct coupling of the electrolyzer with renewables. A literature review is provided in section Literature Review. Section Methodology describes the underlying methodology, which is applied to two scenarios in section Application to real-world scenarios. Results are discussed in section Results, followed by conclusions in section Summary, conclusion and outlook.

Electrolysis and purchase options of electrical energy

Electrolysis splits water into hydrogen and oxygen molecules with the help of electrical energy. There are different sources for electrolyzer's operators to obtain energy from: forward market, spot market, over-the-counter trading, control reserve markets or direct usage of renewable energy sources. The electrolyzer's flexibility can be harnessed when participating in spot market or control reserve market as well as in combination with renewables. However, participation in the German (secondary) control reserve market has already been evaluated in detail [13,14]. In contrast, this analysis focuses on using near-site renewables, complemented by spot market participation.

Spot market

The European spot market is divided into day-ahead market and intraday market. On the day-ahead market, hourly contracts are traded within an auction on the previous day at 12 o'clock noon (market clearing price). The intraday market comprises an auction of quarter-hourly contracts at 3 p.m. on the previous day (market clearing price) followed by continuous trading until 30 min before fulfillment (pay-as-bid). The electrolyzer's flexibility allows purchasing energy in times of low prices and avoiding high load when prices are high. In Germany, energy obtained from these markets is taxed and surcharged. Also charges for using the electrical grid as well as the utility's margin apply. These additional costs are assumed to be 136.04 €/MWh in total. This assumption is based on data on an electricity price breakdown for 2017 [15] and the average spot market price [16]. Participation in this market leads to further costs (e.g. exchange fee) which are neglected in this analysis [17].

Direct coupling with renewables

When electrolysis is combined with renewable energy sources like photovoltaic power plants or wind energy power plants, surcharges and taxes depend on whether the electrolyzer's operator also operates the renewable energy power plant (REPP) and where it is sited. In this analysis, it is assumed that the REPP is sited in vicinity to the electrolyzer and that both are operated by the same operator. In this case, taxes and surcharges amount to 27.52 €/MWh (40% of renewable energy law surcharge of 68.8 €/MWh). If the power provided by the REPP is below the electrolyzer's maximum power, either its load has to be reduced or additional energy needs to be purchased, e.g. on the spot market. If the power provided by the REPP exceeds the electrolyzer's maximum power, surplus can be sold.

Literature review

Operation of hydrogen refueling stations

Operation of an HRS with onsite electrolysis in combination with renewables or energy market participation has been repeatedly considered in literature. Nistor et al. (2016) [18] simulated and evaluated an HRS with onsite electrolysis and wind farm connection on an island. Their simulation comprised detailed non-linear component models, but lacks an elaborate operating strategy. Hydrogen demand was estimated rather roughly. Moreover, forecasts of neither wind energy availability nor hydrogen demand nor energy price were taken into account. As a consequence, hydrogen demand cannot be fulfilled at all times.

A similar configuration with onsite electrolysis was investigated by Zhao et al. [19]. They additionally integrated solar energy production and a fuel cell for reconversion of hydrogen into electricity. Three discrete, simple strategies for plant operation were designed and investigated. Hydrogen production costs were estimated and a topology analysis was conducted. However, the simple strategies do not take forecasts into account and therefore are not suitable for real HRS.

Carr et al. [20] developed and employed an operating strategy for an HRS comprising electrolysis, wind farm connection and grid connection. The strategy actually is an optimization procedure minimizing operation cost and maximizing earnings from wind energy feed-in, respectively. It uses forecasts of wind energy availability, electricity price and hydrogen demand. The forecast horizon is 24 h and simulation step size amounts to 30 min. Simulation is conducted over one month. However, the approach can only handle linear component models and neglects investment costs. Moreover, all forecasts presume perfect foresight, which is not available for real HRS operation.

García Clúa et al. [21] also evaluated three different operating strategies for a grid-assisted wind-hydrogen system. These strategies either optimize wind power capture, maximized hydrogen production rate or maximized renewable hydrogen production. Hydrogen demand is not used as a constraint and all strategies are not predictive but reactive.

Dagdougui et al. [22] focused on an HRS network supplied by renewables and one central electrolyzer instead of single service stations. Operation was simulated in terms of hydrogen and energy flows between system components. They determined technically feasible solutions of the hydrogen supply chain via linear optimization but did not develop operating strategies for single HRS.

Kopp et al. [23] evaluated project “Energiepark Mainz” in terms of the electrolyzer's technical and economic performance. The project includes an electrolyzer producing hydrogen, some of which is delivered to HRS. Three different operating modes were simulated and tested: Spot market participation, secondary control reserve market participation, and usage of excess electricity from wind farms. Forecasts were not taken into account except for wind energy forecasts. These were used for determining the amount of excess energy only, though. Rather low hydrogen production costs of between −6 €/kg and 6 €/kg were calculated (negative values occur when earnings, e.g. from control reserve market participation, exceed costs), but investment costs of electrolyzer and compressor were not taken into account. This is especially misleading, since no boundary conditions concerning the produced hydrogen are set. Accordingly, utilization rates are very low (between 4% and 25%), leading to low operating cost (hours of lowest energy prices can be used for hydrogen production) while actual hydrogen production cost including investment cost would be very high. Thus, the presented operation modes only serve scientific purposes.

