Multi-Layer Agent-Based Decision Making Model with Incomplete Information Game Theory to Study the Behavior of Market Participants for Sustainability

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Abstract

This paper presents a new stochastic multi-layer agent-based decision making model to study the behavior of market participants in the future smart grid. In the agent-based model proposed, wholesale market players are modeled in the first layer. The players include renewable/sustainable power producers, optimizing the bidding/offering strategies to participate in the electricity markets. In the second layer, responsive customers include electric vehicle owners and consumers who participate in demand response programs, being modeled as independent agents. The objective of the responsive customers is to increase their benefit while retaining welfare. The interaction between market players in day-ahead and real-time markets is modeled using an incomplete information game theory algorithm. According to the high uncertainty of resources and customers’ behavior, the model is developed using a stochastic framework. A case study containing wind power producers, aggregators and retailers providing demand response is considered to confirm the usefulness of the proposed multi-layer model.

1. Nomenclature

- $c$: index of DR providers’ customers
- $d$: index of DR providers
- $i$: index of Gencos
- $j$: index of retailers
- $p$: index of PEV aggregators
- $v$: index of PEV owners
- $\omega$: index of scenarios
- $C_{\text{del}}$: degradation cost of battery
- $C_{\text{del}}^{\omega}$: probability of being called to generate
- $D^X$: bid to the market $X$
- $E_{\Omega}$: expected value from set of scenario $\Omega$
- $F_{i,k,\omega}^{\text{nw}}$, $F_{i,k,\omega}^{\text{nw}}$: branch flow in normal and contingency
- $\text{FOR}^{\text{MW}}$: PEV aggregator’s unavailability
- $I$: variable of unit commitment
- $P^X$: offer to the market $X$
- $P_{\text{E}}$: energy of injected to PEV $v$
- $P_{\text{v}}$: energy of PEV $v$ injected to grid
- $P_{\text{Energy}}$: power limit for energy trade
- $P_{\text{Res}}$: power limit for spinning reserve
- $\text{PEV}_{\text{tot}}$: number of connected PEVs
- $R_{v,i}$, $R_D$: ramp up and down constraints
- $\text{SOC}_{\text{sys}}$: state of charge
- $\text{SOC}_{\text{sys}}^{\text{Connect}}$: state of charge when reconnecting
- $\delta_{\text{up}, \text{down}}$: estimated coefficients of cost function
- $\delta_{\text{up}}, \delta_{\text{down}}$: estimated coefficients of revenue function
- $i_{\text{Charge}}, i_{\text{Discharge}}$: rate of charge and discharge of PEV
- $i_{\text{v,t}}$: duration of charging
- $i_{\text{v,t}}$: duration of participation in market $X$
- $\lambda_{\text{Tariff}}$: waiting factor for function $F$
- $\lambda_{\text{TariffOff}}$: starting-up and shutting-down variables
- $\lambda_{\text{TariffCharge}}$: charging and discharging efficiencies
- $\lambda_{\text{Tariff}}$: round-trip efficiency
- $\lambda_{\text{TariffOff}}$: price of market $X$
- $\Lambda_{\text{S}}$: estimated start-up and down costs
- $\Delta_{\text{S}}$: tariffs for participating in the market $X$
- $\Delta_{\text{S}}$: charging tariff
- $\Delta_{\text{S}}$: occurrence probability of scenario $\omega$
- $\Delta_{\text{S}}$: positive and negative deviations of balance market

2. Introduction

Over the past couple of decades, the power system has experienced important changes towards competition for improving economic efficiency. Since one of the major risks of the electricity market is limited information to predict the behavior of competitors, the main factor for obtaining the mentioned efficiency is to advance the accuracy and objectivity of the forecast for the market players. For this purpose, several reports have modeled the competition in electricity markets. Most of the models have been presented to study uncompetitive behavior of players by means of game theory (e.g. [1] and [2]).
In [3], a stochastic model of game theory has been presented based on reinforcement learning. Most of the mentioned reports have considered only two market producers. In [4], an evolutionary game has been used by means of genetic algorithm to study more complex power markets. Additionally, since network limits can form locational market power, in some reports (e.g. [5]) the constraints have been considered in the market simulation. However, in these reports, security constraints have not been modeled whereas one of the aims of the Independent System Operator (ISO) is to supply them and they absolutely affect market prices.

In the above mentioned models, there is only one market layer and all market producers compete with each other in one level, but these models are not practical in the future smart grid. Since the importance of energy conservation and environmental protection are growing, renewable/sustainable resources, Plug-in Electric Vehicles (PEVs) and Demand Response (DR) can favorably affect the future smart grid [6]-[8]. On this basis, renewable/sustainable power plants participate in electricity markets to maximize their profits like the other market producers, in spite of their uncertainty. Also, information and communication improvements cause customers’ behavior in demand side to play a crucial role in the future smart grid. On the other hand, retaining the stability and quality of the power systems containing plenty of PEVs and other equipment for generating and storing energy (e.g. micro generators, Combined Heat and Power (CHP) and heat storages) will be challenging [9]. On this basis, some new market players (e.g. PEV and DR aggregators) or existing players (e.g. retailers that implement Demand Response Programs (DRPs)) should manage the customers. For instance, in [10], an approach has been proposed to coordinate the system operator and a PEV aggregator to enhance the stability of the power system. However, these players have to compete with other market players while motivating consumers to take part in the market. Since these players are the link between customers and electricity markets, they have a critical role.

