IMBALANCE PRICE PREDICTION FOR THE IMPLICIT DEMAND RESPONSE POTENTIAL EVALUATION OF AN ELECTRODE BOILER

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ABSTRACT

Increasing Renewable Energy Sources (RES) penetration in the electricity grid increases the electricity market price volatility. This mechanism could be economically exploited by electrifying the heat demand in industry. An electrode boiler could assist the existing gas-fired boiler in steam production, decreasing the overall CO2 intensity of the produced steam. In this work, the predictability of the Net Regulation Volume is shown and used to estimate the imbalance price for a current quarter-hour. The electrode boiler is steered based on the predicted imbalance price, making use of the price volatility and single imbalance pricing mechanism as used in Belgium.

KEYWORDS

Implicit demand response, electrode boiler, imbalance market

INTRODUCTION

Steam is one of the main raw materials in most of the major industries today and is used for process heating, atomisation, cleaning, distillation, etc. The electrification of steam production in industry is considered technically comparatively easy to implement and could represent a greenhouse gas saving of up to 15.9 Mt of CO2 eq/annum in the long run [1]. An electrode boiler is an electricity driven alternative for a gas-fired steam boiler. The start-up and control characteristics of an electrode steam boiler are suited to participate in the balancing market. An estimate of 70MW of control power to the German balancing market is already provided by a single manufacturer of electrode boilers [1]. The increased penetration of Renewable Energy Sources (RES) in the grid, with the encompassed volatile power infeed, is found to increase the EEX spot price volatility [2]. In Belgium, the volatility of the imbalance price, as well as the EPEX Spot DAM price, increased over the years 2015 and 2016 [3]. While the electricity price volatility can be seen as a risk compensation in the market [2], it improves the conditions for electrical flexibility valorisation using implicit demand response (DR). The largest price differences and lowest minimum prices are found in the imbalance market, as in Belgium a single imbalance pricing mechanism is implemented. A single imbalance market price is determined based on the cost of activation of reserves, therefore reflecting the state of the grid. As the imbalance market price is only defined ex-post, this work presents a prediction algorithm for the imbalance price based on market structure patterns in combination with close-to-real-time grid data. The predicted quarter-hour imbalance price is used as input for the electrode boiler control in a hybrid steam production setup. The prediction time horizon is thus very short. In [4], Salem et al. look into the forecasting on intra-hourly imbalances in the Norwegian system. They as well make use of a method which relies on historical imbalance and features related to date and time. This is a quite novel technique, other publications on this topic, such as [5] and [6], focus on time series prediction methods such as Seasonal Autoregressive Integrated Moving Average (SARIMA) models.

IMPLICT BALANCING

In Belgium, Elia uses a single imbalance pricing mechanism, based on the Marginal Incremental Price (MIP) or Marginal Decremental Price (MDP), in case of upward or downward regulation respectively. A quarter-hourly price is set, which is used to bill the Balance Responsible Parties (BRPs). As the System Imbalance (SI) hovers around the balanced point, being 0 MW, so does the Net Regulation Volume (NRV). As a result, the imbalance price fluctuates between a lower and higher price level.
It is this effect of the imbalance market design which can be beneficially used by consumers and producers to adapt their electricity consumption and production pattern. The adaptation of electricity consumption or production based on an

external price signal is referred to as implicit demand-side flexibility or price-based demand-side flexibility. Here the valorisation of the electrical flexibility is voluntarily and does not need to be committed to any third party, e.g. TSO or aggregator [7]. In [8], Möller investigated the German electricity balancing market and concluded that producers anticipate the imbalances, taking advantage of it by producing more when there is an expected need of upward balancing, less when there is an expected need of downward balancing. The Belgian imbalance market design is closely related to the German one, making it possible to extrapolate the findings of Möller. Indeed, by studying the Belgian markets and contact with large industrial consumers, they often take the same approach. For example, a power-intensive and flexible process such as electrolysis, can be quickly steered to consume more or less electricity. It does has to be noted that the legal aspect of this implicit demand-side flexibility strategy on the imbalance market is questionable. The standard procedure for a significantly large consumer or producer is to nominate its consumption or production profile with a BRP on a quarter-hourly basis, who will aggregate with others and share the information with the TSO. In the BRP contract it is stated that *the BRP is legally bound to do it's best to stick to the nominations*. The purposefully deviation from the nomination, for financial or other reasons, is not allowed. One could say that this method is located in a grey area as in practice the method is used and control from an authority is difficult.

