Models for the EV Aggregation Agent Business

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***Abstract*—It is foreseeable that electricity retailers for electrical mobility will be market agents. These retailers are electric vehicle (EV) aggregation agents, which operate as a commercial middleman between electricity market and EV owners. Furthermore, with the foreseen evolution of the smart-grid concept, these agents will be able to control the EV charging rates and offer several ancillary services. This paper formulates an optimization problem for the EV aggregation agent participation in the day-ahead and secondary reserve market sessions. Forecasting issues are also discussed. The methodology was tested for two years (2009 and 2010) of the Iberian market, considering perfect and naïve forecast for all variables of the problem.**

***Index Terms*—Electric vehicles, electricity market, aggregator, forecasting, optimization, secondary reserve.**

I. Nomenclature

A. Sets and Indexes

t: index of time intervals (e.g. hour)

Δt: duration of each discrete interval

H^F: set of flexible time intervals, or flexible periods

H: complete set of time intervals (e.g. 24 hours)

N: number of flexible periods

k: charging level group, k=1,2,3

B. Parameters

$\hat{p}_t$: forecasted electricity market price of the day-ahead spot market for time interval *t*

$\hat{R}_t$: forecasted charging preferences for time interval t

$\hat{P}_t^{line}$: forecasted maximum available power for charging at time interval *t*

$\hat{\gamma}_t^{down}$: binary variable corresponding to the forecasted system deviation sign, 1 when the system needs downward reserve and 0 otherwise

$\hat{pf}_t^{down}$: forecasted/estimated participation factor on secondary downward reserve

$\hat{p}_t^{down}$: forecasted price for energy delivered as secondary downward reserve

$\hat{p}_t^{cap}$: forecasted price for available reserve capacity

$p_t^{surplus}$: price of positive (surplus) deviation between bid and consumption

$p_t^{shortage}$: price of negative (shortage) deviation between bid and consumption

C. Variables

E_t^F : quantity of electrical energy purchased in the day-ahead market for time interval *t*

P_t^{down} : downward reserve capacity bid

Δ_t^+ : increment in the electrical energy bid

Δ_t^- : decrement in the electrical energy bid

E_t^{cons} : electrical energy consumed for charging EV

II. Introduction

DIFFERENT business opportunities will emerge with the proliferation of electric vehicles (EV). For instance, in the position paper of Oliver Wyman [1], electrical energy storage, smart metering and charging points were identified as the most relevant business opportunities. Moreover, it is foreseen the emerging of non-utility companies, such as electricity retailers and charging infrastructure owners, that can either become partners or disruptors of utilities business models.

Andersen *et al.* [2] discuss the Better Place business model, where the core business consists in a charging grid with a smart metering infrastructure and partnership with vehicle, batteries and hardware manufacturers. In addition to recharging points, battery replacement stations are also considered. A different business model is being implemented in Portugal by the industrial and scientific network MOBI.E [3]. The MOBI.E charging network is accessible to all users, and each user has a card that provides access to the charging points. The users may liberally select a retailer for electrical mobility.

In both business models, distribution of electricity, retailing and charging station ownership (and/or operation) are separated. There is an entity responsible for providing charging infrastructures and coordinating all the information, power flows and available power capacity. A discussion of policy and regulation issues related with the structure of the future electrical mobility market can be found in [4] and [5].

The figure of an electricity retailer for electrical mobility is generally called in the literature as an EV aggregation agent (aggregator in abbreviated form). This aggregator concept was

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introduced in the literature by Kempton *et al.* [6] and further enhanced by Lopes *et al.* [7] and Guille and Gross [8].

The aggregator serves as a middleman between the EV owners and the electrical utilities or electricity market. The aggregator might control both dispersed vehicles and on-site vehicles (e.g. corporation's fleet). The drivers communicate their driving needs to the aggregator and the aggregator manages all the information received. With all the driving profiles the aggregator can buy electrical energy in the spot market and sell ancillary services (e.g. secondary reserve).

Bessa and Matos [9] present an overview about the economic potential of electric vehicles in the electricity market. Technical details and aggregator's business models are also addressed by the authors.

In what respects algorithms for EV aggregator management there are several works in the literature. Caramanis and Foster [10] developed a decision support method for an EV load aggregator aiming to achieve cost savings in battery charging and provision of regulation services required by a wind farm. Galus and Andersson [11] describe a demand management scheme for the aggregator based on mechanism design theory. The aggregator tries to recharge all EV plugged in its control area while maximizing their total utility in each time step. Wehinger *et al.* [12] applied an agent-based market simulation model to account for gambling and market power exercise in system with high EV and wind power generation deployment. Sundstrom and Binding [13] describe a method for planning the individual EV charging taking into account the distribution network constraints and the electrical energy costs.

