Market Design for Perishables

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Abstract– A standard double auction market collects bids from traders and matches them to find the most efficient allocation, assuming that the value of unsold items remains unchanged. In the market for perishable goods, sellers suffer a loss when they fail to sell their goods, because their salvage values are lost when the goods perish. To solve this problem, we investigate the design of an online double auction for perishable goods, where bids arrive dynamically with their time limits. Our market mechanism aims at improving the profitability of traders by reducing trade failures in the face of uncertainty of incoming/departing bids.

Keywords: Online double auction, Mechanism design, Perishable goods

1 INTRODUCTION

In recent years, several types of auction mechanisms are vigorously investigated to solve large-scale dynamic resource allocation problems in the societies such as cloud computing [3] and electric power grids [11]. In those problems, the resources to be allocated to demands have capacity limitations, but they are seldom supposed to have temporal limitations. In other words, the resources are *durable* but not *perishable*. Perishability of the resources increases complexity of the allocation problem because they must be allocated to the demands before losing their value without satisfying the demands.

The primary and tertiary industries produce perishable goods or services, and make profits by allocating their products to dynamic demands before they lose their value. In services industries such as airlines and accommodation, which provide perishable services to customers, several revenue management techniques [10] have been studied. Their objective is maximizing revenues of a single seller since revenue management is typically practiced by the seller for its own profit. Therefore, those techniques are difficult to apply to the markets, where perishable products of multiple sellers should be coordinately allocated to the demands for maximizing social utilities.

This paper discusses the problem of allocating perishable goods such as fish and vegetables to fluctuating demands in the market, where many sellers and buyers dynamically participate in trading the commodities. In wholesale markets for perishable goods, one-sided auctions are widely used because the traditional markets are *spot markets* that trade already-produced goods whose costs are *sunk*. However, in the one-sided auctions, sellers cannot straightforwardly influence price-making.

In order to solve the problem, we develop a prototypical marketplace for the perishable goods, in which sellers can also trade their unproduced goods in *forward markets*. Our market adopts online *double auction* (DA) [4] as a *market mechanism* to solve the problems by realizing fair price-making among traders while reducing allocation failures [6]. In the online DA, multiple buyers and sellers arrive dynamically over time with their time limits. Both buyers and sellers tender their bids for trading commodities. The bid expresses a trader's offer for valuation, quantity of the commodity to be traded. The arrival time, time limit, and valuation for a trade are all private information to a trader. Therefore, the online DA is uncertain about forward trade. It collects bids over a specified time interval, and clears the market on expiration of the bidding interval using pre-determined rules.

In the online DA market for perishable commodities, the market mechanism should decide matching among the bids with different prices and time limits to increase total utilities of traders and reduce trade failures in the face of uncertainty about forward trades. The online market also presents the tradeoff for clearing all possible matches as they arise versus waiting for additional buy/sell bids before matching. Although waiting could engender better matching, it can also hurt matching opportunities because the time limit of some existing bids might expire.

Until recently, not much work had addressed online double auction mechanisms [1, 2, 12]. These studies examine several important aspects of the problem: design of matching algorithms with good worst-case performance within the framework of competitive analysis [1], construction of a general framework that facilitates truthful dynamic double auctions by extending static double auction rules [2], and development of computationally efficient matching algorithms using weighted bipartite matching in graph theory [12]. Although their research results are theoretically significant, we cannot directly apply their mechanisms to our online DA problem because all of their models incorporate the assumption that trade failures never cause a loss to traders, which is not true in our market for perishable goods.

In this paper, we advocate a heuristic online DA mechanism for the markets of perishable goods, which improves revenue of the traders by reducing allocation failures in the market. And as a preliminary step of developing the real field application, we study multi-agent simulations of the designed DA mechanism in an imaginary market.

The rest of the paper is organized as follows: Section 2 introduces our market model. Section 3 presents the mechanism design in our online DA market. Section 4 explains the settings of multi-agent simulations and in Section 5 we analyze the performance of various types of agents in the markets and investigate the market equilibria. Section 6 concludes the paper and discusses future research directions.

2 MARKET MODEL

In our model of a market, we consider discrete time rounds, $T = \{1, 2, \cdots\}$, indexed by t. For simplicity, we assume the market is for a single commodity. Agents are either sellers (S) or buyers (B), who arrive dynamically over time and depart according to their time limit. In each round, the agents trade multiple units of the commodity. The market is cleared at the end of every round to find new allocations.

Each agent i has private information, called *type*, $\theta_i = (v_i, q_i, a_i, d_i)$, where v_i is agent i's valuation of a single unit of the good, q_i is the quantity of the goods that agent i wants to trade, a_i is the arrival time, and d_i denotes the departure time. The duration between the arrival time and the departure time defines the agent's trading period $[a_i, d_i]$ indexed by p, and agents can repeatedly participate in the auction over several trading periods.

We model our market as a wholesale market for B2B transactions. In the market, seller i submit a bid [1] of her goods at arrival time a_i. At departure time d_i, the salvage value of the goods evaporates because of its perishability unless it is traded successfully. Seller i must bring her goods to the market before her departure. Therefore, seller i incurs production cost in her trading period and considers the production cost as valuation v_i of the goods. Because of advance production and perishability, sellers face the distinct risk of failing to recoup the production cost in the trade.