IMBALANCE PRICE PREDICTION BASED ON NRV AND SI

Day-ahead, all activation remuneration bids of ancillary services are aggregated and the marginal activation price is defined for each quarter-hour and each volume level. Table 1 shows an extract of the day-ahead made available dataset, also referred to as Available Regulation Capacity (ARC). With this data, it is possible to define an imbalance price based on a value of the NRV. For example, if during quarter-hour 3 (QH3) an average NRV of -186 MW would be activated, an imbalance market price of 10.32 euro/MWh would be to expect. Nevertheless, three distinct mechanisms could influence the imbalance price as it would be set according to available ARC dataset.

Table 1. Example of day-ahead available marginal balancing energy prices per volume level

NRV [MW]	QH1	QH2	QH3	QH4	…	QH96
-1000	-273.01	-273.01	-273.01	-320.15	…	-451.34
-900	-254.51	-254.51	-254.51	-273.01	…	-342.98
…	…	…	…	…	…	…
-200	10.32	10.32	**10.32**	1.20	…	1.20
-100	10.32	10.32	**8.65**	8.65	…	15.62
100	60.20	60.20	60.20	62.50	…	62.50
…	…	…	…	…	…	…
1000	245.10	245.10	495.44	495.44	…	650.00

First, no single imbalance price is set. While this seems like a contradiction regarding the single pricing strategy, a POS and NEG imbalance price is defined, which is used to bill the BRPs who have a positive or negative imbalance respectively. For SIs smaller than 140 MW, the POS and NEG price is identical, hence the single pricing strategy. As soon as the SI exceeds this limit, a parameter is used to disperse the POS and NEG prices, which is calculated according to (1), with QH_c the current quarter-hour, QH_{c-7} the current quarter-hour minus seven quarter-hours and SI_{QH} the System Imbalance of the corresponding quarter-hour. The application of α to the POS and NEG price is done according to Table 2. Referring to the example above, this could result in a POS price of only 9.56 euro/MWh, considering that α would be 0.76 euro/MWh. The NEG price would still be the presumed 10.32 euro/MWh.

$$\alpha = \frac{X \sum_{QH_{C-7}}^{QH_C} SI_{QH}^2}{120000} \left[\frac{euro}{MWh}\right] \tag{1}$$

Table 2. Application of α

	Negative NRV	Positive NRV
Positive BRP perimeter	MDP - α	MIP
Negative BRP perimeter	MDP	MIP + α

Secondly, the volumes of automatic Frequency Restoration Reserves (aFRR) exchanges in the light of the International Grid Control Cooperation (IGCC) are not taken into account in the published marginal balancing energy prices with volume levels as shown in table 1. The IGCC project currently consists of 11 European TSOs operating an imbalance netting procedure, where a negative SI in one control zone can be compensated with a positive SI in another or vice versa, decreasing the volume of aFRR which is needed to be activated in either control zones. Applied on the previous example, this could result in an effective activation of reserves in the Elia control zone of less than -186 MW, e.g. only -86 MW, resulting in an imbalance market price of 8.56 euro/MWh instead of 10.32 euro/MWh (see table 1). A third reason for deviation is the data incorrectness. Elia publishes, close to real-time, minute data on the SI, NRV, etc. This data is made available under reservation and is always checked, and corrected if necessary, afterwards. The validated data is published with a considerably longer time lag, making it unusable for short-term predictions. The published ARC dataset can thus be used to make an estimation of the imbalance price of the current quarter-hour, taking into account the discussed limitations and assuming that a correct NRV is inputted for the current quarter-hour.

PREDICTABILITY OF THE NRV

The Net Regulation Volume is the total sum of the activated reserves in a single control area, this to counter the System Imbalance. The NRV is thus fully defined by the SI, which reflects the state of the overall grid. As stated by Möller [8], balancing energy can be regarded as a forecasting error, as it accounts for the fluctuations and unpredictable events, which are not taken into account in the nominations made by the BRPs. In [6], Klæboe et al. sum up three main causes for imbalance, under normal grid circumstances, being the loss of a large consumer or generator, stochastic fluctuations of both consumption and generation and the weakness of the market design. While the first two are unable to predict, the latter could be modelled based on the existing markets and their characteristics. Möller [8] investigated the German balancing energy market for predictable components, contradicting the theoretic approach of it being fully unpredictable. Indeed, Möller found some predictable components, related to the specific energy market structure and timings.

