Development of Reinforcement Learning Algorithm to Study the Capacity Withholding in Electricity Energy Markets

H. Bakhshandeh* and A. Akbari Foroud*(C.A.)

Abstract: This paper addresses the possibility of capacity withholding by energy producers, who seek to increase the market price and their own profits. The energy market is simulated as an iterative game, where each state game corresponds to an hourly energy auction with uniform pricing mechanism. The producers are modeled as agents that interact with their environment through reinforcement learning (RL) algorithm. Each producer submits step-wise offer curves, which include the quantity-price pairs, to independent system operator (ISO) under incomplete information. An experimental change is employed in the producer's profit maximization model that causes the iterative algorithm converge to a withholding bidding value. The producer can withhold the energy of his own generating unit in a continuous range of its available capacity. The RL relation is developed to prevent from becoming invalid in certain situations. The results on a small test system demonstrate the emergence of the capacity withholding by the producers and its effect on the market price.

Keywords: Electricity Energy Market, Agent-based Simulation, Capacity Withholding, Reinforcement Learning, Price-maker Producer.

1 Introduction

In recent years, electrical power industries worldwide are moving from vertically integrated environments to a competitive and deregulated environment where participants are looking for maximizing their profits rather than minimizing the overall cost of the system. In the short-term, two kinds of markets are dominant: the day-ahead market, which is a forward market for next day delivery in one-hour or half-hour transaction intervals, and the real-time or spot market, which acts as a balancing mechanism for the next hour or half-hour [1]. The day-ahead market may be in the form of either power exchanges or power pools. In the day-ahead market the profit of the strategic seller depends, in addition to his own decision (supply offer), on the decision of his rivals, who may also act strategically.

The optimal bidding strategy models for the energy producers depend on how the relationship between them is formed. Different relations between producers are as follows: 1) The singular firm's optimization models, which relinquish the strategic interaction between the market participants, which consists of the price-maker and the price-taker producers. 2) The oligopolistic optimization models, which consider the strategic interaction of all the participants. There are several equilibrium models to study the electricity markets, (e.g., Bertrand, Cournot, supply function and conjectured supply function equilibrium, etc. [2]). These models attempt to find the market equilibrium point (also told as Nash equilibrium), which is defined as no players can solely increase his profit by changing his offer in case other players have maintained their offers.

Such equilibrium models are organized by substituting each producer's mathematical program with equilibrium constraints (MPEC) optimization sub-problems with its Karush-Kuhn-Tucker (KKT) first-order optimality conditions, which leads to a set of nonlinear relations known as equilibrium problem with equilibrium constraints (EPEC). Other way is a fixed point diagonalization algorithm, in which each participant solves his profit maximization problem assuming all the other participants offers as fixed (to the quantities of the past iteration) until convergence to a fixed point. Next method to investigate the market equilibrium is via agent-based models which in general elude the computational complication posed by the pure equilibrium models. The agent-based models usually apply the iterative processes and can be classified in phrases of different learning algorithms, such as genetic algorithms (GA), Q-learning, computational learning and etc. [3], [4].

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The producer profit maximization may damage the system reliability for some reasons. Each reduction in offered capacity to produce inherently leads to obtaining higher market prices. Such results can be obtained through the physical and economic capacity withholding. The physical withholding is the deliberate action of the producer to reduce the offered output below the available capacity, while the economic withholding is the action to offer the generation prices above the marginal costs. The physical and economic withholding have same impacts on the result of market clearing price, but the physical withholding has an additional impact on the power system. If the capacity is scarce in the electricity market, the physical capacity withholding will be possible to explicitly prevent the settlement of the market due to supply shortage. This shortage would cause some loads not supplied despite their desire to pay, thereby damaging system reliability [5].

A simulation model based on the diagonalization algorithm for the study of the short-term performance of a pool-based oligopolistic electricity market in parallel implementation is introduced in [3]. Authors have incorporated in the diagonalization algorithm the RL relation to improve its convergence process. The diagonalization algorithm is an iterative solution process and its basic steps are presented in [6].

In [4], the problem of the producer's optimal offering strategies in day-ahead energy auction with step-wise energy offer format is introduced. The producer energy offer optimization is formulated as a bi-level optimization problem, which first is converted to a mathematical program with equilibrium constraints (MPEC), and then turns into a mixed integer linear program (MILP). In [7], the capacity withholding within an agent-based modeling of a spot energy market operating over a two-bus transmission grid is studied. The energy market is formulated as a repeated game with locational marginal pricing rule. Generators learn through SA-Q-Learning algorithm to withhold capacity in order to leave the transmission line uncongested and be paid at the node with higher LMP. The action of each generator as a player is the selection of the quantity-price pair for his offer energy, where his action space is a discrete Cartesian space. This space is achieved by discretizing the interval of the constraints of the producer profit maximization problem. The main weaknesses of that method are the discretization of the action space, so a lot of possible choices for bidding will be lost, and the low speed of convergence, therefore the iterative process will converge in high iterations.

