Reputation Tracking Procurement Auctions

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Abstract. The introduction of e-markets has created great challenges for both buyers and suppliers. Buyers have to decide how to take advantage of the possibilities offered on e-markets (i.e., higher savings, expanding the supplier base) but at the same time they should preserve values that are associated with their long-term relationships. As the use of reverse auctions in the industry grows, involved parties are increasingly concerned with how these auctions influence their previously established business relationships. Due to those existing relationships, reverse auctions should not be analyzed as stand-alone auctions. If the relationship is specified as a value-generating asset in the procurement process, then neither business party should expect relationships to be harmed. We propose a reputation tracking reverse auction model that exploits the advantages reverse auctions bring to buyers, while decreasing the disadvantages they bring to sellers. Several experiments were conducted and the analysis was focused on auctions that have different outcomes depending on whether they took reputation into account or not.

Keywords: reputation, reverse auctions, procurement, multi-attribute auctions, B2B e-market

1 Introduction

In the past, available markets and their associated choices were much more limited than today. Consequently, the volatility of supply and demand functions was much more inert. Under such market conditions, companies based their business transactions on long-term partnerships. However, the advent of the Internet and the accelerated economic globalization trend in the past decade is leading us closer to the existence of just one market - the global one. On this global market, electronic commerce (e-commerce) has emerged as the new way of conducting business transactions (i.e., including buying, selling and/or exchanging products, services and information), communicating primarily via the Internet [1]. In this new regime, most attention is focused on Business-to-Business (B2B) and Business-to-Consumer (B2C) e-commerce. B2B e-commerce is considered to be the more lucrative of the two, due to its larger trading volumes and the fact that businesses are less fickle than consumers [1].

Electronic markets (e-markets) can be seen as Internet-based business transaction platforms that serve as digital intermediaries that create value by bringing consumers and providers together. In most industries, e-markets provide opportunities for increasing supply chain management efficiency by changing competition mechanisms [2]. By reducing transaction costs and supporting the exchange of information, they create transactional immediacy and supply liquidity.

In this paper, we focus on the B2B e-market since it is widely believed that it will become the primary way of doing business [3]. Transactions conducted on B2B e-markets are a lot more that just one-shot deals. The relationships between the parties involved in the transactions are ongoing, systematic exchange structures and can affect behavior of all the parties involved over the course of the transaction [4]. Special intention is paid to the negotiation phase of the transaction since the outcome (i.e. financial efficiency) is still the premier performance measure for most businesses [5, 6].

The paper is organized as follows. Section 2 gives an overview of research in the area of reverse auctions. A reputation tracking reverse auction model is proposed in Section 3. Section 4 presents the conducted experiments and the obtained results, while Section 5 concludes the paper and gives an outline for future work.

2 Related Work

Due to their well defined protocols, auctions are suitable enablers of negotiations in e-markets. Auctions are defined as a market institution that acts in pursuit of a set of predefined rules in order to compute the desired economic outcome (i.e., high allocation efficiency) of social interactions [7]. Based on bids and asks placed by market participants, resource allocation and prices are determined.

According to [8], buy-side (i.e., reverse, procurement) auctions are one out of three commonly used auction types on B2B e-markets. In a reverse auction we have one buyer that negotiates the purchase of a particular item (i.e., good, service) with multiple sellers. As the use of reverse auctions in the industry grows, involved parties are increasingly concerned with how these auctions influence their previously established business relationships. Due to those existing relationships, reverse auctions should not be analyzed as stand-alone ones.

Various studies concerning buyers' and sellers' points of view on reverse auctions have been conducted. Most buyers feel that such auctions will enhance their productivity and improve their relationships with suppliers [9]. Buyers also believe that suppliers will embrace participating in reverse auctions since they open new opportunities to increase their sales and penetrate new markets [10]. On the other hand, one of the most common sellers' beliefs includes suspicions of buyers' opportunistic behavior. Suspicions grow as the number of sellers participating in an auction decreases. Furthermore, such suspicions are higher in open-bid auctions than in seal-bid auctions [11]. However, as the economic stakes of the auction increase, the suspicions of buyer's opportunistic behavior decrease [12]. Suppliers' willingness to make dedicated investments towards a buyer increases as the price visibility in an auction decreases. Looking at suppliers' trading history with buyers, this willingness is higher with current and incumbent suppliers than with new suppliers [12]. Willingness to make specific investments shows suppliers' willingness to develop long-term relationships with buyers, but also results with suppliers' decreased bid activity (i.e., submitting fewer bids, bidding less often) and a decrease in making price concessions [4].

