Electric Power Systems Research 95 (2013) 319–329

Contents lists available at SciVerse ScienceDirect

Electric Power Systems Research

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

Global against divided optimization for the participation of an EV aggregator in the day-ahead electricity market. Part II: Numerical analysis

R.J. Bessa*, M.A. Matos

INESC TEC – INESC Technology and Science (formerly INESC Porto) and FEUP, Faculty of Engineering, University of Porto, Portugal

ARTICLE INFO

Article history:
Received 31 January 2012
Received in revised form 21 May 2012
Accepted 15 August 2012
Available online 5 September 2012

Keywords:
Electric vehicles
Aggregator
Electricity market
Forecasting
Optimization
Operational management

ABSTRACT

This paper presents numerical analysis of two alternative optimization approaches intended to support an EV aggregation agent in optimizing buying bids for the day-ahead electricity market. A study with market data from the Iberian electricity market is used for comparison and validation of the forecasting and optimization performance of the *global* and *divided* optimization approaches. The results show that evaluating the forecast quality separately from its impact in the optimization results is misleading, because a forecast with a low error might result in a higher cost than a forecast with higher error. Both bidding approaches were also compared with an *inflexible EV load* approach where the EV are not controlled by an aggregator and start charging when they plug-in. Results show that optimized bids allow a considerable cost reduction when compared to an *inflexible load* approach, and the computational performance of the algorithms satisfies the requirements for operational use by a future real EV aggregation agent.

1. Introduction

Policy makers and researchers working in electrical mobility have conducted studies for assessing the impact of electric vehicles (EV) in power system operation and planning [1] and the possible business models for companies operating in this activity [2]. The figure of an EV aggregation agent (aggregator in abbreviated form) has been proposed as an intermediary between vehicle driver, the system operators of the transmission and distribution grid and the electricity market [1,3]. The aggregator is an electricity retailer that has direct control over the charging process of the EV in its portfolio of clients and is responsible first for purchasing electrical energy for these clients in the electricity market and then to control the charging process to comply with the contracted quantities of electrical energy.

A number of optimization algorithms for supporting the aggregator activity in the short-term horizon (i.e. participation in day-ahead markets) have been presented [4–9]. Two alternative bidding approaches (*global* and *divided*) for minimizing the cost of purchasing electrical energy in the day-ahead market are described in a companion paper [10]. The *global* approach uses aggregated values of the EV variables and the optimization model determines the bids exclusively based on total values. The *divided* approach uses individual information from each EV. Moreover, an operational management algorithm is used for minimizing the deviation between market bids and consumed electrical energy for charging EV. The models take as inputs forecasts from market prices and EV variables.

This paper presents numerical analyses for a realistic case-study with synthetic time series of availability and consumed electrical energy from an EV fleet, generated using statistics from the traffic patterns in Portugal. The two optimization approaches are evaluated and compared, and an assessment of the EV variables forecast's quality and value (i.e. economic benefits) is also presented.

This paper is organized as follows: Section 2 describes the case-study; Section 3 presents the forecast evaluation results for the market and EV variables; Section 4 compares the costs of the *global*, *divided* and *inflexible load* bidding approaches; Section 5 presents the conclusions.

2. Case-study description

This section presents the case-study used for comparing and evaluating the bidding approaches. The case-study is more representative as possible and uses real electricity market data. Only EV data is synthetic and tries to simulate a forthcoming situation.

2.1. EV synthetic time series

For producing time series of the EV availability and consumption, the generation mechanism for synthetic EV charging

* Corresponding author at: INESC TEC (formerly INESC Porto), Campus da FEUP, Rua Dr. Roberto Frias, 378, 4200-465 Porto, Portugal. Tel.: +351 22 209 4208; fax: +351 22 209 4050.
E-mail address: rbessa@inescporto.pt (R.J. Bessa).

0378-7796/$ – see front matter
http://dx.doi.org/10.1016/j.epsr.2012.08.013

Table 1
Three types of behavior regarding EV charging.

Type	Behavior	Percentage of the responses
A	EV charge at the end of the day	57%
B	EV charge whenever possible	20%
C	EV charge only when it needs	23%

time series described in [11] was used. The movement of a fleet with 3000 battery EV along one year was simulated using a discrete-time-space Markov chain at each time step of half-hour, in accordance with the common traffic patterns in the northern region of Portugal [12]. The statistical post-processing of these traffic patterns is described in [13]. Having the EV movements fully defined, their power requirements were computed.

Each EV was initially characterized in terms of battery capacity, energy consumption and battery state of charge (SOC) in the beginning of the simulation. These values were defined according to truncated Gaussian probability density functions. The mean, standard deviation, maximum and minimum values are given in [11]. The initial battery SOC values were defined as a parameter in the simulation, while the other two variables were gathered from the information made available by 42 different EV manufacturers. The charger efficiency was assumed to be 90%.

