# Diverse Demand Side Portfolio: Another Step towards Smart Grids

S. S. Mohtavipour, *Student Member, IEEE*, G. R. Yousefi, *Member, IEEE* and F. Fallahi

***Abstract*—The deployment of diverse demand side portfolio in smart distribution systems has given rise to more flexible distribution companies (Discos). Distributed generator (DG) and interruptible load (IL) are seen as an additional instrument to Discos to achieve targets for promoting competition, increasing the reliability of smart distribution systems and alleviating the market power of generation companies (Gencos). This paper deals with day-ahead electricity market auction concept which Discos operating in a smart distribution system need perception to tackle. We provide complementary economic and technical insights by developing an agent-based simulation. This is a detailed double sided model with an active specification of the Gencos and Discos equipped with DG and IL. Gencos and Discos are modeled as adaptive agents capable of reinforcement learning through the interaction with their environment. A case study with three scenarios is presented considering seven competitive Discos and Gencos. Scenarios are constructed to analyze the Discos' strategies with respect to their diverse portfolio options.**

***Index Terms*—Smart Distribution System, Electricity Market, Distributed Generation, Interruptible Load, Reinforcement Learning.**

## I. Introduction

A Smart distribution system is an interdisciplinary paradigm [1], formed by the interconnection of a great variety of sensors, protocols, communication equipment, small modular generations, and controllable loads. The operation of smart distribution systems in the deregulated environment of competitive electricity markets introduces considerable complexity in the operation of a low voltage grid, but at the same time, it can provide definite benefits to the overall system performance, if managed and coordinated efficiently. While generation and transmission systems under competitive environment have attracted considerable effort from researchers, distribution system has received less attention. With further development of electricity markets, researches related to distribution system have gradually started to thrive and clear up all imaginations that the electricity markets will only work properly if there is an active smart demand side. Now, it is widely acknowledged that the markets will work better when a significant level of diverse demand side portfolio is available. Two means of approaching this diverse portfolio, namely DGs and ILs can be used by the distribution companies to improve their market response capabilities, and accordingly change their status of commitment on the market and replace their passive position by a high-ranked active situation.

In an IL program, the customer enters into a contract with the ISO or a load serving entity (LSE) to reduce its demand when requested [2]. ISO and LSE benefit by means of a reduction in system peak demand and thereby avoiding costly reserves, peak shaving and making secure reliability. Diversity of demand side portfolio, in addition to IL, is intensified by DG which is the main subject of various publications [3], [4] and is widely recognized as a means to highlight demand side flexibility. DG can provide similar benefits as interruptible load under certain circumstances. It is possible that distribution companies can operate the distributed generators for peak load reduction and risk management of high electricity price volatility during utility peak load periods. A Disco energy procurement market model equipped with ILs and DGs is presented in [5] with a market structure based on pool and bilateral contracts. However, the energy procurement model in [5] is a static one-shot model and it does not regard the impact of other Discos' decision making. Risk management and hedging price volatility via interruptible load is widely used in electricity markets. Using IL in the case of financial compensation is well described and modeled in [6].

The complexities of technical and economical aspects of electricity markets rush most classical modeling toward their restrictions. Game theoretical analysis usually limited to stylized trading situation among few actors, and place rigid assumptions on the players' behavior [7], [8]. Agent-based (AB) modeling is one of the appealing new methodologies that have the potential to overcome some shortcomings of traditional methods [9]. An AB model is a class of computational models for simulating the actions and interactions of autonomous agents with a view to assessing their effects on the outcome of the system. The model uses reinforcement learning (RL) mechanism that advances the simulation and stimulates the agents' preferences to be influential in improving gaming strategies (see Fig. 1).

In this paper, agent-based simulation is born out of a need

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for reinforcement learning. Demand and generation sides including Discos and Gencos do not have the information on

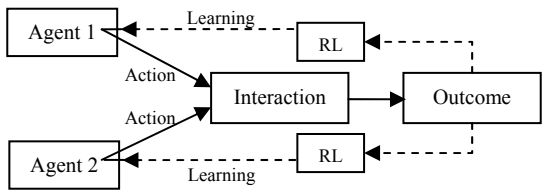


Fig. 1. Agent-based modeling

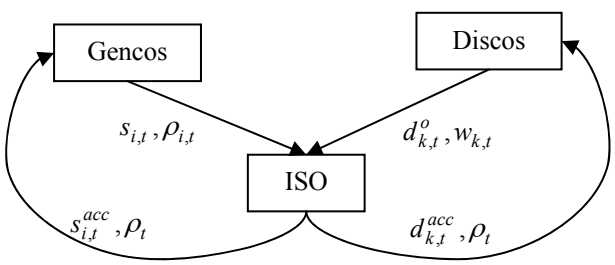


Fig. 2. Market coordination mechanism of ISO

the competitor energy offers and bids that the ISO has when solving the market-clearing problem. By using a reinforcement learning mechanism and based only on publicly available information, namely market clearing price, Discos and Gencos can "learn" through the repetition of the day-ahead energy auction to select the parameters of their energy offers and bids.

