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A novel forecasting approach to schedule aggregated electric vehicle charging

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HIGHLIGHTS

- Novel approach to forecast all required aspects to optimize charging of an EV fleet.
- The effectiveness of the approach is tested using real-world EV charging session data.
- Results report high forecasting performance, especially for large EV fleets.
- Forecasting performance is similar for different forecasting models.
- Only a few predictor variables are required for a good forecasting performance.

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ABSTRACT

To be able to schedule the charging demand of an electric vehicle fleet using smart charging, insight is required into different charging session characteristics of the considered fleet, including the number of charging sessions, their charging demand and arrival and departure times. The use of forecasting techniques can reduce the uncertainty about these charging session characteristics, but since these characteristics are interrelated, this is not straightforward. Remarkably, forecasting frameworks that cover all required characteristics to schedule the charging of an electric vehicle fleet are absent in scientific literature. To cover this gap, this study proposes a novel approach for forecasting the charging requirements of an electric vehicle fleet, which can be used as input to schedule their aggregated charging demand. In the first step of this approach, the charging session characteristics of an electric vehicle fleet are translated to three parameter values that describe a virtual battery. Subsequently, optimal predictor variable and hyperparameter sets are determined. These serve as input for the last step, in which the virtual battery parameter values are forecasted. The approach has been tested on a real-world case study of public charging stations, considering a high number of predictor variables and different forecasting models (Multivariate Linear Regression, Random Forest, Artificial Neural Network and k-Nearest Neighbors). The results show that the different virtual battery parameters can be forecasted with high accuracy, reaching R^2 scores up to 0.98 when considering 400 charging stations. In addition, the results indicate that the forecasting performance of all considered models is somehow similar and that only a low number of predictor variables are required to adequately forecast aggregated electric vehicle charging characteristics.

1. Introduction

1.1. Problem definition

The rapid introduction of Electric Vehicles (EVs) in different countries increases the number of distributed energy assets in the energy system. Due to the high charging power and long connection time of EVs, the potential to shift their charging demand over time is high [1]. This high charging flexibility can serve a wide range of applications if EV smart charging is deployed. From a customer perspective, smart charging can considerably reduce costs and emissions [2,3]. From the perspective of electricity grid operators, implementation of EV smart charging is the most cost-effective option for mitigating the increasing number of grid congestion problems [4,5]. In addition, EV smart charging can be used to solve power quality issues [6,7] and to provide balancing reserves to Transmission System Operators (TSOs) [8,9].

One of the main problems hindering the large-scale deployment of EV smart charging is the wide range of uncertainties faced when optimizing the charging patterns of an EV fleet. These uncertainties

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Nomenclature

List of Abbreviations

EV	Electric Vehicle
SoC	State of Charge
GCT	Gate Closure Time
TSO	Transmission System Operator

Sets and indices

$i \in \mathcal{I}$	Set of charging sessions
$t \in \mathcal{T}$	Set of timesteps in the assessment timeframe

Parameters

Δt	Timestep duration [h]
$E_{max,t}$	Max. aggregated charged energy since the beginning of the assessment timeframe at time t [kWh]
$E_{min,t}$	Min. aggregated charged energy since the beginning of the assessment timeframe at time t [kWh]
$P_{ch,coa,t,i}$	Charging power of charging session i at time t in a 'charging on arrival' scenario [kW]
$P_{ch,latest,t,i}$	Charging power of charging session i at time t in a 'latest charging' scenario [kW]
$P_{max,i}$	Max. charging power of charging session i [kW]
$P_{max,t}$	Max. aggregated charging power at time t [kW]

include the number of charging sessions occurring in the scheduling timeframe, their charging demand, charging power, arrival time and departure time.

These uncertainties can be reduced by forecasting those EV charging session characteristics. Typically, EV smart charging sessions are controlled by an energy aggregator. In all cases, the aggregator needs to forecast the departure time and energy demand of an EV when optimizing the charging session, to assure that the charging demand of an EV is met at departure. However, when participating in electricity markets using an EV fleet, an aggregator needs to extend their forecasts. In addition to forecasting the departure time and charging demand of each charging session, it also needs to forecast the number of charging sessions during the bidding period, their arrival time and maximum charging power. This is because the Gate Closure Time (GCT) of most electricity markets (i.e., the last moment until market parties can make bids) is well-before actual operation (e.g., 12-36 h before operation for the day-ahead market in Europe [10]). An incorrect forecast could force aggregators to deviate from their accepted bid to the electricity market, resulting in high imbalance costs.

Two challenges complicate the forecasting of those different EV charging session characteristics. First, the number of charging sessions in the assessment timeframe is unknown at the moment of scheduling for different smart charging applications. Hence, it is complex to forecast the charging session characteristics (i.e., arrival/departure time, charging power and charging demand) with an unknown set of charging sessions. Second, the different charging session characteristics are highly interrelated (i.e., a higher charging demand is likely to result in a higher connection time). For this reason, alternative forecasting frameworks are required for scheduling an EV fleet under uncertainty.

1.2. Literature review

Surprisingly, a low number of scientific studies have looked into developing methods to perform comprehensive forecasts of all EV charging characteristics that are required to schedule an EV fleet. A large number of studies have proposed a wide variety of methods to forecast the load of one or multiple charging stations when EVs charge in an uncontrolled manner (e.g., [21–24]). These forecasts are valuable for grid impact studies of EV charging, but do not provide insight in the required aspects to optimize the charging schedules of an EV fleet using smart charging (i.e., number of charging sessions, arrival/departure time, charging demand and maximum charging power).

Another group of papers proposes forecasting approaches that only consider some of the aspects that are required to schedule an EV fleet under uncertainty, as summarized in Table 1. Aabrandt et al. [11] propose a method to forecast the connection time of an EV to a charging station. Markov Chains were used to account for the uncertainty in EV availability by Iversen et al. [12], Sundström et al. [13] and Wan et al. [14]. Bikcora et al. [15] forecast the availability and maximum charging power of single EVs, and Islam et al. [16] forecast the arrival State-of-Charge (SoC) distribution for an EV fleet. Habibifar et al. [17] forecast the charging demand and departure time of individual EV charging sessions, but this study did not consider the uncertainty in the total number of charging sessions. Since the forecast approaches proposed in these studies do not cover all relevant aspects required to schedule an EV fleet, these methods can only be used to a limited extent when implementing EV smart charging for an EV fleet. Huber et al. [18] use quantile forecasts of the charging demand and connection time of individual charging sessions to identify the charging sessions with the highest flexibility. Giardano et al. [19] estimate the number of charging sessions, arrival time, departure time and energy demand for an individual EV, using clustering methods. Similarly, Aguilar-Dominguez et al. [20] use clustering techniques to forecast the connection hours of individual EVs. To guide users in finding an available charging station, Majidpour et al. [29] forecast the available charging capacity for a charging station.

Instead of using forecasting techniques, some studies (e.g., [30] & [31]) propose to ask for user input, such as the expected arrival and departure time and the expected arrival SoC, to reduce uncertainty when optimizing EV charging schedules. However, this is generally undesirable for different reasons. First, different studies have shown that adding complexity to users reduces their willingness to participate in smart charging [32,33]. Second, it is questionable whether users are able to provide detailed and accurate charging information hours in advance of actual operation, i.e., 12-36 h ahead in case of bidding into the day-ahead market.