Relationships on B2B markets gain on importance if we consider that the number of participants in a certain industry does not have large oscillations. Exceptions are always possible, but they are not common. From time to time a new participant appears on the market or an old one goes out of business, but this does not have a significant influence on other existing relationships. Participants on the market must be aware that their actions (e.g., avoiding commitments, late deliveries, respecting the negotiated terms) influence their reputation and relationships with other participants. B2B trading can be viewed as an ongoing process that connects conducted and ongoing business transactions into a complex arranged structure that can affect future behavior [4]. If the relationship is specified as a value-generating asset in the procurement process, then neither business party should expect relationships to be harmed [13].

3 A reputation tracking reverse auction model

In this section, we give a formal description of our reputation tracking reverse auction model and present the environment the model is placed in.

Item characteristics (i.e., attributes) represent an important factor in deciding which auction should be used. Negotiation on commodities focuses mainly on the price of the item. These items are mostly sold in conventional single-attribute auctions. On the other hand, complex items often require negotiation of several attributes, and not just the price [14]. Such items are sold in multi-attribute auctions [15]. Multi-attribute auctions have been attracting more and more attention in B2B markets, since the price is not the only attribute considered in the decision making process[1]. Most reverse auctions are so-called buyer-determined auctions in which the buyer chooses the winner by integrating non-monetary attributes into the winner determination process [4].

The first step in a multi-attribute auction is for the buyer to specify his preferences regarding the item he wishes to purchase. Preferences are usually defined in the form of a scoring function based on the buyer's utility function [14]. In order to familiarize sellers with buyer's valuations of relevant attributes, the buyer can publicly announce his scoring function. Sellers are not obligated to disclose their private values of an item. The winner of the multi-attribute auction is the seller that provided the highest overall utility for the buyer.

Our model is based on reverse auctions and takes into account the price, as well as other non-monetary attributes of the purchased items. Furthermore, exogenous attributes (e.g., the quality of suppliers' offers in previous auctions and the orderly fulfilment of suppliers' obligations) are also considered.

[1] http://www.cindywaxer.com/viewArticle.aspx?artID=149

3.1 Motivation for introducing reputation tracking

The introduction of e-markets has created great challenges for both buyers and suppliers. Buyers have to decide how to take advantage of the possibilities offered on e-markets (i.e., higher savings, expanding the supplier base) but at the same time they should preserve values that are associated with their long-term relationships [16]. Buyers usually granted various privileges (e.g., volume discounts, higher service levels, favorable credit terms) to strategically important suppliers. Those privileges do not exist on e-markets were all suppliers are treated as equals. This can result in suppliers' withdrawal from participating on the e-market. If a significant number of suppliers refuse to participate, adequate liquidity cannot be achieved and the likelihood of market manipulation increases.

The reputation tracking reverse auction was developed primarily for maintaining good business relationships between buyers and their strategically important suppliers, as well as those suppliers who deliver their items in an orderly manner. For this purpose, we developed an auction model that takes into account two important facts. First, that traded items usually require negotiation on different attributes, and not just the price. Second, that with the advent of the Internet, a global market is forming and market conditions are changing. Consequently, long-term relationships between business partners are slowly being replaced by short-term arrangements with new and sometimes unknown suppliers that offer the most favorable deal.

Most of the work in the area of reputation auctions assumes that purchased items are delivered on time and does not take into account possible delays in delivery. Unfortunately, late deliveries are not very unusual and can cause significant financial damage considering the buyer is often just a link in the supply chain and not the end user of the purchased item. Namely, the buyer commonly uses the purchased good to manufacture new goods or combines purchased services into new value added services. These items are then sold further to other business entities on the B2B market or to consumers on the B2C market.

The buyer most often forms arrangements with his business partners in accordance with his planed production schedules and on-time delivery assessments. Due to other arrangements and limited resources (e.g., production plant capacities, available man power, resources used in ongoing projects), project schedules are not subject to significant changes. The damages caused by disturbances in the delivery of items that are used as resources in further production are twofold. First of all, the value of the item will most probably fall compared with the value it would have had on the agreed delivery date. Second of all, late delivery of the resources will probably cause a delay in the production of the buyer's items. Consequently, the delivery of the items will also be late and will cause financial damage and/or a tainted reputation to other buyer's business partners.

