Optimized Bidding of a EV Aggregation Agent in the Electricity Market

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***Abstract*—An electric vehicle (EV) aggregation agent, as a commercial middleman between electricity market and EV owners, participates with bids for purchasing electrical energy and selling secondary reserve. This paper presents an optimization approach to support the aggregation agent participating in the day-ahead and secondary reserve sessions, and identifies the input variables that need to be forecasted or estimated. Results are presented for two years (2009 and 2010) of the Iberian market, and considering perfect and naïve forecast for all variables of the problem.**

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

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 requirements for time interval t
$\hat{P}_t^{\max}$: 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
$\hat{\gamma}_t^{up}$: binary variable corresponding to the forecasted system deviation sign, 1 when the system needs upward reserve and 0 otherwise
$\hat{pf}_t^{down}$: forecasted/estimated participation factor on secondary downward reserve
$\hat{pf}_t^{up}$: forecasted/estimated participation factor on secondary upward reserve
$\hat{p}_t^{down}$: forecasted price for energy delivered as secondary downward reserve
$\hat{p}_t^{up}$: forecasted price for energy delivered as secondary upward 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
P_t^{up}: upward 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

I. INTRODUCTION

THE foreseeable deployment of electric vehicles (EV) will represent an important impact in power system operation and electricity markets. Recent research has thus studied the integration of EV, where several authors are extending the traditional power system analysis tools to include EV as a distributed flexible load. For instance, Fernández *et al.* [1] present an assessment methodology for evaluating the impact of different EV penetration levels on the distribution network investments and energy losses; Lopes *et al.* [2] present steady-state and dynamic simulations for impact/benefits assessment of EV integration in distribution networks.

In all these works there is a common and important conclusion: with smart-charging strategies it is possible, until a certain point of EV penetration level, to avoid incremental investments and high energy losses, prevent wasting renewable energy and network congestion. As examples: with smart-charging it is possible to avoid up to 60%-70% of the required

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incremental investment [1]; smart charging allows attaining the highest EV penetration level without violating the network technical limits [2].

One of the main challenges to integrate a large quantity of EV at the lowest cost is to design a new framework for power system management and operation. Lopes *et al.* [2] presented a grid control architecture where EV are embedded under the MicroGrid and MultiMicroGrid concepts, with a hierarchical control scheme. Galus *et al.* [3] described a framework for the integration of EV within the power system planning and operation tasks.

In both frameworks the EV aggregation agent (or aggregator as abbreviated term) plays an important role as a middleman between EV owner, the electricity market, the distribution system operator (DSO) and the transmission system operator (TSO). The aggregator concept was introduced in the literature by Kempton *et al.* [4], and further enhanced by Lopes *et al.* [2] and Guille and Gross [5]. According to these authors, the need for an EV aggregation agent comes from the understanding that each EV owner will not be able, either to bid in the electricity market or to have bilateral transactions with electrical utilities, due to a low power capacity (in the order of few kW). Furthermore, an aggregation agent responsible for controlling the EV charging rates technically facilitates the smart charging approaches.

In fact, EV aggregation is a concept already implemented in some countries. For instance, in Portugal the industrial network MOBI.E is implementing a charging network accessible to all users [6]. The business model includes aggregation agents (retailers for electrical mobility) that users may liberally choose. A similar business model, from Better Place, is described in [7]. In these two business models, the aggregator is a common load aggregator that buys electrical energy in the market for its clients and do not have any direct control over the EV charging rates.

However, we propose in this paper a more elaborated EV aggregation agent. This aggregation agent explores the smart-grid concept, in particular the solutions for communication based on bidirectional monitoring and control data exchange. With this communication capability, it is possible to control the charging rates of the EV and offer more services (e.g. ancillary services, peak shaving) when compared to a common load aggregator.

A complete literature overview about the economic and technical management of an EV aggregation agent can be found in [8]. In what respects algorithms for EV aggregator management there are several works in the literature. Caramanis and Foster [9] 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 [10] describe a demand management scheme, where the aggregator tries to recharge all EV in its control area while maximizing their total utility in each time step.

The problem addressed in this paper consists of EV aggregator that manages and controls an EV fleet (i.e. charging of batteries) under the smart-grid paradigm. The aggregator controls the individual EV charging to increase its profits, and decreases the EV owners retailing price by minimizing the cost of purchased electricity. Hence, the aggregator presents buying bids in the day-ahead electrical energy session for satisfying the consumption of all EV under contract [11]. Moreover, it is also possible to offer bids in the ancillary services market, such as secondary reserve.

The main contribution from this paper consists of a method, based on an optimization approach, to support the aggregator participation in the day-ahead and reserve sessions (upward and downward) of the electricity market. Moreover, it establishes which variables are necessary to be forecasted or estimated, and how to include these variables in the optimization problem.

It is common to find in the literature methods to produce optimal bidding strategies of conventional load aggregators. However, the approach proposed in this paper differs from the existing ones in two important aspects: i) EV have more consumption flexibility than common loads, which allows the provision of upward and downward secondary reserve; ii) the consumption and availability pattern of EV presents an higher daily variability compared to common loads. Therefore, the proposed approach allows the participation of EV in day-ahead spot and secondary reserve market.