To facilitate the scheduling of an EV fleet, different aggregation methods are proposed in scientific literature. An aggregation method combines the charging characteristics of a set of EV sessions into a few parameters for scheduling their aggregated charging schedule. Aggregation methods for EV fleets are presented in different forms, but all aggregation methods consider the temporal (i.e., arrival and departure time of individual EVs) and energy dimensions (i.e., charging demand and maximum charging power of individual EVs) of the charging flexibility of the respective EV fleet. Lilliu et al. [34] and Pedersen et al. [35] present the FlexOffer approach, in which the charging flexibility of an EV fleet is illustrated by two sets of constraints: i) constraints on the usable amount of energy at each timestep and ii) total energy constraints. Schlund et al. [36] describe the total flexibility by identifying the time and energy flexibility. The most common aggregation methods are to aggregate the charging session characteristics of an EV fleet by identifying the dispatchable region of the charging energy over time [27,37] or by transforming these charging session characteristics to a virtual battery (e.g., [38,39]). In this latter approach, all charging session characteristics are reduced to a set of three parameters for each

Table 1
Overview of relevant literature on the forecasting of charging transaction parameters for every individual charging transaction.

Paper	Considered charging transaction characteristics for scheduling an EV fleet					Used forecasting method	Considered predictor variables
	Number of transactions in assessment timeframe	Arrival time of charging transactions	Departure time of charging transaction	Charging demand of charging transactions	Charging power of charging transactions		
[11]	No	Yes	Yes	No	No	Statistical modeling using historical data	Historical parameter values
[12]	No	Yes	Yes	No	No	Markov decision process	Historical parameter values
[13]	No	Yes	Yes	Yes	No	Markov decision process	Historical parameter values
[14]	No	Yes	Yes	Yes	No	Markov decision process	No predictor variables used.
[15]	No	Yes	Yes	No	Yes	Generalized linear models	Historical parameter values
[16]	No	No	No	Yes	No	Maximum likelihood estimation	Historical parameter values
[17]	No	Yes	Yes	Yes	No	Autoregressive models	Historical parameter values
[18]	No	No	Yes	Yes	No	Quantile regression, Multivariate conditional kernel density estimator	Historical parameter values
[19]	Yes	Yes	Yes	Yes	No	Clustering using k-medoids technique	Historical parameter values
[20]	No	Yes	Yes	No	No	Gradient Boosting	Historical parameter values

Table 2
Overview of relevant literature on the forecasting of parameters associated with aggregated EV modeling and an overview of the aspects covered in this work.

Paper	EV aggregation parameters considered in forecast				Used forecasting methods	Considered predictor variables	Conducted forecasting analyses
	Total daily charging demand	Hourly max. charging power	Hourly max. aggregated charging energy	Hourly min. aggregated charging energy			
[25]	Yes	Yes	No	No	Seasonal autoregressive model	Historical parameter values	Model performance of aggregation parameters
[26]	Yes	Yes	Yes	No	Autoregressive model	Historical parameter values	Model performance of one aggregation parameter
[27]	Yes	Yes	Yes	Yes	Autoregressive model	Historical parameter values	None
[28]	Yes	Yes	Partly	Yes	Autoregressive model	Historical parameter values	Model performance of aggregation parameters for different EV fleet sizes
This work	Yes	Yes	Yes	Yes	Multivariate Linear Regression, Random Forest, Artificial Neural Network & k-Nearest Neighbors	Temporal data, Historical parameter values & Weather forecasts	Model performance of aggregation parameters for different EV fleet sizes & forecasting models, predictor variable importance, optimal hyperparameter sets

timestep; i) a minimum aggregated charging energy, ii) a maximum aggregated charging energy and iii) a maximum total charging power.

The reduction in the number of parameters through aggregation simplifies the incorporation of uncertainty into the scheduling of an electric vehicle fleet. This can be done by considering the uncertainty in the parameter values in the scheduling process. Many studies used simplified approaches to account for the uncertainty of aggregation parameters. Lilliu et al. [34] and Bessa et al. [40] assumed unverified probability density functions for different aggregation parameter values when scheduling an EV fleet. Similarly, González Vayá and Andersson [41] added noise around the actual parameter values in their model. Yan et al. [42] considered simplified scenarios to account for uncertainty. Ruelens et al. [43] generate scenarios using Markov chains and simulated EV data, without considering forecasting techniques.

Despite the use of an EV aggregation method as an efficient way to schedule an EV fleet, the integration of forecasting techniques into aggregation methods has received little attention, as visible in Table 2. Visser et al. [25] use forecasts of the daily aggregated charging demand and 15-minute forecasts of the total available charging power of all EVs to schedule the charging patterns of an EV fleet. Similarly, Bessa and Matos [26] forecast the total charging requirement for each day and the maximum charged energy and power at each hour. Although the methods proposed in both studies cover most aspects that should be considered for aggregated scheduling of an EV fleet, they do not account for the minimum aggregated volume that should be charged at each timestep in the assessment timeframe. This minimum aggregated charging volume assures that the charging demand of EVs that depart during the assessment timeframe is met at their departure. Visser et al. also did not consider the maximum aggregated charging demand at each hour of the day, which should be considered to account for the fact that the charging demand of EVs cannot be until their arrival moment at the charging station.

1.3. Contributions

These aspects are considered in the previously-introduced virtual battery approach. To the best of our knowledge, only Zhou et al. [27] & Pertl et al. [28] applied forecasting techniques to an aggregation method that considers all required aspects to schedule an EV fleet. However, the main focus of these studies is not on forecasting and they did not attempt to maximize the forecasting performance. Hence, the insight into the forecasting potential of an EV aggregation approach that considers all required aspects to schedule an EV fleet is currently very limited.

As highlighted in Table 2, this study addresses this literature gap by presenting the first work that comprehensively analyses the forecasting potential of all required parameters to schedule an EV fleet. The presented forecasting approach adopts the virtual battery approach, is generic and can be applied to any scheduling timeframe, EV charging session data set and EV smart charging application. In this analysis, different forecasting models are compared, including machine learning methods, and insight is provided into the optimal predictor variable sets to maximize the forecasting performance. In addition, the impact of the considered EV fleet size on the forecasting performance is analyzed. A case study of real-world charging data from a large number of charging stations in Utrecht, the Netherlands is used for the analysis.

The contributions of this work can be summarized as follows:

- A forecasting approach to forecast all required parameters for scheduling the charging of EV fleets under uncertainty;
- An in-depth assessment of the forecasting potential of parameters associated with an EV aggregation method;
- A comparison between the performance of different forecasting models with varying EV fleet sizes;
- An analysis of the most relevant predictor variables when forecasting all parameters associated with the EV virtual battery method.

This work is structured as follows. The concept of an EV virtual battery is explained in Section 2. This is followed by the methodology in Section 3, which introduces a generic approach to forecast EV virtual battery parameters. Section 4 introduces the considered case study and describes the considered forecasting models and considered predictor variables. The results are presented in Section 5. The discussion and conclusion in Sections Section 6 & 7 are the last two sections of this work.

