Applied Energy 308 (2022) 118280

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

An operational bidding framework for aggregated electric vehicles on the electricity spot market

L.R. Visser [a,*], M.E. Kootte [b], A.C. Ferreira [c], O. Sicurani [d], E.J. Pauwels [e], C. Vuik [b], W.G.J.H.M. Van Sark [a], T.A. AlSkaif [f]

[a] Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands
[b] Delft Institute of Applied Mathematics, Delft University of Technology, Delft, The Netherlands
[c] Operations and Management, University of Amsterdam, Amsterdam, The Netherlands
[d] Sympower, Amsterdam, The Netherlands
[e] Centrum Wiskunde & Informatica, Amsterdam, The Netherlands
[f] Information Technology Group, Wageningen University and Research, Wageningen, The Netherlands

ARTICLE INFO

Keywords:
Smart charging
Forecast
Electric Vehicles
Day ahead electricity market
Operational bidding framework
Market trading
Machine learning

ABSTRACT

Fluctuating electricity prices offer potential economic savings for the consumption of electricity by flexible assets such as Electric Vehicles (EVs). This study proposes an operational bidding framework that minimizes the charging costs of an EV fleet by submitting an optimized bid to the day-ahead electricity market. The framework consists of a bidding module that determines the most cost-effective bid by considering an electricity price and an EV charging demand forecast module. In this study we develop and evaluate several regression and machine learning models that forecast the electricity price and EV charging demand. Furthermore, we examine the composition of a most optimal operational bidding framework by comparing the outcome of the bidding module when fed with each of the forecast models. This is determined by considering the day-ahead electricity price and imbalance costs due to forecast errors. The study demonstrates that the best performing self-contained forecast models with the objective of electricity price and EV charging demand forecasting, do not deliver the best overall results when included in the bidding framework. Additionally, the results show that the best performing framework obtains a 26% cost savings compared to a reference case where EVs are charged inflexibly. This corresponds to an achieved savings potential of 92%. Consequently, along with the developed bidding framework, these results provide a fundamental basis for effective electricity trading on the day-ahead market.

1. Introduction

In recent years, many countries experienced rapid growth in the installed capacity of Renewable Energy Sources (RES). This trend is expected to continue in the future, as an additional capacity of at least 1,200 GW of RES is foreseen by 2024. Most of this growth will come from solar Photovoltaics (PV), approximately 60%, followed by wind, which is expected to account for 30% of the growth [1]. The intermittent nature of electricity generation from these variable RES (vRES) pose challenges to grid operators to maintain the power quality and balance the supply and demand at all times [2]. Meanwhile, the increasing penetration of electric appliances including electric boilers, heat pumps and Electric Vehicles (EVs), raise the grid load. This electrification results in increased peak demands and may congest the grid [3].

Demand side management of flexible electric appliances can support the operation of the power system as the shift of electricity demand in time can prevent both grid congestion and imbalances [4]. In previous research, EVs have been identified as the most beneficial asset for flexibility in the local grid [5]. This is explained by their rapid rise in numbers [6], high electricity demand [7] and flexible nature [7]. Particularly EVs that are charged at home show a high potential, since flexibility is high [8]. Adjusting the EV charging demand can prevent grid congestion and imbalances [3], and EV flexibility can be monetized when demand is shifted to times when prices are low [9]. In addition, demand will be naturally steered away from peak load periods, since prices tend to be low at times when there is an abundance of (renewable) electricity [10]. However, a single EV does not accommodate the required capacity nor volume to participate in any of the

* Corresponding author.
E-mail address: l.r.visser@uu.nl (L.R. Visser).

https://doi.org/10.1016/j.apenergy.2021.118280
Received 12 July 2021; Received in revised form 11 November 2021; Accepted 24 November 2021
Available online 14 December 2021

Nomenclature

Abbreviations

AACC	Aggregated Available Charging Capacity
ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto-Regressive Moving Average
BEV	Battery EV
CECD	Cumulative Electricity Charging Demand
DA	Day-Ahead
DAM	Day-Ahead Market
EV	Electric Vehicle
GB	Gradient Boosting
GCT	Gate Closure Time
ISO	Independent System Operator
ISP	Imbalance Settlement Period
K-SVR	SVR with radial basis function kernel
L-SVR	SVR with linear kernel
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLR	Multi-variate Linear Regression
PHEV	Plug-in Hybrid EV
PTU	Program Time Unit
PV	Photovoltaic
RES	Renewable Energy Sources
RF	Random Forest
SARIMA	Seasonal ARIMA
SARIMAX	SARIMA considering exogenous variables
SVD	Support Vector Decomposition
SVR	Support Vector Regression
TSO	Transmission System Operator
V2G	Vehicle-to-Grid
vRES	Variable RES

Variables

$\hat{V}$	Forecasted cumulative electricity charging demand
$\hat{\mathbf{c}}_{da}$	Forecasted day-ahead electricity price
$\hat{\mathbf{p}}$	Forecasted aggregated available charging capacity
$\mathbf{c}_{da}$	Day-ahead electricity price
$\mathbf{c}_{imb}$	Imbalance price
$\mathbf{P}$	Matrix of the aggregated available charging capacity with rows q and columns d
$\mathbf{p}$	Aggregated available charging capacity
$\mathbf{v}$	Vector of the cumulative electricity charging demand per day
$\mathbf{X}$	Matrix of price forecast variables with rows h and columns n
$\mathbf{x}$	Electricity demand
$\mathbf{x}^*$	Scheduled electricity demand
$\mathbf{p}_e$	Available charging capacity per EV
C_{da}	Total day-ahead electricity costs
C_{imb}	Total imbalance costs
C_{total}	Total costs
D	Day
$d \in T$	Days in the test set
$e \in E$	EVs in the EV fleet
$h \in N$	Hours in the test set
$q \in Q$	Quarters in the test set
V	Cumulative electricity charging demand
V_e	Electricity volume demand per EV

electricity markets. Consequently, EV loads need to be gathered into a portfolio of sufficient size that can then be submitted as an aggregated bid. Aggregators develop business models that monetize flexibility on electricity markets by pooling distributed assets, i.e. EVs, together [11]. Next, in order to monetize the flexibility of EVs, an operational bidding framework must be developed that considers both, prices and demand.

Recently, several studies have assessed the economic potential of flexible assets and EVs to participate in the Day-Ahead (DA) electricity market. Yet, in many of these studies the focus is laid upon the optimization technique. For example, Jin et al. [12] apply a linear programming model to schedule the EV charging demand. Alahäivälä et al. [13] propose a control framework that monetizes the flexibility of electric heating systems by participating in the DA market. Similarly, a DA bidding framework for EVs that relies on stochastic optimization is developed by Vagropoulos et al. [14]. DeForest et al. [15] propose a DA bidding framework that utilizes a mixed integer linear program to minimize the daily EV charging costs and maximize the revenues of providing ancillary services with a vehicle-to-grid (V2G) set up. Besides, all these studies consider so-called perfect forecasts, in which both the DA electricity price and the EV demand is assumed to be known. Consequently, these studies only present the market potential and do not provide assistance on the implementation of an operational bidding framework for e.g. aggregators and energy utilities. Alternatively, Wu et al. [16] investigate the effectiveness of approximate dynamic programming to decide when to charge EVs. The approach considers an Auto-Regressive Moving Average (ARMA) model to forecast the electricity price, while considering the arrival time of EVs unknown. Hence, the latter approach prohibits to participate in the DA market. Few studies were found to cover the uncertainty of the EV demand on a DA basis. For example, Rehman et al. [17] propose a multi-stage hierarchical method to effectively schedule the EV charging load while considering the uncertainty of EV charging by assessing previous charging behavior, where the DA price is assumed to be given. In addition to simulating the uncertainty of the EV charging demand in their bidding strategy, Zheng et al. [18] consider an Auto-Regressive Integrated Moving Average (ARIMA) model to predict the DA price. Furthermore, Baringo et al. [19] develop a DA bidding framework, in which confidence bounds are created to describe the limits to EV charging on a DA basis. The uncertainty in the DA price is described in 20 scenarios that are generated with an ARIMA model. A similar approach is developed by Iria et al. [5], where the bidding framework adopts a gradient boosting model to forecast the DA electricity prices. This study generates several scenarios to describe the EV charging demand in the optimizer. Finally, one other study proposes a DA bidding framework including two linear models that forecast the EV demand and DA price [20]. In their study, Bessa et al. test this framework on two synthetic datasets of 1,500 EVs each with a 30-min time resolution. Moreover, the study evaluates the implementation of two different EV demand forecast strategies, agent-based and aggregated, in the overall bidding strategy.

