Comparison of Small EV Charging Station's Load Forecasts and it's Impact on the Operational Costs

Alexander Stein
Institute of Electrical Engineering (ETI)
Karlsruhe Institute of Technology
Karlsruhe, Germany
alexander.stein@kit.edu

Anna Sina Starosta
Institute of Electrical Engineering (ETI)
Karlsruhe Institute of Technology
Karlsruhe, Germany

Bernhard Schwarz
Institute of Electrical Engineering (ETI)
Karlsruhe Institute of Technology
Karlsruhe, Germany

Nina Munzke
Institute of Electrical Engineering (ETI)
Karlsruhe Institute of Technology
Karlsruhe, Germany

Marc Hiller
Institute of Electrical Engineering (ETI)
Karlsruhe Institute of Technology
Karlsruhe, Germany

***Abstract*—For an energy management system (EMS) of a charging station (CS), information on future load is crucial. Existing models primarily focus on load forecasting for large charging stations. In this study, three different load forecasting models based on real data from a public CS with two charging points are developed. The models include two persistent models and one model that utilizes a machine learning algorithm.**

To assess the impact of forecasting accuracy on operational costs, a case study with dynamic electricity prices and a stationary battery storage is conducted. Using the load predictions, a mixed-integer linear programming problem is formulated to optimize the scheduling of the stationary battery charging.

***Index Terms*—charging infrastructure, load forecast, energy management system (EMS), stationary battery storage**

Nomenclature

AWM	Average Week Model
BESS	Battery Energy Storage System
CS	Charging Station
EMS	Energy Management System
EV	Electric Vehicle
LWM	Last Week Model
LSBoost	Least Squares Boosting
i	Day Interval Number
d	Weekday
w	Week Number

I. Introduction

A. Motivation and Background

In today's world, the mobility and energy sector aim to reduce carbon emissions worldwide, due to the impact of global climate change. With an expansion of renewable energies such as photovoltaic (PV) and wind power plants comes the disadvantage of increasingly fluctuating and less controllable energy generation that requires adjusting the load to the generation. To address this, the German Federal State passed a law that obliges electricity suppliers to offer dynamic electricity tariffs from 2025 [1]. Since the high availability of renewable electricity is associated with low prices, load shifting by end consumers is economically advantageous.
A charging station (CS) equipped with solar rooftops allows for the charging of vehicles using locally generated renewable energy. In combination with a battery energy storage system (BESS), the power drawn from the grid can be shifted to periods when electricity prices are low. Optimized scheduling of the BESS charging and discharging requires a forecast of future load and energy production.

In this study, the impact of the accuracy of load forecasts is investigated by using a case study of a PV-powered CS with BESS and dynamic electricity prices. Three different load forecast models are developed and compared to a perfect prediction. The prediction models include a machine learning algorithm and two persistent models based on the weekly average and the charging behavior of the week prior.

B. Relevant Literature

Existing research on charging station (CS) forecasting can be categorized based on the algorithms used and in terms of their focus. Predicted parameters include occupancy [2]–[5], load demand and parking duration of an individual charging session [6]–[8]. The following focuses on work that develops forecasts of the load of CSs.
The range of studies predicting charging power varies from entire regions [4], [5], [9] or entire cities [5], [10] to individual charging stations. Kim et al. [11] compare predictions for these three observation levels and conclude that predictions at the city and regional levels provide good results, while predictions at the charging station level have room for improvement. Individual CSs studied vary significantly in size, with loads in the megawatt range [10], [12], [13]. Smaller CSs have up to 10 charging points [14], [15].

Load forecasting algorithms can be divided into linear and nonlinear models. A commonly used linear model is the autoregressive integrated moving average (ARIMA) algorithm used by Amini et al. [16]. ARIMA can be further improved to the seasonal autoregressive integrated moving average (SARIMA) and by adding an external variable to the SARIMAX model [17].

Nonlinear methods include artificial neural networks (ANN) and long short-term memory networks (LSTM), a special type of neural network optimized for time series processing [18]. Other nonlinear methods are ensemble learning methods, that combine multiple regression trees, and support vector regression [19]. Boosted trees, a popular ensemble learning algorithm, have been utilized by Almaghrebi et al. [6] and Xue et al. [20].

The literature presented focuses on load forecasts for CSs with six or more charging points. As the data analysis of the next chapter shows, most public CSs in Germany consist of only two charging points. To evaluate the forecasts, the most commonly used metrics are mean absolute error (MAE) and mean squared error (MSE). None of the work compares the impact of the accuracy on a CS's energy management system (EMS).