Harnessing excess energy from wind farms due to forecast errors was also investigated by Grüger et al. [13]. Results indicate that this electrolyzer operation mode can be a viable option and leads to hydrogen production costs between 2 €/kg and 3 €/kg. Additionally, they focused on electrolyzer participation in the German secondary control reserve market and evaluated different strategies for market participation. They found that production costs can be low (1 €/kg). However, in simulating both modes they included neither applicable taxes and surcharges on obtained energy nor costs of other components, e.g. compressor or storage. Furthermore, hydrogen demand was not incorporated as a boundary condition.

Guinot et al. [24] investigated an electrolyzer's profitability when participating in the French primary control reserve market. They found that the current conditions lead to an increase in production cost and make this operating mode unattractive.

Operation of energy systems

An HRS with onsite electrolysis can be considered an energy system. Hence, if relevant, publications for optimized operation of energy systems in general are also reviewed.

Maroufmashat et al. [25] considered a system of multiple energy and hydrogen demand areas, called energy hubs, including electrolysis and renewables. Operation and topology are optimized with the help of a mixed integer linear programing approach. This methodology is limited to linear component models and perfect foresight, e.g. of energy prices.

Chen and Garcia [26] investigated optimal operation of hybrid energy systems while participating in different energy markets. Fluctuating energy production from renewables is also taken into account. Although energy market participation can be relevant for HRS, other important aspects like limited forecast horizon or missing methods for predicting energy prices reduce the practical applicability of this approach.

Brka et al. [27] developed a predictive operating management system for wind/hydrogen/battery-systems based on neural networks. Hydrogen is regarded for energy storage only and is not used as a fuel. The algorithm predicts electrical load and renewable energy production for the respective next time step. The forecast horizon is therefore one time step. This predictive strategy only addresses energy production in cases of positive residual load but uses simple rules for energy storage. Since neither grid connection nor hydrogen demand nor sufficient forecast horizons are included in this approach, it cannot be applied to real HRS with onsite electrolysis.

Guandalini et al. [28] set up a model of a grid balancing system comprising conventional gas turbine based power plants, renewables and electrolysis. Produced hydrogen is assumed to be fed into the natural gas grid. Wind energy availability is forecasted via a statistical approach but only used for calculating forecast errors. Thus, forecasts are not used to optimize operation which makes this approach inapplicable to the problem addressed in this paper.

Main contributions of this paper

This paper presents an intelligent operating strategy for HRS with onsite electrolysis, which reduces hydrogen production cost and increases shares of produced renewable hydrogen. In contrast to previous, aforementioned research, it employs non-linear component models (e.g. of the electrolyzer) and is capable of taking forecasts into account. As a novelty, imperfect forecasts of energy price, wind energy availability, and hydrogen demand are used instead of unrealistic perfect foresight. This makes this approach applicable to real-world HRS. It is evaluated via simulation in comparison to common simple operating strategies in terms of hydrogen production cost and share of renewable hydrogen. All relevant cost components including taxes and surcharges are considered and discussed.

Methodology

The proposed operating strategy provides quarter-hourly indications regarding ideal electrolyzer load and operating points of all other components, e.g. compressor or hydrogen storage. In order to determine the optimum, it is required to not only simulate the system's current but also future behavior based on forecasts of energy prices, wind energy availability, and hydrogen demand.

Spot market model and forecast of prices

In this model, the HRS operator participates in the continuous European intraday market. Data from 2015 are used [16], since these are the most recent data of one complete year available to the authors. It is assumed that energy can be obtained at the current intraday price at any simulation time step. Therefore, the restriction, that trading is only possible until 30 min before fulfillment is neglected. Also, the energy price is assumed to amount to the 15 min weighted average price. In reality, intraday prices are unknown in advance. In order to avoid unrealistic perfect forecasts in this model, prices are forecasted with the help of day-ahead market prices. Thus only pieces of information that would be available in reality as well are used. At any given time step t on day n, forecasts are made for all time steps from $t+1$ to $t+z$, with z being the forecast horizon. For time steps of day n, the day-ahead price of the respective hour (determined at noon of the previous day) is used as a forecast. If step size is below 1 h, the forecasted value is used for all steps within the respective hour. For time steps of day $n+1$, the forecasted value depends on whether t is before noon of day n. If it is, day-ahead prices for day $n+1$ have not been determined yet and the mean price of all hours of day n is used as a forecast. Otherwise, day-ahead prices for day $n+1$ are available and used as a forecast. For time steps of days later than $n+1$, the mean price of all hours of day n is used as a forecast.

Modeling hydrogen demand and demand forecast

Hydrogen demand from private cars is assumed according to HRS class “small”, which was defined by H2 Mobility [29]. Daily demand amounts to 168 kg on average and 212 kg maximum. The number of refueling events must not exceed 38, while the average number is 30. Maximum hydrogen hourly throughput is 33.6 kg. These boundary conditions are used as an input of a specially developed algorithm, which generates synthetic demand profiles. In order to gain realistic profiles, data on real refueling behavior is required. Therefore, hourly refueling data of two conventional refueling stations (each dataset comprising two weeks) is used. The algorithm uses the boundary conditions of the HRS class as well as the data on refueling behavior to stochastically distribute refueling events over one year in quarter-hourly resolution. Thus, the resulting demand profile exhibits no repetitive patterns but realistic refueling behavior in accordance with the aforementioned boundary conditions (see Fig. 1).