Section II describes the EV aggregation agent framework adopted for this work. Section III presents the optimization approach that will be used to support the aggregator participation in the day-ahead and reserve market sessions, and identifies the EV variables that it is necessary to forecast or estimate. Section IV presents a generation mechanism of synthetic EV charging data. Section V presents the case-study results. Finally, conclusions are presented in section VI.

II. EV Aggregation Agent Framework

A. The Aggregator Model

The aggregator definition found in [2]-[5] was closely followed. In this paper, the aggregator is an electricity retailer for electrical mobility, which defines tariffs for their customers. Nonetheless, it could also be an agent developing another activity that sees business opportunities and decides to become an EV aggregator (e.g. a battery manufacturer, a cell phone company), or a last resource supplier (the retailing prices would be set by the regulator).

The aggregator buys electrical energy for EV charging and offers ancillary services in the electricity market. However, it does not have any control over the individual EV driving behavior, so the driver needs must still be respected and are the main priority.

Two different groups of clients (or contracts) are foreseen: type A) a client who allows the aggregator to control the charging process during a period defined in their contract, which means this flexible demand must be met but presents a degree of freedom regarding when this load can be supplied; type B) a client who does not allow the aggregator to control the charging process, being the aggregator just an electricity provider.

In order to promote the maximum number of EV plugged-in during the flexible period, the aggregator can offer time-of-use tariffs which are much lower if the EV is connected during a fixed number of hours (e.g. four hours) of the flexible period. The aggregator represents these clients in the electricity market and retains a profit that depends on its bidding strategy and charging control strategy.

The benefits for the aggregator are the possibility of increasing its profit by selling ancillary services, and decreasing the charging costs by minimizing the cost of purchased electrical energy. In exchange, the aggregator offers cheap retailing prices or a discount in the monthly electricity bill, in particular for type A clients.

The retailing price adopted by the aggregator will depend from the business model and should be established by considering a trade-off between expected profit and competiveness. The definition of this price value is thus a commercial issue not addressed in this paper.

B. 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.

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 is congestion in the network. The bids correction should be seen as a remunerated service. Therefore, it is necessary to develop new management procedures for the DSO and change the current electricity market rules; details about possible frameworks can be found in [2] and [3];
- 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 (i.e. reserves). This reserve bids could be in the form of profit for decreasing consumption (upward reserve), or cheap charging (downward reserve).

C. Communication Requirements

It would be very demanding to have a DSO or TSO directly controlling and receiving information from thousands of EV. Therefore, it should only be available communications between the TSO/DSO and the aggregator and between the aggregator and the EV [12].

This communication should be bidirectional: upstream information (e.g. absorbed electrical energy, charging period) from the EV to the aggregator and, from the aggregator to the DSO/TSO; downstream information (e.g. charging rate set-points, charging interruption) from the DSO to the aggregator and, from the aggregator to the EV. Note that bidirectional power measurement of active power must also be metered for billing purposes.

Details about a possible communication infrastructure can be found in [12] and [13]. An overview of communication technologies for smart charging of EV can be found in [14].

Presently, in the industry there are already information and communication technology (ICT) that allows the communication between an aggregator and each EV. In [15], it is described a Charge Point Network of EV charging stations with smart metering technologies. These stations are in permanent bidirectional communication with the Charge Point Network Operating System, enabling functions such as remote diagnostics and demand side management. Another example is described in [16], where ICT that controls the flow of electricity between the network and the EV (enabling smart charging) is described.

D. Short-term Management

The optimization models presented in the next section are inserted in the short-term management of an aggregation agent. Short-term is a time horizon ranging from hours to two days ahead with time steps of one hour.

At time step t of day D the aggregator forecasts for each hour of day D+1: total EV electrical energy consumption; EV availability; spot and reserve prices. Afterwards, based on the forecasted variables, it defines the hourly bids for buying and selling electrical energy in the day-ahead and ancillary services markets. The optimized decisions related with these markets are performed on a daily basis and the result is not discriminated by individual EV.

III. Participation of an Aggregator in the Electricity and Reserve Markets

A. General Framework of the Markets

In this paper only day-ahead and reserve markets are considered, and the reserve market session is launched after the spot market. This framework is based on the Iberian electricity market. However, the methods described in this paper can be easily adapted to different market rules.

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 almost a price-taker that only presents bid for energy quantities. The market gate closure occurs at 10h.

The reserve market structure considered for this work is consistent with EV literature [4][17], and deals only with 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 (or steady-state) values. Secondary control makes use of a centralized and continuous Automatic Generation Control (AGC), modifying the active power set points of generation units/controllable loads in the time-frame of 30 seconds (at the latest) up to typically 15 minutes (at the latest) after an incident [18].

The reserve market allows upward and downward reserve separated bids for each hour of the next day. 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.

B. *EV as Controllable Loads*

The load flexibility of EV allows their participation as reserve resources, in both downward and upward directions.

Brooks *et al.* [20] proposed the idea of an EV operating at a preferred operating point (POP) from what provides upward and downward regulation. In the case of EV the POP could be zero or negative (consumption), in contrast to conventional units in which it is positive.