2. EV virtual battery method

As proposed by [41,44], the aggregated charging demand of an EV fleet can be optimized by modeling it as a virtual battery. Using this method, the characteristics of a set of charging sessions are reduced to a set of three virtual battery parameters for each timestep: the minimum and maximum aggregated charging energy since the beginning of the assessment timeframe (E_{min}&E_{max}, respectively) and the maximum aggregated charging power (P_{max}). These parameters are determined as follows:

- E_{min}: This parameter represents the minimum required charged energy since the beginning of the assessment timeframe to assure that the charging demand of EVs departing during the assessment timeframe is met. The parameter values of E_{min} at each timestep are determined by summing the total charged energy since the beginning of the assessment timeframe in a '*latest charging*' scenario for all considered charging sessions. This scenario represents the case in which the charging of an EV is delayed until the latest possible moment that the charging demand of an EV can be met before departure. Hence, to assure that the charging demand of all considered EVs is satisfied before departure, the aggregated charging energy since the beginning of the assessment timeframe should be higher or equal to E_{min} at all timesteps. The mathematical formulation of E_{min} is as follows:

$$E_{min,t} = \sum_{i}^{I} \sum_{\tau=0}^{t} P_{ch,latest,\tau,i} \Delta t \ \forall t. \tag{1}$$

  In this equation, $\mathcal{I}$ represents the set of EV charging sessions, indexed by $i = 0, 1, \ldots, I$, τ represents a timestep between the start of the assessment timeframe and timestep t, $P_{ch,latest,\tau,i}$ represents the charging power of charging session i at timestep τ in a '*latest charging*' scenario and Δt represents the duration of one timestep.
- E_{max}: This parameter poses an upper limit to the total charged energy since the beginning of the assessment timeframe. It is introduced to account for arriving EVs during the assessment timeframe, whose charging demand can only be met after their arrival. The parameter values are determined by summing the total charged energy since the beginning of the assessment timeframe in a '*charging on arrival*' scenario for all considered charging sessions. A '*charging on arrival*' scenario represents the case in which an EV charges at the maximum available charging power directly after arrival until the charging demand is met. Hence, E_{max} represents the maximum possible aggregated charged energy since the beginning of the assessment timeframe at each timestep, and the aggregated charging energy since the beginning of the assessment timeframe should be lower or equal to E_{max} at all timesteps. The mathematical formulation of E_{max} is as follows:

$$E_{max,t} = \sum_{i}^{I} \sum_{\tau=0}^{t} P_{ch,coa,\tau,i} \Delta t \ \forall t, \tag{2}$$

  where $P_{ch,coa,\tau,i}$ represents the charging power of charging session i at timestep τ in a '*charging-on-arrival*' scenario.
- P_{max}: This parameter defines the maximum total charging power at a specific timestep. The parameter value at a specific timestep

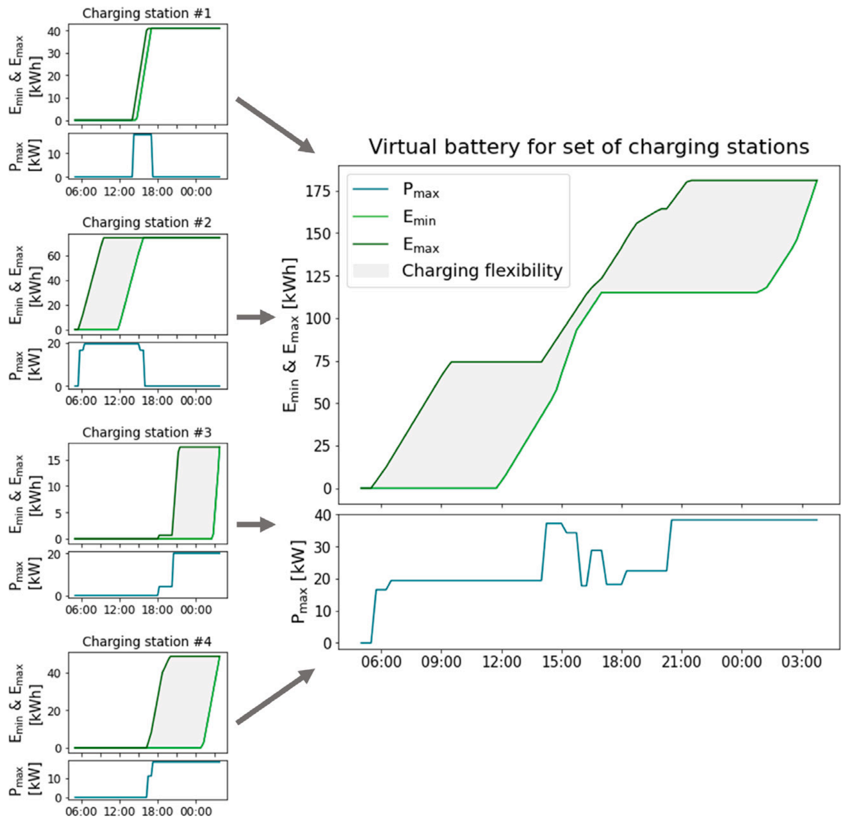

Fig. 1. Example of EV virtual battery parameters for a set of four charging stations for an assessment timeframe of one day, with a start/end time of 06:00.

is determined by summing the maximum charging power for all EVs connected to a charging station at the considered timestep:

$$P_{max,t} = \sum_{i}^{I_t} P_{max,i} \ \forall t, \tag{3}$$

where I_t represents the set of ongoing charging sessions at time t and $P_{max,i}$ represents the maximum charging power of charging session i.

When scheduling an EV fleet, the aggregator must assure that the aggregated charging demand since the beginning of the assessment timeframe stays between E_{min} and E_{max}, and that the combined charging power does not exceed P_{max}. The EV virtual battery method can be applied for different scheduling timescales and is generic for any EV charging session data set. Fig. 1 presents an example of the EV virtual battery method for an assessment timeframe of one day. Since E_{min} and E_{max} represent the minimum and maximum aggregated charging energy since the beginning of the assessment timeframe, their parameter values increase over the course of the assessment timeframe. The difference between E_{min} and E_{max} (highlighted in gray in Fig. 1) is an indicator of the EV charging flexibility: a large difference means that there is considerable room to shift the EV charging demand over time. At the end of the assessment timeframe, E_{min} and E_{max} should converge to assure that the charging demand of all considered charging sessions is met at their departure.

3. Methodology

This section presents an approach to determine the optimal forecasting performance, optimal sets of predictor variables and the predictor variable importance for EV virtual battery parameter forecasts. The approach is described in a generic manner, to assure it can be applied to any EV charging session data set, scheduling timeframe, predictor variable set, forecasting model and EV fleet size. Section 4 discusses how this generic approach was applied to the specific case study studied in this paper.

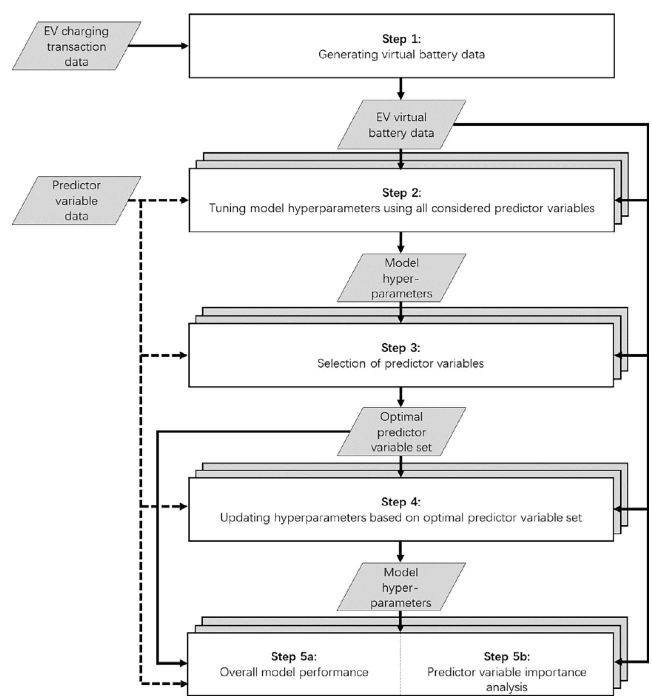

Fig. 2. Overview of methodological steps in the analysis.

