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MODELING ELECTRICITY MARKET FOR POWER-TO-X APPLICATIONS IN SWEDEN: EFFECTS OF DIFFERENT BIDDING STRATEGIES ON PLANT PERFORMANCE

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ABSTRACT

H_2 production through water electrolysis for power-to-X applications is being investigated by comparing different bidding strategies on the electricity spot market in Sweden. For that, a price independent order (PIO) strategy was developed assisted by forecasting electricity prices with neural networks (NN). For comparison, a price dependent order (PDO) with a fixed bid price was used. The optimization of the NN showed that increasing the number of neurons in the hidden layer did not reduce error in forecasting due to possible overlapping of data making the model unnecessarily complex. By using different combinations of data for in-sample training and data from 2016-2018 for out-of-sample testing, preliminary results showed similar trends for PIO and PDO when bid prices are increased. However, the PIO marginally reduced the average cost of electricity when compared to PDO in all scenarios, but this was at the expense of increased non-operating hours (cold and warm mode). Further investigations with a mathematical optimization approach will reveal ideal conditions to run the system with low H_2 production costs and increased profitability.

Keywords: Variable renewable energy, Nord Pool, day-ahead market, water electrolysis, hydrogen production, process optimization.

1. INTRODUCTION

The concept of using excess electricity from variable renewable energy (VRE) sources to produce H_2 through water electrolysis has gained attention in the recent years [1]. 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 [2,3]. Such energy concepts, frequently referred to power-to-X (PtX or P2X), proposes to 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 produce recycled carbon fuels through carbon capture and utilization (CCU), e.g. $4H_2 + CO_2 \rightarrow CH_4 + 2H_2O$; $\Delta H = -164$ kJ [3].

Different studies on H_2 production through water electrolysis have shown that electricity purchase is the main cost driver [4,5]. Additionally, McDonagh et al. [3,6] demonstrated that for power-to-methane ($PtCH_4$) production, when H_2 and CO_2 are converted to CH_4 in a catalytic process, just having low-cost electricity (i.e. less than 10 €/MWh) is not sufficient for reducing production costs, but instead a minimum number of run hours is necessary to offset the investments of a project.

Furthermore, with increasing shares of VRE in the energy mix, electricity markets and prices become less predictable. In particular, sudden and unexpected price peaks or seasonality of prices at daily, weekly and yearly level have been observed [7]. Under this scenario, different operational strategies for water electrolyzers operation might have a direct influence on the profitability of PtX processes.

Knowing the electricity prices in advance could be useful for developing an operational strategy to control costs, run hours of the system, penalties for start-up from cold mode as well as providing H_2 according to the specific requirements of each PtX concept. Thus, depending on how electricity is purchased for PtX applications, it may result in different average prices, total number of run hours and consecutive hours of operation. The latter is particularly important when alkaline electrolysis (AEL) is used due to its longer time for start-up (cold: 1-2 h and warm: 5-10 min) in comparison to proton exchange membrane electrolysis (PEMEL) (cold: 5-10 min and warm: < 10 s) [8].

To the best of the authors' knowledge, the operation of electrolyzers assisted by electricity price forecasting has never been previously investigated in details. In addition, Frank et al. (2018) have introduced the concept of annual performance by assessing the energy consumption of electrolyzers during standby and start-up time, however such dynamics have not been reported with real electricity market data yet. 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.

Therefore, the present study proposes to investigate different bidding strategies for electricity purchase in the Nord Pool day-ahead spot market. For that, price forecasting based on a neural network (NN) model is used to assist electricity purchase and control non-operating hours (NOH) under cold and warm mode, as well as energy penalties for bringing the system into service. Different water electrolysis technologies, namely AEL and PEMEL, will be compared in the final assessment. Also, a mathematical optimization is foreseen to find the lowest possible levelised cost of H_2 ($LCOH_2$) as well as a sensitivity analysis on key aspects of the process, including technological developments in the next years (CAPEX, OPEX and efficiency), time for cold start-up in AEL and different H_2 storage sizes will be performed. Thus, allowing the assessment to cover future developments in water electrolysis and possible uses of H_2 in further processes (e.g. $PtCH_4$).

