An Agent-based Electricity Market Simulator

Javid Khorasani[1], Habib Rajabi Mashhadi[2]

[1] Assistant Professor, Department of Electrical Engineering, Khorasan Institute of Higher Education, Mashhad, Iran
JKhorasani@khorasan.ac.ir
[2]Professor, Department of Electrical Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran,
h_mashhadi@um.ac.ir

Abstract:
In a real electricity market, complete information of rivals' behavior is not available to market participants. Therefore, they make their bidding strategies based on the historical information of the market clearing price. In this paper, a new market simulator is introduced for a joint energy and spinning reserve market, in which market participants' learning process is modeled using Q-learning algorithm. The main feature of this simulator is simulating a real market, in which market participants make decisions based on incomplete information of the market. Using the proposed simulator, the clearing price for each submarket is computed considering the participants' behavior, under different load levels and/or contingency conditions. The results show that Q-learning approach can modify the agent's strategy under different market situations.

Keywords: energy market; reserve market; market simulator; Q-learning algorithm; bidding strategy.

1. Introduction

Many countries all over the world, have introduced competition and privatization in their power sectors through electricity markets. A deregulated electricity market is composed of several submarkets such as energy and reserve markets.

Different approaches can be seen in the literature, in the field of simultaneous bidding in energy and reserve markets. The major viewpoint is utilizing different methods (e.g. stochastic optimization) to solve electricity multimarket clearing problem under different conditions such as uniform or pay-as-bid pricing, multi area networks, different submarkets and etc. (e.g. [1-7]). The other approach such as [8-12] analyzed scheduling problem or bidding behavior of market participants under different market structures and different conditions. The last viewpoint is to analyze the interaction between energy and reserve market prices. [13] simulated a day-ahead uniform market using GridView market simulator and discussed the interaction between energy and reserve using energy and reserve hourly prices, up to one week with and without enforcing reserve requirement. The stated above paper did not consider the bidding behavior of market participants and used only the historical network information. However, the energy and reserve prices may differ for similar load levels because of the different market conditions and strategic behavior of the market agents. [14-18] use different learning methods, such as reinforcement learning and genetic algorithm to model the strategic behavior of market participants considering uniform pricing structure.

Q-learning (QL) is usually used in single environment problems. The main aim of this paper is to design a QL algorithm to find optimal strategy from the viewpoint of an agent, which interacts with two environments: energy and reserve markets under pay-as-bid pricing mechanism. In the proposed simulator, the learning process of power suppliers is modeled using QL. In this simulator, as a real market, each supplier learns how to bid in the electricity market while competing with the other suppliers to get more profit. Therefore, the market clearing prices and strategic behavior of market participants in different conditions can be analyzed.

In the rest of the paper, the proposed market

[1]Submission date: 19, 05. , 2013
Acceptance date: 05 , 05 , 2014
Corresponding author: Javid Khorasani

simulator is described and is used to simulate the electricity multimarket in some different conditions such as different load levels and units' outages conditions.

2. Problem Description

The wholesale electricity markets all over the world are operated based on agents' competition. This competition is sometimes implemented through auction markets. In an electricity auction, power producers offer their generation capacity and corresponding price(s). An independent system operator clears the auction based on bids and the system requirements such as load, reserve etc. Such a market is called generally, a "single sided auction market". In this market, competition is established between power suppliers, and ISO procures energy and reserve on behalf of the other customers.

There are two pricing mechanisms in electricity markets. In the uniform pricing, all suppliers receive a uniform price, and in the pay-as-bid (PAB) pricing mechanism, each supplier receives his offered price. In this paper, the focus will be on PAB pricing.

In several electricity markets e.g. California, New York and Australia electricity markets, ISOs clear energy and reserve simultaneously [19]. This structure has the advantage of minimum procurement or social costs, based on the ISO objective function.

In this paper, a single-sided electricity market based on PAB pricing is simulated. The market agents are modeled using Q-learning method.

3. Electricity Market Structure

Fig (1) shows an overview of the considered joint energy and spinning reserve market. The market consists of two major parts: Electricity market and agents. The agents may include power producers, consumers or etc., which bid or offer their generation capacity or demand and corresponding prices in the energy and reserve markets. In the electricity market, ISO clears the joint energy and reserve market, and informs market clearing prices and each participant's accepted bids and offers. In the following, each section of the simulator is described in detail.

