Optimization Models for EV Aggregator Participation in a Manual Reserve Market

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Abstract—**The charging flexibility of Electric vehicles (EV) when aggregated by a market agent creates an opportunity for selling manual reserve in the electricity market. This paper describes a new optimization algorithm for optimizing manual reserve bids. Furthermore, two operational management algorithms covering alternative gate closures (i.e., day-ahead and hour-ahead) are also described. These operational algorithms coordinate EV charging for mitigating forecast errors. A case-study with data from the Iberian electricity market and synthetic EV time series is used for evaluating the algorithms.**

Index Terms—**Electric vehicles, aggregator, optimization, electricity market, forecast errors, reserve.**

I. Introduction

THE full participation of demand-side resources in the electricity market is presently a reality in several electricity markets [1]. The goal is to have demand-side treated equally with the supply-side and providing similar services (e.g., reserve) without compromising power system reliability.

The electric vehicle (EV) due to its charging flexibility is a good candidate for supplying ancillary services [2]. The existing market rules do not allow the individual participation of small loads, thus, EV are aggregated by an agent that serves as an intermediary between vehicle drivers, the electricity market, system operator (SO) of the transmission and distribution grid. The concept of an EV aggregator using bidirectional communications for direct control over the EV charging process is discussed in [3][4].

The present paper explores a solution where the EV aggregator controls directly the charging of EV plugged-in to slow charging points and offers manual reserve in the electricity market.

Manual reserve (which can also be called balancing reserve) is a general term adopted in this paper, for avoiding wrong interpretations because of different nomenclatures and reserve categories across countries. It consists in active power manually requested by the SO for maintaining the balance between load and generation. This reserve can be supplied by synchronized and non-synchronized units with a small response time, generally less than 10/15 min for full delivery. It contrasts with regulation (or secondary) reserve that is mobilized via AGC (automatic generation control) for restoring frequency and interchange levels to their nominal values, with response time around 30 seconds.

In general, the manual reserve when mobilized, supplies the full power during a long period (e.g., one hour). Conversely, the regulation reserve is only used during small periods of time (e.g., 5 min). Another difference is that regulation reserve usually handles minute-to-minute random variations inside the operation period, while the manual reserve handles inter-hour variations (i.e., slow events) such as forecast errors (i.e., which are more predictable) [5][6], and can be used to solve network congestions or supplement regulation reserve.

The vehicle-to-grid (V2G, bidirectional power injection) mode was not considered. The reserve is supplied by establishing a preferred operating point (POP) from which the EV provides upward and downward reserve [7]. The POP is similar to the operating point of conventional generators for spinning reserve. A conventional generator can increase or decrease the generation around the POP, limited by the maximum and minimum generation levels. Conversely, the POP of an EV is its consumption level that can be increased (downward reserve) or decreased (upward reserve) limited by zero and by the maximum charging power. For instance, an EV charging at 2kW means that it could provide 2 kW of upward reserve and 1 kW of downward reserve if the maximum charging power is 3 kW.

According to [7], this approach entails several advantages over V2G: it does not require additional capital costs with V2G equipment; reduces the costs with battery degradation; lower losses in the charger and battery. Note that in the long-term, V2G could be more profitable than this approach (see the results in [8]). However, note that the provision of reserve services with V2G is highly dependent from the market prices (energy and capacity payments) and battery degradation costs [9][10].

The POP approach means that the EV charger should be able to operate at values different from zero and maximum charge power. Presently, with charging mode 3 (defined by IEC 61851-1 standard), it is possible to have a variable charge power [11]. Still, since manual reserve handles "slower" events (e.g., hourly deviation from schedule) compared to

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regulation reserve, the variation in the charging power is expected to be slower during the mobilization period. In contrast, regulation reserve will take more use of a variable charging power to handle random variations in shorter time-scales. As an alternative, the aggregator can combine on/off charging signals within the fleet in order to provide ramp up/down response.

Research work related with the participation of EV in ancillary services markets has been conducted in the recent years. Sortomme and El-Sharkawi [12] propose three heuristic strategies and equivalent optimal analogues for defining the POP and regulation (or secondary) reserve bids of an EV aggregator. Rotering and Ilic [13] describe two dynamic programming optimization algorithms for an optimal controller installed in an EV. One algorithm minimizes the cost by optimizing the charging rates and periods, and the other maximizes the profit from selling regulation reserve. Han *et al.* [14] describe a dynamic programming model for exploring the possibility of an EV aggregator offering regulation reserve.

A critical limitation of the previously mentioned algorithms is the assumption of perfect knowledge for all the variables involved in the problem. Sundstrom and Binding [15] although using perfect forecasts in their optimization algorithm mentioned the importance of having a trip-forecasting module. Other authors addressed this issue. For example, Pantos [16] describes a stochastic linear optimization algorithm considering several uncertainties related with the participation in the day-ahead energy and regulation reserve market. Han *et al.* [17] propose a probabilistic model for modeling the achievable power capacity of an EV aggregator when providing regulation reserve.

Bessa *et al.* [18] used a naïve forecasting approach for optimizing the bids for the day-ahead energy and secondary reserve market. Bessa and Matos [19] compared two alternative approaches (divided and global) for optimizing the bids of an EV aggregator in the day-ahead energy market (without reserve), considering statistical forecasting algorithms for all the variables. Compared to the two preceding papers, the present paper describes new optimization algorithms for a different reserve market (i.e., manual reserve that handles imbalances due to forecast errors).

Compared to other authors, the present paper makes several contributions. The optimization algorithms presented here, in contrast to the models from [16]-[18], characterize the information by individual EV, which as shown in [19] is a more accurate representation. The influence of forecast errors related with the driving behavior, identified as a future research topic in [15], is addressed. Furthermore, the described operational management algorithms coordinate the individual charging of plugged-in EV for reducing deviation costs and ensuring a reliable delivery of manual reserve. This was also identified as a future research topic in [16].

The rest of the paper is organized as follows: section II describes the electricity market and the aggregator model; section III presents the day-ahead optimization algorithm; section IV describes the operational management algorithms; section V describes the market settlement phase; the case-study results are presented in section VI; section VII is the conclusions.

II. Problem Description

A. Market Framework

The EV aggregator participates in the day-ahead electrical energy market with bids for purchasing energy, which is paid at a single marginal price. The gate closure[1] is the 10th hour.

Furthermore, a market for manual reserve is also considered. For this reserve, several electricity markets have a session where loads offer bids to increase (downward reserve) or decrease (upward reserve) their power consumption and the SO is the buyer. Some examples are the tertiary reserve market in the Iberian market (MIBEL), the balancing market in Spain [20], the regulation power market in the NordPool [21], the load-following reserve markets in U.S.A. [22] and the balancing reserve market in Hydro-Québec [5].

This paper covers two alternative gate closures: (a) the reserve market opens right after the energy market closure, and the submitted bids for the next day are binding[2]; (b) the submission of bids starts on the day prior to the operating day, can continue during the operating day and closes one hour before the operating hour. This second gate closure is more common. For example, in MIBEL and Nordpool the reserve bids can be submitted, adjusted, or removed 45 minutes before the operation hour; in U.S., the real-time reserve markets close one hour or 75 minutes before the operation hour [22].