The following papers use the supply function equilibrium (SFE) model to study the electricity market. In [8], authors analyze a double price cap electricity market using agent-based simulation and investigate the emergence of the capacity withholding and its effects on the market outcomes. When inelastic demand for electricity is high, relatively high-cost suppliers are called into the market and, as a result, market clearing price rises. At such times, there is still adequate supply to serve the inelastic demand that is willing to pay the relatively high offer cap (primary price cap). If, instead, market clearing is infeasible, owing to capacity shortage, a scarcity situation arises. The market prices in these cases are the administratively set market cap (secondary price cap). An optimal control problem is embedded in the SFE modeling framework that provides a tool for firms, enabling them to bid a supply curve with vertical segments. In [9], an iterative procedure is used to solve the game problem in a centralized market in which electrical energy and spinning reserves is traded simultaneously. A two-level optimization technique and a MPEC theory have been used. In [10], the SFE approach and a MILP scheme are used to find Nash equilibrium in electricity market without utilization of the approximation or the repetition. In [11], the capacity withholding in an oligopolistic electricity market is analyzed and evaluated by the capacity withheld index, the capacity distortion index and the price distortion index. In [12], authors use a coevolutionary theory to investigate the result of the price elasticity of demand, capacity and forward contract on tacit collusion in a duopoly. In [13], authors explore the economic and physical capacity withholding in a wholesale double-auction electricity market that operates over a transmission grid through an agent-based simulation. In [14], a new approach of evolutionary games and the concept` of near Nash equilibrium to simulate the oligopolistic market is introduced and also an appropriate genetic algorithm has been developed. In [15], the impact of demand elasticity and forward contracts on capacity withholding in an oligopolistic electricity market that all generation companies (GenCos) bid in a Cournot model was analyzed. The relationship between capacity withholding of GenCos and market price distortion was acquired.

In [16], authors introduce a formulation for modeling the withholding of three decision variables. The problem was formulated as an MPEC, where the upper level is a profit maximization task solved by the strategic firm owning several generating unit. The firm can strategically choose bids for the capacity, ramp and price offers of the units. In [17], authors present a nonzero sum stochastic game theoretic model and a reinforcement learning (RL)-based solution framework that allow assessment of market power in day ahead markets. Since there are no available methods to obtain exact analytical solutions of stochastic games, an RL-based approach is utilized, which offers a computationally viable tool to obtain approximate solutions. These solutions provide effective bidding strategies for the day ahead market participants.

Among the studies in this field, we have mostly used the papers by Bakirtzis et al. [3], [4], [7]. In this paper, the agent-based simulation is employed to analyze the energy market, which is formulated as a repeated game. The producers are modeled as agents that are able to interact with their environment through a RL algorithm. The producers under conditions of incomplete information submit step-wise energy offer curves, which include the quantity-price pairs in general. The system load is assumed inelastic. The transmission and the operational constraints are ignored for the sake of simplicity. Since our main purpose is the analysis of the physical withholding in the energy market, it is assumed that the producer can only manipulate the energy offer quantity. The main motivation is providing a simple and conceptual model for investigating the physical capacity withholding in markets based on iterative auction. In this model the complexity of analytical methods was avoided. The specification of this model is its ability in checking of producers' withholding by applying minor changes in producer's profit maximization problem and adding reinforcement learning to it. The reinforcement learning algorithm is used since it is easier in comparison with other methods of learning algorithm, such as genetic algorithm and Q-learning and etc. Also, a simple solution was presented to fix RL weakness in becoming invalid in some situations.

The main contributions of this paper are:

1- The incorporation of producer's profit maximization modeling with RL algorithm under a sole model that attempts to illustrate the outcome of the day-ahead energy market which is simulated as an iterative game.

2- An experimental change of producer's profit maximization model that causes the convergence of the iterative algorithm and the emergence of the capacity withholding in a continuous range of the available capacity relating to the generating unit.

3- The development of the RL relation to prevent from becoming invalid in some situations.

The paper is organized as follows. Section 2 describes the formulation of the producers' profit maximization problem and the ISO market clearing algorithm. Section 3 presents the agent-based market simulation model detailing the use of RL and the innovative changes. In section 4, numerical results of a test system are discussed. The concluding remarks are provided in section 5.

