Framework for the Participation of EV Aggregators in the Electricity Market

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***Abstract*—The Electric Vehicle (EV) is one source of flexibility to the electric power system. When aggregated by a market agent, it can offer its flexibility in the balancing reserve market. In order to meet this goal, a framework of optimization and forecasting algorithms must designed to cover the different time horizons of the decision process. This paper describes a full framework for EV aggregators participating in different electricity market sessions. This framework is illustrated for the balancing reserve market and the impact of forecasts of different quality for the balancing reserve direction is evaluated. The test case consists in synthetic time series generated from real data for 3000 EV participating in the Iberian electricity market.**

Keywords—Electric vehicles; electricity market; optimization; balancing reserve; forecasting; smart grid.

I. INTRODUCTION

In the European Union (EU), the GHG emissions from the transport sector increased around 36% since 1990, which degraded the environmental quality [1]. This sector, because of its oil-dependency, is responsible for around a quarter of EU GHG emissions, and the road transport represents about one-fifth of the EU's CO_2 total emissions [2]. Moreover, concerns such as the dependency on oil supply and a foreseen ``end of cheap oil'' during this century have motivated a wide range of policy and technological measures for the transport sector.

The electric vehicle (EV) is one element that helps to decarbonize the transport sector and decrease oil-dependency [3]. There are three main types of EV: battery, hybrid and fuel cell. This paper only covers the battery EV type.

The deployment of EV technology establishes a connection between the transport and electric power sectors. In fact, this EV deployment can contribute to a sustainable development of the electric power system, but their positive effect depends on two aspects: (a) the impact on GHG emissions varies with several factors, such as the power system generation portfolio, season of the year and geographical location of EV charging; (b) the EV charging strategy, in particular whether it is controllable or not, impacts the power system operation.

The second aspect, and which is related to this paper, is that, even in countries with a high penetration of renewable energy sources, if the EV are charged during peak hours, peak power units with intensive GHG emissions are likely to be dispatched, which undermines the benefits from EV. This is likely to happen if the EV charging is uncontrollable, e.g. the EV starts charging when the drivers plug-in at home after returning from work. This uncontrollable charging can create technical problems in the distribution network [4] (e.g., branches congestion and voltage limits violation).

Therefore, in order to take full advantage of the EV benefits to the system and avoid technical problems, it is essential to directly control and coordinate the charging process of each EV. Moreover, direct control also enables the provision of ancillary services (e.g., reserves) from the EV [5].

The backbone that enables EV charging control is a smart grid infrastructure, which provides additional capabilities for the observability and controllability of the distribution network level, and is strongly supported by the Information and Communications Technology (ICT) and the Advanced Metering Infrastructure (AMI). This enables new features, such as a two-way connection infrastructure, which creates conditions for demand management.

The massive deployment of the EV and necessary interaction with the power system operators can be supported by an agent (called aggregator) responsible for aggregating EV and managing their charging process within the smart grid paradigm [6]. From the system operators' viewpoint, the EV aggregator is part of a hierarchical control architecture and coordinates the EV charging in response to the system operators' signals, which decreases their communication requirements [7]. From the EV owners' viewpoint, the aggregator uses their available flexibility to purchase electrical energy at low price and sells ancillary services in the electricity markets, which ultimately lead to a retailing tariff reduction.

Related to this context and considering the potential benefits from EV aggregators for the power system, this paper aims to contribute with a framework that includes the necessary interdisciplinary computational models (from operations research, statistics, data mining, etc.) for each market session.

Within this framework, the participation in the balancing reserve market is addressed. More specifically, the impact of incorrect reserve direction forecasts provided by different algorithms will be studied in terms of reserve not supplied and total cost for the aggregator.

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This balancing reserve topic covers an unexplored area in the current literature, since most of the optimization techniques either assume perfect forecast (e.g., [8][9]) or neglect the impact of having reserve not activated as foreseen (e.g., [10][11]). Furthermore, it departs from the forecasting techniques for EV variables described in [12] and the optimization problem for balancing (or manual) reserve described in [13].

This paper is organized as follows: section II describes a general framework for EV participation in the electricity market; section III presents the day-ahead and operational management algorithms; section IV presents the test-case results; finally, section V presents the conclusions.

II. Framework for EV Participation in the Electricity Market

A. General Architecture

The architecture adopted in this paper consists of a hierarchical direct control, illustrated in Fig. 1 and described in the following paragraphs.

