Optimised Performance of a Plug-in Electric Vehicle Aggregator in Energy and Reserve Markets

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Abstract

In this paper, a new model is developed to optimize the performance of a plug-in Electric Vehicle (EV) aggregator in electricity markets, considering both short- and long-term horizons. EV aggregator as a new player of the power market can aggregate the EVs and manage the charge/discharge of their batteries. The aggregator maximizes the profit and optimizes EV owners' revenue by applying changes in tariffs to compete with other market players for retaining current customers and acquiring new owners. On this basis, a new approach to calculate the satisfaction/motivation of EV owners and their market participation is proposed in this paper. Moreover, the behaviour of owners to select their supplying company is considered. The aggregator optimizes the self-scheduling program and submits the best bidding/offering strategies to the day-ahead and real-time markets. To achieve this purpose, the day-ahead and real-time energy and reserve markets are modelled as oligopoly markets, in contrast with previous works that utilized perfectly competitive ones. Furthermore, several uncertainties and constraints are taken into account using a two-stage stochastic programing approach, which have not been addressed in previous works. The numerical studies show the effectiveness of the proposed model.

Keywords: EV aggregator, batteries charge/discharge management, power market strategies, long-term profit.

1. Introduction

1.1. Motivation and Aim

Today, replacement of combustion vehicles with electric ones makes the management of this resource more important than before. Since the importance of energy conservation and environmental protections is growing, plug-in Electric Vehicles (EVs) can significantly affect the grid and play a major role in the future smart grid [1]-[4]. References [1]-[4] showed that, if there was not a comprehensive plan for EVs management, not only the EVs would deteriorate the conditions of distribution network, but also their charge time might be simultaneous with the system load peak and increase the stability, reliability and economic problems of the power system.

At any given time, at least 90% of the EVs are theoretically available to behave as a generation unit and participate in the electricity market [5], [6]. Ref. [7] has indicated that, the daily average travel distance in the United States is less than 51

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kilometres, leading an average time of 52 minutes to commute, although the commuting times vary from one city to another one. On this basis, in average, EVs are located in the parking spaces about twenty-three hours per day and the distance driven is less than the EVs' battery capacity. It can be concluded that, the entire energy of EVs is not consumed during daily travel [7].

Although EVs are able to provide various ancillary services [8], the simultaneous connection of numerous EVs to the network can be a major threat for the power quality and even the power system stability [9]. EV aggregator as a new player of the power market can aggregate the EVs and manage the charge/discharge of their batteries.

Recent advances in smart metering technologies provide a bi-directional communication between the utility operator and the consumers. To this end, the EV aggregators offer incentives to the EV owners, usually in the form of monetary rewards, to allow them to operate their EV batteries. In this context, smart metering devices can positively affect the future of smart grid by obtaining precise information and effective involvement of the EV owners. On the other hand, since a large number of managing and controlling data in the network imposes market participants to employ new computational methods to mitigate the system operation time, the utilization of future advanced analysis techniques is required. Therefore, development of the future advanced analysis techniques can significantly facilitate the aggregation of EVs. Therefore, both smart metering technology and advanced analysis techniques (e.g. collective awareness systems [10] and cloud-based engineering systems [11]) are required to support the participation of EVs in the electricity markets and they can be an effective solution to increase the participation of EV owners in the markets.

As a matter of fact, the EV aggregators can provide connectivity communication capabilities for EV owners' components in order to connect them to the analysis system and they are responsible for the installation of the smart meters at EV owners' premises. This can reduce the technical complexity and the required efforts to increase the local computational resources at the level of each EV owner's component. On the other hand, the advanced techniques can improve the security of the mechanisms and consequently they can increase the robustness of collecting data by the aggregators.

In this paper, a new model is described to optimize the performance of the EV aggregator in electricity markets. The EV aggregator as a financial agent in the power market has to compete with other players to sell or purchase electricity in the day-ahead and real-time markets. In the business competition, the aggregator has to compete for keeping the existing customers and attracting new owners. In other words, the aggregator should struggle with other market participants in three sides: offering strategy with Generation companies (Gencos), bidding strategy (with retailers) and customers (also with retailers).

The aggregator is considered as a private entity who wants to maximize its own profit. The player is able to manage its customers' charge and discharge pattern using a direct control approach when they are plugged-in. The paper models that the EV owners can select their supplying company for buying/selling electricity, so the EV aggregator should compete with other market players to preserve and increase the number of customers by optimizing its proposed prices in the contract. The competition of the EV aggregator for customers has not been addressed in previous works. The competition space of the aggregator is illustrated in Fig. 1.

The new model developed in this paper considers the impact of tariffs to motivate the owners to participate in the electricity market and to connect to the aggregator.

"See Fig. 1 at the end of the manuscript".

On this basis, short- and long-term objectives of the EV aggregator are simultaneously considered, involving both grid-to-vehicle (G2V) and vehicle-to-grid (V2G) capabilities. The short-term objective is to maximize the profit obtained from offering/bidding strategy of the aggregator in the electricity markets, while the long-term one is to maximize the profit resulted from grabbing the market share from other competitors. The participation of EV owners (both new and existing customers) in each month is also calculated, using a motivation function.

1.2. Literature Review and Contributions

Many reports have presented the advantages and disadvantages of EVs without V2G capability [9], [12]-[13]. In [9], a stochastic programming method was presented to demonstrate the influence of EVs' charging on the distribution network. In [12], the charging strategies have been studied to achieve the lowest energy losses in the distribution network. In [13], a decentralized control of EVs has been presented to coordinate their charging. In other researches the diverse impacts of EVs with V2G capability have been studied [14]-[16]. In [14], the economic advantages of V2G systems have been reported. In [15], a centralized control strategy based on a dynamic programming method has been accomplished to obtain the maximum of EVs' income from frequency regulation. In [16], the aggregated EVs have been modelled to be utilized in long-term simulation.

From the EV aggregator's point of view, several frameworks have been proposed to improve the participation of EV aggregators in electricity markets. In [17], a framework has been described to integrate the EVs in the planning and operation studies. In [18], a heuristic charging strategy has been presented to provide the regulation service. Moreover, a heuristic algorithm has been developed to manage the EVs charging in reaction to prices in a traditional power system [19]. In [20], the bidding strategy of an EV aggregator has been optimized by using a stochastic approach, considering the uncertainty for the energy content of regulation signals. In [21], a methodology has been presented to maximize EV aggregator profit considering the uncertainties of market prices and fleet mobility. In [22], an optimization algorithm has been proposed to manage the individual charging of EVs, in order to ensure a reliable supply of manual reserves. In [23], a model has been proposed to support the participation of an EV aggregator in day-ahead spot and secondary reserve markets. In [24], the energy and reserve scheduling have been studied by both EV aggregators and the distribution system operator. In [25], an approach has been proposed to coordinate the system operator and an EV aggregator in order to enhance the efficiency and security of the power system. Reference [26] addressed EV charge patterns and the electricity generation mix and competitiveness of next generation vehicles. In [27], the effects of changes in market rules and regulations on the EV aggregator's profit have been reported.

Nevertheless, in most of the reports it has been assumed that EV variables are deterministic, so no uncertainties have been considered and perfect forecasts are assumed. In addition, no appropriate model has been presented to predict the behaviour of vehicle owners, and these models are not able to consider the long-term effects of changing the tariffs. Moreover, many constraints have been ignored for the aggregator and EV owners in previous reports. Furthermore, in former researches there is no accurate electricity market model from the aggregator's point of view. All these issues are now addressed in this paper as new contributions.

In the proposed model several uncertainties have been considered, such as behaviour of market player in energy and spinning reserve (SR) markets, number of connected EVs, the connection duration of EVs to the aggregator, the quantity of energy stored in the batteries, and regulation requests to the aggregator by the Independent System Operator (ISO) for power generation. In addition, the constraints of minimum connection duration of EVs to the aggregator and minimum battery charge of EVs have been considered. Since the customers' profits have significant effects on the customers' satisfaction, the model also considers the costs of the charging infrastructure, including V2G inverters, battery degradation and fleet management. Furthermore, the tariffs are proposed in such a way that they encourage EV owners to take part.

In previous reports, modelling the EV aggregator in the electricity market can be categorized in two major approaches:

1) Modelling the aggregator in the perfectly competitive electricity market;

2) Modelling the aggregator in the electricity market from the ISO's point of view.

In some reports [27], the EV aggregator in an oligopoly market has been considered. However, these reports studied the EV aggregators from the ISO's viewpoint and they supposed that all characteristics of market players are available (complete information game theory). Although, these kinds of models are suitable for ISO that has more information about characteristics of market players, they are not convenient for market participants such as EV aggregators that have only some limited information about other players. In the future, by increasing the number of EVs, the EV aggregators will play a more important role in power market prices. On this basis, modelling the aggregators as price making players in an oligopoly power market is vital. Therefore, this paper proposes a new model for the EV aggregator in the oligopoly electricity markets as far as it is concerned. In this model, it is supposed that all information of market competitors (e.g. cost function of generation units) is not available for the aggregator, very similar to reality (incomplete information game theory [28]).

According to the above expression, the new contributions of the paper can be summarized as follows:

- Modelling the oligopoly behaviour of an EV aggregator in an incomplete information electricity market
- Modelling the long-term objective of an EV aggregator to enhance its market share by modelling EV owners' satisfaction
- Optimizing the long-term behaviour of an EV aggregator by calculating the optimal tariffs

1.3. Paper Organization

The paper continues as follows: Section 2 models the uncertainty characteristics related to competitors' cost and revenue functions and EV owners' behaviour. In section 3, the formulation of EV aggregator's self-scheduling is explained. Modelling the oligopoly electricity market from the aggregator's point of view is shown in section 4. Modelling the customers' motivation to contract with the aggregator is expressed in section 5. Numerical studies are implemented in section 6. Finally, last section is devoted to the conclusion.

2. Uncertainty Characterization

EV aggregators are threatened by several uncertainties in order to take part in the electricity markets. In this section, modelling of the uncertainties and the two-stage stochastic programming approach to employ the uncertain variables are presented. In this paper, two major sets of uncertainty are considered, namely regarding the uncertainties of EV owners' behaviour and market uncertainties. Market uncertainties include the uncertain behaviour of market players and being called by ISO to generate energy. Modelling the above mentioned uncertainties is expressed as following:

2.1. Uncertainty of EV owners' behaviour

The EV aggregator has been confronted with plenty of uncertainties to participate in the market because of the probabilistic behaviour of EV owners. The uncertain parameters include the number of EVs connected to aggregator per hour, connection duration and state of charge (SOC) of batteries of EVs (while connecting to the aggregator). The EV owners behave differently due to social and economic concerns. Therefore, connection duration and SOC of each EV will be different from other EVs. The aggregator should estimate the uncertain parameters of probabilistic behaviour of EV owners by using past statistical data.

In this paper, the aggregator models the estimation uncertainty by using a probabilistic approach. For this purpose, the aggregator uses the statistical data of EVs and generates scenarios based on time series of uncertain variables using Roulette Wheel Mechanism (RWM) [29] and [30]. Since the time series of all related stochastic variables have been generated together on the basis of a unique historical data, the correlation between stochastic variables and subsequent hours has been considered.

In this paper, EVs' pattern has been obtained from the real data in [31]. The aggregator should mitigate the risk of unreliable forecasts of EV owners' behaviour; because EVs are its only source to take part in electricity markets. To this end, RWM has been employed to generate probable scenarios to tackle the forecast errors. Considering the scenarios enables the EV aggregator to take into account the plausible deviations around the predicted number of EVs. Normal distribution has been applied to generate scenarios, because forecast errors regularly have a distribution absolutely close to Normal [32].

According to Normal distribution, quantity and the probability of scenarios are associated to mean value, « , and standard deviation, ± , of the predicted number of EVs. Since the closer time to the market closure causes the more accurate forecast of the number of available EVs, the standard deviation in the real-time session is considered to be less than that in the day-ahead session. This means that, the aggregator's forecast of its customers in the real-time stage has a less deviation from the actual value than in the day-ahead stage (i.e. $\sigma^{RT} < \sigma^{DA}$). Moreover, the mean value of the number of available EVs in both the mentioned sessions is considered to be equal to the actual value that will be used in the realization session.

Total accumulated SOC of EVs, as another uncertainty, depends on available EVs, type of EVs and their travelled distances. The battery capacity of each EV depends on the EV class. In [33], twenty four different EV battery classes and their redundancy have been presented. In this paper, the capacity of each EV is considered to be equal to one of the twenty four EV classes and it is associated with a probability equal to the redundancy of that class as illustrated in Fig. 2. In [34], lognormal distribution has been employed to generate probabilistic daily driven distances. On this basis, in this paper lognormal random variables have been generated using (1) [35].

$$M_d = \exp(\mu_m + \sigma_m . N) \tag{1}$$

where M_d denotes the daily travelled distance and N is standard normal variable.

According to historical data, μ_m and σ_m can be obtained from mean value and standard deviation of daily travelled distance that are respectively presented as μ_{md} and σ_{md}, as follows:

$$\mu_m = \ln\left(\mu_{md}^2 \Big/ \sqrt{\mu_{md}^2 + \sigma_{md}^2}\right) \tag{2}$$

$$\sigma_m = \sqrt{\ln\left(1 + \sigma_{md}^2 / \mu_{md}^2\right)} \tag{3}$$

"See Fig. 2 at the end of the manuscript".