The objective of this work is to make an insight to the knowledge of the technical and economic integration of DG units and interruptible load in adopted strategies of distribution companies in electricity market environment. This paper is developed based upon the well designed agent-based simulator [10], [11] in which incorporates knowledge accumulation and own-bidding processes. These processes undergo an adaptive sigmoid decision rule whose parameters are estimated by ordinary least squares regression. The simulated AB market is able to replicate fundamental and technical time series properties of Discos' and Gencos' portfolio. These participants' behavior is shown to be consistent with the features in that they condition on their own decision parameters. Portfolio decision parameters are found to be significant in the time series properties. Our model is designed and equipped by a slack variable based optimization concept to handle the ramp rate constraints of DG units and readjust random decision parameters of Discos. This model is aimed to search for possible demand and generation side agents' action in a two level hierarchical reinforcement learning (RL) algorithm, given all the parameters defining the agents and the market structure. It is intended to build agents that learn about their environment and improve their behavior with experience. By doing so, the learning processes of the market participants, which can play a crucial role in strategy selection, are accounted for; that is, the time series properties of Discos' and Gencos' portfolio are found out.

After this introduction, simulation structure is discussed in section II. Section III is devoted to the learning process and a case study is presented in section IV. Section V includes the main conclusions.

## II. Simulation Structure

### A. Market Characteristics for Wholesale Power Trading

The wholesale power market is structured by the day-ahead (DA) electricity market. In this market generation and demand sides consist of sell and buy agents including Gencos and Discos whose bidding strategies are evaluated in the simulation study. In an independent manner, each agent seeks to extend his own utility function to the extreme value as close as possible. Based upon the previous bidding results hereafter called learning phase, each trader accumulates knowledge for his future bidding/offering process, hereafter called learnt phase, in DA electricity market.

Market coordination mechanism of ISO in the DA market is depicted in Fig. 2, which is an electricity market settlement process cleared by merit order. Each Genco owns and administrate generating units constructing supply function by reordered announced supply side combinations. Meanwhile, each Disco undertakes his own consumers' electricity demand constructing demand function by announced reordered demand side combinations. Each Genco is characterized by the generating plants. Plants owned by each Genco are specified at the generating set level and constant marginal cost. Each Disco is characterized by his own electricity demand, DG units and available interruptible load contracts. With the availability of day-ahead DG units' output capability and possible IL contracts being estimated in the most distribution networks, the 24-h market operation outcome is a robust tool for the disco and can interpret the links between technical and economic aspects of his own diverse portfolio. It should be mentioned that in this paper, we only consider utility-owned or disco-owned DG units, which are therefore dispatchable in electricity market.

### B. Model Formulation

Let us consider a wholesale market with a daily merit order settlement mechanism for day-ahead auction, where n Gencos (i=1,…,n) and m Discos (k=1,…,m) participate for 24 periods (t=1,…24).

*Gencos in DA:* the $i$th generator at the $t$th period bids $s_{i,t}$ ($s_{i,t} \le s^{m}_{i,t}$) where $s^{m}_{i,t}$ is the maximum amount of power generation capacity. The bidding amount is expressed by $s_{i,t} = \alpha_{i,t} s^{m}_{i,t}$, where $\alpha_{i,t}$ $(0 \le \alpha_{i,t} \le 1)$ is a decision parameter to express the ratio of the bidding amount to the maximum generation capacity. The bidding price of the generator is determined by $\rho_{i,t} = (MC_{i,t})/(1-\beta_{i,t})$. Here, $MC_{i,t}$ is the marginal cost of the generator and $\beta_{i,t}$ is a markup ratio that indicates how much the bidding price of the generator is increased from the marginal cost. The mark-up ratio reflects

the pricing strategy of the generator.