Figure 1 shows a heatmap of the NRV as activated in Belgium in 2017, with minute based data. The figure represents an average for each minute of each hour, for the whole of 2017. As the SI and NRV are, theoretically presumed, unpredictable and Gaussian distributed, the average should be close to zero for each minute of each hour. It can clearly be seen that a pattern is visible, immediately showing that predictable components are present. Figure 1 shows that for the hours 6 and 17, there is a high chance of having a negative NRV at the beginning of the quarter-hour, and a positive NRV at the end of the quarter-hour. For the hour 23 we see a vice versa pattern. An explanation can be found in the hourly energy markets and hourly time schemes of generators. For example, the hours 6 and 17 coincide with an electricity consumption increase, due to the synchronisation of working hours of industry and energy demand in households. The amount of electricity to consume or generate during these hours is defined on an hourly basis, while the imbalance market works on a quarter-hourly time base. The pattern shows that generators start to ramp up during these hours, to supply the needed electricity. As the ramp-up of the generators is not infinitely fast, a shortage will be seen during the first quarter-hour which reflects as a negative NRV. The generator increases its output, which will result in a surplus of energy in the last quarter-hour which reflects as a positive NRV. The mean load and production on hourly bases will be balanced, i.e. as it is traded on the hourly energy markets, but is not balanced on a quarter-hourly time base, i.e. balancing energy is used to compensate for this. This phenomenon is described by Möller and named the gradient effect [8]. A similar explanation can be given for the hour 23, with the difference that a load decline occurs, resulting in a vice versa effect on the sign of the NRV. Both patterns are also visible at other hours, but less pronounced, as the slope of the demand curve is less steep.

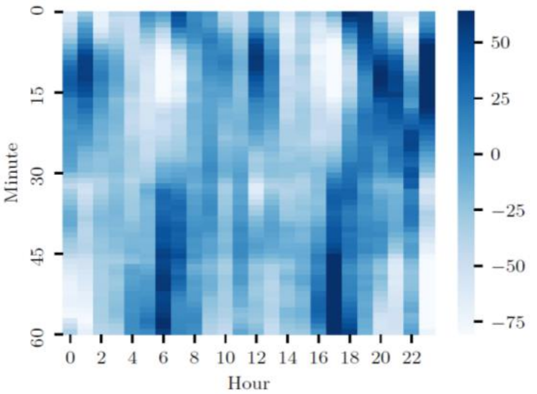

Figure 1: Heatmap of the Net Regulation Volume in the Belgian Elia control zone for the year 2017, averaged by minute and hour to obtain a single day pattern.

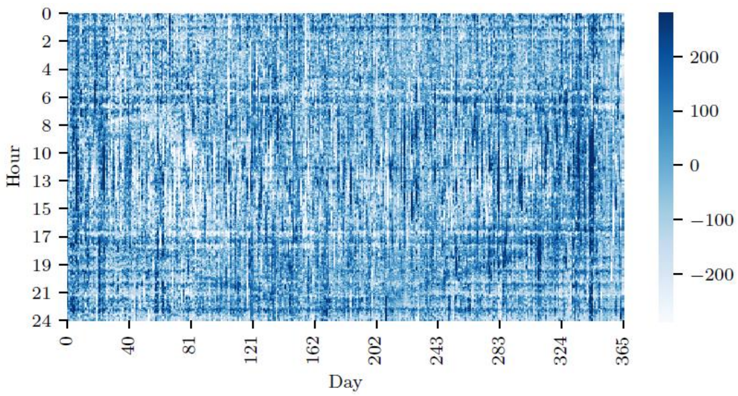

Figure 2: Heatmap of the Net Regulation Volume in the Belgian control zone for the year 2017,

Figure 2 visualises the full dataset of minute NRV data of a complete year (2017). The patterns as visible on Figure 1 are here represented as horizontal lines. These horizontal lines are visible for almost every hour, but are most pronounced for hours 6 and 17. Another pattern emerges, being a concave curve at the bottom of the figure, and a convex curve at the top of the figure. This corresponds with the seasonal pattern of electricity consumption and thus the explanation boils down to the same as before, i.e. the load incline or decline is linked to the NRV.