A specific 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 [14]. The results revealed that there are three major types of behavior regarding EV charging, as presented in Table 1.

For the drivers who charge their EV only when it needs, it was defined that the battery SOC threshold for charging equal to 40%.

The simulation methodology assumes that, at every time interval, each EV can be in one of the following states: 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. At each time interval, the EV battery SOC is updated according to the energy spent traveling or according to the energy absorbed from the electrical network.

Three charging levels were considered for the simulation: EV "parked in a residential area" and "parked in an industrial area" charge at 3 kW (slow charging mode), EV "parked in a commercial area" charge at 12 kW (normal charging mode) and the charging power in fast charging stations is 40 kW (fast charging mode) [14]. When an EV is parked, the decision of whether or not plugging it in for charging is made taking into consideration its driver behavior (see Table 1) and its current SOC (only for type C drivers). This case-study only studies EV parked in residential area (slow charging mode).

The simulation methodology provides, for a one-year period with 30 min time intervals, the following time series: the periods where EV are plugged-in and available to charge, the EV power absorbed at each time interval (assuming that the EV starts charging when plugs-in), the EV battery SOC evolution and the EV traveled distances. These time series are used for training the forecasting algorithms (as historical data) and testing the optimization and forecasting algorithms.

2.2. Electricity market

The case-study follows the data and rules of the day-ahead Iberian electrical energy market [15]. The market agents may present buy and sell hourly bids that cover all 24 h of the next day (physical delivery period). The gate closure occurs at the 10th hour. Two types of simple hourly bids are possible: a price independent bid for all hours regardless of the price level, with only a price cap, or a price dependent hourly bid for all hours where a stepwise curve is submitted.

In general, the day-ahead session structure and rules do not change from market to market. Therefore, the *global* and *divided* algorithms can be directly applied to different electricity markets without significant changes.

The total cost, in addition to the cost of purchasing electrical energy in the electrical energy market, also includes costs associated to deviations from planned consumption. When the aggregator has surplus of electrical energy in the market bid it has to sell this extra electrical energy at a regulation price (p_t^{surplus}) in general below the day-ahead electrical energy price; if the situation is shortage of electrical energy, it has to pay a regulation price (p_t^{shortage}) in general above the day-ahead electrical energy price [16]. This corresponds to the following equation for the total cost:

$$\text{Total cost} = \sum_t \left(E_t^{\text{cons}} \cdot p_t + \begin{cases} (p_t - p_t^{\text{surplus}}) \cdot (E_t^{\text{bid}} - E_t^{\text{cons}}), & E_t^{\text{bid}} > E_t^{\text{cons}} \\ (p_t^{\text{shortage}} - p_t) \cdot (E_t^{\text{cons}} - E_t^{\text{bid}}), & E_t^{\text{bid}} < E_t^{\text{cons}} \end{cases} \right) \quad (1)$$

where E_t^{bid} is the electrical energy purchased in the day-ahead electrical energy market for time interval t, p_t is the day-ahead electrical energy price, E_t^{cons} is the consumed electrical energy, p_t^{surplus} is the regulation price for positive deviations and p_t^{shortage} is the regulation price for negative deviations.

The second component of this equation is the surplus or shortage costs, where the price difference $p_t - p_t^{\text{surplus}}$ is the positive deviations price (π_t^+), and the difference $p_t^{\text{shortage}} - p_t$ is the negative deviations price (π_t^-).

The regulation prices, in the Portuguese control area, are related with the tertiary reserve (or regulation reserve) prices.

The electricity market data of the case-study is from a three years period (2009–2011) and consists of: electrical energy price of the day-ahead market for Portugal (downloaded from [17]); price of upward and downward reserve for Portugal (downloaded from [18]); interconnection exchanges (imported electrical energy) between Portugal and Spain (downloaded from [19]); load and wind power forecast in the Iberian peninsula for the next day (downloaded from [17]).

In general, the European market designs have different penalization prices for negative and positive real-time deviations from the market dispatch [20]. These prices result from regulation market sessions (e.g. with manual reserve bids cleared in real-time by the system operator) or are established by the regulator to provide incentives for better resources' scheduling. The operational management algorithm can be generalized for any electricity market with asymmetric or symmetric regulation prices. Other market designs, such as the U.S. markets, have a real-time market session where the price difference for the day-ahead market price can induce significant losses in case of deviation from the day-ahead bid [21]. In this case, the objective function of the operational management algorithms needs to be redesigned to include this price difference, which, depending on the deviation sign, might represent a profit for the aggregator (sell surplus of electrical energy at a higher price).

Finally, this paper does not consider the participation in intraday and hour-ahead markets [22], although this is an important topic for future work. The participation in the intraday market