*Discos in DA:* A Disco possesses an electricity demand

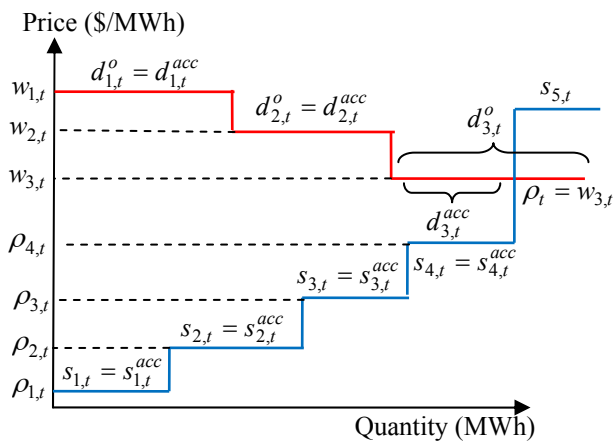


Fig. 3. Auction process in DA electricity market

prediction $(d_{k,t})$ on a delivery day, using a forecasting method. This model is aimed at day-ahead framework analysis, so the fluctuating retail price which allows Disco to be modeled as profit maximizing agent is beyond the scope of this paper. In this context, retail price $(\rho_k^{ret})$ is not a crucial variable and assumed to be fixed. The Disco determines an offering amount as a two level decision-making process. In the first level, the Disco chooses DG output $P_{k,t}^{DG}$ $(P_{k,t}^{DG} \le P_{DG}^{\max})$ and IL contract $P_{k,t}^{IL}$ $(P_{k,t}^{IL} \le P_{IL}^{\max})$ where $P_{DG}^{\max}$ and $P_{IL}^{\max}$ are the maximum output capability of DG unit and available interruptible load contracts, respectively. The choosing amount is executed by $P_{k,t}^{DG} = m_{k,t} P_{DG}^{\max}$ and $P_{k,t}^{IL} = y_{k,t} P_{IL}^{\max}$, in which $m_{k,t}$ and $y_{k,t}$ $(0 \le m_{k,t}, y_{k,t} \le 1)$ are decision parameter chosen in accordance with the Disco portfolio. In the second level Disco determines an offering amount of demand: $d_{k,t}^{o}$ $(d_{k,t}^{o} = d_{k,t} - P_{k,t}^{DG} - P_{k,t}^{IL})$ will be announced to the ISO to handle the market clearing process. The offering price of the Disco is determined by $w_{k,t} = \gamma_{k,t} \rho_k^{ret}$. Here $\gamma_{k,t}$ $(0 \le \gamma_{k,t} \le 1)$ is a decision parameter to express the reduced offering price as to the fixed retail price.

*Auction Process:* The auction process of the merit order settlement mechanism in the ISO is visually summarized in Fig. 3. In this process the supply side combinations $(s_{i,t}$ *and* $\rho_{i,t})$ are reordered according to the ascending order of the bidding prices. The demand side combinations $(d_{k,t}^{o}$ *and* $w_{k,t})$ are reordered according to the descending order of the offering prices. As depicted in Fig. 3, ISO clears the market, announces the market price $(\rho_t)$ and allocates the amounts of acceptable generation $(s_{i,t}^{acc})$ and demand $(d_{k,t}^{acc})$. It is obvious that each Disco takes on some electricity market demand and is responsible for continuous power supply, so as indicated in Fig. 3 we define a parameter, $d_{k,t}^{acc}$. Discos will be forced to acquire their out of equilibrium demand $(d_{k,t}^{o} - d_{k,t}^{acc})$ at a high external price $\rho_t^{ext}$. The Discos inside the equilibrium point are immune to this external acquisition because of $d_{k,t}^{o} = d_{k,t}^{acc}$. So, the Discos, whose offering demand lies beyond the equilibrium point, have an extra cost of $\rho_t^{ext}$ $(d_{k,t}^{o} - d_{k,t}^{acc})$.

### C. Disco's Cost Minimization Problem

According to the instances from the previous section, the total day-ahead cost of operation of the disco system is considered as the cost function. The Discos' objective is to minimize this utility function in the day-ahead market, by selecting the parameters of his energy offer, $(m_{k,t}, y_{k,t}, d_{k,t}^{o})$:

$$\begin{aligned} J_k^{Disco} = \sum_{t=1}^{24} \{ & \rho_t d_{k,t}^{acc} \\ & + (A_k (m_{k,t} P_{DG}^{\max})^2 + B_k m_{k,t} P_{DG}^{\max} + C_k X_{k,t}) \\ & + y_{k,t} P_{IL}^{\max} C_{IL} \\ & + (d_{k,t}^{o} - d_{k,t}^{acc}) \rho_t^{ext} \} \end{aligned} \tag{1}$$

where $A_k$, $B_k$ and $C_k$ are operating cost parameters of DG units, $X_k$ is a binary variable denoting DG unit commitment status at the *t*th hour. $C_{IL}$, denotes the IL contract cost. The first component of $J_k^{Disco}$ in (1) is the total payment to be made by the Disco for its accepted demand in the day-ahead market. The second component is the total 24-h cost of generation from DG units. The third component is the Disco's cost of IL contracts. Finally, the last term is the out of equilibrium purchase at high external price. The generation from DG units should respect the ramp-up and ramp-down constraints at every hour, as given in the following:

$$m_{k,t+1} P_{DG}^{\max} - m_{k,t} P_{DG}^{\max} \le RUP_k \tag{2}$$

$$m_{k,t} P_{DG}^{\max} - m_{k,t+1} P_{DG}^{\max} \le RDN_k \tag{3}$$

where $RUP_k$ and $RDN_k$ are ramp up and ramp down constraints of each Disco's total DG capacity, respectively.

