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Machine Learning Based Forecasting of EV Charging Load in a Parking Lot for Optimal Participation in Frequency Services

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Abstract

This work assesses the potential of electric vehicles participating in frequency services in the Nordics. For this, data from a workspace parking lot is used to create artificial load profiles to take the perspective from an aggregator. The study is then divided into two parts: Firstly, a machine learning model is developed to forecast the parking lot load. In a second step, the predictions are given to a rolling-horizon mixed integer linear program that optimally allocates the capacities to Frequency Containment Reserve services. It is found that the machine learning approach almost doubles the profitability compared to offering bids just based on historical values. Finally, a hypothetical market structure is considered, where the FCR-D late auction is moved to an hour-ahead intra-day auction. The analysis shows that the opportunity to correct bids intra-day improves participation in frequency services and triples profits compared to the day-ahead auction.

1 Introduction

According to the United Nations, climate change is the single biggest threat humanity has ever faced [1]. The main driver for the increase of the average global temperature is the emissions of greenhouse gases, such as CO_2 [2]. To mitigate the increase in emissions, countries are implementing various carbon free technologies, such as wind power and photovoltaic for energy production and electric vehicles for transportation. Yet, switching to these intermittent renewable energy sources brings several challenges, among others large power fluctuations, making demand-supply balancing a crucial and challenging task. EVs increase the overall electricity demand, and may introduce high peak grid loading due to coincidence of the charging process. However, the transition to distributed energy resources (DER) also brings various opportunities. The Danish Transmission System Operator (TSO), Energinet, states that the transition to 100% renewable energy requires innovative solutions to maintain a stable power system operation [3]. For this, technologies can offer flexibility in their consumption or production as frequency services. To facilitate the integration of DERs for grid stabilisation in the Nordics, the TSOs allow flexible units to offer bids to reserve markets according to a probability of availability of at least 90%. A particular type of DERs are electric vehicles (EVs), which on top of transportation, can adjust their power consumption during the charging process based on the frequency of the grid, thus stabilising it. Specifically for EVs, [4] classifies ancillary services for electric vehicles into 8 frequency and 32 flexibility services. A frequency regulation control method is developed in [5], where the architecture also considers charging urgency as defined by the user. In [6], the focus is put on optimal participation in frequency markets with an aggregation of electric vehicles, while accounting for network constraints. The work in [7] uses battery electric storage systems to optimally participate in Nordic frequency markets. In [8], pools of domestic EVs charging are used to participate in the Nordic frequency services FCR-D up and aFRR. The work in [9] and [10] investigates the potential of an aggregation of EVs to participate in frequency containment reserve for disturbance operation (FCR-D). For this, charging patterns of residential users are analysed and used in an aggregation. An optimisation program is formulated that offers capacities. Since the capacity bid on the ancillary services market needs to be done the day before the activation of the service, forecasting of EV charging demand is crucial for the economic feasibility of providing frequency support with EVs. Artificial intelligence (AI) is nowadays extensively applied for this kind of task. For example, in [11], a machine learning approach is used to optimise the economic profitability of a residential users energy management system. In [12] instead, the authors make use of deep learning techniques to forecast electric vehicle charging load in Spain, considering seasonality effects.

This study aims to quantify the economic gain from participating in ancillary service markets with an aggregation EVs consisting of 360 outlets. Specifically, FCR-D and FFR are considered in this study. In order to do that, we perform load forecasting via machine learning, and optimally bid the predicted capacities in several sequential ancillary service markets of the Nordics. By doing so, this research supports the objectives of the Horizon Europe-funded EV4EU* and FLOW†

*`https://ev4eu.eu/portfolio-item/denmark/`
†`https://www.theflowproject.eu/meet-our-demo-copenhagen/`

projects, providing valuable insights into the practical deployment and management of ancillary services with EVs. The remainder of this paper is structured as follows: In chapter 2, the applied methodology is explained. Chapter 3 introduces the case study, while chapter 4 provides results. Conclusions are drawn in chapter 5.

2 Methodology

In this section, the methodology behind the paper is described. Firstly, the forecasting algorithm for EV load is going to be described, and secondly, the decision-making market participation algorithm is introduced.