In summary, although price and demand forecast models are essential to operate a bidding framework and participate in the DA market, very few studies are found to consider these. Besides, when included, the performance of the individual forecast models are not evaluated nor are they compared to alternative forecast models. Lastly,

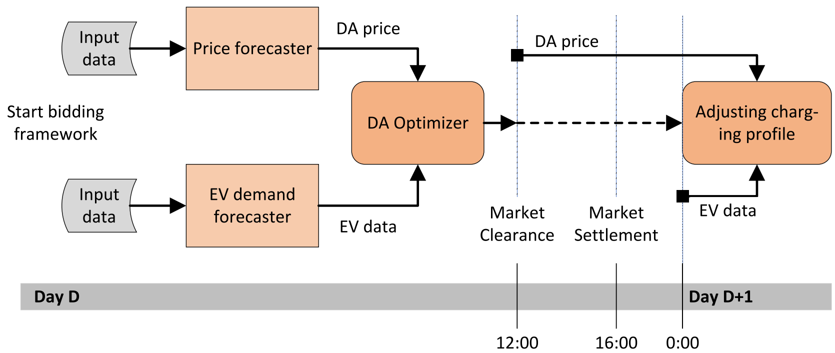


Fig. 1. Overview of the bidding framework. The framework starts with operating the price and EV demand forecast modules, which can be run in parallel. The bidding module, which is fed with the price and EV demand forecasts, runs sequential to these modules and provides a bid to the DA market. Note that it takes only a couple of seconds to run the entire framework. At day D + 1, the charging profile is adjusted every 15 min to meet the actual EV charging requirements.[1]

as Bessa et al. [20] point out, the performance of the forecast models should also be considered in context of the results obtained by the bidding framework. This aspect is particularly relevant as it provides insights into the effectiveness of the different components of the bidding framework, including the demand and price forecast models. Moreover, such an assessment will expose what component has most potential to improve its overall performance. Besides, it can provide information on what type of forecast model is preferred. Finally, these insights may lead to the development of alternative bidding strategies, e.g. through capping the bid to a certain percentage of the predicted charging demand. Nevertheless, in current literature no other study was found to assess the effect of the integration of different forecast models on the performance of the bidding framework.

The present study aims to bridge the identified research gaps by conducting a systematic analysis on the implementation of an operational DA market bidding framework for e.g. aggregators and energy utilities who manage an EV fleet. This framework exists of three modules that respectively (i) generate a price forecast, (ii) generate an EV demand forecast, and (iii) submit a bid to the DA market. The main contributions of this paper can be summarized as follows:

1. A ready-to-use, DA bidding framework is developed that operates fully according to the market requirements. Besides, the effectiveness of the framework is tested on a real-life case study of a fleet of 2366 EVs in the Netherlands considering the Dutch DA electricity and imbalance prices.
2. Eight DA price forecasting models are developed and compared. Additionally, to test its impact on the bidding framework the performance of the framework is evaluated separately for each of the DA price forecast models.
3. Three models that forecast the DA EV charging demand are developed and compared. Moreover, to measure the effect of the forecast models on the performance of the bidding framework, the framework is evaluated for each of these models.
4. The performance of the proposed framework is evaluated for all unique combinations of forecast models. Consequently, the most cost-effective combination of models within the bidding framework is discovered. Besides, by considering all unique configurations, the impact of the interaction between the price and EV demand forecast models on the overall performance of the framework is revealed and the potential for potential improvements is exposed.

The next Section 2 provides an overview of the system design by elaborating on the proposed application and the imposed requirements. The methods are presented in Section 3, which discusses the different modules that are included in the framework. The data that is used in this study is presented in Section 4. Section 5 presents the results obtained by the individual modules as well as the overall bidding framework. Section 6 holds the discussions, which is followed by the conclusions in Section 7.

2. System design

The operational bidding framework that we develop in this study and that can be deployed by e.g. aggregators who aim to minimize EV charging costs, is defined by a set of requirements. Moreover, these requirements result from market characteristics as defined by the Transmission System Operator (TSO) and interactions between the EV owners and the aggregator. This section explains the environment in which the bidding framework operates (see Fig. 1, the bidding framework itself is further explained in Section 3).

2.1. Aggregator - Market interaction

Since the aggregator participates in the DA market as a trader of electricity, the framework should meet the market requirements. In general, on the DA market electricity is bought at day D for every hour of the following day D + 1. For each hour, the aggregator must provide a bid containing the electricity volume in MWh and the price per MWh that it is willing to pay. These bids must be submitted before the Gate Closure Time (GCT). Like most European markets, the GCT in the Netherlands is at 12:00 (noon) on day D. Next, the market is cleared and by 16:00 on day D the price is set for each hour of day D + 1. After market clearance, the aggregator must define the electricity consumption per 15-min, this is referred to as a Program Time Unit (PTU). Consequently, other than the price forecast, the EV demand forecast should have a 15-min time resolution.

Furthermore, if in real-time the electricity consumption deviates from the original bid submitted to the DA market, the TSO may penalize the responsible market party (e.g. aggregator) by raising an imbalance price. The imbalance price depends on the electricity balance state and is set per 15-min time period, which is called the Imbalance Settlement Period (ISP) [21]. This ISP overlaps with the PTU.

2.2. Aggregator - EV owner interaction

The aim of the framework is to minimize the EV charging costs by shifting the electricity demand in time. As a result, the aggregator must be permitted to shift the charging demand of each EV. This shift of demand comes at the condition that the charging requirements of every EV is met at all times, i.e. the EV is fully charged before departure. Additionally, the charging power during a charging session is constrained by the maximum charging capacity of the EV. For simplicity reasons we assume that these EVs do not require time to ramp-up or down its charging power. Lastly, as the application of V2G is excluded in this study, a negative charging power is not permitted.

[1] The figure is not subject to the scale of the timeline.

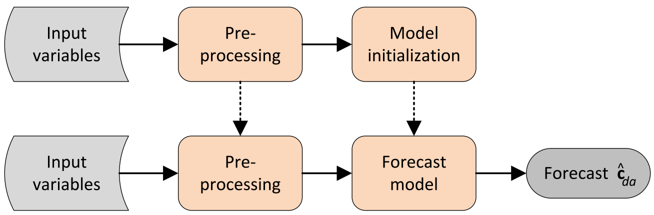


Fig. 2. Overview of the price forecast module.

3. Methods

The proposed operational DA bidding framework is subdivided in three independent modules (see Fig. 1). These comprise a price forecast, an EV demand forecast and a bidding module. This section discusses each module separately. Next, we present the performance indicators we use to evaluate the framework and its modules.

3.1. Module I: Price forecast

The first module of the framework comprises a price forecast model. The objective of this module is to predict the hourly DA electricity market price. As discussed in Section 2, the price forecasts need to be available before GCT, i.e. 12:00. Consequently, every day a forecast is generated for each hourly block ($h_1, \ldots, h_{24}$) of the next day D + 1, such that the price forecast ($\hat{\mathbf{c}}_{da}$) is composed of a time-series of 24 values. The forecast is characterized by a 12-hour lead time, a 24-hour time horizon, an hourly resolution and a daily update rate.

3.1.1. Background

Since statistical and learning models, including time-series based models, that include external variables are found amongst the best state-of-the-art price forecast models and easy to implement [22], this study focuses on these models. These statistical and learning models predict the future state based on historic values, possibly including external variables. Consequently, to this end the models are first trained to establish a relation between the input variables and the DA price.