In this paper, the probabilistic travelled distance is applied as a parameter of calculating the SOC. The lognormal distribution function is utilized to generate the probabilistic daily travelled distance [34]. The general assumptions to generate the scenarios are based on [31] where an average of 4.2 trips per day, yielding an average daily distance of 63.57 kilometres is considered for each vehicle. On the other hand, an EV takes approximately 0.22 kWh to recharge for each kilometre travelling.

2.2. Modelling the uncertainties of being called by ISO

Being called by ISO is one of the uncertainties of EV aggregator to participate in the reserve market. In this paper, Poisson distribution is proposed to model the probability of being called to generate energy in the spinning reserve market. Since being called has a discrete probability distribution and it can be considered as an event that occurs in a day with a known average rate and it is independent of the number of being called during the previous day, it can be modelled by Poisson distribution. Thus, the Probability Distribution Function (PDF) can be expressed by (4):

$$f(k, \mu) = \frac{\mu^k . \exp(-\mu)}{k!} \quad , \quad \mu > 0 \quad , \quad k = 0,1,2,... \tag{4}$$

where µ and k denote the expected value and the number of being called, respectively. Considering the mentioned PDF, different outcomes of ISO's behaviour for calling EV aggregator are considered by a RWM-based scenario generation process [29] and [30]. The uncertain amount of activated reserve, $Act_{t,\mu}^{Res}$, has been taken into account to be uniformly distributed between zero and EV aggregator's offered quantity. Therefore, PDF of quantity of activated reserve can be formulated as:

$$f(x) = \begin{cases} \dfrac{1}{Offer_{t,\mu}^{Res}} & , \quad 0 \le x \le Offer_{t,\mu}^{Res} \\ 0 & , \quad Otherwise \end{cases} \tag{5}$$

According to Eqs. (4) and (5), diverse regulation requests to the aggregator by the ISO have been considered by employing RWM-based scenario generation [29] and [30].

2.3. Uncertainty of competitors' cost/revenue functions

The behaviour of EV aggregators relies on the behaviour of EV owners and market participants. Incomplete information about market participants' cost/revenue functions enables the aggregator to simply predict their behaviour in the power market. It should be noted that, the range of coefficients of the cost/revenue functions can be estimated [36]. In other words, the cost functions of Gencos are related to type, size, manufacturer, age, etc., of their power plants and the revenue functions of retailers are associated with tariff, number and demand of their customers. On this basis, this basic information is available for the aggregator to estimate coefficients of the above mentioned functions. However, realizing the accurate cost/revenue functions is difficult even to their owners with detailed data [36]. On the other hand, making decisions based on inaccurate models of competitors can create inappropriate results. Therefore, the aggregator should decrease the risk of unreliable estimation. In order to overcome the problem, this paper proposes RWM-based scenario generation to cover the uncertainty of the mentioned estimated coefficients. On this basis, the scenarios for amounts of the cost/revenue function coefficients of market players are generated by RWM. Since estimation errors have a distribution very close to Normal [32], Normal distribution is employed to generate the scenarios of competitors' cost/revenue functions. Therefore, the value and the probability of each scenario is associated to mean value, « , and the standard deviation, ± , of the estimated coefficient (i.e. $a_{i,\mu}$, $b_{i,\mu}$, $c_{i,\mu}$, $e_{j,\mu}$, $f_{j,\mu}$, $a_{i,\mu}^{up}$ and $a_{i,\mu}^{down}$).

2.4. Stochastic Programming Approach

In order to consider the impact of the sources of uncertainty mentioned previously on the strategic behaviour of EV aggregator, they have been characterized as stochastic procedures and the problem has been solved by using a two-stage stochastic programming approach.

In the proposed approach, each stage denotes a market horizon as illustrated in Fig. 3. It should be noted that, the EV aggregator forecasts the prices of the day-ahead and the real-time markets by simulating the proposed oligopoly market framework. It is noteworthy that, the realization session is equivalent to employ the actual EVs' variables and the actual coefficients of the market players' cost/revenue function. The classification of decision variables of each stage is based on the time horizon of electricity markets (day-ahead and real-time) and it is presented as follows:

- Ω1: The first stage (*here-and-now*) stochastic decision variables are $D_{j,t,\mu}^{DA}, Offer_{t,\mu}^{En}, Offer_{t,\mu}^{Res}, Offer_{t,\mu}^{NRes}, P_{i,t,\mu}^{DA}$, $P_{i,t,\mu}^{Res}, P_{i,t,\mu}^{NRes}$, $\text{a}_{t,\mu}^{DA}$, $\text{a}_{t,\mu}^{Res}$ and $\text{a}_{t,\mu}^{NRes}$. In the *here-and-now* stage, the EV aggregator offers/bids both hourly prices and quantities to the day-ahead market. According to the probable realizations of the stochastic procedures consist of EVs' pattern, regulation requests to the aggregator by the ISO and market players' behaviour, decisions of this stage are made.
- Ω2: The second stage (*wait-and-see*) stochastic decision variables are $D_{j,t,\mu}^{RT}, I_{i,t,\mu}, SOC_{v,t,\mu}^{Disconnect}, SOC_{v,t,\mu}, P_{t,\mu}^{del}$, $Act_{t,\mu}^{Res}, P_{i,t,\mu}^{RT}$, $P_{v,t,\mu}^{\mathrm{G2V}}, P_{v,t,\mu}^{\mathrm{V2G}}, r_{v,t,\mu}^{charge}, r_{v,t,\mu}^{discharge}, \Delta_{t,\mu}^{+}, \Delta_{t,\mu}^{-}$, and $\text{a}_{t,\mu}^{RT}$. The *wait-and-see* stage is relevant to the real time market. In the second stage, although hourly prices and quantities of the day-ahead market are known, the prices of the real time market, the regulation requests to the aggregator by the ISO and EVs' behaviour are still unknown. At the end of this stage, the mentioned variables will be known and consequently, hourly deviations incurred by the EV aggregator will be obtained and the subsequent imbalance costs can be calculated.

"See Fig. 3 at the end of the manuscript".

3. EV Aggregator's Self-Scheduling Formulation

Considering several kinds of uncertainties mentioned in Section 2, the EV aggregator should manage the charge/discharge of EVs. In this paper, the constraint of minimum connection duration of EVs to the aggregator has been modelled. Additionally, in order to ensure the owners about the desired charge of their batteries, the model cares about the minimum charge of EVs. The objective function of EV aggregator can be expressed as:

$$\max \sum_{t} \Big\{ \mathrm{E}_{\substack{\Omega 1 \\ \circledR_{t,\mu}}} \Big[Income_{t,\mu}^{Energy} + Income_{t,\mu}^{Res} + Income_{t,\mu}^{NRes} \\ + \mathrm{E}_{\substack{\Omega 2|\Omega 1 \\ \circledR_{t,\mu}}} \Big[Income_{\mu}^{Charge} + Income_{t,\mu}^{Call} + Income_{t,\mu}^{Imb} - Cost_{t,\mu}^{Imb} - Cost_{t,\mu}^{Charge} - Cost_{t,\mu}^{Obl} - Cost_{\mu}^{Res} \Big]\Big]\Big\} \tag{6}$$

$$Income_{t,\mu}^{Energy} = Offer_{t,\mu}^{En} . \text{a}_{t,\mu}^{DA} \tag{7}$$

$$Income_{t,\mu}^{Res} = Offer_{t,\mu}^{Res} . \text{a}_{t,\mu}^{Res} \tag{8}$$

$$Income_{t,\mu}^{NRes} = Offer_{t,\mu}^{NRes} . \text{a}_{t,\mu}^{NRes} \tag{9}$$

$$Income_{\mu}^{Charge} = \sum_{v \in PEV_{tot}} \left[\sum_{t=t_{Connect(v,\mu)}}^{t_{Full(v,\mu)}} P_{v,t,\mu}^{\mathrm{G2V}} . \text{a}_{t}^{ContEn} \right] U_{v,\mu} \tag{10}$$

$$Income_{t,\omega}^{Call} = Act_{t,\omega}^{Res}.\lambda_{t,\omega}^{RT}.P_{t,\omega}^{del} \quad (11)$$

$$Income_{t,\omega}^{Imb} = \lambda_{t,\omega}^{DA}.r_t^{+}.\Delta_{t,\omega}^{+} \quad (12)$$

$$Cost_{t,\omega}^{Imb} = \lambda_{t,\omega}^{DA}.r_t^{-}.\Delta_{t,\omega}^{-} \quad (13)$$

$$Cost_{t,\omega}^{Charge} = \sum_{v \in PEV_{tot}} P_{v,t,\omega}^{G2V}.\lambda_{t,\omega}^{DA} \quad (14)$$

$$Cost_{t,\omega}^{Obl} = FOR^{Agg}.Act_{t,\omega}^{Res}.P_{t,\omega}^{del}.\lambda_{t,\omega}^{RT} \quad (15)$$

$$Cost_{\omega}^{Res} = \sum_{v \in PEV_{tot}} \left[\sum_{t=t_{Connect(v,\omega)}}^{t_{Full(v,\omega)}} P_{v,t,\omega}^{\mathrm{G2V}}.\lambda_{t}^{ContRes} \right] U_{v,\omega} \quad (16)$$

$$\Delta_{t,\omega} = P_{t,\omega} - Offer_{t,\omega}^{En} \quad (17)$$

$$\Delta_{t,\omega} = \Delta_{t,\omega}^{+} - \Delta_{t,\omega}^{-} \quad (18)$$

where $U_{v,\omega}$ is a binary number equal to 1, if the EV owner respects to the minimum connection duration in scenario ω, and 0 otherwise. $P_{t,\omega}$ is the actual amount of the generated power.

Eq. (6) indicates the objective function of the scheduling problem and denotes the components of aggregator's profit. The objective of the aggregator is maximizing the profit in a certain period. Obviously, the profit is dependent on the behaviour of the aggregator in the markets and, subsequently, it is a function of uncertain variables that occur in day-ahead and real-time study horizon. The aggregator income resulted from participation in the day-ahead energy market has been considered in (7). The aggregator income resulted from the participation in the non-spinning and spinning reserve markets have been considered in (8) and (9), respectively. Eq. (10) represents the aggregator income resulted from receiving the batteries charge cost from EV owners who have respected the minimum connection duration. Eq. (11) considers the aggregator income resulted from being called by the ISO in order to generate electrical energy in the reserve markets. Eq. (12) represents the imbalance income because of the surplus of injection compared to day-ahead offers. Eq. (13) represents the imbalance cost due to lack of injection in comparison with day-ahead offers. Eq. (14) denotes the purchase cost of electrical energy from the energy market in order to charge the battery of EVs in scenario ω. The inability of the aggregator to generate energy at the time of being called by ISO may be caused by an error in predicting uncertain parameters. In order to model the reliability of the distribution system FOR^{Agg} is considered. Eq. (15) represents the purchase cost of electrical energy in order to meet the aggregator obligations while being called to generate energy in the reserve markets. Eq. (16) denotes the cost of the contract with EV owners to persuade them to participate in the reserve markets. Equations (17) and (18) have been employed to obtain energy deviations using the scheduled energy. The objective function is maximized considering the constraints described below:

$$[SOC_{v,t,\mu}^{Disconnect} \geq MCB].U_{v,\mu} \tag{19}$$

$$0 < SOC^{\min} \leq SOC_{v,t,\mu} \leq SOC^{\max} < 1 \tag{20}$$

The constraints of MCB (minimum charge of battery) of EVs are formulated as (19), and these limitations should be met by the aggregator for the EV owners who respected the minimum connection duration. Eq. (20) is applied to avoid being overcharged and to take into account the depth of discharge of all connected EVs during their connection.

$$SOC_{v,t,\mu} = SOC_{v,t-1,\mu} + \delta_{v,t,\mu}.\eta_v^C.P_{v,t,\mu}^{\text{G2V}} - (1-\delta_{v,t,\mu}).P_{v,t,\mu}^{\text{V2G}} \tag{21}$$

Eq. (21) introduces changes in SOC of EVs. Binary variable δ ensures that an EV is not charged and discharged at the same time.