Also, the nomenclature of the paper is as follows.

d	System load demand in one hour in MW.
j	Index (set) of producers.
b	Index (set) of types of the generating units.
π_{jb}	Offer price of type b unit of producer j, in \$/MWh.
Q_{jb}	Offer quantity of type b unit of producer j in one hour, in MW.
Q_b^{max}	Available capacity of type b unit.
q_{jb}	Quantity of type b unit of producer j accepted by the ISO in one hour in MW.
Q_{jb}^{adjust}	Adjusted offer quantity of type b unit of producer j offer by learning algorithm in one hour, in MW.
λ	Market clearing price (MCP) in \$/MWh.
μ_{jb}	Marginal benefit of increasing the offer quantity of type b unit of producer j, in \$/MWh.
c_b	Marginal cost of type b unit, in \$/MWh.
K	Index (set) of algorithm iterations (Round).
γ	Learning rate in the range (0, 1].
s_{jb}^{k}	Weight attributed to each of the past energy offer quantities of type b unit of producer j at iteration k.

2 Problem Mathematical Formulation

A number of producers, who possess a number of generating units, take part in a day-ahead energy market. It is considered that the market have both price-maker (strategic) and price-taker (non-strategic) producers. Each producer submits non-decreasing step-wise energy offer curves to the ISO for each trading interval (hourly) of the next day. The ISO processes the energy offers submitted by all producers and clears the market. The day-ahead market is arranged as a sequence of twenty-four independent hourly auctions under the uniform pricing rule. The system load is assumed to be inelastic and the transmission and operational constraints are ignored for simplicity. An hourly ISO market clearing problem and the producer's profit maximization problem in one hour is introduced below.

2.1 ISO Market Clearing Problem

The ISO collects the energy offers submitted by all producers and clears the market by solving the following linear optimization problem and computes the quantities (q_{jb}) and the price (λ):

$$\text{Min} \sum_{j,b} \pi_{jb} \cdot q_{jb} \quad (1)$$

$subject\ to$

$$\sum_{j,b} q_{jb} = d \quad : \lambda \quad (2)$$

$$q_{jb} \leq Q_{jb} \quad : \mu_{jb} \geq 0 \quad (3)$$

$$q_{jb} \geq 0 \quad (4)$$

The first order (Karush, Kuhn, Tucker-KKT) conditions of the ISO market clearing problem are:

$$\sum_{j,b} q_{jb} = d \quad (5)$$

$$Q_{jb} \geq q_{jb} \perp \mu_{jb} \geq 0 \quad (6)$$

$$0 \leq q_{jb} \perp \pi_{jb} + \mu_{jb} - \lambda \geq 0 \quad (7)$$

By processing the complementarily conditions (6) and (7), the following single relationship is obtained as (proof of equation (6) is illustrated in the Appendix):

$$\lambda . q_{jb} = \pi_{jb} . q_{jb} + \mu_{jb} . Q_{jb} \quad (8)$$

The left hand side of (8) shows the revenue of type b unit of producer j. The right hand side of (8) includes two terms. The first term is the revealed cost reimbursement while the second term is the capacity scarcity rent collected by the energy offer of this unit of producer j as shown in Fig. 1.

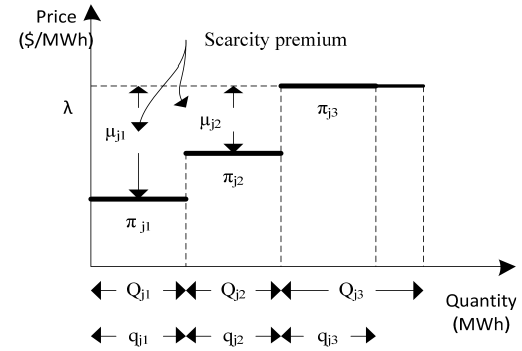

Fig 1. Scarcity premium collected by a producer.

2.2 Producer Profit Maximization Problem

Price-taker producer is considered to offer always his full available capacity at the marginal cost. It is considered that the price-maker producer solves his profit maximization problem (strategic seller problem: SSP) to determine his optimal offers, which is modeled as following mathematical optimization problem. It is assumed that the unit marginal cost is fixed over the unit's full range of output.

$$\text{Max} \quad \sum_b \lambda . q_{jb} - c_b . q_{jb} \quad (j\text{: a certain producer}) \tag{9}$$

subject to

$$0 \leq Q_{jb} \leq Q_b^{max} \tag{10}$$

By replacing the revenue term in (9) by the right hand side of (8), the objective function (9) is changed as:

$$\text{Max} \sum_b (\pi_{jb} . q_{jb} + \mu_{jb} . Q_{jb}) - c_b . q_{jb} \tag{11}$$

Generally, the decision variables of the price-maker producer j are (π_{jb}, Q_{jb}) [4]. Since our main purpose is analysis of the physical withholding in the energy market, the price-maker producers are considered to manipulate only the energy offer quantity, means that they offer the energy price at the marginal cost of the generating unit ($\pi_{jb} = c_b$). Therefore the only decision variable for each unit of price-maker producer is the energy offer quantity (Q_{jb}). Also, in (11), the revenue term is deleted by the cost term, thus (11) is simplified as:

$$\text{Max} \sum_b \mu_{jb} . Q_{jb} \tag{12}$$

According to (12), it is clear that only μ is sufficient to solve the producer profit maximization problem. With the assumption that all producers offer the energy at the marginal cost, thus the market has no primary price cap but has secondary price cap, which is determined administratively to clear the market in scarcity situation.