The smart grid is described by a bi-directional flow of electricity and data to form an automated, widely distributed energy delivery network. Thus, the role of the aggregators is not limited only to what is mentioned above. From another point of view, they can reduce the volume of communications transferred directly between the market operator and market participants [11]. Therefore, the complexity of determining the auction winners will be decreased for the market operator and the cyber security will be improved. The presence of these linking players causes the smart grid to be transformed into a multi-layer environment from the electricity market perspective.

In other words, considering only one level of competition means whether ignoring the role of customers or direct participation of them in wholesale markets, both far from reality.

In previous reports, the behavior of new market players such as the mentioned aggregators and renewable/sustainable power plants has not been taken into account in oligopoly power markets. Therefore, in almost all previous studies, the new market players have been considered as price takers.

In the future smart grid, by increasing the number of PEVs and participation of customers in DRPs, the players will have a more important role in electricity market prices. On this basis, modeling them as price maker players in oligopoly power markets is vital.

A multi-agent model not only is able to preserve the non-convexity and discontinuity features of electricity markets, but also it is very useful in modeling the new market players. Hence, in this paper, in order to adequately model the oligopoly electricity market a new multi-layer environment is developed based on a multi-agent system. This environment is modeled from agents’ viewpoints; thus, an incomplete information dynamic game theory is applied. Based on this, the market players do not know the cost function of their competitors, nor do they know the competitors’ likely offering/bidding strategies. Since the mentioned market players are energy limited, modeling them only in a certain hour is not precise, so their daily behavior should be considered. Accordingly, their self-scheduling to make decisions about the offering/bidding strategies should be conveniently modeled.

This paper considers that customers can select their supplying company for buying/selling electricity in another layer, so the company (aggregator or retailer) should compete with other market players to preserve and increase its customers by optimizing its tariff. The competition of the player for customers has not been addressed in previous works. Hence, a new model is developed in this paper by considering the market players’ strategies to motivate the customers to connect to them. In addition, from the ISO’s viewpoint, the equilibrium point of the markets is obtained using Security Constrained Unit Commitment (SCUC) and Security Constrained Economic Dispatch (SCED) to model day-ahead and real-time electricity markets (energy and reserve), respectively.

In next section, the proposed stochastic multi-layer agent-based electricity market model is introduced. Section 4 presents the agent’s models in the first layer of competition. The agent’s models of consumers and PEV owners in the second layer of competition are presented in Section 5. Section 6 accurately models the uncertainty characteristics. Section 7 is devoted to the case studies. Finally, Section 8 concludes the paper.
3. The proposed multi-layer model

In this paper, a multi-agent system is developed to model the smart grid from the aspect of power market. For this purpose, each market participant is individually modeled by means of an agent that maximizes the participant’s profit. These players are categorized into two layers namely; First-layer and Second-layer agents. The first-layer agents are introduced as players that directly participate in electricity markets. Whereas the second-layer agents connect to one of the first-layer agents in order to take part in the markets. Figure 1 shows the proposed multi-layer environment to model the behavior of electricity market in smart grid.

As it can be seen, the market players that have connection to customers (e.g. retailer who provides DR, DR aggregator and PEV aggregator) are the link between customers and electricity markets. In other words, the players cause the two mentioned layers not to be independent. Because of the presence of customers, the second-layer can be called demand side layer. The large number of responsive demands in smart grid makes the market operator clear the market in multi layers using the linking players. Based on this, the market in the second layer should be cleared using a competition between the second-layer agents and another competition for the customers between the linking first-layer agents. At the same time, the first layer of market should be cleared based on competition between the first-layer agents. The results of second layer market can affect the behavior first-layer agents, as the results of the first layer market affect the behavior of linking agents and consequently the behavior of second-layer agents. Therefore, the market clearance of these two layers should be modeled, simultaneously. Details of modeling the layers are presented in the rest of the paper.

4. Competition in the first layer

The first layer is introduced as an environment to compete between first-layer agents. In the layer, each market player determines the offering/bidding strategies to participate in the both day-ahead and real-time markets. For this purpose, each first-layer agent receives the daily price of energy and reserve markets from the previous iteration. Afterwards, as the agent does not know the cost/revenue function of its competitors (incomplete information game theory) it considers the uncertainties of the estimated coefficients of players’ cost/revenue functions using the method explained in Section 6 in order to reduce the risk of estimating mistakes. On this basis, in addition to the estimated coefficients of cost/revenue functions, higher and lower amounts that competitors might have are thus considered. These coefficients and their probabilities are computed using the discrete normal distribution discussed in Section 6. Considering the uncertainties, above mentioned agents solve individually their self-scheduling problem to maximize the profit and offer/bid their suggestion to electricity markets. For this purpose, in this paper, Supply Function Equilibrium (SFE) is utilized. Because of player’s simultaneous decision on its price and quantity, SFE has the highest accuracy to simulate the game theory. Based on this, it is worth mentioning that in the multi-layer model all first-layer agents are considered as price-making participants in the market.