The problem addressed in this paper consists in an EV aggregation agent that purchases electrical energy in the day-ahead spot market at wholesale price, and sells to its clients at retailing price. In order to minimize operational costs and increase profit margin, the aggregator controls the charging process and offers additional services, such as secondary reserve. The role of the aggregator and framework for participating in the electricity market are described in [14].

Optimization and forecasting methods are important for supporting the participation in the day-ahead spot and secondary reserve markets. Therefore, this paper presents, a method based on an optimization approach, to support the aggregator participation in the day-ahead and downward secondary reserve sessions.

Section III describes the EV aggregation agent framework. Section IV presents the optimization approach that will be used to support the aggregator activity. Section V describes a simulation methodology for the EV fleet movement. Section VI presents the case-study results for different strategies and discusses forecasting uncertainty issues. Finally, conclusions are presented in section VII.

III. Aggregator and Electricity Market Framework

A. The Aggregator Concept

The aggregator is a retailer of electricity for electrical mobility that buys electrical energy for EV charging and offers ancillary services. It could be, for instance, a battery manufacturer, a cell phone company or even an energy services company (ESCO).

The aggregator does not have any control over the individual EV driving behavior. Two different groups of clients are considered in this paper: Type A) a client who allows the aggregator to control the charging process during a period defined in their contract (normally when plugged-in at home during the night); Type B) a client who does not allow the aggregator to control the charging process, the aggregator being just an electricity provider (price taker client).

Type A clients will benefit from cheap charging prices, but the driver needs must still be respected and are the main priority.

B. Electricity Market Framework

This paper only addresses the day-ahead spot and secondary reserve market. The market rules adopted are based on the Iberian market. Nevertheless, these rules are similar to other markets, as described in [6] and [15].

The participation in intraday and hour-ahead markets is not discussed in this paper.

The day-ahead electrical energy market (spot market) has a uniform price and double-side auction. The market agents may present buy and sell hourly bids that cover all 24 hours of the next day. The aggregator is assumed to be a price-taker; hence, it only presents price independent bids for all hours. The market gate closure is 10h.

The secondary reserve session accepts separated downward and reserve day-ahead bids from agents capable of providing secondary reserve. As secondary reserve we considered load and generators that deliver reserve power in order to bring back the frequency and the interchange programs to their target values. Secondary control makes use of a centralized and continuous Automatic Generation Control (AGC), modifying the active power set points/adjustments of generation sets/controllable loads in the time-frame of 30 seconds (at the latest) up to typically 15 minutes (at the latest) after an incident [16].

The agents present capacity bids (quantity in MW and price in €/MW), and the amount of reserve contracted to each unit is settled at the market clearing price.

The price of delivered electrical energy, if reserve is mobilized, is defined by the real-time price that results from the tertiary reserve market.

C. Interaction with DSO, TSO and Electricity Market

The DSO sees the aggregation agent as an important actor in the distribution grid operation, while the TSO sees the aggregator as a possible source of ancillary services. It would be very demanding to have a DSO or TSO directly controlling and receiving information from thousands of EV. Therefore, the communications should be performed between the TSO/DSO and the aggregator and between the aggregator and the EV [17].

The interaction between the TSO, the DSO and the aggregator is performed as follows:

- at the beginning of each electrical energy market session (e.g. day-ahead, intraday) the aggregator buys electrical energy for charging its EV fleet;
- the DSO makes an ex-ante validation (and bid correction if necessary) of the aggregators' bids, e.g. determining the consumption reduction when there are congestions in the network. This is a new management procedure for DSO (more details can be found in [7]);
- the TSO defines the requirements of ancillary services for the next hours or days and buys, in the market, services from the market agents. The EV aggregator may present bids for selling ancillary services.

IV. Models for the Aggregator Short-term Management

This paper is about the short-term technical and economical management of an aggregation agent. Short-term management is for a time horizon ranging from hours to two days ahead with time steps of one hour.

A. *Modeling the EV Fleet*

1) EV charging and availability: The aggregator controls the EV charging of Type A clients in a period defined in the contract (named "flexible period"). The EV owner communicates to the aggregator (e.g. when arrives at home), the preferred battery state of charge (SOC) for the next day or hours. Since this information is only provided after the bidding in the day-ahead market, the aggregator needs to forecast or estimate the charging preferences for the next day.

For example, an EV owner that plugs-in the EV at 20h, with 60% of SOC, and wants to have 100% SOC (27.4 kWh) before 7 h, requires a charging schedule for 10.96 kWh. The aggregator can distribute this load (named flexible load) along the available charging period.

