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An adaptive attitude bidding strategy for agents in continuous double auctions

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Abstract

A continuous double auction (CDA) is an efficient market institution for real-world trading of commodities and electronic marketplaces. In this paper, we present the design and analysis of a new bidding strategy for buyer and seller agents participating in agent-based CDAs. The strategy employs heuristic rules and a reasoning mechanism based on a two-level adaptive bid-determination method, including short-term and long-term attitudes. Agents adopting the strategy dynamically adjust their behaviors in response to the changes of the supply and demand relationships in the market. Experimental results show that agents adopting the strategy outperform agents using other strategies reported in the literature.

Keywords: E-commerce; Continuous double auctions; Bidding strategy; Autonomous agents; Adaptive behavior

1. Introduction

Due to the advent of global computer networks, in particular the Internet and the World Wide Web, more and more electronic marketplaces have emerged in industrial and commercial domains, such as electricity markets [1]. Among these electronic marketplaces, auctions are widely adopted as efficient mechanisms to allocate goods, resources, etc., to the entities that value them most highly [2]. While there are many different types of auctions, one popular type of auctions is double auction where multiple sellers and multiple buyers can trade simultaneously. In double auctions, sellers are allowed to indicate the goods they offer at various prices (called asks); buyers are allowed to indicate the goods they desire and the price they are willing to pay (called bids). One of the most common forms of double auction is the continuous double auction (CDA), which allows buyers and sellers to continuously update their bids and asks at any time throughout the trading period and which permits trade at any time.

Because many auctions are complicated [3], it is nontrivial for traders (sellers and buyers) to consider all factors in their bid-determination strategies. Many different strategies have been developed for agent-based CDAs.

This paper develops and evaluates the adaptive attitude (AA) strategy [4], a strategy that autonomous software agents can employ to submit bids and asks in a series of CDAs. The agent using AA strategy exploits both the short-term and long-term attitudes, and utilizes a set of heuristic rules with two thresholds α and ω in bid determination. All the experimental results show the superior performance of the agents that adopt AA strategy when competing with agents adopting various strategies proposed in the literature in both static and dynamic CDA markets. These results also demonstrate the effectiveness of the heuristic rules with α and ω, and eagerness which is formed on the basis of two-level adaptive attitudes.

The remainder of this paper is organized as follows. Section 2 gives a short survey and introduces related work. Section 3 presents the AA strategy. The performance evaluation of agents employing the AA strategy via experi-

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Nomenclature

OA	outstanding ask; the lowest ask in the current market
OB	outstanding bid; the highest bid in the current market
$TransR_i$	transaction rate of agent i
$TransP_i$	transaction percentage of agent i
TR_i	the short-term attitude of agent i
TP_i	the long-term attitude of agent i
$W_S(TR_i)$	the weight of the short-term attitude
$W_L(TP_i)$	the weight of the long-term attitude
F_{eager}	eagerness of agent i
U	a positive real number specified beforehand
δ	a small arbitrary positive real number
θ, β	two independent small arbitrary positive real numbers
$\gamma_1, \gamma_2, \gamma_3, \gamma_4$	four independent random real numbers
α, ω	two thresholds in a set of heuristic rules
P_{ul}	upper limit; the highest acceptable price in the market
P_{ll}	lower limit; the lowest acceptable price in the market
P_{target}	target price which gives a target profit for the agent to jump towards
P_{basic}	basic price which gives a starting profit to the agent to start from
C_{ik}	reservation price for seller i on the unit k of goods
D_{jk}	reservation price for buyer j on the unit k of goods

ments can be found in Section 4. Section 5 concludes this paper and discusses the limitations and future work.

2. Background

Auctions have been used to allocate resources since a long time ago [5]. In the modern world, auctions account for a significant portion of the overall economic transactions. Governments employ auctions to sell treasury bills, foreign exchange, mineral rights, and other assets. Houses, cars, livestock and flowers are commonly sold by auctions in everyday life. The range of items sold by auctions has been greatly increased by e-commerce. In the last decade, there has been an explosion of interest in utilizing auctions to build new markets for commodity items like electricity markets, transport permits, and mobile phone licenses.

An agent in auctions is usually a software system. It can be viewed as a delegate of its user who may be a buyer, seller, or an auctioneer. The goal of the agent is to achieve a good profit for its user [6–9].

There are two major research directions related to auctions. One is the research into auction protocols. An auction protocol defines the valid behaviors of agents. The other research direction is on bidding strategies that agents can employ to compute bids and asks in auctions. There are some other research issues related to auctions, such as security [10], trust [11], and collusion, which however are not the main focuses of this paper.

2.1. Auction protocols

Different types of auctions have been designed and implemented [12]. The basic type of auctions is single-sided auction where either buyers are permitted to submit bids or sellers are permitted to submit asks. Representative examples are first-price ascending (English auction), first-price sealed-bid auction, second-price sealed-bid (Vickrey auction), and first-price descending (Dutch auction) [13,14].

Another type of auctions is double-sided auction where multiple sellers and buyers submit their asks and bids, respectively, together in a market. The variants include continuous double auction, iterated double auction [15], etc. In the iterated double auction, agents first enter the mock market to determine the transaction price; after the transaction price is found, all trades actually take place at this price. However, in the continuous double auction, there is no mock market and all the trades are carried out actually and dynamically. The focus of this paper is continuous double auction.

A combinatorial auction is a special type of auctions where agents can submit asks or bids on a collection of goods [16–18]. In this context, one agent has to express its preference and places asks or bids on different bundles of goods. Much work has been done on collaborative action [19], preference elicitation [20], and so on.

2.1.1. Continuous double auctions

A continuous double auction (CDA) refers to an auction market where there are seller agents and buyer agents trading homogeneous goods. In this market, at any time sellers and buyers can submit their asks and bids to sell and buy one unit of goods. The CDA terminates after a transaction or a specified period of inactivity. An *ask* refers to the price submitted by a seller to sell one unit of goods. The currently lowest ask in the market is called the *outstanding ask*, denoted as OA. A *valid ask* is an ask lower than the current OA. Any ask not lower than OA is called an *invalid ask* and will be ignored by the market. A *bid* refers to the price submitted by a buyer to buy one unit of goods. The currently highest bid in the market is called the *outstanding bid*, denoted as OB. Any bid higher than the current OB is called a *valid bid*. An *invalid bid* refers to any bid not higher than *OB* and will be ignored by the market.

When *OB* is higher than or equal to *OA*, the seller who submits *OA* and the buyer who submits *OB* will make a transaction. In each transaction, only one unit of goods is traded. The transaction price will be equal to the earlier one of *OB* and *OA*. A *round* starts from the beginning of an auction and ends when a transaction is settled or when there is no new *OB* or *OA* in a pre-specified time interval. In each round, at most one transaction is made. After the current round terminates, a new round will begin. When all the sellers have sold all the units of goods or all the buyers have bought all the units of goods, a *run* is terminated. A run is often composed of a series of rounds. The *supply* of a run of CDAs is defined to be the total number of units of goods that all the sellers need to sell in a run. The *demand* is defined to be the total number of units of goods that all the buyers desire to buy in a run. For example, the supply is 30 and the demand is 40. Thus there are 30 rounds in a run of CDAs where at most 30 transactions can be made.

For each seller or buyer, there is an *acceptable price range*, which has been used by some agents in CDAs, such as ZI-U agent or ZI-C agent, and will be further explained in the subsequent section. P_{ll} denotes the lowest acceptable price and P_{ul} denotes the highest acceptable price. The price range is formed based on the seller or buyer's experience and the trading history of the market. For any seller or buyer, each unit of goods has a *reservation price*. If a seller submits an ask lower than the reservation price, it will lose profit. If a buyer submits a bid higher than the reservation price, it will also lose profit.

2.2. Bidding strategies for agents in CDAs

In agent-based auctions, bidding strategies are usually utilized by agents to maximize their profit [21]. Some auctions are known to have dominant strategies which are always better than any other strategies in all situations. For example, in Vickrey auctions, an agent's dominant strategy is to submit its true reservation price [22]. In English auctions, an agent's dominant strategy is to bid a small amount more than the current highest bid while the bid does not exceed the agent's reservation price [14]. In Dutch auctions, first-price sealed-bid auctions, and CDAs, there is no dominant strategy. In the following, we focus on the analysis and discussion of various bidding strategies for agents in CDAs.

Gode and Sunder, in [23], proposed zero intelligence (ZI) agents. Each ZI agent generates random asks or bids depending on whether it is a seller or a buyer. These asks or bids are distributed independently and uniformly over the entire range of trading prices. The agent has no intelligence, does not seek to maximize the profit, and does not observe, remember, or learn. There are two versions of ZI agents, ZI with constraint (ZI-C) agents and ZI unconstrained (ZI-U) agents. A ZI-C agent is a ZI agent and is subject to the budget constraint which forbids the agent to buy or sell at a loss. Thus, a ZI-C buyer submits a bid which is a random value, larger than the lowest acceptable price range of the market and less than the reservation price. Similarly, a ZI-C seller submits a randomly generated ask, less than the highest acceptable price of the market and larger than the reservation price. For a ZI-U agent, it is free from the budget constraint. A ZI-U seller or buyer can submit an ask or a bid which is a random value, within the acceptable price range of the market, without considering the reservation price.