Similar problems are modeled in the Trading Agent Competition Supply Chain Management Game (TAC SCM) [17, 18]. In TAC SCM on the B2B market participants trade by using sell-side auctions and suppliers can deliver the purchased item late. Due to limitations of the game (i.e., small number of suppliers) the buyer cannot efficiently apply penalties nor change his supplier base.

3.2 The formal model description

The reputation tracking auction is designed for businesses with high purchasing frequencies on a market with a limited number of suppliers. In our simulated environment, the buyer uses a sealed-bid multi-attribute reverse auction to determine the winning seller. The basic assumption is that a single buyer uses an auction to purchase a non-commodity item from one out of n_s sellers. The buyer sends a request for quotes (RFQ) to n_s sellers that produce the item he is looking to buy. The sellers decide to participate in the auction depending on their current production capacity. Based on his current schedule, the seller calculates his on-time delivery probability for the item. If this probability corresponds with his risk policy, he sends an offer. After the auction closes, the buyer evaluates received offers and determines the winner by taking into account the total utility of the offered item and sellers' reputations.Research has shown that participants of reverse auctions consider that single-attribute auctions, where the bidding evolves only around the price, are not constructive in the development of long-term relationships between buyers and suppliers [19].

In our work, we make the following assumptions; the number of sellers invited to participate in an auction is known to all sellers while the number of sellers that decide to participate in an auction in not known to other sellers. Sellers are also allowed to drop out of a current auction and join another auction later.

A reverse auction can be defined as a tuple $< b, S, t >$, where

- b is the buyer agent;
- S (of size s) denotes the set of all seller agents that are invited to participate in buyer b's reverse auction; while $S' \subseteq S$, where S' (of size s') denotes the set of seller agents that decide to participate in the auction;
- $t : \mathbb{R}^{s'} \rightarrow \mathbb{R}$ is the winner determination function.

The reputation tracking auction consists of two descriptions and three functions: an *item evaluation model* that contains a description of all the relevant attributes of an item that is being sold in an auction; a *reputation tracking model* containing a description of sellers' reputation for all sellers that participate in reverse auctions; a function that assigns values to the item; a function that assigns values to sellers' reputations; and a function that combines the two previous ones and determines the auction outcome.

The *item evaluation model* is represented with a tuple $< x, w_I, I >$, where

- $x = (x_1, \ldots, x_j, \ldots, x_n)$ is the set of attributes used to describe an item; each attribute j has a reserve and aspiration value, denoted as x_j^r and x_j^a, respectively, determined by the buyer;
- $w_I = \{w_{I1}, \ \ldots, \ w_{Ij}, \ \ldots, w_{In}\}$ is a set of weights that determines the importance of each attribute from x for the buyer, where w_{Ij} is the weight of attribute j;
- $O \in \mathbb{R}^{s' \times n}$, is the offer matrix which describes the attribute values of offered items, where O_{ij} denotes the value that seller i places for attribute j;
- $I : \mathbb{R}^{s' \times n} \times \mathbb{R}^n \rightarrow \mathbb{R}^{s'}$ is a utility function that calculates the buyer's utility of sellers' offers.

Utility function $I(O_i)$ takes as input an offer placed by seller i (i.e., row i of the offer matrix denoted as O_i) and, together with the set of weights w_I maps it to a real value. Function $I(O_i)$ can be defined as an additive scoring function that assumes the existence of mutual *preferential independence* between attributes [20]. In order to calculate the utility of the multi-attribute item, reserve values and weights for each attribute need to be considered [21]. Function $I(O_i)$ is defined as follows:

$$I(O_i) = \sum_{j=1}^{n} w_{Ij} I(O_{ij}), where \sum_{j=1}^{n} w_{Ij} = 1 \tag{1}$$

Existing models of multi-attribute auctions use different approaches to calculate the buyer's utility of an item (e.g., by defining utility functions [15, 20], by using fuzzy multi-attribute decision making algorithms [22], by introducing pricing functions and preference relations for determining acceptable offers [23], by defining reserved and aspiration levels of attributes and distinguishing negotiable and non-negotiable attributes [24]).

