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Abstract. This paper addresses a development of a support management system for a power system aggregator managing a fleet of electric vehicles and bidding in a day-ahead electricity market. The support management system is modeled by stochastic mixed integer linear programming approach. The charge and discharge of the batteries of the fleet of vehicles are brought about to a convenient contribution for the maximization of the expected profit of the aggregator. The optimization takes into consideration the profiles of usage of the vehicle owners and the battery degradation of the vehicles. The vehicles are assumed as bidirectional energy flow units: allowing grid-to-vehicle or vehicle-to-grid operation modes. A strong interaction of information exchange is assumed between the aggregator and vehicle owners. A set of scenarios is created by a scenario generation method based on the Kernel Density Estimation technique and are subjected to a reduction by a K-means clustering technique. A case study with data of Electricity Market of Iberian Peninsula is presented to drive conclusion about the support management system developed.

Keywords: Electric vehicles aggregator; day-ahead market; scenario generation; scenario reduction; stochastic programming.

1 Introduction

The anthropogenic greenhouse gas emission is mostly coming from fossil fuels usage, being the sector of transports in charge of approximately 15% of total emission [1] and said to be responsible for 28% of the total energy usage in most countries [2]. Although in the recent past, measures have taken to reduce greenhouse gas emissions from transports. For instance, measures to persuade for the heightening of the usage of an electric vehicle (EV), appealing to this usage instead of the conventional fossil fuels vehicles [3]. The desired rise on the EV market penetration has remained limited, due to issues concerned with: EV acceptance; high costs; short driving range; high battery price; time to recharge the battery, battery degradation and the scarce concentration of geographic handy public charging stations. Although, integration in the electric power system of numerous EVs seems to be a menace for the grid in the sense that, if most vehicles are parked for charging during the night or the day at some periods, these periods are likely to be new peaks of consumption. At the same time, the penetration of EV is an opportunity of new business in energy markets. Hence, EV electric power management is an opportunity and an important line of research [4] to deliver knowledge for power system EV aggregators (EVA) as market agents with functionality of: i) acting as an intermediary between EV owners and the market operator; ii) preventing degradation of batteries by a convenient energy management; iii) deciding for profitable bids in a day-ahead electricity market. Hence, an EVA must be supported with computational applications to convenient face the functionality [5].

Although the problem of bidding in electricity markets has already a significant state-of-art, the participation of an EVA in electricity markets justifies a specific research approach due to the functionality to be faced. EVA management has been researched according to the consideration of flow of electric energy relatively to the grid: unidirectional [6], i.e., grid-to-vehicle (G2V); bidirectional [7], i.e., G2V and vehicle-to-grid (V2G). Two lines of research address this management and have been developing computational application for market environments. The first line considers that EVs although random units can be modelled as deterministic ones [8,9], implying a lack of consideration of uncertainty. Following this line: [8] proposes an optimization algorithm to manage optimal charging and discharging of EVs controlled by aggregators, offering, also, ancillary services in electricity markets; [9] proposes an algorithm for EVs providing unidirectional vehicle-to-grid regulation. The second line considers uncertainty in the EVs [10-16]. Following this line: [11] proposes a stochastic dynamic programming model in order to optimize the EV charging periods and the frequency regulation capacity bids; [12] proposes a stochastic optimization methodology for management of EV and considers the participation of the EVA in both day-ahead market and regulation market; [13] proposes a methodology based in stochastic optimization for aggregators having demand-side resources, e.g., plug-in electric vehicles and distributed generation, including in the formalization the risk management; [14] proposes a stochastic programming model for EVA participation in both day-ahead market and ancillary service markets, including in the formalization equilibrium constraints; [15] proposes a methodology based in robust optimization for the charging strategy of an EVA to reduce the charging costs and taking into account renewable generation; [16] proposes a stochastic scheduling of EVA for participation in energy and ancillary service markets, including in the formalization the consideration of uncertainty in EVs energy requirements and risk management. The state-of-the-art mainly addresses the simulation of EV owners and EVA or market participants managing EV in coordination with other power sources, e.g., renewable energy sources or even conventional power sources based on fossil fuels. This paper follows the second line of research and has contributions to the knowledge of this line on the modeling of: the uncertainty, regarding not only market prices, charging and discharging, but also on driving requirements of the owners of the EVs; the G2V and V2G incorporation for the support information management. The problem is treated as stochastic optimization problem reformulated as a mixed-integer linear programming (MILP) approach in order to benefit from well-established and successful commercial solvers.