In the hour-ahead bidding [situation (b)], the SO during the operation hour selects reserve bids following a price merit order and mobilizes the units in real-time. A marginal price for the upward and downward reserve results from this real-time mechanism. The reserve bids consists in a quantity (in MW) and a price for delivered energy (in €/MWh)[3].

B. Participation in the Electricity Market

The aggregator participates in the energy market for purchasing energy and offers manual reserve capacity in upward or downward directions.

With an appropriate bidding strategy, the aggregator can decrease the wholesale cost. With this cost reduction, the aggregator either decreases the retailing tariffs for attracting new clients or maintains the tariffs for increasing the retailing profit. The value of the retailing tariffs, which is a commercial issue, is not addressed in this paper. However, the algorithms here described would provide the economic basis to the establishment of these tariffs.

Fig. 1 depicts a diagram with the sequence of tasks for the participation in the electricity market. The time intervals are based on the Iberian market [20]. Before the 10th hour of day

[1] Time instant when participants cannot change their bids.

[2] This gate closure is common for secondary (or regulation) reserve in Europe.

[3] Some markets also have a capacity price (in €/MW), but it is more common to find this in regulation reserve markets.

D, the aggregator forecasts the market prices and EV variables, optimizes the energy and reserve bids, and then submits bids in the (a) energy and reserve market or (b) energy market. The market settlement process takes place between the 11th and 14th hours of day D.

Afterwards, during the operation day, with an operational management algorithm the aggregator coordinates the EV charging for fulfilling the market commitments. If hour-ahead reserve bids are allowed, the operational algorithm also calculates, before the beginning of time interval t_0, the reserve bid for time interval t_0+1. The EV are dispatched for each time interval until departure, and the charging power for interval t_0 are transmitted and followed by each EV.

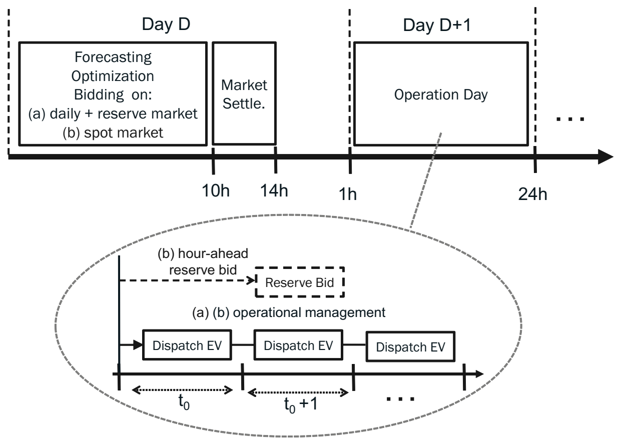

Fig. 1. Diagram with the sequence of tasks for participating in the electricity market.

III. Day-ahead Optimization

A. Description of Input Variables and Forecasting Methods

In this work, the aggregator controls directly the EV charging, and the approach of forecasting the load for each time interval cannot be followed because the aggregator is forecasting a variable that controls at the same time. Bessa and Matos [19] proposed an alternative approach, which consists in forecasting the two variables illustrated in Fig. 2: the EV charging requirement and availability.

The availability is the time-period where the EV is plugged-in for charging. In the example of Fig. 2, 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 SOC defined by the EV driver for the next trip, including the charger efficiency. In Fig. 2, 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. Metered values of these variables can be obtained from the advanced metering infrastructure installed in households. Historical data from these two variables is used for fitting forecasting models.

In this framework, it is assumed that when the EV driver parks for charging, it communicates the target SOC and expected departure time to the aggregator, and the initial SOC is metered and communicated to the aggregator. If the driver fails to communicate this information, a default profile is assumed (e.g., target SOC of 100%).

The availability period is modeled as a binary variable, indicating the time intervals where the EV is plugged-in and available for charging. This time series is forecasted with the generalized linear model (GLM) [23] of Eq. 1, where the response variable follows a binomial distribution.

$$prob(y_t = 1 \mid y_{t-l}) = 1 \Big/ \left(1 + \exp\left(-\begin{pmatrix} \phi_0 + \phi_1 \cdot y_{t-1} + \\ \cdots + \phi_l \cdot y_{t-l} \end{pmatrix}\right)\right) \quad (1)$$

$prob(y=1|y_{t-l})$ is the posterior probability that is a function of lagged variables (y_{t-l}) of the response variable y, ϕ_1 are the model's coefficients, and $1/(1+exp(-a))$ is the inverse of a *logit* link function.

After forecasting the availability period, the corresponding charging requirement is forecasted with non-parametric bootstrapping. The bootstrapping technique consists in resampling from the historical consumption of the same time interval, and the sum of the bootstrap samples over the availability period gives the charging requirement forecast.

A complete description of these two forecasting approaches can be found in [19].

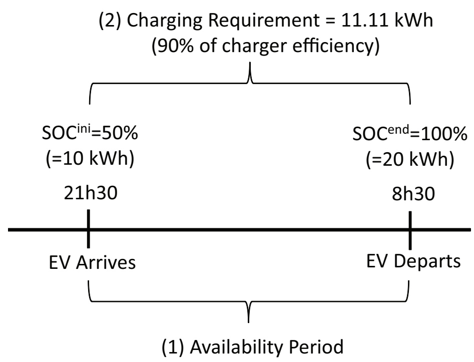

Fig. 2. Availability period and charging requirement of an EV.

The following market variables are also necessary to forecast: day-ahead energy price, reserve direction and price.

The day-ahead energy price is forecasted with the following additive linear model [23]:

$$p_t = p_{t-1} + \phi_1 \cdot p_{t-1} + \phi_2 \cdot p_{t-2} + \phi_3 \cdot p_{t-3} + f(\hat{w}p_t) + H_t + D_t \quad (2)$$

where p_{t-l} are lagged variables of the response variable, wp_t is the forecasted wind power penetration, H_t is a periodic function for the hour of the day and weekday, D_t a periodic function for the weekday, f is a smooth function estimated using cubic basis splines. The term p_{t-1} comes from differencing the time series (taking the difference p_t - p_{t-1}) for removing the nonstationarity.

Forecasting the reserve direction consists in anticipating if the power system will need upward or downward reserve in each time interval of the next hours and day. For modeling the reserve direction, two binary variables are used: τ_t^- for upward reserve and τ_t^+ for downward reserve. For instance, τ_t^- takes value "1" if upward reserve is used and "0" if not.

The two binary variables are forecasted with a GLM model with a binomial response variable. The following set of variables were used in a feature selection process from the R package "caret" [24]: lagged variables of the response variable, forecasted energy price, forecasted wind power penetration, periodic function for the hour of the day and weekday.