Buyers procure the goods to resell them in retail markets. Arrival time a_j is the first time when buyer j values the item. For buyer j, valuation v_j represents the expected payment of her customers for the goods in a retail market, which regulates her maximum budget to procure the goods. In other words, buyer j tries to gain some profit by retailing the goods if she succeeds to procure them before her departure time d_j, which is a due time for a retail opportunity.

Agents are self-interested and their types are private information. At the beginning of a trading period, agent i submits a bid by making a claim about its type $\hat{\theta}_i = (\hat{v}_i, \hat{q}_i, \hat{a}_i, \hat{d}_i) \neq \theta_i$ to the auctioneer. Furthermore, in succeeding rounds in the trading period, the agent can modify the value of its unmatched bid [2]. However, once agents depart from the market, they are not allowed to reenter the same bid.

2.1 Agent's Utility

In our market model, an agent can place bids in the auction over several trading periods that may overlap with each other. In order to simplify the notation hereafter, we assume that the agent's trading periods do not overlap and each agent has a unique bid in any round t.

Let $\hat{\theta}^t$ denote the set of all the agent's types reported in round t; $\hat{\theta} = (\hat{\theta}^1, \hat{\theta}^2, \ldots, \hat{\theta}^t, \ldots)$ denote a complete reported type profile; and $\hat{\theta}^{\leq t}$ denote the reported type profile restricted to the agents with reported arrival no later than round t. In each trading period p, agent i has a specific type $\theta_i^p = (v_i^p, q_i^p, a_i^p, d_i^p)$. Report $\hat{\theta}_i^t = (\hat{v}_i^t, q_i^t, a_i^p, d_i^p)$ is a bid made by agent i in round t within trading period p (i.e., $t \in [a_i^p, d_i^p]$). The report represents a commitment to trade at most q_i^t units of goods at a limit price of $\hat{v}_i^t$ in round t within trading period p [3]. We assume agent i reports truthful values about quantity q_i, arrival time a_i, and departure time d_i at any round t based on the reasons explained in Section 2.2.

In an online DA mechanism, $M = (\pi, x)$ is composed of an allocation policy π and a pricing policy x. Allocation policy π is defined as $\{\pi^t\}^{t \in T}$, where $\pi_{i,j}^t(\hat{\theta}^{\leq t}) \in \mathbb{I}_{\geq 0}$ represents the quantity traded by agents i and j in round t, given reports $\hat{\theta}^{\leq t}$. The pricing policy x is defined as $\{x^t\}^{t \in T}, x^t = (s^t, b^t)$, where $s_{i,j}^t(\hat{\theta}^{\leq t}) \in \mathbb{R}_{\geq 0}$ represents the payment seller i receives from an auctioneer as a result of the trade with buyer j in round t, given reports $\hat{\theta}^{\leq t}$. Furthermore, $b_{i,j}^t(\hat{\theta}^{\leq t}) \in \mathbb{R}_{>0}$ represents a payment made by buyer j to the auctioneer as a result of the trade with seller i in round t, given reports $\hat{\theta}^{\leq t}$. In this paper, we assume that seller i receives the entire amount paid by buyer j, so that $b_{i,j}^t(\hat{\theta}^{\leq t}) = s_{i,j}^t(\hat{\theta}^{\leq t})$.

Most studies on DA mechanisms assume agents with simple quasi-linear utility, $\sum_j (s_{i,j} - \pi_{i,j} v_i)$, for seller i and $\sum_i (\pi_{i,j} v_j - b_{i,j})$ for buyer j. However, in order to represent characteristics of a wholesale market for perishable goods, we define the idiosyncratic utility for sellers and buyers.

For seller i, when $\pi_{i,j}^t$ units of goods are sold to buyer j at price $s_{i,j}^t$ in round t within period p, then seller i obtains incomes $s_{i,j}^t$. Since the production cost of the seller is v_i^p, seller surplus is $s_{i,j}^t - \pi_{i,j}^t v_i^p$. If a unit of goods perishes in round t without being traded, seller i loses valuation v_i^p.

Definition 1 (Seller i's utility at time round t)

$$
\begin{aligned}
U_i(\hat{\theta}^{\leq t}) = & \sum_{\{p|a_i^p \leq t\}} \sum_{t' \in [a_i^p, d_i^p]} \sum_{j \in B \wedge \pi_{i,j}^{t'} > 0} (s_{i,j}^{t'}(\hat{\theta}^{\leq t}) - \pi_{i,j}^{t'}(\hat{\theta}^{\leq t}) v_i^p) \\
& - \sum_{\{p|d_i^p \leq t\}} (q_i^p - \sum_{t' \in [a_i^p, d_i^p]} \sum_{j \in B} \pi_{i,j}^{t'}(\hat{\theta}^{\leq t})) v_i^p. \quad (1)
\end{aligned}
$$

The second term in Equation (1) represents the loss of unsold and perished goods, which are calculated dynamically at the bid's departure time (i.e., when $d_i^P \leq t$). With the effect of the second term, sellers are motivated to lower their valuation in the bid when the departure time approaches.