2.1 Forecasting Algorithm

In order to forecast the EV load in the parking lot at a specific hour, which is going to be used by the decision making algorithm, a machine learning methodology is used. Formulated as a supervised learning model, it aims to predict the *aggregated parking lot load* in a minute resolution. The predictions are based on various features, which are the external conditions influencing the EV load. As the behaviour of the parking lot is strongly dependent on the time of the day and the weekday, both are used as features. Moreover, since the charging location is a university parking lot in Denmark, additional information such as Danish public holidays and the semester/exam/holiday periods are included as binary features. Information about the weather is also considered, with data taken from the Danish Meteorological Institute. The weather station measurement point from which the observations are taken is the Copenhagen airport CPH, as this station provides all necessary measurements in the best resolution and with the fewest empty measurements. Specifically, the precipitation, ambient temperature, the visibility, the humidity and wind speeds are used. The data points are resampled to match the minute resolution of the load curve. Lastly, to accurately represent the prediction horizon of the model, the label load is also used as a feature of the model, albeit with a lag. This is a common practice in time-series forecasting, and describes the information that the model has on the EV load at the instants preceding the point in time it makes the prediction. Based on an autocorrelation analysis, the lags introduced are 48, 72, 96 hours, as well as one and two weeks. For the late FCR-D auction, an additional lag is introduced with 24 hour lag, due to the shorter prediction horizon. The same lags are repeated with a feature that represents the amount of electric vehicles that are charging. Finally, the data frame is split into two parts, where the majority is used for training, and the remainder remains unseen in the training process and is only used for testing. The training data spans from September 2022 to September 2023, while the testing data spans from September 2023 until February 2024. This split is made so that the model can be trained with a full year of data, to accurately represent seasonal EV load variations.
The machine learning model is based on *Quantile Random Forests*, which can be seen as an extension to Random Forests. The major benefit of this technique is that the ensemble of predictors has the possibility to return not only one deterministic prediction, but a range of probabilistic predictions. Therefore, to align with the requirements from Energinet, the model predicts the 10^{th} quantile of the load. Moreover, by default, Random Forests are less prone to overfitting and generate robust models. The necessary hyperparameters of the Quantile Random Forests, used to increased the accuracy, are the number of trees, the number of minimum sampled per leaf, the minimum number of samples for a node to split and the maximum depth of each tree.
In the training process, the four hyperparameters of the model are tuned with the cross-validation technique *Grid Search*. In this process, various combinations of the hyperparameters are tested, and the combination of the hyperparameters with the best performance is returned. The performance measures considered are the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE) and the R^2 score.

2.2 Multi-Market Bidding Algorithm

The capacities that are forecasted by the machine learning model need to be bid in the Nordic ancillary service markets, hence a decision-making model based on a mixed-integer programming approach is proposed. The services considered are FCR-D upregulation and FFR, as both of them are not activated frequently and thus the charging process remains mostly undisturbed. FCR-D consists of two Danish-Swedish auctions on the day prior to operation (D-1), where the early auction takes place at 00:30 and the late auction at 18:00. FFR is purchased by Energinet in a national auction (Denmark only) on D-1 at 15:00. The hourly demand for FCR-D up and down is fixed, where each Nordic country is obliged to supply a share of the total demand, based on the countries own electricity consumption. Differently, the demand for FFR is not constant and dependent on the systems inertia. Only in hours where the inertia is low, FFR is demanded to stabilise the grid in case of large frequency drops. Yet, the system inertia is based on the units that produce electricity, and with fluctuating resources the inertia of the system is coupled to uncertainty. Therefore, Energinet constantly forecasts the demand for FFR for the following days, which they release at 10:00. The projected values for the 24 individual hours of the following day are binding and used as a cap for the auction. Figure 1 shows a timeline of the gate closure times for the different considered services: The model considers four important time points, indicated in Figure 1 as well:

1. At 10:00 two days prior to operation, the non-binding forecast for FFR demand is released by Energinet.
2. At 00:30 on D-1, the early auction for FCR-D takes place. In this auction, the decision variables for the early auction p_t^{up-e}, p_t^{down-e} and $p_t^{FFR-pre}$ are allocated based on the predictions. Since the binding FFR demand for day D are not public yet, the bid for FFR is only preliminary and not binding.