The zero-intelligence-plus (ZIP) strategy was developed by Cliff and Bruten [24]. Each ZIP agent has a profit margin which determines the difference between the reservation price and the ask or bid to be submitted. If there was a transaction in the last round and the agent was the winner, the agent would increase its profit margin in the current round. If there was a transaction in the last round and the agent was not the winner or there was no transaction in the last round, the agent would decrease its profit margin in the current round.

Preist and Tol [25] presented a strategy which is based on the ZIP strategy and later on called CP strategy in this paper. The main idea of CP strategy is that if there was a transaction in the last round, an agent should submit a value, slightly better than the outstanding ask or bid in the last round, so that it may obtain a trade in the current round; otherwise, the agent should try to compete with its rivals by submitting a value slightly better than its rivals. This procedure allows the agent to squeeze a little more profit from the market.

P strategy [26] was designed by and named after Park et al. The idea is to model the auction process with a Markov chain (MC). However, this strategy only works with the assumption that the probability values for the MC model, such as the transition probabilities and the probabilities of success and failure for trading actions, are available. In addition, the computation involved in this approach is huge.

Gjerstad and Dickhaut [27] developed a more sophisticated strategy which is to be called GD strategy in this paper. A GD agent records all the asks and bids occurred in the previous rounds. Based on the recorded history, it computes a subjective belief of a bid or an ask being accepted and then the expected utility. The bid or ask corresponding to the highest expected utility is submitted to the market.

Tesauro and Das [28] proposed some improvements to the GD algorithm. For example, the highest transaction price and the lowest transaction price from the trading history are recorded to solve excessive volatility of the original GD algorithm. A principal limitation is that they assume that demand and supply do not fluctuate over time. This assumption is not valid in real CDA markets, where demand and supply constantly change due to the dynamic economic condition.

Tesauro and Bredin [29] developed a bidding strategy on the basis of dynamic programming in CDAs. They use the belief function together with a forecast of the changes of beliefs over time. However, the belief function resembles that of the original GD strategy except slight modifications.

He et al. [30] proposed the FL strategy, which was the first time that fuzzy sets and fuzzy reasoning were introduced into the heuristic rules for agents. A fuzzy logic (FL) based approach can cope with uncertainties in a timely manner. An FL seller or buyer calculates an ask or a bid by considering the relationship among the outstanding bid, the outstanding ask, and the reference price which was the median of the ordered price history. A-FL strategy is an adaptive version of the FL strategy. With this strategy, if a seller or buyer waits for too many rounds with no transaction made, it should become more risk-averse in the next round. On the contrary, it should become risk-seeking if it transacts too often. This adaptability helps the agent earn more profit from the market.

Although all the aforementioned bidding strategies have been proposed for CDAs, many differences exist among them regarding each specific rules and factors being considered which include the history of transaction prices, the outstanding ask and the outstanding bid, reservation prices, the transaction price of the last round, making compromise when computing asks or bids, upper threshold and lower threshold of asks or bids, the calculation of the first ask or bid in the market, the combination of sellers or buyers, the number of units of goods that can be dealt with in one round, the risk attitude of an agent, the forecast of future market behavior, adaptability, etc. For example, some strategies, such as ZI-U, ZI-C, and GD, pay no attention to adaptability. Others, A-FL, ZIP, CP, and P strategy, focus on adaptability in a short term. In this paper, we propose a new strategy, named AA strategy, which employs a set of heuristic rules and two levels of adaptability, long term and short term. Experimental results demonstrate that the agents utilizing AA strategy perform better than agents using ZI-U, ZI-C, ZIP, GD, A-FL, and CP strategies.

3. The adaptive attitude bidding strategy

3.1. Eagerness in agent interactions

Eagerness is a feeling of "enthusiastic or impatient desire or interest".[1] Eagerness is a kind of human feelings. In the literature, there are several pieces of work which enable agents to have the feeling of eagerness.

Sim defined that eagerness is a measure of an agent's interest to negotiate and come to a deal [31]. It models whether there is an absolute need to acquire the goods under negotiation. The level of interest may be categorized as must deal, desirable, nice to have, optional, unessential, and absolutely unessential. The value of eagerness is always specified by human traders before the experiments begin. During each experiment, the value is constant.

Dumas et al. [32,33] proposed eagerness which represents the minimum probability of obtaining the goods by the deadline. A low value of eagerness means that the agent is willing to take the risk of not getting the goods by the deadline, if this can allow the agent to find a better price. An eagerness close to 1 means that the agent wants to get the goods by the deadline at any price if the reservation price permits. However, the value of eagerness is also fixed at the beginning of experiments and does not fluctuate with the market.

In real CDA markets, human traders will usually become eager for more transactions if they have not been able to trade their goods successfully for a long time; on the other hand, they will become eager for more profit if they have made a lot of transactions recently. Generally speaking, eagerness will be affected by human traders' feeling in a short time, their feeling in a long time, etc. The human traders' feeling in a short time is affected by their trading situation within a short time. Similarly, the human traders' feeling in a long time is related to their trading situation during a long time in the past. In view of the human traders' feeling and behavior, we propose to enable agents to have the feeling of eagerness similar to that of human traders and then to mimic human traders' behavior in the market. Similar to human traders, if an agent has made a lot of transactions in the past several rounds of the current run, it will be eager for more profit in the current round. On the contrary, if the agent cannot gain any transactions, it will be eager for more transactions in the current round. However, considering only the trading situation in the current run is not enough because there are multiple consecutive runs of CDAs. The agent's feeling in the current run will be affected by its trading situation in the last run and the run before the last, and so on. If the agent has made a good transaction record in the last run, it will be encouraged and will be eager for more profit in the current run. Otherwise, if it has made very few transactions in the last run, the agent will be eager for more transactions in the current run. Since the time of several rounds is short compared with a run, we call the feeling formed during several rounds the *short-term attitude* and the feeling developed during a run the *long-term attitude*.

In this paper, we propose a possible function to express and compute eagerness and is demonstrated to perform superiorly through extensive experiments in Section 4. The value of eagerness is not a constant during the experiments. Instead, the value is changing with the dynamic market environment and affected by the real-time supply and demand relationship, which makes it a meaningful indicator of the agent's feeling in the market.

[1] http://www.webster.com/dictionary/eagerness.

3.2. Eagerness for agents in CDAs

Before presenting the function to compute eagerness, we first give four important definitions related to eagerness.

Definition 1. Let $\mathrm{NUM}_{\mathrm{winner}=i}$ be the number of successful transactions in the past r rounds in which agent i is the winner, and $\mathrm{NUM}_{\mathrm{total}}$ be the total number of successful transactions in the past r rounds. The *transaction rate* $TransR_i$ is defined as

$$TransR_i = \mathrm{NUM}_{\mathrm{winner}=i}/\mathrm{NUM}_{\mathrm{total}}.$$

Definition 2. Let $\mathrm{NUNIT}_{\mathrm{traded}}$ be the number of units successfully traded by agent i in the last run, and $\mathrm{NUNIT}_{\mathrm{owned}}$ be the total number of units agent i wanted to trade in the last run. The *transaction percentage* $TransP_i$ is defined as

$$TransP_i = \mathrm{NUNIT}_{\mathrm{traded}}/\mathrm{NUNIT}_{\mathrm{owned}}.$$

Definition 3. The *short-term attitude* of agent i, TR_i, is an increasing function of $TransR_i$.

Intuitively, if the value of $TransR_i$ is large, the value of TR_i will be large, which means that the agent's short-term attitude is eager for more profit. If the value of $TransR_i$ is small, the value of TR_i will be small, which means that the agent's short-term attitude is eager for more transactions.

Definition 4. The *long-term attitude* of agent i, TP_i, is an increasing function of $TransP_i$.

The value of TP_i will be large with a large value of $TransP_i$. This means that the agent has a long-term attitude of being eager for more profit. The value of TP_i is small with a small value of $TransP_i$, which means that the agent has a long-term attitude of being eager for more transactions.

