Analysis of Price Fluctuation in Double Auction Markets consisting of Multi-agents using the Genetic Programming for Learning

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https://doi.org/10.15017/8706

出版情報：經濟學研究. 73 (2/3), pp.147-167, 2006-11-28. 九州大学経済学会
バージョン：
権利関係：

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Xiaorong Chen and Shozo Tokinaga

1 Introduction

Auction mechanisms have been attracting increasing attentions in recent years motivated by selling systems over the Internet as well as conventional ones [1]-[5]. Most of theoretical researches in auction theory assume that bidders will be making competitive bids, and these bidders are symmetrical in size and are risk neutral. However, many real auctions involve various complicated trades such as an oligopoly of asymmetric bidders who repeatedly meet and bid for the same commodity. Then, theoretical analyses become very hard to find the different rules which govern the auction process and affect the market price. Then, simulation studies are expected to bring us novel results.

Moreover, auction mechanisms are now expected to bring deregulation and competitive prices in markets of items such as network access rights, telecommunication channels, gas and electric utilities[1]. However, most of theoretical researches in auction theory assume that bidders will likely to be competitive, and bid only a unique good. Rather than conventional auction markets, we find various auction market such as electricity markets where many seller and buyers (bidders) are allowed to bid/ask each other, and theoretical approach is very difficult. Sometime, it is noted that we see very rapid changes and fluctuations of bid price. About 10 times larger price jump compared to ordinary price is reported in the electricity market [21][22].

In this paper, we show the analysis of price fluctuation of artificial double auction markets consisting of multi-agents who learn from past experiences based on the GP [6]. By assuming multi-agents as bidders who learn from past results of auctions based on the GP, we can analyze the capability to learn successful auctions by agents, and the change of profit of agents in various conditions of auctions in a range of multi-unit, multi-period auction settings.

The GP method has been successfully applied to the estimation of chaotic dynamics using the observed time series, and a direct control method for chaotic dynamics is proposed based on the GP [7]-[16]. Moreover, the GP method has been widely used to emulate the agents' behavior in various markets such as the stock market[11][12]. In this paper, we utilize the GP method to model agents' behavior in auction markets.

We apply the GP procedure to model learning of agents[5]-[8]. Each agent has a pool of individuals represented in tree structures to predict future bid price and the volume of items to be supplied to the market using the past result of auctions. The fitness of individuals is defined by using the successful bids and the utilization of units, and agents improve their individuals based on the fitness to get higher return in coming auctions.

In the simulation studies of duble auction markets, we can see the rapid changes of prices depending on the demand curves. We also see that the net prices suggested by the sellers are usually higher than that are originally expected. The result show us that the double auction not necessarily bring good and effective market structures, as several observations claim the change of auction systems for public utilities [21][22].

2 Auction mechanism realized by agents

2.1 Two types of auction models

We assume well-known two types of auction models in the following [1]-[3]. The first one is the sealed-bid auction where bidders can exhibit price for successful bid (bid price) only once, and they cannot know prices of other bidders. The auction model is employed in many bidding of construction of public utilities. In the scheme, a bidder who exhibits the highest bid price can win the bid.

The other type of auction is the English auction where the auction is carried out in real time (sometime the auction model is called as online auction), and bidder can know current highest price of bidding, and they can exhibit bid price repeatedly. Usually, a bidder exhibiting the highest bid price can win the bid, but it is also assumed that a bidder exhibiting second highest bid price can win the bid (called the Vickrey auction).

Originally, there are three types of agents in the artificial auction market, namely, bidders who wish to suppress the bid price as low as possible, sellers who wish higher bid price, and the auctioneer who manages the auction. For simplicity, we assume that the seller and the auctioneer is the same agent in the following.

We also assume at the first stage that only one seller agent shows only one kind of item (commodity) in the market, and is traded by many bidders (agents).

2.2 Behavior of agents in sealed-bid auctions

In the sealed bid auctions, each bidder can tender his price only once to the market. After all of the bidder tendered their bidding price to the market, the only one bidder who tendered the highest bid price win the bid.

In general, the evaluation of the item exposed in the market are different form one bidder to another bidder, we introduce the indicator to express the willingness to bid the auction called as the private evaluation. The agent i ($i = 1, 2, \cdots, n$) assigns the private evaluation v_i to the item shown in the market by sellers. As the private evaluation, we assume following three kinds pf values.

(1)same values

Each agent takes the same value of private evaluation v_i. For example, $(v_1, v_2, v_3, \cdots v_n) = (100, 100, \cdots, 100)$.

(2)uniformly distributed random number

Each agent select a random number form a uniformly distributed density function and assigns as the private evaluation. For example, $v_2, v_3, \cdots v_n) = (106, 97, 92, \cdots, 101)$.