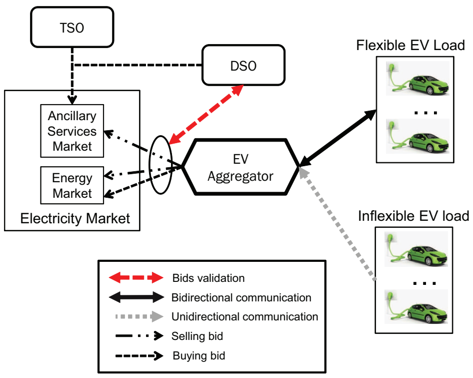

Fig. 1. EV aggregator architecture.

The owners of plug-in EV, seeking the lowest electricity tariff, establish a contract with an aggregator. The aggregator is an electricity retailer and represents the EV drivers in the electricity market. The retailing activity is only for electrical mobility, which allows separate pricing of electricity for this purpose and the inclusion of taxes from the government.

Two different groups of clients are foreseen for the EV aggregator:

- inflexible EV load: a client who does not allow the aggregator to control the charging process. For this client, the aggregator is only an electricity provider;
- flexible EV load: a client who allows the aggregator to control the charging process (bidirectional communication), which means that its requirements (i.e., final SoC and departure time instant) must be satisfied, but presents a degree of freedom regarding when this load can be supplied.

The aggregator can present the following bids in the electricity market:

- *buying bid in the energy market*: the aggregator purchases electrical energy for charging the EV at the lowest price. The sellers are generators;
- *selling bid in the energy market*: if V2G is available, the aggregator can offer electrical energy in the electricity market in hours with high prices. The buyers are other electricity retailers;
- *selling bid in the ancillary services market*: the aggregator offers reserve services and the buyers are the TSO and DSO.

The DSO makes an *ex-ante* technical validation of the aggregator's bids. The TSO purchases reserve services from the aggregator for load-generation balancing.

The V2G mode is not considered in this paper and reserve services are provided using the preferred operating point (POP) approach [5].

B. Electricity Market Framework and Algorithms

The framework proposed in this paper covers three different time horizons [14]:

- *short-term*: time horizon up to two days ahead with hourly or half-hourly time steps (depending on market rules). The aggregator participates in day-ahead markets to buy electrical energy and sell ancillary services;
- *very short-term*: time horizon ranging from 1 to 6 hours ahead with hourly and half-hourly time steps. The aggregator participates in intraday markets to adjust the day-ahead bids, reserve markets or in real-time (or hour-ahead) markets;
- *operational (or ``almost'' real-time)*: the starting point is the short or very short-term schedule and the aggregator coordinates the EV individual charging to fulfill the market commitments (and avoid financial penalizations) and EV owners' needs. The aggregator may also respond to signals from the DSO under abnormal operating conditions (such as network operated near its technical limits).

As the time horizon decreases, more information is available since all plugged EV are monitored by the aggregator and it is assumed that the EV drivers communicate their preferences for the charging process (otherwise, a default profile is used).

For inflexible EV, an optimization model for the market bids is not necessary. The aggregator only needs to forecast the total consumption in each hour and purchase, in the energy market, the forecasted quantity.

Fig. 2 depicts the proposed framework of electricity market sessions and optimization/forecasting algorithms for flexible EV. This framework covers the majority of electricity markets schemes across the world, it is divided by time horizons and a separation is made between input information and market processes.