The function to compute eagerness has two parameters: the short-term attitude TR_i and the long-term attitude TP_i. A high value of eagerness means that the agent is eager to gain more profit by selling (buying) each unit of goods at high (low) prices. A low value of eagerness means that the trader is eager to make more transactions by submitting low asks (high bids). In this paper, we use the following function to compute eagerness. This function is experimentally shown effective:

$$F_{\mathrm{eager}}(TR_i, TP_i) = W_{\mathrm{S}}(TR_i) \times W_{\mathrm{L}}(TP_i). \tag{1}$$

$W_{\mathrm{S}}(TR_i)$ is the weight of the short-term attitude and computed by Eq. (2), where W_1, W_2, and W_3 are positive real numbers and $W_1 < W_2 < W_3$. $W_{\mathrm{S}}(TR_i)$ is a generally nonlinear and increasing function of TR_i. If the value of TR_i is large, it means that the agent is eager for more profit because the agent has easily made a lot of transactions in the short term. With a large value of TR_i, the value of $W_{\mathrm{S}}(TR_i)$ is large because TR_i^2 is multiplied by a large number W_3, which leads to a large value of eagerness. This means that the agent is eager for more profit. If the value of TR_i is small, it means that the agent is eager for more transactions since the agent can hardly trade some of its goods. The value of $W_{\mathrm{S}}(TR_i)$ is small and equal to $W_1 \times TR_i^2$. Therefore, the value of eagerness is small, which means the agent is eager for more transactions. Otherwise, the value of $W_{\mathrm{S}}(TR_i)$ is medium and consequently the agent is not eager for more profit or more transactions:

$$W_{\mathrm{S}}(TR_i) = \begin{cases} W_1 \times TR_i^2, & \text{small } TR_i, \\ W_2 \times TR_i^2, & \text{medium } TR_i, \\ W_3 \times TR_i^2, & \text{large } TR_i \end{cases} \tag{2}$$

$W_{\mathrm{L}}(TP_i)$ is the weight of the long-term attitude. In a series of CDAs, any seller or buyer can compare successive runs and remember useful information from previous runs. As a seller, if the value of TP_i is large, it means that the agent is eager for more profit because it has sold all the units it wanted to sell in the last run. Therefore, the value of $W_{\mathrm{L}}(TP_i)$ is increased towards a large value which causes the value of eagerness to be large. This means that the seller is eager for more profit in the current run. The seller believes that it has left a lot of profit for buyers in the last run and it should increase its asks on each unit of goods in the current run so as to grab more profit back from buyers. Otherwise, the seller agent is eager for more transactions when the value of TP_i is small. The reason is that the agent can hardly trade even a few of the goods. The value of $W_{\mathrm{L}}(TP_i)$ becomes small and the value of eagerness is small accordingly. The seller is eager for more transactions in the current run and is willing to decrease its asks. $W_{\mathrm{L}}(TP_i)$[2] is calculated in the following equation:

$$W_{\mathrm{L}}(TP_i) = \begin{cases} U + \delta, & TP_i = 1.0, \\ U - \delta, & TP_i < 1.0, \end{cases} \tag{3}$$

where δ is a small arbitrary positive real number. U is a positive real number specified at the beginning of CDAs. The computation of $W_{\mathrm{L}}(TP_i)$ for buyers is similar to that of sellers.

3.3. Bidding strategies for sellers and buyers

Suppose a human seller wants to sell 50 apples in 100 rounds of CDAs. Assume in each round only one apple can be traded. The human seller has successfully sold 40 apples in the past 50 rounds because he has submitted too many low asks to sell his apples. He only has 10 apples left for the rest 50 rounds. Hence, he will not be eager to trade these 10 apples as soon as he can. Instead, he will increase his asks to sell each apple and be eager to gain more profit from each apple. On the contrary, if the seller finds that he has sold only 5 apples in the past 50 rounds since his asks were too high, there are 45 apples left for the rest 50 rounds. Therefore, he will be eager to grab more transaction opportunities since he is afraid that he cannot trade all his apples and gain a good profit in the end. In general, the feeling of eagerness is changing with the

[2] If the number of the units of goods is very large, TP_i is not necessarily equal to 1.0. TP_i, less than 1.0, is acceptable.

dynamic trading situation of the seller, which as a result will affect the asks submitted by the seller.

Another typical behavior of a human seller is that he makes judgement of asks and bids submitted by other sellers and buyers. Suppose the current outstanding bid for buyers to buy one apple is \$4.0. If the cost of one apple is \$1.0, then the human seller can gain a profit of \$3.0 if he accepts the outstanding bid. Assume \$3.0 is a very good profit for him. The seller accepts \$4.0 immediately. If the seller does not accept the outstanding bid, other sellers in the market may accept the price and make the transaction. If, the cost of one apple is \$1.0 while the current outstanding ask for sellers to sell one apple is \$1.03, the human seller can only gain a profit of less than \$0.03 if he tries to submit an ask even lower than \$1.03 and at the same time higher than the cost \$1.0. Such kind of transactions is not profitable at all. The seller will prefer to keep this apple for selling it at a good price in the future transaction rather than selling it immediately. Hence, the seller will not submit any asks in this situation. It will leave such unprofitable transactions to the rest sellers.

Normally, a human trader will decide what asks or bids to submit according to the available information. When nobody has submitted asks or bids to the market, there is very little information available for the human trader. Later on, when traders have submitted asks or bids to the market, the outstanding ask or the outstanding bid is available for the human trader to consider. Consequently, the human trader submit their asks or bids by considering different available information at different phase.

Based on the above observation of human sellers' feeling and behaviors, we design a bidding strategy in the subsequent section for seller agents to adopt. The bidding strategy for buyer agents is also designed in a similar manner.

3.3.1. Bidding strategy for sellers

At the beginning of a round, there is no seller to submit asks and no buyer to submit bids. Consequently, there is no OA or OB in the market, which is the first phase of the market. Later, some buyer (seller) may firstly submit its bid (ask) to the market. So there is only OB (OA) in the market, which is the second phase. Finally, there are both sellers to submit asks and buyers to submit bids. There are OB and OA in the market, which is the third phase.

Suppose seller i is selling unit k in a round. In the first phase of the round, the seller has no information other than the reservation price C_{ik} of unit k and the acceptable price range of the CDA market. The seller tends to submit a high ask and computes its ask as follows:

$$\text{ask} = C_{ik} + (P_{\text{ul}} - C_{ik}) \times \gamma_1, \tag{4}$$

where γ_1 is a random real number.[3] A high ask can give all the sellers more opportunities to bargain with buyers.

When there is only either OB or OA in the market, it is the second phase of the round. The seller will utilize OB or OA to compute its ask. If there is OB and no OA, the seller will use the following equation:

$$\text{ask} = \begin{cases} OB, & OB \geqslant \omega, \\ OB + (P_{\text{ul}} - OB) \times F_{\text{eager}}, & OB < \omega \text{ and } OB > C_{ik}, \\ C_{ik} + (P_{\text{ul}} - C_{ik}) \times F_{\text{eager}}, & OB < \omega \text{ and } OB \leqslant C_{ik}, \end{cases} \tag{5}$$

where F_{eager} is the eagerness of the agent. ω is a threshold in the heuristic rules for sellers. If OB is higher than or equal to ω, the seller will submit an ask equal to OB since it thinks the OB is quite profitable. Otherwise, the seller will compute an ask according to its feeling of eagerness. The new ask must be higher than the reservation price C_{ik} in case of losing profit. At the same time, the ask must be higher than the current OB because OB is not high enough. If the current OB is higher than C_{ik}, the new ask will be calculated by $OB + (P_{\text{ul}} - OB) \times F_{\text{eager}}$. If not, the new ask will be calculated by $C_{ik} + (P_{\text{ul}} - C_{ik}) \times F_{\text{eager}}$.

If there is OA and no OB in the round, the seller will calculate its new ask according to OA. If OA is lower than α which is another threshold in the heuristic rules for sellers, the seller will submit no new ask because it thinks that the current round is not profitable at all. Otherwise, the seller will give a new ask slightly lower than the current OA.

In the third phase, both OA and OB exist in the market. If OB is higher than or equal to ω, the seller will submit an ask equal to OB. If OA is lower than α, the seller will submit no new ask. If OA is not too low and OB is not so high, the seller will compute its ask according to its eagerness. The seller computes the basic price and the target price, denoted as P_{basic} and P_{target}, respectively. If there was a transaction in the last round, the seller would take the maximum of the transaction price and the outstanding bid as the target price. If there was no transaction in the last round, the seller would take the maximum of the last outstanding ask and the outstanding bid as the target price. The basic price is given by the following:

$$P_{\text{basic}} = C_{ik} \times \gamma_2, \tag{6}$$

where γ_2 is initially a random real number.[4] Intuitively, the basic price can give the seller a bit of profit according to the reservation price.

If there was a successful transaction in the last round, the seller would employ the following equation to calculate the target price because the seller believes that the transaction price of the last round is the possible transaction price in the current market and at the same time the target price should be not higher than the OB in the current round:

$$P_{\text{target}} = \max(P_{t\_\text{last}} + \theta, OB_{\text{current}}), \tag{7}$$

where θ is a small arbitrary positive real number, OB_{current} is the current outstanding bid, and P_{t_last} is the transaction

[3] For example, γ_1 can be located in [0.85, 1.0] to obtain higher asks.

[4] For example, γ_2 can be located in [1.0, 1.5].

price of the last round. Intuitively, the seller aims to achieve a transaction price which is higher than that of the last round. The value of θ is the amount of the increase.

If there was no transaction in the last round, the seller would employ the following equation:

$$P_{\text{target}} = \max(OA_{\text{last}} - \beta, OB_{\text{current}}), \tag{8}$$

where β is a small arbitrary positive real number, OA_{last} is the outstanding ask of the last round.