(3) different but piecewisely fixed values

The private evaluations are different from agents to agents, but are piecewisely fixed in several stages. For example, $(v_1, v_2, \cdots, v_{n/2}, v_{n/2+1}, v_{n/2+2}, \cdots, v_n) = (100, 100, \cdots 100, 90, 90, \cdots, 90)$.

We concisely summarize the way of agents' learning in sealed-bid auctions. It is assumed that each bidder agent has its own pool of functions (individuals) for deciding bid price. To simplify the simulation in reasoning of agents, we restricted ourselves to the cases where the functions can be represented in binary tree structures. But, the restriction has no serious effect on generalization of the method.

For example, an agent has following function including if-then rules.

```
if (vi>72) then 1.2 P1-0.1 else 0.9 MAX
```

Fig.1 shows the corresponding tree structure of function. In this case, the agent exhibits bid price as 1.2 P1-0.1 if the condition $v_i > 72$ is satisfied, otherwise exhibits bid price as 0.9 MAX. We also show general form of functions in Fig.2 using symbols R, M and T which mean the root node, intermediate node and terminal node, respectively.

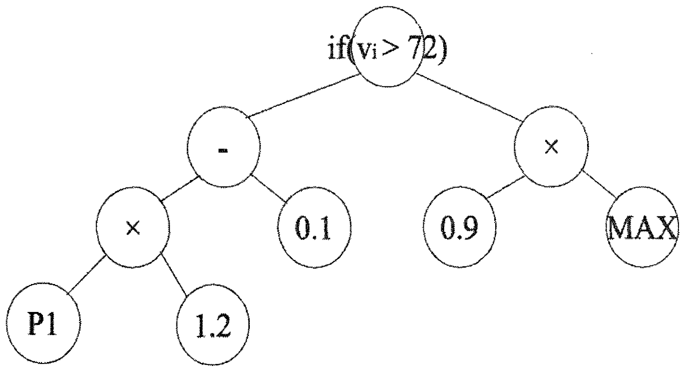

Figure 1: Example of Tree structure representing agents' behavior

2.3 Behavior of agents in English auctions

Different from sealed-bid auctions, in English auctions agents can exhibit bid price repeatedly at multiple times. It is also assumed that agents are allowed to wait for another exhibition of bid price in the auction as well as to join the auction. Then, the agents' behaviors are described by programs rather than functions. We also use tree structures to represents these programs, but their terminal nodes include action part of rules, and on their intermediate nodes if-then-else type rules are placed. As the result of rules, agents take one of two actions, namely, "wait" (no action) and "join" (exhibit bid price).

In case of "join", the agent must determine the bid price. Then, we assume that the agent use one of following two methods for decision.

(1) incremental price

By adding price increment inc to the present price s by several times, then $s + m \times inc$ will be the bid price.

(2) random selection of multiple

Assuming set $[b_1, b_2, ..., b_l] = [1.1, 1.2, ..., 2.0]$, then the agents select one of these numbers to obtain bid price as $s \times b_i$.

The if-then-else type rules treated here are the same as used in the sealed-bid auction, but in place of terminal node we use "wait" or "join".

The interpretation of trees (individuals) is slightly complicated. For example, in a tree structure in Fig.2, we start if-clause at the root node. If the current bid price s is 80, and the condition is true, then we go to left branch and meet "div" node which means we go further to left branch. Then, we meet if-clause, and depending on the condition, we choose whether left branch of right branch. These two branches are denoting "join" showing the bid prices, and the action taken by the agent is terminated in this step. In this example, if $s < v_i$, then the agent

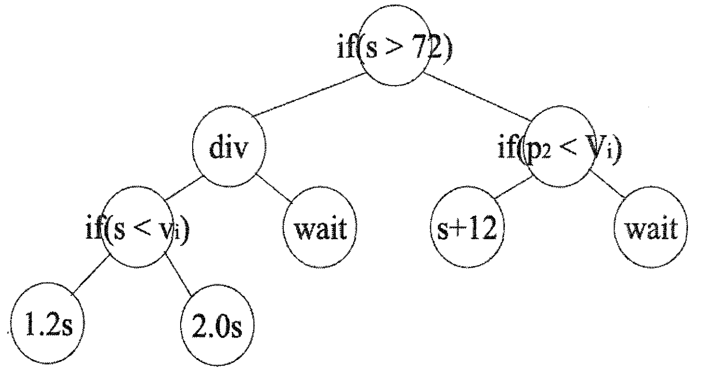

Figure 2: Example of tree structure representing agents' behavior

exhibits $1.2s$, otherwise $2.0s$.

In the next auction, the agent goes backward to "div" node, and restarts the action. Since the node is "wait", then the agent takes no action for bidding. Further, in the next auction, the agent goes back to root node again, and select appropriate action. The agent repeat these behavior until the end of underlying auction.

Even though the English auction plays a important role in various market such as online-auctions, but in the following discussion, we mainly consider the sealed-bid auction. Then, the further description about the English auction is omitted.