When bids are matched and buyer j receives $\pi_{i,j}^t$ units of goods at price $b_{i,j}^t$ in round t within period p, buyer j obtains surplus $\pi_{i,j}^t v_j^p - b_{i,j}^t$. As for failed bids, buyer j is penalized by the auctioneer with a payment of a minimal bid-ask gap.

[1] When we must distinguish between claims made by buyers and claims made by sellers, we refer to the *bid* from a buyer and the *ask* from a seller.

[2] When we must distinguish between claims made by buyers and claims made by sellers, we refer to the *bid* from a buyer and the *ask* from a seller.

[3] Successful trade in previous rounds of period p make the current quantity of goods reduce to $q_i^t \leq q_i^p$.

Definition 2 (Buyer j's utility at time round t)

$$U_j(\hat{\theta}^{\leq t}) = \sum_{\{p|a_j^p \leq t\}} \sum_{t' \in [a_j^p, d_j^p]} \Big(\sum_{i \in S \wedge \pi_{i,j}^{t'} > 0} (\pi_{i,j}^{t'}(\hat{\theta}^{\leq t}) v_j^p - b_{i,j}^{t'}(\hat{\theta}^{\leq t})) - \sum_{i \in S \wedge \pi_{i,j}^{t'} = 0} \big(\min_{\{i | t' \in [a_i^p, d_i^p] \wedge \hat{v}_i^{t'} > \hat{v}_j^{t'}\}} \hat{v}_i^{t'} - \hat{v}_j^{t'} \big) q_j^{t'} \Big). \quad (2)$$

The second term in Equation (2) represents the penalty of unsuccessful tenders, which are partly caused by buyers' greedy low biddings. With the effect of the second term, buyers are motivated to raise their valuation in the bid.

Agents are modeled as risk-neutral and utility-maximizing. Equation (1) shows that a seller gains profits by selling low-value goods at high prices but loses money if the goods perish without being sold. The seller's bidding strategy on valuation of the goods is intricate because she can enhance her utility in the trade by either raising the market price with higher valuation bidding or increasing successful trades (i.e., preventing the goods from perishing) with lower valuation bidding. Equation (2) reveals that a buyer makes profits by procuring high-value goods at lower prices and retailing the procured high-value goods but loses money if she fails to procure goods. Therefore, in this market, the buyer also has difficulty to find the optimal bidding strategies since she can improve her utility by either bringing down the market price with lower valuation bidding or by increasing successful trades (i.e., enhancing retail opportunities and reducing penalties) with higher valuation bidding.

2.2 Agent's Truthfulness

An agent's self-interest is exhibited in its willingness to misrepresent its type when this will improve the outcome of the auction in its favor. However, misrepresenting its type is not always beneficial or feasible for the agent.

Reporting an earlier arrival time is infeasible for a seller and a buyer because the arrival time is the earliest timing that they decide to sell or buy the goods in the market. Reporting a later arrival time or an earlier departure time can only reduce the chance of successful trade for the agents. For a seller, it is impossible to report a later departure time $\hat{d}_i > d_i$ since the goods to be sold in the market perish by the time d_i. For a buyer, misreporting a later departure time $\hat{d}_j > d_j$ may delay retailing the procured goods.

As for quantity, it is impossible for a seller to report a larger quantity $\hat{q}_i > q_i$ because the sold goods must be delivered immediately after trade in a market. Moreover, it is unreasonable for a buyer to report a larger quantity $\hat{q}_j > q_j$ because excess orders may produce dead stocks for her.

A seller can misreport a smaller quantity $\hat{q}_i < q_i$ with the intention of raising the market price, but in that case, she might need to throw out some of the goods she produced for sale. If a buyer misrepresents a smaller quantity $\hat{q}_j < q_j$ to lower the market price, she loses a chance of retailing more goods. Although these misreports might create larger profits for sellers and buyers, finding the optimal quantity values for increasing their profits is not a straightforward task. Therefore, in this paper, we assume that the agents do not like to misrepresent a quantity value in their type.

On the other hand, we suppose that an agent has incentives to misreport its valuation for increasing its profit because it is the most instinctive way for agents to influence market prices. When sellers do not care about trade failures, sellers have an incentive to report a higher valuation and buyers like to report a lower valuation. In a perishable goods market, a seller may also report a lower valuation $\hat{v}_i < v_i$ when she desperately wants to sell the goods before they perish. Consequently, we consider that agent i can misrepresent only its valuation v_i for improving its utility among all the components of its type information θ_i.

3 ONLINE DA MECHANISM

In perishable goods markets, sellers raise their asking price and buyers lower their bidding price as a rational strategy to improve their surplus as long as they can avoid trade failures. In such markets, agents have to manipulate their valuation carefully for obtaining higher utilities. Our goal is to design a market mechanism that secures desirable outcomes for both individual agents and the whole market without the need for strategic bidding by the agents.

The well-known result of [7)] demonstrates that no Bayes-Nash incentive-compatible exchange mechanism can be simultaneously efficient, budget-balanced, and individually rational. Therefore, we aim to design an online DA mechanism that imposes budget-balance, feasibility, and individual rationality while promoting reasonable efficiency and moderate incentive-compatibility. Since an auction mechanism consists of an allocation policy and a pricing policy, we discuss our design for each policy in the following sections.