Fig. 2 provides an overview of the required methodological steps to make optimal EV virtual battery parameter forecasts. In this approach, E_{min}, E_{max} and P_{max} are forecasted separately. Hence, the steps in Fig. 2

are repeated for all considered forecasting models and for all considered EV virtual battery parameters. Each step is outlined below.

3.1. Step 1: Generating virtual battery data

This step converts EV charging session data from an EV fleet to a time-series of EV virtual battery parameter values. This is done using the methods outlined in Section 2. This EV virtual battery data serves as input data for the forecasting models. The number of EV charging sessions that are combined into one virtual battery depends on the desired scheduling timeframe. For instance, if the scheduling timeframe is 24 h, EV virtual batteries are generated for 24-hour periods and all charging sessions that start within the same 24-hour period are considered for one EV virtual battery.

The selected start and end time of each scheduling timeframe for an EV virtual battery should depend on the specific charging characteristics of an EV fleet. As discussed in Section 2, E_{min} and E_{max} should converge at the end of the scheduling timeframe. This is only possible if the charging demand of each EV charging session can be met before the end of the scheduling timeframe. Therefore, the time of the day that provides the maximum number of charging sessions with the opportunity to meet their full charging demand should be selected as the end time of each scheduling period. In case the charging demand of an EV charging session cannot be met before the end of the scheduling timeframe, the charging demand of the specific charging session should be reduced to the maximum possible charging energy during the assessment timeframe. The remaining charging demand could be considered for the next scheduling timeframe.

3.2. Step 2: Tuning model hyperparameters using all considered predictor variables

The learning process of different machine learning forecasting models is controlled by their hyperparameter values. Since these values affect the forecasting performance of a specific model, hyperparameter values of all considered forecasting models need to be tuned.

In this step, the optimal hyperparameter values are set for each considered model and for each EV virtual battery parameter when considering all predictor variables. This can be done by evaluating the model performance on a large number of hyperparameter sets, and by selecting the hyperparameter set with the best model performance. This process is repeated for each model and each EV virtual battery parameter. To avoid overfitting of the forecasting model, the virtual battery data should first be split into a training and testing set. Next, the training set is used to compute the optimal hyperparameter values using k-fold cross-validation [45].

The performance of the forecasting model can be assessed using R^2 (i.e., the coefficient of determination) as an evaluation metric. Since R^2 is a normalized score between 0 and 1, it allows for a comparison of the forecasting model performance of different virtual battery parameters and a varying number of charging stations.

3.3. Step 3: Selection of predictor variables

In some cases, predictor variables can have a negative impact on the performance of a forecasting model, for instance due to multicollinearity [45]. Therefore, the optimal predictor variable set for each considered forecasting model and each considered virtual battery parameter should be determined.

The most common methods to select the optimal predictor variable set are backward or forward sequential (floating) feature selection, as explained in [46]. To avoid model overfitting, it is recommended to apply one of these methods to the training data set while using k-fold cross-validation. Subsequently, the forecasting performance with a different number of predictor variables can be determined by applying the trained model to the separate testing data set. These steps can be repeated multiple times in order to increase the robustness of the results. The predictor variable set with the highest average performance on the testing data set should be selected as the optimal predictor variable set.

3.4. Step 4: Updating hyperparameters based on optimal predictor variable set

Since the optimal hyperparameter set could change with a different number of predictor variables, Step 2 should be repeated for each forecasting model and for each virtual battery parameter using the optimal predictor variable set determined in Step 3.

3.5. Step 5a: Overall model performance

To evaluate the overall performance per forecasting model, each virtual battery parameter and every model should be trained with a training data set, using the optimal predictor variable set from Step 3 and the optimal hyperparameter set from Step 4. The trained models should be applied to the testing data set to determine the model performance using the R^2.

3.6. Step 5b: Predictor variable importance analysis

A predictor variable importance analysis evaluates the impact of each predictor variable on the forecasting performance. A permutation importance analysis can be used in this step. In this analysis, each model is trained using the training data set, and a reference model performance is determined using the testing data set. Subsequently, the values of one predictor variable in the testing set are permuted (i.e., randomly shuffled), and the model performance with this one set of permuted predictor variable values is determined. This should be repeated multiple times for each predictor variable to increase the robustness of the results. The predictor variable of which the permutation of its values results in the largest decrease in model performance compared to the reference model performance can be considered as the predictor variable with the highest impact on the results.

4. Analysis outline

To provide insights into the performance of different forecasting models and their most important predictor variables when forecasting EV virtual battery parameter values, the approach from Section 3 has been applied to a case study. In this analysis, a 24-hour virtual battery timeframe is considered, which allows for bidding to the day-ahead electricity market. This section will introduce the case study, discuss the considered forecasting models and predictor variables and provide details on the model simulations.

4.1. Case study introduction

This study used historical EV charging session data from public stations operated by charge point operator *We Drive Solar*. These charging stations are located in residential areas in the city of Utrecht, the Netherlands and are located on-street. The charging stations can be used by any EV owner, and no specific subscription was required to be able to use the charging station. Users paid a fixed tariff per kWh and uncontrolled charging was applied to the considered charging stations. The considered charging stations allowed for charging up to a charging power of 22 kW. Hence, fast charging was not possible at these locations. In the used data, the arrival time, departure time, charging demand and maximum charging power of each charging session is logged. This charging session data is logged between 9 January 2019 and 1 December 2021. During the course of this period, the number of charging stations operated by this company grew considerably. Also, during a large share of this period, the Netherlands faced numerous

Table 3
Overview of the considered predictor variables for the forecasting of EV virtual battery parameters.

Category	No.	Explanation	Short notation	Source
Temporal	1.	No. of hours since start of optimization timeframe	Hour	–
	2.	Whether the considered day is a weekend day	Weekend	–
	3.	Whether the considered day is a school holiday	SH	–
	4.	Whether the considered day is a public holiday	PH	–
Historical	5.	Parameter value week ago at the same time	H:W-1	–
	6.	Parameter value day ago at the same time	H:D-1	–
	7.	Parameter value 2 days ago at the same time	H:D-2	–
	8.	Parameter value 3 days ago at the same time	H:D-3	–
	9.	Average parameter value at the same time during the last week	H:W-AV	–
	10.	Average parameter value at the same time at the same weekday during the last month	H:M-AV	–
Weather forecasts	11.	Forecast of average daily temperature	W:AT	[48]
	12.	Forecast of daily precipitation volume	W:PV	[48]
	13.	Forecast of daily average windspeed	W:WS	[48]
	14.	Forecast of daily number of sunshine hours	W:SH	[48]

lockdowns due to the COVID-19 pandemic, which had a considerable impact on EV charging patterns [47]. In order to provide a realistic insight into the ability to forecast EV charging patterns under normal circumstances, the main analyses in this study were conducted using charging session data from between 9 January 2019 and 12 March 2020, during which no COVID-19 restrictions were imposed. During this period, charging data was available from 20 charging stations. Charging data from these charging stations was considered in the analysis. The average daily number of charging sessions for the considered set of charging stations equaled 30.3 during the considered time period, while the average daily charging demand during this time period equaled 519.4 kWh for the considered charging stations.

To get insight into the impact of the EV fleet size on the forecasting performance (see Section 5.1), data from additional EV charging stations is required. For this analysis, charging data from between 28 April 2021 and 12 November 2021 was used, during which relatively few COVID-19 restrictions were in place in the Netherlands. 405 charging stations were operating throughout this whole period and data from these charging stations was used to conduct an analysis of the impact of the considered EV fleet size on the forecasting performance.