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

The consequence of this assumption is that the aggregator does not need to own the battery or support battery degradation costs, because the degradation is mostly due to the EV use for driving.

C. *Forecasting Issues*

The aggregator controls the EV charging of type A clients in a period defined in the contract (named “flexible period”). It is assumed that the EV owner defines, when arrives at home, the desired battery state of charge (SOC) for the next day. Since this information is only provided after the bidding in the day-ahead market, the aggregator needs to forecast the charging requirements for the next day.

Let’s consider the example of an EV owner that plugs-in the EV at 22:00, with 60% of SOC, and wants to have 100% SOC (27.4 kWh) before 7:00. For satisfying this requirement the EV must be charged with 10.96 kWh. If the aggregator forecasts this charging requirement, it will be possible to distribute this value (named “flexible load”) along the available charging period. Note that the extra consumption due to a charger’s efficiency below 100% is already embedded in the charging requirements.

A standardization of the charging equipment is foreseen, in particular the physical connectors into three (or four) charging levels [19][12]. The maximum connection power will be given by the nominal voltage times the rated ampere capacity of the charging equipment. Moreover, it is also expected that the DSO will set a limit in the charging capacity in the contracts that the aggregator signs with DSO, similar to how it is done with consumers nowadays in some countries.

Hence, in addition to forecast the charging requirements, the aggregator needs to forecast the maximum available power in each hour divided by three charging levels (which are described with more detail in section IV). This variable gives information about the maximum charging rate (as a function of the number of EV plugged-in) available in each hour.

For participating in the day-ahead market it is not suitable to deal with each EV individually. Hence, the aggregator forecasts the charging requirements and maximum available power of the whole fleet (i.e. total values). The main advantage is a lower seasonal variability of the time series. Fig. 1 depicts a seasonal plot for one year of the maximum available power time series, considering two EV and one thousand EV connected in residential charging points with a maximum available power of 3 kW. The plot shows the time series data grouped by the individual seasons (i.e. days) in which the data were observed. Note that the data from each day is overlapped.

This shows that as the aggregation number increases, the seasonal pattern becomes more pronounced.

Fig. 2 depicts an example of a charging requirements forecast of one thousand of EV at 10:00 of Day D for the period between 20:00 of day D and 10:00 of day D+1.

For instance, from the information of Fig. 2, the aggregator knows that until 8:00 at least 1.8 MWh of charging requirements 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 consumption in each hour (named “inflexible load”).

A naïve forecasting method for seasonal data was adopted for this paper. The model produces a forecast equal to the last observation from the same season. For instance, for data with daily cycle, forecast for the 10:00 is equal to the last available observation for the same hour. The same method is applied for the market prices data.

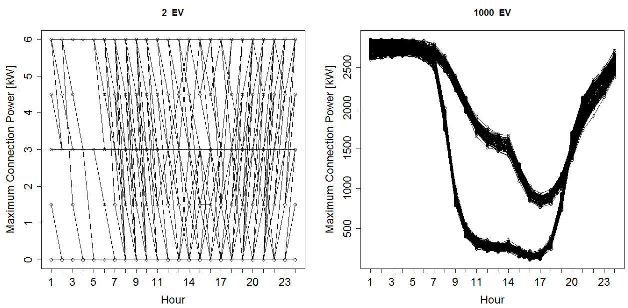

Fig. 1. Seasonal plot for maximum connection power with two EV and one thousand EV.

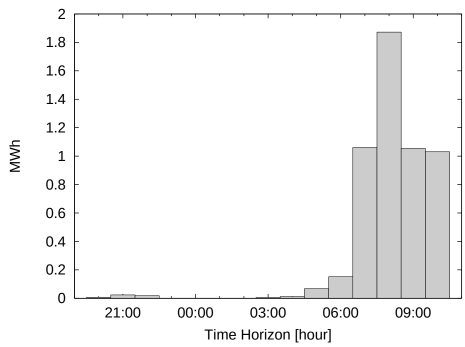

Fig. 2. Forecasted total charging requirements for the next flexible period.

D. *Bidding in the Day-ahead Spot Market*

The first model (M1) to be presented addresses the participation in the day-ahead spot market. The objective is to buy 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 model has two constraints. The first constraint is Eq. 2, and guarantees an electrical energy bid equal or below to the maximum available power for charging all EV plugged-in at time step *t* on charging level *k*. The second constraint is Eq. 3, and assures that the charging requirements (like the ones depicted in Fig. 2) are satisfied with the energy purchased in the market in each hour *t* of the flexible period H_i^F (beginning at time step t_{ini}). With this constraint it is guaranteed that when an EV departures the electrical energy required to satisfy the required SOC was purchased in the spot market.

Each flexible period H_i^F has an initial and final time instant (Eq. 4) and *i* is the number of flexible periods (Eq. 5).

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

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

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

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

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

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

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

Fig. 3 illustrates the day-ahead spot market bids (optimized bids with Eq. 1-5) for a flexible period between 20:00 of day D and 10:00 hour of day D+1 for the charging requirements of Fig. 2. The bids when all the clients are type B clients (named in the literature as dumb charging [1][2]) are also depicted. As shown, with all EV as inflexible loads (i.e. the aggregator does not control charging) the consumption is placed in high prices hours (e.g. the EV start charging when they arrive home).