3.1 Allocation Policy

Many studies on the DA mechanism investigate a static market and use social surplus from successful trade as the objective function, with the assumption that agents never suffer a loss from trade failures. A common goal of the allocation policy is to compute trades that maximize social surplus, which is the sum of the difference between bid prices and ask prices for all matched bids. The ratio of achieved social surplus against the maximal social surplus at the competitive equilibrium is called *allocative efficiency*.

The allocation policy that maximizes allocative efficiency in a static DA market arranges the asks according to the ascending order of the seller's price and the bids according to the descending order of the buyer's price, and matches the asks and bids in order [4]. We refer to this allocation rule as a standard allocation policy in the paper.

The standard allocation policy is efficient for the DA markets that assume trade in forward markets or trade in durable goods, in which agents do not lose their utility even if they fail to trade. However, sellers of perishable

[4] FIFS rule is used to break a tie among bids or asks.

goods can lose the value of perished goods when they fail to sell the goods during the trading period. Consequently, in addition to increasing social surplus from trade, increasing the number of successful trades is also important in the perishable goods markets for maximizing social utility.

In a static market, all the bids and asks to be matched should exist in the market simultaneously, and hence, combinatorial optimization methods can find the allocation that maximizes the social utility. However, in online DA markets, the number of bids in the market changes dynamically and cannot be predicted in advance. Therefore, if every bid is matched immediately when a matchable counter bid arrives in the market, the number of bids remaining in the market might always be insufficient for finding more desirable allocations that can produce larger utility. Because incoming bids have a possibility of producing a better matching result with existing bids in the market, quality of the allocation can be improved if we accumulate the bids without matching them immediately and decide the allocation from the aggregated bids. At the same time, deferring allocation decisions might prevent the existing bids from being matched, and hence, increase trade failures.

In this paper, we advocate a *deferred allocation policy* and investigate its effectiveness in the online DA market. In the deferred allocation policy, matching between a seller's ask and a buyer's bid is deferred when any of the following conditions is satisfied:

(Deferring Condition 1) The matching ask is for selling already-produced goods and both matching ask and bid have slack time before their departure times.

(Deferring Condition 2) The matching ask has slack time before its departure time and there are other asks waiting to be allocated, which can be matched only with the matching bid.

The first condition expresses that matching of the ask should be postponed when the seller's goods are already produced and their cost are sunk. And the second condition suggests that matching of a seller's ask with a limited matching candidate should be prioritized over other asks.

3.2 Pricing policy

The pricing policy is important to secure truthfulness and prevent strategic manipulation by agents, which should promote stability of agent bidding and increase efficiency of a market. Nevertheless, obtaining truthfulness in DA markets while guaranteeing other desirable properties is impossible. In our market, we impose both budget-balance and individual rationality, and also promote reasonable efficiency. Hence we adopt k-double auction [8], in which clearing price is determined as $(1-k)\hat{v}^t_j + k\hat{v}^t_i$, as our pricing policy, and set the value of k as 0.0 because of the following reasons.

1. Seller i does not have an incentive to overstate her true valuation v^p_i, because it does not change the clearing price without losing matching opportunities. She does not have a strong incentive to understate her valuation either, if our allocation policy can reduce the risk of loss caused by perished goods.
2. The bid-ask gaps are usually small in competitive B2B transactions. In such cases, buyer j may make bigger profits in retail markets than her surplus in wholesale markets. Therefore she has an incentive to increase the possible number of matching $\pi^t_{i,j}$ (i.e., enhancing retailing opportunities) in the wholesale markets by reporting high valuation under a budget constraint.

Additionally, To encourage buyers' high valuation, the auctioneer imposes a penalty on buyers when they fail to trade in the auction. When buyer j cannot obtain q^t_j units of goods at at a limit price of $\hat{v}^t_j$ in time round t, in which sellers' lowest ask is $\hat{v}^t_i$, the buyer is charged $(\hat{v}^t_i - \hat{v}^t_j)q^t_j$ by the auctioneer.

4 MULTI-AGENT SIMULATION

With the above defined allocation policy and pricing policy, we speculate that our mechanism can make the online DA market for perishable goods yield a high utility with moderate incentive-compatibility while maintaining properties of budget-balance and individual rationality. Since our market model and mechanism are much more complex than traditional continuous double auctions, even for which theoretical analysis is intractable, we perform empirical evaluation of the market mechanism using multi-agent simulation.

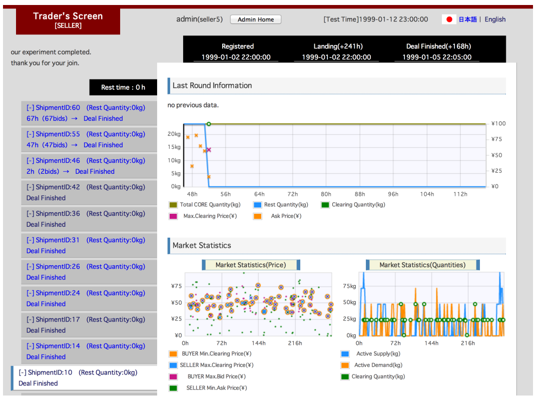

Fig. 1: Screenshot of multi-agent market simulator

For the purpose, we developed a web-based market simulator using Java, PHP, JavaScript, and MySQL. In the simulator, any number of human subjects as well as software agents can participate in the market either as buyers or as sellers from the remote computer. The graphical displays of the simulator shown in Fig. 1 can present several types of data to a user such as the bidding history of a trader and several market statistics such as transition of bidding prices, clearing prices, demand quantities, and supply quantities along the timeline. These data can be used to support making bidding decisions online and analyze trading performances offline.