It should be noted that, in order to optimize the objective function of each agent, the state enumeration method is utilized so the occurrence probability of uncertain parameters has been considered to achieve agent’s expected profit. The stages of the first layer model are explained below:

4.1. Modeling agents of traditional Gencos

To maximize the profit in a period, Genco agents solve their self-scheduling problems and offer to the markets. The objective of Genco agent $i$ is formulated as below [12]:

$$\text{max} \{E_{\text{Expected Profit}}\} =$$

$$\max \sum_{s_{\text{gen}}} \left[ E_{\text{DG}} \left( P_{\text{DA}}^{\text{DG}} + P_{\text{RES}}^{\text{RES}} + P_{\text{NRES}}^{\text{NRES}} \right) + E_{\text{RT}} \left( P_{\text{RT}}^{\text{RT}} - a_{\text{RT}} P_{\text{RT}}^{\text{RT}} - b_{\text{RT}} P_{\text{RT}}^{\text{RT}} - c_{\text{RT}} P_{\text{RT}}^{\text{RT}} \right) \right]$$

$$\left(1\right)$$

$$P_{\text{DA}}^{\text{DA}} = P_{\text{RT}}^{\text{RT}} + P_{\text{RES}}^{\text{RES}} + P_{\text{NRES}}^{\text{NRES}} \quad \left(2\right)$$

$$P_{\text{DA}}^{\text{DA}} I_{\text{DA}}^{\text{DA}} \leq P_{\text{DA}}^{\text{DA}} \quad \left(3\right)$$

$$I_{\text{DA}}^{\text{DA}} - I_{\text{DA}}^{\text{RES}} = \gamma_{\text{DA}}^{\text{DA}} - z_{\text{DA}}^{\text{DA}} \quad \left(4\right)$$

$$y_{\text{DA}}^{\text{DA}} + z_{\text{DA}}^{\text{DA}} \leq 1 \quad \left(5\right)$$

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4.2. Modeling agents of wind power producers

Among the renewable/sustainable energies, wind power assigns a significant share of the generation portfolio. Therefore, these resources can play a dominant role in future of power system. On this basis, in this paper, this type of power plants is presented as a renewable-based Genco in the proposed multi-layer model. There are several papers which are addressed the optimal offering strategy of wind power producers in electricity market (e.g. [13]). In the reports, the Wind Power Producers (WPPs) have modeled as a passive producer in the electricity market. The proposed model of smart grid makes the agent of renewable based power plant be able to effect directly on the electricity market transactions. The objective of a WPP is to maximize expected profit considering the risk constraints. The objective function of the first-layer agent can be expressed as (10) [14]:

$$\max \{\text{Expected Profit}\} = \max_{\pi_{\omega}} \sum_{\omega} \left\{ \mathbb{E}_m \left[ P_{DA}^{DA} y_{i,t,\omega} + z_{i,t,\omega} - P_{RT}^{RT} I_{i,t,\omega} \right] \right\}$$

(10)

$$P_{DA}^{DA} = P_{i,t,\omega} - P_{RT}^{RT} I_{i,t,\omega}$$

(11)

$$\Delta_{i,t,\omega} = P_{i,t,\omega} - P_{RT}^{RT} I_{i,t,\omega}$$

(12)

where $P_{DA}^{DA}$ is the power production scheduled for the WPP and $P_{RT}^{RT}$ is the actual amount of produced power. The first two terms in (10) denote the income achieved from selling energy in the day-ahead and real-time markets, respectively. The next two terms represent positive and negative imbalance incomes resulted from the difference between day-ahead and real-time prices.

4.3. Modeling agents of traditional retailers

Another group of market players are traditional retailers that do not provide DR. The players are modeled as agents with the formulated objective function as following:

$$\max \{\text{Expected Profit}\} = \max_{\pi_{\omega}} \sum_{\omega} \left\{ \mathbb{E}_m \left[ -D_{DA}^{DA} \lambda_{DA}^{DA} - D_{RT}^{RT} \lambda_{RT}^{RT} \right] \right\}$$

(13)

$$+ \mathbb{E}_m \left[ -D_{DA}^{RT} \lambda_{DA}^{RT} - f_{j,\omega} D_{RT}^{RT} \right]$$

It should be noted that, even traditional retailers achieve benefit from DR implementations. The retailers are exposed to financial risks due to market price volatility, because they purchase electricity from the wholesale market at volatile rates and sell it to consumers at a flat rate [15]. By reducing consumption during price spikes period, retailers may cover a part of these risks [16].

4.4. Modeling agents of PEV aggregators

The PEV aggregator should manage the charge/discharge of PEVs considering several kinds of uncertainties. The aggregator as a financial agent in the power market has to compete with other players for selling and purchasing electricity. In the business competition, the aggregator has to compete for keeping the current customers and attracting new owners. In the other words, the aggregator is considered as a private entity who wants to maximize its own profit. It can manage customers’ charge and discharge pattern using a decentralized control when they are plugged-in.

In this paper, in addition to the uncertainties of number of PEVs, the uncertainties of connection duration of PEVs to the aggregator, state of charge of PEVs, and the uncertainty of calling the aggregator for power generation are also considered. Moreover, the constraint of minimum connection duration of PEVs to the aggregator has been modeled. In order to ensure the owners about desired charge of their batteries, the aggregator should care about the minimum charge of PEVs. The costs of the PEV aggregator consist of the purchase costs of the energy and reserve from PEVs for selling to market, and the purchase costs of the electricity from the market for charging the batteries of PEVs. The revenues of the PEV aggregator include incomes of participating in the energy and reserve markets, and revenues of receiving the cost of battery charging from PEV owners. The objective function of PEV aggregator can be expressed as (14).

$$\max \{\text{Expected Profit}\} = \max_{\pi_{\omega}} \sum_{\omega} \left\{ \mathbb{E}_m \left[ -D_{DA}^{DA} \lambda_{DA}^{DA} - D_{RT}^{RT} \lambda_{RT}^{RT} \right] \right\}$$

(14)
The objective of the aggregator is maximizing the profit in a certain period. Obviously, the profit is dependent to the behavior of the aggregator in the market and subsequently, it is a function of uncertain variables. On this basis, it is reasonable that the aggregator behaves proportional to the occurrence probability of each uncertain variable.