3 GP learning of agents

3.1 Agents' learning using the GP

In the following, we assume that agents learn from past results of auctions to find appropriate bid price for future auction based on the GP. The GP is an extension of the conventional GA in which each individual in the population (pool of individuals) is a computer program composed of the arithmetic operations, standard mathematical expressions and variables [7]-[20].

For simplicity, we show the GP procedure for the approximation of functions for the prediction of time series. In the GP, the system equations are represented in the tree structure (called individuals). In the parse tree, non-terminal nodes are taken from some well-defined functions such as binomial operation $+, -, \times, /$, and the operation taking the square root of variable. For example, in case of prediction of time series, terminal nodes consist of arguments chosen from set of constant and variable such as $x(t-1)$ which is the time lag of $x(t)$. Usually, we calculate the root mean square error between $x(t)$ and $\tilde{x}(t)$ where $\tilde{x}(t)$ is the prediction of $x(t)$ obtained by an individual, and use it to define the fitness.

By using the measure of fitness to evaluate each individual, we apply the GP to the population to derive better description for future auctions promising higher profit. By selecting a pair of individuals having higher fitness, the crossover operation is applied to generate new individuals. Two subtrees from a pair of individuals are extracted and swapped each other.

To keep the crossover operation always producing syntactically and semantically valid programs, we look for the nodes which can be a subtree in the crossover operation and check for no violation. The crossover operation creates new offsprings by exchanging sub-trees between two parents.

Besides the crossover operations, we use the mutation operations. The goal of the mutation operation is the reintroduction of some diversity in an population. Two types of mutation operation in GP is utilized to replace a part of the tree by another element.

(Global mutation :G-mutation)

Generate a individual I, and select a subtree which satisfies the consistency of representation. Then, select at random a subtree in the individual J in the pool, and replace the subtree by the subtree of the individual I. After the mutation, we only retain the modified individual J in the pool.

(Local mutation:L-mutation)

Select at random a locus in a parse tree J to which the mutation is applied, we replace the place by another value (a primitive function or a variable).

We iteratively perform the following steps until the termination criterion has been satisfied.

(Step 1)

Generate an initial population of random composition of possible functions and terminals for the problem at hand. The random tree must be syntactically correct program.

(Step 2)

Execute each individual (evaluation of system equation) in population, then, assign it a fitness value giving partial credit for getting close to the correct output. Then, sort the individuals according to the fitness S_i.

(Step 3)

Select a pair of individuals chosen with a probability p_i based on the fitness. The probability p_i is defined for ith individual as follows.

$$p_i = (S_i - S_{min}) / \sum^{N} (S_i - S_{min}) \tag{1}$$

where S_{min} is the minimum value of S_i, and N is the population size.

(Step 4)

Then, create new individuals (offsprings) from the selected pair by genetically recombining randomly chosen parts of two existing individuals using the crossover operation applied at a randomly chosen crossover point. Then, we gather these new offsprings in the pool P-B which is different from the initial pool P-A. Iterate the procedure several times, and we gather sufficient number of new offsprings necessary for the replacement of individuals. Then, we replace individuals in the pool P-A having lower fitness by individuals in the pool P-B.

(Step 5)

At a certain probability, we apply the mutation operations for the pool of individuals. If the result designation is obtained by the GP (the maximum value of the fitness become larger than the prescribed value), then terminate the algorithm, otherwise go to Step 2.

3.2 Learning processes of agents

Each agent has a pool of individuals each of which corresponds to the estimation of appropriate bidding for the next time point. The individuals are represented by using arithmetic operators, comparative operators, and the observation of past successful bid. Since the ability (called fitness) of each individual can be evaluated after the bidding is realized (ended), agents can improve the estimation of individuals by applying the GP operations (crossover and mutation) to the pool of individuals.

It is assumed that the first N_1 times of biddings are used for learning for agents, and no commodity is delivered to bidder, and seller gets no money. In this learning period, each agent try to improve the estimation of individuals by using the GP procedure. Then, in successive N_2 times of bidding, agents apply the estimation using the pool of individuals. After N_2 times of auctions, the profit of each agent is determined.

4 Agent model of sealed-bid auction

4.1 GP learning of agents

The function includes various terminal symbols as well as constants. At first, we introduce the private evaluation v_i for ith agent as the terminal symbol. Each bidder agent i reacts to the commodity offered by seller, and assigns a value v_i representing the private evaluation (preference). The function predicting bid price at time t can have also the symbols P1=$CP(t-1)$ where $CP(t-1)$ is the successful bid price in previous auction. The function has also symbols AV, MAX and MIN defined by taking the average, maximum and minimum of successful bid prices in previous t_1, t_2, t_3 time periods of auctions, respectively.

$$AV = \sum_{j=t-t_1-1}^{t-1} /t_1 \quad (2)$$

$$MAX = \max[CP(t-t_2-1), CP(t-t_2), ..., CP(t-1)] \quad (3)$$

$$MIN = \min[CP(t-t_3-1), CP(t-t_3), ..., CP(t-1)] \quad (4)$$

The nodes of tree structure are composed of arithmetic operators $+, -, \times, /$, and comparative operators $=, \neq, <, >, \geq, \leq$

4.2 Fitness of individuals

The ability of individuals corresponding to the functions is defined as the fitness in the GP. As the first ability measure, we use following value based on the number of successful bids.

$$pr_{ik} = \sum_j [CP(j) - v_i(j)]/N_{ik}^w \quad (5)$$

where $v_i(j)$ is the ith agent's private evaluation of bidding in jth auction, and N_{ik}^w is the number of successful bid obtained by using kth individual in the pool. Then, the numerator of equation (5) corresponds to average profit obtained by successful biddings.