PREDICTION STRATEGY OF THE NRV

It was decided, for this work, to use the produced day pattern (see Figure 1) in combination with close-to-real-time data of the NRV. On average, a delay, of 2 minutes is observed for the publication of the data on the Elia website, which is also the value used here. The estimated NRV of the quarter-hour, $NRV_{qh,e}$, is defined as the average of 15 datapoints, depending on the current time, T, part of the datapoints (NRV_r) are obtained through the close-to-real-time datastream, part are taken from the predefined heatmap set (NRV_p), see (2).

$$NRV_{qh,e} = \sum_{0}^{t} NRV_r\,(t) + \sum_{15-t}^{15} NRV_p\,(t) \;\; with \;\; t = T - \delta \tag{2}$$

Figure 3 shows the timing. In Figure 3a current time T=2, e.g. at 13h47, and no datapoint for the current quarter-hour is available, thus t=0. The $NRV_{qh,e}$ is completely defined by the sum of the NRV_p. In Figure 3b, T=8, e.g. at 13h53, and 6 real datapoints of the NRV of the current quarter-hour NRV_r are available. $NRV_{qh,e}$ is defined by the sum of 6 datapoints of NRV_r and the sum of NRV_p for the remaining 9 minutes. At last, in Figure 3c, T=15, e.g. at 14h00 and thus the end of the quarter-hour. No more control opportunity is present as the quarter-hour has passed and $NRV_{qh,e}$ is defined by 13 NRV_r datapoints and 2 NRV_p datapoints. Note that uncertainty about the actual averaged quarter-hourly NRV still exists at this point, as only 13 real datapoints are available at the end of the quarter-hour. Also, a simple average of the quarter-hourly NRV is calculated, based on the available information of the current quarter-hour, $NRV_{qh,a}$. Here $NRV_{qh,a}$ is defined by a variable length dataset of 1 to 13 datapoints. For T < 2, $NRV_{qh,a}$ is set to zero. For 3 < T < 15, i.e. 1 < t < 13, $NRV_{qh,a}$ is defined by 1 to 13 NRV_r datapoints respectively. To benchmark, the optimum NRV value, $NRV_{qh,o}$, is also defined and is set according to the validated quarter-hourly value as published ex-post by Elia. This value encompasses all possible corrections which needed to be applied to the close-to-real-time data and therefore represents a perfect prediction algorithm.

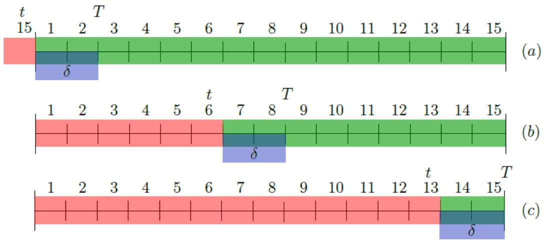

Figure 3: Respresentation of the data availability, with the close-to-real-time data of the current quarter-hour in red, the time delay in blue and the predefined heatmap values in green.

HYBRID STEAM PRODUCTION UTILITY

This work is focussed on the large industry, and takes a hybrid gas-fired and electrode boiler setup as example. A gas-fired boiler is one of the most classical ways of producing steam in the industry. Natural gas is burned and the hot fumes are used to heat, and evaporate, water. This setup is highly flexible but is fossil-fuel based, causing a large CO_2 emission. An electrode boiler generates heat by applying a high voltage to a tank of water, using the water's resistance to induce an electric current. This technique only uses electricity and is therefore, depending on the origin of the electricity, considered less CO_2 intensive. The dynamics of an electrode boiler are quite similar to the ones of a gas-fired boiler, with a warm ramp-up time of 30 seconds from zero output to full load. Assuming a linear ramp-up characteristic, a correction factor of 0.75 should be taken into account for the energy consumption of the boiler during the first minute of operation. The ramp-down is assumed to be instantaneous, therefore no correction factor is taken into account. For the following paragraph, where the simulation is explained and results are given, we assume a hybrid system where a gas-fired boiler is assisted by an electrode boiler.