Since refueling events of private cars cannot be foreseen, it is crucial to avoid perfect foresight approaches in order to gain realistic results. Therefore, demand is forecasted with the help of a “worst-case” approach utilizing the characteristics of the chosen HRS class. This approach is based on the assumption that the maximum allowed hydrogen demand (according to HRS class specifications) occurs as soon as possible. If, for example, the maximum hydrogen mass of 212 kg has been dispensed within the first 20 h of a given day, the forecasted demand for the remaining 4 h of that day is 0 kg. In case of only 170 kg being dispensed until hour 20, the forecasted demand for the next hour amounts to 33.6 kg, since this is the maximum allowed mass per hour. Beyond this example, the algorithm can be described as follows.

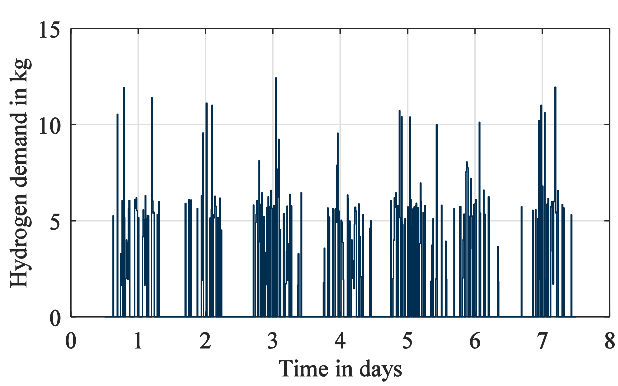

Fig. 1 – Hydrogen demand profile of one exemplary week.

The HRS class definition provides the maximum dispensable hydrogen mass per day (m_d) and per hour (m_h). At any given time step t, forecasts are made for all time steps from $t+1$ to $t+z$, with z being the forecast horizon. These time steps are referred to as $f_i(t)$ with $1 \leq i \leq z$. Given the actual demand according to the demand profile of time steps $\leq t$, the already dispensed hydrogen masses in the respective hour h_t of t (m_{ht}) and on the respective day d_t of t (m_{dt}) are determined. Then, the remaining maximum hydrogen throughput r_d of day d_t and the remaining maximum throughput r_h of hour h_t are derived ($r_d = m_d - m_{dt}$; $r_h = min(r_d, m_h - m_{ht})$). The amount of r_h then is equally distributed among all time steps $> t$ within h_t. The resulting hydrogen mass is the forecasted demand for all $f_i(t)$ within h_t. r_d then is reduced by r_h. In case of h_{t+1} being part of day d_t, the process is repeated for this hour, i.e. the maximum throughput in h_{t+1} is determined with the help of r_d and the forecasted demand for all $f_i(t)$ within h_{t+1} is calculated. If h_{t+1} is the first hour of day d_{t+1}, r_{h+1} is set to m_h and r_d is set to m_d. This process is repeated until h_{t+z} has been reached, so all $f_i(t)$ have been determined.

Forecast of wind energy availability

Wind turbines provide electrical energy in a fluctuating manner. In order to participate in energy markets, wind energy yield has to be forecasted in hourly or quarter-hourly resolution.

The production profile as well as forecasts used in this analysis are based on real wind farm production and forecast data of a wind farm with 53 MW rated power [30]. Measured data are available in 1-min-resolution for the year 2012, while the corresponding forecast data on wind energy production are provided in 12-h-resolution with 240 h forecast horizon in 30 min steps. These pieces of information are used to generate forecasts in quarter-hour-resolution by assuming that forecasted wind turbine power is constant within each 30 min time frame. A production profile is generated in quarter-hourly resolution by aggregating the available measured data. Both time series (production and forecast) can be scaled according to the simulated wind farm's rated power.

Basic framework and HRS-Component models

The presented approach extends a basic, existing framework and uses non-linear models of relevant HRS components: electrolyzer, compressor, storage, and dispenser. Furthermore, the aforementioned models of electricity intraday spot market as well as hydrogen demand from passenger cars are also included. Additionally, a wind turbine is integrated into the HRS model.

The basic framework also comprises the aforementioned component models and is based on section-wise linearization and adapted linear equation system optimization [31]. For each simulated time step, the possible behavior of each component is simulated. For example, the electrolyzer can produce amounts of hydrogen between 0 kg and 10 kg within one time step (corresponding to 0% and 100% load). Its demand for electrical energy varies accordingly between 0 and 560 kWh, while its temperature changes by −3 K and 20 K, respectively. In general, this behavior is non-linear, so more than two sampling points (in this example: 0% and 100% load) can be used. Between each two sampling points, linear behavior is assumed and expressed in dependence of the respective operating point. One linear operating section of each component is selected and all selected sections are combined. From this combination, a linear equation system (LES) can be derived, requiring all mass and energy flows to be balanced while the optimization target is to be minimized. In this analysis the optimization target is lowest cost, but the methodology and simulation framework allow for choosing any target. In fact, since energy provided by the wind turbine is cheaper than energy obtained on the spot market, this optimization target also leads to maximizing wind turbine utilization. The LES's resulting solution represents all components' optimal operating points, which guarantee a working system (e.g. all demands of hydrogen are fulfilled) while minimizing operation costs. In order to capture all possibilities of component operation, not only one combination of linear operating sections is taken into account, but all possible combinations are evaluated. The best result among all combinations is chosen.