The constraints of maximum charging/discharging rates depend on their infrastructures [37] and they can be formulated as below:

$$r_{v,t,\mu}^{charge} = \left(SOC_{v,t,\mu} - SOC_{v,t-1,\mu}\right) / \eta_v^C \leq r_v^{charge,\max} \tag{22}$$

$$r_{v,t,\mu}^{discharge} = \left(SOC_{v,t-1,\mu} - SOC_{v,t,\mu}\right).\eta_v^D \leq r_v^{discharge,\max} \tag{23}$$

Eqs. (24) and (25) ensure that the aggregator will offer to the energy and reserve markets, based on the power of EVs in V2G mode.

$$Offer_{t,\mu}^{En} \leq \sum_{v \in PEV_{tot}} \left[\eta_v^D.P_{v,t,\mu}^{\text{V2G}}\right]U_{v,\mu} \tag{24}$$

$$Offer_{t,\mu}^{Res} + Offer_{t,\mu}^{NRes} \leq \sum_{v \in PEV_{tot}} \left[\eta_v^D.SOC_{v,t,\mu}.C_v^{EV}\right]U_{v,\mu} \tag{25}$$

4. Modelling the Oligopoly Electricity Market from Aggregator's Point of View

In this paper, by the aim of improving the reality of the studies, the electricity market is modelled as an oligopoly market instead of being perfectly competitive. Therefore, in order to model the oligopoly electricity market, a multi-agent environment based on bi-level optimization has been developed. The basis of the proposed model is the reality of market players' behaviour in the electricity market. Therefore, each agent should behave as if it is a real market participant. On this basis, the structure of the model has been inspired by the real world electricity markets. One of the main differences between the proposed model and the previous ones is that the market is modelled as an oligopoly also from EV aggregator's viewpoint, so the aggregator does not have all information about its competitors. Therefore, the mentioned environment for the aggregator becomes an incomplete information game theory [28]. On this basis, the aggregator and other market players neither know the cost/revenue functions of their competitors nor the competitors' bidding/offering strategies. Each player only knows the generating capacities of every other player. It is noteworthy that the expressed method in Section 2 has been developed to overcome the uncertainties of incomplete information game theory. The details of proposed electricity market model from the aggregator's viewpoint have been expressed as follows.

4.1. Market Players

In order to simulate the electricity market from the aggregator's point of view, an agent-based virtual environment is developed. Each market player (e.g. Gencos and retailers) has been independently modelled by using agents, so that their objective functions correspond to maximize their profit. In this paper, it is supposed that Gencos participate in the spinning and non-spinning reserve markets.

The objective function of each Genco can be formulated as follows:

$$\begin{aligned}\max\{Expected\ \ Profit\} = \max_{\circledR_{t,\mu}} \sum_{t} \Big\{ \mathrm{E}_{\Omega 1}\Big[P_{i,t,\mu}^{DA}.\lambda_{t,\mu}^{DA} + P_{i,t,\mu}^{Res}.\lambda_{t,\mu}^{Res} + P_{i,t,\mu}^{NRes}.\lambda_{t,\mu}^{NRes} \\ + \mathrm{E}_{\Omega 2|\Omega 1}\Big[P_{i,t,\mu}^{RT}.\lambda_{t,\mu}^{RT} - a_{i,\mu} P_{i,t,\mu}^{2} - b_{i,\mu} P_{i,t,\mu} - c_{i,\mu}.I_{i,t,\mu} - \lambda_{i,\mu}^{up}.y_{i,t,\mu} - \lambda_{i,\mu}^{down}.z_{i,t,\mu} \Big]\Big]\Big\}\end{aligned} \tag{26}$$

Subject to:

$$P_i^{\min}.I_{i,t,\mu} \le P_{i,t,\mu} \le P_i^{\max}.I_{i,t,\mu} \tag{27}$$

$$I_{i,t,\mu} - I_{i,t-1,\mu} = y_{i,t,\mu} - z_{i,t,\mu} \tag{28}$$

$$y_{i,t,\mu} + z_{i,t,\mu} \le 1 \tag{29}$$

$$y_{i,t,\mu} + \sum_{j=1}^{MU_i - 1} z_{i,t+j,\mu} \le 1 \tag{30}$$

$$z_{i,t,\mu} + \sum_{j=1}^{MD_i - 1} y_{i,t+j,\mu} \le 1 \tag{31}$$

$$I_{i,t,\mu}.I_{i,t-1,\mu}.(P_{i,t,\mu} - P_{i,t-1,\mu}) \le RU_i \tag{32}$$

$$I_{i,t,\mu}.I_{i,t-1,\mu}.(P_{i,t-1,\mu} - P_{i,t,\mu}) \le RD_i \tag{33}$$

where $y_{i,t,\mu}$ and $z_{i,t,\mu}$ are binary values to show the time of start-up and shut down of the power plant *i* and $P_{i,t,\mu}^{RT} + P_{i,t,\mu}^{DA} = P_{i,t,\mu}$.

Equation (27) denotes the unit output limits. The constraints of minimum up and down times are linearly expressed in (28)-(31). The constraints of unit ramp up and ramp down are presented in (32) and (33), respectively. It should be noted that, in addition to day-ahead and real-time energy markets, the aggregator should compete with the Gencos to supply SR capacity. The other market players are retailers which are modelled as agents with the formulated objective function as follows:

$$\max\{Expected\ \ Profit\} = \max_{\circledR_{t,\mu}} \sum_{t} \Big\{ \mathrm{E}_{\Omega 1}\Big[-D_{j,t,\mu}^{DA}.\lambda_{t,\mu}^{DA} + \mathrm{E}_{\Omega 2|\Omega 1}\Big[-D_{j,t,\mu}^{RT}.\lambda_{t,\mu}^{RT} + e_{j,\mu} + f_{j,\mu}.D_{j,t,\mu} \Big]\Big]\Big\} \tag{34}$$

where $D_{j,t,\mu}^{DA} + D_{j,t,\mu}^{RT} = D_{j,t,\mu}$.

Like the EV aggregator, its competitors use the prices of reserve and energy markets, obtained from the previous iteration of clearing the transactions of the market, to determine their bidding/offering strategies in order to participate in the markets for the next iteration. For this purpose, each agent maximizes its profit by using the mentioned prices to obtain the optimal amount of bid/offer in each hour of the next iteration. Afterward, the agents generate their bidding/offering strategies by applying the optimal quantity and price using Supply Function Equilibrium (SFE) model [28]. Therefore, each player uses the SFE vector $(\sim_t^{SFE}\,,\ {}_t^{SFE})$ to submit its offers/bids to the markets, where $\sim_t^{SFE}$ and ${}_t^{SFE}$ are the variables of bidding/offering strategy that denote the slope and the y-intercept of the price-quantity curve, respectively. It should be noted that all market participants are considered as the price-makers, including the EV aggregator. On this basis, after maximizing the players' profit and obtaining the optimal prices and quantities for participating in the markets, the SFE vector is formed. Since the amount of optimal quantity and price ($P_{i,t}^*, \text{a}_t^*$) is known, by assuming $\sim_{i,t}^{SFE} \big/ {}_{i,t}^{SFE}$ equals to a_i / b_i , $\sim_{i,t}^{SFE}$ and ${}_{i,t}^{SFE}$ are obtained as follows:

$$\sim_{i,t}^{SFE} = \frac{a_i \cdot \text{a}_t^*}{b_i + a_i . P_{i,t}^*} \tag{35}$$

$$ {}_{i,t}^{SFE} = \frac{b_i \cdot \text{a}_t^*}{b_i + a_i . P_{i,t}^*} \tag{36}$$

4.2. Clearing the Electricity Market Transactions

The most conventional method to clear power market transactions is Optimal Power Flow (OPF). However, in this paper, the role of ISO in clearing the electricity market and determining auction winners has been defined by using a Security Constrained Unit Commitment (SCUC) problem, which maximizes social welfare considering security constraints.

The main reason for utilizing the SCUC instead of OPF is the inherent nature of EV aggregators. The new players of power market are limited energy participants. Therefore, simulation of their behaviour in an hour (or even in some independent hours) is not accurate, so their behaviour should be modelled in a specific period. Based on this, the SCUC problem is utilized to obtain the most economical solution of electricity market (maximizing the offer-based social welfare) in a certain period of operation as expressed in (37). Additionally, the objective of ISO in real-time market is accomplished by a Security Constrained Economic Dispatch (SCED) as presented in (38). It should be noted that the additional costs due to the network congestions and supplying the system security are considered in the prices resulting from the SCUC program, which increases the accuracy of the method. From ISO's point of view, some other constraints should be considered as presented in below:

$$\max\{Social\ \ Welfare\} = \max \sum_{t=1}^{T} \left(\sum_{j \in \left\{ \substack{Retailers,\\ Aggregators} \right\}} D_{j,t,\mu}^{DA} \cdot \text{a}_{t,\mu}^{DA} - \sum_{i \in \left\{ \substack{Gencos,\\ Aggregators} \right\}} \left(P_{i,t,\mu}^{DA} \cdot \text{a}_{t,\mu}^{DA} + P_{i,t,\mu}^{Res} \cdot \text{a}_{t,\mu}^{Res} + P_{i,t,\mu}^{NRes} \cdot \text{a}_{t,\mu}^{NRes} \right) \right) \tag{37}$$

$$\max\{Social\ \ Welfare\} = \max \sum_{t=1}^{T} \left(\sum_{j \in \left\{ \substack{Retailers,\\ Aggregators} \right\}} D_{j,t,\mu}^{RT} \cdot \text{a}_{t,\mu}^{RT} - \sum_{i \in \left\{ \substack{Gencos,\\ Aggregators} \right\}} P_{i,t,\mu}^{RT} \cdot \text{a}_{t,\mu}^{RT} \right) \tag{38}$$

$$\sum_{j \in \left\{ \substack{Retailers,\\ Aggregators} \right\}} D_{j,t,\mu}^{DA} = \sum_{i \in \left\{ \substack{Gencos,\\ Aggregators} \right\}} P_{i,t,\mu}^{DA} \quad , \quad \sum_{j \in \left\{ \substack{Retailers,\\ Aggregators} \right\}} D_{j,t,\mu}^{RT} = \sum_{i \in \left\{ \substack{Gencos,\\ Aggregators} \right\}} P_{i,t,\mu}^{RT} \tag{39}$$

$$\sum_{i \in \left\{ \substack{Gencos, \\ Aggregators} \right\}} P_{i,t}^{\max} . I_{i,t,\mu} = \sum_{j \in \left\{ \substack{Retailers, \\ Aggregators} \right\}} D_{j,t,\mu} + SR_t \tag{40}$$

$$-F_k^{\max} \leq F_{t,k,\mu} \leq F_k^{\max} \quad , \quad -F_k^{\max} \leq F_{t,k,\mu}^{cg} \leq F_k^{\max} \tag{41}$$

Equation (39) ensures the balance between supply and demand. Required spinning reserve is expressed in (40). Inequality (41) considers the network limits in normal and contingency states.

4.3. Relationship between Model Elements

Fig. 4 shows the proposed EV aggregator's model to simulate the oligopoly behaviour of the electricity market. The details of the proposed oligopoly electricity market model from the EV aggregator's point of view are explained in the following steps:

- Step 0 – In this step a set of initial prices for both the day-ahead and the real-time markets is considered.
- Step 1 – In this step, each agent (including EV aggregator) self-schedules the operation of its resources to maximize its profit based on the initial prices of the day-ahead (energy and reserve) and the real-time markets. The EV aggregator tackles the uncertainties of the estimated coefficients of players' cost/revenue functions, using the method explained in Section 2. On this basis, in addition to the estimated coefficients of cost/revenue functions, the higher and lower amounts that players might have, are considered as well, by using the discrete normal distribution. In addition, the scenarios of available EVs in the day-ahead session are employed. In order to optimize the objective function of each agent, the stochastic programing based on the state enumeration method is utilized. Since this step of the market takes place before the closure of the day-ahead market, the prices of both mentioned markets are unknown. This step is equivalent to the *here-and-now* stage from the agents' point of view. The output of this step is the agents' offers/bids $(\sim_t^{SFE} , \ _t^{SFE})$ to participate in both the day-ahead and real-time markets resulting from (6), (26) and (34).
- Step 2 – In this step, the agents' offers/bids are the input to the SCUC program. Then, ISO obtains the economic solution for the participant agents in the day-ahead market, considering the security constraints of the system. It should be noted that, in this step, ISO does not consider the agents' offers/bids for the real-time market; therefore it only aims to maximize the social welfare in the day-ahead market. This step is equivalent to the *here-and-now* stage from the ISO's point of view. The output of the step is prices of the day-ahead market and auction winners in the day-ahead energy and reserve markets. The output results from (37) and includes the mentioned prices and auctions for all 24 hours of the day ahead.
- Step 3 – In this step, the won prices and quantities of the agents in each hour of the day-ahead market are known. Although the uncertain data of EV behaviour are updated by the real-time scenarios, the decisions to participate in the real-time market are still unknown. On this basis, each agent maximizes its profit by obtaining the best real-time offer/bid in hour t=*t1* to have the best participation in the real-time market by using (6), (26) and (34). To this end, the hourly

offered prices and quantities of the day-ahead market (i.e. *here-and-now* variables) are considered known. This step is equivalent to the *wait-and-see* stage from the agents' point of view.

- Step 4 – In this step, the ISO considers the agents' offers and bids to the real-time market in hour t=*t1* and maximizes the social welfare using the SCED program by (38). This step is equivalent to the *wait-and-see* stage from the ISO's point of view. The output of this step is the won auctions and prices of the real-time market for hour t= *t1*.
- Step 5 – In this step, the steps 3 and 4 are iterated for hour t= *t2* to t= *t24* to obtain all real-time market prices. At the end of this step, all hourly prices and auctions of both day-ahead and real-time markets are obtained.
- Step 6 – In this step, the obtained prices of the day-ahead and the real-time markets are set as input prices (i.e. instead of initial prices) and steps 1 to 5 are iterated until the convergence constraints are achieved.