A different model is fitted for the upward and downward reserve direction. After the feature selection process, the model for day-ahead τ_t^- (upward reserve) forecast is as follows:

$$prob(\tau_t^- = 1|\cdot) = 1 \Bigg/ \left(1+\exp\left(-\left(\begin{array}{c}\phi_0+\phi_1\cdot\tau_{t-24}^-+\phi_2\cdot\tau_{t-48}^- \\ +\phi_3\cdot\tau_{t-96}^-+\phi_4\cdot\tau_{t-120}^-+\phi_5\cdot\tau_{t-168}^- \\ +\phi_6\cdot\hat{w}p_t+\phi_7\cdot\hat{p}_t+D_t+H_t\end{array}\right)\right)\right) \quad (3)$$

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:

$$prob(\tau_t^- = 1|\cdot) = 1 \Bigg/ \left(1+\exp\left(-\left(\begin{array}{c}\phi_0+\phi_1\cdot\tau_{t-1}^-+\phi_2\cdot\tau_{t-2}^- \\ +\phi_3\cdot\tau_{t-3}^-+\phi_4\cdot\tau_{t-24}^-+\phi_5\cdot\tau_{t-48}^- + \\ \phi_6\cdot\tau_{t-168}^-+\phi_7\cdot\hat{w}p_t+\phi_8\cdot\hat{p}_t+H_t\end{array}\right)\right)\right) \quad (4)$$

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

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

In this problem, the GLM compared to machine learning algorithms (neural networks, support vector machines and naïve Bayes) achieves the best performance [25].

The downward and upward reserve prices are irregular time series since it only occur in hours where the SO mobilizes the corresponding reserve direction. The Holt-Winters method with periodic seasonal terms [26], suitable for irregular time series, is used to forecast these two prices.

B. Optimization Problem

The decision variables are: energy purchased by the aggregator in the energy market for the j[th] vehicle and time interval t ($E_{t,j}$); downward reserve capacity ($P^{down}_{t,j}$); upward reserve capacity ($P^{up}_{t,j}$). The bid is the aggregation of the individual contribution from each EV for the same time interval t. Note that when hour-ahead reserve bids are allowed, the result from the optimization is only an initial plan that can be updated during the operating day.

The aggregator is assumed a price-taker, which means that the decisions made by the aggregator do not affect the market-clearing price.

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:

$$\min \sum_{t\in H}\left(\begin{array}{c}\hat{p}_t\cdot\sum_{j=1}^{M_t}\left(E_{t,j}\right)+\hat{p}_t^{down}\cdot\sum_{j=1}^{M_t}\left(P_{t,j}^{down}\cdot\Delta t\right) \\ -\hat{p}_t^{up}\cdot\sum_{j=1}^{M_t}\left(P_{t,j}^{up}\cdot\Delta t\right)\end{array}\right) \quad (5)$$

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.

Note that if time step Δt is lower than the market time step (typically one hour), the energy bid is the sum of each E_t contained in the market time step, and reserve power is the average value of P_t^{down} and P_t^{up} in the market time step.

The 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:

$$E_{t,j}/\Delta t + P_{t,j}^{down} \le P_j^{\max},\ \forall j\in\{1,\cdots,M_t\},\ \forall t\in H \quad (6)$$

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:

$$P_{t,j}^{up} \le \left(E_{t,j}/\Delta t\right)\cdot\hat{\tau}_t^-,\ \forall j\in\{1,\cdots,M_t\},\ \forall t\in H \quad (7)$$

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":

$$P_{t,j}^{down} \le P_t^{\max}\cdot\hat{\tau}_t^+,\ \forall j\in\{1,\cdots,M_t\},\ \forall t\in H \quad (8)$$

With the constraint of Eq. 9, the aggregator can only offer upward reserve in a specific interval if the EV is able to consume the corresponding quantity both in the same and subsequent time intervals. This increases the robustness of the bidding optimization since it forces the EV to be capable of consuming the quantity that is offered as upward reserve. Otherwise, considerable penalization (section V) could be incurred if upward reserve cannot be supplied. This constraint consists in postponing EV charging by offering upward reserve.

$$\sum_{k=t}^{k=t_{final}\in\hat{H}_j^{plug}}\left(P_{k,j}^{up}\cdot\Delta t\right)\le\sum_{k=t}^{k=t_{final}\in\hat{H}_j^{plug}}\left(E_{k,j}+P_{k,j}^{down}\cdot\Delta t\right)/2 \quad (9)$$
$$\forall j\in\{1,\cdots,M_t\},\ \forall t\in H$$

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

In Eq. 9, the total consumption reduction between t and t_{final} must be below or equal to half of the energy consumed in the same period. For example, if the aggregator in time interval $k=t$ offers $E_{k,j}$ and $P^{up}_{k,j}$ equal to 1.5 kW, it must consume additional 1.5 kW in any interval $k\geq t$ of the availability period.

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

$$\sum_{t \in \hat{H}_j^{plug}} \left(E_{t,j} + P_{t,j}^{down} \cdot \Delta t - P_{t,j}^{up} \cdot \Delta t\right) = \hat{R}_j, \forall j \in \{1, \cdots, M_t\} \quad (10)$$

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

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

$$\sum_{t \in \hat{H}_j^{plug}} \left(P_{t,j}^{up} \cdot \Delta t\right) \leq \hat{R}_j, \forall j \in \{1, \cdots, M_t\} \quad (11)$$

Not including Eq. 11 would lead to a risky bidding strategy (i.e., high penalization costs for reserve shortage) because the aggregator could offer a total upward reserve greater than the total energy that the EV fleet can consume (i.e., charging requirement).

IV. Operational Management Algorithms

This section presents two sequential optimization models that cover the two alternative gate closures.

A. Operational Management for Day-ahead Reserve Bids

The central idea of the operational algorithm consists in scheduling the EV charging independently of the realized τ^+ and τ^- values, and which are unknown at the beginning of each time interval.

The aggregator follows the strategy from the optimization model by minimizing the difference between the total charging and day-ahead plan (E_t, P_t^{down}, P_t^{up}). This guarantees 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:

$$\min \sum_{k=t_0}^{T} \left(\varphi\left(E_k + P_k^{down} \cdot \Delta t - P_k^{up} \cdot \Delta t - \sum_{j=1}^{M_t} \left(E_{k,j}^*\right)\right)\right) \quad (12)$$

where $E_{k,j}^*$ is the energy consumed by the jth 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

$$\varphi(u) = \begin{cases} u \cdot \theta_k^+, u \geq 0 \\ -u \cdot \theta_k^-, u < 0 \end{cases} \quad (13)$$

where θ_k^+ and θ_k^- are constants that penalize situations with positive and negative deviations correspondingly. For example, in time intervals with downward reserve bids, θ_k^+ must be higher than θ_k^-, because negative deviation ($u<0$) means that the offered downward reserve is fully supplied. The ideal is to have $u=0$, and in this case there is no penalization.

