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A Bidding Strategy based on Genetic Network Programming in Continuous Double Auctions

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***Abstract*—Nowadays, along with the increasing convenience of internet, there becomes popular electronic type of double-side auctions, $continuous\ double\ auction$ (CDA), where multiple sellers and multiple buyers can update their asks and bids continuously at the same time through the trading period. In this paper, a bidding strategy using Genetic Network Programming (GNP) with Rectifying Node has been proposed to deal with CDA automatically based on our previous works of English auction and Dutch auction. The stategy considers various aspects of environments to determine the most competitive and suitable bid price at each time step without losing profit. The agent can manage complex CDA situations more effectively and efficiently by empolying the GNP structure using the auction information and heuristic control functions. Experiments were conducted on a series of CDAs under different settings, and compared with some other methods.**

***Keywords*—Genetic Network Programming; Bidding; Continuous Double Auctions.**

I. Introduction

Nowadays, along with the increasing convenience of internet, the electronic marketplaces start to play an important role for trading commodities or service. Among all of the e-commerce market mechanisms, on-line auction is usually an attractive and common choice. Besides the well known types of online auctions, such as English auction and Dutch auction, which are single sided types, there is another auction type called Double Auction (DA). As the name says, DA allows both the buyer side and seller side to trade simultaneously. The most common type of DA is $continuous\ double\ auction$ (CDA), which permits multiple sellers and multiple buyers to update their asks and bids through the trading period continuously, and the trade can be made at any time throughout the trading period once a couple of an ask and a bid is satisfied each other. As many uncertainties and many factors can influence the auctions, the CDA environments are complex and dynamic [1].

Aiming to make CDA more intelligent and efficient, this paper has proposed a new bidding strategy based on Genetic Network Programming (GNP), where the seller agents and buyer agents can submit asks and bids automatically on behalf of their owners. GNP is one of the evolutionary optimization techniques developed as an extension of GA and GP, which uses compact directed graph structures as solutions instead of strings or trees. In the GNP structure, judgment nodes (JNs) work as if-then type conditional branch decision functions, and they return judgment results for assigned inputs and determine the next node to move, while processing nodes (PNs) work as action/processing functions [2][3]. Moreover, we also exploits the basic heuristic logic into the JNs and PNs for helping agents to make bidding determinations.

Consequently, the main features of the proposed method are: (1) GNP-based agent can use its structure to collect and judge many kinds of information from the ongoing auctions, and make bid decisions according to the judgment results. (2) Under the complicated environments, without knowing which factors are more important or what kinds of combinations of information are more useful, the GNP-based agent can automatically find the general best strategy from a large numbers of potential ones generation by generation. (3) The agent can deal with various situations very well. It is possible for the agent to choose the pertinent solution for a certain situation when the GNP structure is systematically organized.

The organization of the paper is as follows. The CDA model is formulated with some classical assumptions in section 2. The GNP structure used in the proposed strategy and the details of the nodes are described in section 3. Section 4 reports the simulations of either GNP-based seller or buyer agents' performance under different market conditions. Section 5, the conclusion, summarizes the studies and discusses the future work.

II. Continuous Double Auctions (CDA)

This section introduces the basic concept of CDA and gives a description of the protocol used in our models.

As implied by the name, in a CDA, usually, there are more than two goods to be traded in the market; there is only one single good to be traded at any time step; both sides of the bidders, sellers (s) and buyers (b), exist and the numbers of bidders on each side are greater than three. The CDA terminates when either side of the bidders (sellers side or buyers side) has no goods to trade any more [4].

Specifically, each bidder wants to trade several goods, and has distinct private limit price (P^P) for each good he wants to trade. For seller i (s_i), the private limit price for the $n\ th$ good g_n he wants to sell is the good cost of him, denoted c_{in}. For buyer i (b_i), the private limit price for the $n\ th$ good g_n he wants to buy is the good valuation of him, denoted v_{in}.

In more detail, the sellers submit $asks$ to sell goods and the buyers submit $bids$ to buy goods. An $ask\ a$ is the current

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outcry price at which a seller is willing to sell the good. Analogously, a $bid\ b$ is the current outcry price at which a buyer is willing to buy the good. So, it is easy to see that if a seller s_i submits an ask lower than c_{in} for the $n\ th$ good he wants to sell, or a buyer b_i submits a bid higher than v_{in} for the $n\ th$ good he wants to buy, he will lose profit.