4.1 Simulation Settings

We evaluate the market mechanism by running simulations with specific settings. In the simulation, five sellers and five buyers participate in the market. For the simulations, we use two types of markets with distinctive demand-supply curves depicted in Fig. 2 and Fig. 3.

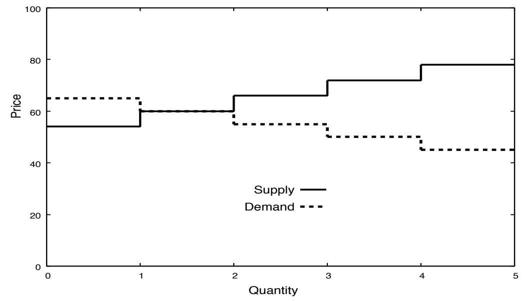

Fig. 2: Market with high risk of trade failures

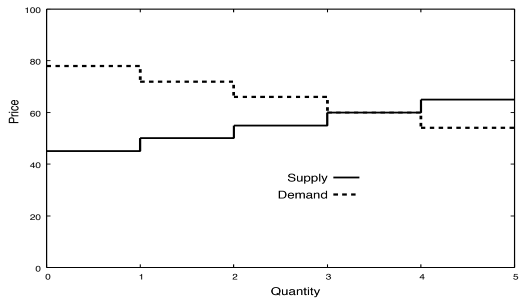

Fig. 3: Market with low risk of trade failures

Figure 2 represents the market with a high risk of trade failures, in which the average valuation of goods by the buyers is much lower than that by the sellers. Figure 3 represents the market with a low risk of trade failures, in which the average valuation of goods by the buyers is much higher than that by the sellers.

Each simulation runs for 44 days and the market is cleared every hour. Every day the agents submit one bid or ask, each of which has one unit of demand or supply for the homogeneous perishable goods.

Arrival time of the agents is randomly decided for every bid submission. In the time interval of arrival and departure, agents can freely modify their reported valuation in the bid.

The seller's ask departs the market 48 hours after its arrival, assuming that a seller's goods are produced 24 hours after bidding and lose their value after 24 hours from their production. This means that both forward and spot trades occur in the market simultaneously.

The departure time of a buyer's bid is 24 hours after its arrival, which simulates the situation of buyers procuring goods for retail sales of the next day.

For each result shown in the following sections, 100 randomized trials are executed to simulate diversified patterns of agents' arrival and departure.

4.2 Agent's Bidding Strategies

Experimental analyses of complex markets necessarily focus on a restricted set of bidding strategies. In this paper, we prepare several types of bidding strategies for both sellers and buyers to simulate the behavior of different agents in reporting their valuation, and investigate agent behavior in different market situations. For this purpose, we model the strategies of agents based on typical behaviors of human traders in the market for perishable goods.

Seller agent i reports her valuation in the bids based on her true valuation v_i^p. And buyer agent j reports the valuation based on her budget, which is determined by deducting prospective retail profits from her expected customers' valuation v_j^p. We model buyer j's budget as $\gamma_j^p v_j^p$, assuming that it is proportional to the expected customers' valuation v_j^p. In this paper we set 0.5 as the value of γ_j^p.

We model agent's strategies based on typical behaviors of human traders in the perishable goods market as follows:

1. Modest strategy (MOD) : only for sellers

   Seller i always reports her valuation as

   $$\hat{v}_i^t = 0. \tag{3}$$

   This strategy is developed to simulate one-sided auction markets where only buyers submit their bids.

2. Truth-telling strategy (TT)

   With this strategy, an agent always reports its valuation truthfully.

   (a) Seller i's reported valuation at time round t is

   $$\hat{v}_i^t = v_i^p. \tag{4}$$

   (b) Buyer j's reported valuation at time round t is

   $$\hat{v}_j^t = \gamma_j^p v_j^p. \tag{5}$$

3. Truth-Telling to Modest strategy (TTMOD) : only for sellers

   When t is before production time of seller i's goods (i.e., forward trade),

   $$\hat{v}_i^t = v_i^p. \tag{6}$$

   When t is after production time of seller i's goods (i.e., spot trade),

   $$\hat{v}_i^t = 0. \tag{7}$$

   This strategy is simple but reasonable for sellers, since production cost of the goods become sunk after their production and value of the perishable goods evaporates eventually.

4. Monotonous strategy (MONO)

   An agent monotonously tunes its report on valuation along with the elapsed time after the arrival of the bid in the market.