The learning process of market agents is based on the hypothesis that each agent can observe the final market prices of previous iterations. Therefore, the price loop is repeated until the prices of market agents equal the market clearing prices. It should be noted that using the iteration-based (dynamic) game theory could help the market simulator to find the process of converging to the market equilibrium point. The flowchart of the mentioned steps is illustrated in Fig. 5.

"See Fig. 4 at the end of the manuscript".

"See Fig. 5 at the end of the manuscript".

5. Optimization of the Long-term Behaviour of EV Aggregator

In order to make an optimal decision, the EV aggregator should pay attention to the possibility of modifying the tariffs and attracting owners to attend the market. Accordingly, the aggregator should estimate the effects of each tariff change on its market share and profit. In the rest of this section, the proposed model of customers' satisfaction is presented. By using the proposed model, an algorithm is proposed to optimize the tariffs.

5.1. Modelling the Customers' Satisfaction to Contract with the Aggregator

In order to ensure the optimal long-term behaviour, the aggregator should know the number of its customers among EVs that will be added to the system in the future. Moreover, they should know how to optimally increase the number of their customers. A new approach is proposed in this paper to investigate the participation of EV owners (including new and former customers).

Several reports have been presented in marketing and managing to show the importance and impacts of customers' satisfaction, discussing how higher customers' satisfaction can cause higher retention and acquire new customers [38]. As a conclusion, the higher customers' satisfaction, the higher market share.

In addition, many criteria have been expressed in the reports to improve the customers' satisfaction. One of the most effective criteria is the price of a product. In [39], the relationship between the price of some different products and the company's market share has been investigated in real-world retailing markets.

Using data details in [39] (as shown in Figs. 6.a and 6.b), the relationship between the market share and the price of a product is obtained as a sample, and it is indicated in Fig. 6.c. According to Fig. 6.c, it can be inferred that by decreasing the price of a product, the market share will improve, but its rate is not steady. At the beginning and in the end the rate is low, but it is high in the middle. In other words, there is inertia in the behaviour of customers to switch to purchase from a new company who has no significant market share. Furthermore, acquiring the majority of the market share needs much higher customers' satisfaction (product price reduction), so that the rate of market share is saturated in the end. Based on the expressed shape of "market share-product price" curve, a hyperbolic tangent function with the mentioned features can be fitted.

"See Fig. 6 at the end of the manuscript".

Since, in this paper, the EVs owners' satisfaction is related to three tariffs (charge, discharge and reserve), the aggregator utilizes the expected annual profit of customers, instead of price, to calculate its market share. Thus, the owners' annual profits are considered as the main motivation factor. It should be noted that, apart from annual profit, other parameters such as customer services can influence the customers' behaviour. In this paper, the mentioned parameters for different companies are assumed practically similar. Due to the competition in the electricity market, the previous assumption is near to reality.

The formulation of EV owner's annual profit is given by:

$$Profit^{cust.} = P_{Res}.\circledR^{ContRes}\,t_{Reserve} + P_{Energy}.\circledR^{ContEn}_{V2G}\,t_{Energy} - P_{Energy}.\circledR^{ContEn}_{G2V}\,t_{\text{Charge}} \Big/ ¦_{sys} - Cost^{cust.}_{Degr} - Cost^{cust.}_{Infras} \qquad (42)$$

$$Cost^{cust.}_{Degr} = P_{Energy}.C_d\,t_{Energy} \qquad (43)$$

$$C_d = C_{battery} \big/ L_{ET} \qquad (44)$$

$$Cost^{cust.}_{Infras} = \left(Cost_{Wiring} + Cost_{On-board}\right).dr \Big/ \left(1-(1+dr)^{-N_y}\right) \qquad (45)$$

where dr is the annual discount rate and N_y is the number of years the device will last. The first two terms in (42) denote owner revenues resulted from participating in the SR market and energy generation, respectively. The third term denotes the owner's cost associated with charging its batteries. Equation (43) presents the customer's annual equipment degradation cost. This cost can be measured as degradation of V2G due to additional battery cycling in \$/kWh. Based on this issue, it can be correlated to battery capital cost and battery lifetime as (44) [14]. Equation (45) denotes the annualized infrastructure costs. As shown in (45), the infrastructure cost includes the on-board incremental cost and wiring upgrade cost [14].

The motivation function is formulated based on the mentioned hyperbolic tangent model. On this basis, the final number of customers can be calculated based on their profits.

The developed model holds the ability to show the saturation of participation, due to a low or high level of owners' profits. However, the mentioned equation can only calculate the steady state number of customers, so that it is unable to model the dynamic of number of customers over time.

On the other hand, the effect of improvement of customers' satisfaction on the market share is a time-related process. Since, the aggregator longs for computing its long-term profit, it needs to obtain the number of customers during the time.

Ref. [40] has considered the dynamic effects of price on the market share. Moreover, in [41], a model based on exponential functions has been presented to compute the market share. The mentioned model has utilized the information about the market share and the product elasticity of other competitors.

This paper supposes that the policy and long-term behaviour of the aggregator's competitors will not change. On this basis, the model presented in [41] can be simplified. The rate of participation of customers is related to features of the market (e.g. cultures, economics and politics) [38].

The features can be considered by factors $rate_{yr}^{ini}$ and ¥ , where ¥ is a weighting factor that can show how much the community is sensitive to changes of product price (in this case, the tariffs). Achieving the factors for a commercial company has been presented in [40].

The proposed approach to calculate the participation of EV owners contains five steps, as follows:

- Step 1- estimating the whole number of EVs at the end of the time horizon.
- Step 2- estimating the annual profit of other competitors' customers in each year of study; in other words, estimating the annual profit of a typical owner who has a contract with other aggregators or retailers.
- Step 3- calculating the number of aggregator's customers at the end of each year using (46).
- Step 4- calculating the rate values based on the rate function using (47).
- Step 5- calculating the number of aggregator's customers in each month using (48).

$$N_{yr}^{cust} = \frac{N_{yr}^{tot}}{2}\left(1+\tanh\left(\text{°}\,\frac{Profit_{yr}^{cust}-Profit_{yr}^{*}}{Profit_{yr}^{*}}\right)\right) \tag{46}$$

$$rate_{yr} = rate_{yr}^{ini} + \text{¥}\left|\frac{Profit_{yr}^{cust}-Profit_{yr}^{*}}{Profit_{yr}^{*}}\right| \tag{47}$$

$$N_{t}^{cust} = \frac{N_{yr}^{cust}.N_{0}^{cust}\exp\left(t.rate_{yr}\right)}{N_{yr}^{cust}+N_{0}^{cust}\left[\exp\left(t.rate_{yr}\right)-1\right]} \tag{48}$$

where ° is a factor that shows the sensitivity of owners to the expected annual profit, being obtained by using the current state of the system.

If the aggregator just concentrates on short-term profit, associated with the effects of contract with owners on competition with market participants, some of its consumers might be missed and it will not have a suitable share of future owners.

Considering the effect of EV owners' contacts on the EV aggregator's market share, optimization of the tariffs is expressed in the remainder of this paper.

5.2. Optimization of tariffs

The profit resulted from the enhancement of customers' satisfaction is not instantaneous. Hence, the aggregator should consider both short- and long-term objectives. On this basis, in this paper, the aggregator selects the best tariffs and participates in the electricity market in such a way that the maximum long-term profit is achieved. For this purpose, several kinds of contracts with customers, based on the tariffs of charging, energy and reserve are considered as a decision space. Afterwards, the effect of each contract on the monthly number of customers is taken into account by calculating the expected annual profit of the owners.

Using the new number of customers, the aggregator simulates its participation in the electricity markets and obtains its expected profit. Finally, by comparing the long-term profits, the aggregator chooses the tariffs associated with the maximum profit. The satisfaction model is illustrated in Fig. 7. The model is developed according to the annual profit of EV owners, so a trade-off has been performed between short- and long-term aggregator's profits.

"See Fig. 7 at the end of the manuscript".

6. Numerical Studies

In this paper, a 6-bus case study is used to illustrate the effectiveness of the proposed model. In this case study, the IEEE 6-bus test system has been expanded to reduce the level of structural market power and improve the similarity to real electricity markets. Accordingly, the number of Gencos has been increased from three to six, while three retailers have been considered to supply the demands. Energy and reserve markets are considered to be cleared as a uniform-pricing auction.

In our experiments, the EV aggregator competes with the mentioned Gencos and Retailers for selling and purchasing electricity, respectively. Moreover, from another perspective, the EV aggregator and retailers compete for the EV owners. In order to calculate the EV owner's profit, the typical EV data, obtained from [14] are used. The details of EV aggregator data and other considered parameters are presented in Table 1. In addition, the details of market players' data are expressed in Appendix.

"See Table 1 at the end of the manuscript".

Based on the mentioned description in Section 2, scenarios related to uncertain amounts of the available number of EVs and total aggregated SOC from the viewpoints of the day-ahead and real-time sessions are generated as illustrated in Fig. 8 to Fig. 11, respectively. In these figures, the generated scenarios and the expected value of uncertain parameters are indicated by blue cross-marked points and black dashed line, respectively. Also, the actual number of EVs and aggregated SOC that are obtained in realization session is shown by the red line. By considering a smaller standard deviation of the number of EVs in real-time market, the more accurate prediction of the EV aggregator due to closer time to realization session has been taken into consideration.

"See Fig. 8 at the end of the manuscript".

"See Fig. 9 at the end of the manuscript".

"See Fig. 10 at the end of the manuscript".

"See Fig. 11 at the end of the manuscript".

The rest of this section is divided into two sub-sections. In section 6.1, in order to investigate the short-term effectiveness of the proposed model, the results of the oligopoly model are compared with those of perfectly competitive models, in where all market players offer their marginal cost to the market, during a typical day. In section 6.2, the proposed owners' motivation model is utilized to obtain the optimal tariffs, and then the impact of the contract on long-term profit of the aggregator is studied. In addition, the impacts of different scenarios of the first stage optimization (i.e. participation in the electricity markets) on the results of the second stage optimization (i.e. finding the optimal tariffs) are investigated.

6.1. Impact of the Proposed Oligopoly Model

The effect of modelling the oligopoly behaviour of market players on the prices of the energy market in a typical day has been indicated in Fig. 12. In order to show the effect, energy market prices of perfect competition are subtracted from the ones of oligopoly environment. Similarly, Fig. 13 shows the mentioned effect on SR market prices. If the aggregator models the power market as a perfect competition, it follows the prices of other players. But, modelling the market as an oligopoly environment enables it to affect the market prices. As it can be seen, although the oligopoly behaviour of the aggregator reduces the price of the energy market in many hours, it can increase the price of the SR market during most of the hours.

"See Fig. 12 at the end of the manuscript".

From another point of view, Figs. 12 and 13 illustrate the effects of transforming the EV aggregator from a price taker market participant to a price maker one. It should be noted that, formerly, it was expected that participation of EVs could decrease the prices of SR market. However, transforming the EV aggregator to a price maker player can increase the prices in comparison with a perfectly competitive market.

"See Fig. 13 at the end of the manuscript".

The effect of modelling the oligopoly behaviour of market players on network loss has been indicated in Fig. 14. As it can be seen, modelling the market as an oligopoly environment enables the EV aggregator to affect the network loss. This effect is because of transforming the EV aggregator from a price taker participant to a price maker one, and consequently the market participant can affect both generation and load. According to Fig. 14, in hours that the EV aggregator increases the purchase of energy in order to charge their EVs (e.g. hours 6 to 8), the network loss increases. On the contrary, in hours that the EV injects energy back to the grid (e.g. hours 9 to 11, 23 and 24), the network loss decreases. By modelling the oligopoly behaviour of market players, the daily network loss has been decreased from 4.56 MWh to 4.44 MWh, which indicates about 2.5% reduction. It should be mentioned that, the optimal performance of an EV aggregator as an energy storage system is to charge its batteries in off-peak period and inject a part of the stored energy back to the grid in the peak period. This behaviour increases the demand in off-peak and decreases the generation in the peak period, subsequently reducing the network loss. On this basis, it can be concluded from the 2.5% reduction in network loss that a price maker EV aggregator can behave more like an optimal energy storage system than the one in the price taking mode.

"See Fig. 14 at the end of the manuscript".

6.2. Impact of the Proposed Owners' Satisfaction Model

The effect of the reserve and charging prices on the participation of EV owners (the final number of aggregator's customers) is illustrated in Fig. 15. An increase in the customer's profit (i.e. a decrease in the charging price or an increase in the reserve price) causes an increase in the number of aggregator's customers. It should be noted that, although the axis of energy price has not been indicated in Fig. 15, the effect of prices on customer's number has also been considered.

"See Fig. 15 at the end of the manuscript".

Fig. 16 shows the effect of owners' expected annual profit on the number of customers in each month. As can be seen, if the aggregator changes the contracts with the owners and increases their profit, the number of its customers will increase.

"See Fig. 16 at the end of the manuscript".

The more customers' profit increases, the faster it is to attract owners. It should be noted that the highest participation sensitivity regarding customer's profits occurs around \$1000, which is equal to the considered owners' annual profit from a contract with other competitors ($Profit_{yr}^{*}$).