Moreover, the *outstanding ask* means the current lowest ask in the market, denoted *oa*. Any following ask not lower than the current *oa* is invalid and discarded by the auction. The *outstanding bid* means the current highest bid in the market, denoted *ob*. Still, any following bid not higher than the current *ob* is invalid and discarded by the auction. Thus, CDA can be described as a place where sellers submit asks to decrease *oa*, while buyers submit bids to increase *ob*, until *ob* is not less than *oa*.

Definition 1. *One single auction* ***round*** *is the time period of bidding process for one good, which is from the beginning of the auction until the transaction for the good takes place or there is no new asks or bids submitted in a pre-determined time.*

In one single auction round, only one good can be traded. Only one seller can sell it and only one buyer can get it. When the ongoing good is traded or there is no new asks or bids submitted in a pre-determined time, the current round ends and the next round starts. In a round, each agent participating in the current auction submits a bid (/ask) to the auction at each time step, and the auction chooses the highest bid and lowest ask to update the current *ob* and *oa*, then the next time step starts. The process repeats until $ob \geq oa$, then the transaction happens between the the seller who submits the *oa* and the buyer who submits the *ob*. The final traded price for the ongoing good is called Final Price (P^F).

Definition 2. *A* ***CDA process*** *is the time period from the beginning of CDA to its end.*

Because there are numbers of sellers and buyers participating, which usually leads to numbers of goods to be traded, the CDA process is often composed of multiple continuous auction rounds.

Definition 3. *In the market, the* ***supply*** *is the total number of goods that all the sellers want to sell, and the* ***demand*** *is the total number of goods that the buyers want to buy.*

III. GNP-based Bidding Strategy

A. Basic GNP Structure

The basic concept of Genetic Network Programming (GNP) is briefly introduced in this section. As an extension of GA and GP, GNP is a graph-based evolutionary optimization techniques[2][3][5], which is composed of a number of different kinds of nodes. The nodes use different functions which are assigned in advance according to the tasks, and they connect with each other by one or more directed branches to solve the solutions for the agents, so the nodes transition guides and models the agents' behaviors to execute the given task.

Basically, in an individual of GNP, there are three types of nodes: (1) A start node, which is the node to start the transitions for the task, points to only one node. (2) Judgment node (JN), which works as a decision function for the agent, usually has two or more outgoing branches. There are several kinds of JNs. Each JN can judge the information of the current situation, and the node transition goes on by selecting one of the branches correspondding to the judgment result. (3) Processing node (PN), which works as an action function, contrary to the judgment nodes, has no conditional branches but usually only one outgoing branch. Also, there are several kinds of PNs. When the node transition reaches a processing node, the agent carries out the action function, and the node transition keeps on. The JNs and PNs can be connected with each other in the GNP structure, so the nodes are reusable and node transition usually won't end until the task is completed. All these characters of GNP produce the compact structure along with many potential solutions which bring the adaptability to the complicated dynamic problems.

In order to find the good solutions, after all the individuals in the GNP population have done the task, each individual is evaluated by the fitness function in the evolutionary phase. The elite individuals with higher fitness can survive to the next generation, and the other weaker ones are replaced by the new ones generated by crossover and mutation. These genetic operations will be executed in every generation until the terminal condition.

B. Overview of GNP-based Bidding Strategy for CDA

we have studied applying GNP-based bidding strategy into multiple English auction and multiple Dutch auction, and it has revealed GNP's effectiveness on guiding bidders' behaviors[6][7]. Based on these previous research, we have proposed the GNP-based Bidding Strategy for CDA using a modified GNP structure.

Each agent applying GNP-based bidding strategy has a population composed of many GNP individuals representing potential bidding strategies. Each individual uses the GNP structure to decide how much to ask/bid at each time step, where JNs judge the auction situations, while PNs indicate different ask/bid actions at each time step. Therefore, in one individual, different judgment results lead to distinct node transitions which mean different bidding decisions, so the agent can make the real-time responses to the changes of auction environment.

Generally speaking, a bidder agent participating in the auction can collect the useful information like: its own P^Ps of the goods, the total number of the goods it wants to trade (NUM), the time steps of the current auction, current *oa* and *ob* and also the previous *oa*s and *ob*s of the past L_{ts} time steps stored in the round history, and the previous P^Fs of the past L_r successful transactions stored in the CDA process history.