C. Contributions and Organization

The existing literature has shown a lack of attention to load forecasts for small CSs and the subsequent impact on the EMS scheduling. This paper aims to address this gap by introducing three load forecasting models designed for small CSs. In addition, the load forecast dependent savings potential for CS operators is determined.

First, a suitable charging point is selected and the corresponding forecasting models are developed. To analyze the operating costs, a case study is conducted using a CS equipped with a PV system and BESS located in Germany. The study includes dynamic electricity prices and selects one week each representing summer, winter, and spring weather conditions. By utilizing historical charging data and PV power generation of these case study weeks, the operating costs are analyzed to compare the impact of the different forecasting models.

II. Load Forecast

The charging data available consist of a total of 7098 charging stations with 4.3 million charging sessions in the years 2020-2021 [21], which are divided into different scenarios illustrated in Fig. 1. The data provides the following information for each charging session:

- Charging station ID
- Charging station scenario
- Charging point ID
- Charging session ID
- Start time and date of the charging session
- End time and date of the charging session
- Charged energy of the charging session
- Maximum power of the charging point

From the available data one public CS is selected for the load forecast. To maximize the amount of training data, CSs that do not provide data over the entire two-year period are excluded. This criterion is met by 77 CSs, with the majority of them having two 22 kW charging points. Among these CSs, one is selected with the characteristics outlined in Table I.

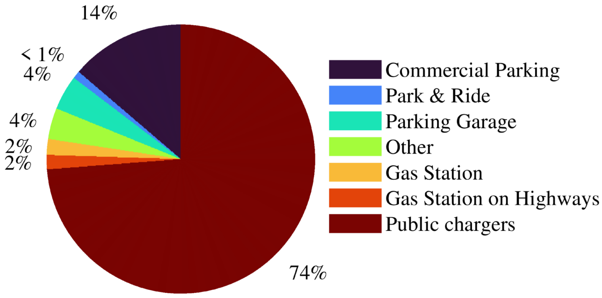


Fig. 1. Share of CSs by scenario (OBELIS data set [21]).

TABLE I
PROPERTIES OF THE SELECTED CS WITH TWO CHARGING POINTS

Total Number of Charging Sessions	3240
Mean Charging Duration	60 min
Mean Charged Energy per Session	17.9 kWh
Power Charging Point 1	22 kW
Power Charging Point 2	22 kW

A. Data Preparation

The aim of the forecasting models is to predict the charging power for an entire day with a resolution of 15 min. The charging data does not provide specific details about the load profile during the charging session. Therefore, it is assumed that the charging power remains constant throughout the entire duration of the charging session. Charging sessions that are shorter than three minutes are excluded from the analysis, as they are considered to be potentially erroneous. Due to the missing information on the location of the charging point, no external location-dependent features such as weather information can be added. For each time interval of the day (denoted as i), the mean charging power P_{Load} (1) is calculated based on the data collected from 2020 to 2021, spanning a total of 104 weeks (w).

$$\begin{aligned} P_{\text{Load}}(w, d, i) \ \text{ with} \\ w \in \{1, 2, ..., 104\} \\ d \in \{Mo, Tu, ..., Su\} \\ i \in \{1, 2, ..., 96\} \end{aligned} \tag{1}$$

Of the available data 10 weeks or approximately 10 % are used for the test data set. The test weeks are chosen in a way that they contain the three weeks of the case studies. The remaining seven weeks are chosen randomly. The set of test weeks w_{test} consists of the following weeks:

$$w_{\text{test}} = \{36, 43, 55, 60, 67, 79, 86, 96, 100, 103\} \tag{2}$$

In the next sections the models are presented starting with the "Average Week Model" and "Last Week Model".

B. Average Week Model (AWM)

The Average Week Model (AWM) calculates the average charging power $P_{\text{AWM}}(d, i)$ over the entire training weeks per day interval i and weekday d as described in (3).