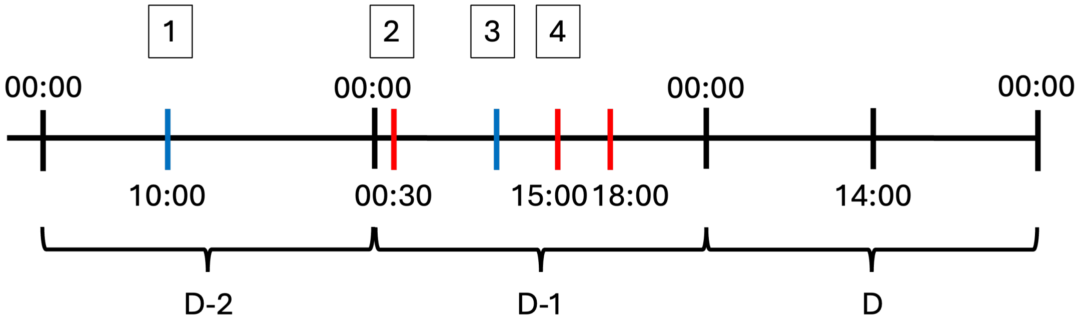

Fig. 1: Timeline for Decision Model

3. At 10:00 on D-1 the binding FFR demand is released by Energinet, and the related auction takes place at 15:00.
4. At 15:00 on D-1, the FFR auction, as well as the FCR-D late auction are optimised jointly. The capacities that can be used in this late auction are the preliminary reserved values for FFR from the early auction, as well as improvements in the forecast. The decision variables are p_t^{up-l}, p_t^{down-l} and p_t^{FFR}

Since the early and late auction models only differ in the variables which are obtained, we present the formulation for the early auction first, and then only/ point out the differences between the two. In the **early auction** decision model, the problem objective is to maximise the daily revenue from bidding in the frequency market:

$$\max_{\delta \in \mathcal{D}} \pi_{exp} = \sum_{t=1}^{24} \Big(p_t^{u-e} \cdot \lambda_t^{u-e} + p_t^{d-e} \cdot \lambda_t^{d-e} + p_t^{FFR-pre} \cdot \lambda_t^{FFR} \Big) \tag{1}$$

where the decision variables δ are formulated as a set $\mathcal{D}$:

$$\mathcal{D} = \{p_t^{u-e}, p_t^{d-e}, p_t^{FFR-pre}, aux_t^u, aux_t^d, y_t^u, y_t^d\}$$

the capacities that can be offered are determined as in equation (2):

$$C_t^{up} = P_t^{pred48} \tag{2a}$$

$$C_t^{down} = \lceil \frac{P_t^{pred48}}{C^{avg}} \rceil \cdot C^{nom} - P_t^{pred48} \tag{2b}$$

As shown in (2a), capacities are based on the predictions with a lag of 48 hours, according to the available information at the time of the early auction. For the upward capacity C_t^{up}, it is expected that the aggregation of EVs can briefly reduce their charging power down to zero. For the *downwards capacity*, it is assumed that every connected outlet increases the charging power to the maximum capacity. Since there is no precise information available about how many vehicles are charging exactly, an assumption is made to determine the amount of vehicles from the forecasted EV load. The average charging rate per outlet during charging process C^{avg} = 7.61 kW, so the predicted load is divided by this value and rounded to the next integer number to find the number of vehicles charging, as shown in (2b). The number of vehicles is then multiplied by the nominal charging power per outlet C^{nom} = 11 kW, and finally the predicted load is subtracted to obtain the down-regulation capacity C_t^{down} for the parking lot. The objective function is based on price expectations for FCR-D and FFR. The prices for FCR-D in the early auction λ_t^{up-e} and λ_t^{down-e} are based on the prices of the day before, as the prices of the early auction show a strong autocorrelation. The prices for FFR are based on an interpolation of historic prices of 2023, where the price λ_t^{FFR} is expressed as a function of the volume x that is expected to be demanded as in (3)

$$\lambda_t^{FFR} = 0.03x^4 - -0.84x^3 + 5.28x^2 + 19.88x + 9.45 \tag{3}$$

The decision model is subject to the following constraints:

Constraint (4) ensures that the volumes offered in the bids are only positive or null.

$$p_t^{u-e}, p_t^{d-e}, p_t^{FFR-pre} \geq 0 \qquad \forall t \tag{4}$$

Constraints (5) restrict the bids to the available capacities.

$$\begin{aligned} \sum p_t^{u-e} + p_t^{FFR-pre} &\leq C_t^u \qquad \forall t \\ p_t^{d-e} &\leq C_t^d \qquad \forall t \end{aligned} \tag{5}$$