We also employ the second evaluation measure for fitness in kth individual for ith agent as follows.

$$r_{ik} = sb_{ik}/N_{ik}^u \quad (6)$$

where sb_{ik} means the number of successful bid, and N_{ik}^u means the number of time where the agent uses the kth individual.

Finally, by changing the weight ω_i between pr_{ik} and r_{ik}, we have aggregated fitness measure for kth individual as follows.

$$s_{ik} = \omega_i(pr_{ik} - \min_j pr_{ij})/R_i^{pr} + (1-\omega_i)(r_{ik} - \min_j r_{ik})/R_i^r \quad (7)$$

where R^{pr}, R_i mean the ranges of two measures to normalize the fitness.

4.3 GP learning

To improve initial set of individuals, we apply following procedure.
A. Select private evaluation v_i. Evaluate AV,MAX,MIN in equations (2),(3),(4). At initial stage, agents have no result of auction, then we assign random numbers

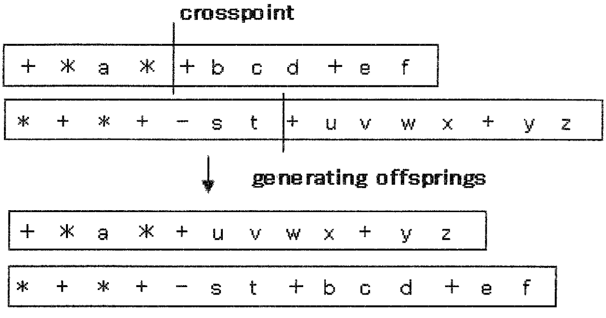

Figure 3: GP operations (crossover)

in place of these equations.
B. Select one (kth) individual from the pool with the probability

$$P^s_{ik} = s_{ik} / \sum_{j=1}^{k} s_{ij} \tag{8}$$

Since under changing environments such as auction market, it is not relevant to use fixed function (prediction) for bid price, then agents are allowed to select an individual in proportion to the fitness values.
C. Seller determines the successful bid $CP(t)$ at time t by observing bid prices given by bidders.
D. Reevaluate fitness of individuals using current $CP(t)$ and equations (1),(2),(3).
E. Iterate procedures from A through D for sufficient times, and then apply following GP.
F. Apply the GP (crossover and mutation operations). Select a pair of individual with probabilities proportional to equation (7), and then exchange portions of tree structure (two subtrees) which are selected at random. An example of crossover operation is shown in Fig.3.

In this example, a terminal node of Parent A and an intermediate node of Parent B are exchanged. We have two offsprings, and to keep the size of pool unchanged, two individuals having lower fitness are replaced by two offfsprings.

Besides crossover operations, we use mutation operations with a certain probability by replacing a portion of tree by another symbol (the Local and Global mutations).

4.4 Price changes in sealed bid auctions

In the following simulation studies, we examine the ability of the GP method to realize artificial auction market by changing parameters of the system. At first, we show the result for artificial auction market of the sealed-bid auctions.

The parameters for simulation studies are selected as follows.

Setting t_1, t_2, t_3:
Number of bidder agents:10
$N_1 = 500000$ (apply GP for 1000 iterations)
$N_2 = 50000$,upper limit of bid price=150
Number of individuals for each pool=50
Maximum number of nodes in trees=50
Duration time of auction $T_E = 200$ Probability of crossover:0.05
Probability of each mutation:0.05
Originally, as probabilities for selecting terminal nodes as arithmetic operations, if-then-else condition, constants and variables we assign $0.4, 0.1, 0.25, 0.25$, respectively. However, if it is necessary to generate intermediate nodes, then the probabilities for arithmetic operators and if-then-else conditions are changed to $0.4/(0.4+0.1), 0.1/(0.4+0.1)$, respectively. The constants used for if-then-else conditions and terminal nodes range from $0 \sim 120$ and $-120 \sim 120$,respectively.

We assume three cases for the definition of private evaluations v_i as follows.
(Case 1)identical:each agent has the same v_i
(Case 2)uniformly distributed:select one v_i from set $(90, 91, .., 100)$ at each iteration of auctions.
(Case 3)piecewise constant:assign two values depending on agent, such as $V = (100, 100, ..., 100, 90, 90, ..., 90)$. Namely, five agents take 100 as v_i, and other five agents take 90 as v_i.