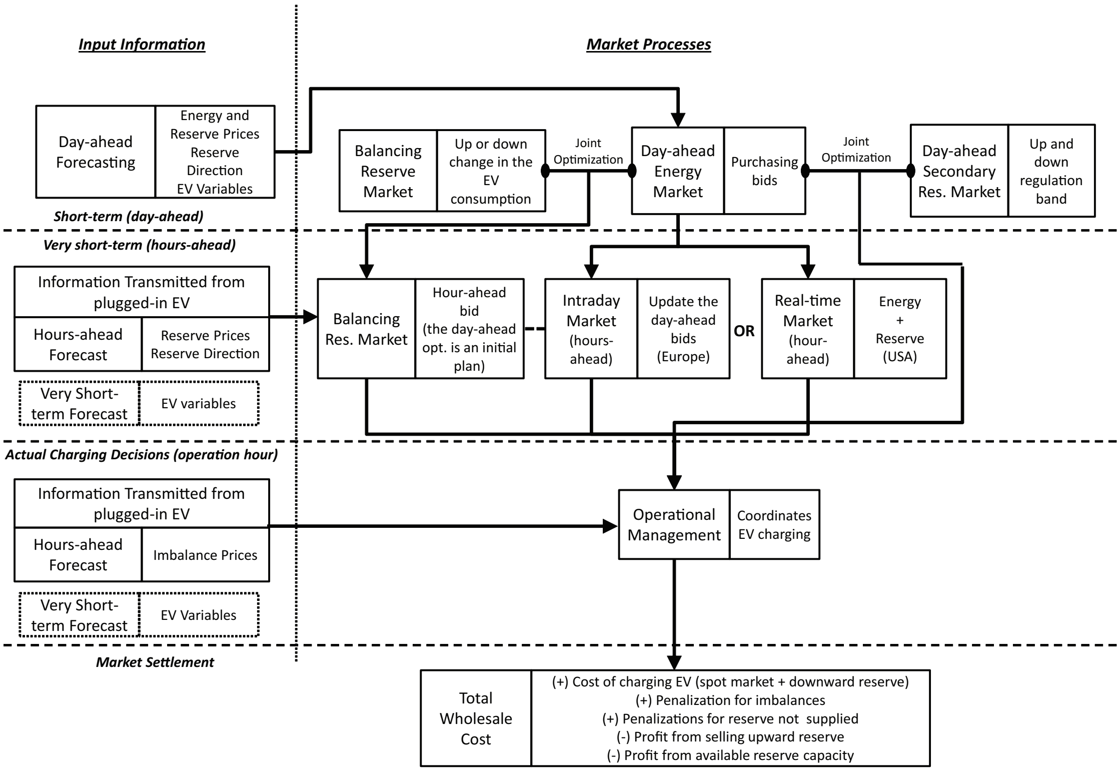

Fig. 2. EV aggregator architecture.

1) Short-term Horizon

The day-ahead (or short-term) optimization processes are intended for energy, secondary reserve and balancing reserve market sessions. The aggregator has different possibilities: (a) optimization of the energy bids [15]; (b) joint optimization of the energy and secondary reserve bids [16]; (c) joint optimization of the energy and balancing reserve bids [13]; (d) joint optimization of energy, secondary and balancing bids.

The outputs from the day-ahead optimization algorithms are: energy bid for each market time interval; upward and downward balancing reserve capacity bid; upward and downward secondary reserve capacity bid (in MW). Since the aggregator is a "price-taker", it is assumed that the bid price is lower enough to be accepted.

Joint optimization algorithms can be developed for sequential markets or joint markets where energy and reserve bids are cleared together.

This framework assumes that secondary reserve is only contracted in a day-ahead session. This is valid for most European markets with daily secondary reserve markets, like the Iberian and Italian markets. In most of the USA markets it can be contracted in the real-time (or hour-ahead) market, but as mentioned in [17], the majority of secondary reserve in the USA is contracted in the day-ahead market. A day-ahead session for the balancing reserve market is also considered.

The day-ahead optimization algorithms require forecasts for different variables: energy and reserve prices, balancing reserve direction and EV variables.

Forecasting the balancing reserve direction (topic discussed in sections III and IV) consists in anticipating if the power system will need upward or downward balancing reserve in each time interval of the next hours and day. Based on this information the aggregator can define a combined strategy for participating in the electrical energy and reserve market (addressed in section III). For example, if in a specific hour the probability of downward reserve is high, the aggregator can offer a bid with a very low quantity (or zero) in the electrical energy market and then offer the required electrical energy for charging as downward reserve.

Since the secondary reserve handles less predictable events, the optimization algorithm for secondary reserve does not use information about secondary reserve direction (see the optimization model in [16]).

The load forecasting task is common in problems related to power systems and electricity markets. However, this problem is different because the aggregator controls EV consumption, which means that the approach of forecasting the EV consumption in each time interval (similarly to classical load forecasting problems) cannot be strictly followed. The approach proposed in [12] is to forecast two EV variables (illustrated in Fig. 3): charging requirement and availability.

The availability is the time-period where the EV is plugged-in for charging. In the example of Fig. 3, it is the time period between 21h30 and 8h30. The charging requirement is the total electrical energy needed to get from the initial (i.e., when the EV arrives for charging) to the target state of charge (SoC) defined by the EV driver for the next trip, including the charger efficiency. In Fig. 3, the charging requirement is the total energy required for getting from a 50% to a 100% SoC, which is 10 kWh, plus the charger's efficiency losses (1.11 kWh). A charging requirement value is always associated to an availability period. The aggregator then distributes this quantity, according to its optimization strategy, by the time intervals of the corresponding plug-in period.