3.1.2. Model operation

In this study, we consider an expanding window approach to forecast the DA electricity price. In this approach, every day the most recent observations of the input and target variables are collected and added to the train data set. This implies that the data set grows over time. After collection of the most recent observations, the input data is pre-processed where the predictor and target variables are scaled to normalize the data representation. Subsequently, these variables are used to train the models and determine the parameter values. Next, the predictor variables that apply to the next day (D + 1) are retrieved and collected in a test data set, and subsequently used as input to the model. The model then generates an output of 24 forecasted prices ($\hat{\mathbf{c}}_{da}$), one for each hour of day D + 1. Once the DA market is cleared, the prices are collected in order to evaluate the model performance. This process is repeated for each day in the test period and is summarized in Fig. 2.

3.1.3. Forecast models

As their effectiveness is proven in various previous studies [22–25], we investigate the following models in this study: Multi-variate Linear Regression (MLR), a Support Vector Regressor with a linear and a radial basis function kernel (L-SVR and K-SVR), Random Forests (RF), Gradient Boosting (GB), Seasonal Auto-Regressive Integrated Moving Average fed with exogenous variables (SARIMAX) and Artificial Neural Network (ANN). In addition, a persistence model is included, where the forecasts are set to the most recent observed prices. If relevant, hyperparameter tuning is conducted considering $k = 4$ fold cross-validation.

3.2. Module II: EV demand forecast

The objective of the second module is to predict the EV charging demand on D + 1. In order to assist the operational bidding framework in scheduling the electricity demand in the bid, this module should also provide information on the availability of the EV that is to be charged. After all, an EV can only be charged if connected to a charging point. Consequently, the EV demand forecast module exists of two separate models. Firstly, this module includes a model that predicts the Cumulative Electricity Charging Demand (CECD) per day in MWh. Secondly, the module considers a model that predicts the availability of all EVs, which is defined by the Aggregated Available Charging Capacity (AACC) in MW per PTU (i.e. quarter, q).

Similar to the forecasted prices, the information of this module should be available before 12:00 on day D. Every day the EV demand forecast module provides a prediction of the CECD ($\hat{V}$) and the AACC ($\hat{\mathbf{b}}$) per PTU ($q_1, \ldots, q_{96}$) of the next day D + 1.

3.2.1. Background

Two different strategies can be adopted to forecast the EV charging demand, i.e. agent-based (single EVs) or aggregated (multiple EVs). The experiments presented in [20] show that an agent-based EV demand forecast model achieves slightly better results than an aggregated model when adopted in an operational DA bidding framework. Nevertheless, this comes at a significant cost in terms of the computational resources needed [20], which will increase as the number of aggregated EVs grow. Besides, as the number of EVs increase, it is expected that the performance of aggregated models improve [26]. Since we consider a fleet of 2366 EVs and the operational framework is meant for e.g. aggregators that consider large number of EVs, the proposed framework must be scalable. Therefore, we focus on aggregated EV demand forecast models. Similar to price forecasting, statistical and learning models, and particularly time-series based models, are preferred for EV demand forecasting due its simplicity and computational stability [27].

3.2.2. Model operation

The EV demand forecast module generates a forecast of the CECD and AACC per PTU separately, for each day of the test period. As in the price forecast module, historic values are utilized to train the EV demand models. These input values are pre-processed by means of Singular Value Decomposition (SVD), which is a dimensionality reduction method that can filter the most relevant information [28]. Furthermore, an expanding window method (see Section 3.1.2) is applied such that at all times the most recent available EV demand information is considered.

3.2.3. Forecast models

In this study we consider two time-series based models to forecast the EV charging demand, namely an ARIMA [29] and a seasonal ARIMA (SARIMA). These models are characterized by their ability to capture patterns, seasonality [27] and therefore suitable to forecast the EV charging demand as the EV charging behavior is prone to weekly patterns [7]. In addition, a persistence model is included where the forecast for day D + 1 is set equal to the most recent observed complete time-series values, which corresponds to day D-1.

3.3. Module III: DA optimization

The DA optimizer is the third module and is used to define the most optimal charging schedule of the EVs according to the predictions of the DA prices and EV charging demand. The objective of the optimization module is to minimize the total EV charging costs per day:

$$\min_{x} \ \mathbf{c_{da}}^T \mathbf{x}, \tag{1}$$

where $\mathbf{c}$ represents the electricity price in €/MWh and $\mathbf{x}$ the charging schedule in MWh per hour. Next, $\mathbf{c}$ and $\mathbf{x}$ are vectors with length N, representing the number of hours in a day. Variable $\mathbf{x}$ is the optimization variable.

3.3.1. Background

Cost optimization models that consider uncertainty in price and resource constraints are usually solved by two-stage stochastic optimization methods [30]. Standard (linear) programming methods are deterministic and cannot handle uncertainty in the data but have the advantage that they are easy-to-use and have proven to be very effective in planning activities in varying applications [30]. As the objective is to define an operational bidding framework for e.g. an aggregator and since the bid should consist of a single value per PTU, we focus on deterministic linear programming.

3.3.2. Optimization constraints

The optimization problem is subject to certain constraints, i.e., the aggregated requirements of the EVs in the aggregators' portfolio. The goal is to find an optimal schedule of $\mathbf{x}^* = [x_1^*, x_2^*, \dots, x_N^*]^T$ based on the forecasted price $\hat{\mathbf{c}}_{da}$, while considering the constraints from the EV charging demand that are expressed by $\hat{V}$ and $\hat{\mathbf{p}}$ (see Section 3.2). Lastly, since a V2G application is excluded in this study, a last constraint is considered to ensure non-negative consumption: $x_h \geq 0$ for every hour $h \in N$.

The optimization problem has the following design:

$$\begin{aligned} \min_{x} \quad & \hat{\mathbf{c}}_{da}^T \mathbf{x}^* \\ \text{s.t.} \quad & \mathbf{x}^*{}_h \leq \hat{\mathbf{p}}_h, \\ & \sum_{h=1}^{N} \mathbf{x}^*{}_h = \hat{V}, \\ & \mathbf{x}^*{}_h \geq 0, \qquad \forall h \in N. \end{aligned} \tag{2}$$

This is a standard Linear Program optimization problem, which we solve using the simplex-method.

3.3.3. DA optimization

On day D, the aggregator runs the entire bidding framework to obtain the predicted EV demand constraints $\hat{V}$ and $\hat{\mathbf{p}}$, the predicted electricity price $\hat{\mathbf{c}}_{da}$ and construct an optimal charging schedule $\mathbf{x}^*$. Moreover, it takes only a couple of seconds to run the entire framework. Next, the predicted electricity price and optimal charging schedule together form the bid for the DA market that needs to be submitted before the GCT, i.e. 12:00 on day D. After market clearance, the actual DA price $\mathbf{c}_{da}$ is settled. The daily costs C_{da} of the scheduled electricity demand is the optimized volume $\mathbf{x}^*$ multiplied by the actual DA price, $\mathbf{c}_{da}$ per hour h:

$$C_{da} = \sum_{h=1}^{N} \mathbf{c}_{da,h} \mathbf{x}_h^*, \quad h = 1, \dots, N. \tag{3}$$

3.3.4. Real-time adjustment

Real-time adjustment of the charging schedule is needed to cope with the uncertainty in the forecast modules and ensure that the actual EV demand is met. Moreover, since the actual charging requirements (i.e. the actual target V and actual max-power constraint $\mathbf{p_h}$) may deviate from the predictions, the consumption schedule needs to be adjusted accordingly. These are penalized by the imbalance price $\mathbf{c}_{imb}$, which is given, either positive or negative, and may fluctuate significantly during the day [31].