Here, the sum of the two services that provide up-regulation to the system FCR-D up and FFR need to be smaller than C_t^{up}, while FCR-D down needs to be smaller than C_t^{down}. Constraints (6), (7), and (8) ensure that the Limited Energy Reservoir (LER) regulation is considered. This means that 20% of the FCR-D bids in the opposite direction need to be reserved for energy management. However, the constraint needs to be linearised using auxiliary variables aux_t^{up} and aux_t^{down}, as linear programming only allows for linear constraints.

$$aux_t^u \geq C_t^u - 0.2p_t^{d-e} \tag{6a}$$

$$aux_t^u \geq 0 \tag{6b}$$

$$aux_t^u \leq C_t^u - 0.2p_t^{d-e} + M(1 - y_t^u) \tag{6c}$$

$$aux_t^u \leq My_t^u \tag{6d}$$

$$
\begin{aligned}
&aux_t^d \geq C_t^d - 0.2p_t^{u-e}\\
&aux_t^d \geq 0\\
&aux_t^d \leq C_t^d - 0.2p_t^{u-e} + M(1-y_t^d)\\
&aux_t^d \leq My_t^d
\end{aligned}
\tag{7}
$$

$$
\begin{aligned}
p_t^u &\leq aux_t^u\\
p_t^d &\leq aux_t^d
\end{aligned}
\tag{8}
$$

The constraints (6) and (7) are implemented in the same way, thus only (6) is explained in detail, but the same logic applies to the downwards regulation in (7).
Due to the LER regulation, the bid volumes for FCR-D up depend on the bid volume of FCR-D down, and the other way around, respectively. However, in case that 20% of the bid for FCR-D up- or down is larger than the capacity in the other direction, the resulting maximum offer volume would be negative, which is not possible due to (4). In this case, the model would not be solvable. Therefore, the auxiliary variables aux_t^{up} are introduced to linearise a maximum function, taking a value of either 0 or the upwards capacity C_t^{up} minus 20% of the bid for FCR-D down p_t^{down-e}. The linearisation is achieved by using four constraints. Firstly, (6a) ensures that aux_t^{up} is larger or equal than $C_t^{up} - 0.2p_t^{down-e}$. (6b) ensures that aux_t^{up} is larger than 0. The next two constraints work inversely by making use of a binary variable y_t^{up}, and M, which is a big number. In case y_t^{up} is 0, aux_t^{up} needs to be smaller than the sum of the big number M and $C_t^{up} - 0.2p_t^{down-e}$. If y_t^{up} takes a value of 1, aux_t^{up} needs to be smaller than M. As a result, aux_t^{up} can only take two values: either 0 or $C_t^{up} - 0.2p_t^{down-e}$. In (8), it is then ensured that the offers are smaller than the corresponding maximum capacity determined by the auxiliary variables. Finally, the constraint in (9) ensures that the bids can not be larger than the capacity that is demanded by Energinet. This constraint is mainly relevant for FFR, since in the majority of hours FFR is not requested, ensuring that the model only makes a bid for FFR in case it is demanded. The notation for the FFR demand in the early auction shows the two day ahead demand forecast by Energinet.

$$
\begin{aligned}
p_t^{u-e} &\leq D_t^{u-e} && \forall t\\
p_t^{d-e} &\leq D_t^{d-e} && \forall t\\
p_t^{FFR-pre} &\leq D_t^{FFR-d2} && \forall t
\end{aligned}
\tag{9}
$$

For the **<u>late auction</u>**, the maximum capacities that can be offered consist of the preliminary reserved volume for FFR and of improvements in forecast in between the two auctions:

$$
\begin{aligned}
C^{u-l} &= C_t^u - p_t^{u-e} - 0.2 \cdot p_t^{d-e}\\
C^{d-l} &= C_t^d - p_t^{d-e} - 0.2 \cdot p_t^{u-e}
\end{aligned}
\tag{10}
$$

and in all the equations (1)-(9), the decision variables with the e apex need to be changed to l, indicating the auction type "late". Moreover, the price expectation for FCR-D in the late auction can not be based on the prices of the day before anymore, since the autocorrelation for the late auction prices is low. Thus, the price expectations for down and up-regulation are modelled using their relationship with spot prices, which is shown in Figure 2. The equation of the interpolation is given in (12).