The effect of various types of contract on the aggregator's annual profit is illustrated in Fig. 17. The best price area for the aggregator's contract with EV owners is around 40 and 80 \$/MWh for charging and reserve prices, respectively. Although by increasing the reserve price or decreasing the charging price the number of customers will be increased, in this situation the aggregator's profit will be dramatically decreased because of imposed prices by market players.

"See Fig. 17 at the end of the manuscript".

The aggregator's annual profit has been compared by taking into account the results of simplified models. The details of the additional case studies are presented in Table 2.

"See Table 2 at the end of the manuscript".

In case 1, the conventional model of EV aggregator has been considered. The power market is modelled as a perfect competitive market and the contract effect on the owners' motivation is neglected. In case 2, the effect of the behaviour of market players has been modelled. As can be seen in Fig. 18, considering the oligopoly behaviour of the electricity market increases the aggregator’s profit. In case 3, the proposed model has been applied. Accordingly, in addition to modelling the oligopoly market, the effect of motivating contracts with EV owners on the long-term profit of the aggregator has been considered. Similarly, as can be seen in Fig. 18, the proposed model increases the aggregator’s profit dramatically. It should be noted that the prices shown in Table 2 for case 3 have been obtained from implementing the proposed model to find the best type of contract. In addition, the annual profit of a typical EV owner with and without using the proposed model is shown in Fig. 18. The results clearly show that by using the proposed model, not only the profits of the EV aggregator and its customers can be increased, but also there are opportunities to enhance the encouragement of other owners to contract with the aggregator instead of the retailers in the long-term.

"See Fig. 18 at the end of the manuscript".

It is noteworthy that, modelling the type of contract gives the aggregator the flexibility which makes it a powerful market player who is able to change its revenue and cost functions. On this basis, the flexibility can carry more weight than the offering/bidding strategy in competition space. In the other words, although the dynamics of customers’ behaviour make the impact of changing the contracts become time consuming, the competition for customers has more effect on the EV aggregator’s profit than competition for prices of the wholesale market.

The computation time of the mentioned cases has been presented in Table 3. The platform that has been utilized to assess the proposed model is a 64-bit Workstation, having two Xeon E5-2687W 8C 3.10 GHz processors with 256 GB of RAM and an interface of MATLAB R2013b (8.2.0.701) and GAMS 24.0.2 has been employed.

"See Table 3 at the end of the manuscript".

In order to investigate the effect of uncertain variables on the optimal tariffs, some different scenarios have been studied. The scenarios are considered to be in two main categories: first, the scenarios to study the impact of the electricity market, and second, the scenarios to analyse the effect of EV owners’ behaviour. It should be mentioned that, for the sake of a precise comparison, in the first category the expected value of EV owners’ behaviour has been considered. Similarly, in the second category, the expected value of market behaviour that is obtained from the first stage of the optimization problem has been taken into account. These two scenario categories have been expressed as follows:

1) Scenarios to study the effect of market behaviour

Two scenarios have been considered to study the market behaviour by using different Gencos’ costs. In scenario A, the market behaviour is considered based on the minimum operation cost of all Gencos. To this end, the coefficients of Gencos’ cost function (i.e. $a_{i,\mu}$, $b_{i,\mu}$, $c_{i,\mu}$, $\alpha^{up}_{i,\mu}$ and $\alpha^{down}_{i,\mu}$) are set to the minimum values. On the contrary, the maximum cost of all Gencos is considered in scenario B. On this basis, the coefficients of the Gencos’ cost function are considered to be equal to the maximum values. As it has been expressed in section 2.3, the value of the coefficients of the Gencos' cost function is considered by using Normal distribution parameters (i.e. the mean and standard deviation). The details of the parameters are presented in Table A.1.

2) Scenarios to study the effect of EV behaviour

Three scenarios have been considered to investigate the impact of EV behaviour. On this basis, three different scenarios of available EVs indicated in Fig. 8 and Fig. 9 have been studied. In scenario C, the highest hourly number of available EVs is considered, while scenario D is associated to the lowest hourly number of available EVs, as well as the least accurate one. Scenario E reflects the most accurate hourly number of available EVs. The accuracy is measured by the Mean Absolute Error (MAE) of each scenario tree of available EVs for 24 hours. The considered scenarios for day-ahead and real-time sessions have been indicated in Fig. 19 and Fig. 20, respectively.

"See Fig. 19 at the end of the manuscript".

"See Fig. 20 at the end of the manuscript".

The results of the mentioned scenarios have been compared in Table 4. By comparing the results of scenario A, scenario B and the expected values, it can be observed that by increasing the cost of the Gencos the EV aggregator intends to increase the tariff of reserve contract with its customers. The reason of this intention is that the increase of Gencos' costs raises the reserve market prices and consequently the EV aggregator can suggest the higher reserve tariffs to attract more customers. Although the V2G tariff in scenario B is 4.9% higher than the one in the expected case, it is significantly lower than the increase of the reserve tariff (i.e. 18.3%). It shows that by increasing the Gencos' cost, the EV aggregator prefers to take part in the reserve market more than the energy one. The reason is that the EV aggregator has to purchase the energy with higher prices to charge its consumers' batteries, while it cannot significantly increase the charging tariff due to the competition with the retailers that their revenue functions are not supposed to be changed. Furthermore, it can be observed that by increasing the Gencos' costs, and accordingly the market prices, the profit of both the EV aggregator and its customers is improved.

By comparing the results of scenario C, scenario D and the expected values, it can be seen that an increase in the number of available EVs can raise the reserve market prices and consequently the profit of the EV aggregator; because, the aggregator achieves more market power in the reserve market. However, in the energy market the aggregator does not have enough market power to increase the prices. On the other hand, since by increasing the number of available EVs the EV aggregator can sell back more energy to the grid, the energy prices can be reduced.

The comparison between the results of scenario D, scenario E and the expected values indicates that the less accurate prediction of EV owners' behaviour enforces the EV aggregator to purchase both the reserve and energy from the EV owners in the lower tariffs. In addition, the EV aggregator increases the tariff of G2V to cover the imbalance penalties. Therefore, scenario

D is the worst scenario from the owner's point of view. It should be noted that, although an inaccurate forecast of EV behaviour decreases just 0.7% the profit of the EV aggregator, it can reduce significantly (46%) the profit of EV owners.

"See Table 4 at the end of the manuscript".

7. Conclusion

In this paper, the long-term behaviour of market participants and EV owners was modelled and optimized from the aggregator's point of view. A bi-level optimization algorithm based on multi-agent systems and dynamic game theory was developed to model the oligopoly energy and reserve markets. The probabilistic formulation of EV aggregator entailed the minimum charge of batteries, the minimum connection duration, and other EV constraints. The model optimized the self-scheduling program and submitted the best bidding/offering strategies to the day-ahead and real-time electricity markets. Several uncertainties were considered, such as calling the aggregator by ISO for power generation and behaviour of market players. In order to model the uncertainties a two-stage stochastic programming was utilized. The competition with market players to attract the customers was also modelled. In addition, a new approach was developed to calculate the motivation of EV owners to participate in the electricity market by selecting the contract. It is possible to conclude that the proposed model was proficient in significantly improving the short- and long-term behaviour of the aggregator. Besides optimizing the offering/bidding strategy, the model could also attain the optimal tariffs to motivate EV owners to connect to the aggregator. The significant increase in aggregator's profit resulted from modelling the oligopoly market and improving the customers' satisfaction.

Nomenclature

Indices

i	index of Gencos
j	index of retailers
t	index of hours
v	index of EV owners
yr	index of years
μ	index of scenarios

Parameters

C_d	degradation cost because of utilizing V2G.
C_v^{EV}	battery capacity of EV *v*.

FOR^{Agg}	aggregator’s unavailability for generating.
$P^{del}_{t,\mu}$	probability of being called to generate
P_{Energy}	EV’s power limit for energy trade.
P_{Res}	EV’s power limit for supplying spinning reserve.
PEV_{tot}	number of connected aggregator’s customers.
RU_i, RD_i	ramp up and down constraints.
r^+_t, r^-_t	positive and negative imbalance ratios.
$rate^{ini}_{yr}$	initial grow rates of customers.
¥	factor of grow rate.
¦$^{C}_{v}$, ¦$^{D}_{v}$	charging and discharging efficiencies.
¦$_{sys}$	round-trip efficiency.
®$_{t,\mu}$	occurrence probability of scenario ω.

Variables

$Act^{Res}_{t,\mu}$	quantity of reserve activated by ISO.
$D^{DA}_{j,t,\mu}, D^{RT}_{j,t,\mu}$	day-ahead and real-time bids of retailer *j*.
E_{Ω}	expected value obtained from set of scenario Ω.
$F_{t,k,\mu}, F^{cg}_{t,k,\mu}$	branch flow in normal and contingency states.
$I_{i,t,\mu}$	variable of commitment of unit *i*.
N^{cust}_{yr}	number of aggregator’s customers.
N^{tot}_{yr}	total number of EVs.
$Offer^{Res}_{t,\mu}, Offer^{NRes}_{t,\mu}$	spinning and non-spinning reserve offers.
$Offer^{En}_{t,\mu}$	offer to participate in energy market.
$P^{DA}_{i,t,\mu}, P^{RT}_{i,t.\mu}$	day-ahead and real-time generation offers of unit *i*.
$P^{Res}_{i,t,\mu}, P^{NRes}_{i,t,\mu}$	spinning and non-spinning reserves of unit *i*.

$P_{v,t,\mu}^{G2V}$	energy of grid injected to EV *v*.
$P_{v,t,\mu}^{V2G}$	energy of EV *v* injected to grid.
$Profit_{yr}^{cust}$	EV owner’s annual profit.
$Profit_{yr}^{*}$	owner’s profit from contract with other competitors.
$SOC_{v,t,\mu}$	state of charge of EV *v* at time *t*.
$SOC_{v,t,\mu}^{Disconnect}$	state of charge when disconnecting.
$a_{i,\mu}, b_{i,\mu}, c_{i,\mu}$	estimated coefficients of cost function.
$e_{j,\mu}, f_{j,\mu}$	estimated coefficients of revenue function.
$r_{v,t,\mu}^{charge}, r_{v,t,\mu}^{discharge}$	rate of charge and discharge of EV *v*.
$rate_{yr}$	annual grow rates of customers.
$t_{Connect(v,\mu)}$	time of connection EV *v* to aggregator.
$t_{Full(v,\mu)}$	time of obtaining full charge of EV.
t_{Charge}	duration of charging.
$t_{Energy}, t_{Reserve}$	duration of participation in energy and reserve markets.
$y_{i,t,\mu}, z_{i,t,\mu}$	variables of starting-up and shutting-down.
$¢_{v,t,\mu}$	binary variable of charging or discharging of EV *v*.
a_{V2G}^{ContEn}	tariff for purchasing energy.
$a_{G2V}^{ContEn}, a^{ContRes}$	tariffs for participating in the energy and reserve markets
$a_{t,\mu}^{DA}, a_{t,\mu}^{RT}$	day-ahead and real-time energy market prices.
$a_{t,\mu}^{Res}, a_{t,\mu}^{NRes}$	price of spinning reserve market.
$a_{i,\mu}^{up}, a_{i,\mu}^{down}$	estimated start-up and shut-down costs.
$\Delta_{t,\mu}$	total deviation of balance market.
$\Delta_{t,\mu}^{+}, \Delta_{t,\mu}^{-}$	positive and negative deviations of balance market.

Appendix

"See Table A.1 at the end of the manuscript".

"See Table A.2 at the end of the manuscript".

Acknowledgements

The work of M. Shafie-khah and J.P.S. Catalão was supported by FEDER funds (European Union) through COMPETE, and by Portuguese funds through FCT, under Projects FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010) and UID/CEC/50021/2013. Also, the research leading to these results has received funding from the EU Seventh Framework ProgrammeFP7/2007-2013 under grant agreement no. 309048.

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Figure captions

Fig. 1. The competition space of the EV aggregator.

Fig. 2. Distribution of battery capacity of EVs.

Fig. 3. The proposed two-stage stochastic framework.

Fig. 4. The proposed EV aggregator's model to simulate the oligopoly behaviour of the electricity market.

Fig. 5. The flowchart of the proposed oligopoly model.

Fig. 6. Relationship between market share and product price.

Fig. 7. EV aggregator's model to consider customers' satisfaction.

Fig. 8. Considered scenarios for the normalized number of available EVs for day-ahead session (black dashed line: expected value, red line: actual value and blue crossed-mark points: scenarios).

Fig. 9. Considered scenarios for the normalized number of available EVs for real-time session (black dashed line: expected value, red line: actual value and blue crossed-mark points: scenarios).

Fig. 10. Considered scenarios for the normalized total aggregated SOC for day-ahead session (black dashed line: expected value, red line: actual value and blue crossed-mark points: scenarios).

Fig. 11. Considered scenarios for the normalized total aggregated SOC for real-time session (black dashed line: expected value, red line: actual value and blue crossed-mark points: scenarios).

Fig. 12. The effect of oligopoly model on expected energy market prices.

Fig. 13. The effect of oligopoly model on expected SR market prices.

Fig. 14. The effect of oligopoly model on hourly network loss.

Fig. 15. The effect of diverse contracts on the final number of customers.

Fig. 16. The effect of owners' expected annual profit on their participation.