The basic price gives an initial profit for the seller. The target price gives the destination for the seller. The seller will not let the ask equal to the target price directly. Instead, the seller will compute the ask according to the feeling of eagerness and try to gain more profit from the market. The size of the step, denoted as S_{step}, is calculated by the following equation:

$$S_{\text{step}} = \begin{cases} (P_{\text{target}} - P_{\text{basic}}) \times F_{\text{eager}}, & P_{\text{target}} \geqslant P_{\text{basic}}, \\ (\max(P_{\text{target}}, C_{ik}) - P_{\text{basic}}) \times (1 - F_{\text{eager}}), & P_{\text{target}} < P_{\text{basic}}. \end{cases} \tag{9}$$

The final ask is calculated by the following equation:

$$\text{ask} = P_{\text{basic}} + S_{\text{step}}. \tag{10}$$

3.3.2. Bidding strategy for buyers

There are also the same three phases in a round for buyers. Suppose buyer j is buying unit k in a round. In the first phase, the buyer has no information other than its reservation price D_{jk} of unit k and the acceptable price range of the CDA market. The buyer tends to submit a low bid and computes the bid by the following equation:

$$\text{bid} = D_{jk} - (D_{jk} - P_{\text{ll}}) \times \gamma_3, \tag{11}$$

where γ_3 is a random real number.[5]

If there exists OA and no OB, the buyer will calculate its bid using the following equation:

$$\text{bid} = \begin{cases} OA, & OA \leqslant \alpha, \\ OA - (OA - P_{\text{ll}}) \times F_{\text{eager}}, & OA > \alpha \text{ and } OA \leqslant D_{jk}, \\ D_{jk} - (D_{jk} - P_{\text{ll}}) \times F_{\text{eager}}, & OA > \alpha \text{ and } OA > D_{jk}, \end{cases} \tag{12}$$

where α is a threshold in the heuristic rules for buyers. If OA is lower than or equal to α, this buyer will think the ask is low enough to be accepted directly. Otherwise, this buyer will compute its new bid by $OA - (OA - P_{\text{ll}}) \times F_{\text{eager}}$ or $D_{jk} - (D_{jk} - P_{\text{ll}}) \times F_{\text{eager}}$ in Eq. (12).

When there exists OB and no OA, the buyer will submit no bid if the current OB is higher than ω, another threshold in the heuristic rules for buyers. Otherwise, the buyer will submit its new bid slightly higher than the current OB.

When there are already OB and OA, the buyer will first judge whether the current OA is profitable or not. If the current OA is lower than or equal to α, the buyer will think that it is profitable and accept the OA directly. If the current OA is not profitable and the current OB is higher than ω, this buyer will not submit any new bid. Otherwise, the buyer will compute the bid by the following steps. First, the buyer will compute the basic price P_{basic} by Eq. (13). Then the buyer will utilize Eq. (14) or Eq. (15) to calculate the target price P_{target} depending on whether there was a transaction in the last round. The size of the step from the basic price to the target price is computed by Eq. (16). Finally, the bid to be submitted is got by Eq. (17):

$$P_{\text{basic}} = D_{jk} \times \gamma_4, \tag{13}$$

where γ_4 is initially a random real number.[6]

If there was a successful transaction in the last round,

$$P_{\text{target}} = \min(P_{t\_\text{last}} - \theta, OA_{\text{current}}), \tag{14}$$

where θ is an arbitrary small positive real number which is the same θ in Eq. (7), OA_{current} is the current outstanding ask, and P_{t_last} is the transaction price of the last round.

If there was no successful transaction in the last round,

$$P_{\text{target}} = \min(OB_{\text{last}} + \beta, OA_{\text{current}}), \tag{15}$$

where β is an arbitrary small positive real number which is the same β in Eq. (8), OB_{last} is the outstanding bid of the last round. The size of the step is calculated by the following equation:

$$S_{\text{step}} = \begin{cases} (P_{\text{target}} - P_{\text{basic}}) \times F_{\text{eager}}, & P_{\text{target}} \leqslant P_{\text{basic}}, \\ (\min(P_{\text{target}}, D_{jk}) - P_{\text{basic}}) \times (1 - F_{\text{eager}}), & P_{\text{target}} > P_{\text{basic}}. \end{cases} \tag{16}$$

The final bid is given by the following equation:

$$\text{bid} = P_{\text{basic}} + S_{\text{step}}. \tag{17}$$

4. Experimental evaluation

We carry out experiments in two groups, including one group of experiments to simulate static CDA markets, and another to simulate dynamic CDA markets. The ultimate goal of the experiments is to evaluate the performance of agents using AA strategy in dynamic CDA markets which resemble CDA markets in practice where all the sellers or buyers are free to join and leave the markets. Through all the experimental results, it is demonstrated that agents using AA strategy perform significantly better than agents adopting a number of other strategies in the dynamic CDA markets.

Our first step is to set up experiments which simulate static CDA markets. The reason is that the static market is a simple environment when compared with the dynamic market. We compare the performance of AA strategy with some commonly adopted ones in the static CDA markets. AA strategy is demonstrated to be superior to others. Then we set up experiments which simulate dynamic CDA markets. In order to clearly evaluate the performance of AA strategy, we compare the performance of agents using

[5] Similarly to γ_1, γ_3 can, for instance, be located in [0.85, 1.0].

[6] Similarly to γ_2, γ_4 can, for instance, be located in [0.5, 1.0].

AA strategy and agents adopting others one at a time in dynamic CDA markets. Through the experimental results, AA strategy is illustrated to be better than those being compared. Finally, we put agents using AA strategy and agents adopting other strategies together to compete in one dynamic CDA market.

4.1. Experiments to simulate static CDA markets

The settings of the experiments to simulate static CDA markets are as follows. First, each experiment is composed of several different values of supply and demand. For each specific pair of supply and demand, 1000 runs are carried out. In each run, a seller is endowed with a number of units of goods whose reservation prices are independently drawn from a uniform distribution within [1.0, 1.5]. A buyer is endowed with a number of units of goods whose reservation prices are independently drawn from a uniform distribution within [3.0, 3.5]. In order for the agents' profit to be comparable, we keep the reservation prices and the number of units of goods for different kinds of agents the same. Second, the time period that an agent is allowed to elapse before submitting an ask or a bid is specified as a randomly distributed variable. Third, to measure how well an agent performs in a CDA, we evaluate its profit. For a seller i, the total profit on all s units sold in a run is $\sum_{k=1}^{s}(P_{ik} - C_{ik})$, where P_{ik} is the transaction price. Similarly for a buyer j, the total profit on all t units bought in a run is $\sum_{k=1}^{t}(D_{jk} - P_{jk})$ where again P_{jk} is the transaction price. In the following, an agent's profit is calculated as the sum of the total profit in 1000 runs. In order to compute the value of the transaction rate and the transaction percentage, the number of rounds, r, is selected first. In our experiments, r is set to be 10. If r is smaller than 10, the simulation results become unstable. If r is larger than 10, the result is not sensitive to the changing market at the expense of increased computational time.

Based on the above settings, we compare AA strategy with ZI-U [23], ZI-C [23], ZIP [24], GD [27], A-FL [30], and CP [25] strategies. These strategies represent the most widely cited strategies in the literature for agents participating in CDAs. Our experiments are carried out to test seven kinds of sellers and seven kinds of buyers. To evaluate the behavior of each kind of sellers and buyers under different conditions, we compare their profits in three situations: supply equal to demand (Figs. 1 and 2), supply larger than demand (Figs. 3 and 4), and supply less than demand (Figs. 5 and 6). In each figure, the horizontal axis shows the supply or demand quantity and the vertical axis shows the profit of agents using different strategies. Each curve represents the profit of one kind of agents. The higher the profit is, the better is the performance of the corresponding agents.

For evaluating the performance of sellers, each kind of sellers is assumed to have 4–10 units of goods to sell. The buyers are all assumed to be ZI-C agents. For each pair of supply and demand, 1000 runs are carried out. Within

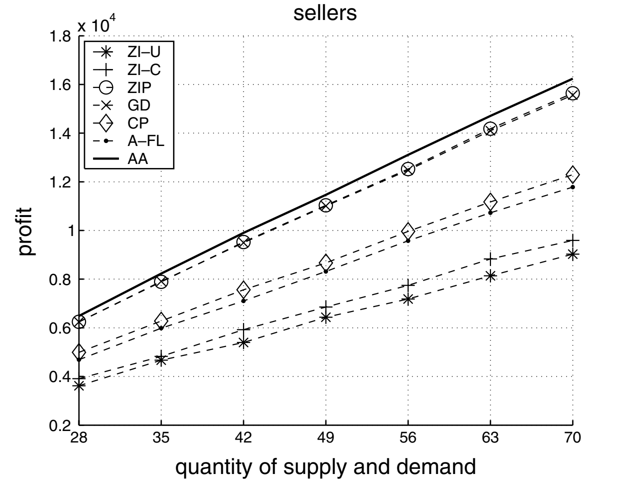

Fig. 1. Performance of seven different sellers in static markets. The supply and the demand increase from 28 to 70.

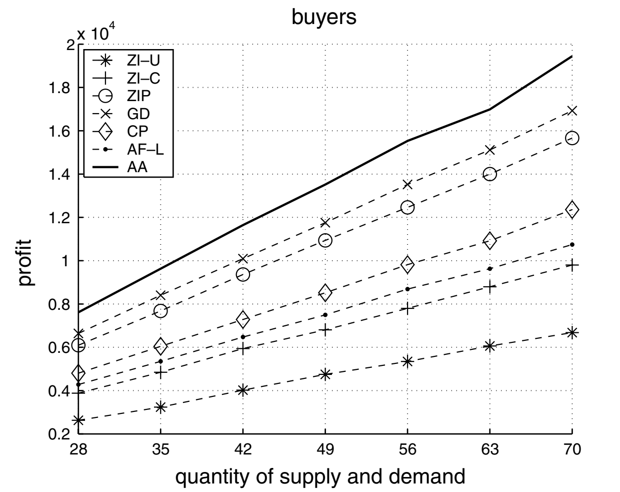

Fig. 2. Performance of seven different buyers in static markets. The supply and the demand increase from 28 to 70.