4.2. Forecasting models

This study compares the performance of five different forecasting models. The selected models are commonly applied in other forecasting studies and cover different categories of forecasting models. The following models are considered in this study:

1. *Multivariate Linear Regression*: This linear regression model predicts the target variable values (i.e., E_{min}, E_{max} and P_{max}) by determining the optimal coefficients of each considered predictor variable.
2. *Random Forest*: This is an example of an ensemble-based regression method. It creates a set of independent decision trees, considering a random subset of the training data points and predictor variables in each tree [49]. The forecast is generated by averaging the outcomes of all decision trees.
3. *Artificial Neural Network*: This forecasting method is based on deep learning and builds a nonlinear relationship between the target variable and the different predictor variables [50]. It connects the input data to one or multiple hidden layers, each consisting of multiple nodes. Each node uses an activation function and weight to process the data and generate an output value. The output value is fed to each node in the following layer, where the forecasted value presents the output value of a single node in the last layer.
4. *k-Nearest Neighbors*: This is a non-parametric forecasting method, meaning that equal weight is given to all predictor variables. This model considers the Euclidean distance function to locate the *k* most-similar data points in the training data set, and takes the average value of these data points as the forecast [51].
5. *Persistence forecast*: This serves as the reference forecasting model. This study considered the value of one week before the considered timestep as the persistence forecast, due to the observed high simultaneity in EV charging characteristics between weekdays.

4.3. Predictor variables

Three main categories of predictor variables are considered to forecast EV virtual battery parameters. The first category considers temporal predictor variables, such as time of the day and the type of day (weekend day, school holiday and public holiday). Second, historical data are used as predictor variables. These predictor variables consider historical values of the forecasted parameter, such as the parameter value one/two/three days before at the same time of the day or the average parameter value at the same time of the day during the past week. The third category consists of predictor variables based on day-ahead weather forecasts (average daily temperature, daily precipitation volume, daily average wind speed and daily number of sunshine hours), since people's choice of transport mode depends on the weather conditions [52]. Day-ahead weather forecast data for the city of Utrecht from ECMWF [48] was used in this analysis. An overview of all 14 considered predictor variables is presented in Table 3.

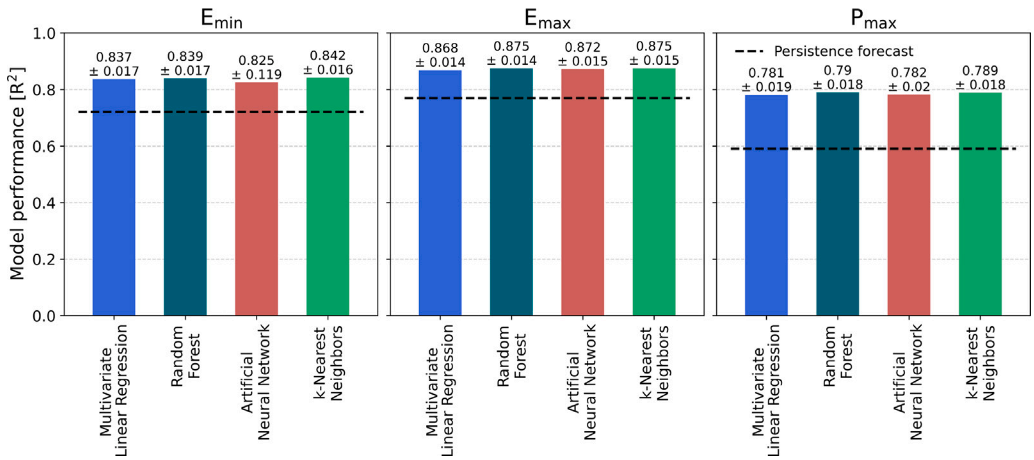

Fig. 3. Average forecasting performance (expressed as the R^2 value) and standard deviation (±-values) of all model runs of the different considered forecasting models for the different EV virtual battery parameters when considering EV virtual batteries based on charging data of 20 charging stations. Persistence forecasts are based on the parameter value one week ago at the same time of the day.

Table 4
Average forecasting performance of all model runs of the different considered forecasting models for the different EV virtual battery parameters when considering EV virtual batteries based on charging data of 20 charging stations. Persistence forecasts are based on the parameter value one week ago at the same time of the day.

		Multivariate Linear Regression	Random Forest	Artificial Neural Network	k-Nearest Neighbors	Persistence Forecast
E_{min}	Mean parameter value	128.6 kWh	128.6 kWh	128.6 kWh	128.6 kWh	128.6 kWh
	MAE	38.1 kWh	36.6 kWh	38.4 kWh	35.9 kWh	47.6 kWh
	RMSE	54.6 kWh	54.1 kWh	56.5 kWh	53.6 kWh	70.8 kWh
	WAPE	29.6%	28.4%	29.8%	27.9%	37.0%
E_{max}	Mean parameter value	252.8 kWh	252.8 kWh	252.8 kWh	252.8 kWh	252.8 kWh
	MAE	56.6 kWh	53.9 kWh	55.1 kWh	53.1 kWh	70.1 kWh
	RMSE	78.8 kWh	76.7 kWh	77.8 kWh	76.7 kWh	103.5 kWh
	WAPE	22.4%	21.3%	21.8%	21.0%	27.7%
P_{max}	Mean parameter value	85.3 kW	85.3 kW	85.3 kW	85.3 kW	85.3 kW
	MAE	20.9 kW	20.3 kW	20.6 kW	20.3 kW	27.4 kW
	RMSE	27.7 kW	27.1 kW	27.6 kW	27.2 kW	37.9 kW
	WAPE	24.5%	23.8%	24.2%	23.8%	32.2%

4.4. Data pre-processing and model simulation setup

In the data pre-processing step, the predictor variable values were determined for each data point in the input data. Subsequently, all parameter and predictor variable values were normalized to the maximum observed value in the assessment timeframe for the considered parameter or predictor variable.

This study used the scikit-learn [53] library in Python version 3.8.5 to perform EV virtual battery parameter forecasts for the different considered forecasting models. An AMD EPYC 7451 core with 5.333 GB of memory was used to generate the forecasts. Forecasts were generated for a 15-minute time resolution. The training data set and testing data set covered 80% and 20% of the input data, respectively, and consisted of randomly-sampled days from the input data. Due to the relatively short time period covered in the input data (see Section 4.1), the tested data set was generated using random sampling of days, instead of using a consecutive time period as the testing data set, to assure that all periods of the year are covered in the training and testing data set. 5-fold cross-validation using randomly-sampled days was used in hyperparameter tuning and predictor variable selection. The predictor variable selection was performed using sequential floating backward feature selection, using the MLxtend Python package [54]. To increase the robustness of results, the predictor variable selection analysis was repeated 10 times for each parameter value and each forecasting model, while the overall model performance analysis and predictor variable importance analysis were repeated 100 times. The required time to perform the forecast differed between the considered forecasting models. The average running time equaled 0.01 s for the *Multivariate Linear Regression*, 4.79 s for the *Random Forest* model, 2.46 s for the *Artificial Neural Network* model and 1.28 s for the *k-Nearest Neighbors* model.

A separate analysis is performed to determine the impact of the considered number of EV charging stations on the forecasting performance. This analysis is repeated 100 times for each considered number of EV charging stations, each time considering a different set of charging stations when generating the virtual battery data. Given the large computational burden that comes with hyperparameter tuning and predictor variable selection, the optimal parameter and predictor variable set of the main analysis were used in this analysis.

The selected start and end time of the forecasting timeframe is 06:00, as the largest share of the EV charging demand in the considered case study (98%) can be met when using this time as the start/end time of one EV virtual battery. In the rare case that the charging demand of an EV charging session cannot be met before the end of the scheduling time horizon, the charging demand is reduced to the value that can be met at the end of the scheduling time horizon to assure that E_{min} and E_{max} converge at the end of the assessment period (see Section 2).