Fig. 17. The effect of various contracts on the aggregator's annual profit.

Fig. 18. Annual profit of the EV aggregator and a typical 24 kWh EV owner.

Fig. 19. The normalized number of available EVs for the scenarios C, D and E (The day-ahead session).

Fig. 20. The normalized number of available EVs for the scenarios C, D and E (The real-time session).

Table captions

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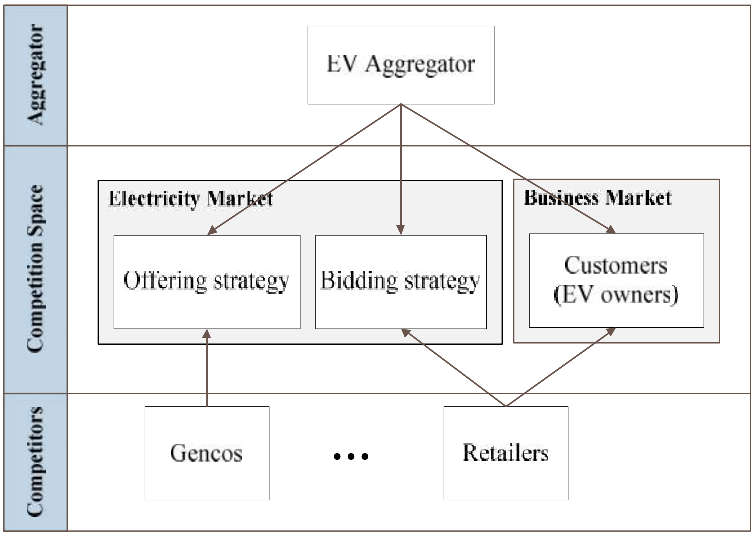
Table 2. The details of the considered case studies

Table 3. The computation time of different cases

Table 4. Effect of different scenarios on the second stage optimization results

Table A.1. Gencos' data

Table A.2. Retailers' data



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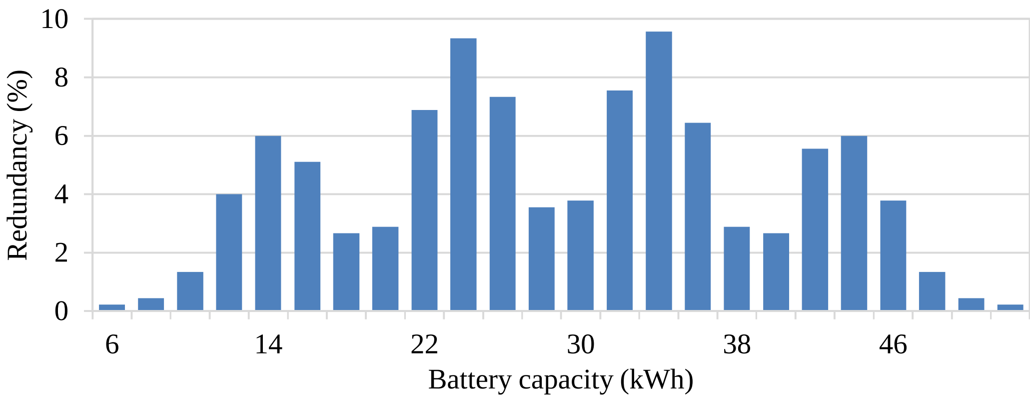

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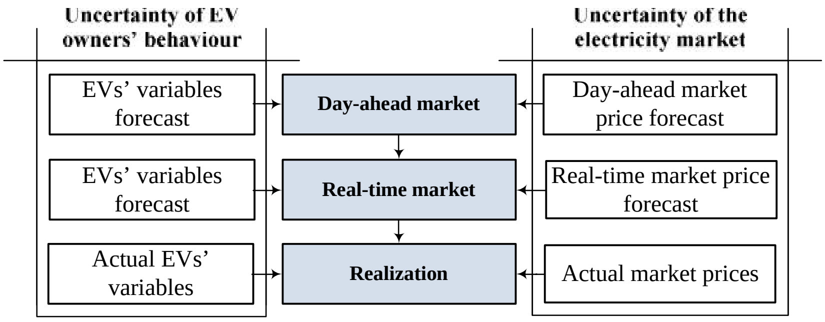

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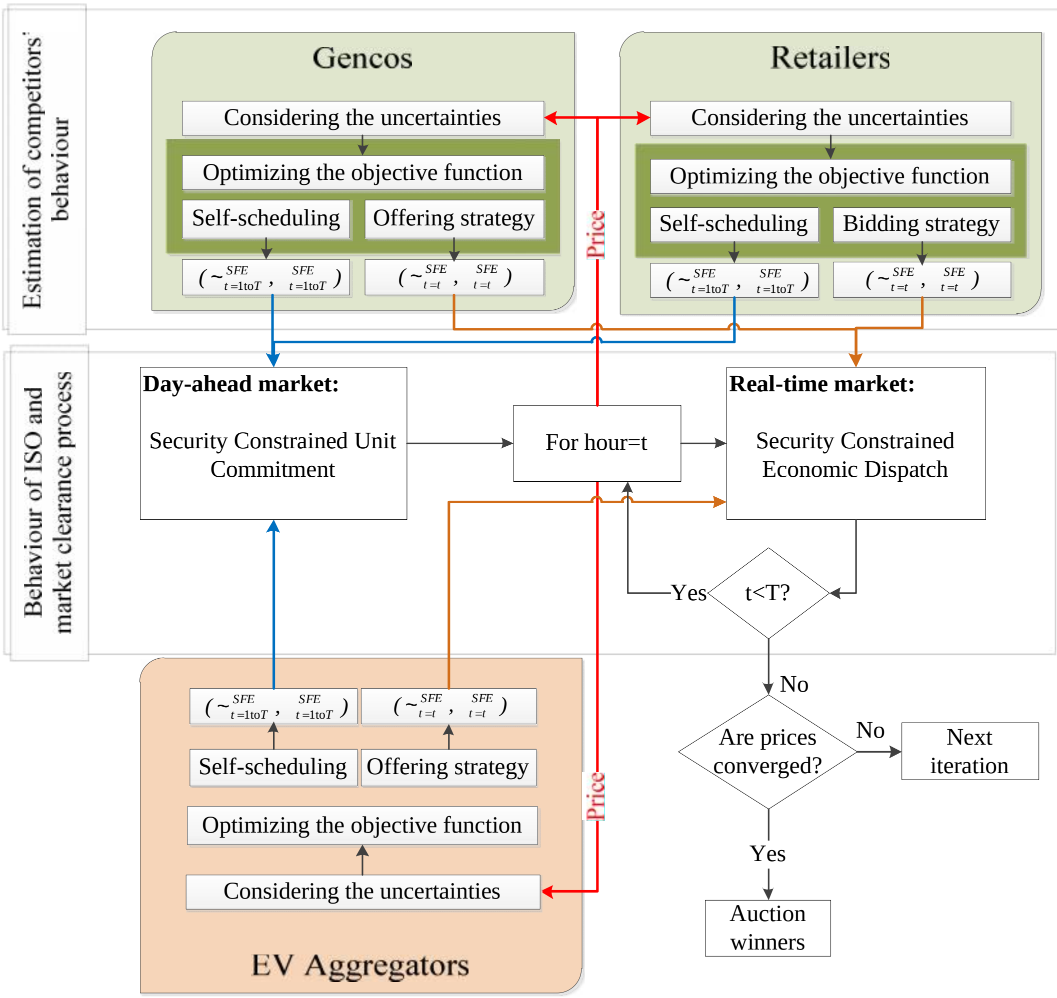

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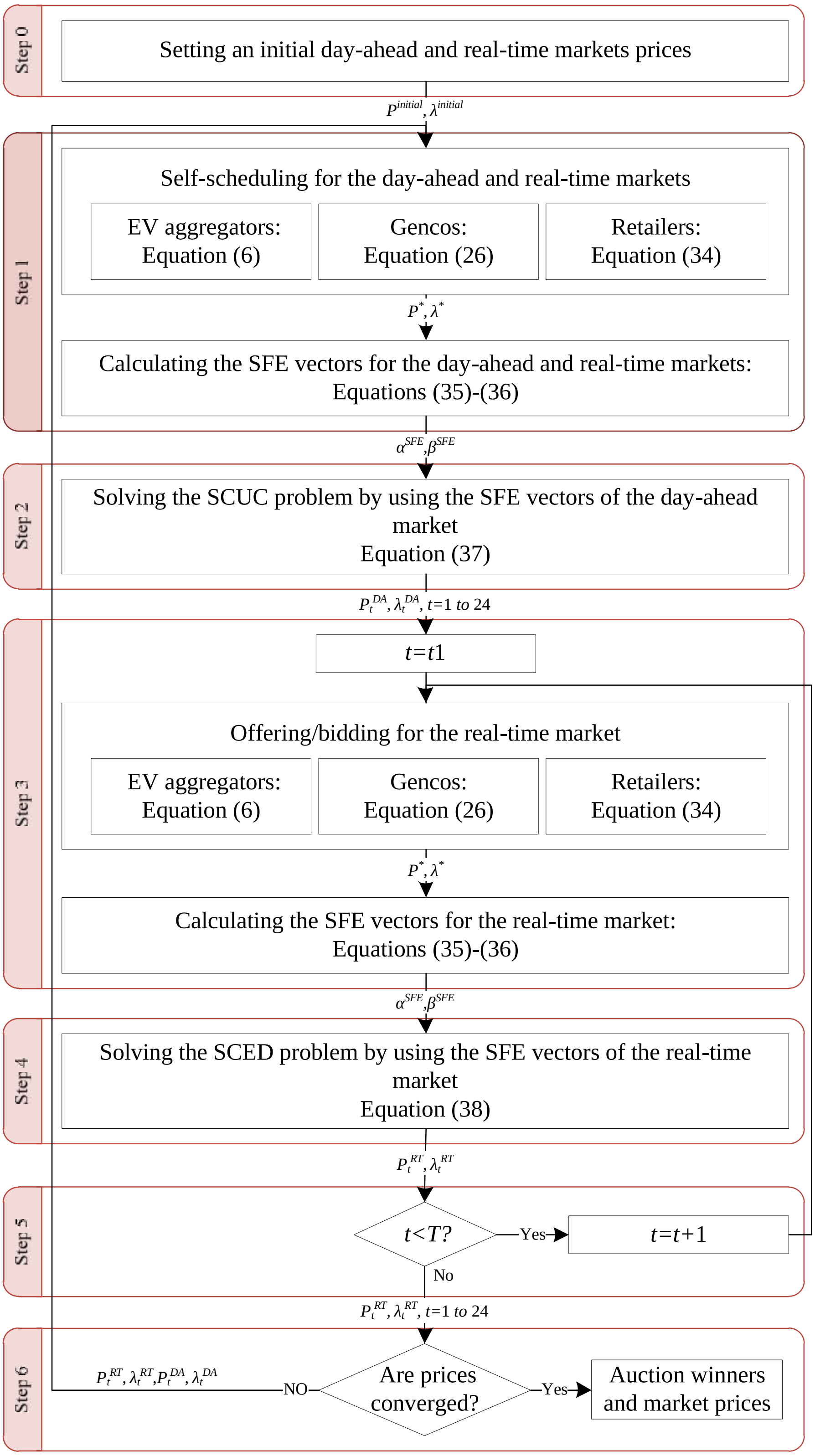

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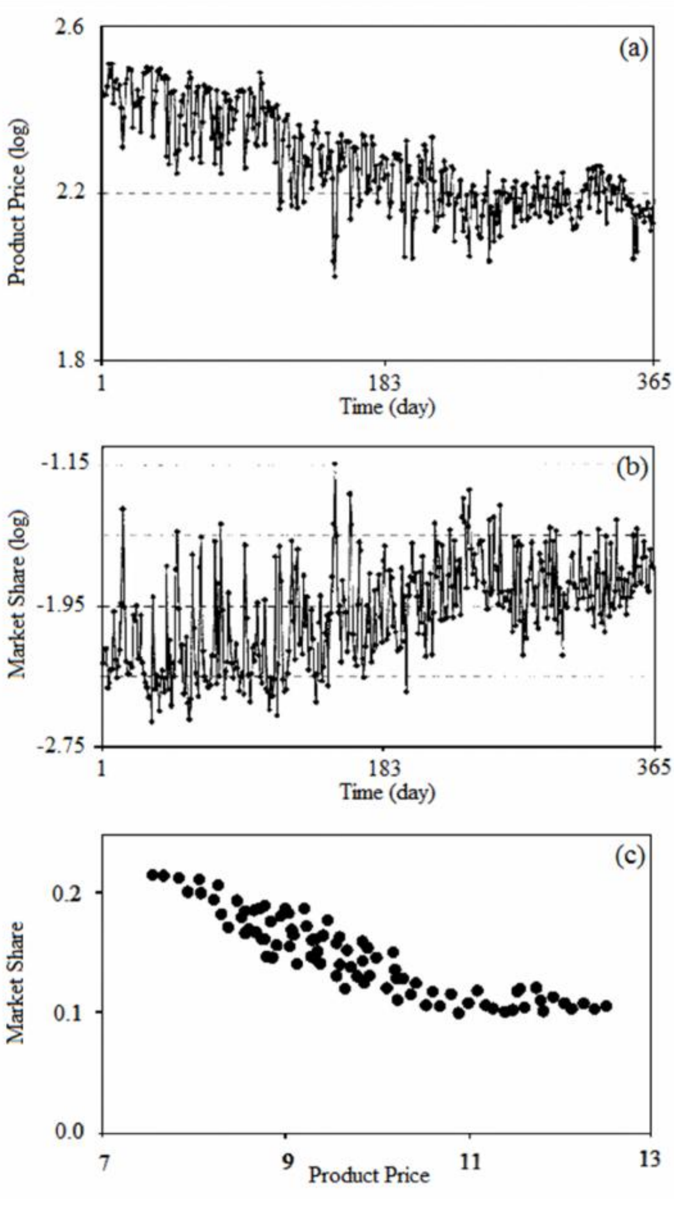