We distinguish between two types of attributes: ascending and descending ones. Ascending attributes are evaluated according to positive criteria, where higher values of the attribute increase its utility (e.g., Quality of Service). On the other hand, the utility of descending attributes increases if the value of the attribute decreases (e.g., price). In our model, $I(O_{ij})$ depends on the reserve and aspiration values, x_j^r and x_j^a, respectively, that the buyer defines for each attribute j. Reserve value x_j^r marks the lowest value of ascending attribute j that is acceptable to the buyer. The aspiration value x_j^a is the highest value of ascending attribute j that the buyer is interested in. Values offered higher than the aspiration value are acceptable, but they do not cause a further increase in the buyer's utility for that attribute. This prevents the seller from increasing the total utility of his offer by assigning unnecessarily high values to some (less important) attributes and unreasonably low values to other important ones. Analogously, for descending attributes, x_j^r marks the highest acceptable value, i.e. any value higher than x_j^r is not acceptable, while x_j^a denotes the lowest value the buyer is interested in after which lower values do not increase the utility for that attribute.

Attribute $j = 1$ marks the price of an item, where x_1^r is the highest price the buyer is willing to pay. The buyer's aspiration price is $x_1^a = 0$ money units, so it is not stated in equation (2). Value N.A. in (2) marks a non-acceptable value for an attribute, i.e., it is worse than the reserve value. An offer is rejected if the utility of at least one attribute is N.A. The utility of an offered value higher than the aspiration value cannot be higher than 1.

$$I(O_{ij}) = \begin{cases} 1 - \frac{O_{ij}}{x_j^r}, & j = 1 \; and \; O_{ij} \leq x_j^r \\ N.A., & j = 1 \; and \; O_{ij} > x_j^r \\ \frac{O_{ij} - x_j^r}{x_j^a - x_j^r}, & j \geq 2 \; and \; x_j^r \neq x_j^a \; and \; x_j^r \leq O_{ij} \leq x_j^a \\ N.A., & j \geq 2 \; and \; O_{ij} < x_j^r \\ 1, & j \geq 2 \; and \; O_{ij} \geq x_j^a \end{cases} \tag{2}$$

The *reputation tracking model* is described by a tuple $< y, w_R, V, R >$, where

- $y = (y_1, y_2, y_3)$ is a set of attributes used to calculate sellers' reputations;
- $w_R = \{w_{R1}, w_{R2}, w_{R3}\}$ is a set of weights that determines the importance of each attribute from y for the buyer;
- V is the buyer's sliding window which is used to store information regarding the last v auctions the buyer participated in;
- $R : \mathbb{R} \to \mathbb{R}$ is a utility function that calculates the reputation of all sellers that participated in a least one auction in the sliding window.

The reputation of seller i is defined as follows:

$$R(i) = \sum_{l=1}^{3} w_{Rl} y_l,\ \ where\ \ \sum_{l=1}^{3} w_{Rl} = 1 \tag{3}$$

The buyer calculates sellers' reputations from information gathered in the last v auctions. There are three attributes we consider relevant when calculating sellers' reputations:

- $y1$ – the average utility of the items the seller offers. We compare the item utility of the seller's offer with the item utility of the winning offer in that auction;
- $y2$ – the share of total transactions carried out by the seller. We calculate the value of all the items the seller sold to the buyer and compare it with the value of all transactions conducted in the observed period of time and stored in the sliding window;
- $y3$ – the financial damage inflicted on the buyer due to the seller's late delivery of purchased items. We keep track of all the damage that was caused by the seller's late delivery and compare it with the overall damage caused by all the sellers. The advantage is given to sellers that deliver items on time or with smaller delays.