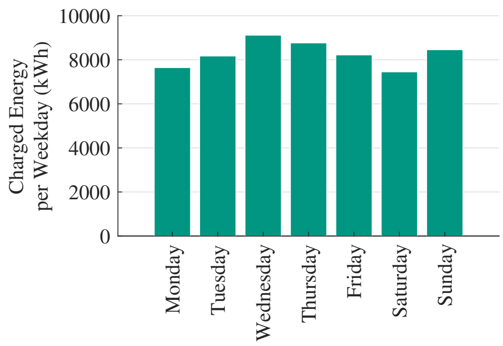


Fig. 2. Charged energy per weekday of the selected CS defined by Table I from 2020-2021.

$$P_{\text{AWM}}(d,i) = \frac{\sum_{m \in w_{\text{fit}}} P_{\text{Load}}(m,d,i)}{count(w_{\text{fit}})} \text{ with } w_{\text{fit}} \in w \setminus w_{\text{test}} \quad (3)$$

C. Last Week Model (LWM)

Similar to persistence forecasts for wind and solar power predictions this model assumes that charging behavior remains similar over time. As can be seen in Fig. 2, charging sessions vary by day of the week. Therefore, instead of using the charging performance from the previous day, this model utilizes the charging performance from the corresponding weekday of the previous week.

$$P_{\text{LWM}}(w,d,i) = P_{\text{Load}}(w-1,d,i) \quad (4)$$

D. Machine Learning Model

The Machine Learning algorithm used is Least-Squares Boosting (LSBoost), an ensemble learning algorithm that uses gradient boosting. It combines multiple weak learning models, in this case regression trees, with gradient boosting. Gradient boosting minimizes the squared-error loss function by constructing the new weak learner to correlate with the negative gradient of the loss function. [22]

LSBoost is combined with the AWM. Instead of directly forecasting the load, LSBoost is used to predict the error of the AWM $P_{\text{Error,AWM}}$:

$$P_{\text{Error,AWM}}(w,d,i) = P_{\text{Load}}(w,d,i) - P_{\text{AMW}}(d,i) \quad (5)$$

This serves the two main purposes:

1) Most of the time there is no electric car connected to any of the charging points. For the response variable, the predicted charging power, this leads to a large proportion of zeros which is disadvantageous for the learning process of the algorithms. By forecasting the error of the AWM instead of the charging power directly, this issue is resolved.
2) By learning the error of the AWM, the model can improve its performance. This means that the model can build upon the already existing knowledge captured by the AWM and refine its predictions.

The features used for training include the historical load data of the previous 14 days and calendar information. The calendar data contain the week number, the day of the week from 1 to 7, a logical distinction if it is a holiday and the day interval number. To reduce the number of features for the time series data, a resolution of 1 hour is chosen. This results in a total of 340 features.

Before training, the data are normalized ($[0, 1]$). Hyperparameter optimization is performed using Bayesian optimization with 50 iterations. The remaining days, excluding the test data set, are further divided into 30 % validation days and 70 % of the days for the training set.

To predict the load, two post-processing steps are added to the LSBoost. First, the prediction of the AWM is added. Subsequently, any negative load values are set to zero since the charging points are unidirectional.

E. Model Comparison

The training results and the used hyperparameters are summarized in Table II. The evaluation of the models on the test dataset is based on the mean absolute error (MAE) and the mean squared error (MSE). The results show that the LSBoost-Model achieves lowest MSE of 61.9 kW^2 and the lowest MAE of 4.29 kW. The AWM has a 4.4 % higher MSE (64.65 kW^2) and a 6.8 % higher MAE. The LWM has the highest MSE of 121.23 kW^2. In contrast its MAE (4.39 kW) it is better than the MAE of the AWM.

TABLE II
MODEL ACCURACY ON TEST DATA SET

Model	Hyperparameters	MSE in $(kW)^2$	MAE in kW
AWM	-	64.65	4.58
LWM	-	121.23	4.39
LSBoost	Learning Rate: 0.0174 Min. Leaf Size: 4440 Max. Splits: 5799 Learning Cycles: 278	61.90	4.29

Fig. 3 depicts the predicted load of an example day, from which it can be concluded, that the LSBoost model is not predicting the discrete behaviour of the charging sessions. Instead, it only learned to adjust the AWM to the temporal trend and could not see any correlations between the features used and the discrete behaviour of the charging sessions. It needs to be clarified whether additional external information can be effectively incorporated to supplement the features used by the model.

III. Case Study

To facilitate a comparison of the models based on their impact on the EMS of a CS, the setup illustrated in Fig. 4 is selected. It consists of the AC coupled components BESS, PV system including the Maximum Power Point (MPP)-tracker, a grid connection and the charging points. Below the considered properties for optimization and simulation are described.