The charging schedule is therefore only adjusted to satisfy the actual EV charging demand. This may occur: (1) when the actual target is not met or exceeded ($V \neq \hat{V}$) or (2) when the charging capacity constraint is exceeded ($\mathbf{x_h}^* \geq \mathbf{p_h}$). In case adjustments are made to the initial charging schedule, the imbalance price must be fulfilled over the corresponding volume difference per ISP. Consequently, the total costs that the aggregator needs to pay to satisfy the charging demand of the EV fleet is the sum of initial DA costs and imbalance penalty:

$$C_{total} = C_{da} + C_{imb} \tag{4}$$

3.4. Performance evaluation

3.4.1. Forecast models

The performance of the price and EV demand forecast modules is evaluated independently from the operational bidding framework for the entire test period (March 12 until December 31, 2018 see Section 4.2.1). For this purpose, several performance indicators that are commonly used to evaluate the performance of forecast models are included [27]. These are the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The MAE, MAPE and RMSE are considered to quantify the observed forecast error both absolutely and relatively.

3.4.2. Bidding framework

In addition, the performance of the overall bidding framework is examined for the entire test period. This is done by evaluating the average charging costs per MWh obtained by the bidding framework (see Eq. (4)). Moreover, the obtained results from the framework are evaluated for every unique combination of the price and EV demand forecast modules applied in this study.

Finally, the outcome of the bidding framework is compared to the common inflexible charging practice, where EVs are charged directly after being plugged-in at the charging point. For this reference case, we assume that we have perfect knowledge of the EV charging demand per PTU, which eliminates the imbalance costs completely.

4. Data

4.1. Price forecast module

Since the bid is submitted at 12:00 on day D, all input variables required by the price forecast module need to be available beforehand. In literature, a wide variety of input variables are used to forecast electricity prices [32]. The input variables found in literature can roughly be subdivided in the categories: lagged electricity prices, (expected) load and supply, fuel prices, temporal variables and weather forecasts. Herein, the supply is often subdivided into several power generation types, including wind and solar power. In addition, a recent study reported the growing importance of considering market integration in price forecasting [24]. This is explained by increasing electricity trading between countries where electricity markets are deregulated.

In this research we aim to describe the full spectrum of commonly used input variables, with the only additional condition that all data must be available from open sources. In total, we have selected $n = 62$ variables (these are reported and discussed in [32]) that describe the lagged prices, historic and expected load and supply [33], temporal variables and relevant weather forecasts [34]. Since in the Netherlands most electricity is imported from Germany and exported to Belgium, variables that describe the load, supply and lagged prices in these countries are also included [35]. Hourly values of each variable are collected from January 2017 until December 2018, such that each variable has a length equal to the number of hourly timestamps in the considered period. These values are then collected in a matrix $\mathbf{X}$, with rows h and columns n.

4.2. EV demand forecast module

Although the methodology expounded in this paper was developed based on actual observations, requirements of confidentiality preclude us from using these proprietary data in the current exposition in case of the EV charging sessions. We therefore used the original data to create artificial time-series that have similar statistical properties. To this end we used singular value decomposition (SVD) to extract week profiles as well as weekly amplitude data. Next, we fitted a lag-1 ARMA model to the observed amplitude data, that we then used as a starting point for the generation of a new time-series of amplitude data.

Table 1
Performance of the price forecast models per error metric for the test period (March 12 until December 31, 2018) [€/MWh].

	MLR	L-SVR	K-SVR	RF	GB	ANN	SARIMAX	Persistence
MAE	5.45	5.56	**5.38**	6.31	5.94	5.69	6.09	8.13
MAPE	10.38	10.37	**10.14**	11.82	11.21	10.82	11.42	15.92
RMSE	**7.70**	8.08	7.91	9.06	8.55	8.20	8.59	11.50

To add independent statistical variation to these data we mixed them with randomly resampled SVD-coefficients from the actual data whereupon the time-series was reconstructed. As a consequence of this procedure the original and reconstructed data have similar statistics in terms of the SVD features.

In this work, we consider a fleet of 2366 EVs consisting of a mix of Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). Data regarding the charging sessions of these EVs is collected for 2018. After aggregation, the electricity demand volume is presented by a vector $\mathbf{v}$, which has the length of the number of days in the data set. The charging capacity is represented in a matrix $\mathbf{P}$, where the rows r and columns f represent the PTUs and days, respectively.

4.2.1. Experiments

All experiments in this study are ran in Python [36]. Furthermore, since the EV demand forecast module requires a minimum of 10 weeks of training and data on EV charging sessions is only available for 2018, the experiments in this study are run for the remainder of 2018. This means that the results in this study are based on the period March 12 until December 31, 2018. Subsequently, the EV demand and the price forecast modules are trained for a period of respectively 10 and 62 weeks before the first predictions are made.

5. Results

This Section firstly discusses the results of the price and EV forecast modules, in Sections 5.1 and 5.2. Next, in Section 5.3 the working principles of the bidding framework are explained and the effectiveness of the framework is evaluated.

5.1. Price forecast module

Fig. 3 presents the actual prices observed for an arbitrary week in September 2018. In addition, this figure presents the average prices per hour and day of the week for the entire test period. Consequently, a few trends can be observed from Fig. 3 that are characteristic for the pattern of DA market prices. First, weekdays present a clear daily trend, with price spikes between 6:00 and 10:00 in the morning, and in early evening between 17:00 and 20:00. Moreover, prices typically are lower during midday and the lowest prices are found between 23:00 and 4:00. Although prices are lower, on Saturdays a similar pattern can be observed. On Sunday the magnitude of the price peak in the evening is similar as found on Saturday, whereas the morning peak almost vanished. Overall, Fig. 3 clearly shows lower prices during the night, indicating the potential economic advantage of consuming electricity (e.g. by charging an EV battery) during these hours.

Furthermore, Fig. 3 depicts the obtained price forecasts per model for the same week in September. In general, the figure shows that the price forecasts are able to capture the observed trends. Table 1 summarizes the performance of the DA price forecast models for the entire test period according to the error metrics discussed in Section 3.4.1. Although differences are small, the table indicates that the K-SVR model is the best performing model according to the MAE and MAPE. Nevertheless, the K-SVR model is outperformed by the MLR model in terms of the RMSE. Furthermore, all proposed models are found to outperform the persistence model in these metrics.

Table 2
Performance of the EV charging demand forecast model of the daily CECD for the test period (March 12 until December 31, 2018) [kWh].

	ARIMA	SARIMA	Persistence
MAE	128	**105**	145
MAPE	12.7	**11.1**	14.1
RMSE	180	**158**	195

Table 3
Performance of the EV charging demand forecast model of the AACC per PTU for the test period (March 12 until December 31, 2018) [kW/PTU].

	ARIMA	SARIMA	Persistence
MAE	10.3	**9.3**	18.7
MAPE	19.5	**18.2**	46.6
RMSE	16.5	**15.9**	24.9

5.2. EV demand forecast module

The EV demand forecast module consists of two independent but complementary models. The first produces a forecast of the CECD per day, whereas the second predicts the AACC per PTU.

5.2.1. Cumulative electricity charging demand forecast

Fig. 4 presents the actual and forecasted CECD per day of an arbitrary week in September as an example (same week as in Fig. 3), as well as the observed average electricity demand per day of the week for the entire test period. The example indicates large variations of over 10% in the daily actual electricity demand of the EV fleet on consecutive days. In addition, Fig. 4 outlines the diverging predictions obtained by the ARIMA and SARIMA models. Furthermore, the averages show a slightly higher (+5%) electricity demand for the EV fleet on Mondays. From Tuesday until Friday the electricity demand is on average relatively constant, whereas the lowest demand is found in the weekend (−10%).

The overall performance of the models that forecast the electricity volume demand is presented in Table 2. The results clearly show the superiority of the SARIMA model over the alternatives, i.e. ARIMA and persistence.

5.2.2. Aggregated available charging capacity forecast

The forecasts of the CECD are accompanied with forecasts of the connected EV capacity per PTU, i.e. the AACC per 15 min. Fig. 5 shows the prediction results for the same week along with the observed AACC per PTU per day of the week for the entire test period. Firstly, the average results in Fig. 5 indicate a high AACC during the night, whereas a low capacity is connected during the day. These observations can be explained as most EVs in the fleet are used for commuting and rely on home charging, so EVs are commonly connected in the late afternoon and disconnected in the morning. Although with a reduced magnitude, this pattern continues over the weekend.