This framework therefore determines the ideal operating decision in terms of costs for all components. The resulting energy and mass flows (e.g. hydrogen produced by the electrolyzer or the amount of hydrogen stored in the low pressure storage) are calculated as well as the component's states (e.g. the electrolyzer's temperature or the storage's state of charge). These states are boundary conditions for the next simulation time step. However, this approach is incapable of considering forecasts or future component behavior, and instead uses rules and heuristics. This is necessary, if decisions made in one time step affect component behavior in one of the subsequent time steps. For example, only if a hydrogen storage is charged in time step one, it can be discharged in time step two. Thus if storages are to be used, the rule “produce as much hydrogen as possible until the storage's state of charge (SOC) reaches 50%” could be applied and incorporated in the LES's cost function. This means that the actual benefit of charging the storage, coming into effect in later time steps, is not quantified and taken into account. Thus the determined operating decision is based on the respective time step and heuristics only. Therefore, this approach can be considered a myopic short-term optimization.

This framework and these component models have been developed within a project on an existing HRS in Berlin, Germany. A basic description of this project and its models is available in the final project report [14].

Advanced framework for intelligent operation

The presented framework extends the myopic approach in order to take forecasts into account instead of using heuristics. All time steps are simulated consecutively as in the myopic approach (in the following referred to as main steps). For each main step, however, several possible decisions (instead of just the ideal one) are calculated and evaluated in terms of previously defined optimization targets, e.g. low costs. This is done by slicing the components' operating ranges into several sections. These sections are independent of the aforementioned linearization sections, but combined with sections of other components in the same way. The resulting LES are solved. Each solution is kept instead of selecting only the best one, because solution assessment at this point is based only on the respective main step but neglects the solution's quality in subsequent time steps.

Then, a hypothetical future of the current main step is also simulated. Since the future situation is dependent on the decision of the main step, the possible behavior in the expected next time step has to be determined for each decision option. This next time step can be referred to as “forecast step 1” (FCS 1). All options in FCS 1 again can result in several options for FCS 2, each. Fig. 2 depicts a possible decision tree. The white circle represents the initial situation in the beginning of simulating the current main step. It is defined by the states of all components (e.g. the storage's SOC). Light grey circles denote possible solutions, i.e. decision options in the main step. The remaining circles represent subsequent decision options in FCS 1 and 2, respectively.

While main step options use actual values of hydrogen demand, energy price and wind energy availability, all forecast step options are evaluated based on forecast values. Instead of using perfect foresight, this approach can process realistic and imperfect forecasts and limited forecast horizons in order to only consider information that would be available when applying this strategy to a real-world HRS. The determined cost of an option is increased by the costs of all predecessors, leading to total accumulated cost. So options of the

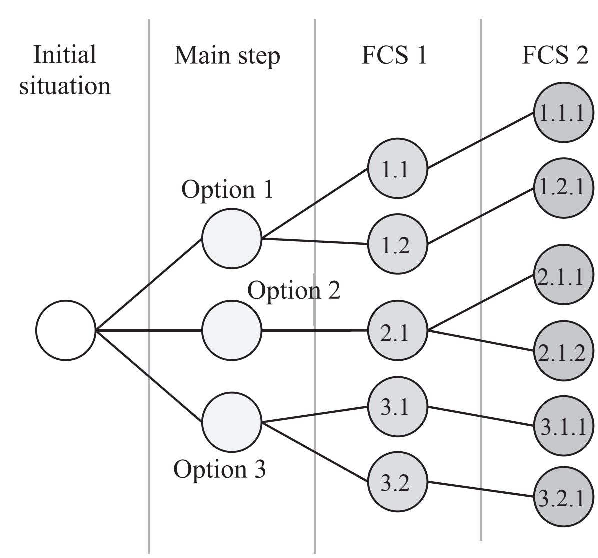

Fig. 2 – Decision tree with two forecast time steps (FCS).

last forecasted step (according to the forecast horizon) provide total costs for choosing the respective decision path. Based on these values, the best path is chosen (i.e. in terms of total expected costs). Since this procedure serves the purpose of deciding on operating options in the main step, the respective option, which is the root of the best path, is executed in the simulation. The simulation is then continued with the next main step and so on.

The described approach is based on evaluating all possible future options, which can require immense computational effort, especially if the forecast horizon exceeds the shown horizon of two steps (Fig. 2). The decision tree grows exponentially with a rising forecast horizon as does the required calculation time. Therefore, a heuristic is applied, that efficiently finds the best or at least a very good path without evaluating all options. Its underlying basic principle is to stepwise generate successors of only the currently most promising option. Using the example of Fig. 2, if the main step's option 3 is most promising, only options 3.1 and 3.2 are generated and evaluated. Afterwards, the most promising option among all existing ones without successors (now including 3.1 and 3.2) is identified. If the newly calculated options evaluate unfavorably in comparison to all other current options available (main step options 1 and 2), the best option among those is chosen, and successors are then generated from this option. This procedure is repeated until the horizon is reached. It requires a criterion for identification of the most promising option. While accumulated costs of options might seem to suggest themselves as a criterion, they are not necessarily a good prediction of total path costs, because all remaining subsequent FCS are not taken into account. Therefore, a different criterion is used to determine the currently most promising option.

This criterion is an estimation of total path costs (see Fig. 3), based on the determined accumulated costs (depicted by green arrow) of the respective option in FCS *n* (black circle) and a cost estimation of the remaining FCS (depicted by red arrow).

