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Optimizing power-to-H_2 participation in the Nord Pool electricity market: Effects of different bidding strategies on plant operation

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ABSTRACT

The operation of power-to-X systems requires measures to control the cost and sustainability of electricity purchased from spot markets. This study investigated different bidding strategies for the day-ahead market with a special focus on Sweden. A price independent order (PIO) strategy was developed assisted by forecasting electricity prices with an artificial neural network. For comparison, a price dependent order (PDO) with fixed bid price was used. The bidding strategies were used to simulate H_2 production with both alkaline and proton exchange membrane electrolysers in different years and technological scenarios. Results showed that using PIO to control H_2 production helped to avoid the purchase of expensive and carbon intense electricity during peak loads, but it also reduced the total number of operating hours compared to PDO. For this reason, under optimal conditions for both bidding strategies, PDO resulted in an average of 10.9% lower levelised cost of H_2, and more attractive cash flows and net present values than PIO. Nevertheless, PIO showed to be a useful strategy to control costs in years with unexpected hourly price behaviour such as 2018. Furthermore, PIO could be successfully demonstrated in a practical case study to fulfil the on-demand requirement of an industrial captive customer.

1. Introduction

Policies and incentives designed to tackle climate change, combined with the declining costs of renewable energy technologies continue to decarbonise the energy system [1]. In particular, variable renewable electricity (VRE), such as wind and solar, is being rapidly integrated into electricity networks. However, high levels of VRE can be challenging due to their intermittency and uncertainty (especially for wind) [2]. High levels of VRE can exacerbate an imbalance between supply and demand resulting in grid congestion, which in extreme cases forces the system operator to accept less VRE than it is possible to produce (i.e. curtailment) and rely on fossil fuel back up generation [1,3].

To minimize such drawbacks, the concept of using difficult to manage electricity from VRE to produce H_2 through water electrolysis has gained attention in the recent years [4]. H_2 as an energy carrier can be used in a variety of processes to produce gaseous (e.g. CH_4 and NH_3) and liquid fuels (e.g. methanol, gasoline and dimethyl ether), heat or even directly used as fuel for mobility [5,6]. Such energy concepts, frequently referred to as power-to-X (PtX or P2X), may assist grid balancing, reduce VRE curtailment, offer large-scale energy storage (e.g. H_2 and CH_4 in natural gas grid), couple different energy sectors, and reduce greenhouse gas (GHG) emissions through carbon capture and utilization (CCU) when H_2 is synthetized with CO_2 (i.e. $4H_2 + CO_2 \rightarrow CH_4 + 2H_2O$; $\Delta H = -165$ kJ) [7].

Different water electrolysis technologies are suitable for PtX applications. The most suitable for short- or mid-term implementation are alkaline electrolysis (AEL) and proton exchange membrane electrolysis (PEMEL) thanks to their higher technology readiness levels (TRL). Other emerging technologies such as anion exchange membrane electrolysis (AEMEL) and solid oxide electrolysis (SOEL) may be considered in the future [8,9]. Due to its maturity, AEL has the advantages of lower investment and maintenance costs compared to PEMEL. Conversely, PEMEL has been specially designed for flexible operation which significantly reduces start-up times from cold or hot standby [10], reducing the associated energy penalty and potentially leading to higher annual

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Nomenclature

List of abbreviations

AEL	alkaline electrolysis
AEMEL	anion exchange membrane electrolysis
CAPEX	capital expenditures
CCU	carbon capture and utilization
CH_4	methane
CO_2	carbon dioxide
GHG	greenhouse gas
H_2	hydrogen
H_2O	water
KOH	potassium hydroxide
$LCOH_2$	levelised cost of hydrogen
MAPE	mean absolute percent error
MLP	multi-layer perceptron
NCF	net cash flow
NH_3	ammonia
NN	neural networks
NOH	non-operating hours
NPV	net present value
SOEL	solid oxide electrolysis
OPEX	operational expenditures
PEMEL	proton exchange membrane electrolysis
PDO	price dependent order
PIO	price independent order
$PtCH_4$	power-to-methane
PtX	power-to-X
TRL	technology readiness levels
VRE	variable renewable electricity

performances of PtX systems [11]. Research and developments are focused on innovations that will improve flexibility, current density, efficiency, durability and the output pressure of AEL and/or PEMEL. Over time, such advancements are expected to deliver improved economic performance [12].

Different studies on H_2 production via water electrolysis have shown that electricity purchase is the main cost driver [13,14]. Additionally, McDonagh et al. [15,16] demonstrated that for power-to-methane ($PtCH_4$) production, when H_2 from PEML is synthetized with CO_2 in a catalytic reactor, low-cost electricity alone is not sufficient to reduce production costs significantly. Instead, a minimum number of run hours is also required to offset the project investment. Furthermore, with increasing shares of VRE in the energy mix, electricity markets and prices become less predictable. In particular, sudden and unexpected price peaks and emerging seasonality of prices at daily, weekly and yearly level have been observed [17]. Therefore, different operational strategies for running electrolysers might have a significant influence on the profitability of PtX.

In cases where electricity is purchased in the spot market, the day-ahead system is one of the most common modalities of trading in different power exchanges [18]. Each market agent submits bids for the upcoming day (24 h) before a set deadline in the previous day (e.g. 12:00 noon). Thus, anticipating electricity prices could be useful for developing an operational strategy to control costs, run hours, penalties for bringing the system into service from standby, as well as providing H_2 according to the specific requirements of a PtX application.

Different methods such as game theory, reduced form, and statistical models have been used for predicting electricity prices [17]. Recent advances have allowed neural networks (NN) to outcompete these traditional methods on time series and energy-related topics like wind power and load forecasting [19]. In general, the basic architecture of NN model consists of an initial layer of input data, a single or multiple hidden layers to concatenate and identify patterns and an output layer of results. Thus, sequential time data (e.g. past electricity prices) is first used for in-sample training of the NN and later for out-of-sample testing (e.g. forecasting) [20].

In Scandinavian countries, electricity is traded on the Nord Pool power exchange, where two different order types can be placed for single hourly trading in a day-ahead market: (a) price dependent orders (PDO); and (b) price independent orders (PIO). For PDO, market agents can specify the minimum and maximum bid prices as well as for the volume of electricity to be traded in each hour of the day. Whereas, for PIO the bid specifies only the volume of electricity at any price pre-defined in the range of −500 to 3000 €/MWh [21]. Thus, a comparison between PDO and PIO (assisted by price forecasting) would be worthwhile, as it may result in different electricity prices paid, total number of hours and consecutive hours purchased. The latter is particularly important when AEL is used due to its lower flexibility in comparison to PEMEL [10].

Electrofuels production directly coupled to VRE and/or electricity grids have been recently investigated in different studies [22–24]. Even though wind forecasting has been used to optimize H_2 production when electrolysers are deployed at wind parks or as a method to control the carbon intensity of the process [25,26], the operation of electrolysers assisted by forecasting day-ahead electricity prices in the spot market has not been previously detailed [14,27]. This is important because the potential benefits of price forecasting might be directly related to the characteristics of each energy market in terms of price fluctuations at daily, weekly and yearly level.

To the best of the authors' knowledge, an in-depth analysis on markets covered by Nord Pool power exchange has never been reported for PtX applications. In volume traded, Nord Pool is the largest spot market in Europe, thus providing a suitable test of model-based tools. Furthermore, Frank et al. (2018) has introduced the concept of annual performance by assessing the energy consumption of electrolysers during cold- and hot standby as well as to bring the system into service, such dynamics however have neither been reported using real electricity market data nor the relevance to the economic performance investigated [28]. Lastly, the present research adds to the existing literature by comparatively assessing the operational and economic performance of different water electrolysis technologies over time up to 2040. Thus, the objectives of this study are to:

- Assess yearly price characteristics in an electricity market covered by Nord Pool;
- Set-up a model based on NN to forecast day-ahead electricity prices in the spot market;
- Investigate the effects of different bidding strategies on H_2 production in terms of operational and economic performance;
- Compare AEL and PEMEL in different technological scenarios.

2. Methodology

2.1. System description

In this study, PtX system refers to a H_2 production facility in which H_2 could be potentially delivered for any further application, including direct use as fuel for mobility. Thus, H_2 is either produced through AEL or PEMEL technologies according to Eq. (1) [29].

$$H_2O \rightarrow_{electrolysis} H_2 + \frac{1}{2}O_2 \qquad (1)$$

The electricity is either obtained from the spot market of the Nord Pool power exchange in a day-ahead trading scheme (planned purchasing of large volumes, see section 2.3) or from the regulated market (purchasing smaller volumes during system downtime, see section 2.2). Different supplies such as deionized water and potassium hydroxide (KOH) as alkaline reagent for electrolyte are considered according to the respective water electrolysis technologies assessed. To allow storage at 500 bar, H_2 is compressed as soon as it is produced in the stacks [30]. To account for H_2 storage requirements, a capacity of 24 h of full load operation of an electrolyser with 1074 kW_{el} was considered. The recovery of low temperature waste heat (60 °C) from the electrolysers is also considered. In contrast, the possibility of selling O_2 is excluded due to the possible saturation of the market in case of large-scale deployment of the technology [13].

The model does not consider reductions in electrolyser performance over time, however, component replacement costs are included in economic assessment. Even though this study uses the most recent literature available, unavoidable uncertainty exists in the capital costs, in particular for the 2030 and 2040 technological scenarios [12]. The assessment of different technological scenarios intends to provide a comparison of water electrolysis technologies over the time, and not necessarily to provide forecasts of H_2 production costs in the future. Fig. 1 and Table 1 show the technical system boundary and the overview of the different characteristics of AEL and PEMEL technologies.

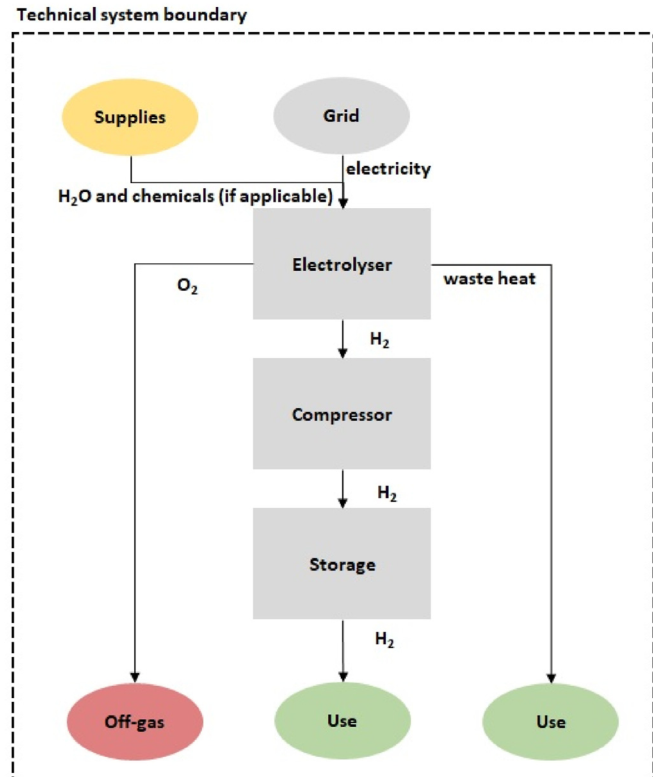

Fig. 1. Description of the technical system boundary.

2.2. Dynamics of electrolyser operation

As day-ahead electricity spot markets can be volatile, the operation of the electrolysers will occur not only on full load but also on two other states, that is cold and hot standby [11]. These are defined as the non-operating hours (NOH) of the system. As 100 kWh is the lowest bidding volume on Nord Pool's day-ahead market, the energy consumption during NOH as well for safety infrastructure is derived from the regulated market with a fixed tariff of 100 €/MWh.

In addition, an energy penalty for bringing the system into service from cold standby is also considered. During this period, the electricity from the spot market is purchased but no H_2 is produced. Details on the power required in each operation mode are presented in Table 2.