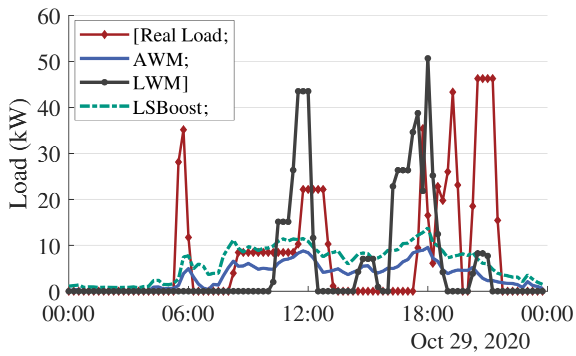


Fig. 3. Predicted load and real load for an example day.

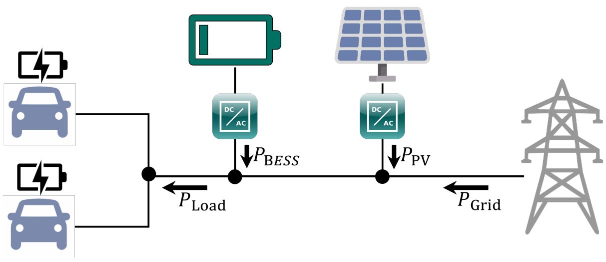


Fig. 4. Charging station structure.

A. Battery Energy Storage System (BESS)

The battery storage is connected via an AC/DC converter. In order to be able to linearize the scheduling optimization problem constant efficiencies are used. For charging and discharging an efficiency of $\eta_{\text{Bat}} = 0.975$ is assumed for the battery based on the work by Munzke et al. [23] on home storage systems. The efficiency selected for the AC/DC converter is $\eta_{\text{AC/DC}} = 0.914$. The BESS capacity, denoted as $E_{\text{BESS,max}}$, is varied in the later case study. Based on Munzke et al. [23] for charging and discharging a C-rate of $c = 0.5$ is chosen which limits the charge and discharge power to $P_{\text{From BESS, max}} = P_{\text{To BESS, max}} = c \cdot E_{\text{BESS,max}}$.

B. PV System

For the PV system, the characteristics of PV plants in the south of Germany are applied. A tilt angle of 30° and a southern orientation is most appropriate for this latitude, for which data are available from the solar park at KIT's North Campus. These already account for losses of the MPP-tracker and are available for the considered period with a resolution of one minute. The data are scaled based on the selected PV peak power of the case study. Since the focus is on load predictions for the PV forecast a perfect prediction with the actual PV data is presumed.

C. Feed-in Tariff and Electricity Price

With a peak power below 100 kWp, the feed-in tariff set by the German Renewable Energy Act 2023 is 0.066 EUR/kWh [24]. Dynamic electricity tariffs use the hourly day-ahead price adding compulsory fees (Table III). Network charges and service fees differ regionally, so an average value is assumed for the service fees of current suppliers. The fixed monthly fees independent of the consumed energy are neglected.

TABLE III
FIXED COSTS DYNAMIC ELECTRICITY TARIFFS [25]

Type of Fee	**Costs €/kWh**
Electricity Tax	0.02
Grid Utilization Fees	0.078
Concession Fee Local Community	0.0166
Total Fixed Costs	0.1146

D. Scheduling

Since the load is assumed to be not adjustable and the MPP-tracker maximises the PV power, one degree of freedom results for the EMS. The following optimization problem is formulated to determine the optimal scheduling of the BESS power for each quarter-hour interval i. The BESS and grid connection are treated separately in terms of power direction. The power balance equation

$$\begin{aligned} 0 = P_{\text{PV}} - P_{\text{Load},i} + P_{\text{From Grid},i} + P_{\text{From BESS},i} \\ - P_{\text{To Grid},i} - P_{\text{To BESS},i} - P_{\text{Loss},i} \end{aligned} \tag{6}$$

forms the basis of the optimization problem. The following conditions ensure that only one of the power directions of the BESS and the grid connection is non-zero.

$$P_{\text{From BESS}} \leq P_{\text{From BESS, max}} \cdot (1-\alpha) \text{ with } \alpha \in \{0,1\} \tag{7}$$
$$P_{\text{To BESS}} \leq P_{\text{To BESS, max}} \cdot \alpha \tag{8}$$
$$P_{\text{From Grid}} \leq P_{\text{From Grid, max}} \cdot (1-\beta) \text{ with } \beta \in \{0,1\} \tag{9}$$
$$P_{\text{To Grid}} \leq P_{\text{To Grid, max}} \cdot \beta \tag{10}$$