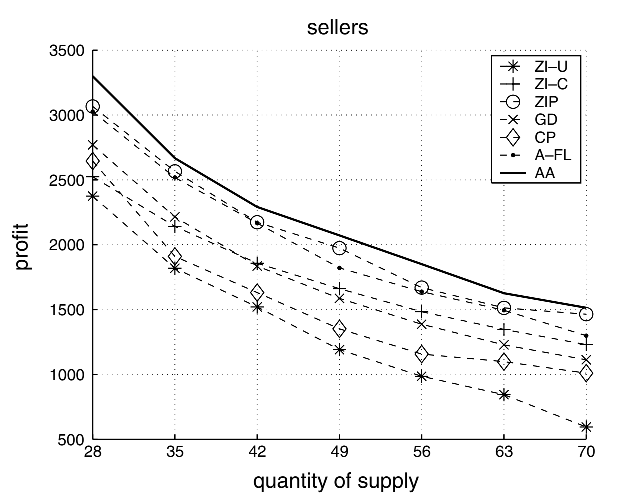

Fig. 3. Performance of seven different sellers in static markets. The supply increases from 28 to 70. The demand is 24.

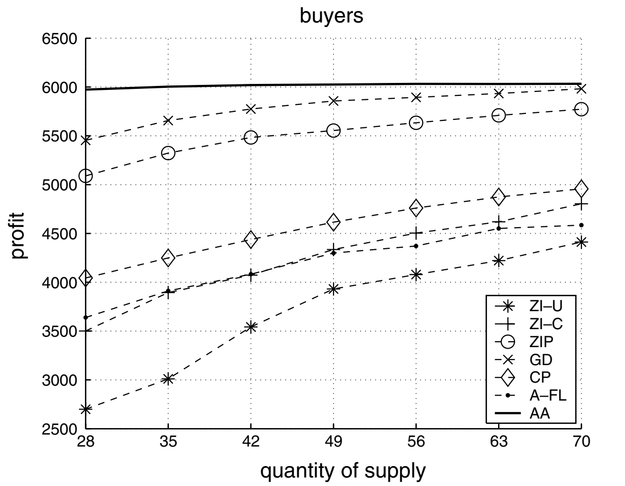

Fig. 4. Performance of seven different buyers in static markets. The supply increases from 28 to 70. The demand is 24.

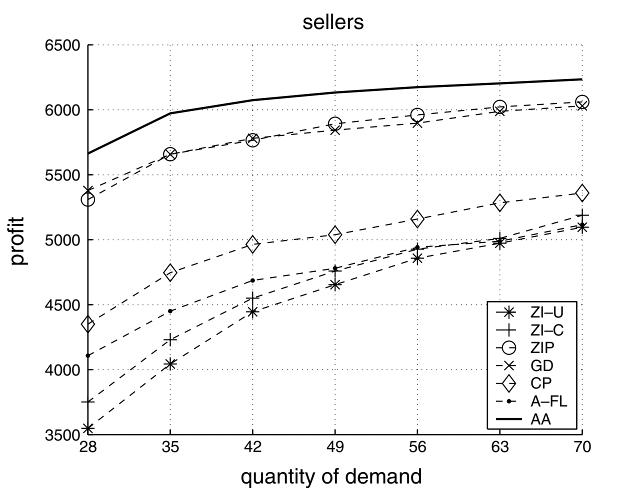

Fig. 5. Performance of seven different sellers in static markets. The supply is 24. The demand increases from 28 to 70.

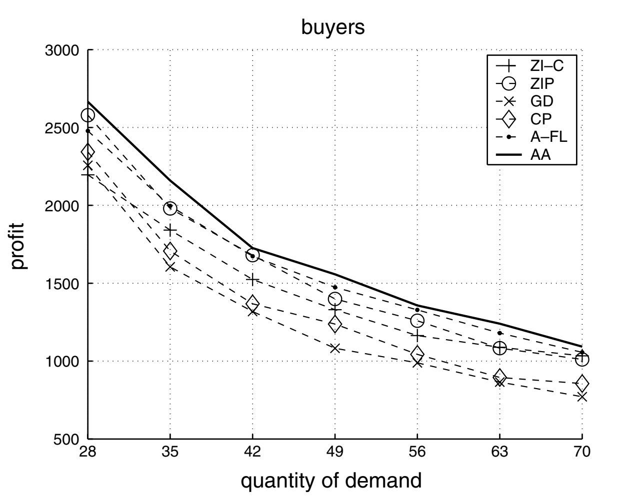

Fig. 6. Performance of six different buyers in static markets. The supply is 24. The demand increases from 28 to 70.

the 1000 runs, we put the same group of sellers to the market at the beginning of each run. Thus, the combination of sellers within 1000 runs is always the same. This means that all the sellers are not allowed to freely join or leave the market as they want. The performance of buyers is evaluated in a similar manner to that of the sellers.

The performance of the agents using other six strategies is found to be statistically worse than that of the agents using AA strategy. ZIP agents behave worse than AA agents because they do not consider the adaptability in several consecutive rounds. CP agents resemble ZIP agents. GD agents show worse behavior because they focus on the history without considering the transaction price of the last round, the outstanding ask, and the outstanding bid in the current round. ZI-U and ZI-C agents submit random asks and bids, which prevent them from achieving a high profit. A-FL agents can be adaptive but the capability of the long-term adaptability is lacking. As a result, their performance is not as good as that of AA agents.

In order to further demonstrate how the long-term attitude affects the overall performance of AA agents, we set up an additional set of experiments. We denote AA without the long-term attitude as AA-NL. Thus, there are altogether eight kinds of sellers, ZI-U, ZI-C, ZIP, GD, A-FL, CP, AA, and AA-NL and the buyers are all ZI-C agents. During each experiment, the number of units of goods and the distribution of reservation prices for these units are kept the same for all kinds of sellers. The number of units of ZI-C buyers is changing randomly every 100 runs, which leads to the fluctuation of the supply and demand relationship within the 1000 runs. Similarly, we set up an experiment to compare the performance of AA buyers and that of AA-NL buyers. Figs. 7 and 8 demonstrate that AA agents gain more profit than AA-NL agents.

4.2. Experiments to simulate dynamic CDA markets

While AA agents show a superior performance when compared with other agents in the simulated static CDA

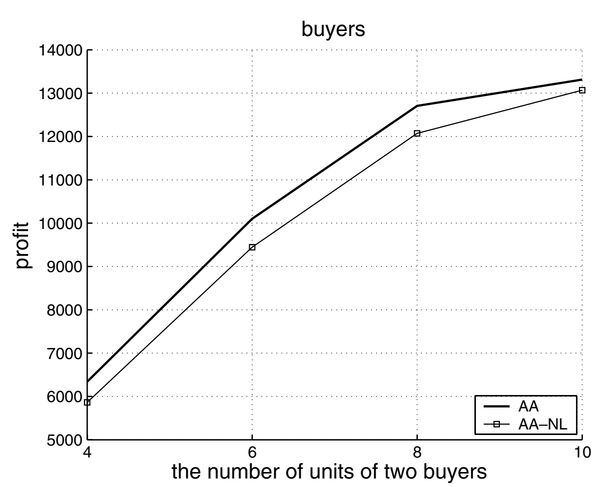

Fig. 7. Performance of AA buyers and AA-NL buyers.

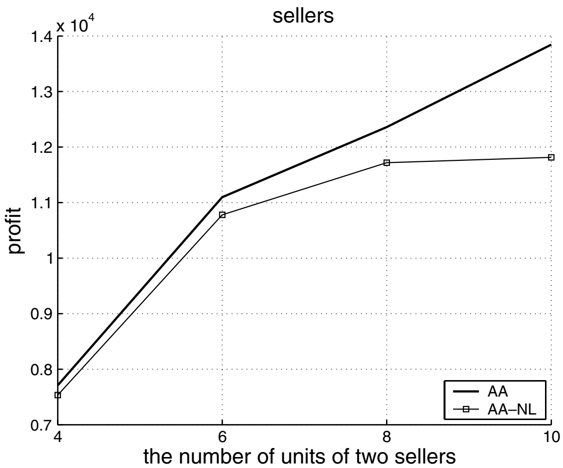

Fig. 8. Performance of AA sellers and AA-NL sellers.

markets, CDA markets in practice are dynamic and the combination of sellers or buyers fluctuates from time to time because agents can join and leave the market at any moment. This causes the supply and demand situation to be time-varying. Furthermore, one bidding strategy that succeeds in one specific environment may not work equally well in other environments. For all the above reasons, we set up experiments to compare the performance of AA agents with others in simulated dynamic CDA markets.

4.2.1. Experiments to compare two kinds of agents

The experimental setup for dynamic CDA markets is as follows. For evaluating sellers, we assume that there are five AA sellers and five another type of sellers in comparison. Each seller has one unit of goods to sell. The rest of the sellers are selected randomly from a pool which consists of 70 sellers. In this pool, there are 10 AA, 10 ZI-U, 10 ZI-C, 10 ZIP, 10 GD, 10 CP, and 10 A-FL sellers, each of which has one unit of goods to sell. Therefore, except that the two kinds of sellers in comparison must have the same number of units of goods in every run, all the other sellers do not. Consequently, the combination of sellers is changing from run to run. This simulates the dynamic joining and leaving of sellers except for the two kinds in comparison. The buyers are all ZI-C buyers in order to be fair.

