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Optimization models for an EV aggregator selling secondary reserve in the electricity market

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

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

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ABSTRACT

Power system regulators and operators are creating conditions for encouraging the participation of the demand-side into reserve markets. The electric vehicle (EV), when aggregated by a market agent, holds sufficient flexibility for offering reserve bids. Nevertheless, due to the stochastic nature of the drivers' behavior and market variables, forecasting and optimization algorithms are necessary for supporting an EV aggregator participating in the electricity market. This paper describes a new day-ahead optimization model between energy and secondary reserve bids and an operational management algorithm that coordinates EV charging in order to minimize differences between contracted and realized values. The use of forecasts for EV and market prices is included, as well as a market settlement scheme that includes a penalty term for reserve shortage. The optimization framework is evaluated in a test case constructed with synthetic time series for EV and market data from the Iberian electricity market.

1. Introduction

The participation of loads in ancillary services markets has gained relevance in the recent years [1], in particular with the deployment of the smart-grid concept with bidirectional communication [2]. The electric vehicle (EV), when aggregated by a market agent, is a suitable candidate for selling reserve services in the electricity market [3].

Secondary (or regulation) reserve consists in loads and generators under direct real-time control of the system operator (SO), via automatic generation control (AGC), for increasing or decreasing generation/consumption. The response time is very fast (e.g., <30 s) and is used to bring back the frequency and the interchange programs to their nominal values (i.e., reduce the area control error – ACE).

The current market rules do not allow the participation of small loads and generators (e.g., the minimum bid is generally around megawatts), and even if small bids are allowed, the AGC would need to send control signals to each EV supplying secondary reserve.

The solution proposed by several authors is an EV aggregator acting as an intermediary between EV drivers, the electricity market and the SO [4,5]. Almeida [6] describes a control scheme for integrating aggregated EV in the AGC operation of interconnected systems. In this framework, the AGC sends set-points to aggregators that, afterwards, distribute individual set-points among the plugged-in EV. This reduces significantly the communication burden and increases its reliability.

The work of this paper explores a solution where the EV aggregator controls directly the charging of EV plugged-in in slow charging points and sells secondary reserve power in the electricity market.

The vehicle-to-grid (V2G) mode was not considered in this paper. Instead, the reserve is supplied by establishing a preferred operating point (POP) [7]. The POP consists in the EV consumption level that can be increased (downward reserve) or decreased (upward reserve) limited by zero and by the maximum charging power. For instance, an EV charging at 2 kW could provide 2 kW of upward regulation until it reaches "zero load" and 1 kW of downward regulation if the maximum charging power is 3 kW. Compared to V2G, this solution does not require additional investment in equipment, and it reduces the costs with battery wear and losses in the charger [7].

Different algorithms for supporting the participation of EV in the reserve market were proposed in the literature. Sortomme and El-Sharkawi [8] propose three heuristic strategies and equivalent optimal analogs to define the POP and regulation reserve bids of an EV aggregator. Han et al. [9] describe a dynamic programming based algorithm to calculate regulation power bids from EV. Rotering and Ilic [10] describe two dynamic programming optimization algorithms for an optimal controller installed in an EV. One algorithm optimizes the charging rates and periods for minimizing the cost, and the other maximizes the profit from selling regulation power. Wu et al. [11] discuss pricing schemes to induce the participation of EV in frequency regulation services.

* Corresponding author at: 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).