Besides the environment information, an agent can also employ some heuristic rules to generate the bidding strategy [8][9][10]. The heuristics are derived based on the common believes: If a seller can make trade frequently, then it will submit new *ask* a little bit higher than the previous P^F in order to gain more profit by selling at a higher price. In the opposite, if the seller can not make a trade, then it is willing to submit a lower *ask* even equal to its P^P to sell the good rather than makes no trade at all. Similarly, if a buyer can make trade frequently, then it will submit new *bid* a little bit lower than the previous P^F in order to gain more profit by buying at a lower price. If the buyer can not make a trade, then it is willing to submit a higher *bid* even equal to its P^P to buy the good rather than makes no trade.

Before the thorough explanation of the proposed strategy, there are some definitions to be introduced.

Definition 4. *A **basic price** (P^B) is the starting price for the agent toward to the ongoing good in the current round.*

For a seller, $P^B = \alpha_1 \times P^P$, where $\alpha_1 \in (1, 1.5)$. For a buyer, $P^B = \alpha_2 \times P^P$, where $\alpha_2 \in (0, 1)$.

Definition 5. *A **target price** (P^T) is the willing price for the agent to make a transaction in the current round.*

With the assumption that all the agents want to make some profit margin from the transactions [9], each agent has a P^T toward to the current good in each round, which is relative to its P^P. Initially, for a seller, P^T is a little bit higher than his P^P, $P^T = (1 + \alpha_3) \times P^P$, where $\alpha_3 \in (0, 0.1)$. And for a buyer, the P^T is a little bit lower than his P^P, $P^T = (1 - \alpha_4) \times P^P$, where $\alpha_4 \in (0, 0.1)$. Apparently, if an agent sets its profit margin too low, it may lose some possible profits. Nevertheless, if the agent sets its profit margin too high, it will lose the chances to make a trade. So, in order to make the appropriate trade with maximal profit, P^T will be modified through CDA period. P^B and P^T are used for guiding the bidding price and making bidding at the competent price quickly in each round.

To sum up, the GNP-based bidding strategy can be simplely discribed as follows: (1) Initialize the GNP population. (2) At the begining of each round, each individual firstly computes a basic price (P^B) and a target price (P^T) based on the knowledge and the relevant environment information introduced above. (3) Then, at each time step, according to the judgment results, the node transition will finally turn to the PNs part and make the corresponding bid action. (4) Repeat (3) until the current round ends. (5) Update the P^B and P^T based on the relevant environment information. Next round starts. (6) When the CDA process is finished, all the individuals' performances are evaluated by the gained profit, and then genetic operations are done and the population move to the next generation.

Fig. 1 illustrates the modified GNP structure. As shown in Fig. 1, each PN is connected to a *Rectifying Node RN*. Because every PN contains a pre-decided heuristic function using P^P, P^T, oa and ob to compute the bid price, the price derived from the function could be modified by adding a small real number δ (positive, negative or zero) in RN so as to avoid the fixed bidding strategies. Moreover, one PN connects to one RN, and each RN has no outgoing branches. After the bid action of PN has been modified by RN, the node transition will continue from the current PN.

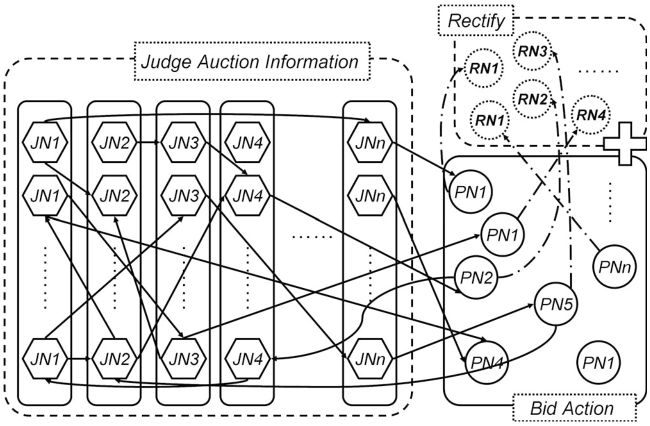

Fig. 1. Structure of GNP individual

C. GNP-based Bidding Strategy for Sellers

Suppose that CDA is in the $r\ th$ round and the current time step is t. GNP-based seller i, who wants to sell totally NUM goods and has already sold num goods, is willing to sell the $n\ th$ good.