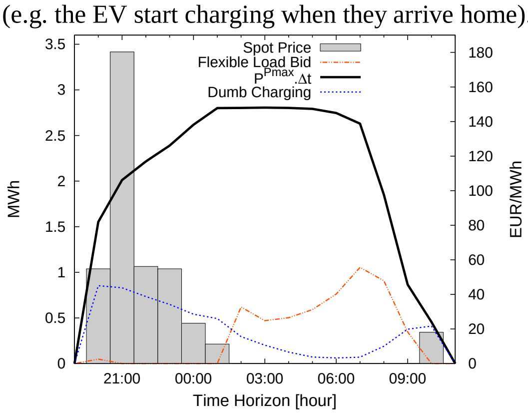

Fig. 3. Distribution of the flexible load bids.

On the other hand, with an optimized strategy where the aggregator controls the charging process (i.e. flexible loads), the bids are mostly placed in hours with low prices (zero in this case). Note that the total energy of both “flexible load” and “dumb charging” bids is the same.

E. *Bidding in the Spot and Downward Reserve Sessions*

In this model (M2), the aggregator participates with bids not only in the spot market but also in the downward reserve market.

The idea consists in buying 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}. For the downward reserve the preferred operating point could be zero or consumption below the maximum available power.

It was assumed that the aggregator is a price-taker in the reserve market. Consequently, the reserve capacity price offered by the aggregator is lower enough for having the bid accepted.

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

Note that the forecasted system deviation sign $\hat{\gamma}_t^{down}$, which is a binary variable with value 1 for positive deviations, is included in the two parts of the objective function [21]. This means that the aggregator only presents downward reserve offers when a positive deviation is forecasted.

The model has two constraints. The constraint of Eq. 7 guarantees that the sum of electrical energy purchased in the spot market and secondary downward reserve capacity bid is equal or below to the maximum available power for charging all EV plugged-in at time step *t* on charging level *k*. Eq. 8 guarantees that the charging requirements for hour *t* of the flexible period H_i^F are satisfied with electrical energy purchased in the spot market plus mobilized downward reserve (according to the participation factor $\hat{pf}_t$**).** The participation factor is the ratio between the mobilized reserve and the available reserve capacity.

The mathematical formulation is as follows:

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

$$E_{t,k}^F / \Delta t + P_{t,k}^{down} \le \hat{P}_{t,k}^{\max}, \quad \forall t \in H_i^F \tag{7}$$

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

$$H_i^F \in \{t_{ini}, \ldots, t_{final}\} \tag{9}$$

$$i \in \{1, \ldots, N\} \tag{10}$$

Fig. 4 illustrates the electrical energy and downward reserve bids for the same day of Fig. 3. With this model the charging requirements are satisfied with electrical energy purchased in the spot market (in hours with low prices) and downward secondary reserve.

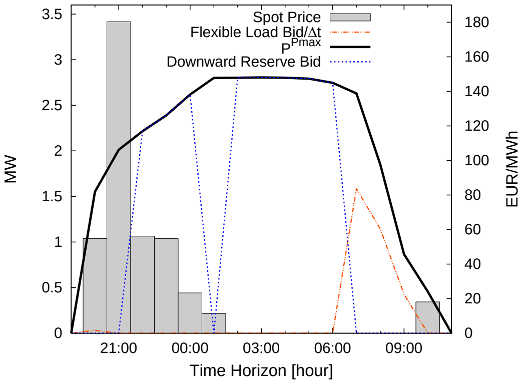

Fig. 4. Distribution of the flexible load and downward reserve bids (with *pf*=0.1).

In this example, the aggregator only offers purchase bids in the spot market between 7:00 and 9:00. In the remaining hours the EV are charged as downward reserve (equal to the maximum available power for charging, Eq. 7) if the value of $\hat{\gamma}_t^{down}$ is forecasted to be one. If the forecasted $\hat{\gamma}_t^{down}$ has value zero, then the downward reserve offer is zero (e.g. 9:00). Note that the aggregator receives an income for having this reserve capacity available.

In some hours the offer for downward reserve is zero because the forecast of the system deviation is zero.

F. *Bidding in the Spot Market and Reserve Sessions*

The last model (M3) addresses the participation in the spot market, downward and upward reserve market.

The upward reserve bid consists in offering a decrease in the consumption assigned by the spot market. This consumption decrease is paid above the spot price, which means a positive income.

The objective function (Eq. 11) consists in minimizing the charging cost, and is divided in five parts: i) cost of buying electrical energy in the spot market; ii) cost of charging the EV with downward reserve; iii) income for having downward reserve capacity available; iv) income for having upward reserve capacity available; v) income for providing upward reserve.

The model has three constraints. The constraint of Eq. 12 is the same of Eq. 7. The constraint of Eq. 13 ensures that the upward reserve bids are equal or below the electrical energy bid in the spot market for each hour *t*. The constraint of Eq. 14 is analogous to Eq. 8, but in this model it is necessary to include the consumption reduction provided as upward secondary reserve.