Similar to Figs. 3 and 4, Fig. 5 also depicts the forecasted AACC per PTU for a week in September. The figure shows that the ARIMA and SARIMA forecast models are able to capture the observed trends discussed above. A striking feature in Fig. 5 is the offset in the predicted connected capacity during midnight. This offset is due to the constraints set by the DA electricity market, where bids are submitted for one day at a time. Subsequently, new insights during the day lead to an update of the predicted EV capacity for the next day. An overview of the performance of the AACC forecast models for the entire test period is presented in Table 3. The results show the superiority of the ARIMA and SARIMA models over the persistence model and highlight the SARIMA model as the best forecast model according to the MAE, MAPE and RMSE.

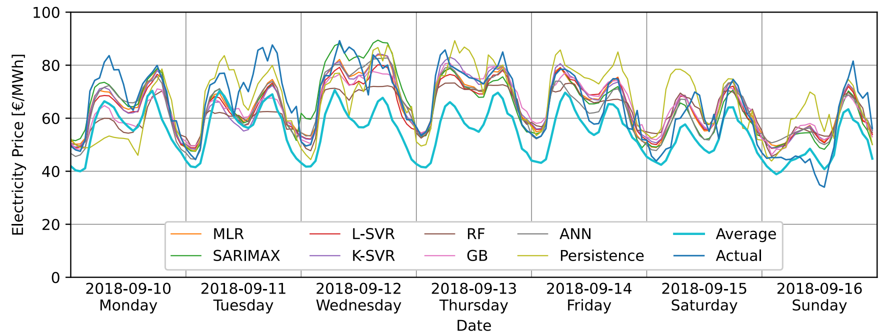


Fig. 3. Time-series of the observed and forecasted prices for an arbitrary week in September 2018, along with the average observed prices per hour and day of the week for the entire test period.

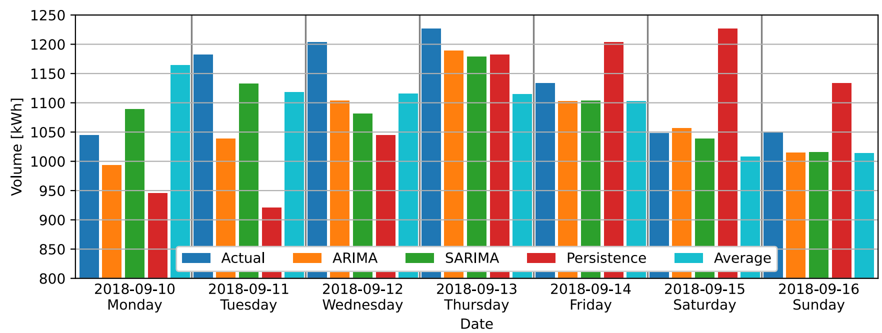


Fig. 4. Observed and forecasted CECD of the EV fleet per day for an arbitrary week in September 2018, along with the average observed CECD of the EV fleet per day of the week for the entire test period.

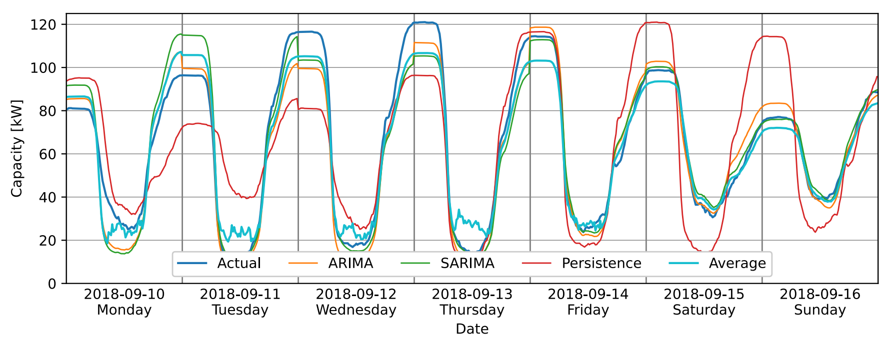


Fig. 5. Time-series of the observed and forecasted AACC per PTU for an arbitrary week in September 2018, along with the average observed charging capacity per PTU and day of the week for the entire test period.

5.3. Operational bidding module

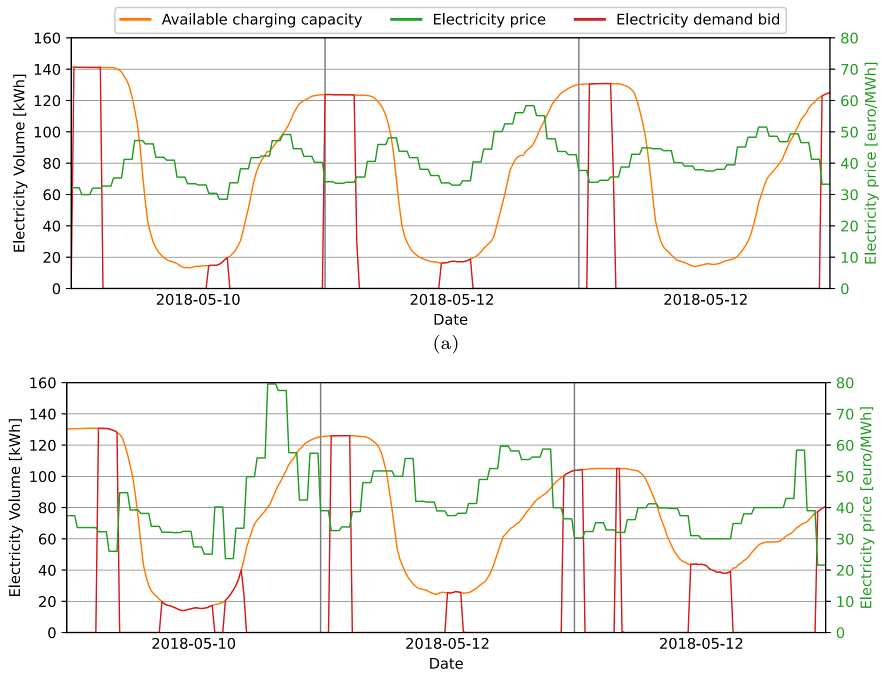
5.3.1. Principles

Fig. 6a presents an example of the forecasts of the electricity price and AACC, as well as the submitted bid for three arbitrary consecutive days. The electricity bid in this figure is generated based on the forecasts, which is scheduled in the hours where the electricity price is expected to be the lowest. Subsequently, the magnitude of the bid is limited to the expected AACC, which then determines the extent of the distribution of the bid over time. The volume made up by the daily bid adds up to the forecasted CECD per day. Moreover, Fig. 6b depicts the most optimal bid that could have been submitted in case of perfect knowledge of the DA prices and EV demand. The difference between Figs. 6a and 6b gives an indication of the impact of the forecast error. These figures show that errors in the price forecast result in charging the EVs at sub-optimal hours, leading to higher charging costs. In Fig. 6 this is the case for e.g. midday on May 10 and the early morning on May 12, where the forecasted bids do not overlap with the observed cheapest hours.

Errors in the EV demand forecast on the other hand, lead to an over- or underestimation of the expected charging demand, causing imbalances. Here, an overestimation would lead to a negative imbalance as too much electricity was bought in the DA market. An underestimation of the required charging demand would lead to a positive imbalance, as additional electricity is needed to satisfy the real-time electricity demand. Examples of this are found in Fig. 7, which presents the interaction between the submitted bid and the real-time charging requirements. In Fig. 7 an overestimation is observed during the early morning on May 10 and May 12, whereas the predicted charging capacity exceeds the AACC, resulting in a negative imbalance. An underestimation is observed during midday at May 10, where the realized charging requirements are found to exceed the bid.