2.3. Nord Pool spot market data

Historical electricity prices from the Nord Pool day-ahead market from 2013 to 2018 were used either for training the NN or for simulating operation of the PtX system. The electricity market in Sweden is subdivided into four different regions: SE1 and SE2 are dominated by hydroelectricity; SE3 is predominately nuclear power generation; and SE4 is the region with the highest share of VRE in the country. Therefore, SE4 was chosen as a case study since this region offers more appropriate conditions for deployment of electrolysers despite its high combined heat and power production partly based on fossil fuels.

An analysis of variance (one-way ANOVA) followed by Tukey pairwise comparison was performed on the hourly electricity prices to verify whether statistical differences could be observed among years with 99% confidence level. The analysis was run with the software Minitab 18 (Minitab, USA).

2.4. Bidding strategies – Price Dependent and Price Independent Orders

Two different bidding strategies were developed for comparison, namely Price Dependent Order (PDO) and Price Independent Order (PIO).

For PDO the minimum bid price was defined as the lowest possible price allowed at Nord Pool (−500 €/MWh) and the maximum bid price was varied to reflect different operational strategies. Thus, every time the prices are equal to or lower than the maximum bid price, the electrolyser will operate. When the electricity price is higher than the maximum bid price, the number of NOH is counted and used to decide whether the electrolyser is put on hot or cold standby (if NOH > 8 h; then put on cold standby). This was decided as the power requirement in hot standby is approximately eight times (39 kW) that of cold standby (5 kW) [11]. PDO is representative of a PtX facility aiming simply to minimize the levelised cost per unit of H_2 produced (see section 2.7), generally by maximizing the economic use of the electrolyser (capacity factor). This strategy is driven by the electricity price in the spot market and is applicable should demand for H_2 significantly exceed potential supply, or when H_2 is injected into geological formations (e.g. salt caverns) for seasonal storage and/or into the natural gas grid within limitations [34].

In contrast, the PIO strategy aims to serve a demand for H_2 by sourcing the cheapest hours in a day-ahead scheme according to a pre-defined operating schedule based on H_2 demand and system load in the electricity grid. An assumption made here is that the fixed demand for H_2 is equivalent to 12 h of production per day, producing above this may be counterproductive unless the load in the system is considered low. In this case, the operating schedule

Table 1
Specifications of the water electrolysis technologies.

Characteristics		2020	2030	2040	Source
AEL	Electricity consumption (kWh/m^3 H_2)[a]	5.3	5.0	4.9	[12,16,31]
	Conversion efficiency (%)[a]	66.8	70.9	72.3	[12,16,31]
	Cold start-up time (ramp up)	2 h	1 h[b]	<1 min[c]	[10]
	Hot start-up time	3 min	<1 min[b]	<1 min[b]	[10]
	Operation pressure (bar)	15	40	100	[32]
PEMEL	Electricity consumption (kWh/m^3 H_2)[a]	4.9	4.6	4.4	[12,16,31]
	Conversion efficiency (%)[a]	72.3	77.0	80.5	[12,16,31]
	Cold start-up time (ramp up)	7 min	3 min[b]	<1 min[b]	[10]
	Hot start-up time	<10 s	<10 s[b]	<10 s[b]	[10]
	Operation pressure (bar)	20	100	>150	[33]

Note:
[a] Based on higher heating value (HHV) and normal temperature and pressure (NTP) values (20 °C and 101.325 kPa).
[b] Estimated to account for technology development.
[c] Ambitious performance, serves to illustrate effects of improvement on total system performance over time.

Table 2
Power capacity requirement for different operation modes of a H_2 production plant with 1074 kW electrolyser.

Operation mode	Power requirement		Operation condition
	Spot market	Regulated market	
Cold standby	-	7 kW	Electrolyser consumption: 5 kW (0% H_2 production) Safety infrastructure consumption: 2 kW
Bringing into service (ramp up)	1074 kW	2 kW	Electrolyser consumption: 1074 kW (0% H_2 production) Safety infrastructure consumption: 2 kW
Hot standby	-	41 kW	Electrolyser consumption: 39 kW (0% H_2 production) Safety infrastructure consumption: 2 kW
Full load operation	1074 kW	2 kW	Electrolyser consumption: 1074 kW (100% H_2 production) Safety infrastructure consumption: 2 kW

Note:
All values obtained from Ref. [11].

also considers seasonal variations in the SE4 system load, which could potentially influence prices in the spot market as well as the carbon intensity of the electricity used [26]. For this reason, different operating schedules were chosen for winter (12 h/d), spring (18 h/d), summer (24 h/d) and fall (18 h/d) to help decide if the system should operate (electricity load is shown in Appendix 1 Fig. 1A). This way demand for H_2 is always served and there is potential to take advantage of low prices for electricity in the non-winter seasons [35]. Also, it allows seasonal energy storage in case the H_2 production above 12 h/d is injected into salt caverns and/or natural gas grid. The PIO strategy purchases volumes of electricity in each hour of the day at any price pre-defined at the power exchange in the range of −500 to 3000 €/MWh. To assist this decision, electricity prices are modelled and stepwise forecasted in a day-ahead scheme (more information is given in section 2.5). Once prices are forecasted, the average value for the next 24 h is calculated and used as reference for the decision whether the electrolyser is put in operation, cold- or hot standby. As the current model does not allow partial load operation, the same volume is purchased from the spot market regardless of the bidding strategy (i.e. 1074 kWh). The decision trees for PDO, PIO as well as a summary of both bidding strategies are shown in Fig. 2 and Table 3.

2.5. Forecasting of electricity prices

A feedforward multi-layer perceptron neural network (MLP-NN) model was set-up to forecast short-term electricity prices in a day-ahead scheme using a MATLAB toolbox [36]. To better reflect local conditions, the pre-defined input data of historical natural gas prices available in the MATLAB toolbox was substituted by hydropower reservoir data obtained from Nord Pool. Historical values of system load and electricity prices were obtained from the Nord Pool SE4 region and used as input data. Dry bulb temperature and dew point data from a meteorological station, Hörby A (55°N 13°E, 114 m altitude), as well as national holidays in Sweden were also used [37]. These input values (including hour of the day and day of the week) were used by the NN to calculate additional predictors such as working day, system load at the same hour in the previous week, system load at the same hour in the previous day, average system load in the previous 24 h, electricity price at the same hour in the previous week, electricity price at the same hour in the previous day, average electricity price in the previous 24 h, hydropower reservoir in the previous 24 h and average hydropower reservoir in the last week.

To assess the accuracy of the model, the mean absolute percent error (MAPE) between electricity price and forecasted electricity price was calculated according to Eq. (2).

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{2}$$

Where:

A_t is the electricity price (€/MWh);
F_t is the forecasted electricity price (€/MWh).

2.5.1. Adjustment of the neural network

In order to minimize MAPE value, the MLP-NN was trained under supervised learning based on backpropagation (gradient-based learning). Therefore, the number of years used for in-sample data training and out-of-sample testing of the NN was adjusted, as well as the number of neurons in the hidden layer being varied between 10 and 100 (Table 4). It was found that a minimum number of years are necessary for training the NN to reduce error in forecasting varied according to the forecasted year. For example, for

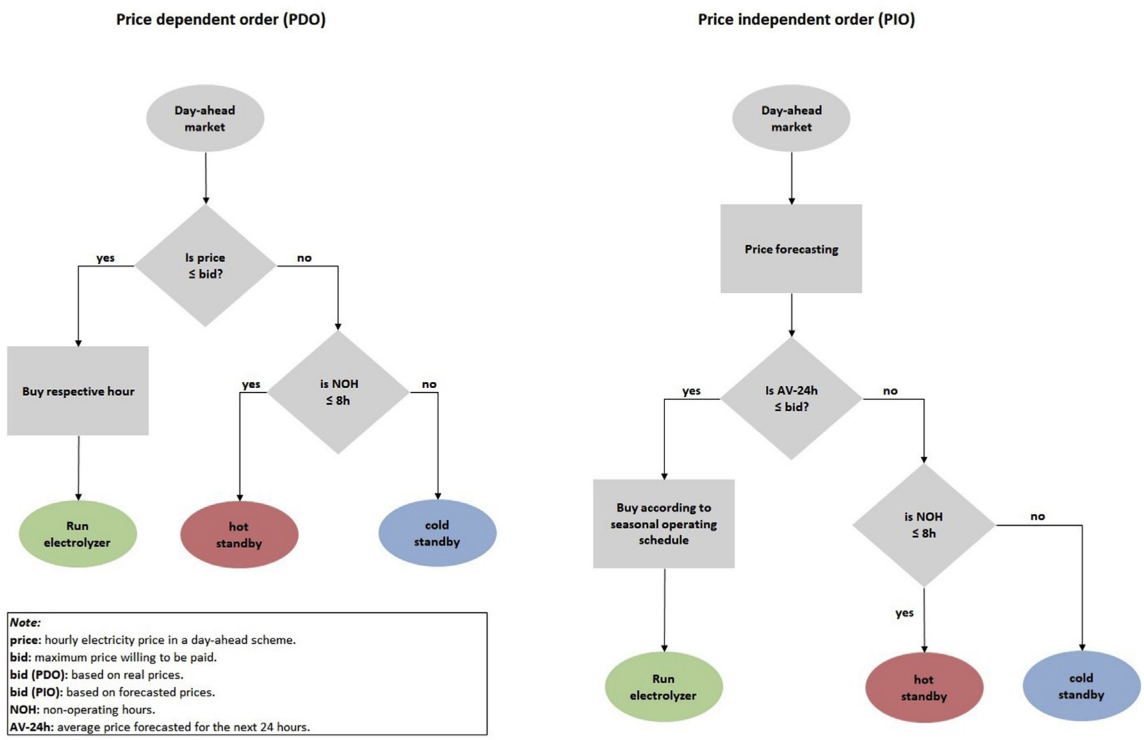

Fig. 2. Decision tree for price dependent order and price independent order bidding strategies.

Table 3
Summary of price dependent order (PDO) and price independent order (PIO).

Aspect	Bidding strategy	
	Price Dependent Order (PDO)	Price Independent Order (PIO)
Bid price	Maximum price willing to be paid is chosen, operates when system marginal price is below this price.	Operates during lowest cost hours of the day in order to supply seasonal demand.
Capacity factor	Dictated by system marginal price. Lower prices, higher operating hours.	Dictated by demand and season. Operate sufficient hours to meet demand.
Suitable business model	Grid injection or other H_2 use whereby storage capacity is not an issue.	Servicing transport and/or local industry. It can be operated to provide seasonal energy storage.

2016, training the NN with 2 previous years showed satisfactory results (MAPE of 9.26%) while increasing the train set to 3 years showed only a minor improvement (MAPE of 9.03%). For 2017, data from at least 3 previous years was needed for a MAPE of 10.64% with minimal improvement seen by increasing the train set to 4 years (MAPE of 10.26%). In general, by increasing the number of neurons from 10 to 100 the MAPE is stepwise increased reducing the accuracy of the forecasting. Overlapping of data making the model unnecessarily complex may explain this. Nevertheless, in an extensive assessment of 27 different forecasting methods, Lago et al. (2018) still found a MAPE of 12.3% in their preferred approach, reinforcing the robustness of the current model with an average MAPE for the test set (2016-2018) of 10.99%.

Even though the trend of decreasing MAPE with increasing number of years in the train set was also found for 2018, the lowest MAPE observed for 2018 was much higher than the others (14.68% with 20 neurons in the hidden layer). This is attributed to the values used for training not describing 2018 as well as they described 2016 and 2017. Nevertheless, simulations were always carried-out by using all available data (prior to the year of testing) for in-sample training as per this assessment. A value of 10 neurons in the hidden layer was used when testing for 2016 and 2017 while in 2018 20 neurons were chosen.