### D. Genco's profit Maximization Problem

The Gencos' objective is to maximize his profit function in the day-ahead market, by selecting the parameters of its energy offer, $(\alpha_{i,t}, \beta_{i,t})$:

$$J_i^{Genco} = \sum_{t=1}^{24} (\rho_t - MC_{i,t}) s_{i,t}^{acc} \tag{4}$$

However, demand and generation sides including Discos and Gencos do not have the information on the competitor energy offers and bids that the ISO has when solving the market-clearing problem, section III describes a reinforcement learning (RL) process by which the Discos and Gencos can "learn" through the repetition of the day-ahead energy auction to select the parameters of their energy offers and bids, based only on publicly available information $(\rho_t)$.

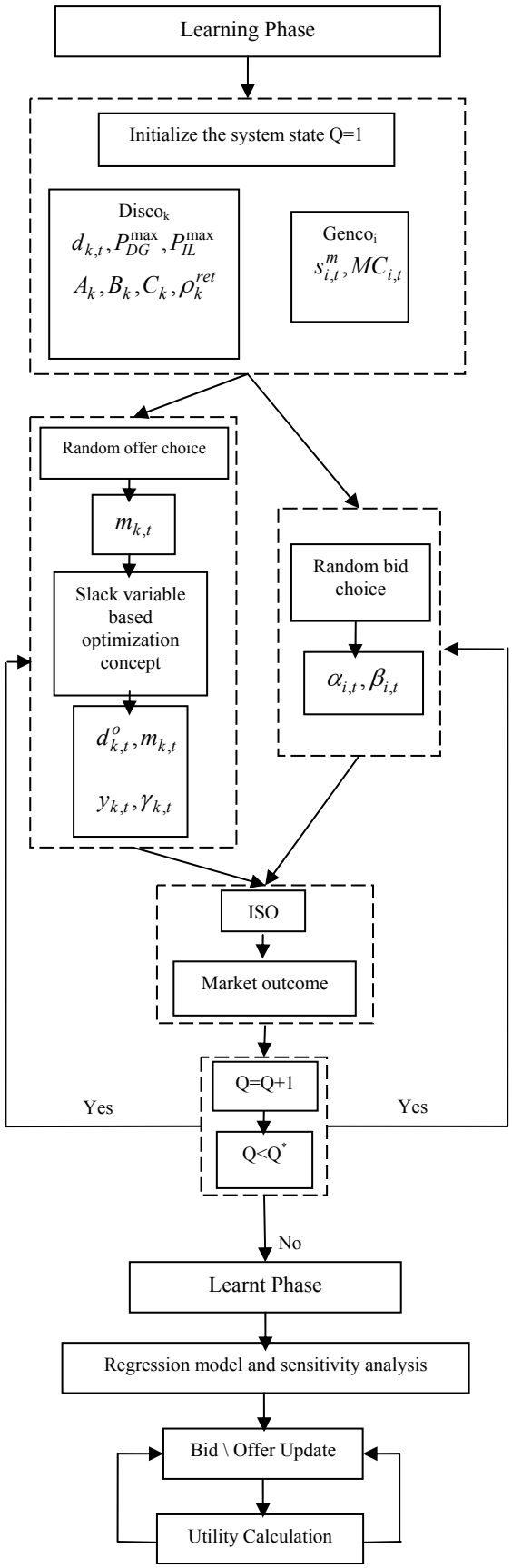


Fig. 4. Reinforcement learning algorithm

TABLE I
GENERATION SIDE PORTFOLIO (CAPACITY & MARGINAL COST)

| Genco # | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| $s_i^m$ (p.u). | 6.5 | 4.5 | 3.5 | 1.5 |
| $MC_i$ ($/Mwh) | 54 | 65 | 80 | 90 |