This convex function expressed in its epigraph form [27] becomes:

$$\min \sum_{k=t_0}^{T} (v_k) \quad (14)$$

$$\left(E_k + P_k^{down} \cdot \Delta t - P_k^{up} \cdot \Delta t - \sum_{j=1}^{M_t} \left(E_{k,j}^*\right)\right) \cdot \theta_k^+ \leq v_k, \forall k \in \{t_0, \cdots, T\} \quad (15)$$

$$-\left(E_k + P_k^{down} \cdot \Delta t - P_k^{up} \cdot \Delta t - \sum_{j=1}^{M_t} \left(E_{k,j}^*\right)\right) \cdot \theta_k^- \leq v_k, \forall k \in \{t_0, \cdots, T\} \quad (16)$$

where v_k are positive slack variables for each time interval k, which can take the following values: zero when there is no deviation, $u \cdot \theta_k^+$ when the deviation is positive and $u \cdot \theta_k^-$ when is negative. Thus, minimizing the sum of v_k in Eq. 14 is analogous to minimize deviations.

The consumed energy in each time interval must be below or equal to the maximum available power for charging:

$$E_{k,j}^* / \Delta t \leq P_k^{max}, \forall j \in \{1, \cdots, M_t\}, \forall k \in H_j^{plug} \quad (17)$$

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

$$\sum_{k \in H_j^{plug}} \left(E_{k,j}^*\right) = R_{t_0,j}, \forall j \in \{1, \cdots, M_t\}, \forall k \in H_j^{plug} \quad (18)$$

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. 18;
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). The values of θ_k^+ and θ_k^- are defined as follows: for the time intervals with $P_k^{down}.\Delta t>0$, θ_k^+ is made equal to a larger number (10^6) and θ_k^- to smaller number (10), and when $P_k^{up}.\Delta t>0$ is the opposite ($\theta_k^-=10^6$ and $\theta_k^+=10$); in time interval t_0, and since the dispatch will be actually followed by the EV and cannot be modified, the value of θ_{t0}^+ is made equal to an even higher number (10^9) if $P_{t0}^{down}.\Delta t> 0$ and θ_{t0}^- equal to 10^3, the same is valid for θ_{t0}^- when $P_{t0}^{up}.\Delta t>0$;
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); the charging requirement $R_{t0,j}$ is updated for the next period, $R_{t_0+1,j} = R_{t_0,j} - E_{t_0,j}^*$.
4. this process is repeated for the next time interval t_0+1 (go to step 1).

Note that in this algorithm, EV arriving for charging more than once during the day are handled as new ones.

If the driver decides to depart before the communicated time interval (and battery SOC might not be in the target level), the responsibility is attributed to the driver, and some penalization may be defined in the contract between aggregator and client. In this case, for safety reasons the driver can define an early departure time.

B. Operational Management for Hour-ahead Reserve Bids

When hour-ahead reserve bids are allowed, the operational management algorithm is used to update the initial plan. In this case, the day-ahead plan is not firmly followed, and the aggregator can update the reserve bids (increase or decrease) or present new bids. The optimization model is a modification of Eq. 14-18 and is described in the following paragraphs.

Without loss of generality, the time interval length Δt for this formulation is half-hour and the market bids are hourly. In the beginning of even intervals, $t_0 \in \{2.\mathbf{Z}\}$, the aggregator defines the final reserve bid for half-hour intervals t_0+2 and t_0+3; in odd intervals, $t_0 \in \{2.\mathbf{Z}+1\}$, the aggregator schedules the EV for charging.

The objective function is as follows:

$$\min \sum_{k=t_0}^{T} \left(\varphi\left(E_k^{DA} - \sum_{j=1}^{M_t}\left(E_{k,j}^*\right)\right)\right) \tag{19}$$

where E_t^{DA} is the initial plan (from the day-ahead optimization) and takes the following values:

- when $t_0 \in \{2.\mathbf{Z}+1\}$, for $k \in [t_0, t_0+2]$ E_k^{DA} is equal to $E_k + P_k^{down} \cdot \Delta t + \Delta_k^{down} - P_k^{up} \cdot \Delta t + \Delta_k^{up}$, and for $k \in [t_0+3, 48]$ is equal to $E_k + P_k^{down} \cdot \Delta t - P_k^{up} \cdot \Delta t$.
- when $t_0 \in \{2.\mathbf{Z}\}$, for $k \in [t_0, t_0+1]$ E_k^{DA} is equal to $E_k + P_k^{down} \cdot \Delta t + \Delta_k^{down} - P_k^{up} \cdot \Delta t + \Delta_k^{up}$, and for $k \in [t_0+2, 48]$ is equal to $E_k + P_k^{down} \cdot \Delta t - P_k^{up} \cdot \Delta t$;

The variables Δ_k^{up} and Δ_k^{down} are for adjusting the initial reserve bids and can take zero, negative and positive values.

The loss function φ is as follows:

- when $t_0 \in \{2.\mathbf{Z}+1\}$

$$\varphi(u) = \begin{cases} u \cdot \hat{\pi}_k^+, u \geq 0 \wedge k \in [t_0+3:48] \\ -u \cdot \hat{\pi}_k^-, u < 0 \wedge k \in [t_0+3:48] \\ u \cdot M, u > 0 \wedge k \in [t_0:t_0+2] \wedge \left(P_k^{down} + \Delta_k^{down}\right) > 0 \\ u \cdot \hat{\pi}_k^-, u < 0 \wedge k \in [t_0:t_0+2] \wedge \left(P_k^{down} + \Delta_k^{down}\right) > 0 \\ u \cdot M, u < 0 \wedge k \in [t_0:t_0+2] \wedge \left(P_k^{up} - \Delta_k^{up}\right) > 0 \\ u \cdot \hat{\pi}_k^+, u > 0 \wedge k \in [t_0:t_0+2] \wedge \left(P_k^{up} - \Delta_k^{up}\right) > 0 \end{cases} \tag{20}$$

where M is large number equal to 10^3, π_k^+ and π_k^+ are deviation prices forecasted with the Holt-Winters method [26];

- when $t_0 \in \{2.\mathbf{Z}\}$

$$\varphi(u) = \begin{cases} u \cdot \hat{\pi}_t^+, u \geq 0 \wedge k \in [t_0+4:48] \\ -u \cdot \hat{\pi}_t^-, u < 0 \wedge k \in [t_0+4:48] \\ u \cdot M, u > 0 \wedge k \in [t_0:t_0+1] \wedge \left(P_k^{down} + \Delta_k^{down}\right) > 0 \\ u \cdot \hat{\pi}_t^-, u < 0 \wedge k \in [t_0:t_0+1] \wedge \left(P_k^{down} + \Delta_k^{down}\right) > 0 \\ u \cdot M, u < 0 \wedge k \in [t_0:t_0+1] \wedge \left(P_k^{up} - \Delta_k^{up}\right) > 0 \\ u \cdot \hat{\pi}_t^+, u > 0 \wedge k \in [t_0:t_0+1] \wedge \left(P_k^{up} - \Delta_k^{up}\right) > 0 \\ -u \cdot M, u > 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{up} > 0 \wedge \hat{\tau}_k^- = 1 \\ u \cdot M, u < 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{up} > 0 \wedge \hat{\tau}_k^- = 1 \\ -u \cdot M, u < 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{down} > 0 \wedge \hat{\tau}_k^+ = 1 \\ u \cdot M, u > 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{down} > 0 \wedge \hat{\tau}_k^+ = 1 \end{cases} \tag{21}$$