The aggregator incomes resulted from participation in the day-ahead energy, spinning reserve and non-spinning reserve markets have been respectively considered in the first three terms of (14). The forth term presents the aggregator income resulted from receiving the batteries charge cost from PEV owners who have respected the minimum connection duration. The fifth term considers the aggregator income resulted from being called by the ISO in order to generate electrical energy in the reserve markets. The sixth term represents the imbalance income because of surplus of injection compared to day-ahead offers. The seventh term represents the imbalance cost due to lack of injection in comparison with day-ahead offers. The eighth term of (14) denotes the purchase cost of electrical energy from the energy market in order to charge the battery of PEVs. Inability of aggregator for energy generation at the time of being called by ISO may be caused by an error in predicting uncertain parameters. Considering the inability, FORagg is very important, because the PEVs are located in distribution system that has a lower reliability. The ninth term presents the purchase cost of electrical energy in order to meet the aggregator obligations while being called for energy generation in the reserve markets. The last term denotes the cost of the contract with owners to persuade them into participate in the reserve markets.

The objective function is maximized considering the constraints (15)-(21):

\[
\text{SOC}_{\text{VM},\omega} \leq \text{MCB} \text{ } U_{\omega,\omega} \tag{15}
\]

\[
0 < \text{SOC}^\text{min} \leq \text{SOC}_{\text{VM},\omega} \leq \text{SOC}^\text{max} < 1 \tag{16}
\]

\[
\text{SOC}_{\text{VM},\omega} = \text{SOC}_{\text{VM},\omega-1} + \delta_{\text{VM},\omega} \text{P}_{\text{VM},\omega} - (1 - \delta_{\text{VM},\omega}) \text{P}_{\text{VM},\omega} - \text{SOC}^\text{Chg} \tag{17}
\]

\[
\text{SOC}_{\text{VM},\omega} = \text{SOC}_{\text{VM},\omega-1} - \delta_{\text{VM},\omega} \text{P}_{\text{VM},\omega} - (1 - \delta_{\text{VM},\omega}) \text{P}_{\text{VM},\omega} - \text{SOC}^\text{D} \tag{18}
\]

\[
p_{\text{dis},\omega} \leq \sum_{v \in \text{PEV}_\omega} \left[ \text{SOC}_{\text{VM},\omega}^\text{V2G} \right] U_{\omega,\omega} \tag{19}
\]

\[
p_{\text{rep},\omega} + p_{\text{net},\omega} \leq \sum_{v \in \text{PEV}_\omega} \left[ \text{SOC}_{\text{VM},\omega}^\text{V2G} \right] U_{\omega,\omega} \tag{20}
\]

\[
\text{where } U_{\omega,\omega} \text{ is a binary number equal to 1, if the owner respects to the minimum connection duration, and 0 otherwise.}
\]

The constraints of MCB (Minimum Charge of Battery) are formulated as (15), and these limitations should be met by the aggregator for PEV owners who respected the minimum connection duration. Eq. (16) is applied to avoid being overcharged and to take into account the depth of discharge of all connected PEVs during their connection. Eq. (17) introduces changes in SOC of PEVs. Binary variable \( \delta \) ensures a PEV is not charged and discharged at the same time. The constraints of maximum charging/discharging rates are presented in (18) and (19). Eqs. (20) and (21) ensure that the aggregator offers to the energy and reserve markets based on the power of PEVs in V2G mode.

4.5. Modeling agents of DR providers

DR aggregators and some kind of retailers can be considered as DR providers. The main difference between the above mentioned players is that the DR aggregators are nonprofit players in the electricity market; while, retailers aims to maximize the profit.

In this paper, it is supposed that the agents of DR provider first purchase electricity from day-ahead market. After that, they adopt real time pricing. Then, they offer hourly day-ahead prices to their customers. The decision making of the first-layer agents is based on the prices of purchasing the electricity, the strategy of adopted retail and the profit obtained from previous iteration of market. Real-time pricing is one of the price-based DR programs in which responsive customers change their loads based on real-time prices. The DR provider agents propose day-ahead prices and experience following customers’ reactions considering agents’ demand. The objective function of the agent can be formulated as:

\[
\max \{ \text{Expected Profit} \} = \sum_{v} \left[ \text{E} \left( \text{P}_{\text{dis},\omega} + \text{E}_{\omega} \left( \text{DR}_{\omega,\omega} \lambda_{\omega,\omega} \right) \right) \right] + \sum_{v} \left[ \text{E} \left( \text{P}_{\text{rep},\omega} + \text{E}_{\omega} \left( \text{DR}_{\omega,\omega} \lambda_{\omega,\omega} \right) \right) \right] \tag{22}
\]

where \( \lambda_{\omega,\omega} \) denotes the candidate price to be suggested to responsive consumer agents in the second layer. 

\[
\text{max} \sum_{\omega} \left[ \text{E} \left( \text{P}_{\text{dis},\omega} + \text{P}_{\text{rep},\omega} + \text{E}_{\omega} \left( \text{DR}_{\omega,\omega} \lambda_{\omega,\omega} \right) \right) \right] + \sum_{v} \left[ \text{E} \left( \text{P}_{\text{rep},\omega} + \text{E}_{\omega} \left( \text{DR}_{\omega,\omega} \lambda_{\omega,\omega} \right) \right) \right] \tag{14}
\]
DR_{d, i, o} represents the model of consumer’s response to the offered price.