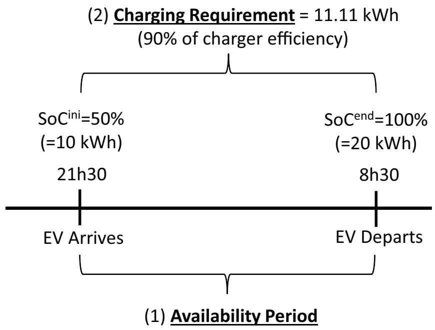

Fig. 3. EV variables: charging requirement and availability.

Note that this approach does not require personal information, such as driving routes (historical and planned) or the number of travelled kilometers.

2) Very Short-term Horizon

The following sessions are included in the very short-term horizon: hour-ahead balancing reserve market; intraday market (typically in Europe); real-time market (typically in the USA).

The participation in the intraday market sessions is not mandatory, but it is foreseen that the aggregator will use these sessions to update day-ahead bids using recent information. The same is valid for the real-time market and, in both cases, the aggregator is mitigating imbalances and corresponding financial penalties. Note that the price difference between real-time (or intraday) and day-ahead price can induce losses and income in case of differences to the day-ahead bid quantity.

Two situations are considered for balancing reserve: (a) day-ahead submission of bids that cannot be changed during the operating day; (b) day-ahead bids that can be adjusted or removed 45 minutes before the operating hour in an hour-ahead market for this reserve.

For instance, a bidding optimization algorithm for the hour-ahead balancing reserve market takes as inputs hour-ahead forecasts for the reserve price and direction, as well as information transmitted by plugged-in EV (*i.e.*, target SoC and expected departure time instant).

3) Operational Management

Since it is not possible to produce perfect forecasts, it is necessary to have an operational management phase were the EV individual charging is coordinated to satisfy the contracted energy and reserve levels (i.e., bids for the short-term and very short-term horizons).

During the operating day, the TSO sends set-points requesting balancing and secondary reserve from the aggregator. Operational management algorithms are developed for the energy and reserve markets and use information from the plugged-in EV as input. These algorithms may include very short-term forecasts for the EV variables. Forecasts for the imbalance prices due to deviations between purchased energy and actual consumption are also used as input.

4) Market Settlement Phase

After the operating day, there is a settlement phase where the deviations from the market schedule (both energy and reserve) are determined using metered data for hourly (or half-hourly) periods and priced according to positive and negative imbalance prices. From this process, it results a cost term that is summed to the cost from purchasing electrical energy. The income from providing secondary or balancing reserve is also computed in this phase.

Market settlement schemes for secondary and balancing reserve are proposed in [11], [16] and [13].

III. Participation in the Balancing Reserve Market

This section describes the day-ahead and operational management algorithms that follow the general framework detailed in section II.

A. Forecasting Phase

The availability period is a binary time series forecasted with a generalized linear model (GLM) with the response variable following a binomial distribution. After forecasting the availability period, the corresponding charging requirement is forecasted with non-parametric bootstrapping. A complete description of the forecasting algorithm can be found in [12].

The day-ahead energy price is forecasted with an additive model (using cubic splines) and using the following variables as explanatory variables: lagged variables of the price (i.e., t-1, t-2, t-3), forecasted wind power penetration, periodic function for the hour of the day and week day.

The balancing reserve price (i.e., price for dispatched reserve) is an irregular time series forecasted with the Holt-Winters model with trigonometric functions [18].

The reserve direction consists in two binary time series, one for upward direction and another for downward. Two separate variables are considered because in a specific hour the reserve can be mobilized in both directions. For this task, a comparison of four different algorithms (i.e., GLM with the response variable following a binomial distribution, support vector machines, neural networks and naïve Bayes) is given in [19].

The best results are obtained with the following GLM model for day-ahead τ_t^- (upward reserve) forecast:

$$prob\left(\tau_t^- = 1|\cdot\right) = 1 \Bigg/ \left(1+\exp\left(-\left(\begin{array}{c}\phi_0+\phi_1\cdot\tau_{t-24}^- +\phi_2\cdot\tau_{t-48}^- \\ +\phi_3\cdot\tau_{t-96}^- +\phi_4\cdot\tau_{t-120}^- +\phi_5\cdot\tau_{t-168}^- \\ +\phi_6\cdot\hat{w}p_t+\phi_7\cdot\hat{p}_t+D_t+H_t\end{array}\right)\right)\right) \quad (1)$$

where τ^-_{t-l} are lagged variables of the response variable, p_t is the forecasted energy price. The model for day-ahead τ_t^+ (downward reserve) forecast is analogous but with an additional coefficient for τ^{+}_{t-144}. The model for hour-ahead τ_t^- (upward reserve) forecast is as follows:

$$prob(\tau_t^- = 1|\cdot) = 1 \Bigg/ \left(1+\exp\left(-\left(\begin{array}{c}\phi_0+\phi_1\cdot\tau_{t-1}^- +\phi_2\cdot\tau_{t-2}^- \\ +\phi_3\cdot\tau_{t-3}^- +\phi_4\cdot\tau_{t-24}^- +\phi_5\cdot\tau_{t-48}^- + \\ \phi_6\cdot\tau_{t-168}^- +\phi_7\cdot\hat{w}p_t+\phi_8\cdot\hat{p}_t+H_t\end{array}\right)\right)\right) \quad (2)$$

The same model is used for hour-ahead τ_t^+ forecast.