2.6. Optimization of bidding strategies

The PDO bidding strategy was optimized by varying maximum bid prices between 20 and 100 €/MWh, thus identifying bid prices that optimally minimized levelised cost of H_2 ($LCOH_2$) and maximized net cash flow (NCF). As PIO does not require a bid price to place a purchase order, the bid price refers to the maximum price willing to be paid based on forecasted values. Therefore, every time the forecasted average price of the next 24 h is lower than the maximum price willing to be paid (i.e. bid price of PIO), the fixed volume of 1074 kW is placed in each hour of the day up to the seasonal operating schedule. For example, for an operating schedule of 50% of maximum production, an order for the twelve cheapest hours in a 24 h period would be placed. For this reason, the bid price in PIO was also varied between 20 and 100 €/MWh in order to minimize $LCOH_2$ and maximize NCF.

2.7. Economic assessment

To provide a more comprehensive assessment of H_2 production the current study focuses on three main economic indicators, namely NCF, net present value (NPV) and $LCOH_2$. For the relevant assessments, a H_2 selling price for industrial applications of 3.2

Table 4
Mean absolute percent error (MAPE) for different composition of train and test sets as well as number of neurons in the neural network (NN).

Train set	Test set	Number of neurons			
		10	20	50	100
2015	2016	12.15	17.88	22.79	29.39
2014-2015		9.26	11.54	11.06	14.79
2013-2015		**9.03**	9.68	9.75	13.35
2016	2017	13.10	18.00	35.52	42.01
2015-2016		12.32	12.78	13.86	14.68
2014-2016		10.64	10.99	11.87	12.67
2013-2016		**10.26**	10.86	10.99	11.57
2017	2018	17.69	20.62	23.29	33.27
2016-2017		18.37	18.16	22.98	24.09
2015-2017		15.15	20.25	18.25	20.82
2014-2017		16.47	20.38	21.44	25.73
2013-2017		15.27	**14.68**	16.68	17.54

Note:

Values are given in %.

Colour scale indicates whether values falls into low (green), medium (yellow) or high (red) MAPE.

€/kg_{H2} (8.1 c/kWh or 81 c/L of diesel equivalent) is assumed throughout, HHV of H_2 is taken as 39.4 kWh/kg [38].

The NCF is the difference between income and expenditure over a period as per Eq. (3):

$$NCF_y = (H_2 sales + Heat\ sales) - OPEX_y \tag{3}$$

Where:

H_2 sales is the yearly income obtained by selling the produced H_2;
Heat sales is the yearly income obtained by selling the produced waste heat at a price of 25 €/MWh [39];
$OPEX_y$ is the yearly operational expenditures of the PtX system.

The NPV is the difference between the sum of the discounted NCFs and the initial investment. The calculation is described in Eq. (4) below:

$$NPV = -CAPEX + \sum_{y=0}^{n} \frac{NCF_y}{(1+k)^y} \tag{4}$$

Where:

CAPEX is the capital expenditures of the PtX system;
k is the discount rate estimated at 6.5% per year for onshore wind projects in Nordic countries [40];

The $LCOH_2$ is the breakeven selling price of the H_2 produced and is given by Eq. (5) below:

$$LCOH_2 = \frac{\sum_{y=0}^{n} \frac{\text{costs in year y}}{(1+k)^y}}{\sum_{y=0}^{n} \frac{\text{kWh of } H_2 \text{ produced in year y}}{(1+k)^y}} \tag{5}$$

All indicators are calculated in 2018 in euros.

The timeline for relevant calculations includes a 3-year commissioning phase, 30 years of operation (during which the electrolyser is replaced 3 times) and one-year decommissioning. CAPEX and OPEX values of AEL and PEMEL used in this study are shown in Appendix 2 Table 2A. Also, additional costs, such as land purchase, permits, transport, site preparation, engineering and design costs, grid connection as well as contingency were calculated according to Eq. (6). Both $LCOH_2$ and additional costs calculations were previously described in detail [16].

$$Additional\ costs = €18.687(kW_e\ of\ electrolysers) + €200,000 \tag{6}$$

3. Results and discussion

3.1. Data set characterization

The price characteristics of the data set are shown in Fig. 3. During 2013-2018, 65% of the hourly price distribution was found between 20 and 40 €/MWh with an average value of 33.80 €/MWh. Within this period significant differences were found in yearly average prices ($p < 0.01$), except when 2014 and 2017 are compared ($p > 0.01$). Also, important differences in price distribution among the years were found. In 2015 and 2016 the majority of the hourly prices were below 30 €/MWh, the lowest prices in the data set with average values of 22.90 €/MWh and 29.53 €/MWh respectively.

In contrast, 2013 and 2018 presented the highest average prices with average values of 39.93 €/MWh and 46.36 €/MWh respectively. In 2018 particularly unfavourable weather conditions (drought) seem to have influenced the highly hydropower dependent Swedish electricity market as 68% of the hourly price distribution in that year was above 40 €/MWh.

Interestingly, the range of prices (difference between minimum and maximum values), was more pronounced in 2016 (210.23 €/MWh) and 2018 (253.43 €/MWh) in comparison with other years (average of 123.27 €/MWh). This demonstrates that even low-price years like 2016 are subject to high short-term volatility in electricity prices, suggesting that a forecast of such events could be beneficial to manage the operation of electro-intensive processes.

3.2. Results of bid strategy optimization

To minimize $LCOH_2$ and maximize NCF, bid prices were varied from 20 to 100 €/MWh with the PDO bidding strategy. The same procedure was used in PIO, however, in this case the maximum price willing to be paid (i.e. bid price of PIO) was varied. In general, it was found that by increasing bid prices in both bidding strategies, the $LCOH_2$ is reduced to optimal values. This is indicated in Figs. 4 and 5 (coloured symbols). Such behaviour is primarily explained by the increase in the system's run hours resulting in higher H_2 production offsetting CAPEX over the life of the project.

By further increasing bids beyond the optimal price indicated, more expensive electricity is used but the resultant increase in H_2 production costs are negligible, the $LCOH_2$ essentially flattens above these values. Here the increased operational costs (more expensive electricity from the spot market) are offset by increased H_2 produced, and the number of NOH (standby costs) are minimized. In terms of sustainability, the additional electricity consumed (beyond optimal) is also more likely to be carbon-intense and would increase the environmental impact of the H_2. This is true of both PDO and PIO.

Independent of the bidding strategy used, major differences can be observed among the simulated years, in particular in 2018. The higher average electricity prices found in that year led to higher optimal bid prices, markedly increasing H_2 production costs. For the same reason, 2017 presented a slightly higher $LCOH_2$ in comparison to 2016. Interestingly, the lower range of prices observed in 2017 did not result in significant economic advantage (reducing $LCOH_2$ or increasing NCF) which demonstrates the higher importance of average price compared to range of price in determining the economic performance of PtX systems.

In contrast to our hypothesis, the bidding strategy based on electricity price forecasting (PIO) resulted in an average 10.9% higher $LCOH_2$ and 32.6% lower NCF compared to PDO. This could be attributed to the seasonal operating schedule (more often in the summer, and less often in the winter, see section 2.4 and appendix 1) used to control the operation at times of high load in the system (e.g. winter). For the same reason, in all analysed scenarios, PIO always showed a considerably lower NCF than PDO which directly influenced the economic attractiveness of this bidding strategy.

If perfect forecasting is considered, only minor improvements in $LCOH_2$ are found, reductions of 1.3%, 1.6% and 2.2% in $LCOH_2$ in 2016, 2017 and 2018, respectively. This demonstrates that it was indeed the seasonal operating schedule based on system load that was responsible for the reduced performance of PIO, as it limited the operation of the electrolysers to a maximum of around 6500 h per year (capacity factor of 0.75). This number of operational hours is considered sub-optimal to minimize $LCOH_2$ given that optimal bid prices for PDO gave capacity factors between 0.80 and 0.99. These high optimal capacity factors are heavily influenced by the low-cost baseload electricity in Sweden (SE4), and the difference observed between PIO and PDO would likely be much smaller in areas with a more diverse electricity mix and/or higher cost generation.

However, the PIO bidding strategy showed to be an important measure to control costs in years of unexpected high electricity prices and thus, would be generally beneficial in avoiding high cost consumption in higher electricity cost regions as described above. For instance, in 2018 optimal bid prices were considerably higher than in 2016 and 2017 regardless of the bidding strategy. If the operator of an electrolyser using PDO would apply in 2018 the optimal bid prices found in the two previous years, the $LCOH_2$ would be on average 10% higher compared to the true optimal bid prices for 2018. Such situation highlights how challenging the operation of electrolyzers with PDO in real-time is independent of its potential higher economic performance.

In the meantime, if the electrolyser had been operated according to the PIO with a high bid price of 100 €/MWh, the average $LCOH_2$ would be very similar to PDO with optimal bid prices from 2017 to 2018. This fact shows that the seasonal operating schedule used in PIO was useful to control the operation at times of peak load and consequently higher prices.

Furthermore, the NCF revealed a trend of reduction in net revenues towards higher bid prices in 2018 when the PDO bidding strategy is used. This is due to the H_2 production costs approaching the selling price of 3.20 €/kg used for assessment, thus by purchasing more expensive electricity, the cash flow is reduced. In contrast, such behaviour was not observed in PIO due to the seasonal operating schedule that limited the purchase of expensive electricity even with high bid prices.

3.3. Energy consumption during idle time

This section presents an assessment of the energy consumption during NOH and time to bring the system into service from cold standby mode (Fig. 6).

3.3.1. Price dependent order (PDO) versus Price independent order (PIO)

For PDO, the optimal bid price tended to decrease as electrolysis improved over time (fewer run hours required), therefore the number of NOH tended to increase. Thus, the more developed the technology, the greater the NOH observed for PDO. However, energy consumption during NOH did not necessarily increase because the ramp up time from cold standby considerably decreased over time (Table 1).

In contrast to PDO (capacity factors of 0.80–0.99), optimal bid prices in PIO resulted in capacity factors of between 0.71 and 0.75 (limited by our seasonal capacity factor constraints e.g. 12 h/day in winter aimed at reducing unsustainable oversupply of H_2). For this reason, the number of NOH in PIO were always higher than those in PDO, and did not vary greatly within the simulated cases (from 2181 to 2540 h/year). Consequently, the energy consumption of PIO during idle time was on average 6 times higher than for PDO. Here the characteristics of the market in which the PtX system operates become very important. On the one hand, higher energy consumption results in higher OPEX for PIO which affects the profitability of this bidding strategy. On the other hand, a lower capacity factor would suggest that less expensive hours would be purchased reducing the average price paid for the electricity derived from the

