Continuous Double Auction for Cloud Market: Pricing and Bidding Analysis

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***Abstract*—Cloud computing has recently attracted a substantial amount of attention from both industry and academia. Its growing demand gives normal users an opportunity to sell their local resources to the cloud market, which introduces new challenges for the existing coarse-grained pricing models.**

In this paper, we examine the potential of applying continuous double auction framework to handle these heterogeneous cloud resources. First, we establish an e-auction platform, on which cloud service providers and users can trade computing and storage resources online. Then we formulate a continuous double auction model for cloud market and further develop a novel belief-based hybrid bidding strategy (BH-strategy) for cloud players to ensure their profit maximization. At last, we conduct three simulation scenarios to compare the performance between BH-strategy and other dominating bidding strategies, and plenty of simulation results show that our BH-strategy outperforms others in all the scenarios on user surpluses by 20% or above. Besides, the BH-strategy can obtain a 16% higher efficiency in 1/3 the amount of time of other strategies.

***Index Terms*—Cloud Computing, Continuous Double Auction, Bidding Strategies, Resource Allocation**

I. Introduction

Powered by reduced costs and unmatched scalability, cloud computing has been drastically improving the existing operations and business models of the IT industry. Such enterprise cloud providers as Amazon, Google, and Rackspace have enjoyed a significant increase in the population of customers, which enforces themselves to constantly upgrade and expand infrastructures of their datacenter [1]. Nowadays, the rising demand of cloud computing also gives users an opportunity to provide their local resources as a cloud service [2], which brings about a great boom to the global cloud market.

To solve this problem, fixed pricing and single-sided auction models [3] are suggested, which allows users to bid on unused resources. But it is known that this single-sided auction cannot support popular cloud applications very well due to its inconvenience to providers [4]. Then many researchers shift their focus on double auctions, which can provide more freedom to both providers and users. Such models are commonly used when the commodity to be priced has an approximately well-known value to both sellers and buyers. These designs however can hardly consider the case when customers are selling their highly heterogeneous local resources to other users in the cloud market, not to mention the possible bargaining behavior among users.

In this paper, we carefully investigate the benefit of applying a Continuous Double Auction (CDA) to cloud markets. In particular, we mainly focus on two jobs. One is to establish an e-auction platform, on which the cloud service providers and users can trade computing and storage resources online. The other is that we develop a novel belief-based hybrid bidding strategy (BH-strategy) for cloud users. Further, lots of experiments indicate that this work can largely improve market efficiency in an asymmetric scenario which is very close to actual cloud markets.

The following of this paper is structured as follows. Section II surveys related works on Internet pricing and auction models. In Section III we design a CDA framework and an e-CDA platform scheme. Section. IV describes the BH-strategy for cloud CDA. The simulation results and the feasibility of CDA in real cloud markets are given in Section V. Finally, Section VI concludes the paper.

II. Related Work

The resource allocation problem has been researched in many fields, such as grid computing and some economic resource allocation frameworks [5]. Although some works on Internet pricing can be applied to nowadays cloud computing, there are some unique natures and characteristics in cloud auctions, and existing methods do not apply in new situations. So in this section, we will first review the concept of Internet resource pricing, and then give some related works on cloud auctions.

A. Internet Resource Pricing

Recently, with a tremendous growth in demand for broadband data, pricing has become a congestion management tool when services are provided. For example, [6] proposes a

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flat rate pricing mechanism with congestion control, called FRPCC, to achieve social welfare. Since time-based pricing strategy is not truly dynamic and the electricity resource cannot be optimally utilized in real time, [7] proposes a usage-based dynamic pricing scheme for smart grid in a community environment, which enables the electricity price to correspond with the electricity usage in real time. Further, Soumya Sen *et al.* carried out the first time-dependent pricing (TDP [8]) trial for mobile data in 10 families in the US, and this trial can not only help ISPs empower users to better control their usage, but also alleviate network congestion. There are also a wide variety of scenarios that adopt auction and market design solutions. [9] shows that single-sided auction designs for divisible goods have been explored fairly well, while suitable double-sided auctions for markets have proved to be rather challenging.

Although the Internet pricing is widely used in many areas, these schemes cannot be used in cloud pricing directly because there are also many differences between [10] and [11]. Many particular methods such as continuous double auctions are then under study, which are brief introduced in the next subsection.