The outputs are the posterior probabilities prob(τ_t^-=1|.) and prob(τ_t^+=1|.). The decision rule for transforming the posterior probabilities into binary values consists in offering a reserve bid in the most probable direction: τ_t^-=1 if prob(τ_t^-=1|x)> prob(τ_t^+=1|x); τ_t^+=1 if prob(τ_t^-=1|x)< prob(τ_t^+=1|x).

B. Day-ahead Optimization Phase (Short-term)

The decision variables are: energy purchased by the aggregator in the energy market for the jth vehicle and time interval t (Et,j); downward reserve capacity (Pdownt,j); upward reserve capacity (Pupt,j). The bid is the aggregation of the individual contribution from each EV for the same time interval t.

The objective function is the minimization of the total cost divided in three components: i) cost of purchasing energy in the energy market; ii) cost from charging EV with downward reserve; iii) income from reducing the consumption (upward reserve). It is written as:

$$\min \sum_{t\in H}\left(\begin{array}{c}\hat{p}_t\cdot\sum_{j=1}^{M_t}\left(E_{t,j}\right)+\hat{p}_t^{down}\cdot\sum_{j=1}^{M_t}\left(P_{t,j}^{down}\cdot\Delta t\right) \\ -\hat{p}_t^{up}\cdot\sum_{j=1}^{M_t}\left(P_{t,j}^{up}\cdot\Delta t\right)\end{array}\right) \quad (3)$$

where $\hat{p}_t$ is the forecasted energy price for time interval t, $\hat{p}_t^{down}$ is the forecasted downward reserve price, $\hat{p}_t^{up}$ is the forecasted upward reserve price, Δt is the length of time interval t, H is the set of time intervals from the optimization period (e.g., for one day with Δt=30 min, H ranges between 1 and 48), M_t is the number of EV plugged-in.

The main constraints are described in the following paragraphs.

The energy purchased in the energy market for charging during Δt plus the downward reserve power must be below or equal to the maximum charging power of the j-th EV in each time interval t:

$$E_{t,j}/\Delta t+P_{t,j}^{down}\le P_j^{\max},\ \forall j\in\{1,\cdots,M_t\},\forall t\in H \quad (4)$$

The upward reserve power should be lower or equal to the energy purchased in the market for charging during Δt in each time interval t:

$$P_{t,j}^{up}\le\left(E_{t,j}/\Delta t\right)\cdot\hat{\tau}_t^-,\ \forall j\in\{1,\cdots,M_t\},\forall t\in H \quad (5)$$

where τ_t^- is the binary variable representing the upward reserve direction, and when its value is “0”, the upward reserve power must be zero.

The downward reserve power should be zero when the forecasted binary variable for the downward reserve direction (τ_t^+) is ”0”:

$$P_{t,j}^{down}\le P_t^{\max}\cdot\hat{\tau}_t^+,\ \forall j\in\{1,\cdots,M_t\},\forall t\in H \quad (6)$$

The constraint of Eq. 7 consists in postponing EV charging by offering upward reserve.

$$\sum_{k=t}^{k=t_{final}\in\hat{H}_j^{plug}}\left(P_{k,j}^{up}\cdot\Delta t\right)\le\sum_{k=t}^{k=t_{final}\in\hat{H}_j^{plug}}\left(E_{k,j}+P_{k,j}^{down}\cdot\Delta t\right)\Big/2 \quad (7)$$
$$\forall j\in\{1,\cdots,M_t\},\forall t\in H$$

where $\hat{H}_j^{plug}$ is the forecasted availability period of the jth EV and t_{final} is the departure interval.

The balance between energy and reserve bids should be equal to the charging requirement of the j-th EV:

$$\sum_{t\in\hat{H}_j^{plug}}\left(E_{t,j}+P_{t,j}^{down}\cdot\Delta t-P_{t,j}^{up}\cdot\Delta t\right)=\hat{R}_j,\forall j\in\{1,\cdots,M_t\} \quad (8)$$

where $\hat{R}_j$ is the forecasted charging requirement of the j-th EV.