It is important to stress that the electrical energy and reserve bids may be constrained by the DSO [2]. For instance, in peak hours, EV may not be able to provide downward reserve due to congestion in feeders. The same is valid for models M1 and M2.

The mathematical formulation is as follows:

$$\min \sum_{t\in H_i^F} \left(\begin{array}{c} \hat{p}_t \cdot E_{t,k}^F + \hat{p}_t^{down} \cdot P_{t,k}^{down} \cdot \hat{\gamma}_t^{down} \cdot \hat{pf}_t^{down} \cdot \Delta t \\ - \hat{p}_t^{cap} \cdot P_{t,k}^{down} \cdot \hat{\gamma}_t^{down} - \hat{p}_t^{cap} \cdot P_{t,k}^{up} \cdot \hat{\gamma}_t^{up} \\ - \hat{p}_t^{up} \cdot P_{t,k}^{up} \cdot \hat{\gamma}_t^{up} \cdot \hat{pf}_t^{up} \cdot \Delta t \end{array} \right) \quad (11)$$

$$E_{t,k}^F / \Delta t + P_{t,k}^{down} \le \hat{P}_{t,k}^{\max}, \quad \forall t \in H_i^F \quad (12)$$

$$P_{t,k}^{up} \le E_{t,k}^F / \Delta t, \quad \forall t \in H_i^F \quad (13)$$

$$\sum_{j=t_{ini}}^{t} \left(\begin{array}{c} E_{j,k}^F + P_{j,k}^{down} \cdot \hat{\gamma}_t^{down} \cdot \hat{pf}_t^{down} \\ - P_{j,k}^{up} \cdot \hat{\gamma}_t^{up} \cdot \hat{pf}_t^{up} \end{array} \right) \ge \sum_{j=t_{ini}}^{t} \hat{R}_{j,k}, \quad \forall t \in H_i^F \quad (14)$$

$$H_i^F \in \{t_{ini}, \ldots, t_{final}\} \quad (15)$$

$$i \in \{1, \ldots, N\} \quad (16)$$

Fig. 5 illustrates the electrical energy and reserve bids. Due to the constraint of Eq. 13, the upward reserve is always below or equal to the electrical energy. In addition to downward reserve, the aggregator offers upward reserve equal to the electrical energy purchased in the spot market in hours 20:00 (day D), 7:00 and 8:00 of day D+1.

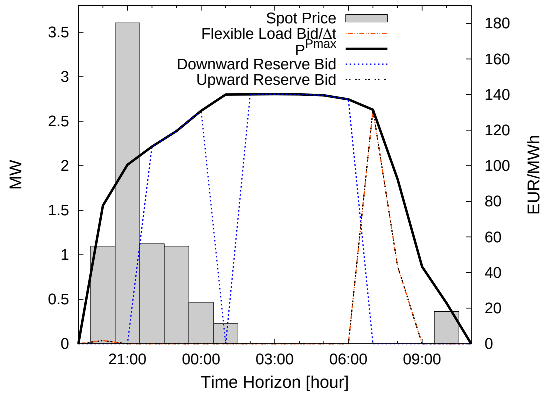

Fig. 5. Distribution of the flexible load, downward and upward reserve bids (with pf=0.1).

IV. Generation of Synthetic EV Charging Time Series

In this section a generation mechanism for synthetic EV charging time series is described. The first step was to individually characterize the one thousand EV assumed to be contained in a Medium Voltage (MV) network. After, it was simulated the movement of the EV fleet along one year, in accordance with the common traffic patterns in a region in the north of Portugal [22]. Having the EV movement fully defined, their power requirements were computed. The data obtained was used in the case study of section VI.

A. *EV Fleet Characterization*

Each 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 presented in Table I.

While the initial battery SOC values were assumed for the purpose of this work, the remaining values were gathered from the information made available by the manufacturers of 42 different EV. It was assumed that the global efficiency of the overall charging process was 90%.

TABLE I
TRUNCATED GAUSSIAN DISTRIBUTIONS FOR EV CHARACTERIZATION

	Average	Std. dev	Max	Min
Battery capacity (kWh)	24.73	17.19	85.00	5.00
Slow charging rated power (kW)	3.54	1.48	10.00	2.00
Energy consumption (kWh/km)	0.18	0.12	0.85	0.09
Initial battery SOC (%)	75.00	25.00	95.00	25.00

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 [12]. The results revealed that there are three major types of behaviors regarding EV charging, as presented in Table 2.

TABLE II
DRIVERS' BEHAVIORS CONSIDERED

	Percentage of the responses
EV charge at the end of the day	57%
EV charge only when it needs	23%
EV charge 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. EV Movement Simulation

The EV movement in a one year period was simulated using a discrete-state, discrete-time Markov chain to define the states of all the EV at each time step of 30 minutes [23]. It was assumed that, at every unit of time, each EV can be in one of the following states: in movement, parked in residential area, parked in commercial area or parked in an industrial area. After defining the EV states for each time instant, a network bus location was attributed to parked EV, according to a probability distribution proportional to the load installed in each bus. For the EV in movement, a procedure was developed to account their energy consumption and the respective reduction in the battery SOC, as defined in [23].