2 Relationship to Industrial and Service Systems

The 18th century industrial revolution, said to be the First Industrial Revolution, brought into force the historically never seen before paradigm of industrialization and urban society. Subsequent research and development have delivered scientific evolution triggering technological innovation for industrial and service systems with significative impact into the society. After a said industrial revolution, a new set of technological innovation with significative impact into the society, i.e., expressively changing the society, is categorized as a consequent born age said to be the following industrial revolution. In nowadays a view of a new set of technological innovation for industrial and service systems points into what is said to be the paradigm of a fourth industrial revolution, i.e., Industry 4.0 [17]. Industry 4.0 indorses the interconnection of physical items such as sensors, devices and enterprise assets, interfacing with one each other directly or by the Internet [17-21], allowing Cyber-Physical Systems (CPS) processes. The main characteristics of these processes are decentralization and autonomous behavior [17]. An EVA having EVs G2V and V2G in the new set of innovation is in the scope of a CPS interfaced with information systems with real-time digital platform services. This EVA must be interfaced with urban infrastructures, allowing capabilities of smart grids to schedule the batteries in an environment of smart cities [22]. Demand side involvement in a power system is a functionality linked with smart grids and EV usage can enable active demand side involvement in the operation of power systems. The communication and computation requirements adopted by an EVA must include advanced metering infrastructure (AMI), supervisory control and data acquisition (SCADA), cellular communications and other wireless communication technology [23]. Technological innovation software for the EVA is needed for taking full advantage of EV G2V and V2G, persuading customer for benefits of being with an EVA and consequently favoring the desired rise on the EV market penetration [22].

3 EVA Problem Formulation

Electricity markets normally impose to the participation a requirement of minimum limit of energy for bidding, either affecting bids for selling or for purchasing energy [24,25]. This requirement implies that power sources or loads that do not satisfy the requirement are not allowed to go into the market, e.g., a singular EV. Then an EVA aggregating EVs is a feasible alternative, acting as a manger intermediator between EV owners and the electricity market. A strong interaction is assumed between EV owners and the respectively EVA to have in due time the information accessibility for taking the most convenient decisions. Hence, the EV owners are assumed to communicate to the EVA the driving requirements of owners and the availability of energy in a time horizon of 24 hours. The communication identify the EV owner requirements and flexibility for charge or discharge energy during the 24 hours. Then the main objective of the EVA is to optimize the management of the fleet of EVs, taking convenient decisions of buying energy to charge the EVs or of selling energy by discharging the EVs and considering battery degradation due to cycling. This objective is modeled in the context of presenting profitable bids in the day-ahead electricity market by deciding the optimal charging and discharging periods, subjected to requirements of the owners of the EVs. Despite the fact that most of the current handy public charging stations only allows G2V mode of operation, in this paper is assumed that the charging stations also allow V2G operation as the possible future setting to be expected in a smart city context. The objective function for this management can be stated as a cost or as in this paper by the expected profit associated with the bidding in the day-ahead market stated as follows:

$$\sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\sum_{e=1}^{N_{EV}}\frac{1}{N_S}\left(\lambda_{st}^{DA}P_{ste}^{D}-\lambda_{st}^{DA*}P_{ste}^{C}+\zeta E_{ste}^{R}-C_{ste}^{Deg}\right) \tag{1}$$

In (1) $\lambda_{st}^{DA} P_{ste}^{D}$, $\lambda_{st}^{DA*} P_{ste}^{C}$, ζE_{ste}^{R} and C_{ste}^{Deg} are the revenue associated with the selling offer, the cost associated with the purchasing offer, the cost of driving requirements, cost of battery degradation of each EV at scenario *s* and period *t*, respectively. N_S, N_T, N_{EV} are the number of scenarios, the number of periods and the number of EVs, respectively. The scenarios are equiprobable ones, i.e., a probability of $1/N_S$ is assumed for each scenario in (1). Considering the driving requirements and the battery size equivalent for the whole EV in the fleet, the EVA can be seen as a manager of one equivalent bulky load/battery. The objective function in (1) is reformulated for convenience and the mathematical programming problem is stated as follows:

$$\max \sum_{s=1}^{N_S} \sum_{t=1}^{N_T} \frac{1}{N_S} \left(\lambda_{st}^{DA} P_{st}^{D} - \lambda_{st}^{DA*} P_{st}^{C} + \zeta E_{st}^{R} - C_{st}^{Deg} \right) \tag{2}$$