It is also possible to replace a downward by an upward bid and vice-versa. This is done by making E_k^{DA} equal to E_k for $k \in [t_0; t_0+1]$ and including the following terms in Eq. 21:

$$\begin{cases} -u \cdot M, u > 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{up} = 0 \wedge \hat{\tau}_k^- = 1 \wedge \hat{\tau}_k^+ = 0 \\ u \cdot M, u < 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{up} = 0 \wedge \hat{\tau}_k^- = 1 \wedge \hat{\tau}_k^+ = 0 \\ -u \cdot M, u < 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{down} = 0 \wedge \hat{\tau}_k^+ = 1 \wedge \hat{\tau}_k^- = 0 \\ u \cdot M, u > 0 \wedge k \in [t_0+2:t_0+3] \wedge P_k^{down} = 0 \wedge \hat{\tau}_k^+ = 1 \wedge \hat{\tau}_k^- = 0 \end{cases} \tag{22}$$

The epigraph form as Eq. 15-17 also represents this convex function φ. The constraints of Eq. 17-18 are also considered. The algorithm is sequentially applied as follows:

1. in the beginning of time interval t_0, new information from the recently plugged EV is available. Forecasts for a time horizon between t_0 and T are produced for π_k^+ and π_k^+, and one hour-ahead forecasts are produced for τ^+ and τ^-;
2. solve the optimization problem with the objective function of Eq. 20-22. The result is the $E_{k,j}^*$ for each EV;
3. after solving the optimization problem, if $t_0 \in \{2.\mathbf{Z}\}$, the reserve bids for the next hour, $k \in [t_0+2:t_0+3]$, are updated by calculating Δ_k^{up} and Δ_k^{down} as follows:

$$\begin{gathered} if \left(\sum_k \left(E_k^*\right) < \sum_k \left(E_k^{DA}\right)\right) \wedge \left(\sum_k \left(E_k^{down}\right) > 0 \wedge \sum_k \left(E_k^{up}\right) = 0\right), \\ k \in [t_0+2:t_0+3] \Rightarrow \Delta_k^{down} = E_k^* - E_k^{DA} \Rightarrow \Delta_k^{down} < 0 \\ if \left(\sum_k \left(E_k^*\right) > \sum_k \left(E_k^{DA}\right)\right) \Rightarrow \Delta_k^{down} > 0 \end{gathered} \tag{23}$$

   a negative Δ_k^{down} decreases the downward reserve bid, while a positive value increases the bid;

$$\begin{gathered} if \left(\sum_k \left(E_k^*\right) < \sum_k \left(E_k^{DA}\right)\right) \wedge \left(\sum_k \left(E_k^{down}\right) = 0 \wedge \sum_k \left(E_k^{up}\right) > 0\right), \\ k \in [t_0+2:t_0+3] \Rightarrow \Delta_k^{up} = E_k^* - E_k^{DA} \Rightarrow \Delta_k^{up} < 0 \\ if \left(\sum_k \left(E_k^*\right) > \sum_k \left(E_k^{DA}\right)\right) \Rightarrow \Delta_k^{up} > 0 \end{gathered} \tag{24}$$

   a negative Δ_k^{up} increases the upward reserve bid, while a positive value decreases the bid;
4. set points corresponding to the charging levels for time interval t_0 are transmitted to the plugged-in EV;
5. this process is repeated for the next time interval t_0+1 (go to step 1).

V. Settlement in the Electricity Market

This section describes the market settlement of the energy and reserve bids.

The following variables are used to compute the total cost: E_t (total energy purchased in the energy market); E_t^{up} (total bid for upward reserve); E_t^{down} (total bid for downward reserve); E_t^* (total charging from the operational phase).The upward reserve consists in reducing the consumption using E_t as baseline.

As underlined by Bushnell *et al.* [28], an incorrect baseline might create an opportunity for windfall profits. In what regards EV, an incorrect baseline might create a chance for gambling with the E_t value. For example, if the aggregator forecasts a $prob(\tau_t^-=1|x)>0.9$ for a specific hour, one potential strategy would be to present an abnormally high E_t knowing that a consumption reduction (upward reserve) will be requested by the SO. If the reserve is used it represents a windfall profit, if not, the aggregator incurs in a financial penalization (but the probability is low).

Thus, in this paper we introduce a baseline that places a cap on the paid upward reserve. The baseline E_t^{base} is given by:

$$E_t^{base} = \min\left(E_t, \sum_{j=1}^{M_t}\left(\min(R_{t,j}, P_j^{\max} \cdot \Delta t)\right)\right) \tag{25}$$

In words, the baseline is the minimum between the bid in the energy market and the total energy that is possible to consume during the time interval (minimum between the maximum charging power and the residual charging requirement at time interval t). This baseline guarantees that the reference for the upward reserve is actually the energy that can be consumed in that hour and not an inflated bid.

With these quantities, it is possible to compute the values of the following variables:

- $if\ \tau_t^- = 1 \wedge E_t^{up} > 0 \Rightarrow E_t^{up*} = \max\left(0, E_t^{base} - E_t^*\right)$, where E_t^{up*} is the supplied upward reserve. It may occur that $E_t^{up*} > E_t^{up}$, in this case E_t^{up*} is made equal to E_t^{up} and the "additional reserve" is calculated as $\Delta E_t^{up*} = E_t^{up*} - E_t^{up}$;
- $if\ \tau_t^+ = 1 \wedge E_t^{down} > 0 \Rightarrow E_t^{down*} = \max\left(0, E_t^* - E_t^{base}\right)$, where E_t^{down*} is the supplied downward reserve. When $E_t^{down*} > E_t^{down}$ the "additional reserve" ΔE_t^{down*} is calculated;
- the consumed energy (after removing the mobilized reserve) is given by $E_t^{cons} = E_t^* + E_t^{down*} - E_t^{up*}$.

After computing these variables, the total cost is calculated as follows:

$$Total\ Cost = \sum_t \begin{pmatrix} E_t^{cons} \cdot p_t + E_t^{down*} \cdot p_t^{down} - E_t^{up*} \cdot p_t^{up} + \\ \Psi\left(E_t^{cons}, E_t\right) + \Phi\left(E_t^{up}, E_t^{up*}, E_t^{down}, E_t^{down*}\right) \end{pmatrix} \quad (26)$$

where Ψ are the costs associated to deviations from the purchased energy (i.e., deviation between E_t^{cons} and E_t), and Φ are the costs associated to reserve shortage (deviation between E_t^{down*} and E_t^{down*}, and between E_t^{up*} and E_t^{up*}).