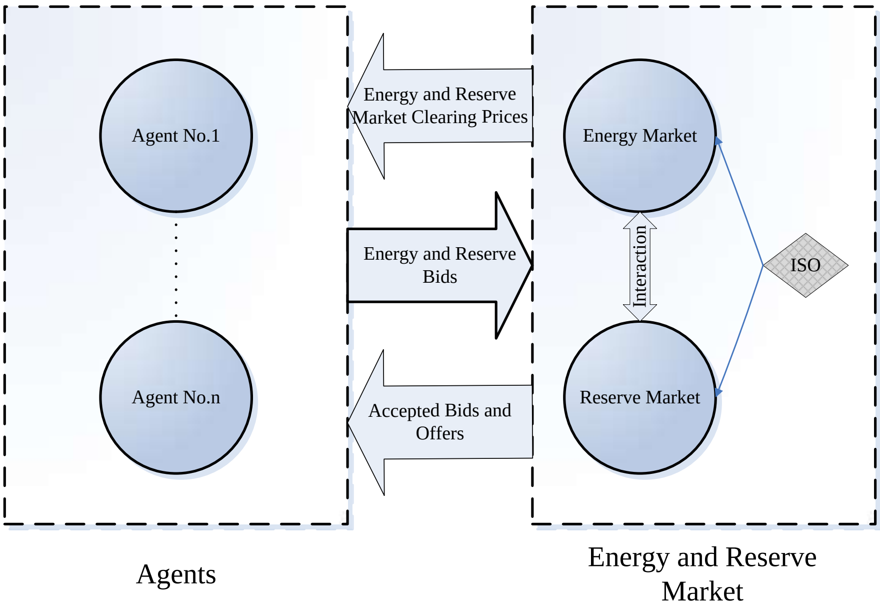

Fig (1): Market overview

3.1. Market Clearing Problem

A one-hour ahead, single sided market is considered for simplicity. The joint market is composed of energy and reserve markets. The two markets are cleared simultaneously by the ISO based on PAB pricing mechanism.

In the considered joint market, power producers submit their supply functions, composed of capacity and corresponding prices to the joint energy and ten-minute spinning reserve market for the next hour. ISO clears the market based to minimize procurement cost. The objective function is defined as (1) in which C_i^e, C_i^r are bid functions of the i^{th} power producer and e_i, r_i are energy and reserve accepted megawatts of the power producer, respectively.

It is assumed that C_i^e is a linear function of e_i and C_i^r is a one-step bid function. In addition, n is the number of power producers, and G_i and $R_i^{\max}$ are the total available capacity and maximum reserve capability of the i^{th} power producer.

$$\begin{aligned} &\underset{e_i, r_i}{Min} \quad \sum_{i=1}^{n}\int_0^{e_i} C_i^e(x)dx + \sum_{i=1}^{n} C_i^r(r_i) \\ &subject \quad to: \\ &\qquad \sum_{i=1}^{n} e_i = \text{Demand} \\ &\qquad \sum_{i=1}^{n} r_i = \text{Reserve requirement} \\ &\qquad 0 \le e_i + r_i \le G_i \\ &\qquad 0 \le r_i \le R_i^{\max} \end{aligned} \tag{1}$$

3.2. Agents

Each market is composed of several types of participants, such as power producers, large consumers, brokers, etc. As stated before, in this paper, a single-sided market is considered in which the power producers participate in the market, only. The assumption does not affect the generality of the problem.

The i^{th} power producer is assumed to have a quadratic cost function:

$$Cost_i(e_i) = FC_i + a_i^e e_i + 0.5 b_i^e e_i^2 \tag{2}$$

All power producers submit a linear function for energy and a stepwise bid function for reserve. In this paper, the slope of the energy bid function is assumed to be fixed at b_i^e. Therefore, the bid functions of the i^{th} producer will be in the form of:

$$\begin{aligned} &\rho_i^e(e_i) = \alpha_i^e + b_i^e e_i \qquad && 0 < e_i \le G_i \\ &\rho_i^r(r_i) = \alpha_i^r && 0 \le r_i \le R_i^{\max} \end{aligned} \tag{3}$$

for energy and reserve respectively.

The Q-learning model of the market agents will be introduced later.

4. THE Q- LEARNING ALGORITHM [20]

In the QL algorithm, an agent interacts with an environment at discrete sequential time steps, $t = 0,1,2,\ldots$. At each time t, the agent selects an action $a_t \in A$ based on $s_t \in S$ (the state of the environment at time t), where, $A = \{a_1, a_2, \ldots, a_m\}$ is the finite set of the agent's admissible actions and $S = \{s_1, s_2, \ldots, s_m\}$ is the finite set of the environment's possible states. As a result of the action, the environment enters the new state s_t.Fig (2) shows the interaction of the agent with the environment [20].

In the QL algorithm, each state-action pair has a value function which is defined as Q-value. Q-value lookup table is initialized randomly at the beginning of the learning process. Then the Q-values are updated as follows:

$$\begin{aligned} &Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha \Delta Q(s_t, a_t) \\ &\Delta Q(s_t, a_t) = [r_{t+1} + \gamma \max_{a'}\left(Q_t(s_{t+1}, a')\right)] - Q_t(s_t, a_t) \end{aligned} \tag{4}$$

where γ is the discount factor and r_{t+1} is the reward of action a_t. Also, the agent's learning rate, α, is defined in this paper as:

$$\alpha(s_t, a_t) = \frac{1}{\beta(s_t, a_t)} \tag{5}$$

where $\beta(s_t, a_t)$ is the number of the state-action pair (s_t, a_t) visited until now.