The exact formulas and explanations of the attributes follow:

$$\begin{aligned} R(i) = w_{R1} \tfrac{1}{a_i} \textstyle\sum_{k=1}^{v} \frac{a_i^k S(x^{i,k})}{S(x^{winner,k})} + w_{R2} \frac{\sum_{k=1}^{v} c_i^k x_1^{i,k}}{\sum_{k=1}^{v} x_1^{winner,k}} + \\ w_{R3}\left(1 - \frac{\sum_{k=1}^{v} c_i^k d_i^k}{\sum_{m=1}^{s} \sum_{k=0}^{v} c_m^k d_i^k}\right) \end{aligned} \tag{4}$$

$$a_i = \sum_{k=1}^{v} a_i^k,\ \ a_i^k = \begin{cases} 1,\ if\ seller\ i\ participated\ in\ auction\ k \\ 0,\ otherwise \end{cases} \tag{5}$$

$$c_i^k = \begin{cases} 1,\ if\ seller\ i\ is\ the\ winner\ of\ auction\ k \\ 0,\ otherwise \end{cases} \tag{6}$$

$$d_i^k = x_1^i(t_{onTime}) - x_1^i(t_{late}^i) \tag{7}$$

In (4), a_i^k (5) denotes seller i's participation in auction k; c_i^k (6) denotes whether seller i won auction k; and d_i^k (7) denotes the decline in the value of the purchased item due to the seller's late delivery.

The *reputation tracking auction model* is defined as a tuple $< x, w_I, I, y, w_R, V, R, b, S, w_T, T, t >$, where

- $< x, w_I, I >$ is an *item evaluation model*;
- $< y, w_R, V, R >$ is a *reputation tracking model*;
- $w_T = \{w_{T1}, w_{T2}\}$ is a pair of weights where w_{T1} denotes the weight of the offered item considered in the winner determination function, while w_{T2} denotes the weight of the seller's reputation;
- T is the total score function.

The total score function $T(i)$ takes as input the value of an item offered by seller i and seller i's reputation and maps it to a total score for the offer. $T(i)$ is defined as follows:

$$T(i) = w_{T1} I(x^i) + w_{T2} R(i), \ \ where \ w_{T1} + w_{T2} = 1 \tag{8}$$

The winner determination function takes as input the total scores of all received offers and maps it to a real value in order to determine the winning offer.

$$t = \max_i \ T(i) \tag{9}$$

4 Experiments and results

In this section, we first give a short description of how sellers determine their on-time delivery probability and how the buyer calculates the amount of damage caused by late deliveries. It is followed by the presentation of the experimental method and obtained results of simulations.

4.1 Supplier settings

The probability that seller i will deliver the purchased item on time $P_i(t)$ is calculated according to the expression shown in (10) while a_i^k (11) denotes seller i's participation in auction k and c_i^k (12) denotes whether seller i won auction k. Since suppliers try to maintain good business relationships with their buyers, they increase the probability of on-time delivery for their more significant ones. However, this causes them to increase the risk of late deliveries to their less significant buyers. Each supplier also has a sliding window keeping track of the v previous transactions conducted with each buyer. He increases his on-time delivery probability proportionally to the ratio of the total monetary value of all transactions won by the seller, compared to the total values of all the auctions the seller participated in. This additional increase has an upper limit of D_{max}. Depending on his preferences and willingness to accept risks, the supplier participates in an auction if his $P_i(t)$ is higher than a certain threshold.

$$P_i(t) = P_i(t-1) + \ random[-0.05, 0.05] + \frac{\sum_{k=1}^{v} c_i^k a_i^k x_1^k}{\sum_{k=1}^{v} a_i^k x_1^k} D_{max} \tag{10}$$

$$a_i^k = \begin{cases} 1, \ if \ seller \ i \ participated \ in \ auction \ k \\ 0, \ otherwise \end{cases} \tag{11}$$

$$c_i^k = \begin{cases} 1, \ if \ seller \ i \ is \ the \ winner \ of \ auction \ k \\ 0, \ otherwise \end{cases} \tag{12}$$

4.2 Buyer damages

The buyer negotiates the delivery date of each purchased item. If the item is delivered after this date, its value is usually lower than it would have been on the negotiated delivery date. In our experiments, we consider only the direct financial damage (i.e., the decrease in the value of the purchased item). However, it is important to note that indirect financial damage (i.e. penalties for late delivery to buyer's business partners, a decrease in the buyer's reputation and the possible loss of new business projects) can be even several times higher. In our experiments, we modeled the decline in value as:

$$D_i = x_1^i(1 - e^{-(1-P_i(t))}) \tag{13}$$

where D_i is the decline in the value of the purchased item in auction i, x_1^i is the price the buyer paid for the item, and $P_i(t)$ is the seller's on-time delivery probability for the purchased item.