The loss P_{Loss} is retrieved from

$$\begin{aligned} P_{\text{Loss},i} = (P_{\text{From BESS},i} + P_{\text{To BESS},i}) \\ \cdot (1-\eta_{\text{Bat}}) \cdot (1-\eta_{\text{AC/DC}}). \end{aligned} \tag{11}$$

The stored energy of the BESS E_{BESS} results from

$$E_{\text{BESS},i} = \int_{t(i-1)}^{t(i)} (P_{\text{To BESS},i} - P_{\text{From BESS},i})\, dt + E_{\text{BESS},i-1}. \tag{12}$$

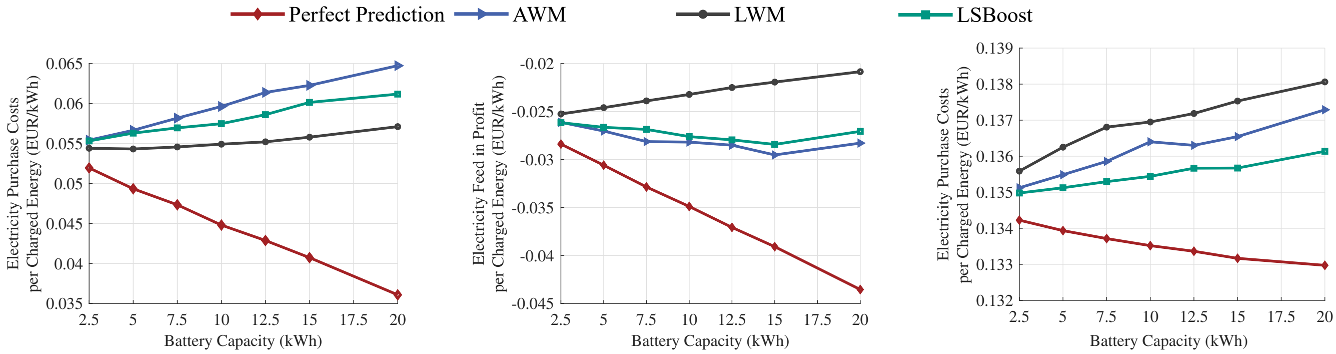
The constraint (13) ensures the state of charge (SOC) of the BESS is 50 % at the start and end of each day. By this, the EMS has the flexibility to charge or discharge the battery at the beginning of the day.

$$E_{\text{BESS},0} = E_{\text{BESS},96} = 0.5 \cdot E_{\text{BESS,max}} \tag{13}$$

The objective function f_{min} is minimized depending on the dynamic electricity tariff $C_{\text{dyn},i}$ and the constant feed in profit C_{feedin} based on the exchanged energy with the grid:

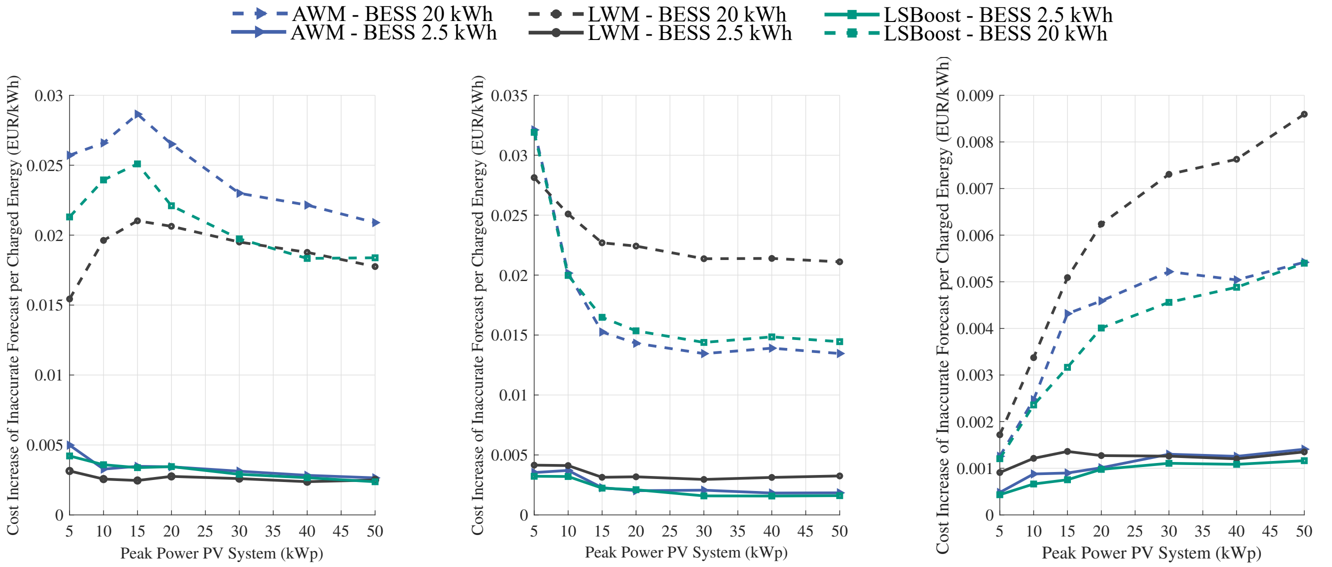
$$f_{\text{min}} = E_{\text{From Grid},i} \cdot C_{\text{dyn},i} - E_{\text{To Grid},i} \cdot C_{\text{feedin}} \tag{14}$$