5.3.2. Evaluation

The minimal costs for EV charging over the entire studied period is 41.19 €/MWh. In order to obtain this result, a perfect foresight of the electricity price and EV charging demand is needed, so a most optimal



(a)

(b)

Fig. 6. (a) SARIMAX-ARIMA framework (b) Perfect foresight framework.

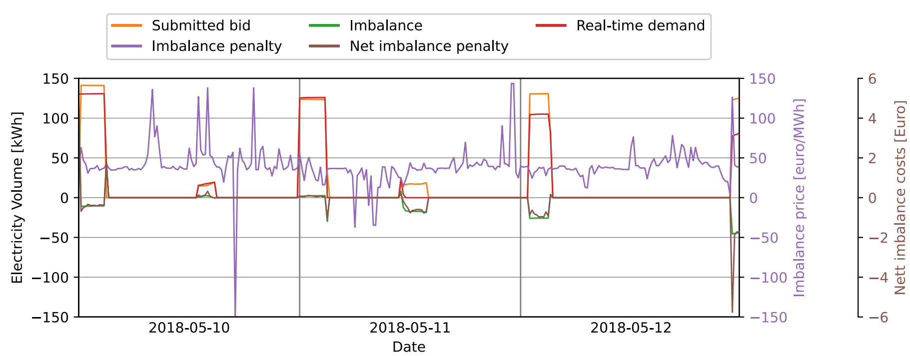


Fig. 7. Interaction between the submitted bid and the real-time charging requirements. If the bid under- or overestimates the real-time EV demand, an imbalance is caused and a penalty is raised.

or perfect bid can be submitted to the DA market that utilizes the flexibility of EVs to the fullest. On the other hand, in case of inflexible EV charging, an average price of 57.55 €/MWh is obtained. Although this still requires a perfect foresight of the EV charging demand to prevent imbalance costs, we consider this as our reference. Consequently, a 28% reduction in charging costs can be obtained by effectively deploying the operational bidding framework. This reduction is the potential cost reductions that can be achieved by the proposed framework.

The effectiveness of the proposed operational bidding framework and its dependencies on the electricity price and EV charging demand forecast is summarized in Fig. 8. This figure presents the average charging costs obtained for each unique combination of forecast models, including perfect foresight, over the entire test period. The depicted results present the sum of the expenditures on the DA market and the imbalance penalty that is levied on the forecast error. Fig. 8 shows that the average charging price can be obtained by the framework varies between 42.57 and 44.52 €/MWh. This is significantly lower than the costs in case of inflexible charging, i.e. 57.55 €/MWh. Additionally, it is noteworthy that the difference between the obtained costs for different forecast models is small. Consequently, even the most simple forecast models considered in this study, i.e. the persistence models, deliver a significant cost reduction. Yet, the bidding framework that obtains the most beneficial results utilizes a SARIMAX model to forecast the electricity price and an ARIMA model to forecast the EV charging demand. This framework obtains an average price of 42.57 €/MWh, which is equal to a cost reduction of 26%, and achieves 92% of the cost reduction potential. Compared to the most simple bidding framework based on the persistence models, the most optimal bidding framework achieves a cost reduction potential of 54%. Remarkably, a bidding framework based on the two models that obtain the highest self-contained forecast accuracy for electricity prices and EV charging demand (i.e. K-SVR and SARIMA) gives a higher average charging costs of 42.94 €/MWh.

Since the perfect foresight is included in Fig. 8, the effect of an improvement in either one of the forecast modules on the overall obtained results can be observed. In Fig. 8 a greater difference in the average charging costs is found along the x-axis (i.e. when the deployed price forecast model is replaced by a model that presents a perfect foresight). As a result, there is a higher potential to reduce the overall charging costs by improving the price forecast module.

Furthermore, Fig. 8 outlines that the average charging costs obtained by the framework depend on the dynamics that occur between the selected forecast models. An example of this is the case of adopting a K-SVR model to forecast the electricity price. Regardless of the model

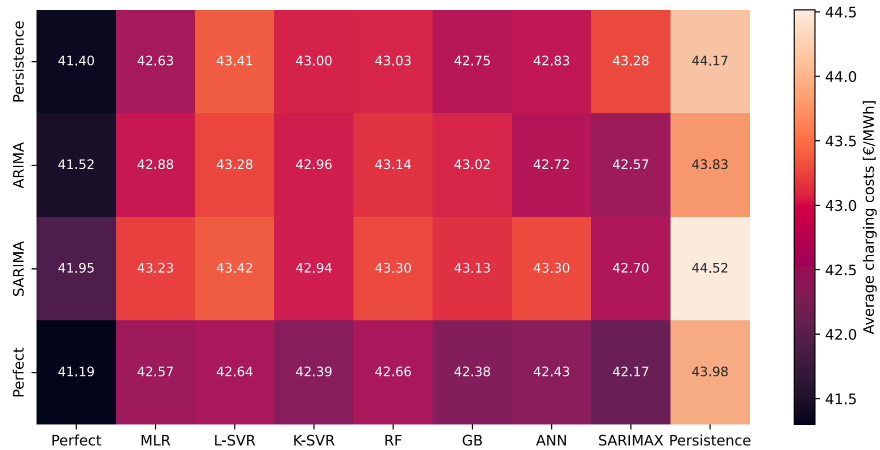


Fig. 8. The average obtained costs (€/MWh) for charging an EV fleet with the operational bidding framework that adopts all combinations of price and EV demand forecast models. This is complemented with a perfect model that presents a perfect foresight of either the electricity price or the EV charging demand.

selected to forecast the EV charging demand, average charging costs are nearly identical, varying between 42.94 and 43.00 €/MWh only. In contrast, if the electricity price is forecasted with the SARIMAX model, the selection of an EV charging demand does make a larger difference that is in the range of 42.57 and 43.29 €/MWh. Another remarkable observation is that the average charging costs in case of an ARIMA and persistence model is lower than the charging costs achieved when the ARIMA model was replaced by actual EV charging demand values. Moreover, in this case the EV demand forecast errors would have resulted in a cost reduction due to trading on the imbalance market.

Finally, Fig. 9 depicts the average costs obtained per day over the test period for a framework that considers a perfect foresight and a most optimal operational bidding framework, i.e. fed with the SARIMAX electricity price and ARIMA EV charging demand forecast models. This figure shows a high variation in the average daily costs, whereas lower costs are observed during the second quarter of the year (April until June, 2018). In general, the average charging costs per day are slightly higher for the SARIMAX-ARIMA bidding module compared to the perfect situation. Nevertheless, for some days the charging costs deviate significantly to both ends, which is triggered by the time-dependent imbalance penalty. Lower charging costs are obtained due to favorable imbalance prices at times of inaccurate predictions, where the imbalance prices are lower than the DA market prices. A major outlier here can be identified on April 3rd, where a net profit is made while charging the EVs. This is shown in Fig. 10a, where the net costs are negative due to a combination of a positive and a negative imbalance prices in the morning. On the other hand, a high imbalance price can increase the average charging prices significantly. An example of this is shown in Fig. 10b on April 25th, where a negative imbalance price applies in the morning at a time the forecasted EV charging demand is significantly higher than the realized volume charged. Consequently, the imbalance price can have a high impact on the average charging costs for a single day. However, we found that over the course of a year the impact averages, which is in agreement with the little observed differences between the obtained average charging costs per framework as presented in Fig. 8.

6. Discussion

The results presented above show the successful operation of the developed bidding framework. Besides, it clearly presents the importance of developing and testing the individual modules as an integral part of the framework. Yet, this research presents a first step in bridging the observed research gap, by developing a complete bidding framework for participating with flexible assets in the DA market. Therefore, the results in this study should be interpreted carefully. Subsequently, in the following we discuss the main research limitations and implications of this study, and set out topics that require attention in future research.