5. Results

5.1. Overall model performance

Fig. 3 presents the model performance of the considered forecasting models for each EV virtual battery parameter, which were determined

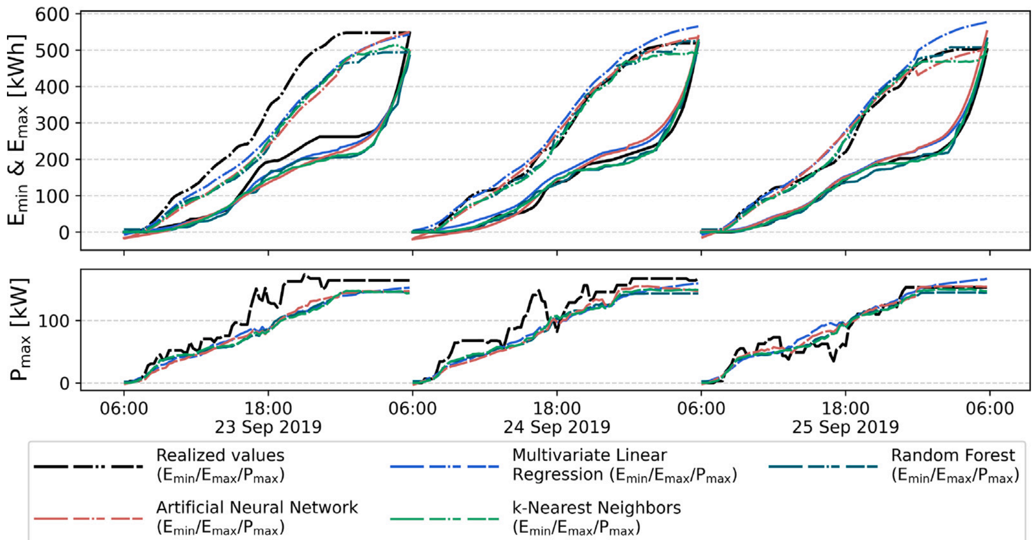

Fig. 4. Realized EV virtual battery parameter values (i.e., actual parameter values in historical data at considered time step) for three consecutive days and the forecasted values for these considered days for 20 charging stations for different forecasting models for one model run.

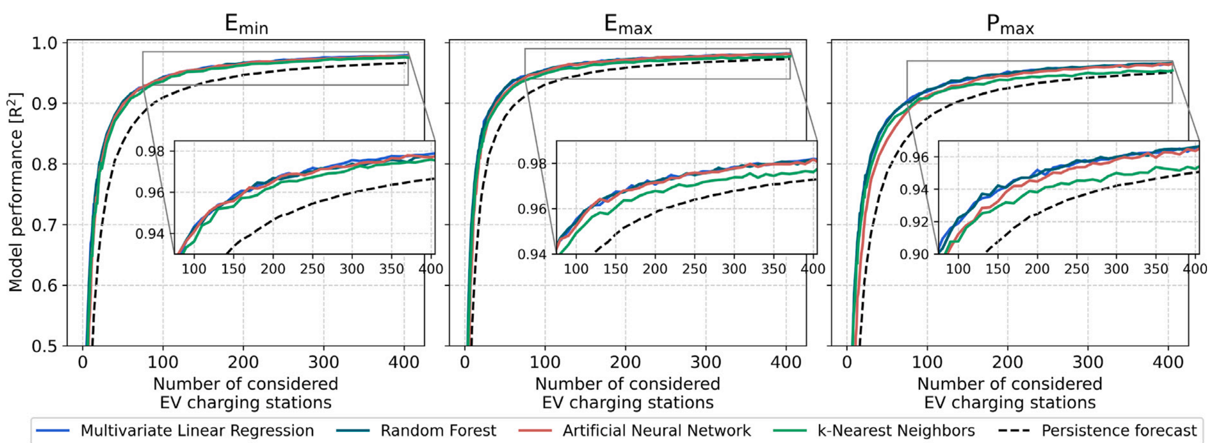

Fig. 5. Average forecasting performance (expressed as the R^2 value) of all model runs for different forecasting models when considering EV virtual batteries based on charging data of a varying number of charging stations. Persistence forecasts are based on the parameter value one week ago at the same time of the day.

using the optimal hyperparameter sets in Appendix and the optimal predictor variable sets in Table 5. The models show a relatively good forecasting performance for all EV virtual battery parameters, with an average R^2 score ranging between 0.78 and 0.88 for all models and virtual battery parameters. The model performance of all considered forecasting models is considerably better than the reference case of using persistence forecasts, which indicates that the use of forecasting models is highly recommended when forecasting EV virtual battery parameters. This can also be observed from Table 4, which reports the model performance using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the Weighted Absolute Percentage Error (WAPE)[1] as performance metrics.

A comparison between the different EV virtual battery parameters shows that the R^2 values are generally lower for P_{max} compared to E_{min} and E_{max}. As explained in Section 2, E_{min} and E_{max} are continuously increasing over the assessment timeframe, while P_{max} is more volatile. Hence, E_{min} and E_{max} are better predictable than P_{max}, explaining the differences in the forecasting performance between the different virtual battery parameters. On the contrary, it is evident from Table 4 that the WAPE scores are highest for the forecasts of E_{min}. This phenomenon can be largely attributed to the nature of E_{min}, which has a relatively low parameter value for most of the day and increases towards the end of the assessment timeframe (see Section 2 and Fig. 4). As a result, the average parameter value for E_{min} is comparatively low. This lower average parameter value directly contributes to higher WAPE values, as the mean absolute forecasting error is divided by the average parameter value when calculating this metric score.

The difference in forecasting performance between all considered models is negligible. Although Multivariate Linear Regression is the worst-performing forecasting model in all considered cases, the minor difference with the other considered models indicates that EV virtual battery parameters do not necessarily need to be forecasted using more-advanced machine learning models.

Fig. 4 compares the forecasted EV virtual battery parameter values of the considered forecasting models with the realized values for three arbitrarily chosen consecutive days for one of the model runs. It shows that the models generally seem to be able to forecast the main trends of E_{min} and E_{max} during the course of the day. The forecasting models do not seem to be able to capture the fluctuations in the values of P_{max} during the day. It is visible from Fig. 4 that some of the forecasted

[1] The WAPE has been used over the commonly-used Mean Absolute Percentage Error (MAPE), since the MAPE can take infinite or extreme values if the realized parameter values are equal or close to zero [55], which is regularly the case in this analysis.