3 Agent-Based Simulation

A day-ahead energy market is modeled as a repeated game. Each state of the game is corresponding to hourly energy auction repeated in rounds. It is assumed that the producers submit step-wise offer curves to the ISO without having any knowledge about the system load and the rivals' offers; consequently the ISO clears the market with uniform pricing rule. The only public information in iterations is the market clearing price while the marginal cost and the offers and dispatched quantities of the rivals are not publicly known.

3.1 Reinforcement Learning (RL)

In RL, an agent learns what action is best in each situation. The agent, in conflict with the environment and with the experiments, finds an action that has more rewarding. Learner (decision maker) is called the agent, and whatever he interacts with is called environment, including everything except itself. In multi-agent (oligopolistic) environment, each agent clearly does not interact with others, his actions don't directly affect other agents, but it impacts on the environment. In this paper, the optimal offer quantity of the price-maker producer in iteration k (Q_{jb}^{k}) is properly adjusted by applying the RL concept including the offer quantities during the previous W iteration making adjusted value ($Q_{jb}^{k\_adjust}$), as shown by Eqs. (13) and (14):

$$Q_{jb}^{k\_adjust} = (1-\gamma).\, Q_{jb}^{k} + \gamma . \sum_{n=k-w}^{k-1} [s_{jb}^{kn} . Q_{jb}^{n\_adjust}] \tag{13}$$

$$s_{jb}^{kn} = \frac{profit_{jb}^{n}}{\sum_{v=k-w}^{k-1} profit_{jb}^{v}} \tag{14}$$

In this study, γ is a learning rate in the range of (0, 1] and turns over the impact of previous information on offer quantity of the producer. After W iterations, the producer adjusts his optimal offer quantity by RL. The weight s_{jb}^{kn} imputed to each of the past W offer quantities depends on the actual benefit found out by the producer with the corresponding offering strategy ($Q_{jb}^{k\_adjust}$). Now, the producer submits the adjusted quantity $Q_{jb}^{k\_adjust}$ to the ISO instead of the optimal offer quantity Q_{jb}^{k} in iterations. According to (14), those repetitions that result in higher actual profits mostly specify the producer offering strategy during the current iteration [3].

3.2 Development of the RL Relation

An innovative mathematical correction is applied in the denominator of the RL relation. In last W iterations, if the offer quantities of producer are in such a way that the profits are zero, then the denominator of the weighting relation (14) will be zero and the RL relation becomes invalid. To solve this problem, a very small constant amount α (e.g. α=0.001) is added into the denominator (14) in order to prevent from occurring the invalid situation. The new form is:

$$s_{jb}^{kn} = \frac{profit_{jb}^{n}}{\alpha + \sum_{v=k-w}^{k-1} profit_{jb}^{v}} \quad (15)$$

3.3 Experimental Change

An experimental change is proposed in the producer's profit maximization model. This causes the iterative algorithm converge and the capacity withholding emerge. Submitting the adjusted offer quantity to the ISO, the oscillations of the iterative algorithm extremely decreases, but it does not converge. Because the producer's profit maximization problem is still subjected to Q_b^{max} that is always constant and is not affected by the adjusted quantity. To overcome this weakness, the upper limit of the constraint of the producer's profit maximization problem (Q_b^{max}) is replaced by the adjusted offer quantity ($Q_{jb}^{k\_adjust}$). By this replacement, the offer quantity relating to the unit of the price-maker producer converges to a specific bidding value. Also, since $Q_{jb}^{k\_adjust}$ is equal to or less than Q_b^{max}, the capacity withholding may emerge.

3.4 Proposed Iterative Algorithm

In this section, the parallel implementation is introduced to simulate the oligopolistic market. Time dependency of the proposed model can be tracked in its procedure via parallel implementation. This procedure contains 6 steps (step 0 until step 5) which starts firstly by offer of the price-maker producers and followed by clearing the market by the ISO and continues by adjusting the offers by the price maker producers. In the parallel implementation, all the price-maker producers interact with the ISO simultaneously. The iterative process in parallel implementation has below steps.

Step 0) The price-maker producers, as the first action of their game, offer their full available capacity at marginal cost, like price-taker producers. The ISO clears the market, and then an initial solution and the values $q_{jb}^{(0)}$ and λ ($\mu_{jb}^{(0)}$) are determined.