The following rule is applied to the cost term Ψ: when the aggregator has surplus of energy it has to sell this extra at a regulation price ($p_t^{surplus}$) in general below the energy price; if the situation is shortage of energy, it has to pay a regulation price ($p_t^{shortage}$) in general above the energy price. Note that situations with "additional reserve" (ΔE_t^{up*} or ΔE_t^{down*}) help solving system deviation, thus the aggregator pays a regulation price equal to the spot price (which means no penalization). This is translated to the following:

$$\Psi = \begin{cases} \left(E_t - E_t^{cons}\right) \cdot \left(p_t - p_t^{surplus}\right), E_t > E_t^{cons} \wedge \Delta E_t^{up*} = 0 \\ 0, E_t > E_t^{cons} \wedge \Delta E_t^{up*} > 0 \\ \left(E_t^{cons} - E_t\right) \cdot \left(p_t^{shortage} - p_t\right), E_t < E_t^{cons} \wedge \Delta E_t^{down*} = 0 \\ 0, E_t < E_t^{cons} \wedge \Delta E_t^{down*} > 0 \end{cases} \quad (27)$$

where the price difference p_t-$p_t^{surplus}$ is the positive deviations price (π_t^+), and the difference $p_t^{shortage}$-p_t is the negative deviations price (π_t^-).

Some electricity markets establish rules for imposing penalizations to reserve shortage situations [29][30]. When the unit fails to deliver the contracted reserve it incurs in a penalty. The scheme proposed in this paper is inspired on the penalization rules of Portugal [29] and ISO New England [30]. The aggregator is paid for the reserve supplied (E_t^{down*} and E_t^{up*}) and a penalization term proportional to the deviation between E_t^{up} and E_t^{up*} (and between E_t^{down} and E_t^{down*}) is imposed. This gives the following:

$$\Phi = \begin{cases} \alpha \cdot p_t^{up} \cdot \left(E_t^{up} - E_t^{up*}\right), E_t^{up} > E_t^{up*} \\ \left(p_t - p_t^{down}\right) \cdot \left(E_t^{down} - E_t^{down*}\right), E_t^{down} > E_t^{down*} \end{cases} \quad (28)$$

In the Demand Response Reserves Pilot Program at ISO New England, α was equal to one [30], and this value is also used in the present paper. For upward reserve, this means that the aggregator must supply more than 50% of the contracted reserve. Otherwise, the penalty term is greater than the payment for partially supplying the reserve. For the downward reserve, the penalization term is different. It is equal to the difference between $p_t^{surplus}$ and p_t, otherwise hours with $p_t^{surplus}$ equal to zero (i.e., expensive reserve) would not be penalized. In [17] different penalization schemes are discussed.

VI. Case-Study Results

A. 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 [31]; day-ahead load and wind power forecasts (that give the forecasted wind power penetration) for the Iberian Peninsula [32].

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. These values were sampled from a truncated Gaussian probability density function where the parameters (mean, standard deviation, max and min values) are computed from the information made available by 42 different EV manufacturers. The charger efficiency was assumed to be 90%. Three different driver's behaviors, obtained from a survey made in the MERGE project [33], 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%). The simulation methodology assumes that, at every time interval, each EV can be in movement, parked in a residential area, parked in a commercial area or parked in an industrial area. When the state is "in movement", the energy consumption and the respective reduction in the battery SOC are computed. This case-study only considers EV parked in residential area (slow charging mode).

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 [34].

For a robust evaluation, a sampling process based on [35] 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.

Then, a sampling process without replacement is used to draw the first hour of the day, x, from the candidate set. This sample is used to split the three years of data in training (between x and x-9 months) and testing (between x and x+3 months) datasets. The process is repeated 30 times (i.e., generates 30 samples), and for each sample, the algorithms are evaluated in the test dataset. The feature selection task of the forecasting algorithms is conducted in each sample.

This sampling process is only used in the electricity market data. Because of a high calculation time, it is not possible to apply this process to the EV data. In order to test the optimization methodologies in different EV data, the synthetic time series for 3000 EV are divided in two groups with 1500 EV: fleet A and B.

The optimization problems are solved using IBM ILOG CPLEX10 [36].

It is assumed that the EV charging does not create problems in the distribution network. This might not be the case in some distribution networks, and in this case, the upward reserve bids can be used for solving congestion and voltage's limits violation cases.

B. *Illustrative Result*

Fig. 3 depicts an illustrative result for one day of the case-study. The results are depicted in hourly intervals since the Iberian market only accepts hourly bids.

Plot (a) shows the day-ahead reserve and energy bids (E_t, P_t^{up}, P_t^{down}), and corresponding prices. Note that there is only a upward reserve price and bid when $\hat{\tau}_t^- = 1$, and downward reserve price and bid when $\hat{\tau}_t^+ = 1$.

For example, in hour 1 the EV fleet is charging 2.89 MW and offer a consumption reduction of 2.81 MW. The hours with downward reserve are hours 11 and 12. In hours 4 and 5, $\hat{\tau}_t^-$ is equal to 1 but there is not upward bid because there is no flexibility for offering consumption reduction and meeting the charging requirement at the same time. The available flexibility was used in the previous hours (between 1 and 3), which also corresponds to the period with highest reserve price. For this day, the strategy of the aggregator was to postpone (i.e., offer upward reserve) the EV charging as much as possible. The predicted profit for this day was 68 €.

Plot (b) compares the upward reserve offered with the day-ahead and hour-ahead bidding. It is possible to see that the hour-ahead bidding adjusts the day-ahead (or initial) plan in several hours. In some hours, such as 4 and 5, the hour-ahead algorithm presents a new upward bid, while in others (1 and 19 for example) it decreases the upward reserve value.

The total cost computed with Eq. 26 (i.e., the realized one) was 185 € with day-ahead bids and 160 € with hour-ahead bids.

Plot (c) shows the percentage of upward reserve shortage obtained with the two bidding possibilities. As expected, the hour-ahead bid results in a much lower percentage and time intervals with reserve shortage. Nevertheless, it is important to note that even with hour-ahead bids, situations with reserve shortage can occur because during the hourly gap some EV without charging flexibility[4] might park for charging. For these time intervals, a possible solution is to establish in the contract between the driver and aggregator, a degree of flexibility for the SOC. The aggregator guarantees only 95% or 90% of SOC (instead of 100%) when there is a risk of reserve shortage. This solution is explored in the next section.