   In trading period p, seller i and buyer j report their valuation as follows:

   (a) Seller i's reported valuation at time round t is

   $$\hat{v}_i^t = v_i^p(1.0+\delta)\frac{d_i^p - t}{d_i^p - a_i^p}. \tag{8}$$

(b) Buyer j's reported valuation at time round t is

$$\hat{v}^t_j = \gamma^p_j v^p_j (1.0 - \delta \frac{d^p_j - t}{d^p_j - a^p_j}). \quad (9)$$

where δ is a parameter to control aggressiveness of the agent's bidding behavior. With a larger value of δ, the agent tends to report greedier valuation. In this paper, we set 0.2 as the value of δ, assuming that the trade surplus equivalent to 20% of its valuation is a reasonable target for the aggressive agent. This strategy simulates a very intuitive behavior of traders, and it is widely used in revenue management as a dynamic pricing rule.

5. Zero-intelligent aggressive strategy (ZIA)

   By reporting the valuation randomly within a certain range, an agent tries to obtain a larger surplus when there is little risk of trade failures and gives up making a profit when there is little time left until its departure.

   In trading period p, seller i and buyer j report their valuation as follows:

   (a) Seller i's reported valuation at time round t is

$$\hat{v}^t_i = v^p_i rand((1.0 + \delta)\frac{d^p_i - t}{d^p_i - a^p_i}, 1.0 + \delta). \quad (10)$$

   (b) Buyer j's reported valuation at time round t is

$$\hat{v}^t_j = \gamma^p_j v^p_j rand(1.0 - \delta, 1.0 - \delta \frac{d^p_j - t}{d^p_j - a^p_j}). \quad (11)$$

   In the above equations, $rand(x, y)$ is a function to produce a random value in between x and y. Thus, ZIA strategy is a randomized variation of MONO strategy.

5 EXPERIMENTAL ANALYSIS

Understanding the interaction among agents with various bidding strategies is important in market design to ensure favorable market properties such as efficiency and stability. The Nash equilibrium is an appropriate solution concept for understanding and characterizing the strategic behavior of self-interested agents. However, computing the exact Nash equilibria is intractable for a dynamic market with non-deterministic aspects such as our online DA market. Therefore, we evaluate the market design by computing the Nash equilibria across the restricted strategy space through simulations.

Sellers and buyers in the B2B market for perishable goods have unique utilities (as explained in Section 2.1) and adopt distinctive bidding strategies (as shown in Section 4.2) for maximizing their utility. In the experiments, we perform a limited strategic analysis by looking for Nash equilibria between restricted types of sellers and buyers based on the simplified market model in which all the agents are homogeneous and follow the same pure strategy. The results obtained in the experiments are not comprehensive, but the degree of success achieved in predicting agent behavior and market outcomes can be used as a benchmark for judging the effectiveness of the proposed mechanisms.

5.1 Results in High-risk Market

Table 1: Payoff matrix with deferred allocation policy in high-risk market

Seller\Buyer	MONO	TT	ZIA
MOD	87%, 44.1, 5,887.3 11,449.4 (233.2) -5,562.1 (159.3)	87%, 55.1, 5,887.3 9,547.8 (193.8) -3,660.5 (192.7)	87%, 27.9, 5,913.3 **14,273.7** (315.4) -8,360.4 (121.2)
TT	26%, 57.5, -6,782.8 1,282.2 (251.3) -10,251.9 (189.1)	32%, 61.4, -5,401.0 **3,900.9** (147.5) -9,301.9 (176.1)	6%, 58.0, -11,646.7 -3,509.0 (928.3) -12,487.6 (173.6)
TTMOD	95%, 53.5, 7,897.2 -726.7 (1,035.8) **-2,950.7** (142.9)	95%, 55.1, 7,695.4 **2,160.3** (1,077.4) **-2,751.5** (154.8)	96%, 41.7, 8,097.3 -7,937.5 (1,942.5) **-5,107.8** (149.6)
MONO	91%, 49.8, 6,975.9 256.3 (851.9) -4,188.8 (144.8)	90%, 55.8, 6,897.1 **4,218.8** (600.9) -3,150.3 (140.3)	90%, 42.5, 6,672.8 -14,593.5 (1,454.2) -5,605.3 (168.3)
ZIA	60%, 55.2, 599.0 -21,883.6 (1,773.0) -6,566.0 (278.7)	61%, 57.9, 990.6 **-12,219.5** (1,823.8) -6,108.6 (361.8)	40%, 46.1, -4,093.7 -30,769.5 (3,245.9) -9,514.9 (378.3)