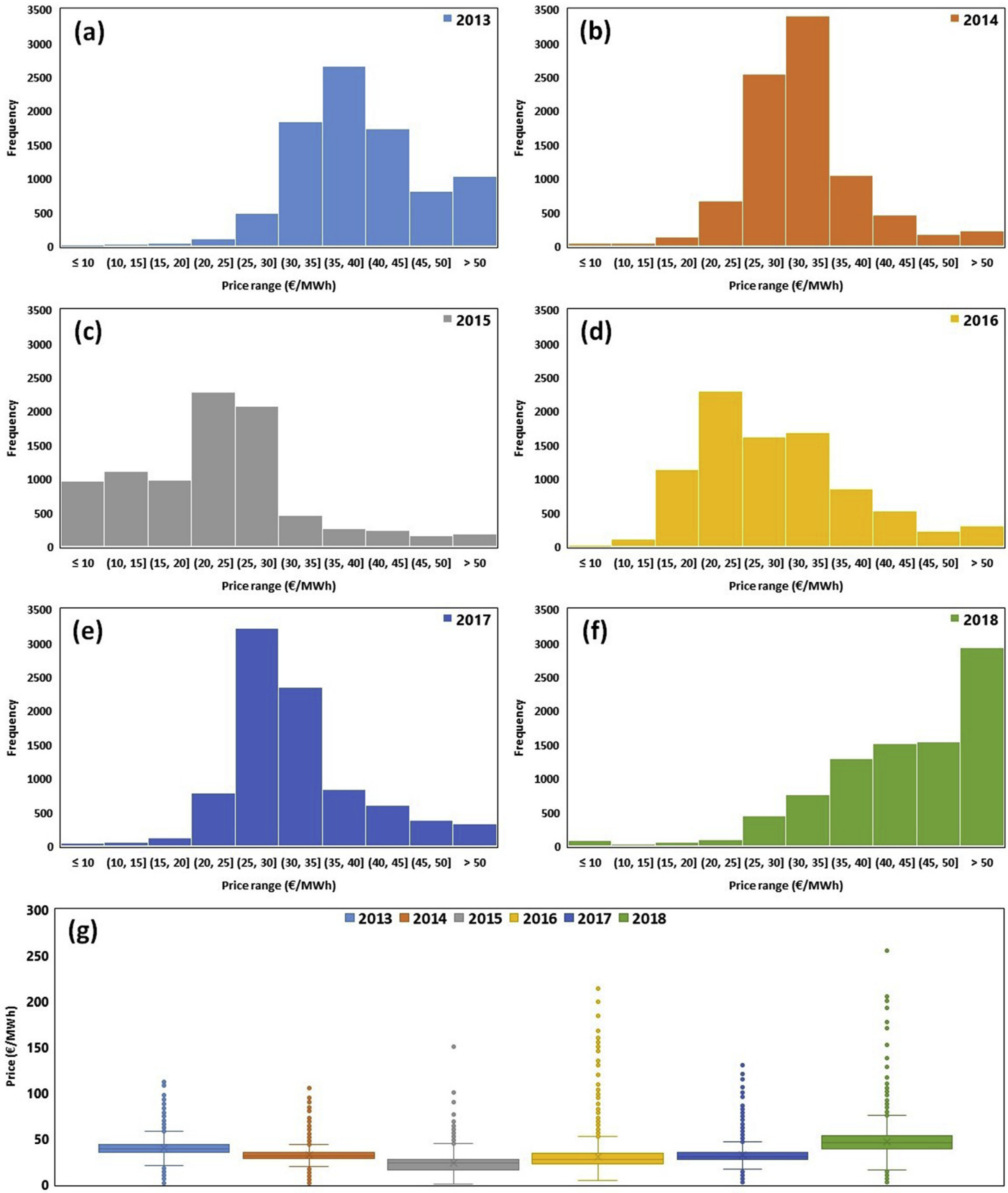

Fig. 3. Price characteristics of the data set (Nord Pool SE4). (a) price distribution in 2013; (b) price distribution in 2014; (c) price distribution in 2015; (d) price distribution in 2016; (e) price distribution in 2017; (f) price distribution in 2018 and (g) box blot of data set.

spot market.

3.3.2. Alkaline electrolysis (AEL) versus Proton exchange membrane electrolysis (PEMEL)

For both AEL and PEMEL a general reduction in energy consumption over their development was observed. The technologies markedly reduce their energy consumption during NOH by an average of 65–70% by 2040, due mostly to faster ramp up times from cold standby to service [12]. However, as AEL is a more mature technology, and is therefore less susceptible to innovation, PEMEL

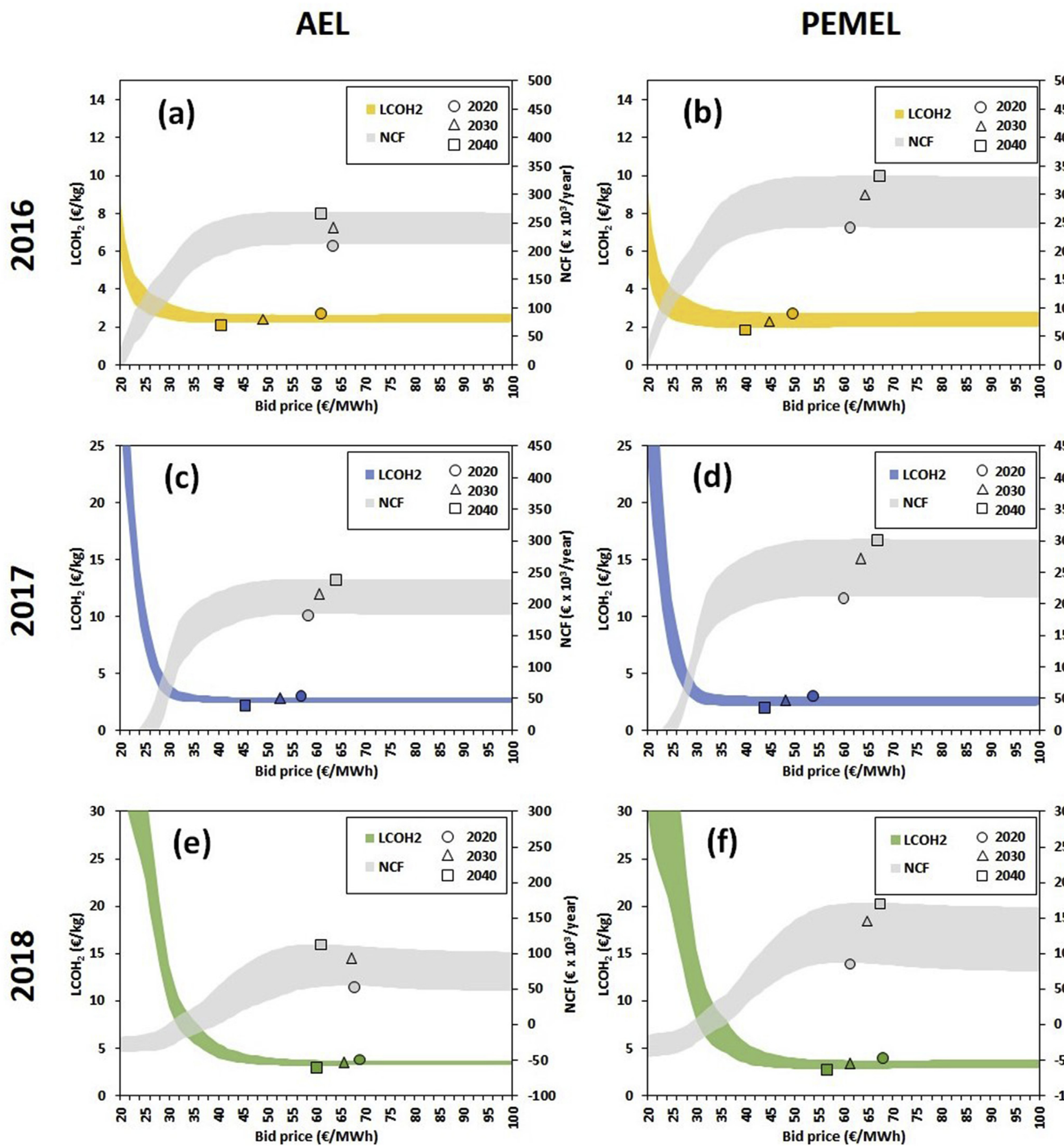

Fig. 4. Bid price variation on levelised cost of H_2 ($LCOH_2$ - left y axis) and net cash flow (NCF - right y axis) for bidding strategy based on price dependent order (PDO). (a) Alkaline electrolyser (AEL) in 2016; (b) proton exchange membrane electrolyser (PEMEL) in 2016; (c) AEL in 2017; (d) PEMEL in 2017; (e) AEL in 2018 and (f) PEMEL in 2018.
Note:
Symbols indicate the optimal bid price to minimize $LCOH_2$ (coloured sections) and maximize NCF (grey sections) where (○) 2020 scenario; (△) 2030 scenario and (□) 2040 scenario.

showed greater improvements within the technological scenarios assessed in terms of reducing H_2 production costs. The differences between AEL and PEMEL are largely explained by: (a) in future scenarios H_2 production is cheaper meaning it can operate for fewer hours (to pay back investment) which increases the NOH (both cold and hot) of the system for both technologies; and (b) PEMEL does not require power on hot standby and ramps up faster than AEL [10,12].

Furthermore, PEMEL continually reduces its energy consumption over time, in fact thanks to the flexibility of PEMEL in shifting from standby into service, an average of 55% lower energy consumption during NOH was observed in all simulated years and technological scenarios compared to AEL. Whereas in some cases AEL performance actually declines, illustrated by 2017 data operated with PDO where the energy consumption during NOH of AEL actually increased with technological development because it

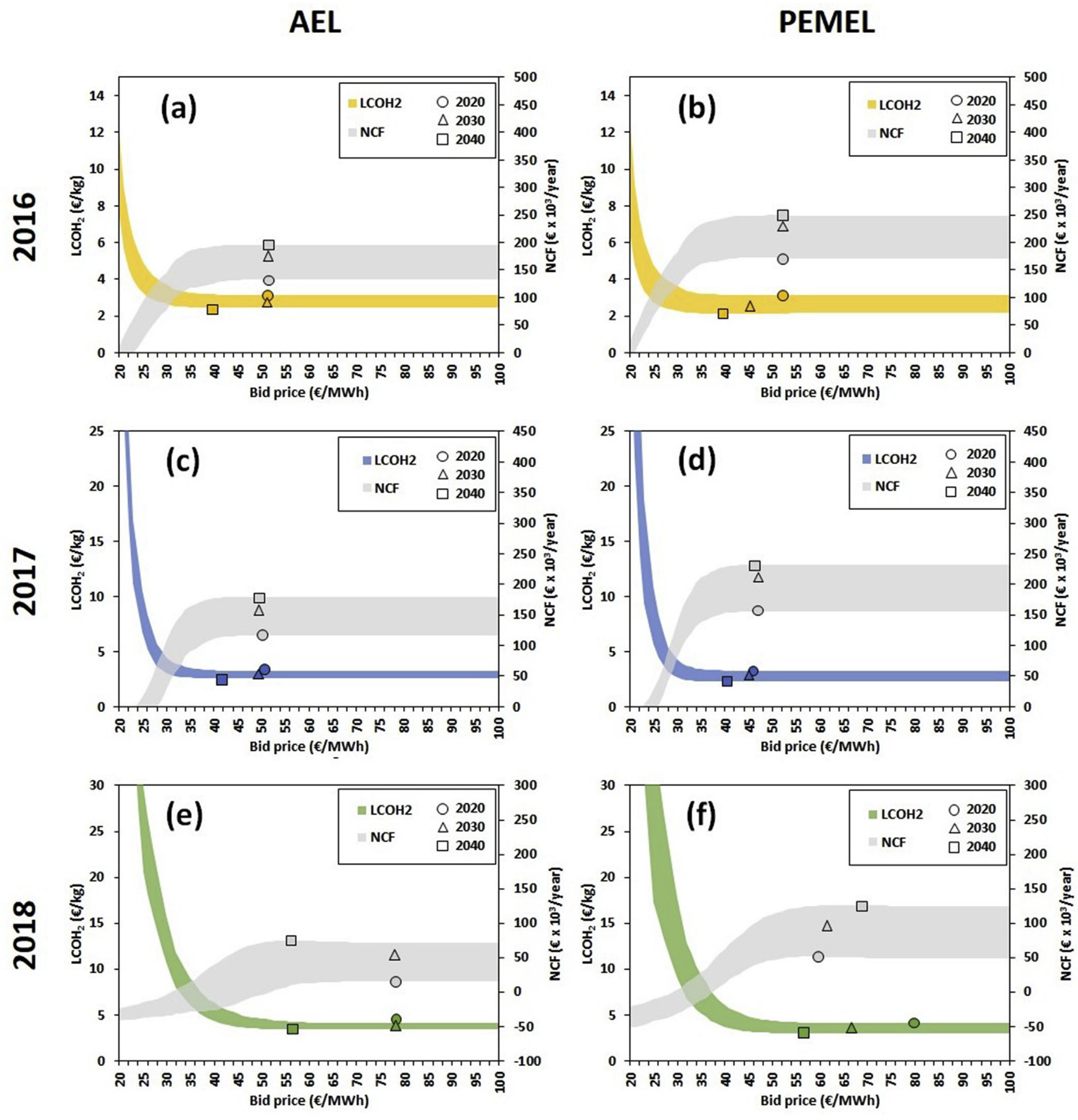

Fig. 5. Bid price variation on levelised cost of H_2 ($LCOH_2$ - left y axis) and net cash flow (NCF - right y axis) for bidding strategy based on price independent order (PIO). (a) Alkaline electrolyser (AEL) in 2016; (b) proton exchange membrane electrolyser (PEMEL) in 2016; (c) AEL in 2017; (d) PEMEL in 2017; (e) AEL in 2018 and (f) PEMEL in 2018.
Note:
Symbols indicate the optimal bid price to minimize $LCOH_2$ (coloured sections) and maximize NCF (grey sections) where (○) 2020 scenario; (△) 2030 scenario and (□) 2040 scenario.

enters in hot standby more often.