Following the experiments for static CDA markets, we also divide the supply and demand relationships into supply-larger-than-demand, supply-equal-to-demand, and supply-less-than-demand. For the case of supply-larger-than-demand, at the beginning of every run, more than 40 sellers which are not in comparison are selected randomly from the pool. Thus the total number of units of goods desired to be traded by all sellers is larger than 50. In every 1000 runs, the number of units desired to be bought by buyers is changing from 10, 20, 30, 40, to 50, which is kept smaller than the supply. Similarly, for the case of supply-less-than-demand, less than 40 sellers not in comparison are selected randomly at the beginning of every run. Therefore, the supply is always smaller than 50. The number of units of goods desired by buyers is changing from 60, 70, 80, 90, to 100, where the demand is higher than the supply. Finally for the case of supply-equal-to-demand, the number of units of goods desired by the sellers which are not in comparison and are randomly selected in each run is changing from 10, 20, 30, 40, to 50, while the number of units of goods desired by

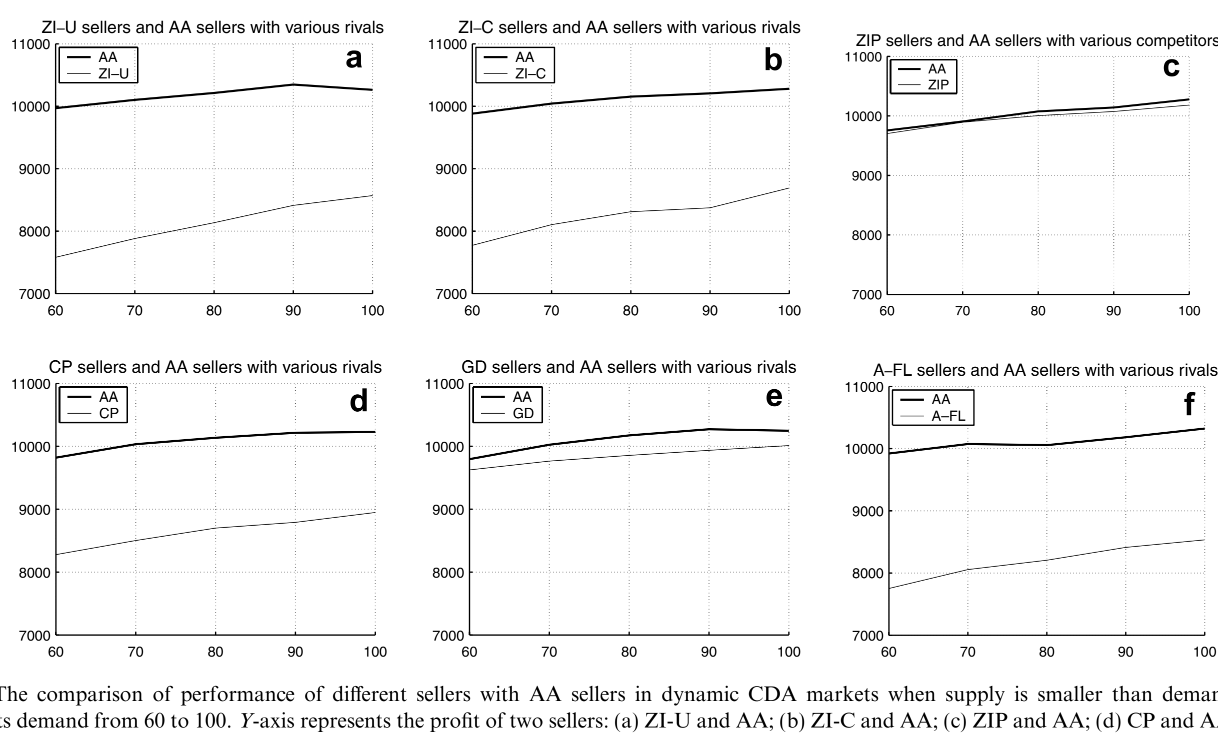

Fig. 9. The comparison of performance of different sellers with AA sellers in dynamic CDA markets when supply is smaller than demand. *X*-axis represents demand from 60 to 100. *Y*-axis represents the profit of two sellers: (a) ZI-U and AA; (b) ZI-C and AA; (c) ZIP and AA; (d) CP and AA; (e) GD and AA; (f) A-FL and AA.

the buyers is kept the same as that of all the sellers. Evaluation of the buyers can be done in a similar manner.

From Figs. 9–14, it can be seen that the performance of AA agents is found to be always superior than any other kind of agents in the dynamic CDA markets. This demonstrates that (1) AA agents adapt to different combinations of competitors; and (2) AA agents adapt to different supply and demand relationships. ZI-U and ZI-C agents behave worse for the reason that they do not analyze the environment and the other agents whom they are competing with.

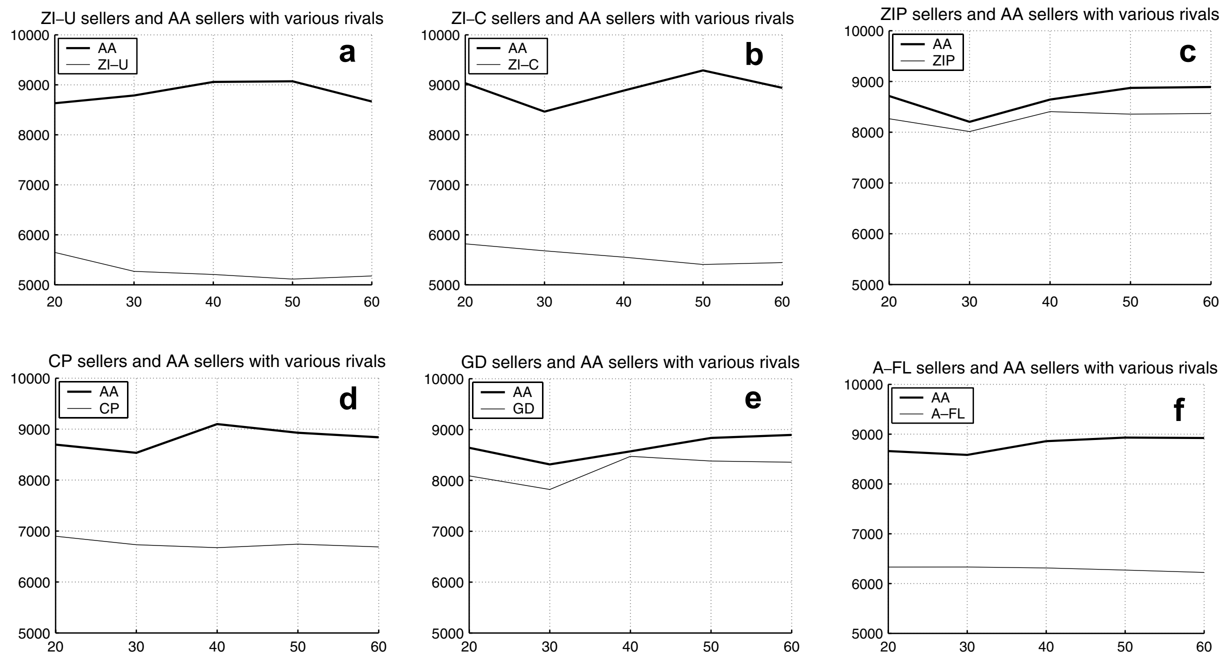

Fig. 10. The comparison of performance of different sellers with AA sellers in dynamic CDA markets when supply is equal to demand. *X*-axis represents demand from 20 to 60. *Y*-axis represents the profit of two sellers: (a) ZI-U and AA; (b) ZI-C and AA; (c) ZIP and AA; (d) CP and AA; (e) GD and AA; (f) A-FL and AA.