In different studies, several kinds of demand function have been utilized in demonstrating the consumers’ response. The load profile of each consumer reflects its use pattern [17]. On this basis, the mentioned different patterns can be modeled by using various benefit functions [16]. Based on this, a combined demand function is applied to better model an integrated consumers with various load patterns as presented in (23).

It should be mentioned that, initial hourly demands are obtained from the first iteration. Eq. (23) formulates the response of second-layer agents to the offered prices based on their initial load levels and preliminary retail price.

4.6. Clearing the power market transactions in the first-layer

The most conventional method to clear the 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 using SCUC and SCED problems, which maximizes social welfare considering security constraints. The main reason of utilizing the SCUC instead of OPF is the inherent nature of new market players (e.g. WPP, PEV and DR aggregators). The new players of power market are limited energy participants. Therefore, simulation of their behavior in an hour (or even in some independent hours) is not accurate and their behavior should model in a specific period. On the other hand, their behaviors are completely uncertain. 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. It is noteworthy that the added expenses due to network congestions and supplying the system security are considered in prices resulted from the SCUC program that increases the accuracy of the model.

After entering the first-layer agents’ offers/bids \((q_{_{\text{STE}}, i}^{_{\text{FE}}}, b_{_{\text{STE}}, i}^{_{\text{FE}}})\) to the SCUC and SCED programs, the best economical solution for the first-layer agents are achieved using (24) and (25).

\[
\text{max} \{ \text{Social Welfare} \} = \\
\max \sum_{i} \left\{ \sum_{j} D_{j,i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} + \sum_{j} D_{j,i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} + \sum_{j} D_{j,i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} \right\} + \left( \sum_{i} \left( P_{i, j, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} + \sum_{j} P_{j, i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} \right) \right) \right) \\
- \left( \sum_{i} \left( D_{j,i, o}^{\text{DA}} + \sum_{j} D_{j,i, o}^{\text{DA}} + \sum_{j} D_{j,i, o}^{\text{DA}} \right) \right) - \left( \sum_{i} \left( P_{i, j, o}^{\text{DA}} + \sum_{j} P_{j, i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} \right) \right) \\
\text{s.t.} \quad \lambda_{i, o}^{\text{DA}} = \sum_{i} \left( \sum_{j} D_{j,i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} + \sum_{j} D_{j,i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} \right) \right) + \left( \sum_{i} \left( P_{i, j, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} + \sum_{j} P_{j, i, o}^{\text{DA}} \lambda_{i, o}^{\text{DA}} \right) \right) \right) \\
\lambda_{i, o}^{\text{DA}} \geq 0, \quad \forall i, j, o \\
(24)
\]

\[
\lambda_{i, o}^{\text{DA}} \geq 0, \quad \forall i, j, o \\
(25)
\]

Eq. (26) ensures the balance between supply and demand in both day-ahead and real-time markets. Required reserve is expressed in (27). Equations (28) and (29) consider the network limits in normal and contingency states, respectively.

4.7. Convergence of the first layer

The learning process is on basis of the hypothesis that each first-layer agent can observe the final market loads and prices related to previous iterations, in addition to the results of its auctions. Therefore, the price loop is repeated until prices of first-layer agents are equal to market clearing ones. It is worth noting that, since the model can simulate a period, it can meaningfully increase the precision of the market model in comparison with previously reported studies, because, behavior of energy limited players can be considered. The agent suggests 24-hour offering/bidding strategies to day-ahead markets. Afterwards, it offers/bids to real-time markets according to uncertainties of wind and demand. This process will be repeated for all hours.

\[
\begin{align*}
DR_{t, o} & = w_{\text{lin}} a_{t, o}^{0, \text{lin}} \left[ 1 + b_{\text{lin}} \left( \lambda_{t, o}^{\text{Cust}} - \lambda_{t, o}^{0, \text{Cust}} \right) \right] + w_{\text{exp}} a_{t, o}^{0, \exp} \exp \left( b_{\text{exp}} \left( \lambda_{t, o}^{\text{Cust}} - \lambda_{t, o}^{0, \text{Cust}} \right) \right) + w_{\text{log}} a_{t, o}^{0, \log} \left[ 1 + \frac{b_{\text{log}} \left( \lambda_{t, o}^{\text{Cust}} - \lambda_{t, o}^{0, \text{Cust}} \right)}{a_{\text{log}} + b_{\text{log}} \ln \left( \lambda_{t, o}^{0, \text{Cust}} \right)} \right] \\
& + \left( \lambda_{t, o}^{\text{Cust}} \right)
\end{align*}
\]  

(23)
5. Competition in the second layer

Since it is difficult for consumers and PEV owners to negotiate directly with ISO, they connect to a first-layer market player and enroll in a program provided by the market player. This can increase the negotiation power of the second-layer agents. On this basis, each second-layer agent is assigned to a DR provider or a PEV aggregator through a contract.

The role of the linking first-layer agents in the second-layer of model is to improve the benefit of their customers in order to retain and increase the market share that can be obtained from customers’ satisfaction. In the remainder of this section the model of agents and their interactions in the second layer of market are expressed.