Finally, the total upward reserve power in the availability period is limited by the charging requirement:

$$\sum_{t\in\hat{H}_j^{plug}}\left(P_{t,j}^{up}\cdot\Delta t\right)\le\hat{R}_j,\ \forall j\in\{1,\cdots,M_t\} \quad (9)$$

More details about this set of constraints can be found in [13] and [14].

C. Operational Management Phase

The central idea of the operational algorithm consists in following the strategy from the day-ahead optimization model by minimizing the difference between the total charging and day-ahead plan (E_t, P_t^{down}, P_t^{up}). The aim is to guarantee lower penalization costs due to reserve shortage, energy surplus and shortage, and increases reserve reliability.

The objective function is convex, and can be formulated for a complete day (with T time intervals of length Δt) as follows:

$$\min\sum_{k=t_0}^{T}\left(\varphi\left(E_k+P_k^{down}\cdot\Delta t-P_k^{up}\cdot\Delta t-\sum_{j=1}^{M_t}\left(E_{k,j}^*\right)\right)\right) \quad (10)$$

where $E_{k,j}^*$ is the energy consumed by the j-th EV, t_0 is the first time interval of the optimization period, Δt is the same interval length of the day-ahead optimization algorithm and φ is a piecewise loss function given by

$$\varphi(u)=\begin{cases}u\cdot\theta_k^+,u\ge 0\\ -u\cdot\theta_k^-,u<0\end{cases} \quad (11)$$

where θ_k^+ and θ_k^- are constants that penalize situations with positive and negative deviations correspondingly.

In terms of constraints, the consumed energy in each time interval must be below or equal to the maximum available power for charging:

$$E_{k,j}^*/\Delta t\le P_k^{\max},\ \forall j\in\{1,\cdots,M_t\},\forall k\in H_j^{plug} \quad (12)$$

The total consumed energy during the availability period must be equal to the charging requirement:

$$\sum_{k \in H_j^{plug}} \left(E_{k,j}^*\right) = R_{t_0,j}, \forall j \in \{1,\cdots,M_t\}, \forall k \in H_j^{plug} \qquad (13)$$

Where $R_{t,j}$ is the residual charging requirement at beginning of time interval t_0.

This optimization problem is applied sequentially as new EV arrive for charging:

1. in the beginning of time interval t_0, new information (expected departure time and target SOC) communicated by recently plugged EV is used, together with the metered initial SOC, to compute the charging requirement and availability period that are included in Eq. 13;
2. using this new information, the aggregator solves the optimization problem for a period between t_0 and the maximum departure time interval of all the EV plugged-in in time interval t_0 (this maximum is updated every time step);
3. set points corresponding to the charging levels for time interval t_0 are transmitted to the plugged-in EV; only the dispatch for time interval t_0 remains unchanged, the charging levels for the subsequent time intervals can be modified in the next iteration (next time interval, t_{0+1});
4. this process is repeated for the next time interval t_{0+1} (go to step 1).

IV. Evaluation Results

A. Test Case Description

The electricity market data of the case-study is from a three years period (2009-2011) and consists of: market prices (tertiary reserve and energy) for Portugal [20]; day-ahead load and wind power forecasts (that give the forecasted wind power penetration) for the Iberian Peninsula [21].

Synthetic time series for the availability and charging requirement of 3000 EV along one year was simulated using a discrete-time-space Markov chain, in accordance with the traffic patterns in Portugal. The simulation time step is 30 minutes.

Each EV was characterized in terms of battery size and consumption per km. The charger efficiency was assumed to be 90%. Three different driver's behaviors, obtained from a survey made in the MERGE project [22], were modeled: i) charge at the end of the day; ii) charge whenever possible; iii) EV charge only when it needs (i.e., SOC below 40%).

These time series are used for fitting the forecasting algorithms (as historical data) and testing the optimization algorithms. A full description about the simulation mechanism can be found in [4].

For a robust evaluation, a sampling process based on [23] is used to generate random repetitions of a test experiment. The objective is to evaluate the optimization algorithms for different market data randomly sampled (but maintaining the temporal sequence) from the three years period. Since the forecasting algorithms require training and testing datasets, a fixed length for these two sets was defined: 9 months for training and 3 months for testing.

The process is repeated 30 times (i.e., generates 30 samples), and for each sample, the algorithms are evaluated in the test dataset. This sampling process is only used in the electricity market data. The synthetic time series for 3000 EV are divided in two groups with 1500 EV: fleet A and B.