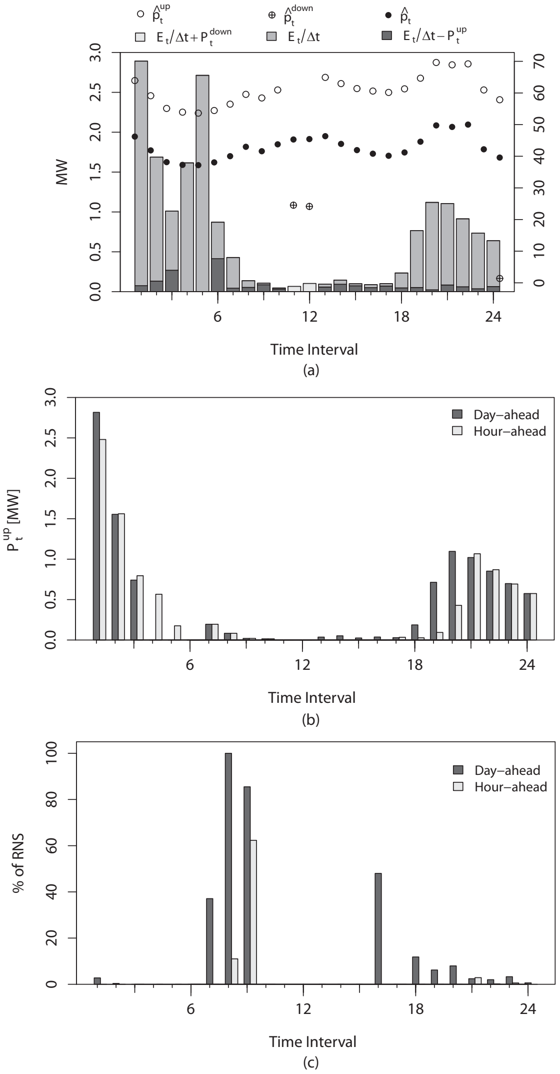

Fig. 3. Illustrative result with the following information: (a) energy and reserve bids, and market prices; (b) upward reserve bid from day-ahead and hour-ahead bidding; (b) percentage of upward reserve shortage.

The results for downward reserve shortage are not presented here. However, in contrast to upward reserve, the hour-ahead bid guarantees that all the offered downward reserve is supplied. This is an expected result because in the hourly gap between the bid and physical delivery, the only event that could occur is the arrival of additional EV for charging, and this does not represent a negative impact on the downward reserve reliability.

C. *Results*

This section presents results from the participation of the two EV fleets in the energy and reserve market sessions. The results related with the forecast quality are presented in the appendix.

Fig. 4 depicts the total cost reduction of day-ahead (section IV.A) and hour-ahead (section IV.B) reserve bidding, using as a reference the total cost from the participation in the energy

[4] EV that need to charge at maximum power in all the intervals of the availability period for meeting the defined target SOC.

market. The hour-ahead bid attains a higher cost reduction than the day-ahead bid in both EV fleets. Nevertheless, the difference is not significant: for the hour-ahead, the median of the cost reduction is 20.7% in fleet A and 18.9% in fleet B; for the day-ahead, it is 18.7% for fleet A and 15.5% for fleet B.

The main contribution to this difference comes from the penalization term for reserve shortage. The algorithm for the hour-ahead bid is mainly used for correcting the reserve bids and avoiding reserve shortage, and there is no sufficient flexibility left by the day-ahead optimization for turning a downward bid into upward (and vice-versa). For example, in the day-ahead optimization intervals with downward reserve bids normally have no energy purchased in the energy market. Then, for the hour-ahead bidding if the aggregator forecasts that the system will need upward reserve in that hour (instead of downward reserve) it is not possible to offer consumption reduction since the energy bid was zero. This might change if intraday trading is considered.

The range of cost reduction in the 30 samples is wide, e.g. in fleet A (hour-ahead) the maximum is 46.4% and the minimum is 7.6%. This difference is mainly explained by the reserve prices: the minimum cost reduction is achieved for a price difference between upward reserve and energy of 6.2 €/MWh and 9.5 €/MWh for the downward reserve; in the maximum reduction, the price differences are 15.9 €/MWh for upward reserve and 12.7 €/MWh for downward.

The quality of the reserve service is evaluated with two metrics: i) percentage of reserve not supplied (RNS), which is the ratio between the total reserve shortage and the total reserve offered in the market; ii) percentage of hours with RNS, which is the ratio between the number of hours with RNS and the number of hours with reserve bids in that direction.

Table I presents the two metrics (average values of the 30 samples) for the downward reserve. As mentioned previously, the hour-ahead bid guarantees that all the offered downward reserve is supplied. Conversely, the day-ahead bid presents RNS in some hours, which increments the total cost with penalizations due to reserve shortage. As shown in Fig. 4, the difference in the total cost is marginal, however from a SO standpoint the reserve offered with hour-ahead bids is more reliable. The number of hours with RNS is high in fleet B, but the shortage magnitude is low as shown by the low values of total RNS (below 5%). The worst performance of fleet B in these two metrics is explained by a higher forecast error compared to fleet A, as shown in the appendix.

Fig. 5 and Fig. 6 depict the results for the upward reserve, considering the three tolerable SOC levels.

The day-ahead bids lead to RNS in some hours, and a tolerable SOC of 95% and 90% provides a reduction in the RNS value. These values show that the reliability of the upward reserve is lower compared to the downward reserve. The hour-ahead bids also present hours with RNS (although a small average value), and this is solved when considering a tolerance for the SOC. The number of hours with RNS is also high, but it is reduced with hour-ahead bids and the SOC tolerance.

Fig. 7 depicts the cost reduction for three cases: hour-ahead reserve bids, perfect forecast for the EV variables; perfect forecast for all the variables. The reference for computing the cost reduction is the day-ahead reserve bidding.

The hour-ahead bidding only accomplishes a cost reduction (in median) of 2.4% in fleet A and 5.2% in fleet B. Furthermore, even when perfect forecasts are used for the EV variables, the cost reduction is of 9.5% for fleet A and 10.4% for fleet B. This shows that the uncertainty in the EV variables have a small impact in the cost, although the impact on the RNS is more significant (as depicted in Fig. 5-6). Finally, when perfect forecasts are used for the reserve direction and price, the impact on cost reduction is very substantial. Note that these variables require day-ahead forecasts, and even with innovative forecasting algorithms it is difficult to accomplish an improvement close to the one with perfect forecasts.

In this figure and in Fig. 4 there is a difference between the cost reduction results of fleets A and B. The drivers of fleet B are characterized by driving more km[5], and consequently their charging requirement is higher. For fleet B this means a lower flexibility for offering reserve.

The analysis of the results for "perfect EV info" (i.e., removing the influence of forecast errors) show that fleet A offers more upward reserve capacity. For instance, on average 61.3% of the energy bid is offered as upward reserve [i.e., $P_t^{up}/(E_t \cdot \Delta t)$] in fleet A, while in fleet B, only 53.2% is offered. This has a direct influence in the income from upward reserve: in fleet A it is 61.8% of the energy cost [i.e., $(P_t^{up*} \cdot p_t^{up})/(E_t^{cons} \cdot p_t)$] on average, while in fleet B it is 51.% on average. The same conclusions are derived for downward reserve. This shows that the economic results cannot be generalized to other fleets (and markets) since they depend from several variables, such as market data, driver's behavior and travelled distance.