3.4. Economic performance

This section presents an assessment of the economic performance, in terms of NCF, NPV and $LCOH_2$, according to optimal bid prices (lowest $LCOH_2$) described in section 3.2.

3.4.1. Price dependent order (PDO) versus Price independent order (PIO)

The economic performance of PDO is shown in Table 5. In general, the more advanced the technology, the lower the optimal bid price, resulting in a higher number of NOH. For this reason, the average price paid for electricity is reduced up to 6.4% towards 2040. Thus, more developed electrolysers are able to reduce production costs by purchasing less expensive electricity.

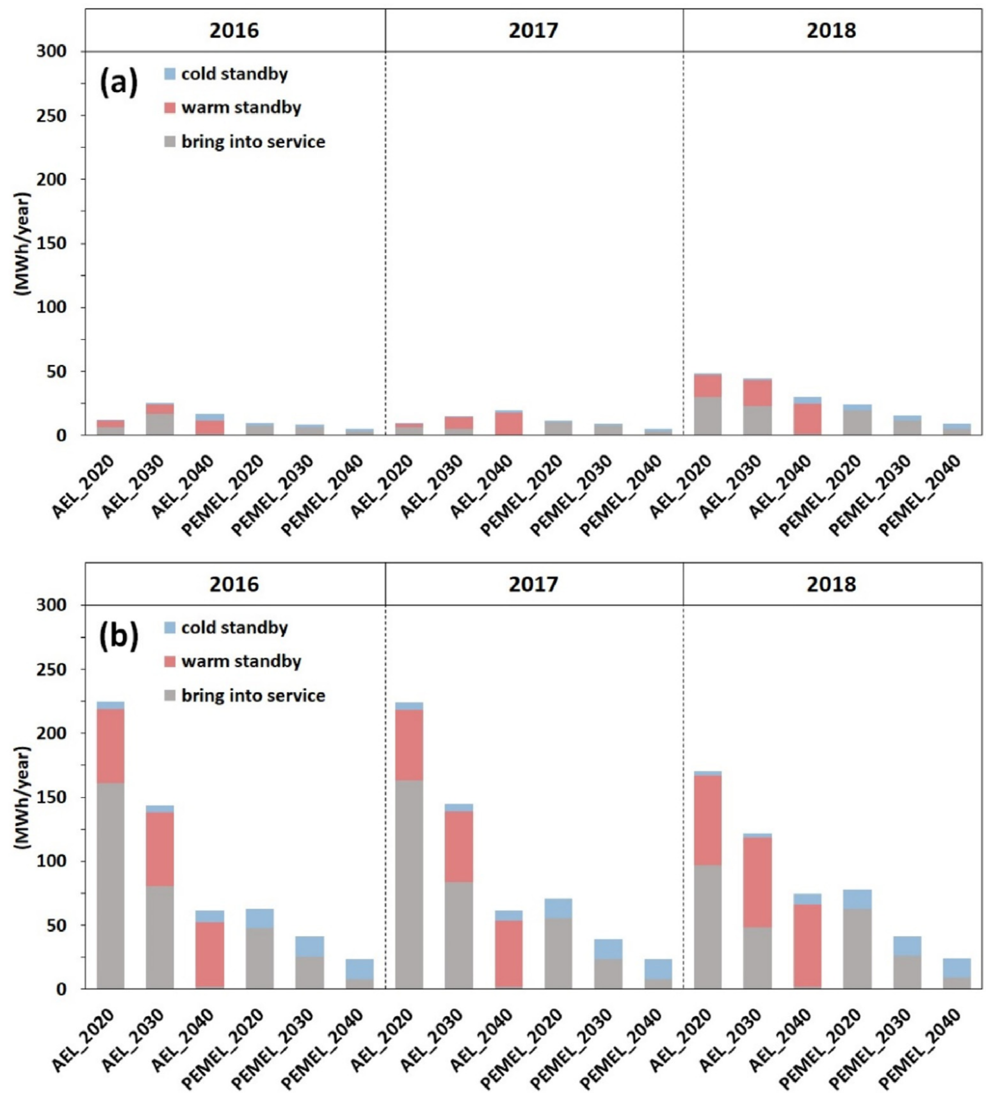

Fig. 6. Energy consumption during idle time for (a) price dependent order (PDO) and (b) price independent order (PIO) for optimal bid prices used to minimize $LCOH_2$.

The economic performance of PIO is shown in Table 6. As the seasonal operating schedule used to control operation at peak loads limited the number of run hours in this bidding strategy, the number of NOH were always higher than in PDO, resulting in more expenses during idle time. However, those NOH and their respective energy consumption to bring the system into service corresponded to less than 6% of the total expenses with electricity purchase during H_2 production. This fact demonstrates that the higher flexibility of PEMEL only provides marginal economic benefits to the process, at least when the price characteristics of the current bidding region is simulated, and when there are no payments available for quick response demand side management.

Furthermore, as approximately 10% of electricity used becomes available as waste heat at 60 °C, sales for district heating at a fixed price of 25 €/MWh can represent an additional income to reduce H_2 production costs [11,39]. For instance, without selling waste heat the $LCOH_2$ would increase up to 4.2% in 2018 depending on the different water electrolysis technologies and technological scenarios. This additional income would be of a great help especially in years of $LCOH_2$ close to the selling price of H_2.

As discussed in section 3.2, PDO showed an average of 10.9% lower H_2 production costs than PIO. However, by analysing the production costs in detail, it is possible to observe a higher difference of 17.6% when AEL is simulated in a year with relatively low electricity prices like 2016 and earlier stage of technological development (2020). In contrast, the advantage of PDO over PIO is reduced to 7.8% when PEMEL is simulated in 2018 in a more developed technological scenario (2040). The reason for that is, in expensive years, with a more developed technology H_2 production costs are minimized by controlling the number of operating hours, resulting in an optimal capacity factor of 0.80, which is closer to the maximum value of 0.75 from PIO.

By performing a sensitivity analysis on $PtCH_4$ production, a previous study demonstrated that the price paid for electricity and the capacity factor of the system are most sensitive parameters to be considered and influence inversely the levelised costs of electrofuels [16]. Even though our results showed that the capacity factor tends to decrease in future technological scenarios, the $LCOH_2$ is minimized in the meantime since higher efficiency and lower CAPEX of the systems as well as the lower price paid for electricity compensates such lower number of running hours.

Moreover, if the seasonal operating schedule used in PIO would be optimized in order to reduce $LCOH_2$, it is likely that differences between PDO and PIO would be further decreased. However, a detailed analysis on the carbon intensity of the produced H_2 would be required in case the electrolysers are excessively operated

Table 5
Results of price dependent order (PDO) in terms of plant and economic performance for optimal bid prices (minimize $LCOH_2$).

Parameters	Units	2016						2017						2018					
		AEL			PEMEL			AEL			PEMEL			AEL			PEMEL		
		2020	2030	2040	2020	2030	2040	2020	2030	2040	2020	2030	2040	2020	2030	2040	2020	2030	2040
Total hours	h/year	8784	8784	8784	8784	8784	8784	8760	8760	8760	8760	8760	8760	8760	8760	8760	8760	8760	8760
Operating hours	h/year	8631	8414	7834	8478	8145	7596	8694	8485	8043	8529	8218	7833	8195	8004	7431	8131	7627	6988
Non-operating hours	h/year	153	370	950	306	639	1188	66	275	717	231	542	927	565	756	1329	629	1133	1772
Cold standby	h/year	25	198	683	176	358	864	3	55	299	47	213	457	143	258	756	175	591	1088
Hot standby	h/year	128	172	267	130	281	324	63	220	418	184	329	470	422	498	573	454	542	684
Capacity factor	-	0.98	0.96	0.89	0.97	0.93	0.86	0.99	0.97	0.92	0.97	0.94	0.89	0.94	0.91	0.85	0.93	0.87	0.80
Optimal bid price	€/MWh	60.00	48.00	41.00	50.00	44.00	39.00	56.00	51.00	45.00	53.00	47.00	43.00	68.00	65.00	58.00	67.00	60.00	53.00
Total price paid	€	2.5E+05	2.3E+05	2.1E+05	2.4E+05	2.2E+05	2.0E+05	2.7E+05	2.6E+05	2.4E+05	2.7E+05	2.5E+05	2.3E+05	3.6E+05	3.5E+05	3.1E+05	3.6E+05	3.2E+05	2.9E+05
Average price paid	€/MWh	28.49	27.86	26.66	28.01	27.27	26.24	31.44	31.19	30.29	31.30	30.62	29.92	44.05	43.52	42.15	43.87	42.58	41.25
NOH cost	€/year	7.3E+02	1.3E+03	1.6E+03	4.4E+02	3.9E+02	2.9E+02	4.6E+02	1.1E+03	1.9E+03	4.8E+02	4.0E+02	2.6E+02	3.2E+03	3.2E+03	2.9E+03	1.3E+03	9.3E+02	6.4E+02
CAPEX	€	2.0E+06	1.8E+06	1.6E+06	2.8E+06	2.1E+06	1.6E+06	2.0E+06	1.8E+06	1.6E+06	2.8E+06	1.8E+06	1.6E+06	2.0E+06	1.8E+06	1.6E+06	2.8E+06	2.1E+06	1.6E+06
NCF	€/year	2.1E+05	2.5E+05	2.6E+05	2.4E+05	2.9E+05	3.1E+05	2.8E+00	2.2E+05	2.3E+05	2.9E+00	2.6E+05	2.9E+05	5.5E+04	9.5E+04	1.1E+05	8.5E+04	1.4E+05	1.6E+05
NPV	€	1.1E+06	1.8E+06	2.0E+06	9.6E+05	2.1E+06	2.7E+06	7.4E+05	1.4E+06	1.7E+06	5.8E+05	1.8E+06	2.4E+06	−9.2E+05	−2.5E+05	1.2E+05	−1.1E+06	1.6E+05	8.6E+05
$LCOH_2$	€/kg H_2	2.65	2.37	2.21	2.76	2.25	1.94	2.83	2.54	2.40	2.94	2.42	2.11	3.67	3.33	3.14	3.71	3.13	2.77

Table 6
Results of price independent order (PIO) in terms of plant and economic performance for optimal bid prices (minimize $LCOH_2$).