SIMULATION & DISCUSSION

As discussed previously, an optimum $NRV_{qh,o}$, simple average $NRV_{qh,a}$ and heatmap estimation $NRV_{qh,e}$ value for the quarter-hourly NRV is defined. For each of the NRV_{qh}s, the imbalance price is looked up in the ARC table. The NEG price is defined based on the ARC value and the parameter as defined in (1). The predicted NEG imbalance price is used to steer the electrode boiler, i.e. if the predicted imbalance price is below a certain threshold, the boiler's output is increased to full load (taking into account the dynamics of the boiler), else the boiler is kept at lowest hot operating point.
Figure 4 shows the calculated $NRV_{qh,a}$ and $NRV_{qh,e}$. Note that during the first two minutes of each quarter-hour $NRV_{qh,a}$ is zero, as no data is available for the current quarter-hour yet. Due to the use of the averaged daily heatmap data for the calculation of $NRV_{qh,e}$, the result is more balanced around zero, i.e. extremes in the close-to-real-time NRV data are flattened out.
Figure 5 is linked to figure 4 and shows the predicted NEG imbalance price for both the heatmap estimation (NEG_e) and the simple average (NEG_a). Due to the more extreme predicted NRV with the simple average method, on minute 17, $NRV_{qh,a}$ drops below -100 MW and therefore NEG_a also drops to a lower price level (volume level steps in the ARC table are 100 MW). This phenomenon is the result of the variable length dataset used to define (NEG_a), e.g. as T = 3, only one datapoint is used, making the $NRV_{qh,a}$ susceptible to extreme NRV values at the beginning of the quarter-hour.
In Figure 6, the energy consumption by the boiler is shown, for a threshold imbalance price of 20 euro/MWh. The warm ramp-up time of the boiler translates into a $P_{boiler} = 0.75 \cdot P_{nom}$ for the first minute as can be seen at minute 17 for E_a.

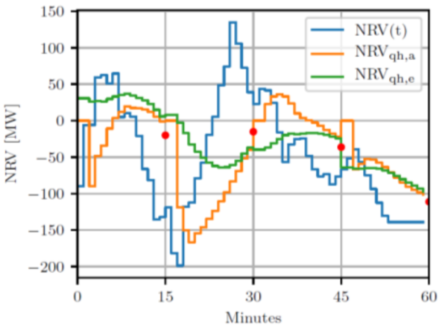

Figure 4: In blue the actual NRV values as gathered close-to-real-time, in orange the calculated simple average and in green the calcualted heatmap average. The red dots represent the actual validated average NRV for the past quarter-hour.

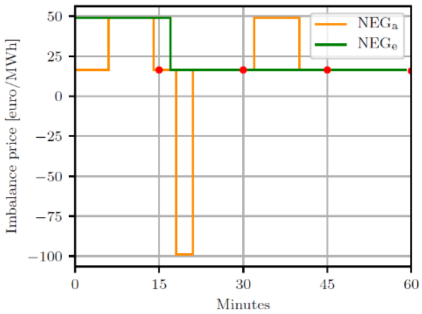

Figure 5: In orange the predicted imbalance prices based on the simple average, in green the heatmap predicted imbalance price. The red dots respresent the actual NEG price for the past quarter-hour.

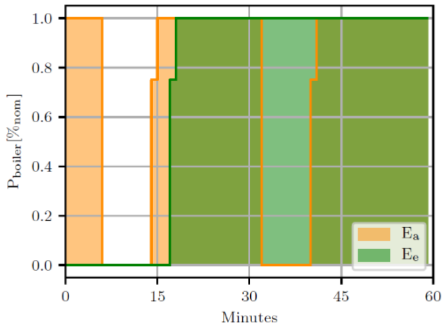

Figure 6: Boiler energy consumption with a threshold imbalance price of 20 euro/MWh, in orange for the simple averaged method, in green for the heatmap method.