5.1. Modeling agents of PEV owners

In order to model the motivation of PEV owners to select between several programs and contracts of different PEV aggregators, the owners’ annual profits are considered as the main motivation factor. It should be noted, apart from annual profit, other parameters such as customer services can influence the customers’ behavior. 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 very near to reality. The formulation of PEV owner’s annual profit is given by:

\[
\text{Max} \{ \text{Expected Profit} \} = \max \sum_{v \in \Omega} \left( \pi_{\text{Cost}} \right) - \sum_{t=1}^{T} \left( P_{\text{Res}, v, t} \lambda_{\text{Res}, t} + P_{\text{Energy}, v, t} \lambda_{\text{Energy}, t} - P_{\text{Charge}, t} \lambda_{\text{Charge}, t} - \text{Cost}_{\text{Wiring}} \right) dr \]

\[
\text{Cost}_{\text{Wiring}} = \sum_{t=1}^{T} P_{\text{Wiring}, t} C_{\text{d}} \quad \text{(31)}
\]

\[
\text{Cost}_{\text{Wiring}} = \frac{\left( \text{Cost}_{\text{Wiring}} + \text{Cost}_{\text{Batteries}} \right) \text{dr}}{1-(1+dr)^{-N_t}} \quad \text{(32)}
\]

where \( dr \) is the annual discount rate. \( N_t \) is number of years the device will last.

The first two terms in (30) 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. \( \text{Cost}_{\text{Res}, t} \) and \( \text{Cost}_{\text{Energy}, t} \) are customer’s annual equipment degradation and annualized infrastructure costs. As presented in (32), the infrastructure cost includes onboard incremental cost and wiring upgrade cost.

Each PEV owner selects its PEV aggregator \( p \) by using (30). Using the stochastic terms of \( t_{\text{Res}, v, p} \) and \( t_{\text{Energy}, v, p} \) for each customer can model the behavior of PEV owners in several clusters considering the uncertainty of their behavior.

5.2. Modeling agents of responsive consumers

Each DR provider attempts to form the load pattern of its customers and achieves compensation for the expenditure saving incurred to ISO due to the shaping. We assume that a DR provider motivates its customers to adjust their electricity consumption profile.

In flat pricing mode, customers tend to use their appliances at the most convenient time throughout the day, driven by their personal preference. In the model, monetary compensation provided by the DR providers motivates consumers to move load out of peak consumption periods. The formulation of a responsive consumer is given by:

\[
\text{Max} \{ \text{Expected Benefit} \} = \sum_{v \in \Omega} \left( P_{\text{Res}, v, t} \lambda_{\text{Res}, t} + P_{\text{Energy}, v, t} \lambda_{\text{Energy}, t} - P_{\text{Charge}, t} \lambda_{\text{Charge}, t} - \text{Cost}_{\text{Wiring}} \right) dr \]

\[
\text{where the function} \ V_{v, t} \ \text{captures the dissatisfaction caused due to deviation from the reference consumption.}
\]

\[
V_{v, t} = V_{v, t} (P_{\text{Res}, v, t} - P_{\text{Res}, t}) \quad \text{(33)}
\]

\[
\text{where} \ V_{v, t} \ \text{is the power consumption for the following day for each demand} \ c \ \text{and} \ V_{v, t} \text{is the inelasticity parameter of demand} \ c. \ \text{It should be noted that, the function} \ V_{v, t} \ \text{may be taken to be convex, since the differential dissatisfaction of a user increases as the amount of deviation from the reference power consumption increases [11].}
\]

5.3. Interconnection between the layers

In order to make an optimal decision, the linking first-layer agents should pay attention to the possibility of modifying the contract with the customers (tariffs) and attracting them to participate in the market. For this purpose, the agents should observe the effects of each tariff change on its market share and profit. In this paper, the mentioned agents select the best tariffs with their customers and participate in the electricity market in such a way that the maximum profit is achieved.

For this purpose, several kinds of contract with customers (e.g. based on agreed prices of charging, energy and reserve for PEVs) are considered as a decision space. Afterward, the effect of each tariff on the number of customers is taken into account by calculating the expected annual profit of owners in second layer market.
Using the new number of customers, the first-layer agent simulates its participation in the electrical markets and obtains its expected profit. Finally, by comparing the profits, the agent chooses the tariff associated with the maximum profit. The behavior of a linking first-layer agent to converge to the optimal tariff is illustrated in Figure 2.

6. Characterization of uncertainties

6.1. Wind power uncertainty modeling

Despite undeniable advancements of wind forecasting, the day-ahead forecasts can cause the uncertainty of electricity systems and imbalances costs to be increased. In order to overcome the uncertainty, different realizations of the wind power generation are modeled using the scenario generation process in based on Roulette Wheel Mechanism (RWM) [18]. A Weibull distribution is considered for wind speed. The produced power, \( P_{GW} \), corresponding to a specific wind speed, \( WS_i \), can be obtained through (35):

\[
P_{Sc} = \begin{cases} \frac{P}{P_r} (A + B WS_i + C WS_i^2) & \text{if } V_c \leq WS_i \leq V_r \\ \frac{P_r}{P} & \text{if } V_r \leq WS_i \leq V_cr \end{cases}
\]

where \( A, B \) and \( C \) are constants that can be computed in accordance with [18], while \( V_c, V_r, \) and \( V_cr \) represent cut in, cut out and rated speeds, respectively.