Parameters	Units	2016						2017						2018					
		AEL			PEMEL			AEL			PEMEL			AEL			PEMEL		
		2020	2030	2040	2020	2030	2040	2020	2030	2040	2020	2030	2040	2020	2030	2040	2020	2030	2040
Total hours	h/year	8784	8784	8784	8784	8784	8784	8760	8760	8760	8760	8760	8760	8760	8760	8760	8760	8760	8760
Operating hours	h/year	6569	6572	6244	6569	6494	6244	6579	6552	6416	6552	6523	6416	6574	6574	6574	6574	6574	6574
Non-operating hours	h/year	2215	2212	2540	2222	2222	2540	2181	2208	2344	2208	2237	2344	2186	2186	2186	2186	2186	2186
Cold standby	h/year	806	807	1302	822	822	1302	834	867	1071	867	902	1071	467	467	467	467	467	467
Hot standby	h/year	1409	1405	1238	1400	1400	1238	1347	1341	1273	1341	1335	1273	1719	1719	1719	1719	1719	1719
Capacity factor	-	0.75	0.75	0.71	0.75	0.75	0.71	0.75	0.75	0.73	0.75	0.74	0.73	0.75	0.75	0.75	0.75	0.75	0.75
Optimal bid price	€/MWh	52.00	52.00	39.00	52.00	45.00	39.00	48.00	47.00	41.00	47.00	45.00	41.00	78.00	78.00	57.00	78.00	64.00	57.00
Total price paid	€	1.8E+05	1.8E+05	1.7E+05	1.8E+05	1.8E+05	1.7E+05	2.0E+05	2.0E+05	1.9E+05	2.0E+05	2.0E+05	1.9E+05	3.0E+05	3.0E+05	2.6E+05	3.0E+05	2.8E+05	2.6E+05
Average price paid	€/MWh	28.13	28.13	27.15	28.13	27.82	27.15	30.49	30.34	29.95	30.34	30.25	29.95	45.06	45.06	43.06	45.06	44.43	43.06
NOH cost	€/year	1.1E+04	8.6E+03	6.0E+03	3.2E+03	2.3E+03	1.8E+03	1.1E+04	8.6E+03	6.0E+03	3.1E+03	2.2E+03	1.8E+03	1.0E+04	8.8E+03	7.4E+03	3.3E+03	2.3E+03	1.8E+03
CAPEX	€	1.9E+06	1.7E+06	1.5E+06	2.7E+06	2.0E+06	1.5E+06	1.9E+06	1.7E+06	1.5E+06	2.7E+06	2.0E+05	1.5E+06	1.9E+06	1.7E+06	1.5E+06	2.7E+06	2.0E+06	1.5E+06
NCF	€/year	1.3E+05	1.8E+05	1.9E+05	1.7E+05	2.2E+05	2.4E+05	1.2E+05	1.6E+05	1.8E+05	1.6E+05	2.0E+05	2.3E+05	1.5E+04	5.3E+04	7.5E+04	4.9E+04	9.7E+04	1.2E+05
NPV	€	1.3E+05	8.2E+05	1.2E+06	1.2E+05	1.2E+06	1.9E+06	−9.0E+04	6.0E+05	1.0E+06	−1.0E+05	1.0E+06	1.7E+06	−1.4E+06	−7.7E+05	−3.4E+05	−1.5E+06	−3.5E+05	3.7E+05
$LCOH_2$	€/kg H_2	3.11	2.70	2.46	3.13	2.50	2.13	3.26	2.84	2.59	3.26	2.62	2.25	4.10	3.66	3.42	4.09	3.40	2.98

during peak loads with associated high carbon emissions.

3.4.2. Alkaline electrolysis (AEL) versus Proton exchange membrane electrolysis (PEMEL)

Large variations in $LCOH_2$ and NPV were noted depending on what year of electricity data was used, but the following insights apply in general. The increasing number of NOH as technology developed did not have a significant effect on system economics. In PEMEL, quicker ramps times offset increased NOH standby costs. And for AEL, where NOH costs may indeed increase (energy-intensive ramp up and hot standby) they corresponded to less than 1.5% of the total electricity purchase cost during H_2 production, with minimal effect on economic performance.

In the 2020 scenario AEL (cheaper but less efficient) resulted in a marginally lower $LCOH_2$ compared to PEMEL (more efficient and more expensive) in all simulated years, but AEL NPV was approximately twice that of PEMEL due to its lower investment cost. Therefore, AEL is a better technology choice pre-2020. Thanks to technological improvements leading to higher flexibility and efficiency, future bid prices can be decreased (to minimize $LCOH_2$), resulting in lower electricity purchase cost for both AEL and PEMEL. In particular, innovations such as thinner membranes, reduction in titanium use and improved electrode coating, will result in lower CAPEX and higher efficiency for PEMEL [12]. In 2030, AEL is modelled with half the ramp up time, allowing the operation to be more flexible to harvest less expensive electricity, resulting in lower average price paid. However, by 2030 PEMEL will outcompete AEL in all economic indicators with around 7.5% lower H_2 production costs. In fact, by examining values of $LCOH_2$ and NPV for 2020 and 2030, it was possible to infer that between 2021 and 2025 PEMEL would give lower H_2 production costs in all scenarios (see appendix 3 Fig. 3A and Fig. 3B). Therefore, PEMEL is clearly a better technology choice after 2025, possibly as early as 2021.

Further improvements between 2030 and 2040 serve to increase system profitability (NPV) thanks to reductions in CAPEX, in particular for PEMEL technology [12,16,31]. Shorter ramp up times mean PtX systems operate more flexibly, allowing for lower bid prices with 2040 electricity cost on average 5% lower than in 2030. In combination with lower CAPEX and higher efficiencies, H_2 production costs could be reduced on average 6% for AEL and 13% for PEMEL from 2030 to 2040. PEMEL remains the better choice in 2040 as its CAPEX will be similar to AEL, with better technical performance resulting in 12% lower H_2 production costs than AEL.

3.5. Applications of PIO or PDO

The ability of electrolysers to ramp-up/down to enable higher shares of VRE has been discussed in literature as a key reason to integrate PtX into electricity systems [10,25,27,41]. Due to the higher capacity factor of PDO compared to PIO, PDO aids balancing the grid to a lesser extent, consuming electricity at times of high demand. Though the benefits in terms of balancing the grid are largely dependent on the regional electricity mix, PIO is more likely to consume lower carbon and more difficult to manage energy than PDO [26].

A PIO bidding strategy though would be more useful for practical applications when the goal is to meet specific requirements of a consumer (i.e. production on demand). In this case, no matter what the electricity prices at the spot market would be, the producer would be bound to a contract securing the delivery of a certain amount of H_2, otherwise penalties for not delivering could apply. Even though with a PDO bidding strategy potential lower $LCOH_2$ could be achieved, it would be more difficult to control the carbon intensity of the H_2 produced, to operate the electrolyzer in real-time and to meet specific requirements of the demand. The latter could negatively influence the economics of the process since the PtX system would eventually need a larger storage capacity, which in turn would increase CAPEX reducing the competitiveness of PDO over PIO. Optimization of this strategy (including the seasonal operating schedule) may be the subject of future work.

To demonstrate how PIO could be used in a practical case study, the seasonal operating schedule used previously were kept while the bid price was set up to the maximum allowed at Nord Pool (3000 €/MWh). Under such conditions the model was ran for AEL with electricity market data of 2018 in the 2020 technological scenario (Fig. 7). When the maximum price willing to be paid reaches that level, it is the seasonal operating schedule that essentially control the number of hours per day purchased in PIO. Thus, at times of high load in the system (e.g. winter), this bidding strategy limits H_2 production to the demand of a potential consumer (in this case equivalent to 12 h of production per day). When the load in the system is reduced, additional hours per day of H_2 production are allowed (e.g. 18 h in spring/fall and 24 h in summer) and it is sold on the spot market (e.g. natural gas grid injection) [42,43]. This strategy controls H_2 production at peak loads to assist grid balance as well as the carbon intensity of the produced H_2. In addition, by producing H_2 not only to fulfil the captive demand (equivalent to 12 h/day) but also on a seasonal basis (when the load in the system is lower), the number of run hours of the plant increases, resulting in a better economic performance of the PtX system as previously discussed.

Furthermore, the dynamics of electrolyser operation confirmed that the bidding strategy worked well in avoiding the purchase of expensive electricity as highlighted in March and May (dotted area). However, possibilities for optimization were also found. For instance, in January the load in the system is as high as in December but the average prices were markedly different, suggesting that from the economic point of view the electrolyser could have been operated more than 12h/day in January. This difference is explained by the severe drought which occurred throughout 2018 and affected the highly hydropower dependent Swedish electrical market. In fact, hydropower reserves were found to be 16% lower between August and October in comparison to the average of the previous 3 years at the same period [35]. Thus, this also led to average electricity prices in fall to be higher than spring.

3.6. Effect of strategies on the carbon intensity of the H_2 produced

In advance of fully renewable electricity grids the carbon intensity of the electricity consumed and hence, the H_2 produced depends on many factors. Although it is not explicitly modelled or calculated in this work, previous studies have addressed this question and their insights can be applied to the results here. For instance, McDonagh et al. (2018) used a “Bid price method” to control the carbon intensity and cost of H_2 produced from grid electricity, similar to what is examined in the present study. They found that by avoiding consuming electricity during high system marginal price, it significantly reduced the carbon intensity of the H_2 produced and that higher capacity factors were associated with greater carbon intensity. This effect was said to increase with increasing shares of VRE. The results of the present study show that PIO best avoided consuming high cost electricity which is often associated in many energy systems with fossil fuel fired plants used to balance the grid [44]. In Sweden, where grid balance is primarily provided by hydropower production, such benefits of PIO strategy may also occur, however, due to a different reason. In this case, cogeneration plants based on fossil fuel are more often operated during colder months to provide district heating as well as electricity, increasing carbon intensity of the electricity grid in winter time. Thus, the PIO strategy with seasonal operational schedule

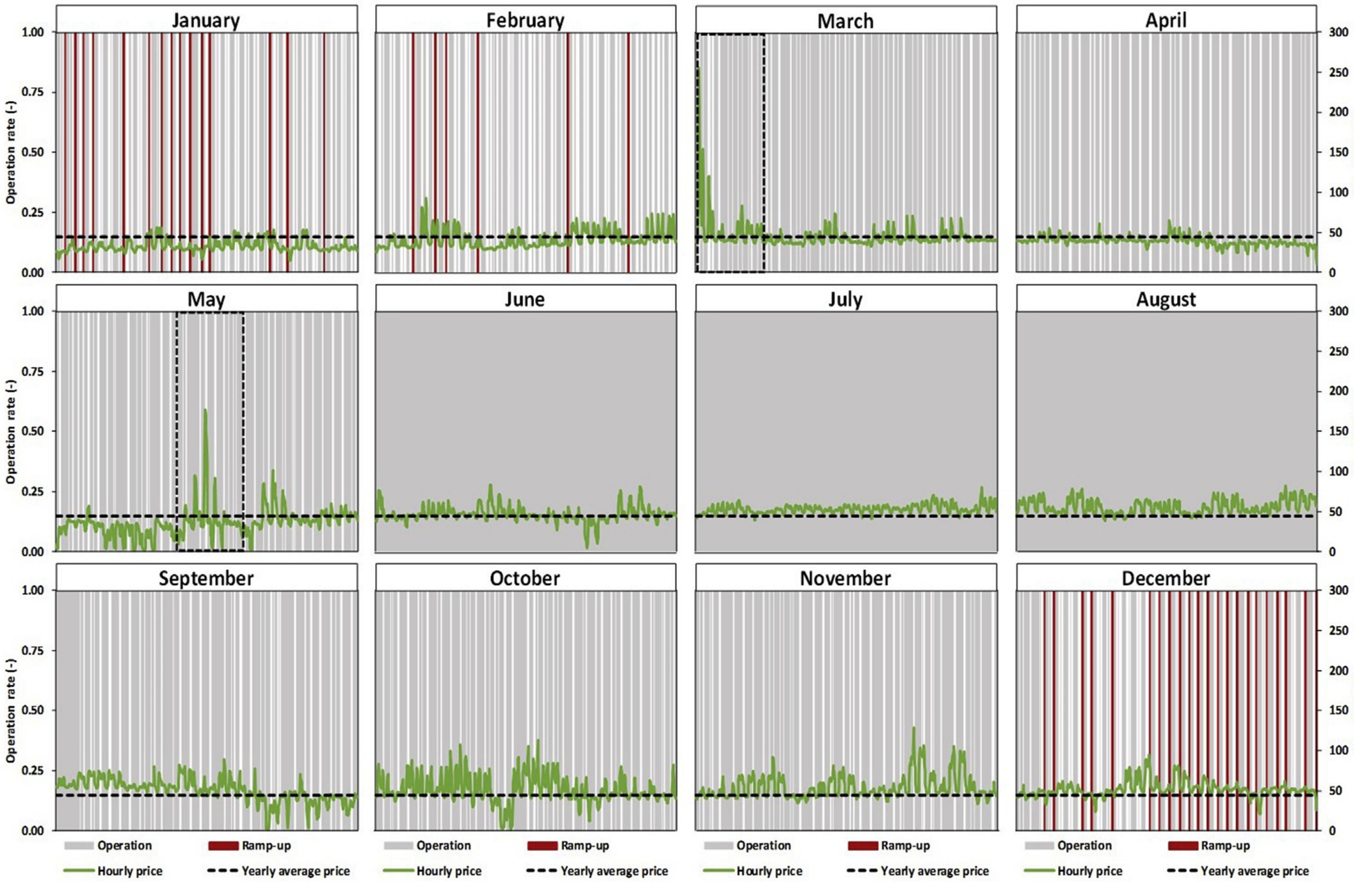

Fig. 7. Dynamics of alkaline electrolyser (AEL) operation with price independent order (PIO) simulated in 2018 for 2020 technological scenario.
Note:
The bid price was set-up in 3000 €/MWh to guarantee a minimum of 12 h of H_2 production per day.