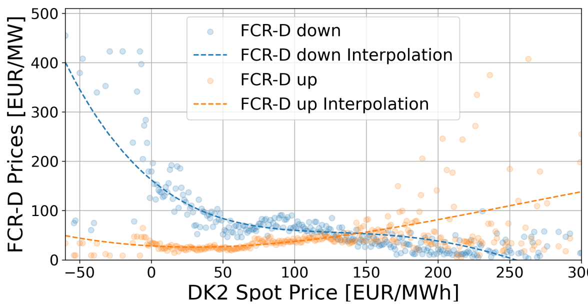

Fig. 2: Relationship of FCR-D late auction prices and spot prices

$$
\begin{aligned}
\lambda_t^{d-l} = 8.6 \cdot 10^{-8}x^4 - 7.6 \cdot 10^{-5}x^3 +\\
0.02x^2 - 2.4x + 162.5
\end{aligned}
\tag{11}
$$

$$
\begin{aligned}
\lambda_t^{u-l} = -2.6 \cdot 10^{-10}x^4 - 3.7 \cdot 10^{-6}x^3 +\\
0.002x^2 - 0.2x + 28.4
\end{aligned}
\tag{12}
$$

3 Case Study

The case study is based on a real-world workspace parking lot, located at the Lyngby campus of the Technical University of Denmark in Copenhagen (Denmark). The parking lot consists of six charging stations of the type EVlink 2S22P22R by Schneider Electric, each holding two outlets, for a total of 12. Data for every charging session is provided by the e-mobility service provider Spirii for a period of 1.5 years, from September 2022 until February 2024. The relevant information from the dataset are: i) the connection/disconnection time of each EV; ii) the timestamps for the starting and stopping of each individual charging process; and iii) the total energy charged in the session. Out of the provided information, a load curve was generated under the assumption that the charging power is constant over the full duration of the charging process, as described in [13]. On average, the whole parking lot accounts for 187.64 kWh of charged energy on weekdays and 60.58 kWh on weekends, indicating higher usage on working days. Additionally, the average duration per charging process is 5.5 hours on weekdays and 4.7 hours on weekend days. However, the average energy charged per session is 18.34 kWh on weekdays and 23.53 kWh on weekends. The charging pattern in the parking lot can be seen in the boxplot from Figure 3, where a similar pattern occur for every weekday from Monday to Friday, while in the weekend days are characterised by less load. On the working days, the majority cars arrive in the morning hours

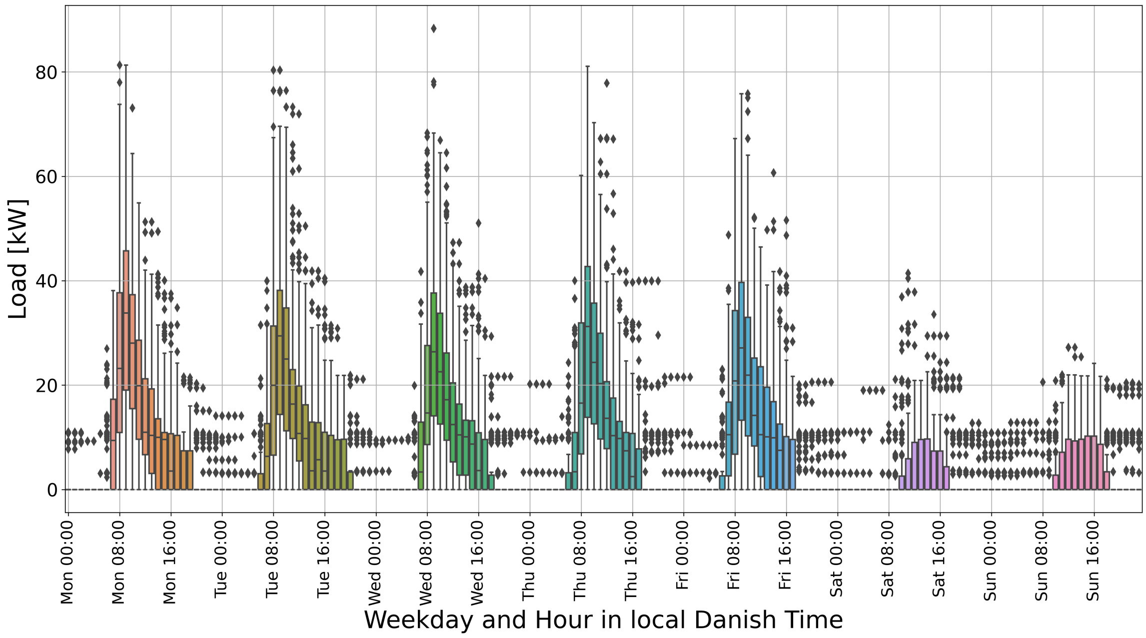

Fig. 3: Boxplot of the EV load in one of the considered parking lots.