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Nomenclature

μ	ratio between upward and downward secondary reserve
Ψ	costs associated to deviations between actual charging and accepted bids
φ	convex loss function
Φ	costs associated to reserve shortage
α	penalization coefficient for secondary reserve capacity shortage
γ	penalization coefficient for reserve not supplied (electrical energy)
Δt	time step (length of the time interval) of time interval t
E_t	optimized electrical energy for time interval t
$E_{t,j}$	optimized electrical energy for charging the jth EV in time interval t
$E^{*}_{t,j}$	electrical energy consumed by the jth EV in time interval t
H	set of time intervals from the optimization horizon
$\hat{H}_j^{plug}$	forecasted availability (or plugged-in) period of the jth EV
H_j^{plug}	availability (or plugged-in) period of the jth EV
$\lambda_t{}^{up}$	number of equivalent minutes of dispatched upward reserve in interval t
$\lambda_t{}^{down}$	number of equivalent minutes of dispatched downward reserve in interval t
M_t	total number of EV plugged-in at time interval t
$\pi_t{}^{-}$	negative imbalance unit cost of time interval t
$\pi_t{}^{+}$	positive imbalance unit cost of time interval t
$P_j{}^{max}$	maximum charging power of the jth EV
$\bar{P}_{t_0}^{\max}$	maximum, constant and feasible charging power of the EV fleet in time interval t_0
$\bar{P}_{t_0}^{\min}$	minimum, constant and feasible charging power of the EV fleet in time interval t_0
$P_{t,j}^{down}$	downward secondary reserve power of the jth EV for time interval t
$P_{t,j}^{up}$	upward secondary reserve power of the jth EV for time interval t
P'_{t_0}	operating point (or actual preferred operating point)
$P'^{down}_{t_0}$	available downward secondary reserve power
$P'^{up}_{t_0}$	available upward secondary reserve power
$\bar{P}_{t_0}^{down}$	downward secondary reserve power that can be sustained during interval t
$\bar{P}_{t_0}^{up}$	upward secondary reserve power that can be sustained during interval t
$\bar{P}_{t_0}^{upper}$	upper power limit that guarantees full availability of downward reserve power in time interval t_0
$\bar{P}_{t_0}^{lower}$	lower power limit that guarantees full availability of upward reserve power in time interval t_0
$p_t{}^{surplus}$	price for positive imbalances of time interval t
$p_t{}^{shortage}$	price for negative imbalances of time interval t
$\hat{p}_t$	day-ahead energy price forecast for time interval t
$\hat{p}_t^{cap}$	forecasted capacity price of secondary reserve
$\hat{p}_t^{down}$	forecasted price for dispatched downward reserve
$\hat{p}_t^{up}$	forecasted price for dispatched upward reserve
p_t	day-ahead energy price for time interval t
$\hat{R}_j$	forecasted charging requirement of the jth EV
$R_{t_0,j}$	residual charging requirement of the jth EV at beginning of time instant t_0
RNS_t^{down}	downward reserve not supplied in time interval t
RNS_t^{up}	upward reserve not supplied in time interval t
T	time interval of the last plugged-in EV to depart
t_{final}	last time interval of the availability period
$t_{initial}$	first time interval of the availability period
ν_k	slack variable

All the aforementioned algorithms assume that perfect forecasts are available for all the variables. In fact, when designing bidding optimization models, it is necessary to consider the need to forecast these variables and the occurrence of forecast errors. Pantos [12] presents a stochastic optimization algorithm for the participation in the electricity market (energy and regulation reserve), which includes uncertainties related to the market price and driver's behavior. Han et al. [13] propose a probabilistic model for modeling the achievable power capacity of an EV aggregator when providing regulation reserve. Bessa et al. [14] described an optimization model for energy and secondary reserve bids. A naïve forecasting approach was used for producing forecasts for aggregated values of the EV variables. Bessa and Matos [15] compared two alternative approaches to optimize the participation of an EV aggregator in the day-ahead energy market (reserve was not considered). The two algorithms use, as input, forecasts for the EV variables produced by statistical models. The same authors present in [16] a day-ahead optimization model and operational management algorithms for day-ahead and hour-ahead manual (or balancing) reserve bids.

Compared to Pantos [12] and Han et al. [13], the optimization approach proposed in this present paper characterizes the EV individually, which as shown in [15], provides a more accurate representation and coordinates the EV individual charging for mitigating forecast errors. Furthermore, the formulation of the optimization models proposed in this present paper contemplates the specific characteristics of secondary reserve. For instance, the models that will be described in Section 3 are formulated to be robust to the variability (in size and direction) of the net electrical energy from the secondary reserve dispatch. The influence of forecast errors is also studied, in particular its impact on reserve shortage situations, and a market settlement scheme with a penalty term for reserve shortage situations is also proposed. Finally, an operational management algorithm is also described, which is essential to coordinate the EV charging during the operating hour to comply with the market commitments, while in [12] this was identified as future work.

Compared to the approach described by Bessa et al. [14], the present paper makes several innovations: the formulation of the optimization problem includes the possibility of offering a reserve band in both upward and downward directions; it disregards the need to forecast the reserve direction and participation factor; the optimization uses forecasts for each EV; an operational management algorithm is proposed for coordinating EV charging and for minimizing the difference between contracted and realized values of energy and reserve. Compared to the approach described by Bessa and Matos [16] for the manual (or balancing) reserve, the day-ahead and operational management problems described in this paper are different, since they were developed taking into account the characteristics of secondary reserve. For example, the proposed day-ahead optimization model does not derive the reserve bids based on the forecasted reserve direction (that was found to be almost random), but it offers a reserve band in both directions and the operational management algorithm is based on a strategy that redefines the EV fleet's operating point in order to maximize the available secondary reserve.