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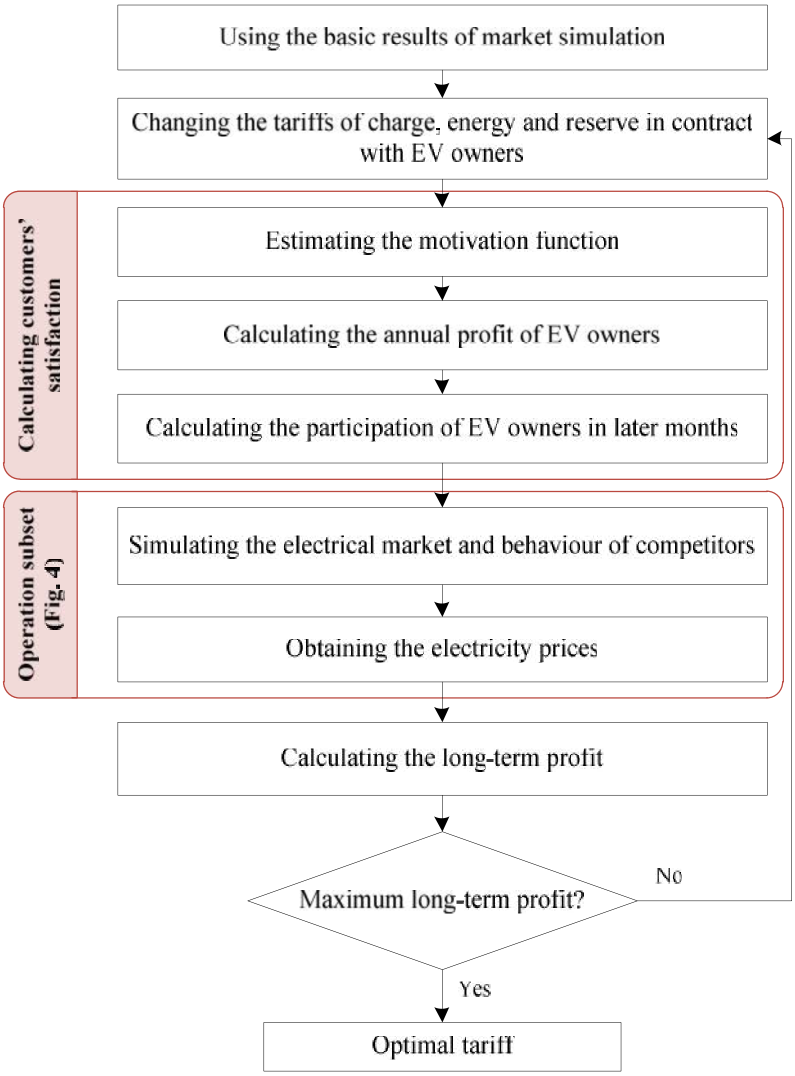

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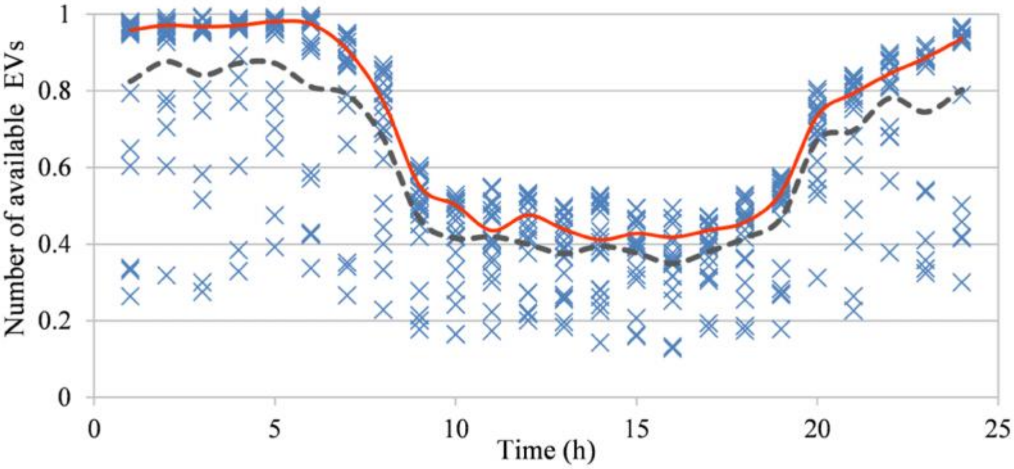

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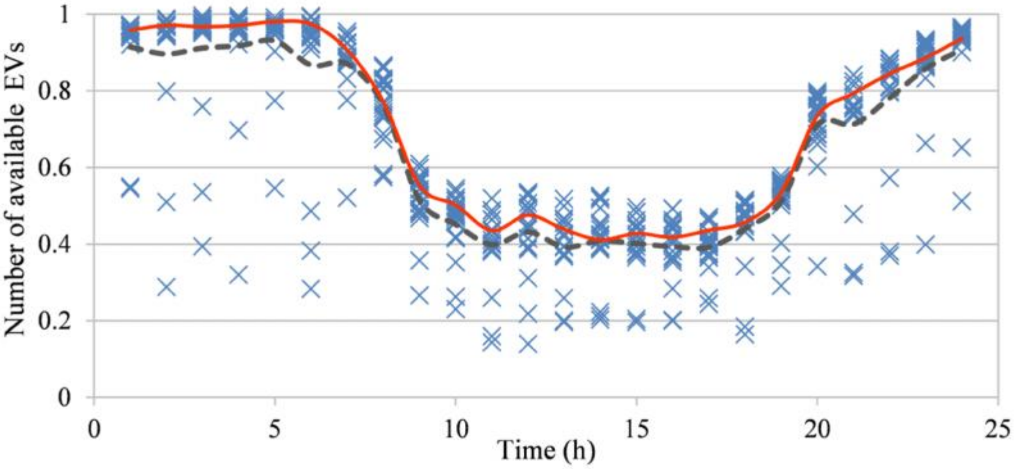

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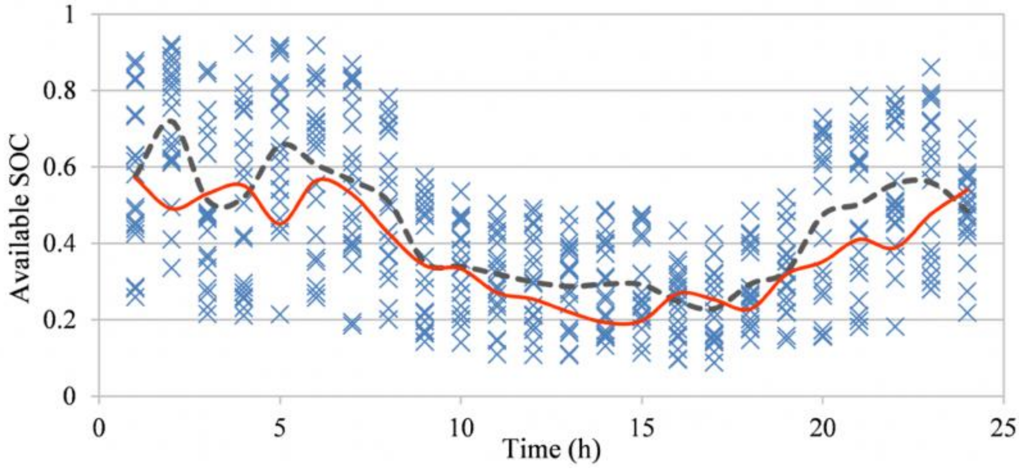

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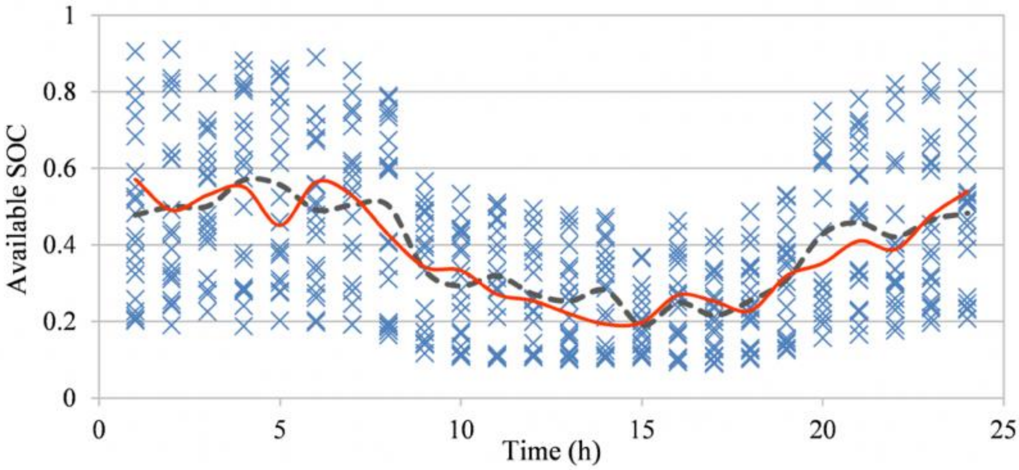

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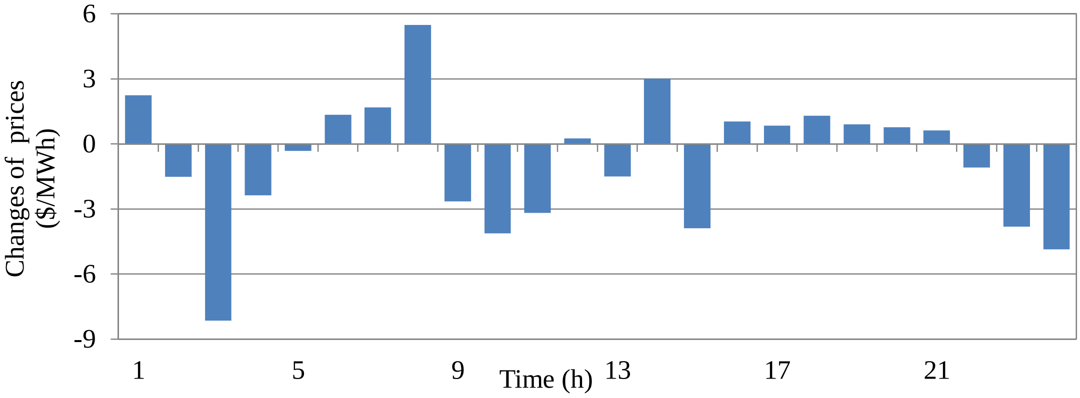

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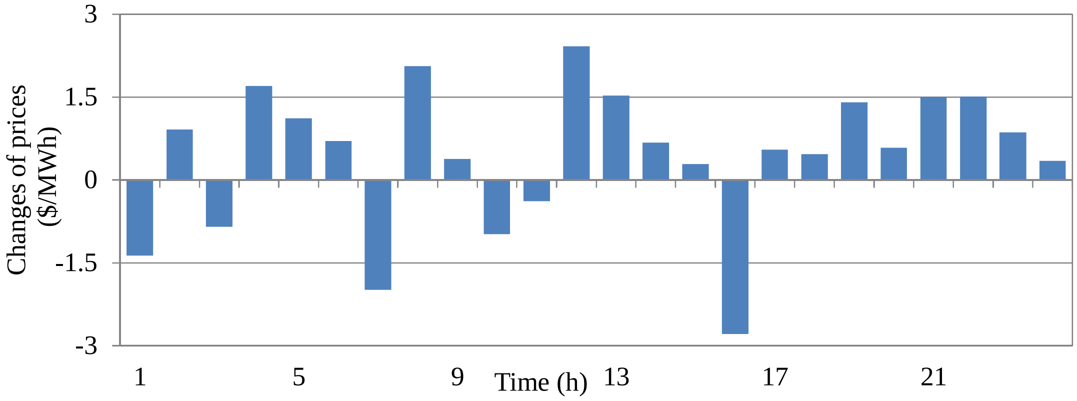