First of all, at the beginning of the $r\ th$ round, the seller's P^B and P^T for the ongoing good should be calculated based on the common believes.

For the first time step, P^B is given by:

$$P^B = \alpha_1 \times c_{in}, \tag{1}$$

where $\alpha_1 \in (1, 1.5)$.

P^T for selling the good is given by:

when $r = 1$,

$$P^T = (1 + \alpha_3) \times c_{in}, \tag{2}$$

where $\alpha_3 \in (0, 0.1)$.

when $r > 1$,

(a) if there was a transaction occurred in the r-1 th round,

- if the successful seller in the r-1 th round is seller i,

$$P^T = P^F_{r-1} + \beta_1 \times \frac{num}{NUM}, \tag{3}$$

where $\beta_1 \in (0.01, 0.05)$ and P^F_{r-1} is the traded price in r-1 th round.

- else

$$P^T = max(\frac{1}{L_r} \sum_{rt=N_t-L_r}^{N_t} P^F_{rt}, (1 + \alpha_3) \times c_{in}), \tag{4}$$

where $rt \in R_{traded}$, R_{traded} is the set of suffixes of rounds in which successful transaction occurred, and N_t is the number of the rounds belong to R_{traded}.

(b) if there was no transaction in the r-1 th round,

$$P^T = max(oa^{r-1} - \beta_2 \times (1 - \frac{num}{NUM}), c_{in}), \tag{5}$$

where $\beta_2 \in (0.01, 0.05)$ and oa^{r-1} is the last oa of the r-1 th round.

The 10 different kinds of judgment functions of the JNs for sellers are set up. So, the seller can judge the following information to make bidding decision:

- $JN1_s$: Seller i sold a good in the last round?
- $JN2_s$: $\frac{num}{NUM} = 1$ or ≥ 0.5 or < 0.5
- $JN3_s$: The ask seller i submitted is the oa in the last time step?
- $JN4_s$: $\frac{N_{Si}^{oa}}{L_{ts}} \geq 0.5$ or < 0.5, where, in the past L_{ts} time steps, the number of the times that seller i submitted oa is denoted as N_{Si}^{oa}.
- $JN5_s$: $\frac{t}{T} \in (0, 1/3]$ or $(1/3, 2/3]$ or $(2/3, 1]$, where, T is the total time steps pre-assigned for a round.
- $JN6_s$: oa_t is closer to P^B, or closer to P^T but still lager than P^T, or smaller than P^T, where, the oa of the current time step t is denoted as oa_t.
- $JN7_s$: ob_t is less than c_in, or lager than c_in but closer to c_in, or lager than c_in but closer to P^T, or lager than P^T, where, the ob of the current time step t is denoted as ob_t.
- $JN8_s$: $oa_{t-2} - oa_{t-1} \geq (P^B - P^T)/2$, or $< (P^B - P^T)/2$
- $JN9_s$: In the past R_J rounds, the number of the successful transactions $< \frac{1}{3} \times R_J$, or $\geq \frac{1}{3} \times R_J$ and $< \frac{2}{3} \times R_J$, or $\geq \frac{2}{3} \times R_J$.
- $JN10_s$: c_in is low, or middle, or high, according to the cost range of the goods in the market.

The 7 different kinds of bidding actions of the PNs for sellers are set up. So, the GNP-based seller i can submit the ask according to the following 7 potential bid actions at each time step:

- $PN1_s$: ask the current ob
- $PN2_s$: ask the current ob + γ_s
- $PN3_s$: ask the last P^F + γ_s
- $PN4_s$: ask the current oa - γ_s
- $PN5_s$: stay. make no new ask.
- $PN6_s$: ask P^T.
- $PN7_s$: ask P^T + γ_s

Here, γ_s is a small real number in the range of [0.01, 0.03]. The final ask price submitted by seller i is obtained by the result of PN combined with the δ adjustment in the connected RN.

What kinds of information should be judged and which action should be taken are determined by the node transition of the GNP individual.