subject to:

$$\underline{P^D} \sigma_{st}^{D} \leq P_{st}^{D} \leq \overline{P^D} \sigma_{st}^{D} \quad \forall s, \quad \forall t \quad \text{and} \quad \underline{P^C} \sigma_{st}^{C} \leq P_{st}^{C} \leq \overline{P^C} \sigma_{st}^{C} \quad \forall s, \quad \forall t \tag{3}$$

$$0 \leq \sigma_{st}^{D} \leq \sigma_{st}^{A} \quad \forall s, \quad \forall t \quad \text{and} \quad 0 \leq \sigma_{st}^{C} \leq \sigma_{st}^{A} \quad \forall s, \quad \forall t \tag{4}$$

$$\sigma_{st}^{D} + \sigma_{st}^{C} \leq \sigma_{st}^{A} \quad \forall s, \quad \forall t \tag{5}$$

$$SoC_{st} = SoC_{st-1} + \frac{\eta^C P_{st}^C}{\overline{E}} - \frac{P_{st}^D}{\overline{E} \eta^D} - \frac{E_{st}^R}{\overline{E}} \quad \text{and} \quad \underline{SoC} \leq SoC_{st} \leq \overline{SoC} \tag{6}$$

In (2), $\lambda_{st}^{DA} P_{st}^{D}$, $\lambda_{st}^{DA*} P_{st}^{C}$, ζE_{st}^{R} and C_{st}^{Deg} are the scenario *s* and period *t* revenue associated with the selling offer, cost associated with an eventual reduced tariff for the purchasing offer, revenue associated with the equivalent total driving requirement and the cost associated with degradation of the batteries of the EV fleet, respectively. In $\lambda_{st}^{DA} P_{st}^{D}$, λ_{st}^{DA} is the day-ahead market price and P_{st}^{D} is the selling offer, i.e., the total energy discharged by the EV fleet. In $\lambda_{st}^{DA*} P_{st}^{C}$, λ_{st}^{DA*} is the eventual reduced tariff in order to favor of the operation in V2G mode and P_{st}^{C} is the purchasing offer associated with the charging of the batteries of the fleet of EVs. In ζE_{st}^{R}, ζ is a fixed tariff between the EVA and the EV owners for the energy due to driving requirementsE_{st}^{R}. A compensation to the EV owners for the eventual degradation of the batteries if called to discharge is modeled by the cost C_{st}^{Deg} stated as in [26] as follows:

$$C_{st}^{Deg} = \left| \frac{m}{100} \right| \left(\frac{P_{st}^{C} + P_{st}^{D} - E_{st}^{R}}{\overline{E}} \right) C^{B} \tag{7}$$

In (7) m is the linear approximated slope of the battery life as function of the number of cycles [26], $\overline{E}$ is the EV fleet battery capacity, and C^B is the total cost of the EV fleet battery. The EVA because of energy driving requirements reduces the cost of the degradation of the batteries by the subtraction of E_{st}^{R} shown in (7). In (3) and (4), σ_{st}^{D} and σ_{st}^{C} are the binary variables to control the discharging and charging cycles and setting lower and upper bounds $\underline{P^D}/\underline{P^C}$ and $\overline{P^D}/\overline{P^C}$ for discharging and charging continuous variables, respectively. In (4) and (5) is constrained the discharging and charging cycles accordingly to the availability variable σ_{st}^{A} stated as follows:

$$\sigma_{st}^{A} = \begin{cases} 1, & EV\ fleet\ \ available \\ 0, & EV\ fleet\ \ unavailable \end{cases} \tag{8}$$

In (4) is set the lower and upper bounds of σ_{st}^{D} and σ_{st}^{C}. Three events can occur to the EV fleet: event 1, discharging ($\sigma_{st}^{A} = 1$; $\sigma_{st}^{D} = 1$, $\sigma_{st}^{C} = 0$); event 2, charging ($\sigma_{st}^{A} = 1$; $\sigma_{st}^{D} = 0$, $\sigma_{st}^{C} = 1$); event 3, unavailable ($\sigma_{st}^{A} = 0$; $\sigma_{st}^{D} = 0$, $\sigma_{st}^{C} = 0$). In (6) is defined the equation of balance of the virtual battery, where SoC_{st},η^{D} and η^{C} are the state of charge, the discharging efficiency and the charging efficiency, respectively. Also, in (6) is set the lower and upper bounds of SoC_{st}, $\underline{SoC}$ and $\overline{SoC}$, respectively.