For participating in the day-ahead market it is not suitable to deal with each EV individually. Hence, the aggregator forecasts the charging preferences of the whole fleet.

Fig. 1 depicts an example of a charging preferences forecast of one thousand of EV at 10h of Day D for the period between 20h (of day D) and 10h (of day D+1).

From the depicted information, the aggregator knows that until 7h at least 0.8 MWh of charging preferences must be satisfied with electrical energy purchased in the market.

For the other time periods and also for type B clients the aggregator just needs to forecast the total load in each hour (named "inflexible load").

A standardization of the EV charging power into three different charging levels is foreseen [17]. Hence, the maximum available power and charging preferences are forecasted for each hour and for the three charging levels.

1) Controllable loads: The possibility of injecting electrical energy in the network, called vehicle-to-grid (V2G) mode, was not considered in this paper. However, the load flexibility of EV allows their participation as reserve resources, in both downward and upward directions.

For instance, if an EV is consuming 1 kW in one hour, and its wire power limit is 3 kW, this EV can provide upward reserve up to 1 kW (no consumption) and downward secondary reserve up to 2 kW (consumption of 3 kW) [18].

B. *Bidding Model for the Day-ahead Spot Market*

The first model (model M1) addresses the participation in the day-ahead spot market, where the objective is to purchase electrical energy for charging in hours with low prices.

The objective function (Eq. 1) consists in minimizing the cost of buying electrical energy E_t^F in the market for charging the EV fleet.

The constraints of the model are: the purchased electrical energy cannot be greater than the forecasted maximum available power in each hour (Eq. 2); the forecasted charging preferences (e.g. Fig. 1) must be satisfied in each hour t of the flexible period H_i^F (beginning at time step t_{ini}) (Eq. 3).

The mathematical formulation for each charging level k (k=1,2,3) is as follows:

$$\min \sum_{t\in H_i^F} \left(\hat{p}_t \cdot E_{t,k}^F\right) \tag{1}$$

$$E_{t,k}^F \big/ \Delta t \le \hat{P}_{t,k}^{line}, \quad \forall t \in H_i^F \tag{2}$$

$$\sum_{j=t_{ini}}^{t} E_{j,k}^F \ge \sum_{j=t_{ini}}^{t} \hat{R}_{j,k}, \quad \forall t \in H_i^F \tag{3}$$

$$H_i^F \in \{t_{ini}, \ldots, t_{final}\} \tag{4}$$

$$i \in \{1, \ldots, N\} \tag{5}$$

In parallel, the aggregator forecasts the inflexible load for each time interval, and makes a bid equal to the forecasted value.

Fig. 2 illustrates the day-ahead bids for 24 hours that contain a flexible period between 20h of day D and 10h of day D+1, and with the charging preferences of Fig. 1. As depicted, the bidding strategy from Eq. 1-5 places the charging in the hours with low prices, in contrast to a dumb charging strategy [7] where all the EV are inflexible loads.

C. *Bidding Model for Spot and Downward Reserve Sessions*

This second model (model M2) addresses the participation in the spot market and downward secondary reserve market.

The objective is to purchase electrical energy for charging E_t^F in hours with low prices, and get cheap charging in the form of downward reserve P_t^{down}.

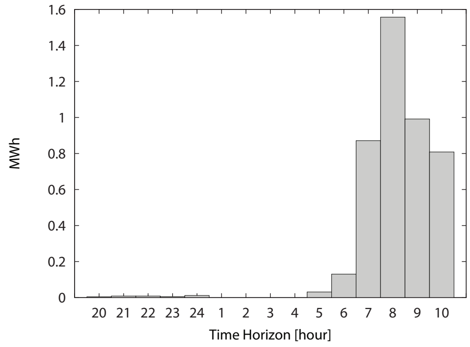

Fig. 1. Forecasted total charging preferences for the next flexible period.

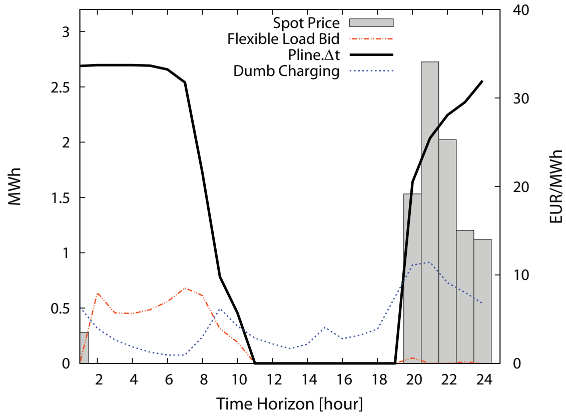

Fig. 2. Distribution of the flexible load bids for the spot market.