B. Impact of Reserve Direction Forecast

Incorrect reserve direction forecasts require a change of the planned EV charging, which might result in higher pRNS (Percentage of Reserve Not Supplied) and total cost for the aggregator (calculated with the methodology described in [13]). In order to understand whether or not the forecasts from the GLM represent additional value and the impact of erroneous forecasts in the total cost and pRNS, the reserve direction forecasts obtained with the following approaches are compared in terms of optimization results:

- *GLM forecast (base case)*: forecast produced by the GLM model described in section III.A;
- *naive predictor*: produces a forecast equal to the last observation from the same hour;
- *random predictor*: in classification problems, it is typical to compare the model's performance with a random predictor (e.g., flip of a coin), and if the performance of both models is comparable, then it is concluded that the advanced model is not valuable [24]. In this case, the random predictor consists in sampling from a uniform distribution between 0 and 1; if the sample value is greater than 0.5, then τt-=1, if not, τt+=1;
- *all upward*: the reserve direction is always upward and the aggregator offers upward reserve bids when possible;
- *all downward*: the reserve direction is always downward and the aggregator offers downward reserve bids when possible.

The forecast accuracy results of the these four algorithms can be found in the appendix sections.

Table I presents the average values of pRNS and cost increase (using the GLM forecast as reference), obtained for fleet A and for the four different forecasts and obtained with day-ahead reserve bidding and operational management algorithm. The results for fleet B are presented in Table II.

The pRNS results for both upward and downward reserves do not differ significantly with the reserve direction forecast, which indicates the optimization models' robustness. However, the results differ in terms of total cost reduction. All four different forecasts present cost increase, compared to the results with GLM forecasts, in almost all the test samples. Only the *naive* predictor in fleet A and the *all downward* forecast in both fleets present a negative cost increase (which means cost reduction) in some test samples, but on average, all the forecasts present a cost increase; in some test samples, the cost increase is greater than 60%. The *naive* predictor is the one that leads to the lowest cost increase.

TABLE I
pRNS OF THE UPWARD AND DOWNWARD BALANCING RESERVE AND TOTAL COST INCREASE WITH DIFFERENT FORECASTS FOR THE RESERVE DIRECTION AND FLEET A

Method	$pRNS^{up}$	$pRNS^{down}$	Cost Increase
GLM forecast	4.95%	2.41%	Ref.
Naive pred.	3.39%	2.88%	7.71% [-5.03%,26.88%]
Random pred.	3.17%	2.67%	37.70% [5.07%,106.07%]
All Upward	4.48%	n.a.	29.95% [9.65%,65.35%]
All Downward	n.a.	2.33%	39.28% [-7.18%,118%]

TABLE II
pRNS OF THE UPWARD AND DOWNWARD BALANCING RESERVE AND TOTAL COST INCREASE WITH DIFFERENT FORECASTS FOR THE RESERVE DIRECTION AND FLEET B

Method	$pRNS^{up}$	$pRNS^{down}$	Cost Increase
GLM forecast	8.67%	3.74%	Ref.
Naive pred.	7.39%	4.41%	8.01% [1.65%,16.76%]
Random pred.	8.13%	4.55%	33.35% [11.95%,73.60%]
All Upward	7.58%	n.a.	35.21% [14.49%,71.11%]
All Downward	n.a.	3.82%	20.28% [-7.13%,59.62%]

In fleet A, the cost increase from the *random* predictor is higher than the *all upward* forecast, meaning that, in this case, a poor forecast in both directions leads to a higher cost compared to offering reserve only in one direction. The same is valid for fleet B, where the cost increase of the *all downward* forecast is lower than the one obtained by the *random* predictor.

An interesting observation is that the difference in the total cost between the different forecasts does not come from a lower income with upward reserve provision but from higher energy imbalance costs. Because of a low accuracy in forecasting the reserve direction, models, such as the *random* predictor, have a higher energy imbalances cost related to changes in the planned EV charging that must be performed when the realized reserve direction is not the same as the forecasted value.

For example, if the downward reserve is not dispatched in one interval, the aggregator will need to consume this electrical energy in that interval anyway or in the subsequent intervals which creates an energy imbalance.

The same is valid for upward reserve, if it is not dispatched in one hour, the aggregator has a surplus of electrical energy (compared to what was planned) and needs to reduce its consumption in this interval or in the next intervals, which also results in an energy imbalance. This leads to an increase of the aggregator's imbalance costs.

The analysis of the total cost's components for one test sample (i.e., 9 months of training dataset and 3 months of evaluation dataset) of fleet A is presented in Table III.