At each time instant, the EV battery SOC is updated according to the energy spent travelling or according to the energy absorbed from the MV network. It was assumed that EV "parked in a residential area" and "parked in an industrial area" charge at 3 kW (slow charging mode, level 1), 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) [12].

When an EV is parked, the decision of plug it in for charging, or not, is made taking into consideration its driver behavior and its current SOC.

C. Output Data

The methodology described in subsections A. and B. allows obtaining, for the one year period simulated, the following data: the periods during which EV are plugged-in and available to charge, the network bus to which EV are plugged-in (only for parked EV), the EV power absorbed at each 30 min interval, the EV battery SOC evolution and the EV travelled distances.

Note that in this paper synthetic time series data was used. However, with advanced meters it is possible to gather this data. For example, in [24], communication protocols between EV and a centralized control agent (e.g. aggregator) are proposed for transmitting status and trip information, electrical energy absorbed during charging and traveling plans defined by the EV owners.

V. CASE-STUDY

A. Description

The models described in section IV were tested for an EV aggregation agent that has one thousand battery EV under contract.

From the analysis of the daily average profile of each EV the following flexible periods were considered: i) for level 1 the flexible period is between 20:00 of day D+1 and 10:00 of day D+2; ii) for level 2 is between 15:00 and 20:00 of day D+1. These periods are agreed in the contract between EV owners and aggregator.

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

The market data is from two years (2009 and 2010) of the Iberian market (Portuguese control area) and can be downloaded from [25]. 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 used in all simulations. Note that this participation factor must be forecasted or estimated and it changes from hour to hour. However, since in Portugal does not exist publicly available data for this variable, a fixed value was assumed.

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 1:00 of day D+1 and 10:00 of day D+2).

Therefore, the energy purchased for the period between 20:00 and 24:00 must be used as input for the subsequent daily bids. Market prices and EV forecasts for lead times up to 48 hours are required.

B. Calculation of Deviations Costs

Forecast errors 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. This procedure was simulated taking into account the following assumptions:

- EV owners communicate to the aggregator their charging requirements when they park the EV for a flexible period. This is a simplification because it may happen that some EV owners do not communicate the charging requirements to the aggregator. In that case, the aggregator could use a default profile or a typical profile learned from historical data.

- 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.

Note also that this paper addresses the problem of participating in the day-ahead spot and reserve markets, not the operational charging management issues.

Following these assumptions, an optimization problem is solved where the objective function is the minimization of the absolute deviations between the forecasted and actual charging requirements. 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 model M3 is as follows:

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

$$P_{t,k}^{up} \cdot \hat{pf}_t^{\,up} \le \left(E_{t,k}^F + \Delta_t^+ - \Delta_t^- \right), \quad \forall t \in H_i^F \tag{18}$$

$$\left(E_{t,k}^F + \Delta_t^+ - \Delta_t^- \right) + \left(P_{t,k}^{down} - P_{t,k}^{up} \right) \cdot \hat{pf}_t^{\,down} \le \hat{P}_{t,k}^{\max}, \quad \forall t \in H_i^F \tag{19}$$

$$\sum_{j=t_{ini}}^{t} \begin{pmatrix} E_{j,k}^F + P_{j,k}^{down} \cdot \hat{\gamma}_t^{down} \cdot \hat{pf}_t^{\,down} \\ - P_{j,k}^{up} \cdot \hat{\gamma}_t^{up} \cdot \hat{pf}_t^{\,up} + \Delta_t^+ - \Delta_t^- \end{pmatrix} \ge \sum_{j=t_{ini}}^{t} \hat{R}_{j,k}, \quad \forall t \in H_i^F \tag{20}$$

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

Note that it is straightforward to adapt this equation to models M1 and M2.

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:

$$\begin{cases} p_t^{surplus} \cdot \left(E_{t,k}^F - E_{t,k}^{cons} \right), E_{t,k}^F > E_{t,k}^{cons} \\ p_t^{shortage} \cdot \left(E_{t,k}^F - E_{t,k}^{cons} \right), E_{t,k}^F < E_{t,k}^{cons} \end{cases} \tag{21}$$

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

It is important to stress that here we are just proposing a method for computing the deviations, and not on how to minimize this deviations during the optimization process. We leave the discussion of strategies for minimizing deviations to a future paper.

C. Results

In this section the total cost obtained by the aggregator from participating in the day-ahead spot market and reserve market is calculated for the two years. Two situations were considered: with and without price per available reserve capacity.

1) Spot market: For comparison, Table III presents the total cost obtained with dumb charging (or type B clients) and optimized bidding.

For the dumb charge strategy, the aggregator just forecasts the load required for charging the EV for the next day, and the bids are equal to the forecasted values. A naive forecast model leads only to a cost increase of around 6% for 2010, and 3% for 2009.

When the aggregator uses optimized bidding (controls the EV charging during the two flexible periods), the results show that optimized bidding 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, the price difference between peak and valley hours was lower in comparison to 2010. This substantiates the increase in cost.

The increase in cost due to forecast errors is around 17% for 2010 and 9% for 2009. Hence an advanced forecasting method will improve the results.