It is assumed that the aggregator does not have market power; consequently the reserve capacity price offered by the aggregator is lower enough for having the bid accepted.

The objective function of the problem (Eq. 6) consists in minimizing the charging cost, and is divided in three parts: i) cost of purchasing electrical energy for charging in the spot market; ii) cost of charging the EV with downward reserve, at a price lower than the spot price; iii) positive income for having reserve capacity available.

In order to limit the downward reserve offers to hours where it is expected a positive system deviation ($\hat{\gamma}_t^{down}$ = 1), the $\hat{\gamma}_t^{down}$ variable is included in parts ii) and iii) of Eq. 6.

The mathematical formulation is as follows:

$$\min \sum_{t \in H_i^F} \left(\begin{array}{c} \hat{p}_t \cdot E_{t,k}^F + \hat{p}_t^{down} \cdot P_{t,k}^{down} \cdot \hat{\gamma}_t^{down} \cdot \hat{pf}_t^{down} \cdot \Delta t \\ - \hat{p}_t^{cap} \cdot P_{t,k}^{down} \cdot \hat{\gamma}_t^{down} \end{array} \right) \quad (6)$$

$$E_{t,k}^F / \Delta t + P_{t,k}^{down} \leq \hat{P}_{t,k}^{line}, \quad \forall t \in H_i^F \quad (7)$$

$$\sum_{j=t_{ini}}^{t} \left(E_{j,k}^F + P_{j,k}^{down} \cdot \hat{\gamma}_t^{down} \cdot \hat{pf}_t^{down} \right) \geq \sum_{j=t_{ini}}^{t} \hat{R}_{j,k}, \quad \forall t \in H_i^F \quad (8)$$

$$H_i^F \in \{t_{ini}, \ldots, t_{final}\} \quad (9)$$

$$i \in \{1, \ldots, N\} \quad (10)$$

The participation factor $\hat{pf}_t$ is the ratio between the dispatched electrical energy reserve and the available reserve capacity.

Fig. 3 illustrates the electrical energy and downward reserve bids. In several hours, the binary variable of the forecasted system deviation is zero, and in these hours the reserve offer is zero. In the remaining periods the offer matches the maximum available power. The quantity of electrical energy purchased in the spot market is lower when compared to Fig. 2, and will lead to lower charging costs.

D. Forecasting Method

The simulations of section V will be for the day-ahead market with a gate close at 10h of day D, and the bids for hours between 1h and 24h of day D+1. Since the flexible period of level 1 goes upon day D+2, the short-term planning must be performed for a 34 hours time horizon (i.e. between 1h of day D+1 and 10h of day D+2).

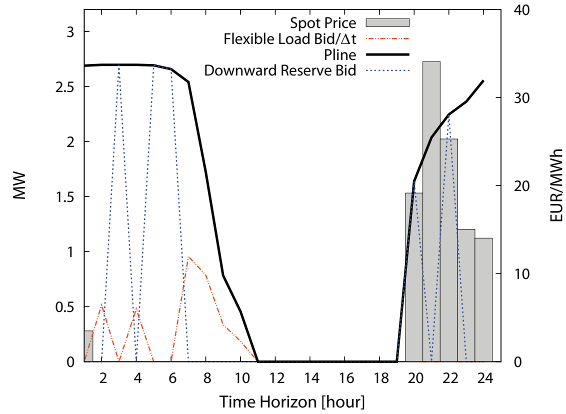

Fig. 3. Distribution of the flexible load and downward reserve bids (with pf=0.1).

Therefore, the energy purchased for hours 20h-24h must be used as input for the subsequent daily. Market prices and EV forecasts for lead times up to 48 hours are also required.

A naïve forecasting method was adopted in this paper. The model produces a forecast equal to the most recent realized value of each hour. The same method is applied for the EV data described in section B and market prices data.

Note that it is not an objective of this paper to address the issue of forecasting methods. Nevertheless, these forecasts can be produced using standard machine learning and data mining techniques [19]. A method for forecasting the system deviations sign can be found in [20].

V. Simulation of the EV Fleet Movement

In this section a procedure to simulate EV movement during one year is described. This procedure uses a discrete-state, discrete-time Markov chain, as explained in [21], and allows computing the periods during which EV are plugged-in and available to charge, the network node to which EV are plugged-in (only for parked EV), the EV power absorbed, the EV battery SOC evolution and the EV travelled distances.