B. Auction Models in Cloud

Traditional auctions can be classified into the following types: English auction (first-price open-cry), first-price sealed-bid auction, second-price sealed-bid auction (Vickery auction), Dutch auction and double auction. Further, Gode and Sunder [12] divided double auction into three categories: synchronized double auction, CDA and semi-continuous double auction (or Hybrid double auction).

There are already some researches that adopt the above auctions into cloud computing. In Radu Prodan's opinion, scheduling of scientific applications in cloud environments can be regarded as a market-based negotiation which aims at optimizing user-centric objectives, so he proposed a new instantiation of the negotiation protocol using a market-based Continuous Double Auction (CDA) model in [13] and concluded that one can benefit by applying an aggressive scheduling strategy. Besides, many literatures such as [14], [15] use combinatorial double auctions to allocate cloud resources and obtain nice results.

However, all these works do not consider the dynamic nature of cloud markets, and ignore that consumers can come into an auction at any time and even leave the auction whenever they want to. Thus, a scheme or a platform that can provide more freedom to both providers and users is in urgent need.

III. CDA Framework

The cloud computing market structure considered in this paper consists of CSPs, cloud users and a uniform platform. This section presents a solution to the resource allocation problem in such a market, including a model of CDA mechanism and its market rules. Then an e-auction platform scheme is proposed to implement the mechanism in a real cloud environment.

TABLE I: Main notations used in CDA.

Notation	Explanation
o_{bid}	The outstanding bid
o_{ask}	The outstanding ask
TR	The trading round
s_o	The bid-ask spread
$\boldsymbol{B}$	The set of bids submitted by bidders
LP	The limit price

A. Auction Platform

For a huge cloud computing market populated by millions of users and CSPs, a uniform trading platform is vital. Currently many kinds of commodities (such as electric energy, petroleum, and stocks) are traded on the e-business platform because e-auction platform is a feasible solution, which can be easily accessed via the Internet and make use of e-business technologies.

On such an e-business platform, it is an efficient trading way in which CSPs and users can submit their orders simultaneously, so the CDA model can be applied. In a specific auction, the platform plays the role of an auctioneer, and users who submit buying orders (bids) act as buyers, while CSPs that submit selling orders (asks) act as providers.

Therefore, we propose an e-auction platform, which applies the customized CDA mechanism to implement pricing and resource allocation in cloud markets.

B. CDA Model

To formulate CDA, we firstly explore some of the basic notions as shown in Table I:

To be specific, o_{bid} is the current maximum demand order submitted by a cloud user in the market, and o_{ask} is the current minimum offer submitted by a CSP at any given time t in the market. TR is the period during which asks and bids are submitted until there is a match or transaction occurs. There are typically several trading rounds in a trading day. At the beginning of a trading round, $o_{bid} = 0$ and $o_{ask} = Max$. s_o is the difference between o_{ask} and o_{bid}, $s_o = o_{ask} - o_{bid}$. The limit price, LP, is both the maximum bid a cloud user is currently willing to pay, and the minimum ask a CSP is willing to supply.

With these notations, CDA can be considered as a discrete system: transforming a series of discrete input value (bids and asks) to a series of discrete output (transaction results, i.e., matching of bids and asks). Therefore, the model can be described as the following:

$$M = F_{L_{TD},\Delta,Max,Min}(B, V, A, C) \quad (1)$$

where TD is a trading day, denoting the period during which users and CSPs are allowed to submit asks and bids. L_{TD} is the length of trading day. Δ is the minimum increment of a bid or ask in the market. Max is the maximum ask allowed in the market, and Min is the minimum bid allowed in the market, usually set as 0.

Input:

$B = \{B_1, ..., B_i, ..., B_m\}$: bid set of m cloud users. B_i is a subset containing all bids of cloud user i, and each bid is noted as b_i^t.

$V = \{V_1, ..., V_i, ..., V_m\}$: limit price set of m cloud users. V_i is the limit price of cloud user i, which is the highest bid it is willing to pay. Normally, V_j is $user_i$s unit valuation for commodity, i.e., redemption value.

$A = \{A_1, ..., A_i, ..., A_m\}$: ask set of n CSPs. A_j is subset containing all asks of CSP j, and each ask is noted as a_j^t.

$C = \{C_1, ..., C_i, ..., C_m\}$: limit price set of n CSPs. C_j is the limit price of CSP j, which is the lowest bid it is willing to submit. Normally C_j is CSP_js unit cost for commodity production.