TABLE I
DOWNWARD RNS AND PERCENTAGE OF HOURS WITH RNS FROM FLEETS A AND B [AVERAGE (MAXIMUM) VALUES OF 30 SAMPLES]

	RNS [%]		% of hours with RNS	
	Day-ahead	Hour-ahead	Day-ahead	Hour-ahead
Fleet A	2.4% (3.3%)	0.0%	3.6% (5.3%)	0.0%
Fleet B	3.7% (4.7%)	0.0%	10.2% (15.7%)	0.0%

VII. CONCLUSIONS

In this paper, a optimization model and two operational management algorithms are described for supporting the participation of an EV aggregator in the day-ahead energy and manual reserve market sessions. An appealing characteristic of the proposed algorithms is that sensitive data related driver's trips is not required. The aggregator only overrides the driver when the EV is plugged-in for charging, and the only required information is when the EV was plugged-in for charging, and how much energy was consumed for meeting the target SOC (defined by the driver).

The results showed that an aggregator participating in the manual reserve market could achieve a substantial reduction of its wholesale costs, even when a capacity price for available reserve is not considered. This cost reduction can increase the competiveness of the aggregator in attracting new clients or the profit from the retailing activity. EV drivers will benefit from cheap charging tariffs when supplying the manual reserve service.

The impact of forecast errors related with the EV behavior cannot be neglected when supplying reserve. The results showed that with day-ahead bidding there are hours with reserve shortage. This from the SO perspective is undesirable. The possibility of presenting hour-ahead reserve bids improves the reserve reliability and availability.

Topics for future research are: consideration of intraday (or real-time) market trading; improvement of the reserve price and direction forecasts; inclusion of probabilistic forecasts in the optimization models.

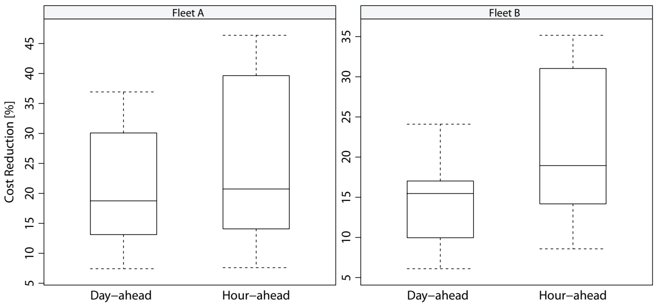

Fig. 4. Reduction in the total cost with the participation in the energy market as reference. The boxplot have five statistics: lowest datum of the lower quartile (lower quartile - 1.5*IQR), lower quartile (25%), median, upper quartile (75%), and the highest datum of the upper quartile (upper quartile + 1.5*IQR). IQR is the interquartile range (lower-upper quartile). The outliers are also identified on the boxplot.

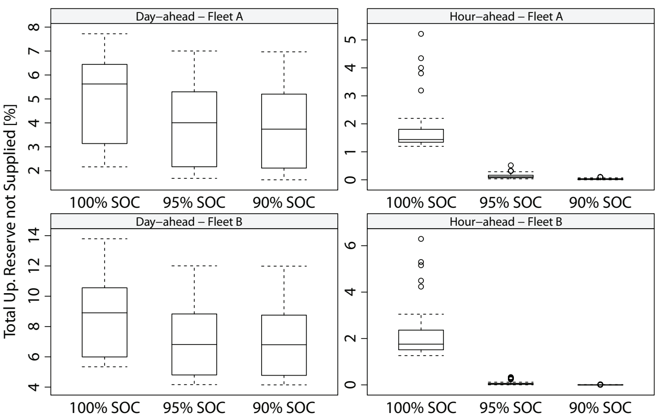

Fig. 5. Percentage of upward reserve not supplied by fleets A and B.

APPENDIX – FORECAST QUALITY

Table II presents the mean absolute percentage error (MAPE) of the availability and charging requirement forecasts for the whole EV fleet (i.e., sum of the individual forecasts for each EV). A detailed evaluation of the forecast accuracy can be found in [37] for these two fleets.

Table III presents the mean absolute error (MAE) and root mean square error (RMSE) of the forecasted energy and reserve prices.

Table IV depicts the accuracy (or hit-rate) of the reserve direction forecasts, and the area under an ROC curve (AUC) related with the forecasted posterior probability. The AUC is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance [38].

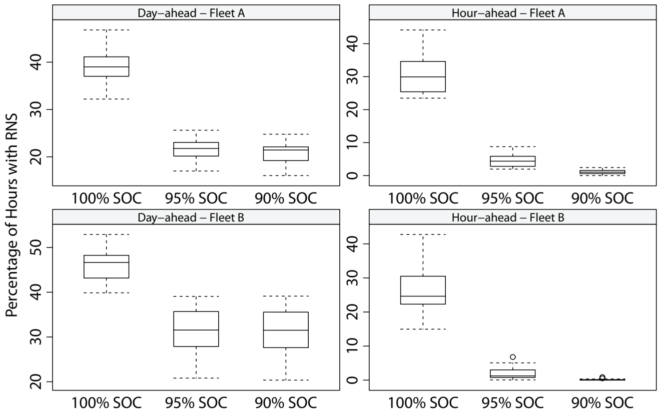

Fig. 6. Percentage of hours with up. reserve not supplied by fleets A and B.

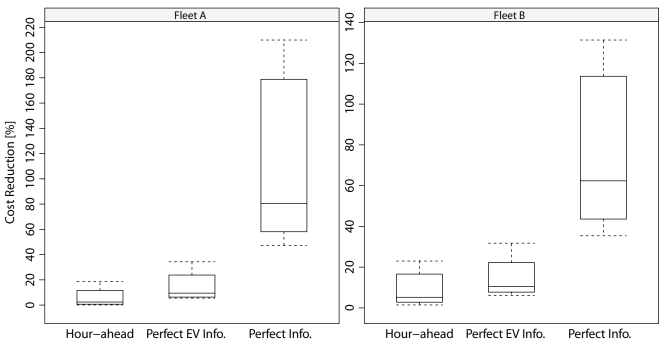

Fig. 7. Total cost reduction of three different sets of available information, and with the day-ahead reserve bidding (section IV.A) as reference.

TABLE II
MAPE OF THE FORECASTED AVAILABILITY AND CHARGING REQUIREMENT FOR THE WHOLE EV FLEET.

	Fleet A	Fleet B
Charging Requirement	29.93%	30.69%
Availability	6.99%	8.09%

TABLE III
MAE AND RMSE OF THE FORECASTED ENERGY AND RESERVE PRICES (AVERAGE VALUES OF 30 SAMPLES).

	Day-ahead		Hour-ahead	
	MAE	RMSE	MAE	RMSE
Elect. Energy Price [€/MWh]	5.1	6.8	-	-
Up. Res. Price [€/MWh]	10.6	16.4	8.3	13.5
Down. Res. Price [€/MWh]	10.8	14.1	8.4	11.2

[5] The battery size and consumption per km of both fleets have the same magnitude.

TABLE IV
ACCURACY AND AREA-UNDER-CURVE OF THE FORECASTED RESERVE DIRECTION (AVERAGE VALUES OF 30 SAMPLES).

	Day-ahead		Hour-ahead	
	Accuracy	AUC	Accuracy	AUC
Up. Res. Direction	59.9%	64.5	75.7%	79.7
Down. Res. Direction	63.8%	66.0	77.2%	80.3

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