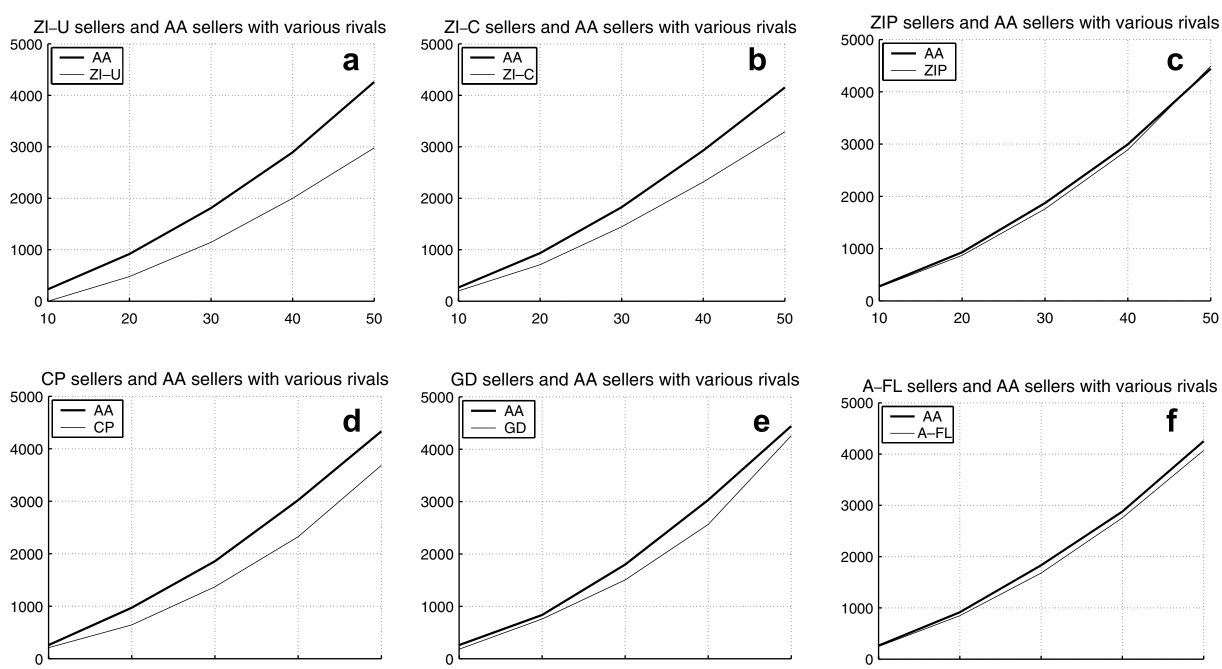

Fig. 11. The comparison of performance of different sellers with AA sellers in dynamic CDA markets when supply is larger than demand. *X*-axis represents demand from 10 to 50. *Y*-axis represents the profit of two sellers: (a) ZI-U and AAl; (b) ZI-C and AA; (c) ZIP and AA; (d) CP and AA; (e) GD and AA; (f) A-FL and AA.

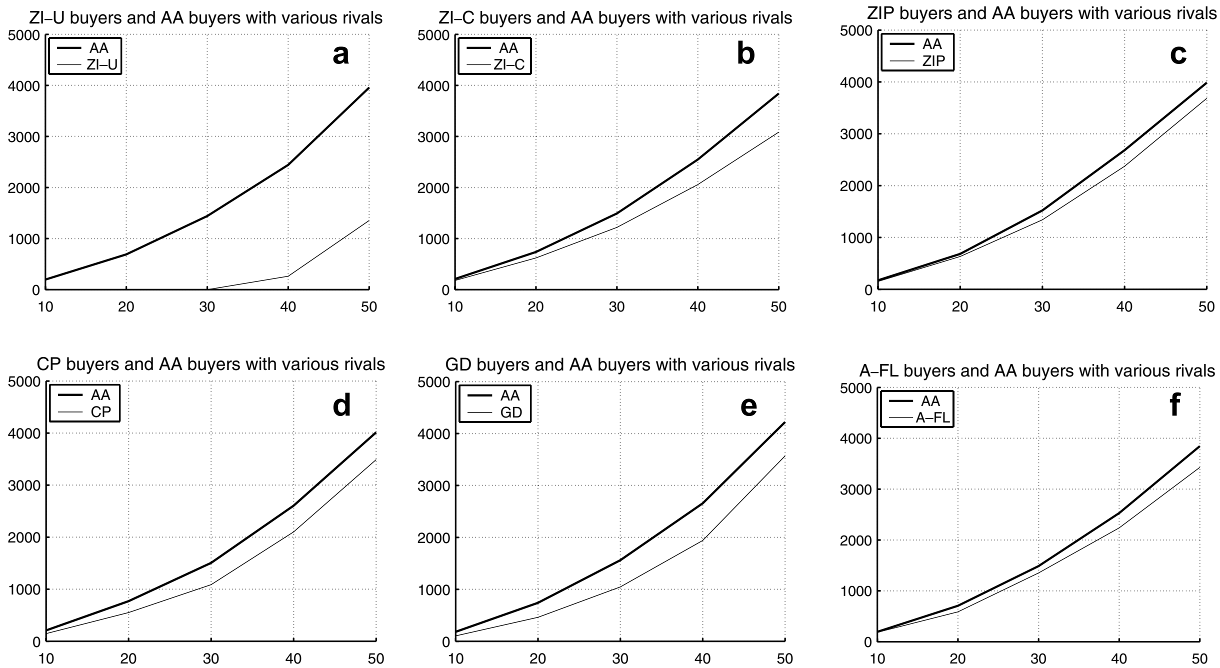

Fig. 12. The comparison of performance of different buyers with AA buyers in dynamic CDA markets when supply is smaller than demand. *X*-axis represents supply from 10 to 50. *Y*-axis represents the profit of two buyers: (a) ZI-U and AA; (b) ZI-C and AA; (c) ZIP and AA; (d) CP and AA; (e) GD and AA; and (f) A-FL and AA.

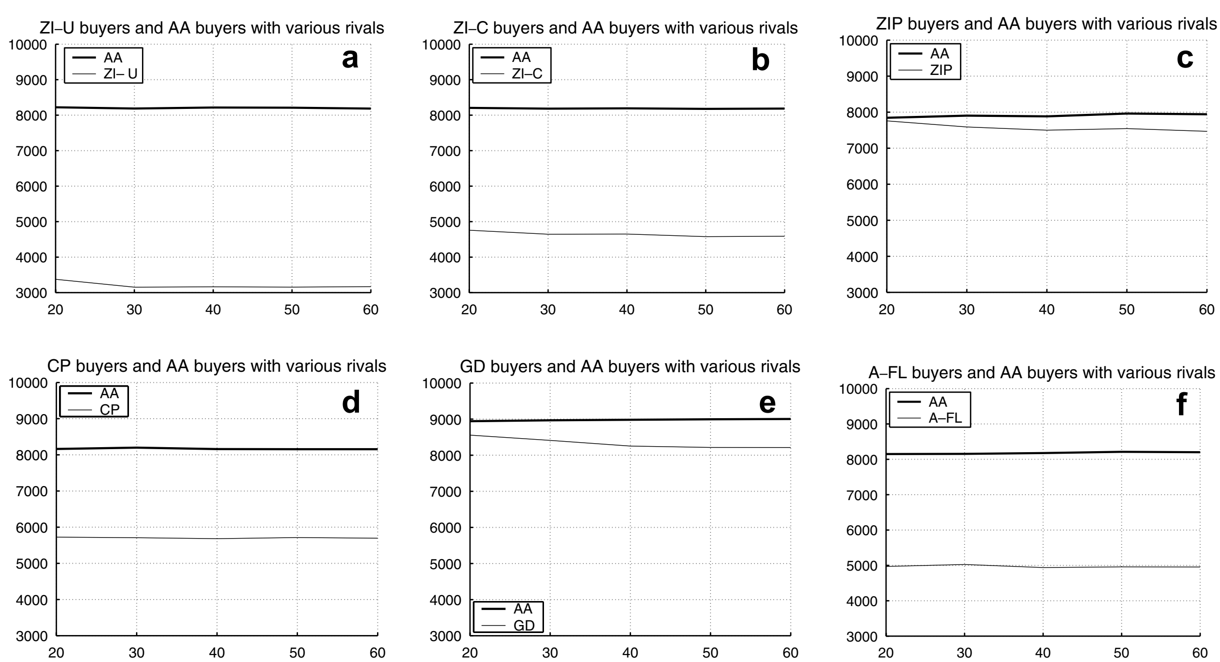

Fig. 13. The comparison of performance of different buyers with AA buyers in dynamic CDA markets when supply is equal to demand. *X*-axis represents supply from 20 to 60. *Y*-axis represents the profit of two buyers: (a) ZI-U and AA; (b) ZI-C and AA; (c) ZIP and AA; (d) CP and AA; (e) GD and AA; and (f) A-FL and AA.

ZIP and GD agents always show a good performance. ZIP agents make use of many factors of the CDA market, such as the transaction price of the last round, the outstanding ask or the outstanding bid of the last round and the profit margin. In addition, ZIP agents use an updating rule to adapt to the dynamic environments. However, they do not consider the history for longer than one round but only pay attention to the information of the last round. CP agents behave worse than ZIP agents. GD agents record a neither too long nor too short history and submit the