This estimation is made by aggregating all steps from FCS $n + 1$ to the forecast horizon and treating them as one (temporally extended) step. Aggregation is applied to all boundary conditions, meaning that the respective values of all aggregated steps are summed up (hydrogen demand, wind energy availability) or averaged over these steps (spot market price). This aggregation causes one single optimization for one time step of size $horizon - n$, which makes the estimation computational efficient at the cost of lower precision. Component behavior is not aggregated directly, which would require simulation of all steps, but aggregation is a consequence of simulating only one step under the previously aggregated boundary conditions. It is unnecessary to find and evaluate different options for this estimation step, but only the one optimal option is needed (as in the basic approach), because no further options beyond the horizon are regarded.

This heuristic is further improved by not only estimating total path costs with an estimation step to the forecast horizon, but evaluating each option in regard to different reference steps. Thus the forecast horizon is only one reference step among others. Reference steps are chosen based on significance (e.g. if showing peaking demand). It can be important to make more steps than only the last (horizon) step a reference step, because extensive aggregation can be misleading and cause unfavorable selections of steps from which successors are generated. For each defined reference step, the option evaluating best in terms of the respective reference step is regarded a promising option and selected. For these steps, again, successors are determined and evaluated in terms of actual costs as well as estimated cost in regard to all reference steps separately. Since this heuristic uses approximations of total path costs instead of actual total path costs, it is not guaranteed that the global optimum is found and selected. In fact, this heuristic can be assumed to find at least a good, plausible path while enabling this methodology to be applicable to real-world problems by accelerating execution drastically.

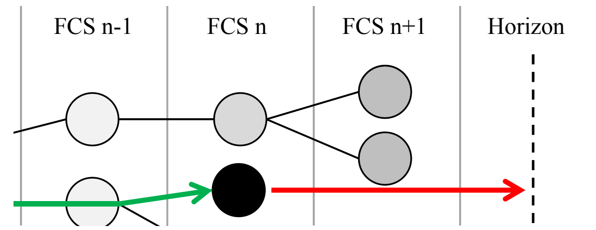

Fig. 3 – Estimation of one option's (black circle) total path costs consisting of aggregated actual costs (green) and an estimation of future costs (red). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Application to real-world scenarios

Scenarios

This approach is applied to two scenarios of an HRS. The first scenario comprises models of an alkaline electrolyzer (450 kW rated power, 630 kW overload power), low pressure storage (45 bar, 380 kg capacity), compressor (33.6 kg/h), high pressure storage (1000 bar, 43 kg capacity) and dispenser including hydrogen cooling. This setup reflects the situation at the aforementioned HRS in Berlin (see Fig. 4) [14]. Furthermore, the hydrogen demand model and the European intraday spot market model are integrated. It is assumed that hydrogen precooling consumes 0.3 kWh electrical energy per kg of dispensed hydrogen and has a stand-by demand of 2.25 kW [32]. Respective forecasts of hydrogen demand and energy price are incorporated.

The second scenario is identical except for an additional wind turbine (1.6 MW rated power) that also supplies an electrolyzer with higher rated power (545 kW) and adjusted storage capacity (770 kg). The rated powers of wind turbine and electrolyzer as well as the storage capacity have been determined through topology optimization using the myopic approach. Produced electricity which cannot be used by the electrolyzer is fed into the electrical grid and sold at current market price. Besides forecasts of hydrogen demand and energy price, the power provided by the wind turbine is forecasted via the aforementioned model.

Fig. 4 – HRS in Berlin as a basis for scenario 1.

Simulation is conducted for one year in quarter-hourly steps. Forecast horizon is 24 h. For better comparison, scenarios are additionally evaluated with the basic, myopic approach. It relies on the rule to fill the low pressure storage, whenever possible. Electrolyzer overload is only allowed, if this storage's pressure drops below 10 bar. The HRS is assumed to be sited in Germany, and respective taxes and surcharges are therefore taken into account. Capital and operational expenditures are considered via annuity calculation.

Cost assumptions

For each component, three different types of costs are considered: capital expenditures (Capex), fixed operational expenditures ($Opex_{fix}$) and variable operational expenditures ($Opex_{var}$). Capex and $Opex_{fix}$ are derived from different sources by applying exchange rates [33] and rates of price increases [34]. Thus in the following all cost information has been recalculated for the amount in € in the year 2016. All cost assumptions are summarized in Table 1.

Furthermore, costs of planning, permitting, and installation are taken into account for all components except the wind turbine, as these costs are already included in its Capex. These additional costs are approximated via the sum of all Capex multiplied by a factor of 0.4 [46]. $Opex_{var}$ are determined in the course of simulation and include energy costs as well as taxes and surcharges on obtained energy.

Results

Results of scenario 1

Results of scenario 1 show levelized costs of hydrogen (LCOH2) of 13.42 €/kg (myopic) and 13.28 €/kg (predictive). Thus the predictive approach leads to cost reductions of 1% (see Fig. 5). Capex and $Opex_{fix}$ are identical for both approaches, because these cost components are not affected by operation. $Opex_{var}$ account for the largest share in costs, while Capex amount to 2.63 €/kg and $Opex_{fix}$ amount to 0.90 €/kg. Different components of Capex and $Opex_{fix}$ are shown in Fig. 6. Electrolyzer (0.89 €/kg), installation (0.77 €/kg) and compressor costs (0.52 €/kg) dominate total Capex, while electrolyzer (0.44 €/kg) and compressor (0.32 €/kg) are most relevant in terms of $Opex_{fix}$.