Table 1 shows the result for average profit of bidders depending on the private evaluations. In Table 1, Prf1, Prf2, Prf 3 mean average profit of agents in Case 1, 2 and 3 defined as the value obtained by final bid price minus the private evaluation. In Table 1, Prc2 and Prc3 mean the bid price in Case 2 and 3.

As is seen from the result, in Case A if $\omega = 1$, Prf1=0, then every bid prices greater than v_i are smoothly removed from the system, and no bid price greater than 100 is realized. But if ω becomes less than 1, agents pay more attentions to the rate of successful bid, and the profit decreases. The fact implies that if there exist many bidder agents who pay more attention to the successful bid, then the seller can enjoys higher price.

In Case 3, we see also almost the same decrease of profit as Case 1 (then, the average price of bidding almost increases) along the decrease of ω form 1. Even though agents use different private evaluation from 90 and 100, final bid price is almost always realized at 100. Then, the average profit of agents using their private evaluation at 90 becomes around -10.00.

In case 2, we find several different features of result. In case of $\omega = 1$, the average profit of bidder is positive, and the final bid price is slightly greater than lowest limit of v_i (90). Even more, along the decrease of ω from 1, the average profit of bidder becomes negative, but the range of the decrease is relatively small compared to Case 1 and 3. The fact implies that the random behavior of bidder agents help them to get more profit, and affect seller to decrease price.

Table 1-Simulation result (sealed bid auction)

	$\omega = 1$	0.9	0.8	0.7	0.6
Prf1	0.00	-8.32	-13.43	-14.79	-46.48
Prf2	9.48	-0.20	-8.79	-19.65	-2.91
Prf3	0.00	-1.94	-9.74	-4.21	-37.26
Prc2	90.04	105.45	109.33	119.32	107.69
Prc3	100.00	100.00	103.52	101.40	150.00

4.5 Gradual price changes

Even though we find various pattern of profit by giving the conditions (situations) of simulation studies, the bid price obtaied by the result of auction is very steady. Fig.4 shows an example of change of average length of individuals along the time where the price finally converged to a constant level. At the same time, in Fig.5 we shows the correspondiong change of the average fitness of individuals where we find the same convergence to a level.

The fact means that the auction mechanism realized by agents who learn form the past experiences comes to be stable, even though each agent try to find best prediction for future bid price. All of the agents can obtain ultimately appropriate rules (prediction formula) for the bid price, and the prediction converged to the same function.

Under the auction with single seller and multi-buyers (bidders) bring us a relatively steady market, event though the agents' behavior bear themselves dynamic changes.

5 System configuration of double auctions

5.1 Characteristics of double auction market

Game theoretic analysis of various auction types generally assume a benchmark model where bidders are risk neutral, symmetric , and have their own private evaluations of goods. As a result, the general results are that the final price achieved is invariant to the auction mechanism. However, despite being a cornerstone of modern auction theory, conventional auction theory is applicable only to a single unit (item) and single-period setting. In contrast, theory is much less well-developed

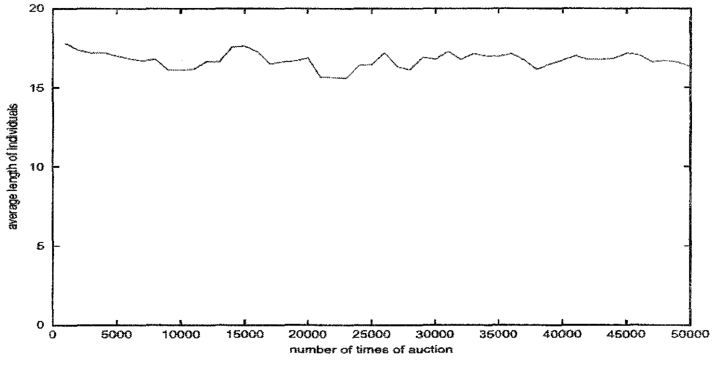

Figure 4: GP operations (crossover)

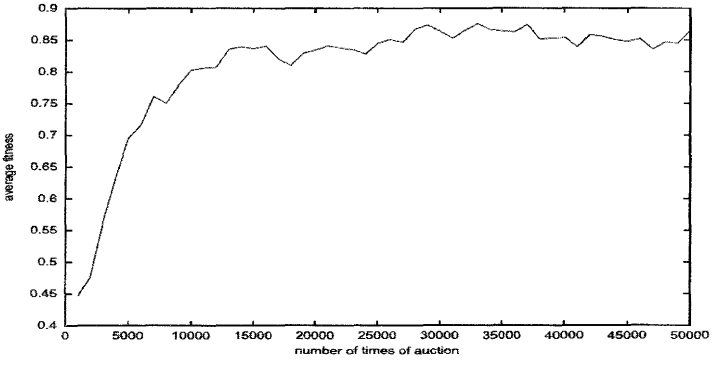

Figure 5: Average fitness of individuals

where these conditions are relaxed. Especially, we find following two notable points in the double auction mechanism where there multiple seller and multiple bidder to trade a single item with various amount of demand by bidders.