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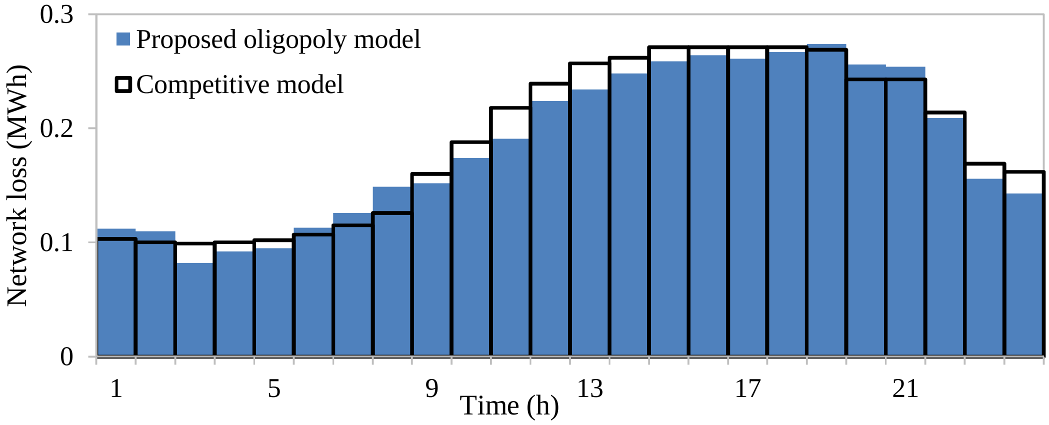

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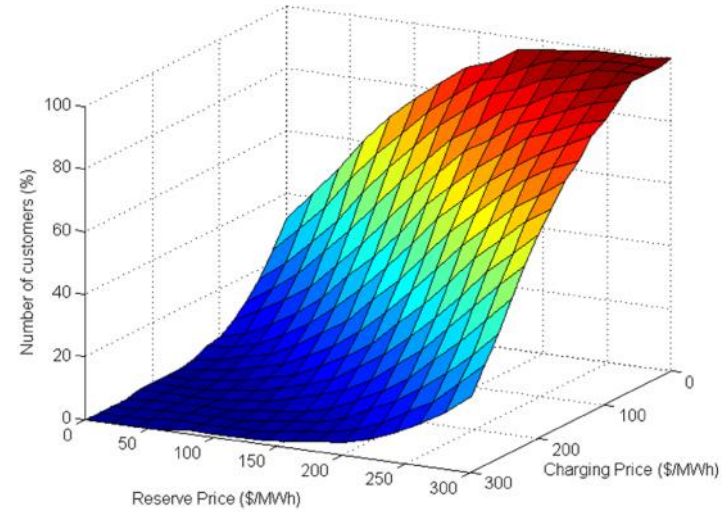

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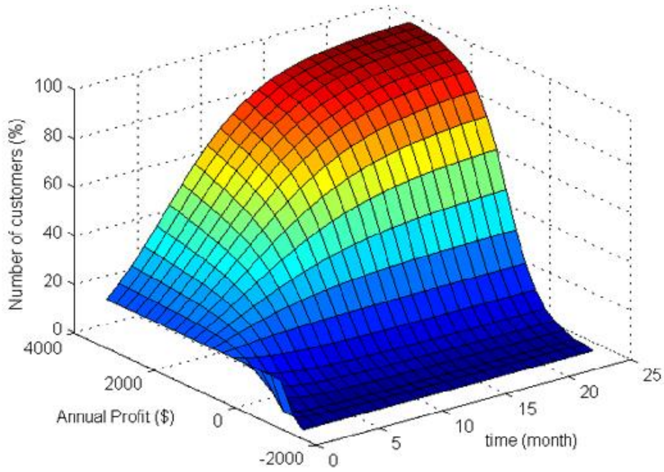

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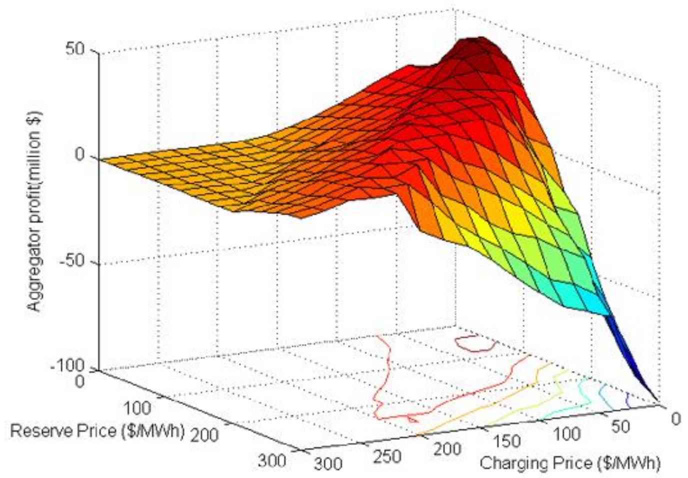

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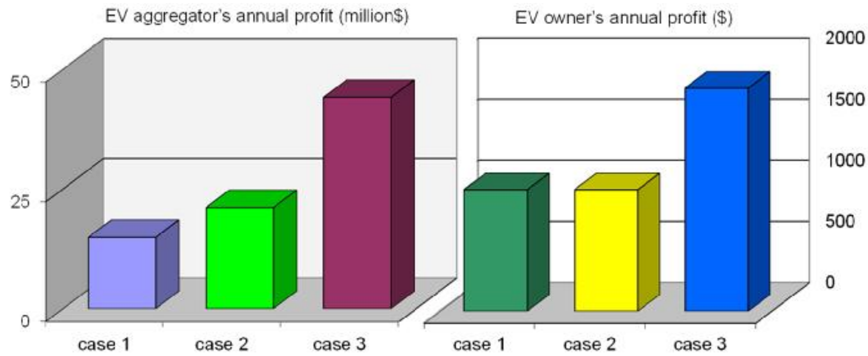

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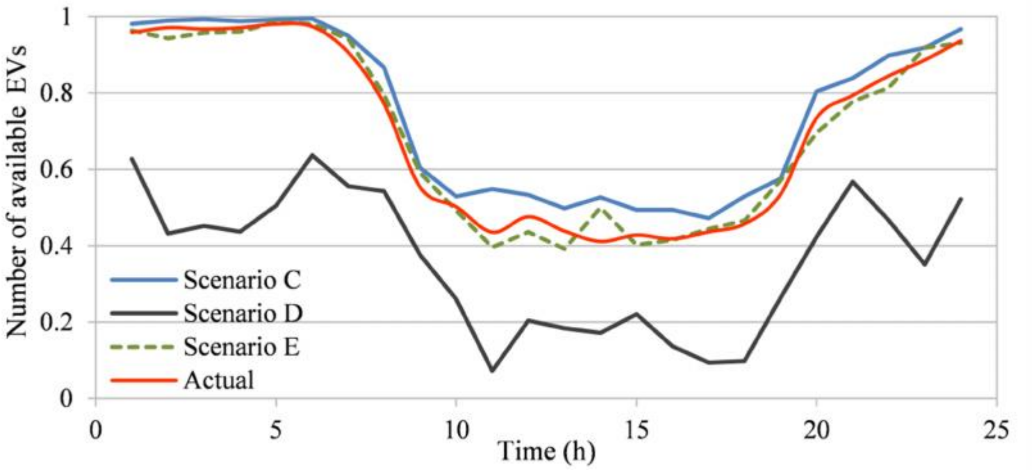

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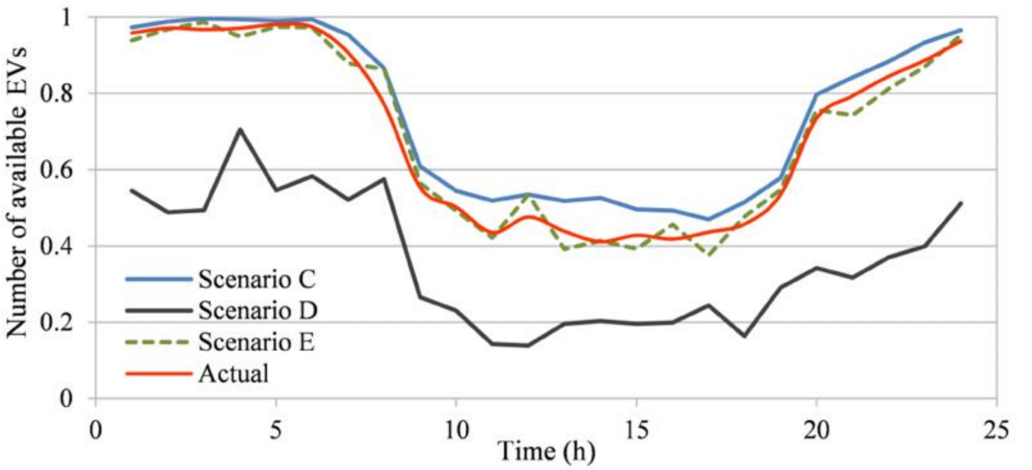

Fig. 20. The normalized number of available EVs for the scenarios C, D and E (The real-time session).

Table 1. The considered data for the EV aggregator model

$rate_{yr}^{ini}$	Time horizon (month)	N_y *(year)*	dr *(%)*	η_i^D *(%)*	η_i^C *(%)*	$Cost_{Wiring}$ *($)*	$Cost_{On\text{-}board}$ *($)*	$Ramp^{C/D}$ *(pu/h)*	γ	N_0^{tot}	MBC *(pu)*	FOR^{Agg}	SOC^{min}	SOC^{max}
0.2	24	10	10	82	90	650	400	0.2	0.03	250,000	0.5	0.05	0.3	0.9

Table 2. The details of the considered case studies

	Case 1	Case 2	Case 3
The electricity market model	Perfect competition	Proposed oligopoly model	Proposed oligopoly model
Modelling the owners' satisfaction	No		Proposed model
®^{ContRes} ($/kWh)	0.150*		0.071**
®$_{V2G}^{ContEn}$ ($/kWh)	0.190*		0.097**
®$_{G2V}^{ContEn}$ ($/kWh)	0.225*		0.044**

* Prices quoted from [27].

** Optimal prices obtained from the proposed model.

Table 3. The computation time of different cases

	Case 1	Case 2	Case 3
Computation time (sec)	23	1338	6927

Table 4. Effect of different scenarios on the second stage optimization results

	Scenarios	$\text{®}^{ContRes}$ ($/kWh)	®^{ContEn}_{V2G} ($/kWh)	®^{ContEn}_{G2V} ($/kWh)	EV aggregator's annual profit (million$)	Typical 24 kWh EV owner's annual profit ($)
Market uncertainty	Scenario A (The minimum Gencos' cost coefficients)	0.062	0.081	0.036	39.7	1616
	Scenario B (The maximum Gencos' cost coefficients)	0.087	0.102	0.047	48.9	2440
EV uncertainty	Scenario C (The highest hourly number of EVs)	0.078	0.094	0.052	47.2	1919
	Scenario D (The lowest and the least accurate hourly number of EVs)	0.065	0.082	0.056	43.8	1248
	Scenario E (The most accurate hourly number of EVs)	0.072	0.100	0.042	44.5	1908
	Expected	0.071	0.097	0.044	44.1	1823

Table A.1. Gencos' data

Genco	Unit cost coefficients			Start-up cost (MBtu)	Shut-down cost (MBtu)	Pmin (MW)	Pmax (MW)	Min down (h)	Min up (h)	Ramp rate (MW/h)
	a (MBtu /MW^2h)	*b* (MBtu /MWh)	*c* (MBtu)							
1	$\mu = 0.01$	$\mu = 38$	$\mu = 190$	$\mu = 200$	$\mu = 120$	50	110	4	4	20
	$\sigma = 2$	$\sigma = 2$	$\sigma = 2$	$\sigma = 2$	$\sigma = 2$					
2	$\mu = 0.01$	$\mu = 40$	$\mu = 160$	$\mu = 250$	$\mu = 180$	50	110	4	4	20
	$\sigma = 2$	$\sigma = 2$	$\sigma = 2$	$\sigma = 2$	$\sigma = 2$					
3	$\mu = 0.03$	$\mu = 40$	$\mu = 200$	$\mu = 140$	$\mu = 100$	15	50	4	4	20
	$\sigma = 0.5$	$\sigma = 0.5$	$\sigma = 0.5$	$\sigma = 0.5$	$\sigma = 0.5$					
4	$\mu = 0.03$	$\mu = 42$	$\mu = 170$	$\mu = 160$	$\mu = 110$	15	50	4	4	20
	$\sigma = 0.5$	$\sigma = 0.5$	$\sigma = 0.5$	$\sigma = 0.5$	$\sigma = 0.5$					
5	$\mu = 0.04$	$\mu = 38$	$\mu = 150$	$\mu = 100$	$\mu = 70$	10	50	3	2	30
	$\sigma = 1$	$\sigma = 1$	$\sigma = 1$	$\sigma = 1$	$\sigma = 1$					
6	$\mu = 0.04$	$\mu = 37$	$\mu = 120$	$\mu = 120$	$\mu = 90$	10	50	3	2	30
	$\sigma = 1$	$\sigma = 1$	$\sigma = 1$	$\sigma = 1$	$\sigma = 1$					

Table A.2. Retailers' data

Retailer	Revenue coefficients	
	e ($)	f ($/MWh)
1	$\mu = 380$	$\mu = -0.10$
	$\sigma = 2$	$\sigma = 2$
2	$\mu = 390$	$\mu = -0.15$
	$\sigma = 1$	$\sigma = 1$
3	$\mu = 370$	$\mu = -0.12$
	$\sigma = 0.5$	$\sigma = 0.5$