The data obtained was used in the case study of section VI.

A. EV Fleet Characterization

EV was initially characterized in terms of battery capacity, charging power, energy consumption and battery SOC in the beginning of the simulation. These values were defined according to truncated Gaussian probability density functions, whose average, standard deviation, maximum and minimum allowed values are given in [21].

A given driver behavior was also assigned initially to each EV. The possible behaviors considered in this paper were obtained from a survey made within the framework of the MERGE project [17].

The results revealed that there are three major types of behaviors: owners that charge the EV at the end of the day (57%), owners that charge the EV only when it needs (23%) and owners that charge the EV whenever possible (20%). For the drivers who charge their EV only when it needs, it was assumed that the battery SOC that triggers the need for charging was 40%.

B. Markov Chain Description

It was assumed that, at every unit of time, one and only one event from a set of a finite number of events can occur to a given EV. Four events were considered: E_M, E_R, E_C and E_I. When the event $E_k(k=M,R,C,I)$ occurs, the EV passes into the state E_k. These events correspond to EV passing to the states "*in movement*", "*parked in a residential area*", "*parked in a commercial area*" and "*parked in an industrial area*".

When the event E_k occurs at the moment t, it is represented by E^t_k.E^0_k denotes that the initial state of the EV k was E_k. As the objective was to simulate EV movement along 365 days plus their initial state, 8760 time steps of 1 hour were considered, so $t \in [0{,}8760]$. Initially, one trial was performed to define every EV state when $t=0$. In this trial, an EV may be in the state E_k with probability $P(E_k)$.

Let's consider that after the trial t-1 a given EV is in the state $E_j(j=M,R,C,I)$. The probability that at the moment t, for $t \in [0{,}8760]$, the EV passes from the state E_j into the state E_k is denoted by $p^t_{j\to k}$:

$$p^t_{j\to k} = P\left(E^t_k \mid E^{t-1}_j\right) \tag{11}$$

This sequence of trials forms a Markov chain, given that for any j and k and for any $t \in [0{,}8760]$, the equalities

$$p^t_{j\to k} = P\left(E^t_k \mid E^{t-1}_j\right) = P\left(E^t_k \mid E^{t-1}_j \cdot E^{t-2}_j \cdot \ldots \cdot E^1_j \cdot E^0_j\right) \tag{12}$$

are arbitrarily satisfied for $E^{t-2}_j,\ldots,E^1_j,E^0_j$ and given that the state transition probabilities are conditioned only by the EV state in the time step t-1.

This Markov Chain is periodically stationary, or cyclostationary [22], as the transition probabilities are periodically repeated. The period of this cycle is one week and will be represented by τ. As time steps of 1 hour are being considered, $\tau=7x24=168$ time steps. To fulfill one complete year (365 days), τ will have to be repeated ≈ 52.14 times (52 weekly cycles plus one day).

One transition matrix with dimensions $4x4$ can be created with the transition probabilities $p^t_{j\to k} = p^{t+\tau}_{j\to k}$ for each moment t, where $t \in [0{,}8760]$. This matrix is denoted by M_t and, given the cyclostationary properties of this Markov chain, it will be periodically repeated every τ time steps.

All the elements $p_{j\to k}$ of the matrix, being probabilities, are non-negative. Supposing that an EV is in the state E_j, the event where, as a result of one trial, the EV remains in the state E_j or passes to any of the states E_k, where $j\neq k$, is the sure event. Since the events E_k are mutually exclusive, for $k=M,R,C,I$, the following equation holds:

$$p\left[\sum_k E^t_k \mid E^{t-1}_j\right] = \sum_k p^t_{j\to k} = 1 \tag{13}$$

Thus, the sum of the terms in each row of the matrix M_t equals one. An overview of the Markov chain developed for this study is presented in Fig. 4.

C. Initial State and State Transitions Probabilities

As referred, the Markov chain developed is cyclostationary and the period of one complete cycle, τ, is one week. This cycle is, in fact, a composition of two sub-cycles with the duration of one day: one for the week days (repeated five times in a row) and other for the weekend days (repeated twice consecutively). Therefore, to have the Markov chain completely characterized, it is only needed to define the initial state probabilities, $P(E^t_k)$ for $t=0$, and the state transition probabilities, $p^t_{j\to k}=P(E^t_k|E^{t-1}_j)$ for $t \in [1{,}24]$, of these two sub-cycles and then repeat them to compose the weekly cycle.