Table 1 10th quantile of parking lot aggregated EV load in kW.

Hour	Mo	Tu	We	Th	Fr	Sa	Su
0 - 6	0	0	0	0	0	0	0
7	24.3	9.9	23.7	28.2	24.6	0	0
8	134.9	49.5	103.5	74.7	55.6	0	0
9	255.7	95.4	181.1	155.8	118.9	0	0
10	213.7	85.3	200.8	133.3	115.5	0	0
11	136.1	111.2	150.9	104.3	45.2	0	0
12	100.9	59.3	85.7	62.0	10.4	0	0
13	27.4	13.6	30.3	27.	2.6	0	0
14	0	6.8	11.0	26.11	0	0	0
15-23	0	0	0	0	0	0	0

and start the charging process. The daily peak is around 9:00 to 10:00 AM.

To simulate the behaviour of an aggregator, the load curve of the single parking lot is used to create 30 artificial parking lots, each one with 12 outlets and similar charging patterns. For the creation of artificial parking lots, the connection and disconnection times of every single charging session from the real data are by a value extracted from a normal distribution with a zero mean and standard deviation of 60 minutes. This simulates different user behaviors, accounting for variations in their arrival times due to daily fluctuations. In compliance with the requirement by Energinet, the hourly 10th quantile load per day for the aggregation is seen in Table 1. This is referred to as *baseline* and is used as a benchmark. The table clearly shows that the requirement is met only in the working hours on weekdays. In the night and afternoon, as well as in the weekends, the value of the 10th quantile is 0.

4 Results and Discussion

The following section provides an overview of the results for frequency service participation of an aggregation of electric vehicles in a time period of 150 days from September 2023 to February 2024. The study considers four scenarios:

1. *Benchmark*: the baseline historical load (10th quantile of the hourly EV load) is bid in the different services using the decision model but without any prediction process.
2. *ML prediction scenario*: the ML model is applied and the predictions are offered in the markets.
3. *Perfect foresight scenario*: both the prices and the available EV capacity are perfectly known in advance. This step is used to find a profit ceiling, representing the maximum possible profit that can be expected.
4. *Hypothetical intra-day market scenario*: the aggregator can offer capacities on the day of operation, since the late auction is an intra-day one, closing one hour before operation.

4.1 Baseline Results

To create a benchmark for the results, firstly a case is considered where the bidding is based only on the baseline, which are the 10th quantiles of the historical EV load, without considering any forecasting. Therefore, the values from Table 1 are used as an input to the decision model. Then, for every day, the rolling horizon optimisation is run. The model allocates the available capacity to the frequency services firstly in the early auction. Then, in the late auction, the model has the opportunity to correct the bids from the early auction. However, as the baseline is not dynamic and consists of fixed volumes, there are no additional capacities expected for the late auction. Thus, there is only one possible scenario where FCR-D can be offered in the late auction, which is when the model reserves capacity for FFR in the early auction based on the D-2 demand forecast from Energinet, but then this need is not confirmed in the binding D-1 demand. In that specific case, the leftover capacity can be offered for FCR-D in the late auction. By using the baseline, a profit of 2053.5 € can be achieved in the considered time period. The profit broken down into the early and late auction can be seen in Table 2 where it is clear that the majority of the profit is generated with the FCR-D up service.

Table 2 Profit from frequency services using the baseline [€]

	FCR-D up	FCR-D down	FFR	Sum
Early	1385.4 *(67.47%)*	622.7 *(30.30%)*		
Late	17.7 *(0.87%)*	12.7 *(0.63%)*	14.9 *(0.73%)*	
Sum	1403.1 *(68.34%)*	635.4 *(30.93%)*	14.9 *(0.73%)*	2053.5 *(100%)*

4.2 Results based on ML predictions

Firstly, the accuracy of the predictions is evaluated. Two forecasts are assessed, based on the gate closure times of the early and the late auctions. For the early auction, we evaluate the performance of the algorithm when predicting the EV load two days in advance (48h). For the late auction, the predictions are combined from one day ahead and two days ahead. Since the gate-closure time of the late auction is at 18:00 a lag of 24 hours can be used for the hours 00:00-17:00, while the remainder of the day from 17:00 to 24:00 is based on the predictions with a lag of 48 hours. Table 3 shows different metrics for the accuracy of the load predictions with the two time horizons. From the table, it can be seen that overall the accuracy of the forecasts improves only little by moving one day closer to real time operation. For both time horizons, the RMSE, that weights larger errors stronger, is significantly higher than the MAE. This indicates, that the model frequently does predictions that have large differences to the real data. Using the predictions from the machine learning model as an input to the decision model provides the profits presented in Table 4.