6.2. Uncertainty of competitors’ cost/revenue functions

Incomplete information about market participants’ cost/revenue functions causes the agents to be unable to simply predict the behavior of competitors in the electricity market. It should be noted that, the range of the mentioned functions is achievable [19]. On this basis, this basic information is available for each agent to estimate coefficients of the above mentioned functions. However, realizing the accurate cost/revenue functions is difficult even for their owners with detailed data [19]. In order to overcome the problem, this paper proposes RWM for scenario generation to cover the uncertainty of the mentioned estimated coefficients. Since estimation errors often have a distribution very close to the normal, scenario generation is accomplished by Normal distribution. On this basis, all possible scenarios for amounts of the coefficients are generated by RWM [18].

6.3. Uncertainty of customers’ behavior

The probabilistic behavior of PEV owners and consumers has made linking second-layer agents to face plenty of uncertainties for market participation.

The users behave differently due to social and economic concerns. Therefore, their behavior will be different from the others. The linking agents should estimate the uncertain parameters of probabilistic behavior of customers by past statistics data. In this paper, the second-layer agents utilize the statistical data of set of customers and forecast the above mentioned parameters. In this paper, the aggregator models estimation uncertainty using a probabilistic approach. For this purpose, the linking agent uses the statistical data and generates scenarios based on time series of uncertain variables using RWM [18]. Since the time series of all related stochastic variables are generated together in the basis of a unique historical data, the correlation between stochastic variables and subsequent hours has been considered. SOC depends on the number of plugged-in EVs and their daily driven distance. The probabilistic traveled distance is applied as a parameter of calculating the SOC. The lognormal distribution function is utilized to generate the probabilistic daily traveled distance [20].

6.4. Stochastic Programming Approach

In order to consider the impact of the sources of uncertainty mentioned previously, they have been characterized as stochastic procedures and the problem has been solved using a two-stage stochastic programming approach. In the proposed approach, the classification of decision variables of each stage is based on time horizon of electricity markets (day-ahead and real-time) and it is presented as follows:

**\( \Omega_1 \): First stage (here-and-now) decision variables are \( (D_{DA}^{it}, P_{DA}^{it}, P_{Res}^{it}, P_{NRes}^{it}, \lambda_{DA}^{it}, \lambda_{Res}^{it}, \lambda_{NRes}^{it}) \).**

**\( \Omega_2 \): Second stage (wait-and-see) decision variables are \( (a_{i,a}^{it}, b_{i,a}^{it}, c_{i,a}^{it}, e_{i,a}^{it}, f_{i,a}^{it}, \delta_{i,a}^{it}, I_{i,a}^{it}, SOC_{i,a}^{it}, D_{UP}^{it}, I_{UP}^{it}, SOC_{UP}^{it}, D_{DOWN}^{it}, I_{DOWN}^{it}, SOC_{DOWN}^{it}, P_{RT}^{it}, P_{G2V}^{it}, P_{V2G}^{it}, P_{V2H}^{it}, P_{H2V}^{it}) \).**

\[\text{Input the expected profit from the first-layer market} \]

\[\text{Modify the tariffs} \]

\[\text{Run the second-layer market} \]

\[\text{Compute the participation of customers} \]

\[\text{Modify the objective function by importing the new participation} \]

\[\text{Run the first-layer market} \]

\[\text{Is the profit converged?} \]

\[\text{Yes} \]

\[\text{Optimal tariffs} \]

\[\text{Figure 2. Interconnection between the layers.} \]
7. Numerical studies

In this paper, a modified IEEE 30-bus system consisting of 5 Gencos (4 thermal plants and one 50 MW WPP), 21 aggregate based loads and 41 branches is taken into account. The Spanish wind data in Feb. 2010 is utilized for the wind farm [21]. In addition, three retailers have been considered to supply the demands include traditional and responsive consumers. It is supposed that 20% of consumers participate in DRPs. In our experiments, the PEV aggregator competes with the mentioned Gencos and retailers for selling and purchasing electricity, respectively. The energy and reserve markets are considered to be cleared in day-ahead and real-time horizons.

In order to investigate the effectiveness of the proposed model, results of the multi-layer model are compared with the common one-layer model during a typical day. Moreover, the proposed model is utilized to obtain optimal tariffs (contracts between linking first-layer agents and second-layer agents), and the impact of the tariffs on the first-layer agents’ profit is studied. The effect of various tariffs on the PEV aggregator’s profit is illustrated in Figure 3. As it can be observed, the best price area for the tariff is around 30 and 70 $/MWh for charging and reserve prices, respectively. Although by increasing the reserve price or decreasing the charging cost 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.

In Table 1, the PEV owner and aggregator’s profits have been compared taking into account results of model without considering the modifying the tariffs. The results clearly show that by using the proposed model the profits of the both PEV aggregator and owners can be increased. It is noteworthy that, modeling the effect of second-layer agents on first-layer ones (e.g. modifying tariff) gives the linking market players a flexibility that makes them powerful market players who are able to change its revenue and cost functions. In order to indicate the effect of the proposed model on DR aggregators, the amounts of DR traded in the market have been illustrated in Figure 4. As can be seen, the proposed multi-layer model has more ability to indicate consumers’ response to DRPs.