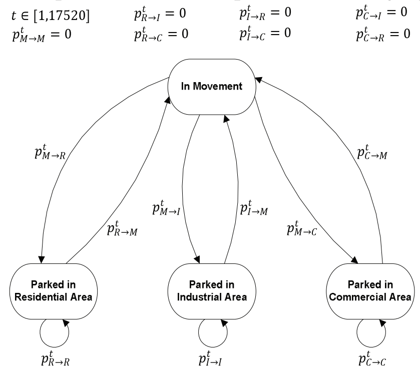

Fig. 4. Discrete-state and discrete-time Markov chain.

The required probabilities were determined in accordance with the common traffic patterns in a region in the north of Portugal [23].

D. Nodes Allocation Probabilities for Parked EV

After defining the EV states for each time instant, a network node location was attributed to parked EV, according to a probability distribution proportional to the load installed in each node. All the network loads were classified as industrial, commercial or residential loads and after, using equations (14) to (16), the probability of an EV be located at a specific node was calculated.

$$P^R(Node\,b) = \frac{Load^R_{Node\,b}}{\sum Load^R} \tag{14}$$

$$P^C(Node\,b) = \frac{Load^C_{Node\,b}}{\sum Load^C} \tag{15}$$

$$P^I(Node\,b) = \frac{Load^I_{Node\,b}}{\sum Load^I} \tag{16}$$

where:

- $P^{R/C/I}(Node\,b)$– probability of an EV be located in $Node\,b$, if "*parked in a residential / commercial / industrial area*";
- $Load^{R/C/I}_{Node\,k}$– residential / commercial / industrial load installed in $Node\,b$;
- $\sum Load^{R/C/I}$ – network total residential / commercial / industrial load.

E. EV Movement Simulation

The EV movement simulation along one year was made by defining the EV states for each time instant according to the Markov chain described in section V.B and to the probabilities referred in V.C. After, for each time instant, a node location was attributed to parked EV, as explained in section V.D.

At each time instant, the EV battery SOC was updated according to the energy spent travelling or according to the energy absorbed from the grid. It was assumed that EV "*parked in a residential area*" and "*parked in an industrial area*" charge at 3 kW (slow charging mode, level 2), EV "*parked in a commercial area*" charge at 12 kW (normal charging mode, level 2) and the charging power in fast charging stations is 40 kW (fast charging mode, level 3) [17]. When an EV is parked, the decision of whether or not plug it in for charging is made taking into consideration its driver behavior and its current SOC.

VI. CASE-STUDY

The participation of an EV aggregation agent with one thousand of battery EV is simulated for two years (2009 and 2010) of the Iberian electricity market. The market data can be found in [24]. The reserve price for delivered electrical energy and penalization prices are equal to the marginal price of the last unit providing tertiary reserve. A participation factor (pf) of 10% was adopted for all simulations.

A. Definition of Flexible and Inflexible Periods

A clustering analysis using the DIANA (DIvisive ANAlysis Clustering) algorithm of the package "cluster" from R [25] was used to determine EV availability profiles. The clustering was performed over the hourly average availability of each EV. The dendrogram of the hierarchical clustering structure is depicted in Fig. 4 for level 1 charging.

Fig. 5 depicts the cluster centroids (mean of the cluster members) that were obtained when the dendrogram tree is cut at height of 15. The profiles show that there are only two notably different availability profiles.

The same exercise was applied for level 2, and the centroids of Fig. 6 were obtained. In this case, there are big group of clients that do not charge in level 2, and another group which have the depicted profile.

From these profiles, the periods with the highest average number of plugged EV were classified as flexible periods: for level 1 the flexible period is between 20h (of day D) and 10h (of day D+1); for level 2 is between 15h and 20h.

The remaining hours of each level and level 3 are considered inflexible load.

Hence, in the contract established between EV owners and aggregator it is stated that the aggregator controls the charging rates during these two periods, but respecting always the clients charging preferences and departing hours.

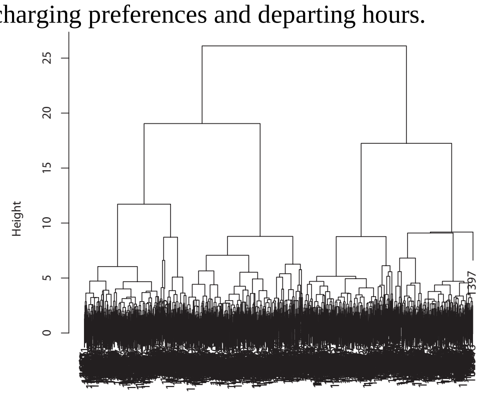

Fig. 4. Dendrogram of hierarchical clustering for level 1 charging.