Step 1) After market-clearing and determining λ by the ISO, μ_{jb} is calculated by the price-maker producer as:

$$\mu_{jb} = \lambda - \pi_{jb} \quad (16)$$

Step 2) Based on the values μ_{jb} and q_{jb}, the price-maker producer solves his profit maximization problem to compute his optimal offer quantity Q_{jb}.

Step 3) The price-maker producer adjusts his optimal offer quantity by using RL, then the adjusted quantity Q_{jb}^{adjust} is obtained. After that, the price-maker producer submits the adjusted quantity Q_{jb}^{adjust} to the ISO instead of the optimal offer quantity Q_{jb} and replaces the upper limit of the constraint of his profit maximization problem Q_b^{max} by the adjusted offer quantity Q_{jb}^{adjust}.

Step 4) The ISO clears market based on the adjusted offer quantities of all producers. The values λ and q_{jb} which are obtained in this step are given to the price-maker producer to solve his profit maximization problem in the next iteration.

Step 5) Go back to step 1 and continue the iterative process until a maximum number of iteration (k_{max}) is reached. k_{max} is determined by the ISO.

Fig. 2 illustrates the flowchart of the proposed algorithm in the parallel implementation, which incorporates with the innovative modifications introduced above.

4 Case Study

In this section the proposed algorithm is tested on a small test system. It is considered that there are three producers as strategic sellers and several producers as non-strategic sellers. Table 1 shows the types, capacity and marginal cost of the generating units. Table 2 shows the number of units which belong to each producer. Fig. 3 presents the aggregated supply function of all producers in the form of a step-wise curve which is sorted in ascending order in case of no withholding. It is assumed that the second price cap of the market, which is determined as administratively, is 100 \$/MWh. Using the concept of the RL, we choose the learning rate equal to 0.9 (γ=0.9). The price-maker producer uses the offer quantities in the previous 7 iterations to adjust his current offer quantity (w = 7), starting after the 8th iteration. The market simulation was performed for 120 iterations (convergence criterion). The models were implemented in GAMS 24.3 using the CPLEX solver [18].

At different hours of a day, the amount of the load is different (basic, intermediate and peak load). Here, three test cases are examined at different load levels. In the first case, all producers offer their full capacity at marginal cost, which is no withholding, so the competitive prices are resulted. This case is also considered as a reference for the evaluation of the exercise of market power by producers. In the second case, only producer A as price-maker producer participates in the repeated energy auction and tries to maximize his profit by the RL, while other producers B and C are regarded to as price-taker producers. In the third case, all producers A, B and C as strategic producers participate in the repeated auction and may emerge the cumulative withholding.

Tables 3-6 represent the energy offer quantity of the units of producers in the various cases and at the different load levels. The shaded areas in these Tables denote the wining energy offers of the units relating to the producers, which the ISO buys.

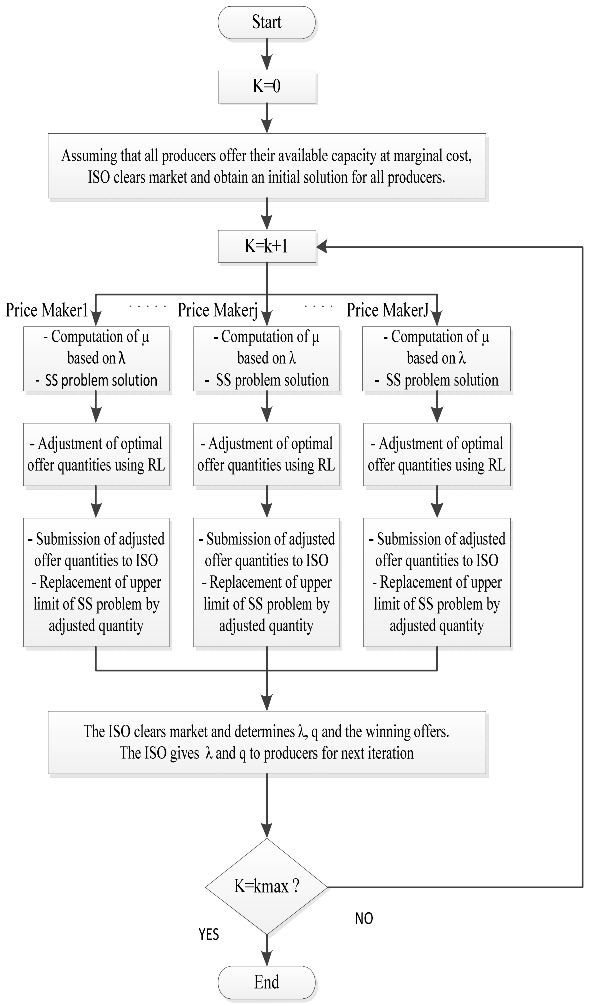

Fig 2. Flowchart of the proposed algorithm in parallel implementation.