6.1. Research limitations

The proposed bidding framework is a ready-to-use solution for aggregators and energy utilities that operate flexible assets (e.g. a fleet of EVs) and wish to participate in the DA market. Additionally, it takes the developed framework only a few seconds to generate a bid. Although the findings prove the success of the framework, the framework and obtained results should be reviewed critically by its user before commissioning. Therefore, in this section we outline the major limitations of the framework. A first limitation of the proposed framework is that it merely considers the ability to submit bids in the DA electricity market. However, charging costs could be further decreased considering additional markets. Firstly, by participating in the intraday market, updated bids closer to the time of operation can be submitted which may limit the amount of imbalance penalties. Besides, the integration of balancing markets should be considered, as an EV fleet can provide ancillary services that can reduce the charging costs as this would yield revenues [37]. Future work should therefore focus on expanding the proposed framework to enable it to participate in additional markets. This would also require the development of dedicated forecast models, which consider the market requirements.

Secondly, attention should be given while interpreting the research findings, since the results are obtained for a case study in the Netherlands for the period March 12 until December 31, 2018. Due to the absence of publicly available data of EV fleets charging sessions, it was not possible to test the proposed framework and models on other case studies. Although the framework is universal and can be implemented anywhere as long as the local market conditions are considered, the results and success of the proposed bidding framework is sensitive to the data and may vary per case study. This is firstly explained as the costs of charging depend on the electricity and imbalance prices, and their variation over time. For example, a larger deviation in the electricity price could increase the potential savings obtained in this study and vice versa. The effect of time on the average obtained daily charging costs is shown in Fig. 9. Secondly, the magnitude of the flexibility of the EVs charging demand determines the extent to which EVs electricity consumption can be shifted in time, affecting the potential to charge at hours where the electricity prices are low. As a result, the framework should be tested on other case studies in order to assess its effectiveness and verify the results found in this study. Ideally, these case studies should focus on different regions, multiple time periods and EV fleets with alternative charging behavior. Besides, it would be interesting to test the efficacy of the proposed framework when applied to other flexible assets, e.g. heat pumps.

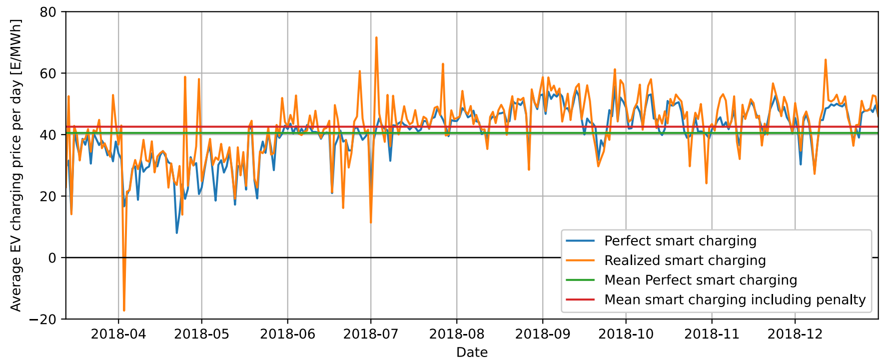


Fig. 9. Average costs for EV charging per day using the operational bidding framework fed with perfect forecasts or the most optimal combination of forecast models (Realized), i.e. ARIMA and SARIMAX.

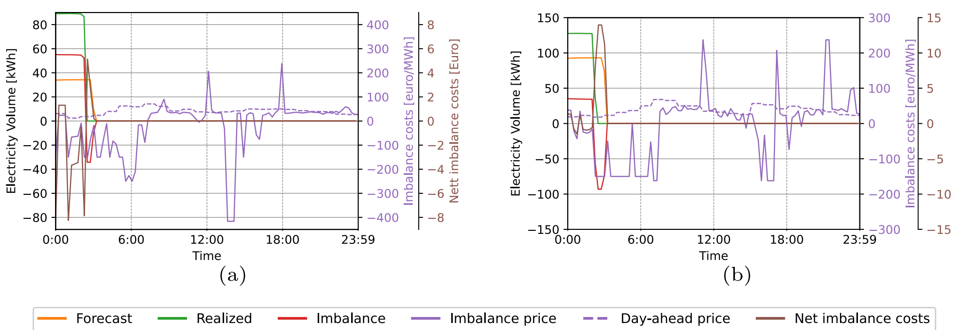


Fig. 10. Observed interaction between submitted electricity bid, real-time EV charging demand, DA market price and imbalance settlement price for (a) April 3rd (b) April 25th, 2018.

6.2. Research implications

What is remarkable from the findings presented in Section 5 is that the best results for the bidding framework are not obtained by simply combining the best performing self-contained forecast models. Moreover, a framework that includes the K-SVR and SARIMA models would give an average EV charging cost of 42.94 €/MWh. However, the results presented in Fig. 8 show that this framework is outperformed by five others. The best performing bidding framework includes a SARIMAX and ARIMA model and obtains an average charging cost of 42.57 €/MWh. There are multiple reasons why these best performing self-contained forecast models do not lead to a best bid, which relate to the model dynamics and objective of the framework. First of all, it is important to note that within the bidding framework the price forecasts are in principle handled in order of the cheapest to the most expensive. Consequently, finding the order of the cheapest to the most expensive electricity prices is more important than forecasting the actual prices. However, this is not examined by the MAE, MAPE and RMSE. Therefore, it is recommended to consider and/or develop additional error metrics that focus on the order (i.e. rank) to complement the common error metrics as the MAE, MAPE and RMSE. From a development perspective, a forecast model that predicts the rank instead of the price may be an interesting alternative strategy.

A second explanation for the discussed observation is related to the goal of the bidding framework, which is to charge the EVs at the lowest costs i.e. during hours with low electricity prices. Consequently, a model that is relatively better in forecasting cheap hours would generate better results. In addition, since an EV can only be charged if it is connected, a high accuracy of the price forecast model during these times is favorable. Subsequently, the price forecast models that will generate the best overall results are those models that have the most accurate forecasts of cheap hours during the connection times of EVs. It would therefore be of interest to develop new error metrics and/or loss functions that emphasize accurate forecasts during cheap hours while fitting and evaluating the price forecast models.

Thirdly, the varying imbalance price is a last explanation for the observation. Moreover, extreme negative and positive imbalance prices may have a high impact on the observed average charging costs. As a direct consequence, the most accurate EV demand forecast model will not automatically result in the most economic profitable outcome. An alternative error metric, one that solely considers the imbalance penalty, could assist the development and selection of electricity demand algorithms. Furthermore, the impact of imbalance penalties can be minimized if for example a safety margin is built in that prohibits the framework to bid the maximum forecasted available power capacity.

Based on the discussions above, future work should continue and review the performance of the individual forecast models from a framework perspective. Moreover, this should include the impact of the forecast errors on the performance of the framework. In addition, other bidding strategies or alterations to the optimizer may provide an alternative way to deal with the forecast uncertainty, and therewith form an interesting direction for future research.

7. Conclusion

In this study we have developed an operational bidding framework for the purpose of DA market trading for EV charging. The objective of this framework is to fulfill the charging requirements of an EV fleet, while minimizing the expenses. To this end we have developed a ready-to-use bidding framework that can be used by aggregators and energy utilities to participate in DA markets, while it utilizes price and EV charging demand forecasts. Subsequently, an individual forecast model can easily be replaced without affecting the logic of the operational framework. In order to come to a most cost-effective bidding framework, we have tested eight price forecast models as well as three EV charging demand models. Although, the framework was tested on a case study, the findings of this study can be generalized to other studies and the framework can be adopted for other DA markets and for alternative flexible assets.

The results of the study show that the proposed framework is able to participate successfully in the DA market. Moreover, in the case study the framework is found to obtain a cost reduction of 26% compared to a reference case where EVs are charged inflexibly. With this cost reduction, 92% of the maximum savings potential is achieved, i.e. in case of perfect price and EV charging demand forecasts. Moreover, this equals a cost reduction of 54% of the savings potential compared to a bidding framework that relies on persistence models. Besides, the results demonstrate that the best performing models for the individual objective of electricity price and EV charging demand forecasting, respectively, do not deliver a most cost-effective bidding framework. This highlights the importance of developing and testing the forecast models as part of its intended application, i.e. in this study as part of the overall DA bidding framework. In conclusion, as it is found in this study that the highest potential to improve the bidding framework lays within the price forecast model, alternative approaches to forecast the electricity price in context of the framework present a particular interesting direction for future work.