4 Scenario Generation and Reduction

Kernel density estimation (KDE) is employed for estimating the probability density curve of day-ahead market prices, availability and driving requirements of the EV fleet managed of the EVA. KDE allows the nonparametric estimation of a density f for a set of observations of a random variable [27]. The kernel density estimator can be stated as follows:

$$\widehat{f}_{h}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{9}$$

In (9), n is the sample size, x_i are random samples from the unknown distribution, h is the bandwidth, and $K(\cdot)$ is the kernel smoothing function. As result of the KDE employment a set of random numbers, the scenarios, are generated from the fitted kernel distribution. In the case study in this paper, a generation of the 1000 scenarios is considered and this number of scenarios is submitted to a K-means clustering algorithm for a convenient reduction, grouping scenarios based on an identification of similarities. The objective is to find groups of scenarios having significant similarity and associate with a group one scenario to be considered as the equivalent scenario in what regards the information needed for taking the convenient decisions [28]. The advantage of the K-means is the simplicity, efficiency and scalability [28]. Let $S = \{S_1 \ldots, S_I\}$ be a set of clusters S_i given by a set of scenarios belonging by clustering to S_i, I the number of clusters and $dist$a chosen metric, providing a way to measure how close two scenarios are. Let the centroid of a cluster S_i be the mean vector, $c_i = \frac{1}{|S_i|}\sum_{y \in S_i} y$, the K-means employs iterative refinement to deliver the set of clusters stated as in [28] as follows:

$$\underset{S}{argmin} \sum_{i=1}^{I} \sum_{y \in S_i} dist(c_i, y)^2 \tag{10}$$

In (10) the final set of clusters is identified by the minimization of the metric, for instance, giving the distance between the day-ahead market prices profiles y and the centroid of the cluster c_i of the day-ahead market prices.

5 Case Study

A bidding strategy of the EVA is accessed with data of Electricity Market of Iberian Peninsula given in [29] and of driving and parking patterns of European drivers given in [30]. The EVA manages 1000 EVs of 25 kWh each one, i.e., 25 MWh. For simplicity, the driving periods of the EVs are assumed to be the same. The cost of each battery is 250 €/kWh and the respective linear approximated slope m is of -0.0013 [26]. The EV distance/consumption ratio is of 6 km/kWh. The maximum charge and discharge power of the EV fleet is of 10 MW. The minimum and maximum SoC of the bulky battery are 20% and 80%, respectively. Considering the uncertainties regarding market prices and EV fleet driving requirements and availabilities, the 1000 scenarios are generated by the KDE. Then, the scenarios are reduced to a set of 10 scenarios for each uncertainty parameter. The original scenarios and the 10 reduced final scenarios of day-ahead market and the driving requirements final scenarios of the EV fleet are shown in Fig. 1.

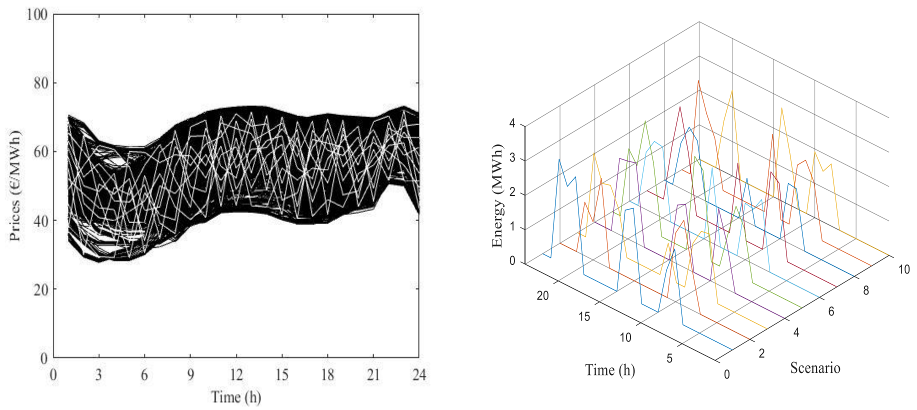

Fig 1. Left: Day-ahead market prices: black – scenarios, white – reduced scenarios; right: scenarios of driving requirements of the EV fleet.