In this paper, cloud users and CSPs are supposed to be rational. Therefore, the bid of user i is no more than the price it is willing to pay, and the ask of CSP j is no less than the unit cost of commodity production, i.e.,

$$Min \leq b_i \leq V_i \tag{2}$$

$$C_j \leq a_j \leq Max \tag{3}$$

Output: M: the successful transaction matching result.

To apply CDA in competitive cloud computing markets, we define the following market rules:

Rules 1. *At each step, only one bid or ask can be submitted. At any step t, if a bid or ask is submitted, then* $t = t + 1$.

Rules 2. *Any new bid or ask must improve on the current outstanding bid or ask in the market, i.e.,* $b^t > o_{bid}^{t-1}$, $a^t < o_{ask}^{t-1}$.

Rules 3. *At any step t, if* $o_{bid}^t \geq o_{ask}^t$, *then a transaction occurs at the price* $p_t = (o_{bid}^t + o_{ask}^t)/2$. *The winning cloud user's revenue is* $(V_i - P_t)$, *and the winning CSP's revenue is* $(P_t - C_j)$. *Then the winning buyer and seller are removed from the market. The current round is over, and the next round begins.*

Rules 4. *At any step t, if CSP's limit price is lower (higher) than the current* o_{bid}^t (o_{ask}^t)*, it cannot submit any bid (ask), and has to wait for the beginning of the next round. However, if it can submit a bid or ask in the cloud market, it considers its set of bidding strategies to form a price.*

Rules 5. *If* $t = L_{TD}$, *the trade is over.*

Obviously, when a CSP (cloud user) decides his/her ask (bid) price, he/she must take other players' action into account, including the action of other CSPs and actions of all cloud users. In Section. IV, we'll analyze the bidding strategies of both CPS and users.

IV. Belief-based Hybrid Strategy

Our e-auction platform provides a feasible solution to the problems of cloud resource allocation and pricing. On such a platform, the selection of bidding strategies for auctions plays an important role for each player to maximize his/her own profit.Therefore, we propose a novel bidding strategy, Belief-based Hybrid Strategy (BH-strategy), for the CDA mechanism. BH-strategy introduces an improved belief function and uses evolutionary programming to decide strategy dynamically.

A. Belief Function

All cloud users and CSPs attempt to maximize their surpluses in cloud computing market. However, only when bids or asks are accepted and a transaction occurs, cloud users and CSPs can obtain surpluses. Therefore, players must evaluate the probability of which these bids or asks get accepted by other sellers or buyers, i.e., beliefs. It is a feasible method to form beliefs based on trade history.

To reduce the computation time and costs, we introduce an improved belief function. It calculates the estimate of the competitive equilibrium price p^* by using recent transaction prices, and then forms the seller's and buyer's beliefs according to the estimate of p^*. Furthermore, the bidding game consists of two stages: the aggressive stage and the unaggressive stage. In the aggressive stage, $o_{ask} > \widehat{p^*}$, sellers can be more aggressive, and choose the best ask based on the belief. In the unaggressive stage $o_{ask} \leq \widehat{p^*}$, sellers can be less aggressive, i.e., sellers choose the best ask without taking history records into account. The same situations also work in buyers. Therefore, the belief function should be defined by two sub-functions.

We use the moving average method to calculate the estimate of p^* based on the prices in transaction history. Different from [16], this paper uses the weighted moving average method to calculate the estimate of the competitive equilibrium price, as shown in Equation 4.

$$\widehat{p^*} = \frac{\sum_{i=T-HN+1}^{T}(w_i \times p_i)}{1 + 2 + ... + HN} \tag{4}$$

where $(w_{T-HN+1}, ..., w_T)$ is the weight given to the latest HN transaction prices $(p_{T-HN+1}, ..., p_T)$, and $w_{T-HN+1} = 1$, $w_i = i - (T - HN)$, and $w_T = HN$, which means we give higher weight to more recent transactions.

To reduce computation complexity, the seller's beliefs at interval $(\widetilde{p^*}, Max]$ can be described as a polynomial based on the data in transaction history. Here we design seller beliefs as a cubic polynomial:

$$\widehat{p}(a) = \begin{cases} 1 & \text{if } a \leq \widehat{p^*} \\ p_1 a^3 + p_2 a^2 + p_3 a + p_4 & \text{if } Max \geq a \geq \widehat{p^*} \end{cases} \tag{5}$$

where p_1, p_2, p_3, p_4 will be fixed by analyzing the data in transaction history in a given market populated by N sellers and M buyers.