$Opex_{var}$ consist of energy costs only and the differences between the two operating strategies (myopic and predictive) are marginal (see Fig. 7). This is due to the fact that the actual energy price is responsible for only a small share (19% in the predictive and 21% in the myopic case) of total energy costs, while taxes and surcharges account for the largest share. The predictive approach reduces energy costs (incl. taxes and surcharges) by 2.6%, but its advantage amounts to 12% in terms of gained energy price.

Table 1 – Cost assumptions.

Component	Capex	$Opex_{fix}$	Source
Electrolyzer (450 kW)	1492 €/kW	60 €/(kW*a)	[35–37]
Electrolyzer (545 kW)	1460 €/kW	58 €/(kW*a)	
Storage (50 bar)	632 €/kg	6 €/(kg*a)	[38–41]
Storage (1000 bar)	1144 €/kg	11 €/(kg*a)	
Compressor	394,398 €	19,720 €/a	[41–43]
Dispenser	107,000 €	5350 €/a	[41,42]
Pre-Cooling	140,000 €	7000 €/a	[41,44]
Wind turbine	1547 €/kW	56 €/(kW*a)	[45]

Results of scenario 2

The setup of scenario 2 leads to LCOH2 of 12.69 €/kg (myopic approach) and 11.52 €/kg (predictive approach). The predictive strategy is thus capable of reducing LCOH2 by 9%.

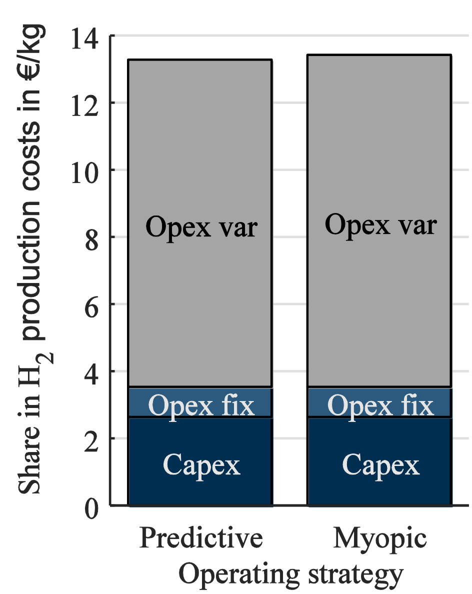

Fig. 5 – LCOH2 in scenario 1.

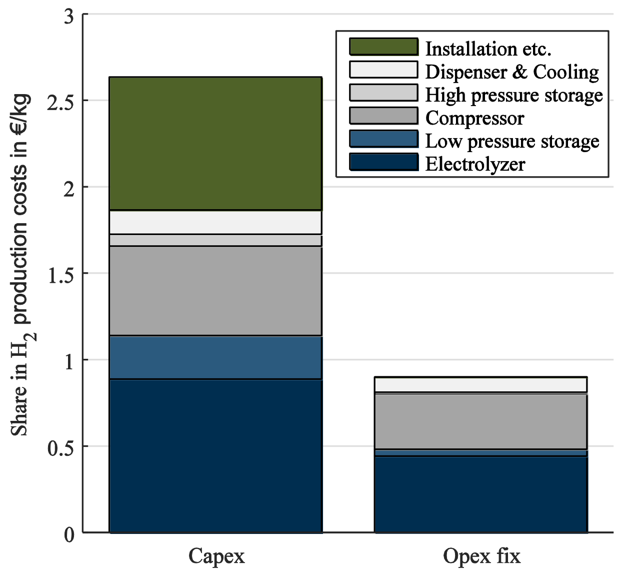

Fig. 6 – Capex and Opex fix in scenario 1.

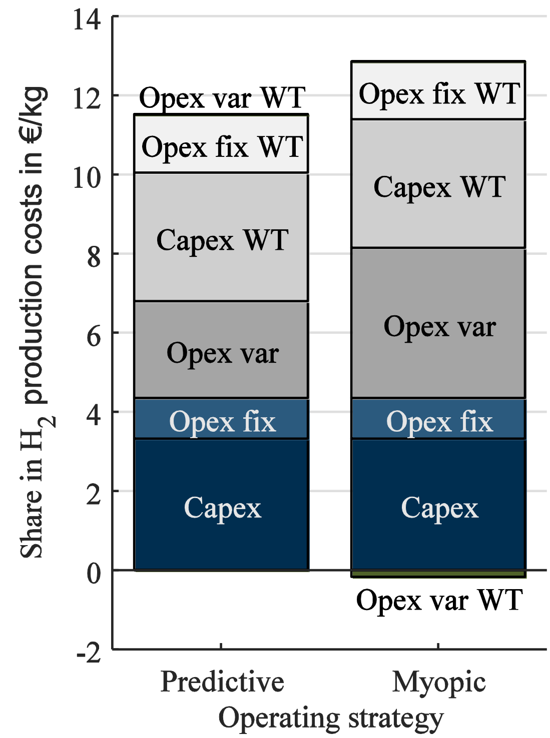

Fig. 8 – LCOH2 in scenario 2.