used in the present study would likely to result in H_2 production with less carbon emissions associated compared to PDO. Furthermore, the lower capacity factor of PIO compared to PDO also demonstrates that PIO does not contribute to demand during times of low VRE production to the same extent as PDO, exemplified by the 2018 drought conditions tested. PIO also focused on producing according to demand and thus, was less likely to overconsume electricity as proposed in PDO. In electricity systems where peak demand is also provided by renewables this point becomes less important for carbon intensity but is still significant in terms of operating as efficient a system as possible.

The energy penalty for cold/warm start was six times higher for PIO than PDO but is still relatively insignificant as a share of total consumption. This energy penalty is set to decrease substantially over time too, especially in the event that PEM becomes the dominant technology and as such does not dictate the choice between PDO and PIO. Therefore, the choice between PDO and PIO is a complex mix of economic and environmental sustainability, and largely depends on the electricity generation mix.

3.7. Summary for policymakers

H_2 is a flexible energy carrier and/or valuable chemical that can displace fossil fuels. In terms of mitigation of carbon emissions, it is desirable that it is developed, however, policymakers should take care not to create perverse incentives when looking to support its use. The results within demonstrate that there may be a conflict in operating electrolysers to minimize $LCOH_2$ while maintaining positive environmental benefits and improving electrical grid management (Section 3.6). The authors suggest that when incentives are being designed, priority should be given to H_2 production facilities that support the integration of VRE by turning on and off to help balance the grid, perhaps through a capacity payment similar to those seen for flexible electricity generation [45]. Otherwise any incentive should be capped to avoid running electrolysers at capacity factors that will mean fossil fuel derived electricity must be consumed. Exploration of such incentive structures will form part of our future research.

4. Conclusion

This study showed that the hourly electricity prices can significantly vary within different years in Sweden, greatly affecting the profitability of H_2 production in power-to-X systems. In order to control costs with electricity purchase from the spot market, two bidding strategies applicable to a day-ahead scheme were developed for comparison (i.e. with and without price forecasting). By forecasting prices, the purchase of high cost electricity was avoided, but it could not improve the economic performance compared to the bidding strategy based on a fixed bid price. This was due to the fact that with price forecasting the purchase was limited at times of high load in the system which in turn resulted in a lesser number of run hours. Regardless of its limitations to provide higher profitability, the bidding strategy based on price forecasting adapted well to years with unexpected variations in spot prices. Also, this bidding strategy was demonstrated in a practical case study to meet the delivery requirements of a captive consumer while controlling the carbon intensity of the H_2 produced.

By investigating the dynamics of electrolyser operation with real electricity market data we found that the energy consumption during idle time, i.e. cold/hot standby mode and to bring the system into service, did not greatly affect the economic performance of PtX systems. Thus, this reinforcing the price paid for the electricity and the number of run hours as the main aspects influencing the economics of PtX systems.

Analyses of net present value and levelised cost of H_2 showed that proton exchange membrane electrolysis will outcompete alkaline electrolysis no later than 2025, possibly as early as 2021, no matter the bidding strategy used.

Declaration of Competing Interest

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

CRediT authorship contribution statement

Leandro Janke: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Shane McDonagh:** Conceptualization, Methodology, Software, Validation, Investigation, Writing - original draft, Writing - review & editing. **Sören Weinrich:** Methodology, Software, Validation, Writing - review & editing. **Jerry Murphy:** Validation, Writing - review & editing. **Daniel Nilsson:** Conceptualization. **Per-Anders Hansson:** Conceptualization. **Åke Nordberg:** Conceptualization, Writing - review & editing, Supervision.

Appendix 1. System load profile used to set-up the seasonal operating schedule of PIO

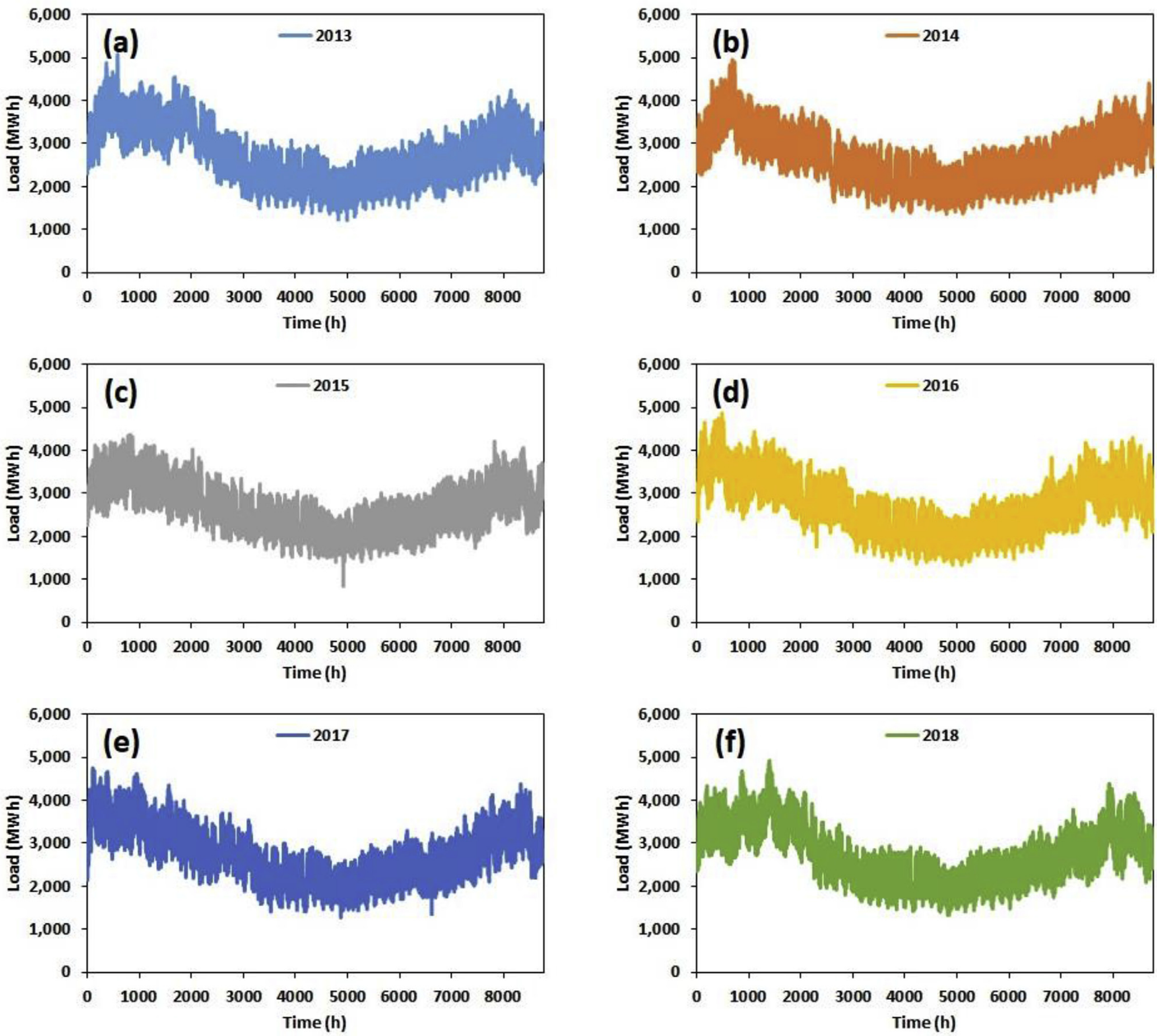

Fig. 1A. Electricity load profile of the data set (Nord Pool SE4). (a) load in 2013; (b) load in 2014; (c) load in 2015; (d) load in 2016; (e) load in 2017 and (f) load in 2018.

Appendix 2. Costs of AEL and PEMEL over time

Table 2A
Capital expenditures (CAPEX), balance of the plant (BoP) and operational expenditures (OPEX) for different technological scenarios.

Costs based on different technologies		2020	2030	2040
AEL	CAPEX (€/kW$_{el}$)	830	730	640
	BoP	0.2	0.2	0.2
	OPEX	0.04	0.032	0.03
	Replacement	0.3	0.3	0.3
PEMEL	CAPEX (€/kW$_{el}$)	1130	800	570
	BoP	0.15	0.15	0.15
	OPEX	0.04	0.032	0.03
	Replacement	0.4	0.4	0.4

Note:
CAPEX includes compression at 500 bar.
All values obtained from Ref. [12,16,31].

Appendix 3. $LCOH_2$ of AEL and PEMEL over time

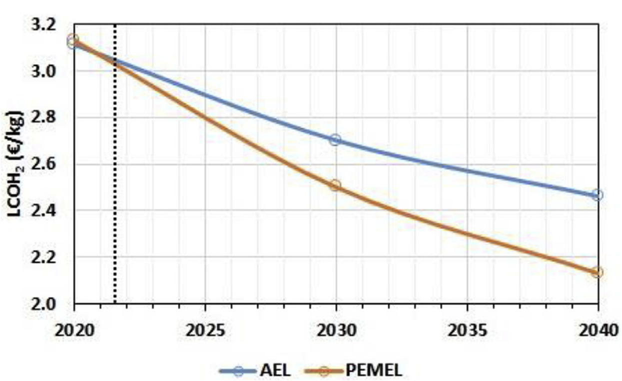

Fig. 3A. Change in $LCOH_2$ for AEL and PEMEL between 2020 and 2040 for PIO using 2016 electricity market data. Dashed line indicates point at which line cross.

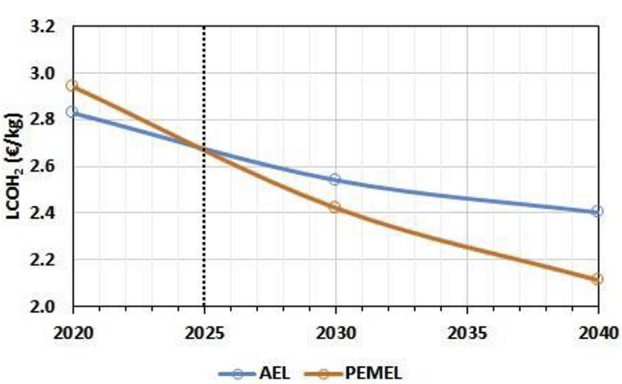

Fig. 3B. Change in $LCOH_2$ for AEL and PEMEL between 2020 and 2040 for PDO using 2017 electricity market data. Dashed line indicates point at which lines cross.