Similarly, the buyer's beliefs at interval $[Min, \widehat{p^*})$ can also be described as a cubic polynomial as follows:

$$\widehat{p}(b) = \begin{cases} 1 & \text{if } b \geq \widehat{p^*} \\ q_1 b^3 + q_2 b^2 + q_3 b + q_4 & \text{if } Min \leq b \leq \widehat{p^*} \end{cases} \tag{6}$$

B. BH-Strategy

Based on our improved belief functions, the buyers or sellers take different actions at different game stages.

Algorithm 1 Bidding Strategy for Seller j

if $C_j \geq o_{ask}$ **then**
  submit no ask
else
  if first trading round, $\widehat{p^*} = 0$ **then**
    submit an ask given by Equation. 13
  else
    if $o_{ask} > \widehat{p^*}$ **then**
      /*aggressive stage*/
      submit an ask computed by Equation. 8
    else
      /*unaggressive stage*/
      submit an ask given by Equation. 11
    end if
  end if
end if

Algorithm 2 Bidding Strategy for Buyer i

if $V_i \leq o_{bid}$ **then**
  submit no ask
else
  if first trading round, $\widehat{p^*} = 0$ **then**
    submit a bid given by Equation. 14
  else
    if $o_{bid} < \widehat{p^*}$ **then**
      /*aggressive stage*/
      submit a bid computed by Equation. 10
    else
      /*unaggressive stage*/
      submit a bid given by Equation. 12
    end if
  end if
end if

1) Aggressive Stage: If $o_{ask} > \widehat{p^*}$, sellers should be in the aggressive stage. A seller should compute the best ask based on the improved belief function. Seller's expected surplus is defined as follows:

$$S_{s,j} = max\{max_a[(a - C_j)\widehat{p}(a)], 0\} \tag{7}$$

For seller j, its best ask is a_j, maximizing $S_{s,j}$. Substituting Equations 5 for 7, we have:

$$a_j = argmax\{(a - C_j)(p_1 a^3 + p_2 a^2 + p_3 a + p_4)\} \tag{8}$$

If $o_{bid} < \widehat{p^*}$, buyers should be in the aggressive stage. Buyers' expected surplus is defined as follows:

$$S_{b,j} = max\{max_b[(V_i - b\widehat{q}(b))], 0\} \tag{9}$$

For buyer i, its best bid is b_i maximizing $S_{b,i}$, i.e.,

$$b_i = argmax\{(V_i - b)(q_1 b^3 + q_2 b^2 + q_3 b + q_4)\} \tag{10}$$

2) Unaggressive Stage: If $o_{ask} \leq \widehat{p^*}$, sellers should be at the unaggressive stage. Similarly, if $o_{bid} \geq \widehat{p^*}$, buyers should be at the unaggressive stage. When at this stage, a seller or buyer submits a new ask or bid, which means it will accept a worse price than history.

In CDA, asks or bids submitted by traders must be subject to Equations 2 and 3. When $o_{ask} \leq \widehat{p^*}$, the interval $[C_j, o_{ask})$ has already been too small to provide the seller j with more choices. Similarly, when $o_{bid} \geq \widehat{p^*}$, the interval $(o_{bid}, V_i]$ has also been too small.

Therefore at the unaggressive stage, a seller just submits a random ask as follows:

$$a_j \sim U(C_j, o_{ask}) \tag{11}$$

$U(C_j, o_{ask})$ is the uniform distribution.

A buyer submits a random bid as follows:

$$b_i \sim U(o_{bid}, V_i) \tag{12}$$

Similarly, $U(o_{bid}, V_i)$ is the uniform distribution.

When in the first trade round, no transaction occurs. So we define bid rules in the first trading round by adopting the method of [16]. Seller j should submit a_j in the first trading round as Equation 13:

$$a_j = o_{ask} - \frac{o_{ask} - max\{C_j, o_{bid}\}}{\eta} \tag{13}$$

And buyer i should submit b_i in the first trading round as Equation 14:

$$b_i = o_{bid} + \frac{min\{V_i, o_{ask} - o_{bid}\}}{\eta} \tag{14}$$

Therefore, the Belief-based Hybrid Strategy can be described as Algorithm 1 and Algorithm 2:

As shown above, in the first trading round, BH buyers and sellers have no information of trade history, so they submit orders based on the current outstanding orders and their limited prices. From the second trading round, $\widehat{p^*}$ can be computed, and BH buyers and sellers take different bidding strategies accordingly.