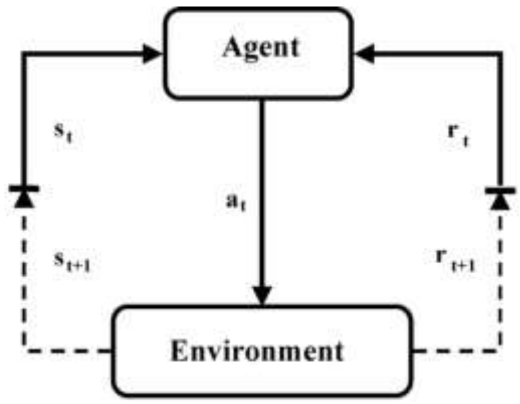

Fig (2): The agent interaction with the environment [20]

The QL algorithm has two stages: learning and converging. In the learning stage, the agents examine the environment most of the times. They test their admissible actions in accordance with different states of the environment. However, in the converging stage, the agents make their best decision and choose the greatest Q-value action in each state of the environment. The selection is performed in this stage based on the past experience.

The QL parameters are determined for each stage, according to the exploration and exploitation mechanisms. To trade-off between exploration and exploitation, the ε-greedy method is selected. In the ε-greedy method, the agent selects the action with the maximum Q-value with the probability of (1-ε) and selects an arbitrary action from A with the probability of ε. In the learning stage, because of high probability of selecting wrong actions, the γ value is low to discount the future reward. However, it has high value in the converging stage to exploit the information strictly. Therefore, the ε and γ have small values in the learning stage, and have zero and high values in the converging stage, respectively.

The proposed market simulator is a multi-agent problem. In this type of problems, learning stage is used as an initializing phase. Consequently, simulation phase will be the convergence stage.

5. AGENTS' MODEL

The main part of this simulator is the learning process of power market participants. In this process, each agent is modeled using the Q-learning algorithm. QL is usually applied to single environment problems. However, in this simulator, an agent interacts with two environments: energy and spinning reserve markets.

The participants' experience is simulated using an iterative process of bidding and market clearing. Energy and reserve market clearing prices are selected as "states" in the QL market simulator. Each agent can bid in both the energy and reserve markets. Thus, the proposed simulator needs two actions: energy bid intercept and reserve bidding price. Fig (3) shows the definition of states of the market and agent's actions.

The process of learning and finding the optimal bid components for each hour can be defined as follows from the viewpoint of each market agent:

(1) State identification: The states of environment for the current step are obtained by solving the market objective function. As stated before, the states are MCPs. It is assumed that the information of market MCPs from the previous steps is publicly available.

(2) Action selection: After obtaining the current state, the agent uses its Q-value lookup table which saves the Q-values for each state-action pair. The action selection through the QL algorithm is done by choosing the action with maximum Q-value in the current state. To tradeoff between exploitation and exploration, the agent utilizes the ε-greedy strategy, as explained before.

(3) Q-value update: At the end of each step and after being notified of the new MCPs and dispatched amounts of energy and reserve, the agent calculates its reward and then updates its Q-value according to Eqs. (4).

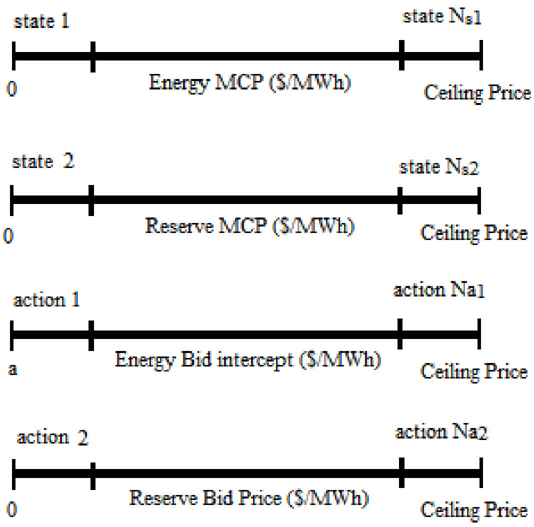

Fig (3): Market states and agents' actions

6. CASE STUDY

The authors, in [21] present a classic bidding problem to find a closed form for the optimal bidding parameters. In [22] similar to [20], we show that the QL can find the optimal values of bidding parameters in a self-play simultaneous bidding problem. Consequently, the QL is used in this paper in a multi-agent problem. The following simulation results seem to be rational in comparison with real competitive markets.

In this section, simulation results for a single-node 4-unit power system are presented. The system information is given in Table (1). The minimum power generation and the fixed cost of the units are assumed zero. The market clearing problem (1) is solved using Matlab quadratic programming tool.

Table (1): The sample power system information

Unit No.	P_{max}(MW)	Res Capability	a ($/MWh)	b ($/MWh)
1	1000	100	16	0.000960
2	1500	150	18	0.000400
3	800	80	19	0.000422
4	1200	120	23	0.000826

In order to control the market price in high load levels and also in the outage conditions, an external supplier with high capacity is assumed to be available. The bidding prices of the supplier are fixed at 30 ($/MW) and 10 ($/MW) for energy and reserve, respectively.

The number of states/actions selected for market simulation is as Table (2).

The Q-learning parameters are fixed during the simulation phase: $\alpha = \gamma = 0.1$, $\varepsilon = 0.05$.

Table (2): Number of States/Actions of Market Agents

State/action	Number of state/action
action 1 (Energy Bid Intercept)	15
action 2 (Reserve Bid Price)	20
State 1 (Energy MCP)*	15
State 2 (Reserve MCP)*	10

*Energy and reserve ceiling prices are set to 30 and 10 in this case, respectively.