CRediT authorship contribution statement

L.R. Visser: Conceptualization, Data curation, Methodology, Software, Writing – original draft. **M.E. Kootte:** Conceptualization, Methodology, Software, Writing – original draft. **A.C. Ferreira:** Data curation, Methodology, Software. **O. Sicurani:** Conceptualization. **E.J. Pauwels:** Data curation, Writing – review & editing. **C. Vuik:** Writing – review & editing. **W.G.J.H.M. Van Sark:** Writing – review & editing. **T.A. AlSkaif:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is part of the Energy Intranets (NEAT: ESI-BiDa 647.003.002) project, which is funded by the Dutch Research Council NWO, Netherlands in the framework of the Energy Systems Integration & Big Data programme.

References

[1] Renewables 2019. Tech. rep., Paris: IEA; 2020, p. 204, URL https://www.iea.org/reports/renewables-2019.
[2] Stenclik D, Denholm P, Chalamala B. Maintaining balance: the increasing role of energy storage for renewable integration. IEEE Power Energy Mag 2017;15(6):31–9.
[3] Khan AR, Mahmood A, Safdar A, Khan ZA, Khan NA. Load forecasting, dynamic pricing and dsm in smart grid: A review. Renew Sustain Energy Rev 2016;54:1311–22.
[4] Terlouw T, AlSkaif T, Bauer C, van Sark W. Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies. Appl Energy 2019;239:356–72. http://dx.doi.org/10.1016/j.apenergy.2019.01.227, URL http://www.sciencedirect.com/science/article/pii/S0306261919302478.
[5] Iria J, Soares F, Matos M. Optimal bidding strategy for an aggregator of prosumers in energy and secondary reserve markets. Appl Energy 2019;238:1361–72.
[6] Global EV Outlook 2019. Tech. rep., Paris: IEA, International Energy Agency; 2019, p. 232, URL https://www.iea.org/reports/global-ev-outlook-2019.
[7] Gerritsma MK, AlSkaif TA, Fidder HA, van Sark WG. Flexibility of electric vehicle demand: analysis of measured charging data and simulation for the future. World Electr Veh J 2019;10(1):14.
[8] Teng JH, Liao SH, Wen CK. Design of a fully decentralized controlled electric vehicle charger for mitigating charging impact on power grids. IEEE Trans Ind Appl 2017;53(2):1497–505. http://dx.doi.org/10.1109/TIA.2016.2622221.
[9] Spencer SI, Fu Z, Apostolaki-Iosifidou E, Lipman TE. Evaluating smart charging strategies using real-world data from optimized plugin electric vehicles. Transp Res D 2021;100:103023.
[10] Kyritsis E, Andersson J, Serletis A. Electricity prices, large-scale renewable integration, and policy implications. Energy Policy 2017;101:550–60.
[11] Lampropoulos I, Alskaif T, Blom J, van Sark W. A framework for the provision of flexibility services at the transmission and distribution levels through aggregator companies. Sustain Energy Grids Netw 2019;17:100187.
[12] Jin C, Tang J, Ghosh P. Optimizing electric vehicle charging: A customer's perspective. IEEE Trans Veh Technol 2013;62(7):2919–27.
[13] Alahäivälä A, Corbishley J, Ekström J, Jokisalo J, Lehtonen M. A control framework for the utilization of heating load flexibility in a day-ahead market. Electr Power Syst Res 2017;145:44–54.
[14] Vagropoulos SI, Bakirtzis AG. Optimal bidding strategy for electric vehicle aggregators in electricity markets. IEEE Trans Power Syst 2013;28(4):4031–41.
[15] DeForest N, MacDonald JS, Black DR. Day ahead optimization of an electric vehicle fleet providing ancillary services in the los angeles air force base vehicle-to-grid demonstration. Appl Energy 2018;210:987–1001.
[16] Wu Y, Ravey A, Chrenko D, Miraoui A. Demand side energy management of ev charging stations by approximate dynamic programming. Energy Convers Manage 2019;196:878–90.
[17] Rehman U, Riaz M, Wani MY. A robust optimization method for optimizing day-ahead operation of the electric vehicles aggregator. Int J Electr Power Energy Syst 2021;132:107179.
[18] Zheng Y, Yu H, Shao Z, Jian L. Day-ahead bidding strategy for electric vehicle aggregator enabling multiple agent modes in uncertain electricity markets. Appl Energy 2020;280:115977.
[19] Baringo L, Amaro RS. A stochastic robust optimization approach for the bidding strategy of an electric vehicle aggregator. Electr Power Syst Res 2017;146:362–70.
[20] Bessa RJ, Matos M. Global against divided optimization for the participation of an ev aggregator in the day-ahead electricity market. part ii: Numerical analysis. Electr Power Syst Res 2013;95:319–29.
[21] Onbalansprijssystematiek. Tech. rep., Arnhem: TenneT; 2020, p. 16, URL https://www.vemw.nl/~/media/VEMW/Downloads/Public/Elektriciteit/Onbalansprijssystematiek.
[22] Halužan M, Verbič M, Zorić J. Performance of alternative electricity price forecasting methods: Findings from the greek and hungarian power exchanges. Appl Energy 2020;277:115599.
[23] Weron R. Electricity price forecasting: A review of the state-of-the-art with a look into the future. Int J Forecast 2014;30(4):1030–81.
[24] Lago J, De Ridder F, De Schutter B. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. Appl Energy 2018;221:386–405.
[25] AlSkaif T, Dev S, Visser L, Hossari M, van Sark W. A systematic analysis of meteorological variables for pv output power estimation. Renew Energy 2020;153:12–22.
[26] Diamantoulakis PD, Kapinas VM, Karagiannidis GK. Big data analytics for dynamic energy management in smart grids. Big Data Res 2015;2(3):94–101. http://dx.doi.org/10.1016/j.bdr.2015.03.003, arXiv:1504.02424.
[27] Elamin N, Fukushige M. Modeling and forecasting hourly electricity demand by sarimax with interactions. Energy 2018;165:257–68. http://dx.doi.org/10.1016/j.energy.2018.09.157.
[28] Khoshrou A, Pauwels E. Short-term scenario-based probabilistic load forecasting: A data-driven approach. Appl Energy 2019;238:1258–68.
[29] Zhou Y, Ravey A, Péra MC. A survey on driving prediction techniques for predictive energy management of plug-in hybrid electric vehicles. J Power Sources 2019;412(September 2018):480–95. http://dx.doi.org/10.1016/j.jpowsour.2018.11.085.
[30] Higle J, Sen S. Two Stage Stochastic Linear Programs. Boston, MA: Springer; 1996, p. 1–33. http://dx.doi.org/10.1007/978-1-4615-4115-8_1.
[31] TenneT. Settlement prices. 2021, URL https://www.tennet.org/english/operational_management/System_data_relating_processing/settlement_prices/index.aspx#PanelTabTable.
[32] Visser L, AlSkaif T, van Sark W. The importance of predictor variables and feature selection in day-ahead electricity price forecasting. In: 2020 international conference on smart energy systems and technologies (sest). IEEE; 2020, p. 1–6.
[33] ENTSO-E. European network of transmission system operators for electricity, entso-e. 2020, URL https://transparency.entsoe.eu/.
[34] ECMWF. European centre for medium-range weather forecasts, ecmwf. 2020, URL https://www.ecmwf.int/en/forecasts/datasets/archive-datasets.
[35] Electricity market insights. Tech. rep., Arnhem: TenneT; 2020, p. 62, URL https://www.tennet.eu/company/publications/technical-publications/.
[36] Van Rossum G, Drake Jr FL. Python reference manual. Centrum voor Wiskunde en Informatica Amsterdam; 1995.
[37] Hoogvliet T, Litjens G, Van Sark W. Provision of regulating-and reserve power by electric vehicle owners in the dutch market. Appl Energy 2017;190:1008–19.