Table 3 Performance metrics for 24 and 48 hour prediction horizon

Prediction Horizon	MAE [kW]	RMSE [kW]	R^2 [p.u.]
48h	104.91	195.533	0.5433
24h	102.64	191.362	0.5626

The results show that a profit of 3749.3 € is achieved, which is significantly larger compared to the baseline benchmark. Even though the model has the possibility to correct the offers in the late auction, due to the small difference between the predictions in the two forecast horizons, the participation in the late auction is low, and so are the profits. Moreover, it can be seen that the profits from FFR are neglectable. The reason for this is that FFR is mostly demanded at night in the summer period from May to October. Since the considered period is from September to February, the demand for FFR is only little. Furthermore, the parking lot aggregation provides the majority of capacity during the working hours, and not during the night where more FFR is demanded.

Table 4 Profit from frequency services [€]

	FCR-D up	FCR-D down	FFR	Sum
Early	2529.2 *(67.5%)*	1115.4 *(29.7%)*		
Late	59.9 *(1.6%)*	24.9 *(0.7%)*	19.9 *(0.5%)*	
Sum	2589.1 *(69.1%)*	1140.3 *(30.4%)*	19.9 *(0.5%)*	3749.3 *(100%)*

4.3 Perfect Foresight Results

To evaluate the profitability ceiling, in this section the decision model considers perfect foresight for both FCR-D and FFR prices, as well as available capacities from the parking lot aggregation. This means that an offer can be made according to the capacity that is available 90% of the time within a certain hour, scaling the minute resolution load curve into hourly resolution. This corresponds to the hourly 10^{th} quantile of the minute resolution load curve. The profit in the considered time period is significantly larger, 26065 € in the considered time period. The breakdown of the profits into the different services and auctions is provided in Table 5. From the table it can be seen that a large amount of profit can be obtained in the late auction for FCR-D. Moreover, it shows that for the parking lot aggregation, FCR-D up is the most profitable service, with a contribution of almost 80% of the total profit. This tendency can be explained by the average charging rate C^{avg}, which corresponds to a larger capacity for upwards regulation. FFR has a

Table 5 Profit from frequency services under perfect foresight [€]

	FCR-D up	FCR-D down	FFR	Sum
Early	7157.8 *(27.46%)*	3496.7 *(13.42%)*		
Late	13544.9 *(51.97%)*	1582.4 *(6.07%)*	283.3 *(1.08%)*	
Sum	20702.7 *(79.43%)*	5079.1 *(19.49%)*	282.3 *(1.08%)*	26065.1 *(100%)*

very low contribution to the overall profits, due to the aforementioned mismatch between the period when it is usually required, and the availability time of the EVs.

4.4 Results with hypothetical intra-day structure

The previous results show that the day-ahead structure combined with a confidence level of 90% makes it difficult to effectively use EVs for ancillary services. Therefore, a hypothetical market structure is evaluated, where the early auction for FCR-D and the FFR auction take place at the same time on D-1, while the late auction is considered to be an "intra-day" auction, with a gate-closure time one hour before the operation (H-1). The movement closer to real-time operation in the late auction, allows to do forecasts with a considerably higher accuracy. While the difference between 48 and 24 hours forecast horizon in Table 3 showed only little improvement, the accuracy with a forecasting horizon of 1-2 hours improves the results drastically, as shown in Table 6. With a gate-closure time of H-1, the predictions with a forecast horizon of two hours can be used as an input. The results of the hypothetical market structure are summarised in Table 7. Table 8 provides an overview of the results with the intra-day late auction. From the table, a significant improvement in profitability can be seen, that is achieved by unlocking a large amount of flexibility that would remain unused otherwise. In the considered time period, a profit of 11,522.23 € results from the participation in frequency services. It can be seen that the The majority of the profits is generated in the late auction (68.14%). It can also be seen that more than half of the earnings are realised with the FCR-D up service, while 44.2% are realised with FCR-D down. On the other hand, as the early auction remains as a day-ahead auction, it is visible that the profits achieved only changed slightly, compared to the current market structure from Table 4.