2. METHOLOGY

2.1 *PtX model*

The PtX model refers to a H_2 production facility in which H_2 could be potentially delivered for any further application. Electricity is obtained from the spot market of the Nord Pool power exchange in a day-ahead trading scheme (more information is given in sections 2.2 and 2.3). Different supplies such as deionized water and potassium hydroxide (KOH) as alkaline reagent for electrolyte use 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. Based on the variety of possible H_2 uses and their respective delivery requirements (constant or intermittent), different H_2 storage capacities of 1, 3 and 7 days are being consider for an electrolyzer of 1074 kW_{el}. The possibility of recovery low temperature waste heat (60 °C) from the electrolyzers is also considered [9]. 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 [4].

The model does not consider reductions in electrolyzers performance over time, however component replacement costs are included in economic assessment. Even though the present study is based on the most recent literature available, unavoidable uncertainty exists in the capital costs, in particular for the years 2030 and 2040 [10].

To find the optimal process conditions that result in the least-cost operation mode in terms of $LCOH_2$, a mathematical optimization procedure will be implemented in MATLAB (MathWorks, USA). This optimization procedure will take into consideration different parameters, such as price of electricity, run hours, electricity consumption during cold and warm modes as well as during ramp ups from cold to operation mode.

2.2 *Electricity market data*

Historical values of electricity prices in the day-ahead market of the Nord Pool power exchange during 2013-2018 were used. The region SE4 (Sweden) was chosen since it offers more appropriate conditions for deployment of electrolyzers based on its energy matrix profile (highest share of VRE in the country).

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).

2.3 *Bidding strategies*

Two different bidding strategies were developed for comparison, namely price dependent order (PDO) and price independent order (PIO). For PDO strategy, bidding price is fixed during the whole assessment period. The electrolyzer is put in operation mode every time the electricity price is less than or equal to the pre-defined bidding price. In case of the electricity price being higher than the bidding price the number of NOH is recorded and used to decide whether the electrolyzer is put on warm or cold mode (NOH ≥ 8 h = cold mode). In contrast, the PIO strategy purchases predetermined volumes of electricity in each hour of the day. To assist this decision, prices of electricity are modeled and stepwise forecasted in a day-ahead scheme (more information is given in section 2.4). Once prices are forecasted, the average value for the next 24 h is calculated and used as reference for the decision whether the electrolyzer is put in operation, warm, or cold mode. Considering seasonal variations in load of electricity which could potentially influence prices in the spot market, different capacity factors are chosen for winter (50%), spring (75%), summer (100%) and fall (75%) to help decide if the system should operate. This approach is intended to avoid electricity consumption when prices are excessively expensive.

2.4 Modelling with neural networks (NN)

A NN model was set-up to forecast short term electricity prices in a day-ahead market according a MATLAB toolbox (MathWorks, USA). Historical values of system load (SYSLoad), electricity price (ElecPrice) and hydropower reservoir (HPReservoir) were obtained from Nord Pool for SE4 region and used as input data. In addition, dry bulb temperature (DryBulb) and dew point DewPnt) obtained from the meteorological station Hörby A (55°N 13°E, 114 m altitude) were also used as input data, as well national holidays. 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, SYSLoad at the same hour in previous week, SYSLoad at the same hour in the previous day, average SYSLoad in the previous 24 hours, ElecPrice at the same hour in the previous week, ElecPrice at the same hour in the previous day, average ElecPrice in the previous 24 hours, HPReservoir in the previous 24 hours and average HPReservoir in the last week.

Differences between ElecPrice and forecasted electricity price were assessed by mean absolute percent error (MAPE) according to Eq. 1.