## III. LEARNING PROCESS

Reinforcement learning (RL) is one the most rapidly developing machine learning methods in recent years. A schematic diagram of the steps of the RL algorithm is shown in Fig. 4 which can be utilized by Discos and Gencos based on their own preferences and attributes. It has two hierarchical layers. The upper layer implements the learning phase, while the lower layer implements the learnt process. The learning phase begins initializing the system state for the DA based on the agents' specific attributes ($d_{k,t}, P_{DG}^{\max}, P_{IL}^{\max}, A_k, B_k, C_k, \rho_k^{ret}$ for Discos and $s_{i,t}^m, MC_i$ for Gencos). For this determined system state the random bid $(\alpha_{i,t}, \beta_{i,t})$ and offer $(d_{k,t}^o, m_{k,t}, y_{k,t}, \gamma_{k,t})$ decisions are made by the participants of the supply side and demand side, respectively. In this step, in order to handle the ramp rate constraints (2) and (3), a slack variable based optimization concept (5)- (8) with auxiliary variables $(slack_{k,t})$ [12] is introduced to adjust random decision parameter $(m_{k,t})$:

$$\min \sum_t (slack_{k,t})^2 \quad \forall k \tag{5}$$

Subject to:

$$(m_{k,t+1} + slack_{k,t+1})P_{DG}^{\max} - (m_{k,t} + slack_{k,t})P_{DG}^{\max} \le RUP_k \tag{6}$$

$$(m_{k,t} + slack_{k,t})P_{DG}^{\max} - (m_{k,t+1} + slack_{k,t+1})P_{DG}^{\max} \le RDN_k \tag{7}$$

$$0 \le m_{k,t} + slack_{k,t} \le 1 \tag{8}$$

After the random decision parameters $(m_{k,t})$ are readjusted by $(m_{k,t} + slack_{k,t})$, corresponding made parameters will be announced to ISO ($s_{i,t}, \rho_{i,t}$ and $d_{k,t}^o, w_{k,t}$ by supply side and demand side respectively). The day-ahead energy market is simulated by ISO, the price $\rho_t$ and quantities $(d_{k,t}^{acc}, s_{i,t}^{acc})$ corresponding to the least cost dispatch are then sent for agents' utility calculation. This upper learning phase will be continued until the end of the iteration number $(Q^*)$ which is determined by trial-and-error search and is fixed in advance. In the lower layer, Learnt phase, agents starts their bid/offer decisions based upon their learning phase. This step utilizes a regression process based upon the agents' utility earned in the learning phase:

$$J_k^{Disco} = c_{k,0} + c_{k,1}m_{k,t} + c_{k,2}y_{k,t} + c_{k,3}\gamma_{k,t} + \varepsilon_t \tag{9}$$

$$J_i^{Genco} = c_{i,0} + c_{i,1}\alpha_{i,t} + c_{i,2}\beta_{i,t} + \varepsilon_t \tag{10}$$

TABLE II

DEMAND SIDE PORTFOLIO ( $\rho_k^{ret}$ , DG AND IL)

| | Disco # | 1 | 2 | 3 |
|---|---|---|---|---|
| $\rho_k^{ret}$ ($/MWh) | | 110 | 130 | 100 |
| DG | $P_{DG}^{\max}$ (p.u.) | 0.5 | 1 | 0.5 |
| | $A_k$ | 0.02 | 0.01 | 0.025 |
| | $B_k$ | 85 | 80 | 90 |
| | $C_k$ | 500 | 1000 | 700 |
| | Ramp Rate | 0.1 | 0.1 | 0.1 |
| IL | $P_{IL}^{\max}$ (p.u). | 0.2 | 0.5 | 0.2 |
| | $C_{IL}$ $/MWh | 90 | 85 | 95 |

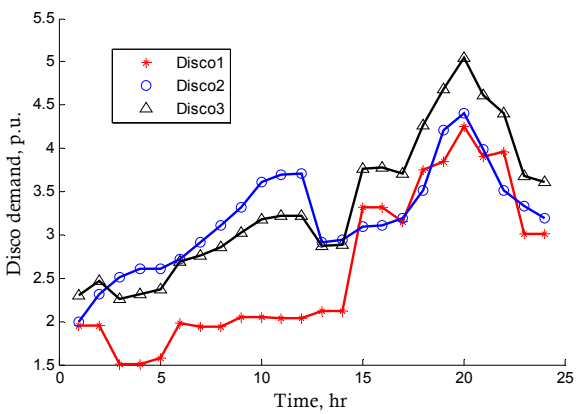


Fig. 5. Day-ahead demand as per Discos

$c_{*,*}$ are agents' sensitivity factors with respect to their bid/offer decision parameters and is an observational error.