Table 6 Performance metrics for shorter time horizons

Prediction Horizon	MAE [kW]	RMSE [kW]	R^2 [p.u.]
2h	79.61	154.16	0.72
1h	47.66	100.39	0.89

Table 7 Gate closure times for frequency service markets with intra-day FCR-D late

Service	Gate-closure	Auction type
FCR-D up/down early	D-1 15:00	Day-ahead
FCR-D up/down late	D H-1	Intra-day
FFR	D-1 15:00	Day-ahead

Table 8 Profit from frequency services with hypothetical market scheme [€]

	FCR-D up	FCR-D down	FFR	Sum
Early	2528.9 *(22.0%)*	1115.9 *(9.7%)*	25.0 *(0.2%)*	3669.8 *(31.9%)*
Late	3874.7 *(33.6%)*	3977.7 *(34.5%)*		7852.4 *(68.1%)*
Sum	6403.6 *(55.6%)*	5093.6 *(44.2%)*	25.0 *(0.2%)*	11522.2 *(100%)*

In Table 9, the results are scaled linearly to a full year for all four scenarios, so the reader can have a clearer idea of the yearly profit.

Table 9 Overview of profits in €

	Baseline	Day-Ahead ML	Perfect Foresight	Intra-Day ML
Sep-Feb	2035.5	3749.3	26065.1	11522.2
Full year	4996.8	9122.0	63425.0	28039.3
Yearly per outlet	13.9	25.4	176.2	77.9

4.5 Discussion

The results also have some limitations that should be considered. Since the analysed dataset is based on a single parking lot that is used to create artificial parking lots, the load curve could be affected by anomalies in the original dataset, which would be transferred to all 30 artificial parking lots. This introduces some instability, that would be unlikely in a real-world aggregation. Thus, with a more stable load curve it is assumed that the profitability per outlet is larger in reality. Moreover, the study considers a time span from September to February, which mostly represents winter months. This time period is linearly scaled to a full year in the study. However, since in the winter months the profitable FFR service is rarely demanded, it can be assumed that the profitability for a full year is higher than the one we calculated. Furthermore, the revenues could also be higher considering that both up and down FCR-D services commonly see an increase in prices in the spring and summer months. Additionally, it is debatable if an aggregation of electric vehicles should be considered as a limited energy reservoir. Even though an individual electric vehicle is limited by the battery capacity, an aggregation of many individual cars can possibly manage a continuous activation for two hours. In this study, LER constraints were applied, as user convenience is prioritised and the charging process of vehicles should not be disturbed. Finally, the hypothetical market structure with intra-day should be considered. On the one hand, giving an option for intra-day correction of bids greatly improves the availability of fluctuating energy resources, such as EVs. Recent price spikes of FCR-D services in the Nordics also show the need for additional supply of capacity, and the demand for ancillary services is expected to increase further with larger shares of DER in the system. On the other hand, safe and secure operation of the power system is essential. Thus, adjustments of the market structure need to be assessed carefully, considering all outcomes including benefits, drawbacks and risks.

5 Conclusions

As a benchmark, the decision model receives the hourly 10^{th} quantile load per day baseline as input, where the late auction remains largely unused, as the historical baseline is static and there is no possibility to correct the bids. With the baseline, the model can achieve a revenue of 13.88 € per outlet per year. An improvement of the profitability can be achieved when using machine learning based load forecasting. By making load predictions for every hour on each day specifically, the capacities that are given to the decision model are increased. Thus, the yearly profit per outlet increases to 25.38 €. Nevertheless, even though the model has the possibility to improve the forecast in between the early and the late FCR-D auction, the late auction remains largely unused. The reason for this is that both the two-day ahead and the day-ahead forecasts of the load that occurs with a probability of at least 90% are very similar. In this way, a large amount of available resources remain unused, as seen by comparison to the case when the decision model optimises the available capacities considers perfect foresight. In that case, a yearly profit of 176.18 € per outlet is estimated. Therefore, a hypothetical market structure is assessed, where the late FCR-D auction is considered to be an intra-day auction, that takes place one hour before the operation. By moving the forecast horizon closer to real-time, the machine learning model can make more accurate predictions. Thus, a large amount of available flexibility is unlocked and the participation in the late auction increases significantly. Under the hypothetical market structure, a profit of 77.89 € per outlet per year is achieved.

Future studies will assess if machine learning and artificial intelligence can be applied successfully integrate the flexibility of EVs into the power system. Moreover, it should be examined how synergies with different technologies or different charging patterns can be used to improve the business case for DER participating in frequency services.

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