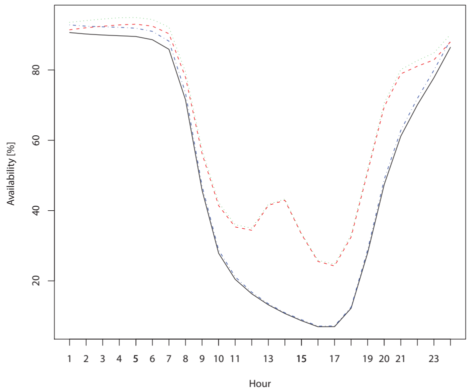

Fig. 5. Centroids of four cluster of EV plugged in level 1.

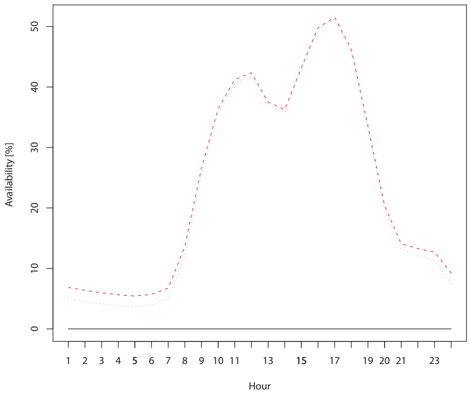

Fig. 6. Centroids of three cluster of EV plugged in level 2.

B. Calculation of Deviations Costs

Forecast errors will lead to penalizations by deviations between actual charging consumption and market bids.

In order to compute the deviations, it is necessary to simulate the operational charging process. Two approximations were adopted. First, it is assumed that EV owners communicate to the aggregator their charging preferences when they park the EV for a flexible period. This is a simplification because it may happen that some EV owners do not communicate charging preferences to the aggregator. In this case, the aggregator could use a default profile or a typical profile learned from historical data.

Second, it is assumed that the aggregator manages only the total deviations, and not individual deviations from each EV. This is a simplification because the aggregator can perform very-short term management (e.g. intraday and hour-ahead markets) and operational management (e.g. control the individual EV charging) to avoid penalization and minimize costs.

Following these two assumptions, an optimization problem is solved where the objective function is the minimization of the absolute deviations between the forecasted and actual charging behavior. In order to directly apply linear programming, the absolute value was replaced by the sum of the increments and decrements (decision variables) in the bid value. The formulation for the model M2 is as follows:

$$\min \sum_{t \in H_i^F} \left(\Delta_t^+ + \Delta_t^- \right) \tag{17}$$

$$\left(E^F_{t,k} + \Delta^+_t - \Delta^-_t\right) + P^{down}_{t,k} \cdot \hat{pf}^{\,down}_t \le \hat{P}^{line}_{t,k}, \quad \forall t \in H^F_i \qquad (18)$$

$$\sum_{j=t_{ini}}^{t} \left(\begin{matrix} E^F_{j,k} + P^{down}_{j,k} \cdot \hat{\gamma}^{down}_t \cdot \hat{pf}^{\,down}_t \\ + \Delta^+_t - \Delta^-_t \end{matrix} \right) \ge \sum_{j=t_{ini}}^{t} \hat{R}_{j,k}, \quad \forall t \in H^F_i \qquad (19)$$

where Δ^+ and Δ^- are greater than or equal to zero.

The formulation for model M1 is straightforward.

When the aggregator has surplus of electrical energy it will sell this extra energy at a price below the spot price. If the situation is shortage of electrical energy it will buy the necessary energy at a price above the spot price. This corresponds to the following penalization equation:

$$\begin{cases} p^{surplus}_t \cdot \left(E^F_{t,k} - E^{cons}_{t,k}\right), E^F_{t,k} > E^{cons}_{t,k} \\ p^{shortage}_t \cdot \left(E^F_{t,k} - E^{cons}_{t,k}\right), E^F_{t,k} < E^{cons}_{t,k} \end{cases} \qquad (20)$$

where $p^{surplus}$ is lower than the spot price, $p^{shortage}$ is greater than the spot price, and E^{cons} is given by $E^F + \Delta^+ + \Delta^-$.

C. Results

This section presents the cost obtained by the aggregator when participating in the day-ahead spot market and downward reserve market for the two years of the Iberian market.

As a reference, Table I presents the total cost obtained by an aggregation agent that has in its fleet only dumb charging clients (or inflexible loads).

With dumb charging clients, the aggregator forecasts the electrical energy consumption in each hour and purchased in the market a quantity equal to the forecasted values.

A naive forecast model leads only to a cost increase of around 6% for 2010, and 3% for 2009.