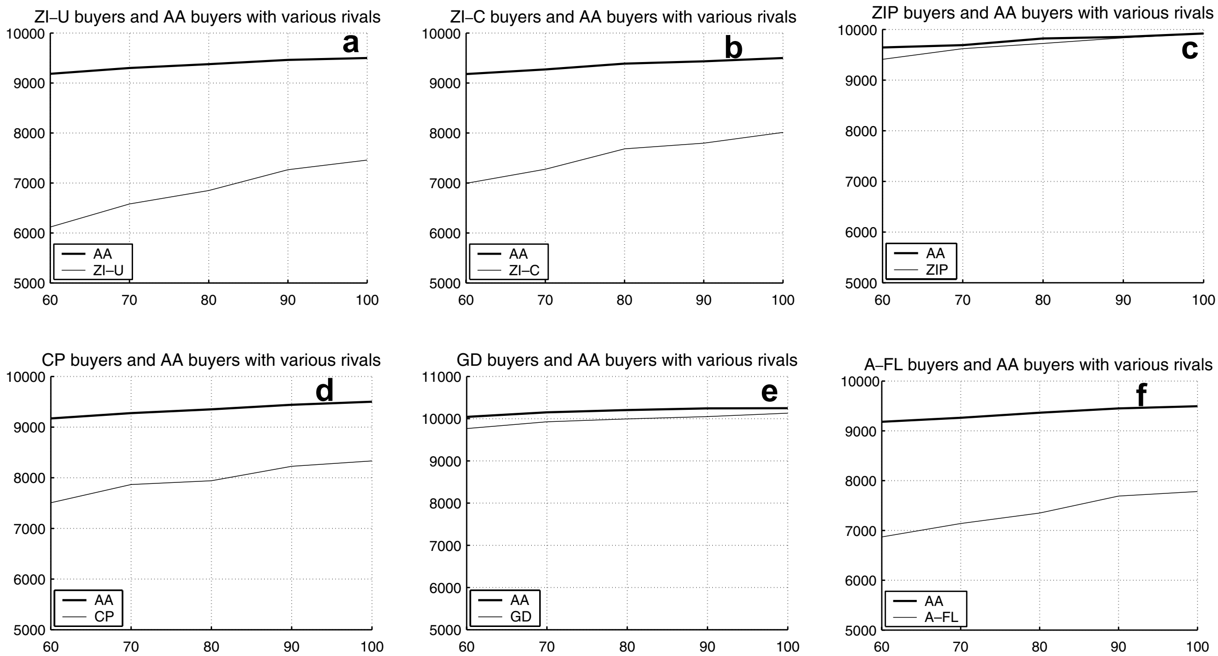

Fig. 14. The comparison of performance of different buyers with AA buyers in dynamic CDA markets when supply is larger than demand. *X*-axis represents supply from 60 to 100. *Y*-axis represents the profit of two buyers: (a) ZI-U and AA; (b) ZI-C and AA; (c) ZIP and AA; (d) CP and AA; (e) GD and AA; (f) A-FL and AA.

ask or bid which maximizes the expected utility. They can utilize the past successful asks and bids of all kinds of agents but cannot guarantee to be adaptive to the changes of supply and demand relationships as well as the dynamic joining and leaving of agents. A-FL agents work well in some situations, especially when it is hard for the agents to trade. However, there are many parameters to be adjusted to suit the market fluctuation, which prevents the agents from being adaptive to dynamic environments.

4.2.2. Experiments to compare all kinds of agents

According to the experiments reported in the previous section, we observe that the performance of AA agents is superior when compared with a particular kind of agents at a time. Thus, we decide to design an experiment to have all kinds of agents together for performance comparison. So, at the beginning of each run, all the sellers or buyers are randomly selected while in the previous experiments, there are two kinds of sellers or buyers fixed and the rest randomly selected. In particular, all the 100 sellers are selected randomly in each run from a pool of 140 sellers containing 20 AA, 20 ZI-U, 20 ZI-C, 20 ZIP, 20 GD, 20 CP, and 20 A-FL sellers, where each seller has one unit of goods to sell. The combination of the sellers is different in each run. This can simulate that all the sellers are free to join or leave the market as they want. All the sellers have the same probability of being selected from the pool. Therefore, in 1000 runs, all kinds of sellers in comparison should have almost the same number of units of goods to be traded. The buyers are all ZI-C buyers in order to be fair to different kinds of sellers. To simulate different supply and demand conditions, the number of ZI-C buyers is changing from 50, 60, 70, 80, 90, 100, 120, 140, 160, 180, to 200 every 1000 runs. The experiment setup for evaluating buyers is similar to that of sellers.

Figs. 15 and 16 clearly show that AA agents still give the best performance in the dynamic CDA markets under different supply and demand conditions. This result reinforces again that AA agents are adaptive to dynamic market environments. In addition, ZIP and GD agents also gain a lot of profit in this experiment, which is consistent to the experimental results in Section 4.2.1. In such a dynamic

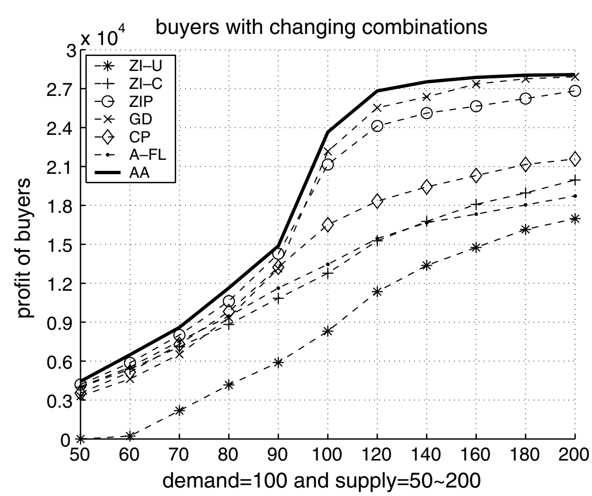

Fig. 15. Performance of different kinds of buyers in dynamic CDA markets.

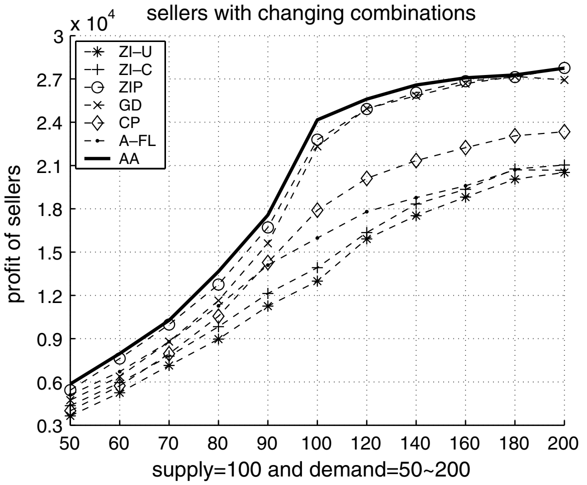

Fig. 16. Performance of different kinds of sellers in dynamic CDA markets.

CDA market, ZIP and GD agents take into account many factors of the market and benefit from their adaptability to the environment.

5. Conclusion, limitations and future work

5.1. Conclusion

This paper presents a formal model of a CDA protocol. A new bidding strategy, named AA strategy, is developed to guide an agent's buying and selling behavior in a series of CDAs. AA strategy uses heuristic rules and a reasoning mechanism based on eagerness and two thresholds α and ω to decide what bids or asks to accept or decline. Our eagerness formulation is defined based on both short-term and long-term attitudes, which reflects the real-time supply and demand conditions from an agent's point of view. Two thresholds α and ω are integrated within the heuristic rules, telling an agent what kind of asks or bids should be accepted or declined directly in the current market environment.

We benchmark the performance of AA strategy against other six prominent alternatives in the literature. The experiments are composed of two groups: experiments to simulate static CDA markets, and experiments to simulate dynamic CDA markets. The experimental results of the first group show the superior performance of AA strategy in static market environments. Supported by the success in static markets, we carry out the second group of experiments to let agents using AA strategy compete with other kind of agents one by one in dynamic market environments. The results also illustrate that AA strategy can outperform any other strategy. Finally, all the bidding strategies are put together in one dynamic CDA market to compete, which again illustrates that AA strategy outperforms the others. These results demonstrate the effectiveness of the use of an eagerness formulation based on two-level adaptive attitudes and the heuristic rules with two thresholds α and ω. We view these as our main contribution. We also notice that in some cases, the performance of ZIP, A-FL, or GD agents is quite good when compared with that of AA agents. The reason is that ZIP, A-FL, or GD agents can make use of different factors in the market and as a result behave adaptively to the dynamic market.

5.2. Limitations and future work

Our current research has the following limitations. First, in our current experiments, the reservation prices are randomly generated from a fixed range for various agents at the beginning of the CDA markets. In view of the depreciation of goods over time, we think it is possible and practical to adjust the reservation prices dynamically with the market situation in the future.

Second, eagerness has been firstly introduced into CDAs and formed in our AA strategy. The aim of introducing eagerness is to enable an agent to behave adaptively according to the current market environment. There may exist other possible ways to express eagerness and guide agents' behavior in such complex and dynamic markets. However, our proposed eagerness provides useful guidance and permits our agents using AA strategy to perform superiorly in the experiments.

Third, we do not consider that supply and demand change abruptly in the current experiments. Nevertheless, in real life markets, sometimes there may be abrupt fluctuation of the number of traders. Future research can explore the impact of these abrupt changes to agents through more experiments.

In the future, we plan to further analyze the performance of AA strategy and reinforce AA strategy. We also aim to exploit more on adaptability which is essential for agents trading in a real CDA market. Moreover, we are interested in exploring the effect of several important factors on the performance of agents, such as making compromise in bid determination and thresholds of asks and bids. All these factors are valuable and should be considered by different bidding strategies for agents in dynamic CDAs.

Normally, bidding strategies which are used for CDAs, such as GD, ZIP, CP, A-FL, AA, and ZI-C are seldom applied to other types of auctions especially single-sided auctions due to the differences in information revelation and allocation processes. Bagnall and Toft [34] have tried to revise GD and ZIP strategy to be used in first-price sealed-bid (FPSB) and second-price sealed-bid (SPSB) auctions. This demonstrates that it is possible and meaningful to utilize these adaptive strategies of CDAs into single-sided auctions, e.g., repeated English auctions, such that different observations can be revealed both on auction protocols' side and on agents' side.

Finally, the basic ideas of eagerness can be easily extended to other auction protocols (e.g., multiple auctions, repeated Dutch auctions, repeated English auctions) because all these auctions are characterized by a series of repeated auctions.

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