Since the optimization problem is linear the solution found is a global optimum which is solved using Matlab.



(a) Spring Week (b) Summer Week (c) Winter Week

Fig. 5. Costs or profits per charged energy for each case study week per battery capacity. The PV power is 15 kWP.



(a) Spring Week (b) Summer Week (c) Winter Week

Fig. 6. Cost increase due to inaccuracies of the forecasts for a large and a small BESS.

IV. Results

Three case study weeks are selected from different seasons (Table IV). For each day of the week, the BESS power is scheduled using the forecasts of the models. With the scheduling result the entire week is simulated employing the historical load data and PV data and the actual operating costs are evaluated. The simulations of the different prediction models and case study weeks are carried out for PV peak powers ranging from 5 kWp to 50 kWp and BESS capacities ranging from 2.5 kWh to 20 kWh. The cost differences between the models arise from the fact that, due to inaccuracies in the forecasts, the scheduling of battery power is not optimal, resulting in higher costs.

Fig. 5 illustrates the relationship between the size of the BESS and the resulting electricity costs. Using the perfect prediction the costs of the charged energy become lower with larger BESS (spring: 0.015 EUR/kWh, summer: 0.015 EUR/kWh, winter: 0.01 EUR/kWh). In contrast, the costs increase or stay constant using the forecasting models. It can be concluded that with larger storage capacities, the impact of suboptimal scheduling increases, negatively impacting operating costs. In this case, a larger BESS would not be profitable.

TABLE IV
PV Characteristics per Weeks (10 kWP)

Case Study Week	Spring	Summer	Winter
Date	12.-17.04.21	14.-19.06.21	26.-31.10.21
Mean Energy/Day	39.6 kWh	58.6 kWh	14.6 kWh
Min. Energy/Day	21.4 kWh	30.9 kWh	4.3 kWh
Max. Energy/Day	56.7 kWh	70.3 kWh	40.0 kWh

Comparing the forecast models, it can be seen that the AWM and LSBoost model perform similarly. The results of the

LWM depend on the considered use case week. Analyzing the different seasons, in winter the operational cost difference per charged energy to the perfect model between 0.003 EUR/kWh (LSBoost) and 0.005 EUR/kWh (LWM) is the smallest for the largest BESS. The operational cost differences in spring and summer are in a similar range between 0.029 EUR/kWh and 0.015 EUR/kWh per charged energy for the largest BESS. The impact of the forecast quality on the operating costs increases with the BESS capacity.

Analyzing the influence of the PV peak power (Fig. 6), it can be observed that the differences in operational costs between the forecast models and the perfect model vary depending on the season. For the spring and summer weeks, the influence decreases as the PV peak power increases. In the winter week, operational cost differences between the prediction models and the perfect model increase with higher PV peak powers. Overall, it is noted that the effect of the BESS capacity on operational costs is more significant compared to the PV peak power.

It is observed that no single model consistently has the lowest costs across all weeks. The overall operational costs vary by up to 0.01 EUR/kWh between the prediction models.

V. Conclusion

Three different models for predicting the load of a small public charging point are presented. It was found to be challenging to predict the discrete behaviour of the load. The persistence model (LWM), which relied on the data from the previous week, exhibited the lowest accuracy. The LSBoost machine learning model, trained to improve the weekly average model, showed only slight improvements. It was concluded that LSBoost, based on the available calendrical input data, was unable to detect load patterns effectively.

In the case study that examined dynamic electricity prices, it was demonstrated that the combination of inaccurate forecasts and increasing storage capacities can result in higher operating costs. By further improving the forecasting models, savings of up to 0.03 EUR/kWh in terms of charged energy for electric vehicles can be achieved when approaching a near-perfect prediction.

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