In Fig. 1 left, the price scenarios show a tendency to have unfavorable values between hour 3 and hour 6 and a tendency to have favorable ones between hour 21 and hour 23. Note that these prices are generated applying the KDE and reduced by K-means clustering. In Fig. 1 right, when the energy requirement is different of 0, means that the EV fleet is unavailable to charge (G2V) or discharge (V2G). When the energy requirement is 0 the EV fleet is not driving, then the EV fleet can operate both in G2V or V2G modes. The result of the EVA management of the fleet of EVs, i.e., the optimal charging/purchasing offers and discharging/selling offers, are shown in Fig. 2.

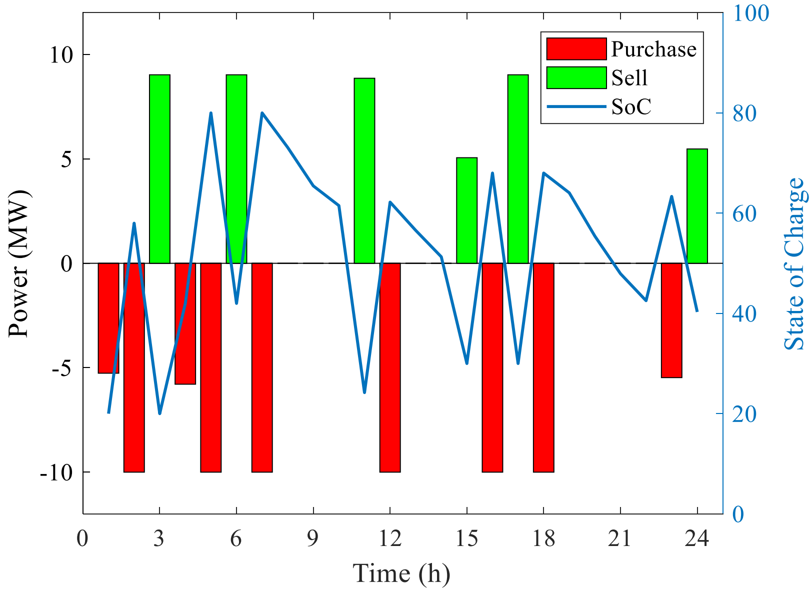

Fig 2. Day-ahead market bids and SoC of the EV fleet.

In Fig. 2 the optimal offers to purchase energy, to charge the fleet of EVs, the optimal offers to sell energy by discharging the fleet of EVs, and the SoC of the EV fleet are shown in red, green and blue, respectively. The SoC starts with a value of 20%, i.e., starts with the mandatory minimum value, and varies during the time horizon due to the charge of the batteries, energy consumption and energy sold to the market. The proposed management system in this paper allows the EV owners to be inflexible in what regards the driving patterns. So, the EVA only has power over the periods in which the EV owners are not driving to contribute to the purchase/sell of energy in the day-ahead market. The EVA management is as expected highly affected by the driving periods, which in some cases are periods of high market prices, where selling of energy is advantage, but inflexible requirements do not allow selling energy. This case study allows an EVA instance with an expected profit of € 338 in the day-ahead market, i.e., covering the costs: of charge of the batteries of the fleet, of driving requirements and of battery degradation. But notice that this EVA instance is with an expected profit having a non-null value, if and only if, the EVA is rewarded for discharge energy to the grid.

6 Conclusion

A support management system for an EVA bidding in day-ahead market is proposed in this paper to contribute with technological innovation in a context of smart grids for smart cities, consenting EV G2V and V2G. The problem is formulated as a stochastic mixed-integer linear programming approach. The scenarios of market prices, driving requirements and availabilities of EV are modelled applying a Kernel density estimation. The scenarios are reduced applying the K-means algorithm. A strong interaction between the EV owners and EVA is assumed, but the EVA is subjected to the requirement of taking only control over the periods in which the EV owners are not driving. This requirement is normal imposed by an owner of an EV, i.e., the driving patterns are valued as inflexible ones. The EVA management has possibility to be with an expected profit having a non-null value, since the difference between selling energy in the day-ahead market can be higher than the total cost incurred by the fleet of EV's: costs of charging batteries, of driving requirements and of battery degradation. But this is possible in an environment of an EV fleet operation in G2V or V2G modes not only due to convenient management of the EVA, but also due to the amplitude of the variation on the prices of energy in the day-a-head market.

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