The energy and reserve MCPs are shown in Fig (4) for 3000MW load level. Reserve requirement is assumed %10 of demand. The mean values of energy and reserve market prices in this load level are 24.7 and 7.31, respectively.

The bidding parameters of market agents are shown in Fig.(5) for energy and reserve markets, respectively.

In addition, accepted capacities in energy and reserve markets are shown in Fig (6).

It can be seen in figures 5 and 6 that low cost GenCos have more chance to sell their production capacity to the energy market. In 3000 MW load level, the first, second and third GenCos supply the demand and set the energy market price competing each other. Furthermore, the first and second GenCos try to sell their reserve capacity in the reserve market because in this load level, their profit in the reserve market is more than energy market. In these conditions, the forth GenCo that has the least chance to win in the energy market, submits the lowest price in the reserve market.

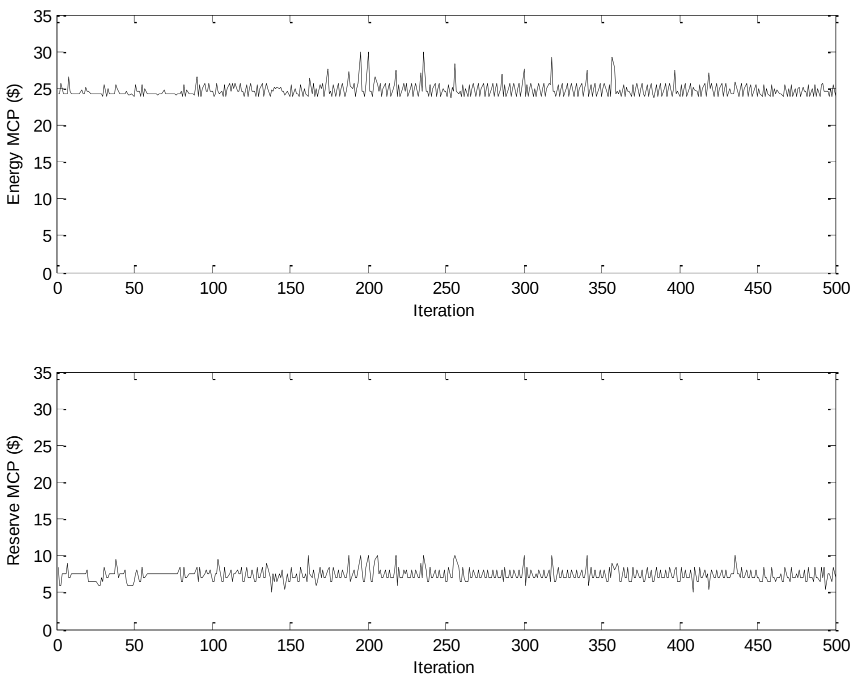

Fig (4). Market clearing prices ($) at 3000MW load

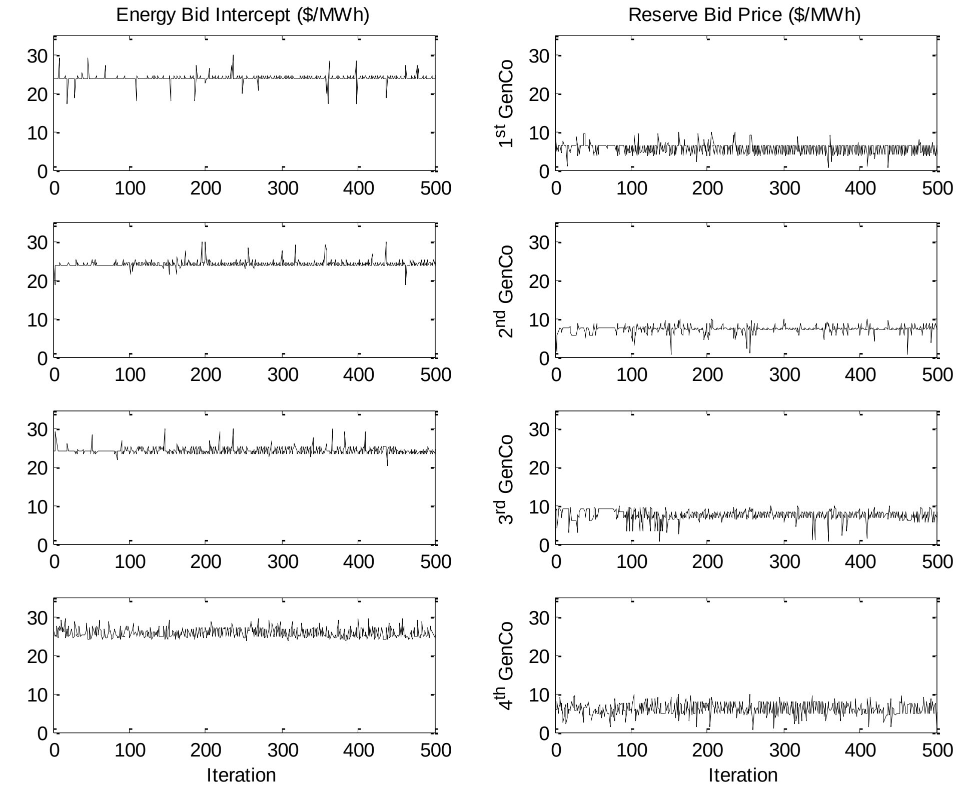

Fig (5): GenCos' bidding parameters ($/MWh)