Each agent looks for a combination of bid/offer decision parameters to make most extreme possible value for his own utility function. These factors are unknown and hence, need to be estimated by ordinary least squares regression. Based upon the estimated signs of the sensitivity factors obtained from the learning phase, each agent updates his bidding/offering strategies. Decision parameters with corresponding positive/negative sensitivity factors will be updated increasingly/decreasingly by a predefined portion which is proportional to the decision maker risk preferences. The detailed explanation of bid/offer updating process can be found in [10], [11]. Thus the parameter estimates of the sensitivity factors provide each agent with information regarding which is the best bidding/offering choice among his own alternatives. Update process in the learnt phase will be continued until the convergence of the agents' utility functions has been reached.

## IV. SIMULATION RESULTS

To ensure consistency with the reality of pool-based trading, the test bed structure of the simulation was developed through a sequence of experiments to test if the simulation was capable of meeting the two following requirements: first, the agents are able to learn strategies when competing in offering/bidding strategies; second, the simulation framework is able to exhibit different effects of diverse demand side portfolio. A simple pool based market structure for day ahead electricity market is considered to evaluate participants' strategies and market outcome. The market structure consists of three competing Discos and four Gencos, each with different sizes, and generation technology portfolios. The total capacity of Gencos, arranged by size, is shown in Table I. Detailed information on Discos, distributed generation capability, possible interruptible loads contracts and retail price are shown in Table II. Each Disco demand profile for 24 trading periods is shown in Fig. 5.

In order to examine the operational strategies, three scenarios are considered as explained below:

- ✓ Scenario-A: *passive demand side:* This scenario represents a passive demand side without utilization of DG units and interruptible loads by Discos.
- ✓ Scenario-B: *Partial active demand side:* This scenario represents an active demand side in which Discos are allowed to use their DG units.
- ✓ Scenario-C: *Full active demand side:* this scenario represents an active demand side in which Discos are allowed to use their whole portfolio including DG units and interruptible loads.

In each scenario, learning phase had been iterated for $Q^* = 1000$ and in the learnt phase, convergence of utility functions was obtained after almost 100 replications of utility calculation and bid/offer updating process. In the figures that come to be pointed out in this section, simulation results are depicted for their last 100 iterations of learnt phase.

Figs. 6 and 7 show the electricity market clearing prices under three different scenarios for peak hour (t=20) and base load hour (t=5) of total system demand, respectively. It is of importance to note this main result of the diverse portfolio of demand side that can be clarified by Fig. 6: "the more diverse demand side portfolio, the less electricity market clearing prices in peak hours is". On the other hand, as can be seen from Fig. 7, diverse portfolio of demand side has a negligible influence on the base hour market clearing prices.

Total Gencos' and Discos' utility functions in three different scenarios are shown in Figs. 8 and 9, respectively. As expected, with more diverse portfolio, Discos are capable of reducing demand side costs and generation side profits, as well.

An important point that should be remarked is the style of individual Disco's learning capability concerning the degree of his own diverse portfolio. Figs. 10 and 11 show the evolutionary decision making of Disco 1 (with smallest diverse demand side tools) about offering announced price to ISO and the corresponding quantity of demand which has been out of the equilibrium point, respectively. Fig. 12 shows the learning style of offering price by Disco 2 which is the possessor of the largest diverse demand side portfolio. Fig. 10 shows Disco 1 has a higher converged offering price in