D. GNP-based Bidding Strategy for Buyers

It is almost the same as the sellers to build up the strategy for buyers.

Similarly, suppose that CDA is in the r th round, and the current time step is t. GNP-based buyer i, who wants to buy totally NUM goods and has already bought num goods, is willing to buy the n th good.

For the first time step, P^B is given by:

$$P^B = \alpha_2 \times v_{in}, \tag{6}$$

where $\alpha_2 \in (0, 1.0)$.

P^T for buying the good is given by:
when $r = 1$,

$$P^T = (1 - \alpha_4) \times v_{in}, \tag{7}$$

where $\alpha_4 \in (0, 0.1)$.
when $r > 1$,

(a) if there was a transaction occurred in the r-1 th round,

- if the successful buyer in the r-1 th round is buyer i,

$$P^T = P_{r-1}^F - \beta_3 \times \frac{num}{NUM}, \tag{8}$$

where $\beta_3 \in (0.01, 0.05)$ and P_{r-1}^F is the traded price in r-1 th round.
- else

$$P^T = min(\frac{1}{L_r} \sum_{rt=N_t-L_r}^{N_t} P_{rt}^F, (1 - \alpha_4) \times v_{in}), \tag{9}$$

The meaning of the parameters is the same as in the seller part.

(b) if there was no transaction in the r-1 th round,

$$P^T = min(ob^{r-1} + \beta_4 \times (1 - \frac{num}{NUM}), v_{in}), \tag{10}$$

where $\beta_4 \in (0.01, 0.05)$ and ob^{r-1} is the last ob of the r-1 th round.

The 10 different kinds of judgment functions of the JNs for buyers are also set up as the sellers. GNP-based buyer i can judge the following information to make bidding decision:

- $JN1_b$: Buyer i bought a good in the last round?
- $JN2_b$: $\frac{num}{NUM} = 1$ or ≥ 0.5 or < 0.5
- $JN3_b$: The bid buyer i submitted is the ob in the last time step?
- $JN4_b$: $\frac{N_{Bi}^{ob}}{L_{ts}} \geq 0.5$ or < 0.5, where, in the past L_{ts} time steps, the number of the times that buyer i submitted ob is denoted as N_{Bi}^{ob}.
- $JN5_b$: $\frac{t}{T} \in (0, 1/3]$ or $(1/3, 2/3]$ or $(2/3, 1]$.
- $JN6_b$: ob_t is closer to P^B, or closer to P^T but still lower than P^T, or larger than P^T.
- $JN7_b$: oa_t is higher than v_in, or lower than v_in but closer to v_in, or lower than v_in but closer to P^T, or lower than P^T.
- $JN8_b$: $ob_{t-1} - ob_{t-2} \geq (P^T - P^B)/2$, or $< (P^T - P^B)/2$
- $JN9_b$: In the past R_J rounds, the number of the successful transactions $< \frac{1}{3} \times R_J$, or $\geq \frac{1}{3} \times R_J$ and $< \frac{2}{3} \times R_J$, or $\geq \frac{2}{3} \times R_J$.
- $JN10_b$: v_in is low, or middle, or high, according to the valuation range of the goods in the market.

The 7 different kinds of bidding actions of the PNs for buyers are also set up as same as the sellers:

- $PN1_b$: bid the current oa
- $PN2_b$: bid the current oa - γ_b
- $PN3_b$: bid the last P^F - γ_b
- $PN4_b$: bid the current ob + γ_b

TABLE I
PARAMETERS SETTING

Items	Value
Number of Goods	20, 50
Number of Agents	5 sellers, 5 buyers
Number of Good agent wants to trade	4, 10
Number of Training environment	30
Number of Testing environment	5
Number of time steps in one round	100
α_1, α_2, α_3, α_4	1.5, 0.5, 0.05, 0.05
β_1, β_2, β_3, β_4	0.1, 0.3, 0.1, 0.3
L_{ts}, L_r, R_J	5, 3, 6
Generation	300
Population Size	200
—Elite	10
—Crossover	80
—Mutation	80
—Randomly Generated	30
Selection	upper 30%
Crossover Rate	0.1
Mutation Rate	0.3
Node	
—Judgment Node	50
—Processing Node	15
—Rectify Node	15
—Start Node	1

- $PN5_b$: stay. make no new bid.
- $PN6_b$: bid P^T.
- $PN7_b$: bid P^T - γ_b

Here, γ_b is also a small real number in the range of [0.01, 0.03]. In the same way, the final bid price submitted by buyer i is obtained by the result of PN combined with the δ cadjustment in the connected RN.