(1) Is discriminatory auction superior to uniform price ?

The multi-unit auction analogue of the first-price auction is the discriminatory auction where bidders make sealed bids indicating the quantity of goods they are willing to buy at a range of prices. The auctioneer allocates the goods to the highest bid first, according to the quantity of demanded, and so on down to the sequence of received bid until al the goods have been allocated.

Some researcher have argued that the uinform price auction has a lower winner's curse and results in greater revenue to the seller than would a discriminatory auction. However, the result is based on the single-unit auction theory, and the some researcher concluded that the uniform price auctions are no longer universally superior to discriminatory auctions. On the other hand, there are always

The objective function to maximize expected total profit is given by

$$\max E[\sum_{t=1}^{T} PR_t], PR_t = l_t R - m_t E_t - CF(P_t) \tag{9}$$

under the constraints

$$E_t + P_t = l_t, P_t = \lambda_t P_c \tag{10}$$

$$P_t^{\min} \leq P_t \leq P_t^{\max} \tag{11}$$

where P_c is the highest (full) capability to supply electricity, and the coefficient λ_t denotes the utilization of unit. The amount P_t of generation of electricity is given through P_c multiplied by the utilization λ_t. If E_t is positive, the electricity is bought from the pool, otherwise sold. Assuming that the price m_t and P_t are estimated based on the GP methods.

The generation of electricity P_t is defined by the Cobb-Douglous type production function as follows.

$$P_t = A_t V_t^{\alpha_t} K_t^{\beta_t} \tag{12}$$

where V_t, K_t are variable and fixed factors for the production, and A_t, α_t, β_t are the parameters to define the efficiency of generation of electricity. For simplicity, we assume these parameters are time-invariant all through the time, and then we drop the subscript t for the parameters. We also assume that $\alpha + \beta < 1$. Assuming that the unit cost for the variable factor V_t is w_t, and the unit cost for the fixed factor is r_t, then the limit cost function $CF(P_t)$ s given by

$$CF(P_t) = w_t V_t + r_t K_t \tag{13}$$

If we assume that the fixed factor is constant through the time $(K_t = K)$, then we have the marginal cost function MC_t as follows.

$$MC_t = A^{-\frac{1}{\alpha}} K - \frac{\beta}{\alpha} \alpha^{-1} w_t P_t^{-1+\frac{1}{\alpha}} \tag{14}$$

In the paper, we use the model that agents improve the prediction functions for the market price of electricity m_t and the amount of relevant purchase of electricity E_t (in cases of E_t is negative, then they supply the electricity) based on the GP procedure. Agents exhibit these prices and amount for purchase (supply) to the market for bids in the double auctions. Then, the relevant level of generation of electricity P_t for their own units are determined.

5.3 Market price and agents' behavior

In the multi-unit auction, bidders make sealed bids indicating the quantity of goods they are willing to buy at a ranges of prices. The auctioneer allocate the goods to the highest bid first, and so on down the sequence of received bids until all the goods have been allocated. Likewise, in uniform price auctions successful bidders all pay the same price regardless of the bids they actually made. The price is equal to the highest (marginal) bid price accepted (called Pay Marginal).

Agents utilize the GP procedure to predict the market price m_t based on past experiences. Then, agents can decide optimal value of generation P_t and utilization of units λ_t.

As a result, agents appear as sellers in the market as well as bidders, since they buy the electricity if they think that the cost to generate electricity is costly than buying electricity. However, the producers are originally join to the market as suppliers using their facilities, then the utilization of units affect the return on initial investments. Then, we introduce the utilization of units as another measure to define the fitness of individuals.

It is assumed that the first N_1 times of biddings are used for learning for agents, and no item is delivered to bidder, and sellers get no money. In this learning period, each agent try to improve the estimation of individuals by using the GP procedure. Then, in successive N_2 times of bidding, agents apply the estimation using the pool of individuals. After N_2 times of auctions, the profit of each agent is determined.

6 GP learning and behavior of agents

6.1 Bidding with sealed-bid auctions

In the double auction market of electricity, we assume that agents exhibit their bid price along the scheme of sealed-bid auctions. In sealed-bid auctions, agent i define the private evaluation v_i denoting the preference of bid price. It is that agents are satisfied if the bid price in the auction is lower than the private evaluation. In the simulation studies, we define the private evaluations as the price of electricity R under contracts between producers and customers.

We assume three cases for the definition of private evaluations v_i as follows.
(Case 1) identical
(Case 2) uniformly distributed
(Case 3) piecewise constant

discriminatory auction equilibria that dominate uniform price equilibria, and vice versa.