Scenario A than Scenarios B and C. Nevertheless, in Scenario C, convergence

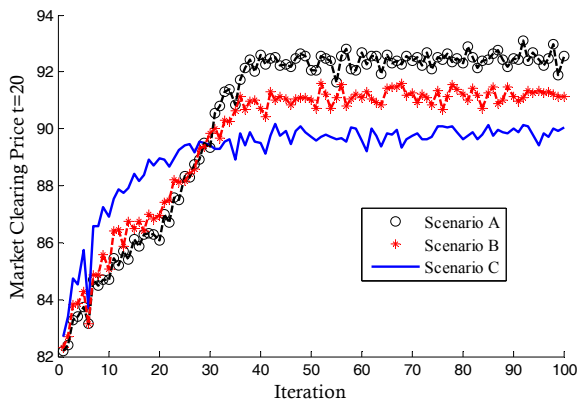


Fig. 6. Market clearing price as per three scenarios, t=20

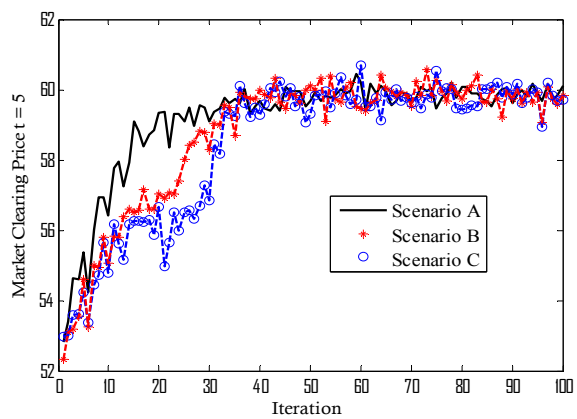


Fig. 7. Market clearing price as per three scenarios, t=5

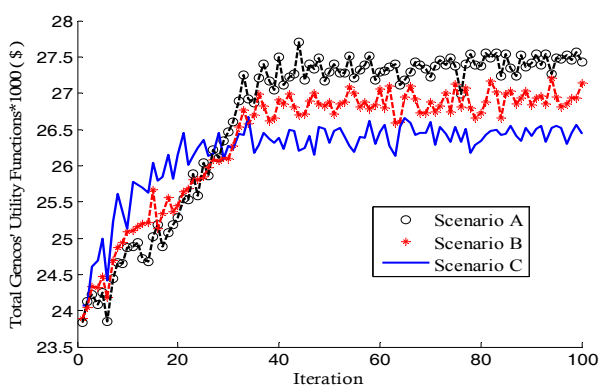


Fig. 8. Total Gencos' utility functions

occurred in most recent iteration. This happening is true in the case of converged out of equilibrium as well. From the other point of view, as a comparison of the pace of converged iteration in Figs. 10 and 12, it is cleared up that "the small the diverse portfolio the fast the pace of learning is".

Figs. 13 and 14 highlight the economic and technical links among Disco 2 portfolio options. In these two figures, the values embody the tag of "no ramp rate, IL" indicate Disco's strategies about DG unit dispatch at hour 19 and 20. In this case, Disco has no ramp constraint on his DG units and has

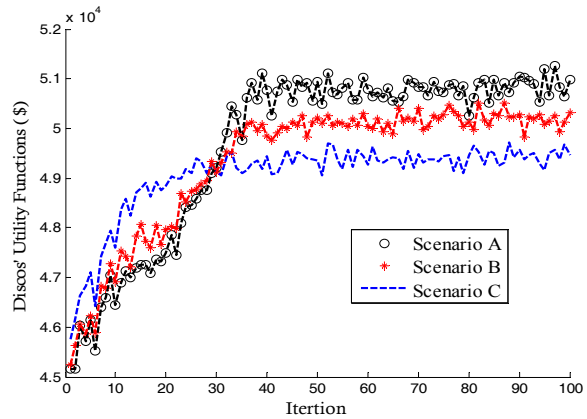


Fig. 9. Total Discos' utility functions

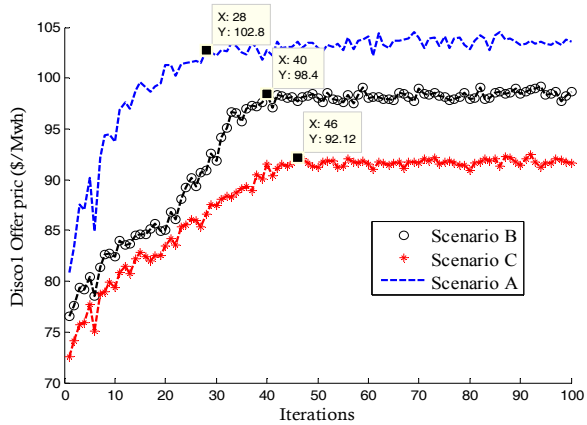


Fig. 10. Disco 1 offering price

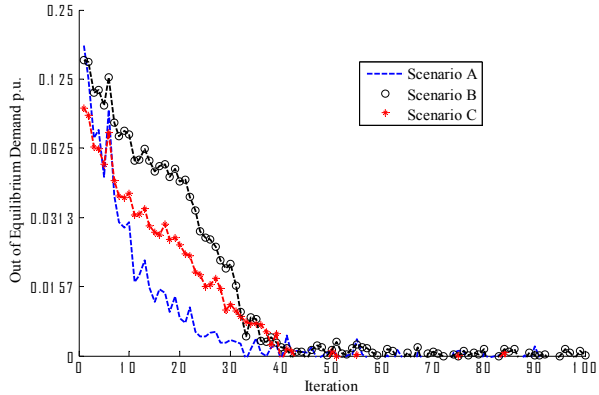


Fig. 11. Out of equilibrium demand as per scenarios for Disco 1

possible IL contracts, so in his decision making process with inter-temporal effects, he chooses his DG units to generate electricity and lower his offered demand announcement than the predicted demand by the level of 0.53 p.u. and 0.73 p.u, at hour 19 and 20, respectively. In this case, because of no ramp limits, the process of demand meeting with own demand side tools is fully allocated to DG units, therefore utilized