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

Where:

$\mathrm{A_t}$ is the ElecPrice (€/MWh)

$\mathrm{F_t}$ is the forecasted electricity price (€/MWh)

The number of years used for in-sample data training and out-of-sample testing the NN was varied as well as the number of neurons in the hidden layer (from 10 to 100) in order to find a reduced MAPE value.

3. RESULTS

3.1 Data set characterization

The data set presented significant differences ($p < 0.01$) in terms of electricity prices, except when 2014 and 2017 are compared ($p > 0.01$) **(Fig 1)**. In 2015 and 2016, the majority of the hourly prices were found to be below 30 €/MWh, resulting in 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 prices in the data set with average values of 39.93 €/MWh and 46.36 €/MWh, respectively. In particular, during 2018 unfavorable weather conditions like drought might have influenced the highly hydropower dependent Swedish electricity market since 68% of the hourly price distribution in that year was found to be higher than 40.00 €/MWh.

In the meantime, 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 to the other years (average of 123.27 €/MWh). This demonstrates that even low price years like 2016 are subjected to at least short-term high variations in electricity prices, suggesting that a forecast of such events could be beneficial to manage the operation of electro-intensive processes.

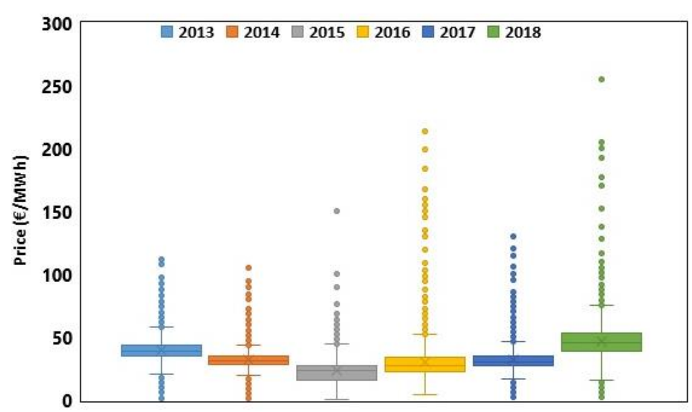

Figure 1 – Box plot of electricity prices from data set.

3.2 Adjustment of the neural network (NN)

To improve the electricity price forecasting, the number of years used for training and the number of neurons in the hidden layer of the NN were varied to try and minimize MAPE **(Table 1)**. In general, by increasing the number of neurons from 10 to 100 the MAPE increased reducing the accuracy of the forecasting. This is explained by a possible overlapping of data making the model unnecessarily complex and less precise in forecasting day-ahead electricity prices.

It was also observed that a certain number of years are necessary for training the NN to reduce error in forecasting the test set. Such period varied according to each forecasted year. For 2016, training the NN with 2 previous years showed satisfactory results (MAPE of 9.26%) while increasing the train set to 3 years showed a minor improvement (MAPE of 9.03%). For 2017, similar conditions were found, however in this case at least data from the 3 previous years was needed for a MAPE of 10.64% while a minimal improvement was obtained by increasing the train set to 4 years (MAPE of 10.26%).

Table 1 – 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

Even though the same trend of reducing the MAPE with higher number of years in the train set was also found for 2018, the lowest MAPE observed for this year was much higher than in the other tested years (14.68% with 20 neurons in the hidden layer). In this case, the different characteristics among years found in the data set might have limited the accuracy of the NN. In particular, the unusual high average and range prices observed in 2018 are the main reason for such higher error in the forecast. Nevertheless, in an extensive assessment of 27 different forecasting methods, Lago et al. (2018) found a MAPE of 12.3% for the best approach. Thus, reinforcing the robustness of the current method since the average MAPE for the whole test set was 10.99%.

Based on this assessment, combinations of years in the train set and number of neurons that resulted in the lower MAPE were further used. For this reason, simulations were carried-out by always using all available data (prior the year of testing) for in-sample training the NN. Furthermore, the value of 10 neurons in the hidden layer was used when testing for 2016 and 2017 while in 2018 the value of 20 neurons were chosen.