(2) Large price fluctuation

In an efficient deregulated market the forces of supply and demand should interact to determine the optimal allocation of resources. For example, in the electricity market, if the market produces too much power, prices will fall and fewer generators will be profitable to operate an this level. Similarly, if the power is scare, the rising price will induce more production. By observing the price time series of deregulated electicity market, we find that the electricity spot prices are unlike those of any other commodity. Electricity prices often jump to 10 or 20 times their current value for few hours before jumping back to normal levels. These trends are the result of the fact that electricity can not be stored in sufficiently large quantities and must be generated as needed.

(3) market power and advantage on sellers

In practice, few if any electricity merkets are perfectly efficient, and in many cases some market participants process enough market power that coordinating multiple generators to affect prices may be possible. As a result, the double auction mechanism is allowing sellers to keep market prices well above their marginal production costs.

5.2 Modeling of electricity market

Since the characteristics of double auction market is observable in the electricity market, we will focus on the deregulated market of electricity. In the market, we assume several agents who are producing electricity, but simultaneously they buy electricity if the cost of power production is relatively higher than purchasing the electricity.

We consider N agents who behaves as an electric power producer with one generating unit and wishes to schedule its unit to maximize profit over a short time period of length T hours[3][4]. Even though the description of problems is restricted to the electricity market, we can easily extend the frameworks to another production systems of goods.

The evaluation function for optimal generation of electricity includes following variables[3][4].

P_t: amount of power at t

$CF(p)$: cost function of unit to generate power p

l_t: volume to be sold under contracts

R: price of electricity to be sold

E_t: amount to be bought (if E_t is negative, to be sold) from market

m_t: market price at power pool

6.2 Fitness of individuals

The ability of individuals corresponding to the functions is defined as the fitness in the GP. As the first ability measure, we use following value based on the number of successful bids.

$$pr_{ik} = \sum_j PR_j / N_{ik} \tag{15}$$

where N_{ik} is the number of successful bid by the agent i obtained by using kth individual in the pool. Then, the numerator of equation (15) corresponds to average profit obtained by successful biddings, and the value is divided by the number of successful bid using kth individual , which provides us the average profit.

We also employ the utilization rate λ_t as the second evaluation measure for fitness in kth individual for ith agent.

Finally, by changing the weight ω_i between pr_{ik} and λ_t, we have aggregated fitness measure for kth individual as follows.

$$s_{ik} = \omega_t(pr_{ik} - \min_j pr_{ij})/R_i^{pr} + (1 - \omega_i)\lambda_t \tag{16}$$

where R_i^{pr} is the range of profit pr_{ik} in equation (16) so that we can normalize the profit between 0 and 1 by subtracting the minimum value form the profits and by dividing them by the range. Then, we can make two terms in the fitness functions to be comparable.

Finally, by changing the weight ω_i between two terms, we have aggregated fitness measure for kth individual. If the weight is set to be zero, then agents are solely interested in the utilization rate of units. On the other hand, if the weight is set to one, then agents mostly feel benefit in obtaining larger profit. If the weight is taken from an arbitrary value among 0 and 1, then agents think about the utilization of units as well as profits.

As the initial value of fitness s_{ik}, we use a set of random numbers.

7 Price changes in double auctions

7.1 Price changes (fixed demand case)

At first, we consider the case where the demand of customers is fixed (constant). The parameters for simulation studies are selected as follows.
Number of agents: 20
$N_1 = 500000$ (apply GP for 1000 iterations)
$N_2 = 50000$,upper limit of bid price: 150
Number of individuals for each pool: 50
Maximum number of nodes in trees: 50

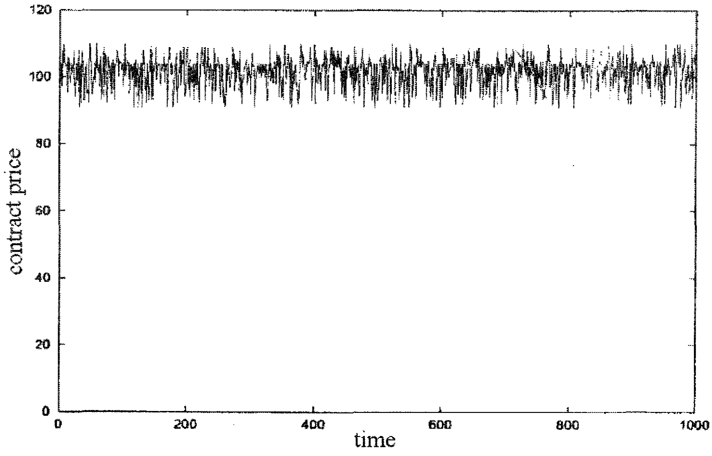

Figure 6: Example of time series of bid price

Duration time of auction : $T = 200$
Probability of crossover: 0.05
Probability of each mutation: 0.05
Parameters: $\alpha = 0.1, \beta = 0.4, w_t = 1, l_t = 100$

In terms of the parameters A, K defining the efficiency of units are given for two groups A and B each of which includes half of agents. For the group $A(B)$, we assign $A = 1, k = 10$ $(A = 5, k = 100)$, and that means agents in the group $A(B)$ have units with relatively lower (higher) efficiency. Then, in principle, agents in Group $A(B)$ tend to be buyers (sellers) of electricity.