Fig. 8 compares both strategies' LCOH2 compositions. In contrast to scenario 1, additional cost components of the wind turbine (WT) are shown. Capex and $Opex_{fix}$ (both for WT and HRS components) are identical for both strategies. WT's $Opex_{var}$ comprise surcharges for usage of energy provided by the WT as well as earnings from selling surplus at the spot market. The difference in $Opex_{var}$ is remarkable, because predictive operation leads to lower $Opex_{var}$ induced by grid usage but slightly higher $Opex_{var}$ of WT (negative in myopic case). This is caused by lower shares of wind energy being fed into the grid using a predictive approach, leading to lower earnings from feed-in while more energy is surcharged at the same time. On the other hand, this reduces energy procured from spot market and leads to significantly lower $Opex_{var}$.

Fig. 9 shows that wind turbine's Capex (3.25 €/kg) account for roughly half of total Capex (6.58 €/kg) and for 59% of total $Opex_{fix}$. The difference in $Opex_{var}$ is explained by Fig. 10. The left column depicts energy costs for spot market participation using a predictive strategy, while the column in the middle represents the myopic approach. Predictive operation leads to reductions in energy costs by 6% and in obtained energy prices by 26%. The column to the right, in

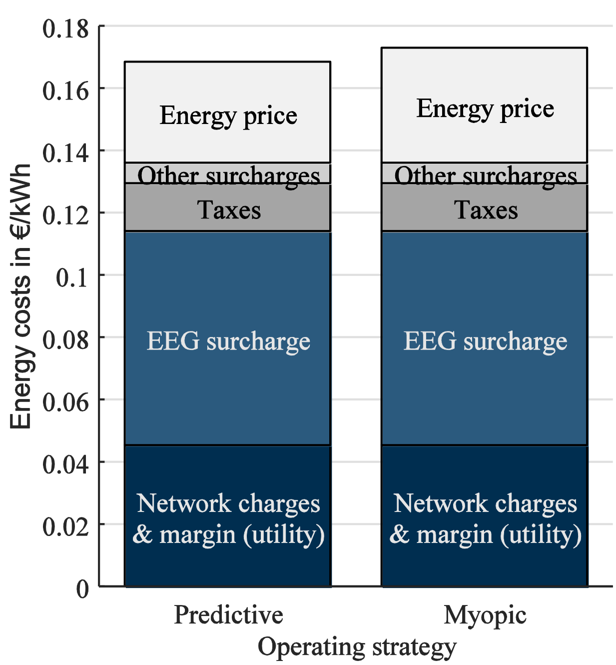

Fig. 7 – Energy costs in scenario 1.

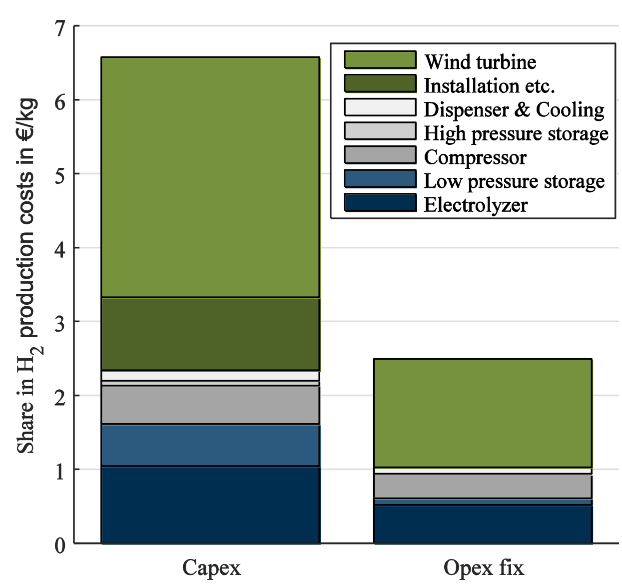

Fig. 9 – Capex and Opex fix in scenario 2.

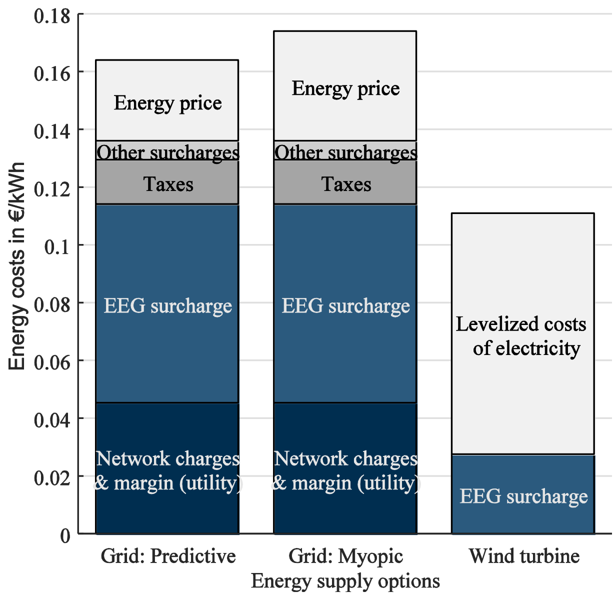

Fig. 10 – Energy costs in scenario 2.