Table 2: Payoff matrix with standard allocation policy in high-risk market

Seller\Buyer	MONO	TT	ZIA
MOD	97%, 44.0, 8,207.2 12,833.6 (144.9) -4,626.4 (102.3)	97%, 55.0, 8,207.2 10,694.7 (120.7) **-2,487.5** (123.5)	97%, 27.8, 8,170.5 **15,952.3** (186.6) -7,781.8 (81.7)
TT	34%, 56.5, -4,650.5 981.7 (241.6) -9,328.3 (143.7)	36%, 61.2, -4,347.0 **4,425.7** (140.3) -8,772.7 (136.2)	21%, 57.0, -7972.8 -11,435.0 (1,075.2) -10,837.5 (185.0)
TTMOD	92%, 47.9, 7,297.5 -3,054.8 (1,107.0) **-4,381.0** (130.5)	91%, 55.9, 7,062.7 **-194.6** (1,001.3) -3,066.8 (154.4)	94%, 34.3, 7,628.4 -23,547.0 (2,232.8) -6,771.7 (113.0)
MONO	92%, 46.9, 7,359.0 3,943.9 (805.6) -4,546.8 (139.9)	92%, 55.7, 7,353.7 **6,840.7** (491.4) -2,923.0 (148.6)	93%, 38.4, 7,554.6 -11,778.4 (1,456.5) **-6,030.4** (118.1)
ZIA	85%, 50.4, 5,940.1 -25,758.3 (1,951.6) -4,643.7 (178.5)	85%, 56.4, 5,970.7 **-13,163.5** (1,487.8) -3,622.3 (192.0)	80%, 42.6, 4,896.4 -59,309.5 (2,562.8) -6,381.9 (120.1)

Table 1 shows the payoff matrix between sellers and buyers in the high-risk market with the deferred allocation policy. Each cell in the table represents the result of interaction between the sellers and buyers with the corresponding strategy. The cell is separated into two parts: the upper part of the cell shows the average matching rate, the average clearing price and the average social utility (including penalties paid by buyers to the auctioneer), and the bottom left corner in the lower part of the cell reveals the average and standard deviation (inside parentheses) of the utility of seller agents and the top right corner shows those of utility of buyer agents. In the table, numbers in boldface represent utilities of the agent's best response to the other agent's bidding strategy.

The table shows that TTMOD strategy is a dominant strategy for seller agents and TT strategy is almost always a best response for buyer agents, and (TTMOD, TT) strategy profile is a Nash equilibrium in the market. Thus, the deferred allocation policy succeeds in leading sellers and buyers to behave reasonably and truthfully in the high-risk market of perishable goods. To be noticed is that the Nash equilibrium does not maximize the social utility in the market but it produces fair distribution of large utility (i.e., $7,695.4$) among different types of agents. Thus, the deferred allocation policy succeeds in leading sellers and buyers to behave reasonably and truthfully in the high-risk market.

Table 2 shows the payoff matrix with the standard allocation policy, which is used in currently operating markets. The table shows that there is no Nash equilibrium in the market. As is the case in current markets, if sellers are not allowed to bid their valuation (i.e., bidding with MOD strategy), a larger social utility (i.e., $8,170.5$) can be achieved in the market at the sacrifice of sellers' larger loss (i.e., $-7,781.8$).

5.2 Results in Low-risk Market

Table 3 shows the payoff matrix between sellers and buyers in the low-risk market with the deferred allocation policy. The table shows similar results to those in the high-risk market. TTMOD strategy is a dominant strategy for seller agents and TT strategy is almost always a best response for buyer agents, and (TTMOD, TT) strategy profile is a Nash equilibrium. The deferred allocation policy succeeds in leading sellers and buyers to behave reasonably and truthfully also in the low-risk market of perishable goods.

Table 4 shows the payoff matrix with the standard allocation policy. The table shows that there is no Nash equilibrium in the market and, when sellers do not bid their valuation, they suffer a big loss (i.e, $-4,576$) even in the low-risk market, where demands have higher valuation than supplies. We think this type of market is not inherently sustainable since suppliers to the market have difficulty in making proper profits.

Table 3: Payoff matrix with deferred allocation policy in low-risk market

Seller\Buyer	MONO	TT	ZIA
MOD	87%, 52.9, 11,907.8 13,739.4 (279.9) -1,831.7 (181.8)	87%, 66.1, 11,907.8 11,457.3 (232.5) 450.5 (225.4)	87%, 33.1, 11,936.3 **17,190.8** (379.8) -5,254.5 (128.8)
TT	77%, 58.3, 10,231.2 10,926.9 (308.1) -2,004.5 (280.0)	83%, 67.5, 11,523.2 **11,267.5** (234.9) 255.7 (247.3)	50%, 54.2, 3,232.2 -3,653.2 (930.3) -5,599.1 (260.2)
TTMOD	91%, 57.5, 13,254.6 9,929.3 (527.9) **-535.1** (192.9)	91%, 66.5, 13,058.1 **11,209.1** (315.1) **1,024.2** (221.3)	93%, 48.7, 13,581.2 -180.9 (1,195.5) **-1,956.7** (157.5)
MONO	90%, 55.8, 12,956.9 **11,656.8** (356.8) -1,001.2 (158.0)	89%, 66.5, 12,517.8 11,248.6 (213.3) 751.0 (200.2)	90%, 44.6, 12,907.0 2,158.3 (1,121.8) -3,014.6 (161.6)
ZIA	82%, 60.5, 11,316.5 -3,252.9 (1,118.4) -1,057.7 (238.4)	85%, 67.7, 11,916.8 **-3,510.0** (791.7) 457.1 (244.5)	68%, 52.6, 7,469.3 -23,024.2 (2,016.9) -3,905.7 (325.9)