It is important to stress that these are costs related with buying electricity at wholesale price. Therefore, when the retailing price is considered, it is expected that the aggregator will make profit from its activity. What the results show is that an aggregator with optimized bidding can decrease the wholesale costs and increase its retailing profit. Furthermore, this also brings benefits to the clients connected during the flexible period, because they will profit from low electricity prices. On other hand, the EV owners preferring dumb charging (inflexible load) will pay a higher electricity price. Nevertheless, since the wholesale operational costs decreased, these inflexible clients may also benefit from low electricity tariffs if the aggregator wants to attract more clients to its portfolio.

2) With reserve capacity price: Table IV presents the results obtained by participating with optimized bidding in spot market plus downward reserve session, and plus upward and downward reserve sessions.

As shown in table IV, the aggregator obtains negative cost by offering downward reserve bids. Therefore, with this strategy the aggregator can offer very low retailing prices to its clients, without decreasing considerably its profit margin. Once again, EV owners will benefit from very low electricity prices.

At first sight, the negative cost seems odd. However, this can be explained by the following reasoning. For example: the total cost for charging the EV (penalizations plus spot market and downward reserve prices) in 2010 is 57.1 k€ for level 1 flexible period and 16.34 k€ for level 2; the income for offering available reserve is 176.4 k€ in level 1 and 65.3 k€ in level 2.

Therefore, the reserve capacity price dominates the cost for charging EV. Note that this result is consistent with what was found in the literature for U.S. markets [8][17].

The forecasting side represents an important role in the final results. The profit 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.

When the aggregator participates in both reserve sessions, the negative cost increases (w.r.t. participation in downward reserve) around 29% in 2010 and 19% in 2009 for the perfect forecast case; for the naïve forecast, the percentages are around 37% in 2010 and 20% in 2009. The naïve forecast model lead to a profit reduction around 33% in 2010 and 26% in 2009.

3) Without reserve capacity price: simulations were performed for the same data but without the reserve capacity price. The results are presented in Table V.

These results show two relevant facts. First, without the reserve capacity price the aggregator moves from a negative to positive cost. Nevertheless, the cost is lower compared to an exclusively participation in the spot market, e.g. cost decreases around 88% in 2010 and 70% in 2009.

Second, the capacity price was covering the real impact of forecast errors. For instance, the annual average price for reserve capacity is 27.8 €/MW in 2010, while the difference between spot price and tertiary reserve is 11.5 €/MWh for upward and 17.5 €/MWh for downward. Therefore, the capacity price offsets the deviations costs.

In fact, the results with the naïve forecast are similar to the ones obtained for the exclusively participation in the spot market (table III), i.e. a cost decrease around 4% in 2010 and 5% in 2009. The forecast errors lead to an increase in cost around 111% in 2010 and 77% in 2009.

Therefore, price and EV variables forecast gains more importance under this condition.

The gains of participating in the upward reserve market are closer to table V without the price per reserve capacity. This means that this market is only attractive if a capacity price is available, i.e. the decrease in cost in around 7% for 2010 and 2% for 2009. For the naïve model, the same conclusions can be derived.

TABLE III
TOTAL COST OBTAINED WITH DUMB CHARGING AND OPTIMIZED BIDDING IN THE SPOT MARKET

	Dumb Charging		Optimized Bidding	
k€	2010	2009	2010	2009
Perfect Forecast	129.20	127.01	97.02	103.58
Naïve Forecast	136.66	131.29	113.11	113.01

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

	Downward Reserve		Up. and Down. Reserve	
k€	2010	2009	2010	2009
Perfect Forecast	-183.69	-235.93	-236.13	-280.72
Naïve Forecast	-129.56	-185.40	-177.87	-222.99

TABLE V
TOTAL COST OBTAINED WITH OPTIMIZED BIDDING IN THE SPOT AND RESERVE SESSIONS, WITHOUT RESERVE CAPACITY PRICE

	Downward Reserve		Up. and Down. Reserve	
k€	2010	2009	2010	2009
Perfect Forecast	55.46	62.48	51.59	61.00
Naïve Forecast	111.03	108.52	108.84	107.82

VI. CONCLUSIONS

In this paper three different optimization problems were presented for supporting the participation of an EV aggregation agent in the day-ahead electrical energy and secondary reserve sessions.

The variables that need to be forecasted or estimated were described. The impact of their forecast errors and uncertainty in the results were assessed by comparing the results of perfect forecast with a naïve forecasting model.

From the simulation results for two years (2009 and 2010) of the Iberian market (Portuguese control area) the following conclusions were derived: i) an aggregator agent with optimized bidding can decrease the charging costs in comparison to the dumb charging strategy; ii) if a reserve capacity payment is available, it is economically attractive the participation in the upward and downward reserve sessions; iii) without a reserve capacity payment, optimized bidding with reserve bids decreases the cost, but forecasting and uncertainty estimation will have a more important role in this problem.

The decrease in costs represents a direct benefit to the aggregator's clients, because it is likely that the low wholesale costs obtained by the aggregator will lead it to offer very cheap charging tariffs.

Note that it was not an objective of this paper to explore algorithms for time series forecasting. Nevertheless, we think that advanced forecasting (point and uncertainty) and stochastic optimization algorithms can improve the results and will deserve our attention in future work.