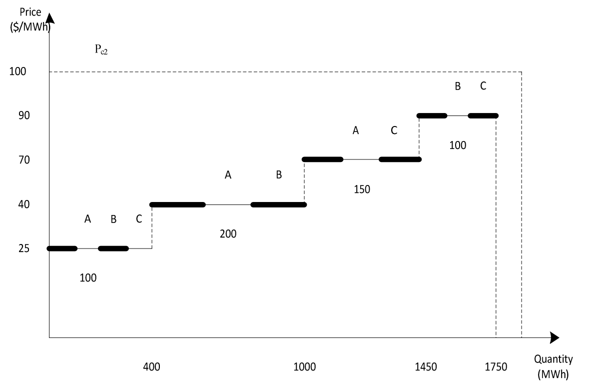

Fig 3. Aggregated step-wise energy offer curve of all producers without withholding.

Table 1 System data.

Unit Type	Capacity [MW]	Marginal Cost [$/MWh]
Type 1	100	25
Type 2	200	40
Type 3	150	70
Type 4	100	90

Table 2 Producers' capacity combination

Producer	Unit Type			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	1	1	1	1
Producer A	1	1	1	0
Producer B	1	1	0	1
Producer C	1	0	1	1

Table 3 Energy offer quantity at load 390 (MW)

(a)

Reference Case (Without Withholding)				
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Taker A	100	200	150	-
Price-Taker B	100	200	-	100
Price-Taker C	100	-	150	100
MCP 25 [$/MWh]				

(b)

Only Producer A is Strategic				**k=120**
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	89.671	0	0	-
Price-Taker B	100	200	-	100
Price-Taker C	100	-	150	100
MCP 40 [$/MWh]				

(c)

All Producers A, B, C are Strategic			**k=120**	
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	96.373	10.727	0	-
Price-Maker B	96.373	10.727	-	0
Price-Maker C	96.260	-	0	0
MCP 40 [$/MWh]				

Table 4 Energy offer quantity at load 1020 (MW)

(a)

Only Producer A is Strategic			**k=120**	
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	100	200	0	-
Price-Taker B	100	200	-	100
Price-Taker C	100	-	150	100
MCP 70 [$/MWh]				

(b)

All Producers A, B, C are Strategic	**k=120**			
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	100	200	0	-
Price-Maker B	100	200	-	0
Price-Maker C	100	-	0	0
MCP 70 [$/MWh]				

Table 5 Energy offer quantity at load 1230 (MW)

(a)

Only Producer A is Strategic				**k=120**
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	100	200	0	-
Price-Taker B	100	200	-	100
Price-Taker C	100	-	150	100
MCP 70 [$/MWh]				

(b)

All Producers A, B, C are Strategic				**k=120**
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	100	200	38.383	-
Price-Maker B	100	200	-	0
Price-Maker C	100	-	40.402	0
MCP 90 [$/MWh]				

Table 6 Energy offer quantity at load 1720 (MW)

(a)

Only Producer A is Strategic				**k=120**
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	100	200	150	-
Price-Taker B	100	200	-	100
Price-Taker C	100	-	150	100
MCP 90 [$/MWh]				

(b)

All Producers A, B, C are Strategic				**k=120**
	Offer Quantity [MW]			
	Type 1	Type 2	Type 3	Type 4
Price-Takers	100	200	150	100
Price-Maker A	100	200	150	-
Price-Maker B	100	200	-	49.806
Price-Maker C	100	-	150	52.215
MCP 100 [$/MWh]				

4.1 Results

4.1.1 The Base Load, 390 (MW)

As given in Table 3a, in the case without withholding, the market clearing price (MCP) is 25 $/MWh. In Table 3(b), producer A withholds alone 10.332 MW of the available capacity of his type 1 unit in 120 iterations and arises the market price from 25 $/MWh to 40 $/MWh. In Table 3(c), all producers A, B and C act strategically and arise the market price with smaller share of the withholding (about 3.63 MW) of their type 1 units, which means they involve in the cumulative capacity withholding. The profit of producer A in Table 3(c) is more than its amount in Table 3(b), because he does less withholding, therefore he has more sale at the same price level.

Fig. 4. shows the convergence procedure of the offer quantities relating to the units of producer A during 120 iterations for Table 3(b). The offer quantities of type 1 unit fluctuate in continuous interval of its available capacity until it converges to 89.671 MW. The RL is not used during first 7 iterations, so the oscillations are severe. Using the RL after 8th iteration, the oscillations have been damped gradually until it converges to a specific bidding value. The remaining offer capacity of types 2 and 3 units is zero during 120 iterations.