Table 4: Payoff matrix with standard allocation policy in low-risk market

Seller\Buyer	MONO	TT	ZIA
MOD	97%, 52.8, 14,682.1 15,400.4 (173.9) -718.2 (115.4)	97%, 66.0, 14,682.1 12,833.6 (144.9) **1,848.5** (140.8)	97%, 33.0, 14,636.1 **19,212.6** (224.6) -4,576.5 (84.5)
TT	76%, 57.4, 9,984.0 9,882.9 (290.0) -2,285.1 (148.9)	81%, 67.9, 11,087.7 **11,048.8** (198.1) 39.0 (192.3)	64%, 53.2, 6,933.5 -8,084.3 (1,038.8) -4,249.9 (203.1)
TTMOD	92%, 55.3, 13,532.2 9,782.3 (606.5) -851.1 (156.4)	91%, 66.7, 13,198.2 **11,003.9** (313.3) 1,099.2 (187.2)	94%, 41.0, 14,065.4 -666.7 (1,352.5) -3,282.5 (147.7)
MONO	95%, 53.9, 14,284.8 **13,465.4** (343.2) -739.9 (139.8)	96%, 66.2, 14,406.7 12,400.8 (208.3) 1,704.8 (154.2)	95%, 40.3, 14,190.7 6,109.9 (1,045.1) -3,359.6 (132.3)
ZIA	92%, 56.7, 13,464.8 149.6 (1,021.7) **-649.3** (166.0)	91%, 67.0, 13,367.5 **5,886.3** (993.1) 1,187.0 (183.6)	90%, 46.6, 13,023.7 -26,917.5 (1,766.1) **-2,639.3** (167.0)

5.3 Effects of Deferred Allocation

When the *deferring condition 1* prioritizes asks of produced goods, matching prices with sellers' MONO, TTMOD or ZIA strategy go up because, with those strategies, sellers bid high valuation before the goods are produced. In addition, the deferring condition 1 lowers matching rates when sellers use MONO or ZIA strategies because with those strategies, sellers overbid aggressively in the early time rounds of their asks.

When sellers adopt MOD strategy, asks are matched based on FIFS ordering since all the asks have the same valuation 0. Therefore, the *deferring condition 2* lowers matching rates of sellers with MOD strategy because it results in prioritizing the asks with more slack time over those with a close departure time. With combined effects of the deferred allocation policy, TTMOD strategy becomes sellers' dominant strategy in the market over the other bidding strategies.

Simulation results obtained in the two types of markets suggest that the current practice of the perishable goods market, which is a one-sided auction such as Dutch auction with the standard allocation policy, causes unfair trades for sellers. The simulation results also show that traders can stably achieve fair and approximately efficient allocation of perishable goods without strategic bidding in the online DA market with the deferred allocation policy.

6 CONCLUSIONS

We developed an online DA mechanism for the market of perishable goods to improve the profitability of traders by considering the loss from trade failures. We explained that sellers have a high risk of losing money by trade failures because their goods are perishable. To reduce trade failures in the perishable goods market, our DA mechanism prioritizes the bids that have a smaller chance of being matched in their time period by deferring matching the bids that have more chances. Experimental results using multi-agent simulation showed that our DA mechanism was effective in promoting truthful behavior on the part of traders for realizing fair distribution of large utilities between sellers and buyers. It suggests that a hybrid market of forward and spot trades running our online DA mechanism is a promising platform for marketplaces of perishable goods.

The experiment results reported in this paper are very limited for any comprehensive conclusion on the design of online DA for perishable goods. We need to investigate other types of bidding practices and test them in a wider variety of experimental settings. Additionally, behavior of human subjects in the market must be examined carefully to evaluate the designed mechanism [5].

Fig. 4: E-marketplace for oysters in Miyagi prefecture (http://www.miyagi-oyster.jp/)

In developing countries, there are strong demands for improving efficiency in argicultural markets [9] and it is also true for rural societies in developed countries incldu- ing Japan. As an application of our online DA mechanism, we developed an e-marketplace for trading fishery products as shown in Fig. 4. Figure 5 shows actual trading results in the e-marketplace from December, 2014 to the beginning of January, 2015. Only local traders used to participate in the fishery markets because the highly perishable nature of the fishery products prevents their trade from being open to wider participants. This leads to low incomes for the fishermen and collapse of the local fishery industries. We hope our online DA mechanism will contribute in promoting the successful deployment of electronic markets for fisheries and improve welfare of local fishermen by attracting more traders from remote areas.

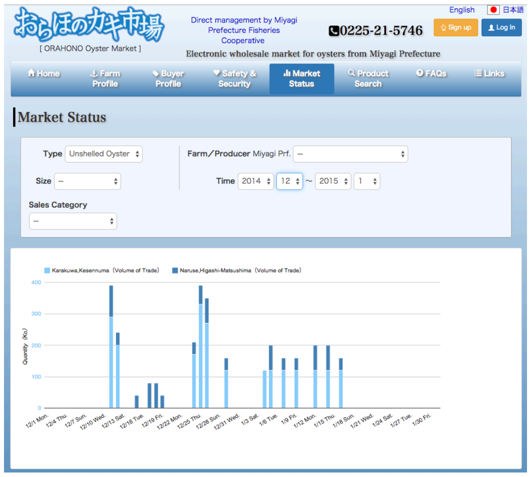

Fig. 5: Trading results in e-marketplace

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