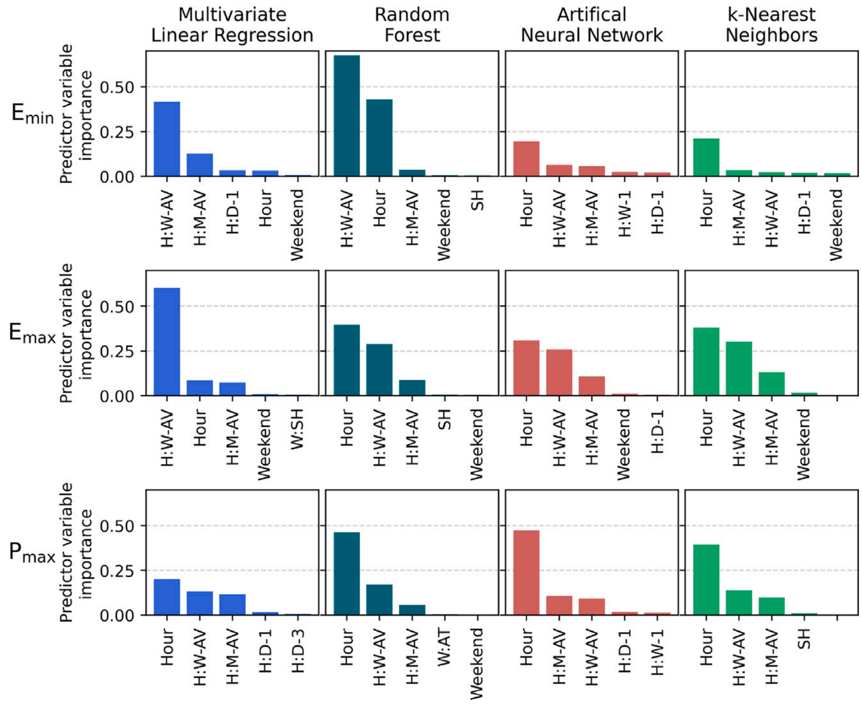

Fig. 6. Predictor variable importance for the five most important predictor variables for each considered forecasting model and for each EV virtual battery parameter. The predictor variable importance is defined as the average reduction in the R^2 score when permuting the predictor variable values. Note that in some cases the optimal predictor variable set only consists of four predictor variables. The used abbreviations for the predictor variables are introduced in Table 5.

EV virtual battery parameter values are infeasible. For instance, some models forecasted negative values for E_{min} and E_{max} for some timesteps. Similarly, the forecasts of E_{min} and E_{max} do not always converge at the end of the assessment timeframe and in rare cases the forecasted value of E_{min} is higher than the forecasted value of E_{max}, which is technically not possible. The latter two effects are caused by the fact that E_{min} and E_{max} are forecasted separately.

As the size of the EV fleet in the EV virtual battery increases, the forecasting performance of all models improves considerably. This is outlined in Fig. 5, which presents the average forecasting performance of all considered models when considering different numbers of EV charging stations. R^2-scores up to 0.98 are reached when considering more than 400 EV charging stations. The arrival and departure of EVs are less stochastic when considering a larger EV fleet, which decreases the volatility in the EV virtual battery parameter values and thus results in better EV virtual battery parameter value forecasts. Considering a larger EV fleet size when forecasting EV virtual battery parameters also increases the performance of the persistence forecast and decreases the relative added value of using forecasting models.

5.2. Predictor variable selection and importance

The optimal predictor variable set per forecasting model for each EV virtual battery parameter is presented in Table 5, while Fig. 6 provides insight into the most important predictor variables for each considered forecasting model and for each EV virtual battery parameter. The hour of the day ('Hour'), the weekly average parameter value at the considered time ('H:W-AV') and the monthly average parameter value at the considered time and day of the week ('H:M-AV') seem to be the most influential predictor variables; these predictor variables are present in almost all optimal predictor variable sets and show the highest predictor variable importance in Fig. 6. The predictor variables linked to the type of day, in particular to weekend days and school holidays ('Weekend' and 'SH'), are included in almost all optimal predictor variable sets, but seem to have limited impact on the model outcomes in Fig. 6. Furthermore, predictor variables related to weather forecasts and using historical parameter values of 1–3 days or one week before the forecasted timestep seem to have little impact on the forecasting outcome. Therefore, only a few predictor variables are needed to produce reliable forecasts of the EV virtual battery parameters.

6. Discussion

This study proposed a novel forecasting approach to forecast all required parameters to schedule an EV fleet. A comprehensive analysis of the effectiveness of this proposed approach has been conducted using a real-world case study. The results indicated that when using the EV virtual battery method, very good forecasting performance can be reached, especially when considering large EV fleets. This is particularly interesting for aggregators, who generally consider a large number of EVs for smart charging applications, including electricity market bidding. These aggregators can use the proposed forecasting approach to reduce uncertainty when scheduling these EV fleets, mitigating the risk of potential imbalance costs.

The results of the analyses applied to the considered case study showed that only a limited number of predictor variables are required to forecast EV virtual battery parameter values and that the difference in forecasting performance between different forecasting models is minor. We encourage others to adopt our methodology and test the EV virtual battery forecasting approach on other data sets, for locations with different climates and mobility patterns.

From the results of this study can be seen that the performance of the *Multivariate Linear Regression* and *k-Nearest Neighbors* (when considering a high number of charging stations) models was minimally lower than the performance of the other considered models, although these models scored best in terms of running times. Their inferior model performance can be attributed to the fact that these models are not able to capture non-linear relationships between the predictor variables and the forecasted parameter values [56]. A superior performance of tree-based or deep-learning forecasting models has been observed in other energy domains as well, including photovoltaic generation [57], wind generation [58] and load forecasting [59]. In addition, the results

Table 5
Optimal predictor variable sets for the considered forecasting models for different EV virtual battery parameters. Green values are included in the optimal predictor variable set. The used abbreviations for the predictor variables are introduced in Table 5.

		Predictor variables													
		Hour	Weekend	SH	PH	H:W-1	H:D-1	H:D-2	H:D-3	H:W-AV	H:M-AV	W:AT	W:PV	W:WS	W:SH
E_{min}	Multivariate Linear Regression	Green	Green	Green	Green	Red	Green	Red	Red	Green	Green	Red	Red	Red	Red
	Random Forest	Green	Green	Green	Green	Green	Red	Green	Green	Green	Green	Red	Green	Red	Green
	Artificial Neural Network	Green	Green	Green	Green	Green	Green	Green	Red	Green	Green	Red	Green	Green	Green
	k-Nearest Neighbors	Green	Green	Green	Red	Red	Green	Green	Red	Green	Green	Red	Red	Red	Red
E_{max}	Multivariate Linear Regression	Green	Green	Green	Red	Red	Red	Red	Red	Green	Green	Red	Green	Red	Green
	Random Forest	Green	Green	Green	Red	Red	Red	Red	Red	Green	Green	Red	Red	Red	Red
	Artificial Neural Network	Green	Green	Green	Green	Red	Green	Red	Red	Green	Green	Green	Red	Red	Green
	k-Nearest Neighbors	Green	Green	Red	Red	Red	Red	Red	Red	Green	Green	Red	Red	Red	Red
P_{max}	Multivariate Linear Regression	Green	Green	Green	Green	Green	Green	Green	Green	Green	Green	Green	Green	Green	Green
	Random Forest	Green	Green	Red	Red	Red	Red	Red	Red	Green	Green	Green	Red	Red	Red
	Artificial Neural Network	Green	Green	Green	Red	Green	Green	Red	Green	Green	Green	Red	Red	Red	Green
	k-Nearest Neighbors	Green	Red	Green	Red	Red	Red	Red	Red	Green	Red	Red	Red	Red	Red

section showed that the forecasting performance for P_{max} is lower compared to the forecasting performance of E_{min} and E_{max}, since the values of P_{max} are more-erratic and thus harder to forecast. Future work should address how the forecasting performance for this parameter could be improved, for instance by using more-advanced forecasting models (e.g., Gradient Boosting [60] or Extreme Gradient Boosting (XGboost) [61]) or by including details about the EV fleet composition (e.g., EV model, maximum charging power of EV models) in the input data.

As the three EV virtual battery parameters were forecasted separately in this study, it could occur that the forecasts of E_{min}, E_{max} and P_{max} are not perfectly aligned (see Section 5.1). For this reason, the forecasted values should be post-processed before using them for EV scheduling. This problem could potentially be reduced by forecasting the flexibility (i.e., the difference between E_{min} and E_{max}) and by adding/subtracting the forecast of the flexibility to/from the forecast of respectively E_{min} or E_{max}. Another way to potentially improve the forecasts is by forecasting each timestep separately, using only the historical data of the considered timestep when training the model. Hence, further research should look into such ways to finetune the forecasting approach proposed in this research to increase forecasting performance.