Fig. 5. shows the convergence procedure of the offer quantities relating to the units of producer A during 120 iterations for Table 3(c). The offer quantities of type 1 unit fluctuate in continuous interval of its available capacity until it converges to 96.373 MW. The remaining offer capacity of type 2 unit goes to zero during 120 iterations. The remaining offer capacity of type 3 unit is zero during 120 iterations.

4.1.2 The Intermediate Load, 1020 (MW)

Without withholding, the MCP is 70 $/MWh. In Table 4(a), producer A cannot solely increase the market price by withholding the full capacity of his type 3 unit. Also, when all producers act strategically and withhold cumulatively, the market price doesn't change and remains equal to the amount of the reference case 70 $/MWh (Table 4(b)), because the type 3 unit of the price-taker producer supplies the load.

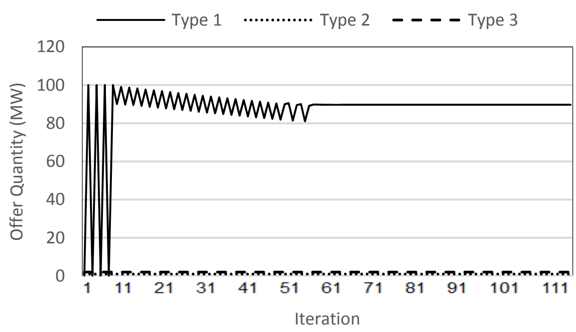

Fig 4. Price-maker A offer quantity during 120 iterations in Table 3(b).

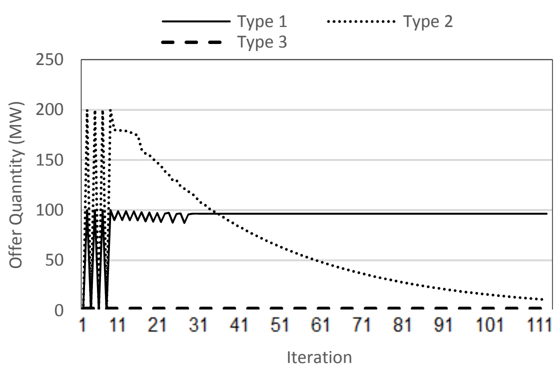

Fig 5. Price-maker A offer quantity during 120 iterations in Table 3(c).

4.1.3 The Intermediate Load, 1230 (MW)

The competitive price is 70 $/MWh. In Table 5(a), when producer A solely withholds his full capacity of type 3 unit, he cannot arise the market price, because other producers supply the load. When all producers A, B and C withhold cumulatively (Table 5(b)), the market price rises one step and becomes 90 $/MWh.

4.1.4 The Peak Load, 1720 (MW)

Without withholding, the MCP is 90 $/MWh. In Table 6(a), producer A does no withholding in his own units, thus it can be concluded that the algorithm does not withhold in units with marginal cost lower than the market price (in the reference case). In Table 6(b), when there are some price-maker producers, the producers B and C cumulatively withhold in their type 4 units and arise the market price to 100 $/MWh, which is the secondary price cap.

4.2 Discussion

The energy offer quantity of each unit is an arbitrary non-negative integer in the range of its available capacity. Therefore the action space of producer as a player is a continuous range over the quantity constraint of his profit maximization problem. Since the demand is inelastic, the producers report their offer capacity less than their available amount, thus the mathematically soluble convex problem with no withholding has an agent-based withholding solution with higher profits. It is observed that the iterative process reaches a steady state. This means that offer quantities relating to units of the price-maker producer converge to a specific bidding value (refer to Figs. 4 & 5).

The price-maker producer can withhold his available capacity at every load level (base, intermediate and peak) and the market price may increase. In general, the capacity withholding at the base load may only increases the market price and will not lead to a lack of total capacity, because other producers have enough generation capacity to supply the load (refer to section 4.1.1 and Table 3). At the intermediate and peak load, the capacity withholding may be in addition to increasing market price, cause lack of total capacity to supply the load, in which situation the market will fail (refer to section 4.1.4 and Table 6(b)).

The algorithm withholds in units with marginal cost equal or higher than the competitive market price (in case without withholding). The value μ of these units is zero, thus the algorithm withholds in order to increase the μ and consequently the market price and profit. According to Tables 1 and 3(a), all units used in this case study have this condition, so the algorithm can withhold all of them (refer to Tables 3(b), 3(c), 4, 5 and 6). The algorithm does not allow withholding in units with marginal cost less than the competitive market price (in case without withholding). The value μ of these units is greater than zero, thus the algorithm offers the maximum capacity of the units. Although theoretically, the producer can withhold in these units and increase the market price, but the fact is he does not have full information about other competitors, so he won't risk withholding the available capacity of the units. In other words, the producer does not want to lose the sale opportunity of the energy relating to units with lower marginal cost which he has won.