Fig.1 shows an example of time series of bid price obtained after sufficient time of biddings. As is seen from the figure, even though the bid price is stable in the range from 90 to 100, but the bid price is still fluctuating and does not converge to a certain constant level. The contract price of electricity is fixed to be 100, but the price of electricity which is actually traded in the market is 101.4 in average. The fact means that in the double auction market, the trades are basically preferable for sellers than for buyers, and buyers are forced to purchase the goods at relatively higher prices than realizable prices.

In this case, the average profit of agents in Group $A(B)$ is -6252 (4736), and that mean agents in Group A are forced to generate at higher cost than the contracted price, and even more they need to purchase electricity from the market at higher prices. On the other hand, agents in Group B possessing units with higher efficiency can get higher profit by selling electricity.

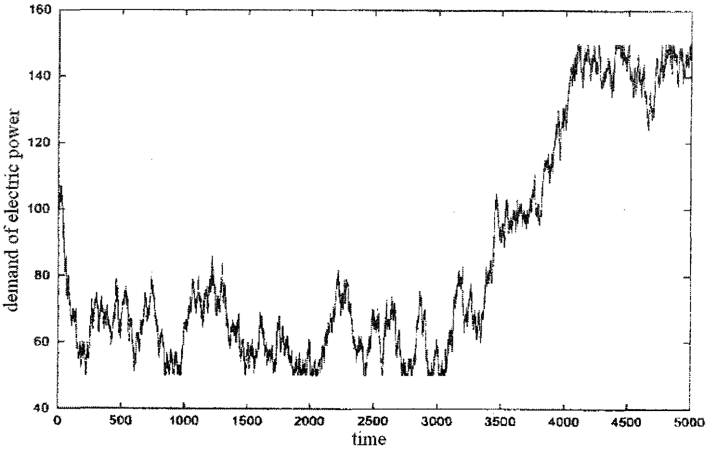

Figure 7: Example of demand time series

7.2 Price changes (Time-varying demands case)

Then, we examine the cases where the demands of customers are time-varying and are not constant along the time. The time series of the electricity demand is assumed to be a random walk which is obtained by adding an incremental value selected from $-2, -1, 0, 1, 2$ at the same probability to the previous demand value. For convenience, the range of demand is restricted between 50 and 150.

Fig.7 shows an example of the time series of bid price under time-varying demand of customers. As is seen from Fig.8, the bid price bears changes and fluctuations, and sometime the ranges between the highest and lowest price are four or five times larger than the range of prices for time-invariant demands of customers. Moreover, we find impulsive (sudden) rise of bid price having about ten times larger amplitude than the price for time-invariant demand cases. The facts implies us that the offers of item done by sellers induce the reaction of bidders, and as a result, a small change of bid price is enlarged (exaggerate) in the bidding process, and the jumps in bid price are observed.

8 Conclusion

In this paper, we showed the analysis of price fluctuation of artificial double auction markets consisting of multi-agents. The fitness of individuals was defined by using the successful bids and the utilization of units, and agents improve their individuals based on the fitness to get higher return in coming auctions. We examined the change of profit of agents in various conditions of auctions in a range of multi-

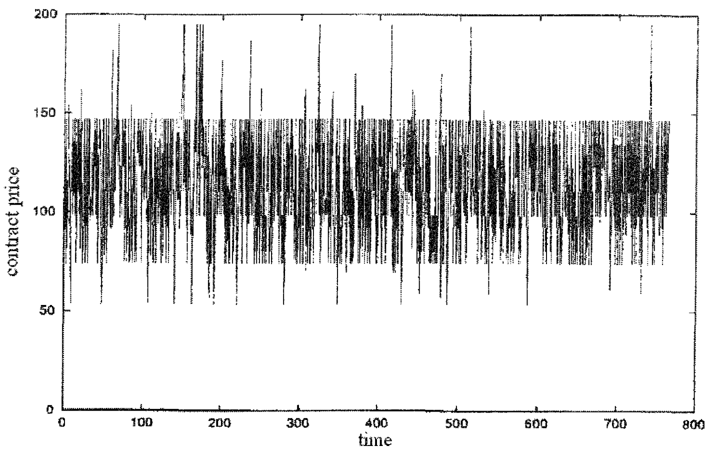

Figure 8: Example of bid price time series

unit, multi-period auction settings. The result showed us that the double bring us a relatively large fluctuation of bid price, and not necessarily bring good and effective market structures.

For future works, we must compare the simulation result with real world data, and exrtend the GP learning scheme to another types of auctions.

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