In Figure 5, the hourly profit of the wind power producer is compared for the proposed multi-layer model and common one-layer one. Figure 5 indicates that although WPP’s profit in the proposed multi-layer model is higher than that in the competitive market, in most hours it is less than the one-layer model. Table 2 compares daily profit of all Gencos with and without modeling the second electricity market layer. As shown, modeling the second layer that indicates the optimal interaction between linking agents and second-layer ones causes the market prices to be decreased and consequently the profit of WPP and most of Gencos to be reduced. In other words, the market prices in one-layer model can be higher than those in competitive market one. Therefore, market players have the potential to increase prices due to their market power.

Table 1. Profits of the PEV aggregator and a typical owner

<table>
<thead>
<tr>
<th>The electricity market model</th>
<th>One-layer model</th>
<th>Multi-layer model</th>
</tr>
</thead>
<tbody>
<tr>
<td>A charging ($/kWh)</td>
<td>0.150</td>
<td>0.067</td>
</tr>
<tr>
<td>B reserve ($/kWh)</td>
<td>0.190</td>
<td>0.061</td>
</tr>
<tr>
<td>Average reserve ($/kWh)</td>
<td>0.225</td>
<td>0.028</td>
</tr>
<tr>
<td>PEV aggregator profit ($/day)</td>
<td>28911</td>
<td>65400</td>
</tr>
<tr>
<td>A typical owner profit ($/yr)</td>
<td>1133</td>
<td>1727</td>
</tr>
</tbody>
</table>

* Optimal tariffs achieved from the proposed multi-layer model

Table 2. Daily profit of the Gencos ($)

<table>
<thead>
<tr>
<th>Model</th>
<th>Genco1</th>
<th>Genco2</th>
<th>Genco3</th>
<th>Genco4</th>
<th>Wind power</th>
</tr>
</thead>
<tbody>
<tr>
<td>One-layer model</td>
<td>46068</td>
<td>16882</td>
<td>14209</td>
<td>27026</td>
<td>24933</td>
</tr>
<tr>
<td>Multi-layer model</td>
<td>44609</td>
<td>13771</td>
<td>14778</td>
<td>24527</td>
<td>21389</td>
</tr>
</tbody>
</table>

Figure 3. The effect of PEV aggregator tariffs.

Figure 4. Hourly traded DR.

Figure 5. Hourly profit of wind power producer.
8. Conclusion

In this paper, in addition to the common one-layer model of electricity market, the interaction of end-users was modeled in the second layer of the proposed market environment using a stochastic formulation. It is possible to conclude that the proposed model was proficient in significantly improving the behavior of all market players, especially players who are connected through the demand side. Besides optimizing the offering/bidding strategy, the model could also attain the optimal tariff for the mentioned market players in order to incentivize consumers and PEV owners to connect to them. Therefore, more active presence of end-users by considering the linking agents improves the competition and efficiency of the market.

9. Appendix

Table A.1. Technical data for the PEV aggregator

<table>
<thead>
<tr>
<th>P (kW)</th>
<th>CPEV (kWh)</th>
<th>$h^D</th>
<th>\eta^D</th>
<th>FOR</th>
<th>Ramp (pu/h)</th>
<th>MCD (h)</th>
<th>MBC (pu)</th>
<th>SOCmin (pu)</th>
<th>SOCmax (pu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>50</td>
<td>0.82</td>
<td>0.9</td>
<td>0.05</td>
<td>0.2</td>
<td>5</td>
<td>0.5</td>
<td>0.3</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Table A.2. Economic data for the PEV aggregator

<table>
<thead>
<tr>
<th>C2 (SAWh)</th>
<th>Cost零售商1 ($)</th>
<th>Cost零售商2 ($)</th>
<th>N (year)</th>
<th>dr (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.225</td>
<td>650</td>
<td>400</td>
<td>10</td>
<td>10</td>
</tr>
</tbody>
</table>

Table A.3. Generation units’ data

<table>
<thead>
<tr>
<th>Generr</th>
<th>e (MWh)</th>
<th>b (MWh)</th>
<th>c (MWh)</th>
<th>Startup (MBtu)</th>
<th>Pmax (MW)</th>
<th>Pmin (MW)</th>
<th>Min down/up (h)</th>
<th>Ramp (MW/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.01532</td>
<td>12.5</td>
<td>199.1</td>
<td>566</td>
<td>84</td>
<td>25</td>
<td>6/6</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>0.00889</td>
<td>12.4</td>
<td>275.6</td>
<td>953</td>
<td>95</td>
<td>34</td>
<td>4/1</td>
<td>70</td>
</tr>
<tr>
<td>3</td>
<td>0.01508</td>
<td>16.2</td>
<td>133.9</td>
<td>596</td>
<td>85</td>
<td>15</td>
<td>1/1</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>0.00208</td>
<td>13.9</td>
<td>209.5</td>
<td>775</td>
<td>80</td>
<td>39</td>
<td>1/2</td>
<td>65</td>
</tr>
</tbody>
</table>

Table A.4. Retailers’ coefficient data

<table>
<thead>
<tr>
<th>Retailer</th>
<th>Retailer1</th>
<th>Retailer2</th>
<th>Retailer3</th>
</tr>
</thead>
<tbody>
<tr>
<td>e ($)</td>
<td>380</td>
<td>390</td>
<td>370</td>
</tr>
<tr>
<td>f ($/MWh)</td>
<td>-0.10</td>
<td>-0.15</td>
<td>-0.12</td>
</tr>
</tbody>
</table>

10. Acknowledgment

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11. References