This study considered a scheduling timeframe running from 06:00 to 06:00 the next day, which does not align with the bidding period for most day-ahead electricity markets (i.e., 00:00 to 00:00 the next day). Using 00:00 as the start and end time of the forecasting timeframe would result in a large number of charging sessions in the considered case study of which the charging demand cannot be met during this timeframe, due to EVs arriving home in the late evening. To account for this discrepancy, one can use the optimized charging schedules between 06:00 and 00:00 to bid in the day-ahead market for one day, and use the charging schedules between 00:00 and 06:00 for the day-ahead market bids for the next day. Also, it should be noted that market bids can be updated in intraday markets.

It should be highlighted that the results when using an EV virtual battery to optimize the charging schedule of an EV fleet show a minor difference compared to the aggregated EV charging schedule when optimizing individual charging sessions [4]. This can be attributed to the fact that P_{max} is based on the aggregated maximum charging power of all connected EVs to the grid, without considering the fact that EVs that already met their charging demand cannot charge anymore. Therefore, the total aggregated charging power at specific timesteps in the virtual battery model could be higher than physically possible. Future research could look into ways to reduce this discrepancy, for instance by considering a reduction factor for the forecasts P_{max} when optimizing an EV fleet using the virtual battery approach.

Lastly, after determining the aggregated charging schedule using the virtual battery approach, this aggregated charging schedule should be disaggregated to individual charging sessions at the moment of real-time operation. Different disaggregation approaches have been proposed. For instance, Vandael et al. [38] propose to prioritize charging sessions with the highest urgency to charge when allocating the aggregated charging power among charging sessions. Danner et al. [62] compare cost-optimal, probability-optimal and proportional disaggregation strategies.

7. Conclusions

The forecasting of EV charging session characteristics for EV smart charging is complex due to the wide range of charging characteristics that need to be forecasted. A forecasting approach that tackles the complexities associated with forecasting for EV smart charging is practically absent in scientific literature. This study is the first work that presented a forecasting approach that considers all required EV parameters for EV smart charging. It uses the EV virtual battery method and requires separate forecasts of only three parameters: E_{min}, E_{max} and P_{max}. The proposed approach is generic and can be applied to any scheduling timeframe or any EV fleet.

The approach was tested on a real-world case study to create 24-hour forecasts, considering a total of four forecasting models and a reference persistence model. When considering charging session data from 20 charging stations, the average R^2 score ranged between 0.78 and 0.88 for different forecasting models and virtual battery parameters. The forecasting performance considerably increases when considering a larger EV fleet, reaching very high R^2 scores of at least 0.96 for all virtual battery parameters. From the results, it can be concluded that adopting the proposed approach to forecast EV virtual battery parameter values significantly improves the forecasting performance compared to using persistence forecasts. The difference in performance between the considered machine learning forecasting models is negligible. Results also showed that only a low number of predictor variables impacts the forecasting results.

Overall, from this study can be concluded that EV virtual battery parameters can be forecasted with very high accuracy, in particular with large EV fleets. This means that the uncertainty associated with the available charging flexibility of EV fleets when applying EV smart charging can be reduced drastically. Hence, the risk of additional costs (e.g., imbalance costs in electricity markets) is reduced, facilitating the rollout of EV smart charging.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Nico Brinkel reports financial support was provided by Dutch Ministry of Economic Affairs and Climate Policy. Wilfried van Sark reports financial support was provided by Dutch Ministry of Economic Affairs and Climate Policy and the Dutch Ministry of the Interior and Kingdom Relations.

Table 6
Optimal hyperparameter sets for the considered forecasting models for different EV virtual battery parameters.

	Forecasting model	Optimal hyperparameter set
E_{min}	Random Forest	Max. tree depth: 5 (tested values: 0, 1, 2, 3, 4, 5) Min. no. of samples at leaf node: 2 (tested values: 1, 2, 3, 4, 5) Min. no. of samples to split an internal node: 2 (tested values: 2, 3, 4, 5) Considered. no. of features: total no. of features (other option: square root of total no. of features) No. of trees in forest: 75 (tested values: 25, 50, 75, 100, 150, 200, 250, 300, 500, 700, 900)
	Artificial Neural Network	Activation function: rectified linear unit function (other options: hyperbolic tan function, logistic sigmoid function and no-op activation) L2 regularization term: 0.01 (tested values: 0.01, 0.001, 0.0001, 0.00001) No. of hidden layers: 3 (tested values: 1, 2, 3, 4) Number of neurons per layer: 14, 10, 7 (tested values: values between 5 and 54) Solver: quasi-Newton (other options: stochastic gradient descent and 'adam')
	k-Nearest Neighbors	Number of neighbors: 169 (tested values: values between 1 and 500) Power parameter for Minkowski metric: 2 (tested values: 1 and 2) Used weight function in prediction: uniform (tested values: 'uniform' and 'distance')
E_{max}	Random Forest	Max. tree depth: 5 (tested values: 0, 1, 2, 3, 4, 5) Min. no. of samples at leaf node: 4 (tested values: 1, 2, 3, 4, 5) Min. no. of samples to split an internal node: 2 (tested values: 2, 3, 4, 5) Considered. no. of features: square root of total no. of features (other option: total number of features) No. of trees in forest: 150 (tested values: 25, 50, 75, 100, 150, 200, 250, 300, 500, 700, 900)
	Artificial Neural Network	Activation function: hyperbolic tan function (other options: rectified linear unit function, logistic sigmoid function, no-op activation) L2 regularization term: 0.001 (tested values: 0.01,0.001,0.0001,0.00001) No. of hidden layers: 2 (tested values: 1, 2, 3, 4) Number of neurons per layer: 7,7 (tested values: values between 5 and 54) Solver: quasi-Newton (tested values: stochastic gradient descent and 'adam')
	k-Nearest Neighbors	Number of neighbors: 139 (tested values: values between 1 and 500) Power parameter for Minkowski metric: 1 (tested values: 1 and 2) Used weight function in prediction: distance (tested values: 'uniform' and 'distance')
P_{max}	Random Forest	Max. tree depth: 5 (tested values: 0, 1, 2, 3, 4, 5) Min. no. of samples at leaf node: 4 (tested values: 1, 2, 3, 4, 5) Min. no. of samples to split an internal node: 2 (tested values: 2, 3, 4, 5) Considered. no. of features: square root of total no. of features (other option: square root of total no. of features) No. of trees in forest: 500 (tested values: 25, 50, 75, 100, 150, 200, 250, 300, 500, 700, 900)
	Artificial Neural Network	Activation function: rectified linear unit function (other options: logistic sigmoid function, hyperbolic tan function, no-op activation) L2 regularization term: 0.0001 (tested values: 0.01, 0.001, 0.0001, 0.00001) No. of hidden layers: 3 (tested values: 1, 2, 3, 4) Number of neurons per layer: 28, 10, 7 (tested values: values between 5 and 54) Solver: quasi-Newton (other options: stochastic gradient descent and 'adam')
	k-Nearest Neighbors	Number of neighbors: 362 (tested values: values between 1 and 500) Power parameter for Minkowski metric: 2 (tested values: 1 and 2) Used weight function in prediction: uniform (tested values: 'uniform' and 'distance')

Data availability

The authors do not have permission to share data.

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Appendix. Optimal hyperparameter sets

The optimal hyperparameter sets for each considered forecasting model for each EV virtual battery parameter are presented in Table 6.

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