E. Fitness Fuction for Agents

When CDA process is done, each GNP individual will be evaluated by the fitness function. The fitness is calculated by the profit gained by the individual.

For the i th seller individual, the profit from all G goods sold in CDA process is calculated by $\sum_{g \in G}(P_g^F - c_{ig})$, and for the i th buyer individual, the profit from all G goods bought in CDA process is calculated by $\sum_{g \in G}(v_{ig} - P_g^F)$.

IV. SIMULATIONS

We compare the proposed GNP-based method with ZI-U, ZI-C, GD and CP strategies [1][4][9].

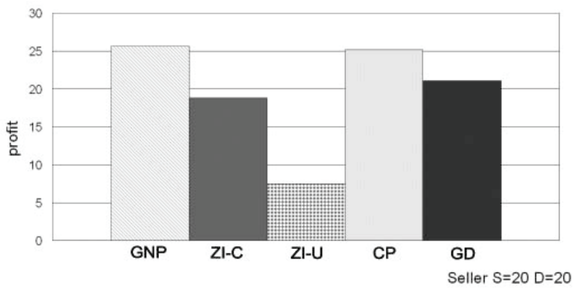

Fig. 2. Performance of 5 different sellers. S=D=20.

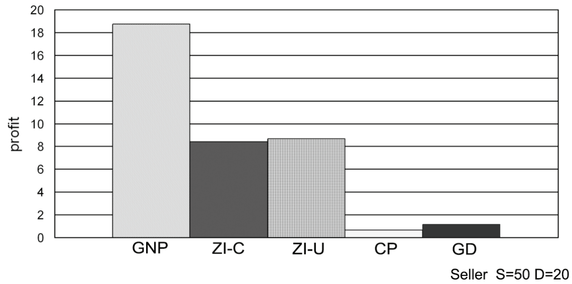

Fig. 3. Performance of 5 different sellers. S=50, D=20.

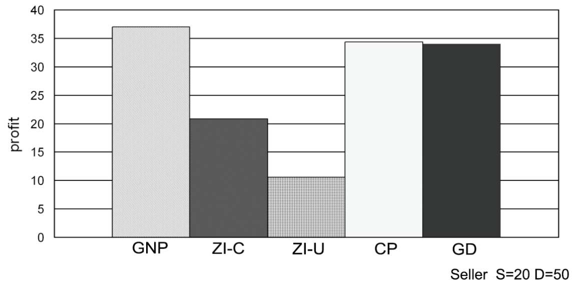

Fig. 4. Performance of 5 different sellers. S=20, D=50.

Zero Intelligence (ZI) is proposed by Gode and Sunder, which includes ZI-C traders and ZI-U traders. ZI-U traders make bid decisions at a random price in the valid range of the market without considering the traders' limit prices. ZI-C traders also make bid decisions at a random price but consider their limit prices. They will not bid over their limit prices. GD strategy is conducted by Gjerstand and Dickhaut. GD agents memorize all the asks(bids) in the bidding history of the last several rounds. Using these information, GD agents compute the probability of one ask(bid) being accepted. Then, the probability is multiplied by the theoretic profits, which can get the expected utility of this ask(bid). The ask(bid) with the highest expected utility will be submitted by the agent. Chris Presit built up the CP strategy which consists of a small number of heuristics and a learning rule. The CP agent does not jump to the target price directly but moves toward to the target price with a learning rate little by little.

In the simulations, we use a modified ZI-C strategy (MZI-C) as a contrastive strategy to compare GNP with other strategies. MZI-C agents make bid decisions to update the current price in a small random value within $(0.01, 0.05)$, so as to bid close to the private price in stead of bidding entirely randomly as ZI-C.

To evaluate the behavior of each agent, the following two kinds of simulations are designed:

For seller side: Each kind of strategy is used by each agent, and the 5 agents represent sellers. At the same time, the buyers are all MZI-C agents in order to be fair for 5 kinds of sellers. (Fig. 2, Fig. 3 and Fig. 4)

For buyer side: Similarly, each kind of strategy is used by each agent, and 5 agents represent buyers. The sellers are all MZI-C agents in order to be fair for 5 kinds of buyers. (Fig.