References

[1] L. Bird, D. Lew, M. Milligan, E.M. Carlini, A. Estanqueiro, D. Flynn, E. Gomez-Lazaro, H. Holttinen, N. Menemenlis, A. Orths, P.B. Eriksen, J.C. Smith, L. Soder, P. Sorensen, A. Altiparmakis, Y. Yasuda, J. Miller, Wind and solar energy curtailment: a review of international experience, Renew. Sustain. Energy Rev. 65 (2016) 577–586, https://doi.org/10.1016/j.rser.2016.06.082.

[2] H. Blanco, A. Faaij, A review at the role of storage in energy systems with a focus on Power to Gas and long-term storage, Renew. Sustain. Energy Rev. 81 (2018) 1049–1086, https://doi.org/10.1016/j.rser.2017.07.062.

[3] M. Steurer, U. Fahl, A. Voß, P. Deane, Curtailment, Elsevier Inc., 2017, https://doi.org/10.1016/B978-0-12-809806-6.00015-8.

[4] M. Robinius, T. Raje, S. Nykamp, T. Rott, M. Müller, T. Grube, B. Katzenbach, S. Küppers, D. Stolten, Power-to-Gas: electrolyzers as an alternative to network expansion – an example from a distribution system operator, Appl. Energy. 210 (2018) 182–197, https://doi.org/10.1016/j.apenergy.2017.10.117.

[5] H. Blanco, W. Nijs, J. Ruf, A. Faaij, Potential of Power-to-Methane in the EU energy transition to a low carbon system using cost optimization, Appl. Energy. 232 (2018) 323–340, https://doi.org/10.1016/j.apenergy.2018.08.027.

[6] H. Blanco, W. Nijs, J. Ruf, A. Faaij, Potential for hydrogen and Power-to-Liquid in a low-carbon EU energy system using cost optimization, Appl. Energy. 232 (2018) 617–639, https://doi.org/10.1016/j.apenergy.2018.09.216.

[7] T.T.Q. Vo, A. Xia, D.M. Wall, J.D. Murphy, Use of surplus wind electricity in Ireland to produce compressed renewable gaseous transport fuel through biological power to gas systems, Renew. Energy. 105 (2017) 495–504, https://doi.org/10.1016/j.renene.2016.12.084.

[8] E.P. Ahern, P. Deane, T. Persson, B.Ó. Gallachóir, J.D. Murphy, A perspective on the potential role of renewable gas in a smart energy island system, Renew. Energy. 78 (2015) 648–656, https://doi.org/10.1016/j.renene.2015.01.048.

[9] D. Bessarabov, P. Millet, Brief Historical Background of Water Electrolysis, PEM Water Electrolysis, 2018, pp. 17–42, https://doi.org/10.1016/b978-0-12-811145-1.00002-2.

[10] A. Buttler, H. Spliethoff, Current status of water electrolysis for energy storage, grid balancing and sector coupling via power-to-gas and power-to-liquids: a review, Renew. Sustain. Energy Rev. 82 (2018) 2440–2454, https://doi.org/10.1016/j.rser.2017.09.003.

[11] E. Frank, J. Gorre, F. Ruoss, M.J. Friedl, Calculation and analysis of efficiencies and annual performances of Power-to-Gas systems, Appl. Energy. 218 (2018) 217–231, https://doi.org/10.1016/j.apenergy.2018.02.105.

[12] O. Schmidt, A. Gambhir, I. Staffell, A. Hawkes, J. Nelson, S. Few, Future cost and performance of water electrolysis: an expert elicitation study, Int. J. Hydrogen Energy. 42 (2017) 30470–30492, https://doi.org/10.1016/j.ijhydene.2017.10.045.

[13] W. Kuckshinrichs, T. Ketelaer, J.C. Koj, Economic analysis of improved alkaline water electrolysis, Front. Energy Res. 5 (2017), https://doi.org/10.3389/fenrg.2017.00001.

[14] F. Grüger, O. Hoch, J. Hartmann, M. Robinius, D. Stolten, Optimized electrolyzer operation: Employing forecasts of wind energy availability, hydrogen demand, and electricity prices, Int. J. Hydrogen Energy. 44 (2019) 4387–4397, https://doi.org/10.1016/j.ijhydene.2018.07.165.

[15] S. McDonagh, D.M. Wall, P. Deane, J.D. Murphy, The effect of electricity markets, and renewable electricity penetration, on the levelised cost of energy of an advanced electro-fuel system incorporating carbon capture and utilisation, Renew. Energy. 131 (2019) 364–371, https://doi.org/10.1016/j.renene.2018.07.058.

[16] S. McDonagh, R. O'Shea, D.M. Wall, J.P. Deane, J.D. Murphy, Modelling of a power-to-gas system to predict the levelised cost of energy of an advanced renewable gaseous transport fuel, Appl. Energy. 215 (2018) 444–456, https://doi.org/10.1016/j.apenergy.2018.02.019.

[17] J. Lago, F. De Ridder, P. Vrancx, B. De Schutter, Forecasting day-ahead electricity prices in Europe: the importance of considering market integration, Appl. Energy 211 (2018) 890–903, https://doi.org/10.1016/j.apenergy.2017.11.098.

[18] R. Weron, Electricity price forecasting: a review of the state-of-the-art with a look into the future, Int. J. Forecast 30 (2014) 1030–1081, https://doi.org/10.1016/j.ijforecast.2014.08.008.

[19] J. Lago, F. De Ridder, B. De Schutter, Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms, Appl. Energy. 221 (2018) 386–405, https://doi.org/10.1016/j.apenergy.2018.02.069.

[20] I.P. Panapakidis, A.S. Dagoumas, Day-ahead electricity price forecasting via the application of artificial neural network based models, Appl. Energy. 172 (2016) 132–151, https://doi.org/10.1016/j.apenergy.2016.03.089.

[21] Nord Pool, Day-ahead trading: order types, accessed, https://www.nordpoolgroup.com/trading/Day-ahead-trading/Order-types/Hourly-bid/,

2019. (Accessed 13 August 2019).
[22] N.D. Nordin, H.A. Rahman, Comparison of optimum design, sizing, and economic analysis of standalone photovoltaic/battery without and with hydrogen production systems, Renew. Energy. 141 (2019) 107–123, https://doi.org/10.1016/j.renene.2019.03.090.
[23] S. McDonagh, S. Ahmed, C. Desmond, J.D. Murphy, Hydrogen from offshore wind: Investor perspective on the profitability of a hybrid system including for curtailment, Appl. Energy. 265 (2020) 114732, https://doi.org/10.1016/j.apenergy.2020.114732.
[24] J. Gorre, F. Ruoss, H. Karjunen, J. Schaffert, T. Tynjälä, Cost benefits of optimizing hydrogen storage and methanation capacities for Power-to-Gas plants in dynamic operation, Appl. Energy. 257 (2020), https://doi.org/10.1016/j.apenergy.2019.113967.
[25] F. Grueger, F. Möhrke, M. Robinius, D. Stolten, Early power to gas applications: reducing wind farm forecast errors and providing secondary control reserve, Appl. Energy. 192 (2017) 551–562, https://doi.org/10.1016/j.apenergy.2016.06.131.
[26] S. McDonagh, P. Deane, K. Rajendran, J.D. Murphy, Are electrofuels a sustainable transport fuel? Analysis of the effect of controls on carbon, curtailment, and cost of hydrogen, Appl. Energy. 247 (2019) 716–730, https://doi.org/10.1016/j.apenergy.2019.04.060.
[27] D. Fischer, F. Kaufmann, R. Hollinger, C. Voglstätter, Real live demonstration of MPC for a power-to-gas plant, Appl. Energy. 228 (2018) 833–842, https://doi.org/10.1016/j.apenergy.2018.06.144.
[28] J. Gorre, F. Ortloff, C. van Leeuwen, Production costs for synthetic methane in 2030 and 2050 of an optimized Power-to-Gas plant with intermediate hydrogen storage, Appl. Energy. 253 (2019) 113594, https://doi.org/10.1016/J.APENERGY.2019.113594.
[29] M. Götz, J. Lefebvre, F. Mörs, A. McDaniel Koch, F. Graf, S. Bajohr, R. Reimert, T. Kolb, Renewable Power-to-Gas: a technological and economic review, Renew. Energy. 85 (2016) 1371–1390, https://doi.org/10.1016/j.renene.2015.07.066.
[30] Linde AG - Gases Division, The Ionic Compressor, 50, 2014. Pullach (Germany).
[31] J. de Bucy, O. Lacroix, L. Jammes, The Potential of Power-To-Gas, 2016. Paris.
[32] J. Proost, State-of-the art CAPEX data for water electrolysers, and their impact on renewable hydrogen price settings, Int. J. Hydrogen Energy. 4 (2019) 4406–4413, https://doi.org/10.1016/j.ijhydene.2018.07.164.
[33] M. Carmo, D.L. Fritz, J. Mergel, D. Stolten, A comprehensive review on PEM water electrolysis, Int. J. Hydrogen Energy. 38 (2013) 4901–4934, https://doi.org/10.1016/j.ijhydene.2013.01.151.
[34] R.C. McKenna, Q. Bchini, J.M. Weinand, J. Michaelis, S. König, W. Köppel, W. Fichtner, The future role of Power-to-Gas in the energy transition: regional and local techno-economic analyses in Baden-Württemberg, Appl. Energy. 212 (2018) 386–400, https://doi.org/10.1016/j.apenergy.2017.12.017.
[35] NordPool, Historical Market Data, 2019. Lysaker (Norway).
[36] A. Deoras, Electricity load and price forecasting Webinar case study. https://se.mathworks.com/matlabcentral/fileexchange/28684-electricity-load-and-price-forecasting-webinar-case-study, 2016.
[37] SMHI - Swedish Metereological and Hydrological Institute, Metereological observations - Hörby A, n.d. https://www.smhi.se/en.
[38] M. Waidhas, Power to Gas -an Economic Approach? Erlagen, 2015. http://www.fze.uni-saarland.de/AKE_Archiv/DPG2015-AKE_Berlin/Vortraege/DPG2015_AKE9.1_Waidhas_P2G-Economics.pdf.
[39] F. Mohseni, M. Görling, M. Llindén, M. Larsson, Genomförbarhetsstudie För Power to Gas På Gotland, 2017. Stockholm.
[40] G. Thornton, Renewable energy discount rate survey results – 2018. https://www.grantthornton.co.uk/globalassets/1.-member-firms/united-kingdom/pdf/documents/renewable-energy-discount-rate-survey-results-2018.pdf, 2019.
[41] M. Kopp, D. Coleman, C. Stiller, K. Scheffer, J. Aichinger, B. Scheppat, Energiepark Mainz: technical and economic analysis of the worldwide largest Power-to-Gas plant with PEM electrolysis, Int. J. Hydrogen Energy. 42 (2017) 13311–13320, https://doi.org/10.1016/j.ijhydene.2016.12.145.
[42] D. Fischer, F. Kaufmann, O. Selinger-Lutz, C. Voglstätter, Power-to-gas in a smart city context - influence of network restrictions and possible solutions using on-site storage and model predictive controls, Int. J. Hydrogen Energy. 43 (2018) 9483–9494, https://doi.org/10.1016/j.ijhydene.2018.04.034.
[43] K. Byman, Locational study — power to gas, Stockholm, http://www.sgc.se/ckfinder/userfiles/files/EF2015-120+Locational+study-Power+to+gas.pdf, 2015.
[44] C. Martin de Lagarde, F. Lantz, How renewable production depresses electricity prices: Evidence from the German market, Energy Policy 117 (2018) 263–277, https://doi.org/10.1016/j.enpol.2018.02.048.
[45] Per Klevnäs, M.B. Hansen, C. von U. Danielsson, Electricity Market Design for a Reliable Swedish Power System, Copenhagen Econ, 2016.