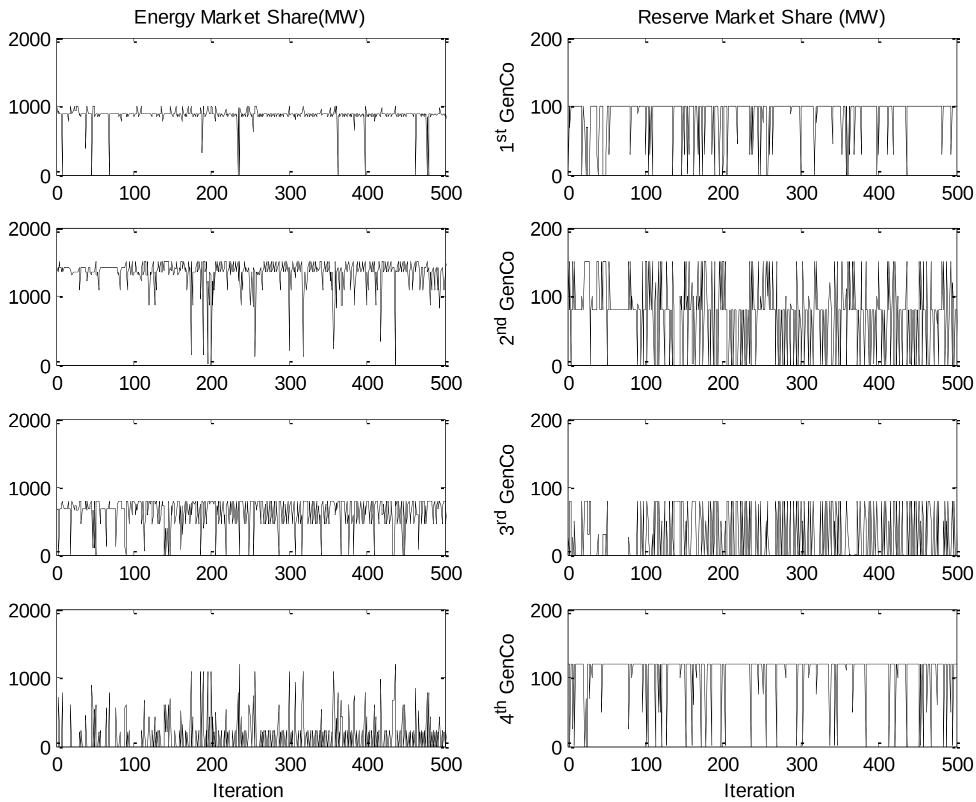

Fig (6): Accepted capacities in energy and reserve market

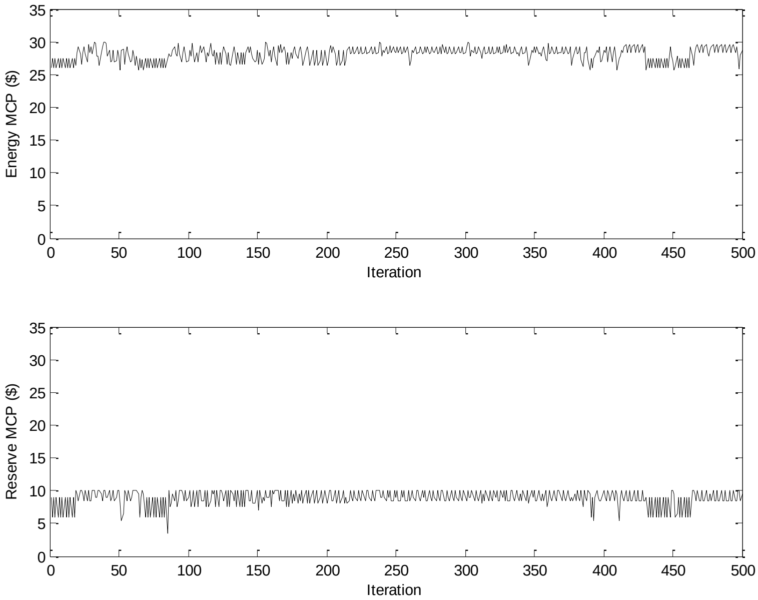

Fig (7): Market clearing prices ($) at 3500MW load

The market prices for 3500MW load are shown in Fig (7). The MCPs' mean values are \$28.5 and \$8.95, respectively. It is clear that an increase in load level can increase the energy and reserve prices. It can be observed comparing figures 4 and 7.

Market clearing prices and GenCos' bidding parameters in 1500 MW load level are shown in Figures 8 and 9.