VII. REFERENCES

[1] L. P. Fernández, T. Gómez, R. Cossent, C. Domingo, and P. Frías, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Trans. Power Syst.*, vol. 26(1), pp. 206-213, Feb. 2011.

[2] J.A. Peças Lopes, F.J. Soares, and P.M.R. Almeida, "Integration of electric vehicles in the electric power system," *Proc. of the IEEE*, vol. 99(1), pp. 168-183, Jan. 2011.

[3] M.D. Galus, M. Zima, and G. Andersson, "On integration of plug-in hybrid electric vehicles into existing power system structures," *Energy Policy*, vol. 38(11), pp. 6736-6745, Nov. 2010.

[4] W. Kempton, J. Tomic, S. Letendre, A. Brooks, and T. Lipman, "Vehicle to grid power: battery, hybrid, and fuel cell vehicles as resources for distributed electric power in California," Report ECD-ITS-RR-01-03, UC Davis Institute for Transportation Studies, Jun. 2001.

[5] C. Guille and G. Gross, "A conceptual framework for the vehicle-to-grid (V2G) implementation," *Energy Policy*, vol. 37(11), pp. 4379-4390, Nov. 2009.

[6] www.mobie.pt (accessed on May 2011)

[7] P.H. Andersen, J.A. Mathews, and M. Raska, "Integrating private transport into renewable energy policy: The strategy of creating intelligent recharging grids for electric vehicles," *Energy Policy*, vol. 37(7), pp. 2481-2486, July 2009.

[8] R.J. Bessa and M.A. Matos, "Economic and technical management of an aggregation agent for electric vehicles: a literature survey," *Euro. Trans. on Elect. Power*, 2011, In Press. DOI: 10.1002/etep.565

[9] M.C. Caramanis and J.M. Foster, "Management of electric vehicle charging to mitigate renewable generation intermittency and distribution network congestion," *in Proc. of the 48th IEEE Conf. on Decision and Control*, Shanghai, P.R. China, 16-18 Dec. 2009.

[10] M.D. Galus and G. Andersson, "Integration of plug-in hybrid electric vehicles into energy networks," in *Proc. of the 2009 IEEE Power Tech Conf.*, Jun. 28 - 2 Jul. 2009.

[11] R.J. Bessa and M.A. Matos, "The role of an aggregator agent for EV in the electricity market," in *Proc. of the 7th MedPower Conf.*, Agia Napa, Cyprus, 7-10 Nov. 2010.

[12] S. Bending, S. Channon, M. Ferdowsi, K. Strunz, E. Bower, A. Walsh, *et al.*, “Specification for an enabling smart technology,” Deliverable D1.1 of the European Project MERGE, Aug. 2010.
[13] D. Rua, D. Issicaba, F.J. Soares, P.M.R. Almeida, R. Rei, J.A. Peças Lopes, “Advanced metering infrastructure functionalities for electric mobility,” in *Proc. of the IEEE PES Conf. on Innov. Smart Grid Tech. Europe*, Gothenburg, Sweden, 11-13 Oct. 2010.
[14] T. Markel, M. Kuss, and P. Denholm, “Communication and control of electric vehicles supporting renewables,” in *Proceedings of the 2009 IEEE Vehicle Power and Propulsion Systems Conference*, Dearborn, Michigan, 7-10 Sept. 2009.
[15] www.coulombtech.com (accessed in May 2011).
[16] J. Lawrence, J. Barghout, K. Dulaney, “PHEV technology demonstration: GridPoint,” Technical Report, Advanced Energy, Dec. 2009.
[17] J. Tomic and W. Kempton, “Using fleets of electric-drive vehicles for grid support,” *Journal of Power Sources*, vol. 168(2), pp. 459-468, Jun. 2007.
[18] UCTE, Operational handbook. P1 – Policy 1: Load-Frequency Control and Performance, March 2009.
[19] Society of Motor Manufacturers and Traders, “Report on the current situation and future direction of electric vehicle charger standardisation,” Technical Report, July 2010. Available online at: www.smmt.co.uk (accessed on May 2011)
[20] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, “Demand dispatch,” *IEEE Power Energy Mag.*, vol. 8(3), pp. 20-29, 2010.
[21] T. Jónsson, “Forecasting of electricity prices accounting for wind power predictions,” MSc Thesis, Technical University of Denmark, Lyngby, Denmark, 2008.
[22] INE - Instituto Nacional de Estatística, “Inquérito à mobilidade da população residente”, 2000 (in Portuguese).
[23] F.J. Soares, J.A. Peças Lopes, P.M.Rocha Almeida, C.L. Moreira, L. Seca, “A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid,” in *Proc. of the17th Power Systems Computation Conference (PSCC)*, Stockholm, Sweden, Aug. 22-26, 2011.
[24] B. Jansen, C. Binding, O. Sundström, and D. Gantenbein “Architecture and communication of an electric vehicle virtual power plant,” in *Proc. of the 1st IEEE Int. Conf. on Smart Grid Communications*, Gaithersburg, Maryland, Oct. 2010.
[25] www.mercado.ren.pt (accessed in May 2011).

VIII. BIOGRAPHIES

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