In general, the optimization happens by the price-maker producer offering the optimal energy offer quantities at marginal cost, and the remaining capacity at price cap [3]. According to our algorithm, since the producer can only manipulate the offer quantities, the results show that the price-maker producer also withholds its remaining capacity in order to have a chance of raising the market price.

The following results are obtained by examining different values for learning rate. Analysis done at each price level: at higher load (e.g. 390 MW at the price level 25 $/MWh) the higher learning rates (i.e. γ=0.9) identifies the withholding well, and at lower load (i.e. 310 MW at the price level of 25 $/MWh) the smaller learning rates (e.g. γ=0.1) identifies the withholding well.

The iterative proposed algorithm may not converge to Nash equilibrium of a day-ahead market game because of using the RL algorithm. The RL does help in damping the oscillations but modifies the offer quantity of the producer profit maximization problem. From perspective of the game theory for infinitely repeated games, the result may not be a Nash equilibrium point of corresponding stage game. The result of infinitely repeated game can be both players choose to cooperate, that is not Nash equilibrium of the stage game. The infinitely repeated prisoner's dilemma game is investigated in [19], [20].

As previously stated, the aim of capacity withholding by a producer is to increase the market clearing price and his profit. So, it is useful to investigate the impact of capacity withholding of offer quantity of a producer as model input on profit of the producer as model output. Fig. 6 shows the profit of producer A with and without withholding at different load levels. Bold curve is the producer’s profit without withholding and dotted curve is the producer’s profit with withholding. As can be seen, at the different load levels the profit curve with withholding is always above it in without withholding condition. So the producer can increase his profit by withholding his offer capacity.

The performance of our proposed method is compared with the other RL algorithm (presented in [7]). A SA-Q-Learning algorithm is used to study of capacity withholding in [7]. The main weaknesses of that method are the discretization of the action space, so a lot of possible choices for bidding will be lost, and the low speed of convergence, therefore the iterative process will converge in high iterations. In comparison with our model, the results of our model are more accurate and the speed of algorithm convergence is higher.

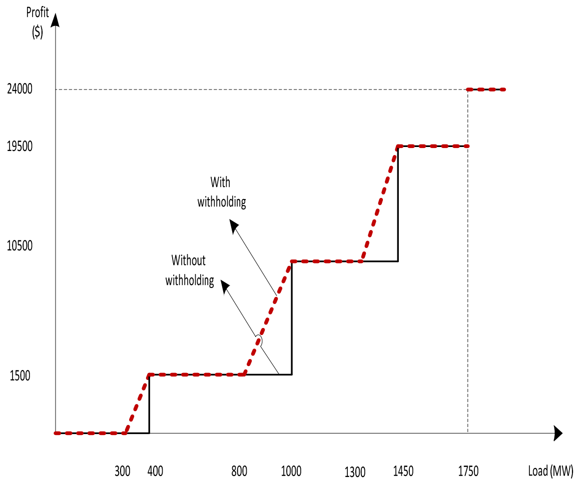

Fig 6. Profit of producer A with and without withholding.

"In our model, it is assumed that the producer can only manipulate the energy offer quantity and is not able to change the energy offer price. With this assumption, the producer withholds the capacity of his units in order to increase the market clearing price. Zero being the offer quantities of expensive units in tables at base and middle loads means that they are off, so there is not overestimation of capacity withholding. Therefore the model output corresponds with reality in the sense that the expensive units are off at base and middle loads."

5 Conclusion

This paper has presented an agent-based simulation model for study of the capacity withholding in a day-ahead energy market. The energy market was formulated as a repeated game, where each producer was modeled as an agent, following a reinforcement learning algorithm. We proposed the modifications in the producer's profit maximization model and the denominator of the RL relation. With these modifications, the iterative algorithm converged and the capacity withholding emerged in continuous range. The parallel implementation tested on a small test system. Test results show well the emergence of the capacity withholding and the increase of the market clearing price. A producer can increase the market clearing price and consequently his profit by capacity withholding. If the producers withhold cumulatively, they may gain more profit with less share of withholding.

6 Appendix

Proof of Equation (6):

$Q_{jb} \geq q_{jb} \perp \mu_{jb} \geq 0 \;\; \rightarrow \;\; 0 \leq (Q_{jb} - q_{jb}) \perp \mu_{jb} \geq 0 \;:$

$(Q_{jb} - q_{jb}).\,\mu_{jb} = 0 \quad \forall j,b$

If $Q_{jb} \neq q_{jb}$ then $\mu_{jb} = 0$

If $\mu_{jb} \neq 0$ then $Q_{jb} = q_{jb}$.

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