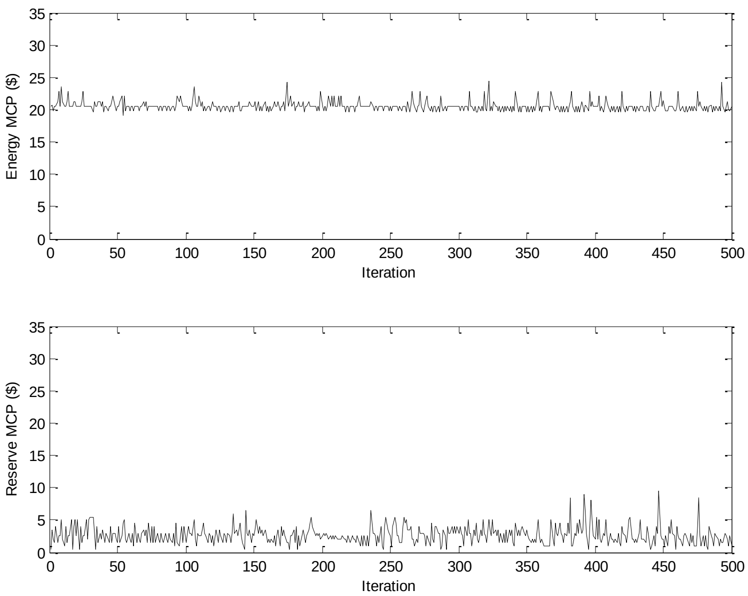

Fig (8): Market clearing prices ($) at 1500MW load

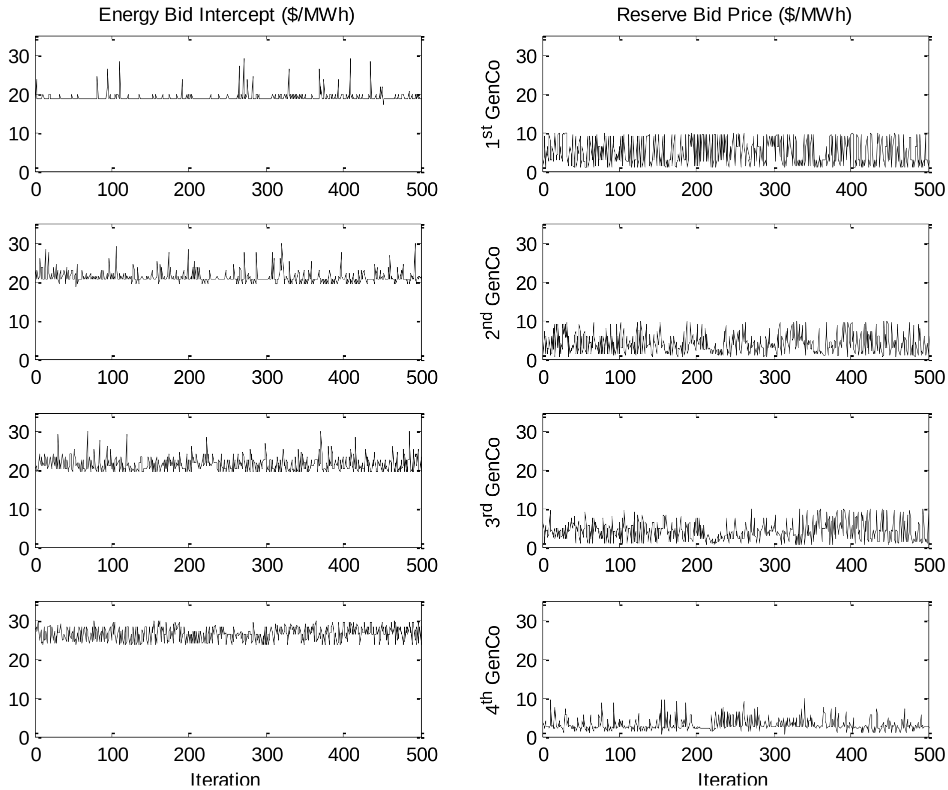

Fig (9):GenCos' bidding parameters in 1500MW load

As seen, the profit of the third GenCo from the energy market is zero and bids the lowest price in the reserve market. The other GenCos compete in the energy market and the lowest-cost GenCo, bids the lowest price in order to sell all of its capacity to the energy market.

The market simulator results in different load levels are summarized in the following tables.

Table (3): mean values of energy MCP and Gencos' energy bid intercepts

Load (MW)	Energy MCP ($)	α_{e1} ($)	α_{e2} ($)	α_{e3} ($)	α_{e4} ($)
1500	20.5766	19.1995	21.0552	21.5461	26.3437
2000	21.7852	20.4333	21.6152	22.0287	26.0567
2500	23.9973	22.1087	23.6368	23.0201	25.7841
3000	24.7027	23.6907	24.0696	24.2287	25.6936
3500	28.4860	25.6945	26.1664	26.0576	28.1385

Table (4): Mean Values of Reserve MCP and Gencos' Reserve Bidding Prices

Load(MW)	Reserve MCP ($)	ρ_{r1} ($)	ρ_{r2} ($)	ρ_{r3} ($)	ρ_{r4} ($)
1500	2.7696	5.2560	4.2425	4.1685	2.9895
2000	4.3776	6.8090	5.2390	4.8790	4.2650
2500	6.8191	5.9145	6.5800	6.3975	6.2005
3000	7.3141	5.5270	7.1500	7.3810	5.9700
3500	8.9501	7.6555	7.8375	7.0030	8.2435

The market clearing prices and bidding parameters of GenCos are shown in figures 10 and 11 following an outage in the 2nd generating unit for 3000MW load.