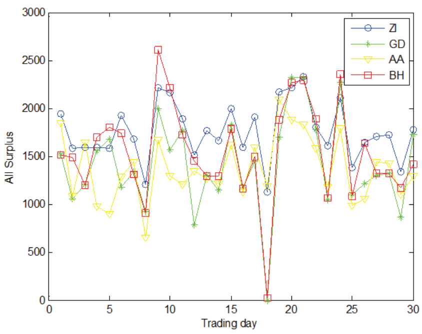
V. Evaluation

In this section, we first detail the simulation design to analyze the strategic interaction of the BH-strategy in CDA markets. Then, we compare our strategy with the ZI strategy, GD strategy and AA strategy, separately. At last, we give the actual empirical study of performance.

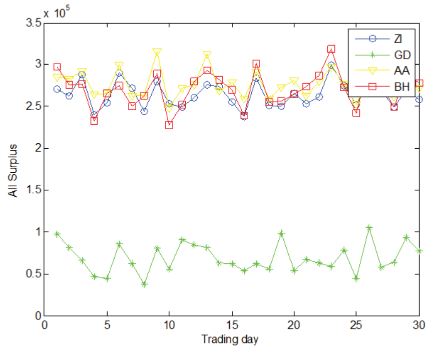
A. Simulation Design

We simulate scenarios with three different kinds of scales to evaluate our strategy.

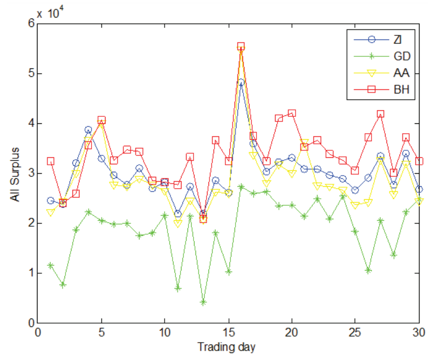
In the small simulation scenario, the market is populated with a set of 10 buyers and 10 sellers on the same scale as [16]. In the large simulation scenario, there are 100 buyers



(a) Small Simulation Scenario.

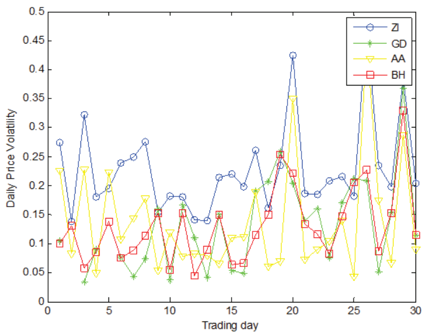


(b) Large Simulation Scenario.

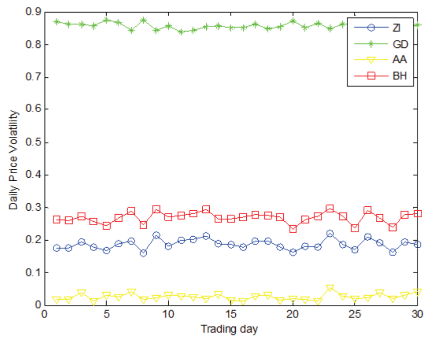


(c) Asymmetric Simulation Scenario.

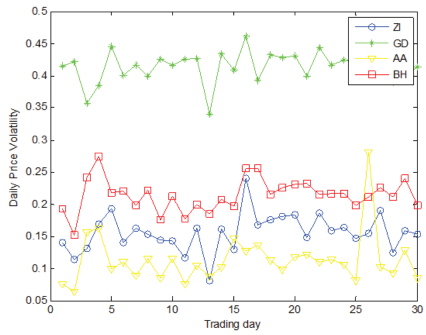
Fig. 1: Total Surplus Evaluation.



(a) Small Simulation Scenario.



(b) Large Simulation Scenario.



(c) Asymmetric Simulation Scenario.

Fig. 2: Daily Price Volatility.

and 100 sellers in the market. In the asymmetric scenario, 1000 buyers and 10 sellers. For each scenario, we simulate 30 trading days.

To evaluate BH-strategy, we will compare it with ZI strategy [17], GD strategy [18] and AA strategy [16], separately.

B. Evaluation

Successful transactions, surpluses and daily price volatility are evaluated to assess the performance of CDA market and BH-strategy.

1) Successful Transactions: The number of successful transactions in one trading day is a basic measurement of auction efficiency. Because the CDA market is a model with constraints, if a transaction occurs, both the winning seller and buyer obtain surpluses. It means that more successful transactions cause more total surpluses.