interruptible load with higher marginal cost tends to zero. The

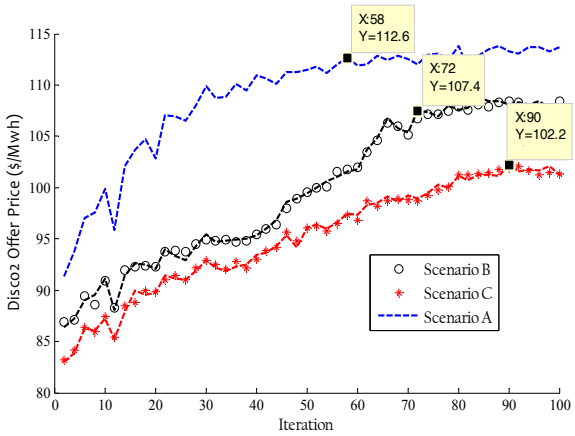


Fig. 12.Disco 2 offering price

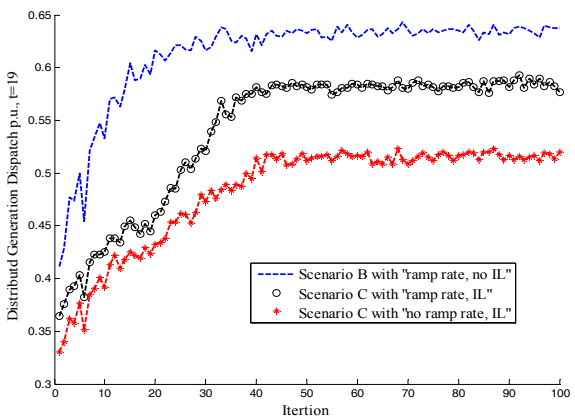


Fig. 13. Distributed generation dispatch at t=19

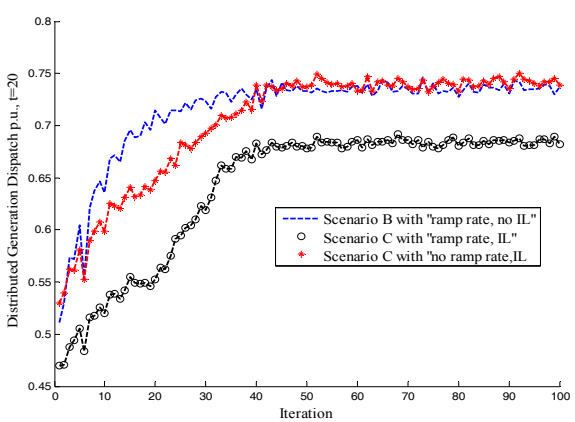


Fig. 14. Distributed generation dispatch at t=20

values with the tag of "ramp rate, no IL" indicate Disco position in a condition that has no interruptible load option and suffering from his DG unit ramp rate constraints. In this case, Disco decision about his DG unit dispatch at hour 19, with respect to "no ramp rate" case, has an increasing trend and converge to 0.63 p.u.; this adopted strategy at hour 19, enable Disco to relax his ramp constraint and execute his decision of 0.73 p.u. DG unit at hour 21. The tag of "ramp rate, IL" indicates Disco in a situation with available IL contracts and DG units constrained with ramp rate. In this case Disco tend to exclude 0.73 p.u. of his predicted demand from ISO auction at hour 20 and lower the electricity market clearing price. Because of the presence of IL, Disco is capable of allocating 0.5 p.u. of his extracted demand to ILs at t=20 and the residual 0.68 p.u. will be assigned to DG, and consequently Disco raises its DG dispatch at hour 19 by 0.5 p.u, as compared to the "no ramp rate, IL" case dispatch and reaches to 0.58 p.u. of its DG dispatch.

## V. Conclusion

An evaluative simulation framework for Discos' strategies in electricity market with two demand side tools, DG and IL, is presented in this paper. Due to the complexities of technical and economical aspects of smart distribution systems, the simulation framework is designed as an agent-based simulator. To imitate the agents' action in electricity market environment, a reinforcement learning algorithm with two hierarchical learning and learnt phase is employed.

The case study with seven competitive agents and three basic scenarios, namely, "passive demand side", "Partial active demand side", and "Full active demand side", demonstrates that the evaluation framework can clarify Discos' decision making strategies in different situations. The inclusion of inter-temporal DG constraints and possible IL may lead to highlight the economic and technical links of Discos' portfolio options. The scenarios presented in this paper also indicate different learning capabilities, those who enjoy more diverse portfolio has a tardier learning pace. Extending the topics to more complicated situations, e.g., for Discos with different mutual correlation in their demands, considering the constraints of transmission and distribution systems, permission to enter bilateral contracts and more comprehensive generation side modeling could be a subject of future research.

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