It is clear that following the outage in the 2ndGenCo, market power occurs for the other GenCos and they can increase their bidding prices toward the energy and reserve ceiling prices.

The results show that Q-learning algorithm can simulate the electricity multimarket and market participants' behaviour. Therefore, the method can be used to analyse the electricity markets in different fields such as prices behaviour, energy and reserve markets interaction, market agents' behaviour in normal or contingency conditions at different load levels, and etc. Also, demand-side bidding can be considered.

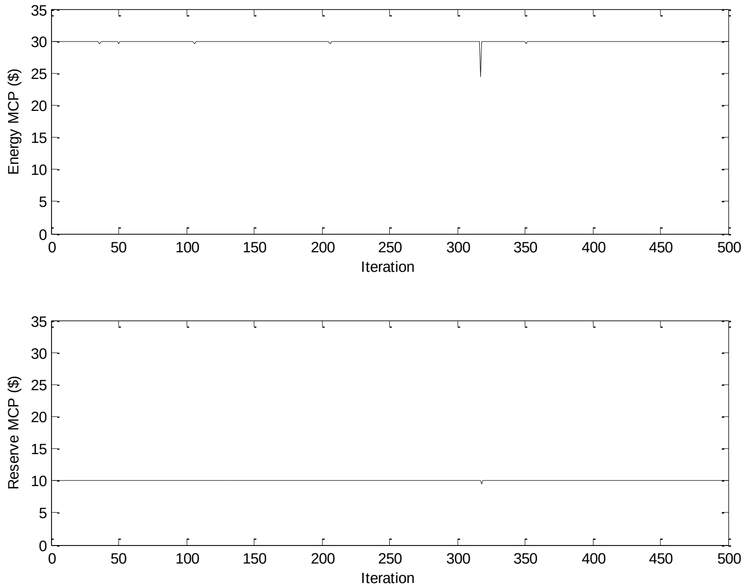

Fig (10): Market clearing prices ($) at 3000MW load, following an outage in 2nd GenCo

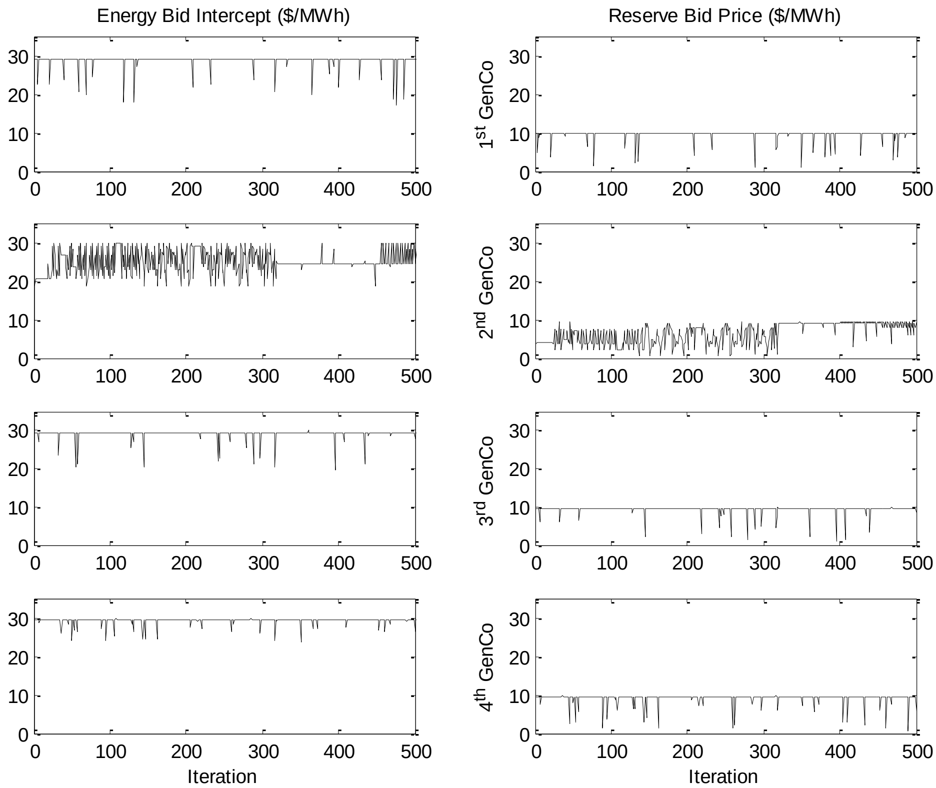

Fig (11):GenCos' bidding parameters at 3000MW load following an outage in 2nd GenCo

7. Conclusion

In this paper, a new electricity market simulator is proposed in which market participant learning process is modeled using Q-learning approach. QL algorithm is applied to a two- environment problem in order to find the optimal bidding strategies in a joint energy and spinning reserve market. It is shown that QL-based agents can learn the appropriate behavior and they can adjust their bidding strategies in different market conditions. Also they can recognize the opportunity to experience market power.

The proposed simulation method can be used to analyze the market from some different points of view such as market rule, market participants' behavior, market power opportunities and etc.

REFERENCES

[1] MA, X., SUN D., CHEUNG, K., 'Energy and reserve dispatch in a multi-zone electricity market', IEEE Trans. Power Syst, Vol. 14, No. 3, pp.913-919, 1999.