The described simulation is executed for a complete year (2018) and for different threshold imbalance prices. The result is shown in Figure 7. The middle graph shows the averaged imbalance price which would be paid in case the boiler was steered based on each of the different methods. For example, for a threshold imbalance price of 40 euro/MWh the $NEG_{avg,a}$ equals 24.5 euro/MWh, NEGavg;e equals 23.5 euro/MWh while the $NEG_{avg,o}$ results to 9.6 euro/MWh. This average imbalance price is the result of all the periods during which the boiler is operated, multiplied by the actual validated NEG imbalance price and the boiler's nominal power. This price should be considered to evaluate the feasibility of the electrode boiler. On the top graph, for a threshold imbalance price of 40 euro/MWh, it can be seen that both $t_{on,a}$ and $t_{on,e}$ are higher than $t_{on,o}$, suggesting that the boiler is operated more than optimally required. This can be explained due to the forecasting errors, which results in steering the boiler to full load, while in reality the validated NEG price will be higher than the set threshold imbalance price. This also translates in the number of times the boiler is switched on (load increased from warm min load to full load), which are visualised on the bottom graph. Here, a pronounced difference is noticeable between the simple average and heatmap method. An explanation for this can be found in the variable length dataset used in the simple average method and the corresponding extremes in the beginning of quarter-hours, as explained in the beginning of this section. The optimum number of boiler switches is significantly lower (below 1000), for a total operating time close to that of the simple average and heatmap methods (top graph), suggesting that longer periods of boiler operation or non-operation are to be strived at.
Note that a realistic price range to operate the electrode boiler, considering the hybrid system, is dependent on the gas price and CO_2 price. A price fork of 15 euro/MWh to 50 euro/MWh is considered viable, considering the prices of the past years. Therefore, the right half of Figure 7 will never be used to operate the electrode boiler. Considering a realistic price of 22

euro/MWh, for the simple average method a threshold price of 20 euro/MWh would need to be set, while for the heatmap method a threshold price of 31.5 euro/MWh could be set. The heatmap method is considered best, with the ability to set a higher threshold price to obtain an identical average price, resulting in an increased operating time of the electrode boiler. Also, the number of activations, which could be linked to boiler maintenance, is lower with the heatmap method.

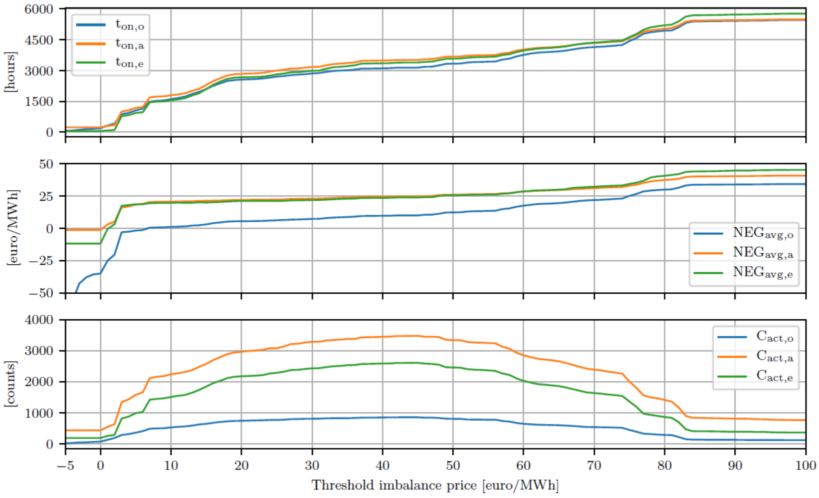

Figure 7: The top graph shows the number of hours the electrode boiler would be switched on, the middle graph shows the averaged paid imbalance price and the bottom graph shows the number of times the boiler would be switched on.

CONCLUSIONS

In this work, a method is shown to estimate the imbalance market price by using the predictability in the Net Regulation Volume. A yearly averaged daily pattern is constructed, showing the predictability of the NRV, resulting from the market design as present in Belgium. The predicted imbalance price is used to steer an electrode boiler in a hybrid setup, i.e. in combination with a natural gas boiler. A simulation of a complete year results in the ability to assess the averaged imbalance price which would be paid in case a specific threshold price would be set. The proposed method shows to be performing better than the standard simple average NRV prediction method, this especially for threshold imbalance prices lower than 65 euro/MWh. While the optimum number of boiler switches is below 1000, the discussed method shows a significant improvement over the simple averaged method. The addition of an electrode boiler to an existing gas-fired boiler for steam production, creating a hybrid steam production system, could result in financial gains when operating the boiler on the imbalance market. Increased RES penetration, causing increased price volatility, could even enhance the economic viability of this system. Ways forward for fine-tuning the model are the inclusion of a yearly pattern, next to the daily pattern.

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