Table II presents the total cost when the aggregator controls the EV charging during the two flexible periods and adopts optimized bidding for the spot market. The results show that optimized bidding combined with charging control decreases the cost around: 33% (perfect forecasts) and 21% (naïve forecasts) for 2010; 23% (perfect forecast) and 16% (naïve forecasts) for 2009.

Note that in 2009, as depicted in Fig. 7, the price difference between peak and valley hours was lower in comparison to 2010. This justifies the increase in cost.

The increase in cost due to forecast errors is around 17% for 2010 and 9% for 2009. Hence, there is a high margin of improvement through an advanced forecasting method.

TABLE I
TOTAL COST OBTAINED WITH DUMB CHARGING IN THE SPOT MARKET

k€	2010	2009
Perfect Forecast	129.20	127.01
Naïve Forecast	136.66	131.29

TABLE II
TOTAL COST OBTAINED WITH OPTIMIZED BIDDING IN THE SPOT MARKET

k€	2010	2009
Perfect Forecast	97.02	103.58
Naïve Forecast	113.11	113.01

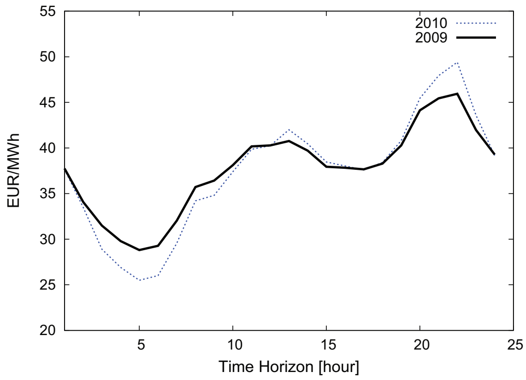

Fig. 7. Annual average spot price for 2009 and 2010.

Table III presents the results obtained from participating with optimized bidding in electrical energy and downward secondary reserve market. The results show that instead of positive cost, the aggregator obtains a negative cost when offers downward reserve bids. Note that we are talking about costs at the wholesale level, of course that at the retail level the aggregator will have profit margin (even in the situations depicted by tables I and II). With this negative cost, the aggregator can offer very low charging prices to its clients, while still get a big profit.

Table IV presents more details about the participation in spot and downward reserve markets. These numbers show that the reserve capacity price dominates the cost for charging EV.

For example, the total cost for charging the EV (penalizations plus spot market and downward reserve prices) in 2010 is 57.1 k€, while the income for having secondary reserve available is 176.4 k€. The conclusions for level 2 charging are analogous.

The forecasting side represents an important role in the final results. The negative cost decreases around 42% for 2010 when a naïve model is used, and it decreases 27% for 2009. Therefore, better forecasts would lead to a significant improvement.

TABLE III
TOTAL COST OBTAINED WITH OPTIMIZED BIDDING IN THE SPOT AND DOWNWARD RESERVE SESSIONS

k€	2010	2009
Perfect Forecast	-183.69	-235.93
Naïve Forecast	-129.56	-185.40

TABLE IV
DETAILS ABOUT OPTIMIZED BIDDING IN THE SPOT AND DOWNWARD RESERVE SESSIONS WITH NAÏVE FORECASTING (LEVEL 1 CHARGING)

	2010	2009
Energy purchased at spot price [MWh]	1521.6	1290.9
Cost of energy purchased at spot price [k€]	36.2	32.3
Energy purchased at down res. price [MWh]	329.1	560.0
Cost of energy purchased at down res. price [k€]	6.7	14.5
Capacity offered as down. res. [MW]	6203.6	7951.7
Income from offering down res. capacity [k€]	176.9	222.1
Cost due to market deviations [k€]	14.2	9.9

VII. CONCLUSIONS

This paper described an EV aggregation agent framework and two optimization problems for the participation in the day-ahead sport and secondary reserve market.

The variables that are necessary to forecast or estimate were also described. The impact of their forecast errors in the results were assessed by comparing the results obtained with perfect forecast and with a naïve forecasting method.

The results in this paper for two years of the Iberian market provide evidence that: i) an aggregator agent capable of controlling EV charging and with optimized bidding can significantly decrease the charging costs in comparison to the dumb charging strategy; ii) the participation in the secondary downward reserve market is economic attractive. In fact, the results show a negative cost which could increase the competiveness of the aggregator in the retailing market (e.g. increase the possibility of offering very cheap charging prices); iii) advanced forecasting algorithms are important to support the EV aggregator business and can improve the results.

Finally, smart-grid concepts are being adopted and implemented by distribution system operators in several countries. Hence, it is foreseeable that aggregators will also invest in ICT technology for increasing their profit margin and competitive capacity.

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