[2] Cheung, K., Shamsollahi, P., Sun D., Milligan, J., Potishnak, M., 'Energy and ancillary service dispatch for the interim ISO New England electricity market', IEEE Trans. Power Syst, Vol. 15, No. 3, pp. 968-974, 2000.

[3] Wong, S., Fuller, J.D., 'Pricing energy and reserves using stochastic optimization in an alternative electricity market', IEEE Trans. Power Syst, Vol. 22, No. 2, Pp.631-638, 2007.

[4] STACKE, F., CUERVO, P., 'A combined pool/bilateral/reserve electricity market operating under pay-as-bid pricing', IEEE Trans. Power Syst, Vol. 23, No. 4, pp. 1601-1610, 2008.

[5] KARDAKOS, E.G. ; SIMOGLOU, C.K., BAKIRTZIS, A.G., 'Short-Term Electricity Market Simulation for Pool-Based Multi-Period Auctions', IEEE Trans. Power Syst, Vol. 28 , No. 3 , pp. 2526-2535, 2013.

[6] SOARES, T. ; MORAIS, H. ; CANIZES, B. ; VALE, Z., 'Energyandancillaryservicesjointmarketsimulation', 8th Int. Conf. Europ. EnergyMarket, pp. 262-267, 2011.

[7] Reddy, S.S. ; Abhyankar, A.R. ; Bijwe, P.R., 'Market clearing of jointenergyand reactive power using multi objective optimization considering voltage dependent load models', IEEE Power Energy Soc. General Meeting, pp.1 – 8, 2011.

[8] Wen, F.S., David, A.K., 'Optimally coordinated bidding strategies in energy and reserve and ancillary service markets', in Proc. Inst. Elect. Eng., Gen., Trans. Dist., Vol. 149, pp. 331–338, 2002.

[9] RAU, N.S., 'Optimal dispatch of a system based on offers and bids-A mixed integer LP formulation', IEEE Trans. Power Syst, Vol. 14, No. 1, pp. 274–279, 1999.

[10] Cheung,C., Shamsollahi, P., Sun, D., Milligan, J., Potishnak, M., 'Energy and ancillary service dispatch for the interim ISO new England electricity market', IEEE Trans. Power Syst, Vol. 15, No. 3, pp. 968–974, 2000.

[11] Arroyo, J.M., Conejo, A.J., 'Optimal response of a power generator to energy, AGC, and reserve pool-based markets', IEEE Trans. Power Syst, Vol. 17, No. 2, pp. 404–410, 2002.

[12] Haghighat, H., Seifi, H., Rahimi Kian, A., 'Gaming analysis in joint energy and spinning reserve markets" IEEE Trans. Power Syst, Vol. 22, No. 4, pp. 2074 – 2085, 2007.

[13] Liao, Y., Feng, X., Pan, J., 'Analysis of interaction between ancillary service markets and energy market using power market simulator', IEEE Int. Conf. Elec. Util. Dereg., Rest. Power Tech., Vol. 1, pp. 117 - 122, 2004.

[14] Vale, Z., Pinto, T., Praça, I., Morais, H., 'Mascem: electricity markets simulation with strategic agents', IEEE Intel. Syst., Vol. 26, No. 2, pp. 9-17 ,2011.

[15] Kladnik, B., Gubina, A., Artac, G., Nagode, K., Kockar, I., 'Agent-based modeling of the demand-side flexibility', IEEE Power Eng. Soc. General Meeting, pp. 1-8, 2011.

[16] Pereira, I., Vale, Z., Morais, H., Pinto, T., Rodrigues, F., 'Multiagent system for adaptive strategy formulation in electricity markets', IEEE Symp. Intel. Agents, pp. 1-8, 2011.

[17] Pinto, T., Sousa, T.M., Vale, Z., Morais, H., Praca, I., 'Intelligent decision making in electricity markets: Simulated annealing Q-Learning', IEEE Power Eng. Soc. General Meeting, pp. 1-8, 2012.

[18] Pacaba, D.D.P., Nerves, A.C., 'Multiagent-based market simulator for the wholesale electricity spot market', IEEE Reg. 10 Conf. , pp. 1-6, 2012.

[19] Cheung, K.W., 'Ancillary service market design and implementation in North America: from theory to practice', 3rd IEEE Int. Conf. Elec. Util. Dereg., Rest. Power Tech., pp. 66-73, 2008.

[20] Rahimiyan, M., Rajabi Mashhadi, H., 'Supplier's optimal bidding strategy in electricity pay-as-bid auction: Comparison of the Q-learning and a model-based approach', Elec. Power Syst. Res., Vol. 78, No.1, pp. 165–175, 2008.

[21] Khorasani, J., Rajabi Mashhadi, H., 'Bidding Analysis in Joint Energy and

Spinning Reserve Markets Based on Pay-as-Bid Pricing', IET Gener. Trans. Dist., Vo1. 6, No. 1, pp. 79-87, 2012.
[22] Khorasani, J., 'Strategic bidding in simultaneous energy and spinning reserve markets considering the interaction between these markets', Ph.D thesis, Islamic Azad Univ., 2012.