TABLE II: The Average of Daily Transactions.

Strategy	Small	Large	Asymmetric
ZI	452	8326	6606
GD	228	677	3535
AA	305	4570	6560
BH	367	6679	7685

TABLE II gives the average of daily successful transactions in these three scenarios.

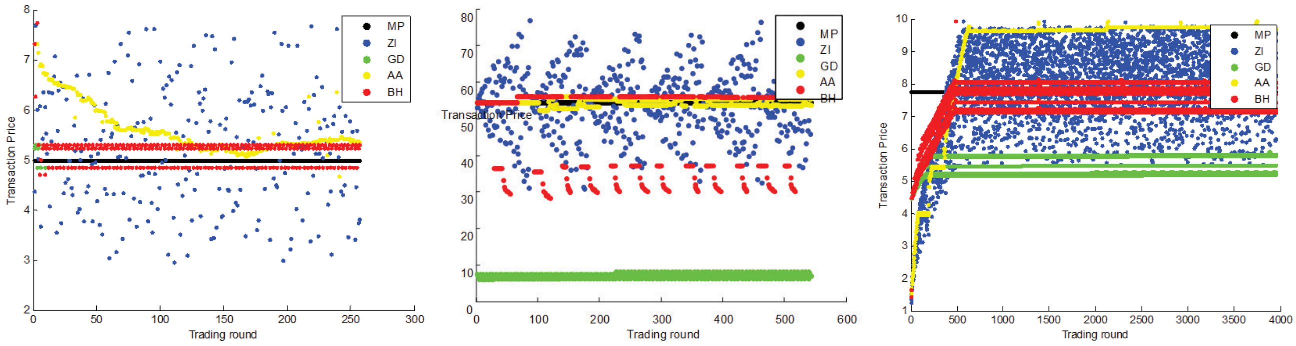
We observe that BH has overwhelmingly more successful transactions than GD, and is slightly better than AA in all the three scenarios. ZI is a non-intelligent bidding strategy, so it usually has more successful transactions. However, in the asymmetric scenario, BH has more transactions than ZI.

2) Surpluses of Sellers and Buyers: Every market mechanism aims at maximizing surpluses or profits attained by sellers and buyers in the market. We select three kinds of surplus criteria: seller/buyer's daily surplus and total surpluses (the sum of seller/buyer's surplus). Daily surpluses depend on the number of transactions and prices. Therefore, it takes a global view of the four bidding strategies by the empirical study on these surplus criteria.

Fig. 1 offers total surpluses (seller's surplus plus buyer's surplus) of ZI, GD, AA and BH in three scenarios.

According to the experiment results, AA strategy obtains the most seller's surplus and BH strategy obtains the most buyer's surplus. But generally BH obtains the most in all the three scenarios.

3) Daily Price Volatility: Daily price volatility α shows how the transaction prices converge to the equilibrium price. Figure 2 gives respectively the daily price volatility of ZI, GD, AA and BH in the three scenarios.



(a) Small Simulation Scenario. (b) Large Simulation Scenario. (c) Asymmetric Simulation Scenario.

Fig. 3: Transaction Prices in One Trading Day.

As shown in Fig. 2, the average volatility of BH is the smallest in the small scenario, and the average α of AA is the smallest in the other two scenarios. Although AA has the best performance based on the average of daily price volatility, our BH performs much better than GD and ZI.

To demonstrate how transaction prices distribute, Fig. 3 gives transaction prices in one trading day. In this figure, MP denotes equilibrium price found by the Marshallian Path (MP). Therefore, all dots of MP form a line, called MP-line. The faster transaction prices converge to MP-line, the smaller the daily price volatility is.

Figure 3 shows how BH converges to the equilibrium price. Although the daily price volatility of BH is not obviously smaller than AA, the difference among transaction prices in one trading day is smaller than the others.

VI. Conclusion

In this paper, a Continuous Double Auction (CDA) mechanism is proposed for cloud resources allocation. We define the market rules to match orders and facilitate trading, and design an e-auction platform and a novel bidding strategy, BH-strategy for CDA, which is a two-stage game bidding strategy based on improved belief functions.

In the evaluation section, we compare BH-strategy with other typical strategies in successful transactions, surpluses, daily price volatility in three simulation scenarios (small, large and asymmetric). These experiment results show that BH-strategy has better performance and is feasible for cloud computing resource allocation.

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