3.3 Preliminary results of plant operation

The preliminary results of simulation an AEL plant operation are shown in **Fig 2**. Regardless the year observed, by increasing bid price from 20-50 €/MWh similar trends for PIO and PDO were found. For both bidding strategies NOH are strongly reduced with higher bid prices suggesting an improvement on plant operation since the electrolyzer would idle under cold or warm mode less. Also, when no H_2 production is required or it is prohibitive due to excessive electricity prices in spot market, electricity is purchased from regulated market to keep the system awake during these NOH. Thus, reducing NOH would increase H_2 output and reduce the consumption of high tariff electricity from the regulated market.

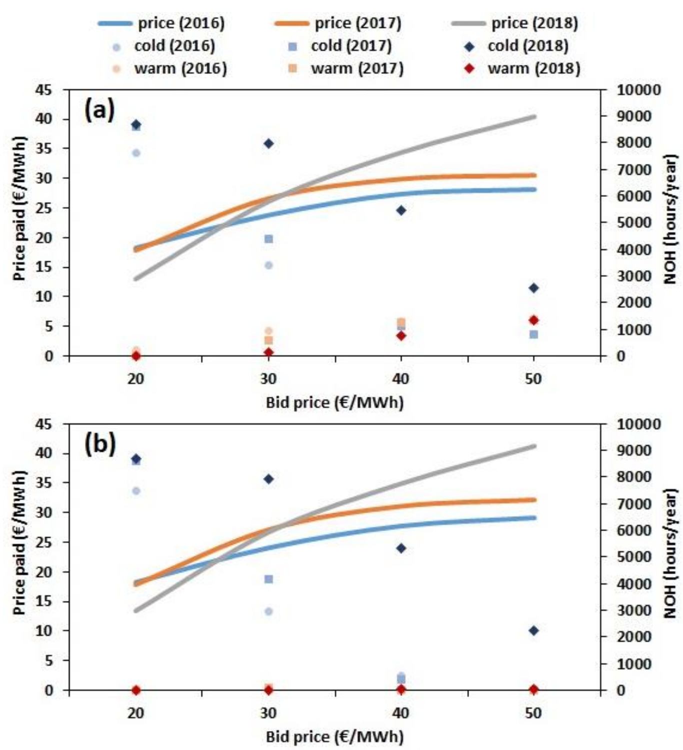

Figure 2 – Results of simulation an AEL plant in 2016-2018. (a) Price independent order (PIO) and (b) Price dependent order (PDO).

Note: Non-operating hours (NOH); lines are price paid (left y axis); and dots are NOH (right y axis).

By increasing the bid price the average price paid for the electricity in the spot market also increases. In particular, in 2018 by varying bid price from 20-50 €/MWh the price paid increased 2.6 fold for PIO and 2.8 fold for PDO. When different bidding strategies are analyzed, PIO reduced the price paid for electricity in up to 5% in comparison to PDO. However, it has generated higher NOH than PDO, especially warm standby hours. This behavior is explained by the different capacity factors used depending on each season of the year which has reduced price paid but increased NOH of PIO strategy.

In addition, considering that there would also be a penalty for bringing the system into service from standby mode, it can be expected that during PEMEL operation the price paid for the electricity would have a higher relevance since PEMEL has a much faster start-up time than the simulated AEL technology. Further investigations will focus on the mathematical optimization to minimize the $LCOH_2$ as well as the comparison of different water electrolysis technologies reflecting the present and future development of H_2 production for PtX applications.

4. CONCLUSION

Major differences in terms of range and average electricity prices were found among 2013-2018 for SE4 region in Sweden. Such characteristics have directly influenced the ability of the neural network in forecasting day-ahead electricity prices, especially for the year 2018 in which a severe drought was observed. Bidding strategy based on electricity price forecasting showed a reduced price paid in comparison to price dependent order, however it has increased the idleness of the system (higher non-operating hours).

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