5, Fig. 6 and Fig. 7)

Additionally, there are 3 cases in each simulation according to different supplies (S) and demands (D): supply is equal to demand, supply is more than demand, and supply is less than demand.

In the case that supply equal to demand, each seller or buyer wants to trade 4 goods. So, $supply = demand = 20$ (Fig. 2 and Fig. 5); In the case that supply is more than demand, each seller wants to trade 10 goods and each buyer only wants to buy 4 goods. So, $supply = 50$ and $demand = 20$ (Fig. 3 and Fig. 6); In the case that supply is less than demand, each seller wants to trade 4 goods, but each buyer wants to buy 10 goods. So, $supply = 20$ and $demand = 50$ (Fig. 4 and Fig. 7).

The cost of each good for each seller is drawn from a normal distribution within [1.0, 2.5], and the valuation of each good for each buyer is within [2.0, 3.5]. The smallest bidding step is 0.01. $\delta \in [-0.03, 0.03]$, which is contained in RNs. GNP-based agents will evolve for 300 generations, and there are 30 environments for training and 10 for testing. Each simulation runs for 10 times, and the result is the average result over 10 runs.

The more specific parameters used in the simulation are shown in Table I. And, all the results are the total results of different environments.

The figures show the performance results that under different market conditions, how much each agent can get profits while competing with each other. The results are the total profits of 10 testing environments. We can see that GNP can get the highest profits under all the conditions. The higher, the profit is, the better, the strategy for the agent is. Moreover, the GNP-based agent can sell all the goods when $S = D = 20$ and $S = 20, D = 50$, and even can sell *7.08* goods on average when $S = 50, D = 20$. Also, GNP-based agent can buy all the goods when $S = D = 20$ and $S = 50, D = 20$, and even can buy *6.34* goods on average when $S = 20, D = 50$.

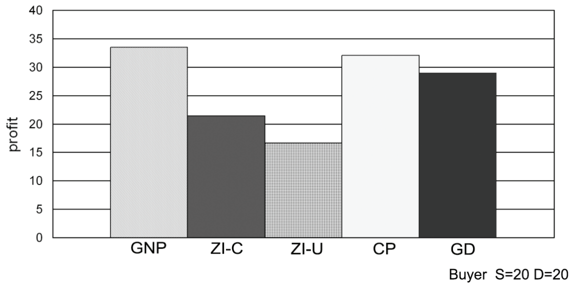

Fig. 5. Performance of 5 different buyers. S=D=20.

V. Conclusions

The proposed method applying GNP to CDA agents does give a good guidance for the intelligent auction systems. The GNP based agent can understand various environments through experiences, then, find the general optimal strategy which suits for many environments. Compared with the conventional auction agents, the use of GNP to choose the suitable function for bidding is more flexible for the various situations of auctions due to the evolutionary feature and well organized structure.

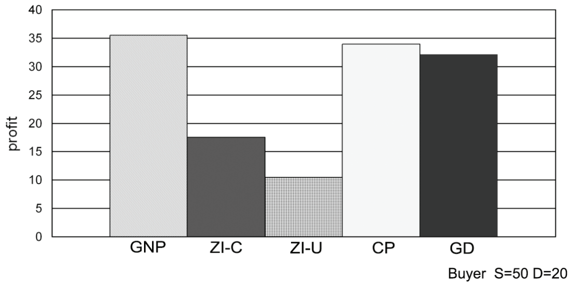

Fig. 6. Performance of 5 different buyers. S=50, D=20.

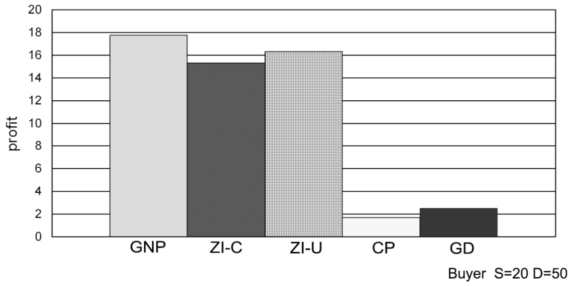

Fig. 7. Performance of 5 different buyers. S=20, D=50.

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