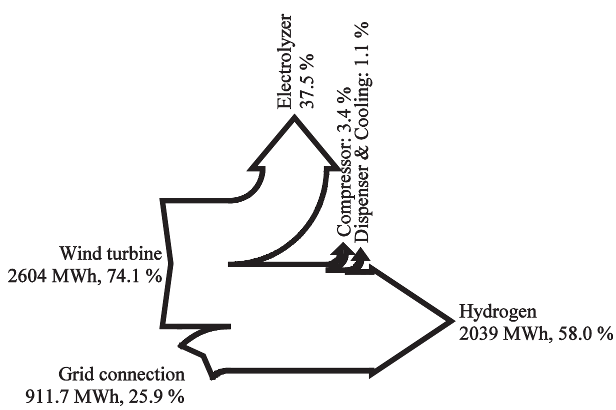

Fig. 11 – Sankey diagram for scenario 2.

contrast, shows energy costs of the WT (predictive case). Only reduced surcharges apply and the WT's Capex, $Opex_{fix}$, and earnings from feed-in are allocated to the electrical energy of the WT used for electrolysis (levelized costs of electricity). Energy obtained from the WT therefore is cheaper than energy bought on the spot market by 32%. The results are only valid for this scenario and grid usage, and WT usage costs are mutually dependent. It is, for example, not possible to avoid grid usage and only use WT energy at the same costs.

A Sankey diagram for predictive operation is given in Fig. 11. 74% of the required electrical energy originates from the WT, while the remaining 26% are drawn from the spot market. Electrolyzer losses amount to 38%, and compressor and cooling are responsible for 3.4% and 1.1% of total energy demand, respectively. While the share of renewable hydrogen is 74% in the predictive case, it is only 62% when using the myopic approach. The predictive strategy therefore increases usage of renewable energy by 19%. Overall efficiency is 58%, based on the lower heating value of hydrogen. In the predictive case, 60% of the electrical energy produced by the WT can be used for electrolysis, while this value drops to 50% when using the myopic approach.

Comparison of both scenarios

When comparing results of both scenarios using a predictive approach, the scenario comprising a WT shows significantly lower LCOH2 of 11.52 €/kg (−13%) compared to spot market participation only. Also, the benefit of prediction is higher (9% vs. 1%). Capex and $Opex_{fix}$ are increased (4.35 €/kg vs. 3.53 €/kg), and costs from spot market participation can be reduced (2.45 €/kg vs. 9.75 €/kg) due to smaller amounts of energy purchased at this market. Additional costs for the WT amount to 7.17 €/kg, but keep total costs below those of scenario 1.

Summary, conclusion and outlook

Electrolysis at an HRS provides flexibility potential in terms of load profile. But until now it has been unclear how it should be operated in order to harness low energy prices and maximize renewable energy utilization when constrained by hydrogen demand. The presented approach provides an intelligent operating strategy, considering forecasts of electricity price, wind energy availability, and hydrogen demand. It minimizes costs under the constraint of hydrogen demand and thereby maximizes wind energy utilization in scenarios with wind turbine integration. The approach is applicable to a real-world HRS with onsite electrolysis. Furthermore, methodologies for the generation of these forecasts have been presented and applied. These methodologies ensure that only information which is also available in reality is used. The predictive approach incorporates non-linear simulation models of electrolyzer, compressor, storage, dispenser, and WT. It was applied to two scenarios, one of these reflecting the setup of an existing HRS in Berlin while the other comprises a complementary WT. Simulation was conducted for one year in quarter-hourly resolution. The predictive approach was compared to a simple myopic one.

Results show that the predictive approach leads to ecological benefits. It effectively maximizes wind energy utilization (74% renewable hydrogen vs. 62% with myopic operation). The presented approach furthermore reduces hydrogen costs by 1%–13.28 €/kg in scenario 1 and by 9%–11.52 €/kg in scenario 2. Accordingly, combining an HRS with a WT leads to 13% lower hydrogen costs compared to spot market participation only.

The economic benefits of WT integration, however, are highly dependent on reduced taxes and surcharges. If regular taxes and surcharges would be applied to wind energy, LCOH2 would amount to 16.15 €/kg (+40%) in scenario 2. Currently, hydrogen is sold at 7.98 €/kg + VAT. Calculated LCOH2 are thus too high, even with reduced taxes and surcharges. When focusing on the case with the lowest LCOH2, scenario 2, a possible path to reaching the selling price could include exempting wind energy from remaining surcharges. This would induce LCOH2 of 10.35 €/kg. Closing the remaining gap of 2.37 €/kg would require decreasing overall Capex and $Opex_{fix}$ by 26%. Increased electrolyzer efficiency could also contribute to cost reductions. A reduction of taxes and surcharges would lead to different results of topology optimization, which further could reduce costs (e.g. a higher rated power of WT, further reducing energy drawn from the grid).

Overall, the results of this analysis give valuable insights into the composition of hydrogen production costs. Moreover, the presented approach opens up avenues to reducing LCOH2 by taking forecasts of hydrogen demand, energy prices and wind energy availability into account. It is applicable to real-world HRS and therefore contributes to making hydrogen as a fuel a viable option for transportation. This analysis points out which further steps need to be completed in order to make the concept of HRS with onsite electrolysis competitive. Furthermore, it shows that in the future, this concept can play an increasingly important role in compensating fluctuating energy production when the share of renewable energy production rises. Predictive operation is then required to effectively utilize fluctuating produced energy.

Future research, following up to this analysis, could investigate the role of predictive HRS operation in scenarios of underutilized refueling stations, since this might be a common case in the initial phase of infrastructure build-up. Alternatively, the myopic approach could be improved by developing and applying more complex rules. It also could be valuable to update cost data and repeat this analysis when hydrogen technology evolves. Since scenario 2 has been designed by topology optimization based on the myopic approach, topology optimization can be improved by incorporating the predictive approach in the future.

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