TABLE III
TOTAL COST'S COMPONENTS FOR ONE TEST SAMPLE WITH DIFFERENT FORECASTS FOR THE RESERVE DIRECTION

Total cost's components [k€]	GLM	Naive pred.	Random pred.	All Upward	All Downward
(+) Cons. Elect. Energy	14.42	17.14	17.72	21.15	8.16
(+) Down. Res. Cost	1.18	1.31	1.65	0.00	2.25
(-) Up. Res. Income	12.00	15.48	17.09	17.72	0.00
(+) Imb. Cost	3.35	6.07	11.11	4.99	7.30
(+) Res. Shortage Cost	1.32	1.16	1.12	2.13	0.36
Total Cost	**8.29**	**10.20**	**14.52**	**10.55**	**18.08**

The *random* and *all upward* forecasts have a higher cost of consumed electrical energy, but also offer more upward reserve. Therefore, in these two cases, the income from the dispatched upward reserve is higher. Nevertheless, this high income does not result in a lower cost as in the GLM, since the imbalance costs are higher, and as shown in Table IV, the ratio between dispatched and offered upward reserve is lower in these two cases. This occurs because of the lower accuracy of the *random* and *all upward* forecasts (see appendix section), which leads to an incorrect placement of upward and downward reserve bids in each time interval resulting in lower dispatched upward reserve and higher imbalance costs. Note that the aggregator must satisfy the driver's requirements even if reserve is not dispatched.

TABLE IV
TOTAL DISPATCHED AND OFFERED BALANCING RESERVE.

	GLM	Naive pred.	Random pred.	All Upward	All Downward
Up. Res. [MW]	388	540	627	709	n.a.
Disp. Up. Res. [MWh]	248	320	352	371	n.a.
Ratio of Up. Res.	64.0%	59.25%	56.2%	52.4%	n.a.
Down. Res. [MW]	317	399	552	n.a.	676
Disp. Down. Res. [MWh]	196	255	268	n.a.	345
Ratio of Down. Res.	61.9%	63.9%	48.5%	n.a.	51.08%

The *naive* predictor is characterized by a higher imbalance cost compared to the GLM forecast, as well as a higher cost with consumed electrical energy (but more upward reserve power is offered). In terms of consumed electrical energy, the higher value of 17.14 k€ (compared to 14.42 k€ of the GLM) is mitigated by a higher income from dispatched upward reserve (17.14-15.48=1.66 k€); note that, for the GLM forecast, this value is rather similar (i.e., 14.42-12.00=2.42 k€). The main difference is on the imbalance costs, mainly because in the upward reserve case the *naive* predictor has a lower percentage of dispatched reserve power compared to the GLM forecast, which ultimately results in higher energy imbalances.

The same is valid for the downward reserve. For instance, the *all downward* forecast leads to a higher total of downward reserve bids, but only 51.08% of this power is actually dispatched, which results in a high imbalance cost and also in a high cost with dispatched downward reserve.

As concluding remarks, these results demonstrate that it is possible to produce forecasts for the reserve direction variable that represent additional value to the optimization problem, otherwise the cost increase values of the four forecasts would be close to zero or even negative compared to the GLM forecast. Furthermore, it should be underlined that both fleets use the same price and reserve direction forecasts, and the cost reduction results were different. This suggests that the value of the reserve direction forecast is not marginal and differs with the EV fleet characteristics and with the forecasted/realized market prices.

V. Conclusions

In this paper, a general framework for the participation of EV aggregator in the electricity market sessions is described. The day-ahead optimization model and operational management algorithms inserted in this framework for the supporting the participation in the balancing reserve market are described.

The impact of different reserve direction forecasts (i.e., from different models) was assessed in this paper, considering the quality of the reserve provision (measured by the percentage of reserve not supplied - RNS) and total costs. The robustness tests conducted over the algorithms showed that reserve direction forecast errors do not have a high influence in the pRNS values, but their influence in the total cost is significant. A poor forecast can result in a lower percentage of dispatched reserve power and in higher energy imbalance costs.

Finally, although the topic of this paper was EV, the proposed algorithms can also be adapted for other types of flexible loads, such as thermoelectric loads.

Appendix

Table V presents the average accuracy [24] of four basic (or heuristic) binary forecasting models in the 30 test samples.

TABLE V
Accuracy of four different basic (or heuristic) binary forecast models.

	GLM	Naive pred.	Random pred.	All Upward	All Downward
Up. Accuracy [%]	59.9%	59.3%	49.9%	53.7%	n.a.
Down. Accuracy [%]	63.8%	59.6%	49.9%	n.a.	58.9%

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