4.3 Experiment settings

We conducted three sets of experiments as follows. In each set we changed the values of reputation attribute weights (i.e., w_{R1}, w_{R2}, w_{R3}) and conducted 10 experiments per set with different total attribute weights (i.e., w_{T1}, w_{T2}). One experiment includes 2700 seal-bid multi-attribute reverse auctions held sequentially one after the other. The size of the buyer's sliding window v is 200, so the first 200 out of 2700 auctions were conducted without reputation tracking but they were used to calculate sellers' reputations later. The remaining 2500 auctions took reputation into account when determining the winner of the auction. The items sold in auctions within one experiment all had different weights, reserve and aspiration values, but the auctions with the same ordinal number in different experiments sold the same item (e.g., in auction 361 with $w_{R1} = 0.35, w_{R2} = 0.35, w_{R3} = 0.3$ and $w_{T1} = 0.85, w_{T2} = 0.15$ the same item was sold as in auction 361 with $w_{R1} = 0.5, w_{R2} = 0.3, w_{R3} = 0.2$ and $w_{T1} = 0.75, w_{T2} = 0.25$). While the reserve and aspiration values for non-monetary attributes were chosen randomly from [0, 1], the reserve prices of items were chosen randomly from [100 000, 1 000 000] in monetary units.

For each experiment, we compared auctions in which we tracked sellers' reputation with auctions in which reputation was not considered. The remainder of the analysis in the paper is conducted only on auctions with different outcomes for these two cases. At the end of the experiment, we calculated the amount of money saved by awarding contracts to suppliers with higher reputations. Figure 1. shows the total savings obtained for all three sets of experiments. In each set the values of reputation attribute weights are different. We can see that the savings are quite close for different values of reputation attribute weights for auctions where the influence of the reputation in the total score (i.e., w_{T2}) was lower than 35%. It is clear that the influence of reputation in the decision making process should not be too high since this can result in significant financial damage.

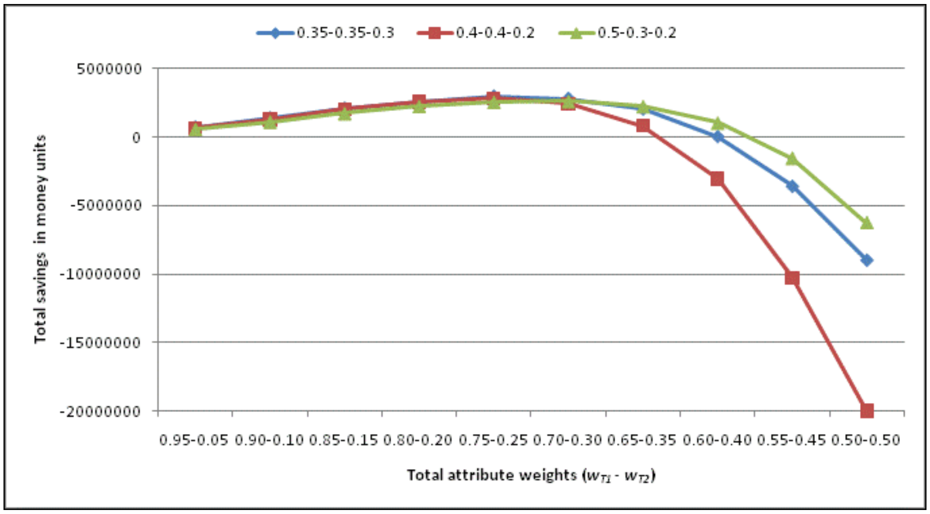

Fig. 1. Total savings in reputation tracking auctions

The total value of all the items the buyer bought in auctions with different outcomes can significantly vary in different experiments. Namely an increase in reputation impact in the decision making process is followed by a higher number of auctions with different outcomes. The value of all items bought in such auctions rises accordingly. Figure 2. shows the ratio of the total savings achieved in auctions with different outcomes in each experiment (shown in Figure 1.) and the value of all items bought in these auctions. As in Figure 1, we can see that reputation tracking only achieves savings in auctions if the impact of the reputation in the total score is lower than 35%.

5 Conclusion and Future Work

In this paper, we presented a reputation tracking model developed for reverse auctions on business-to-business e-markets. As the use of reverse auctions in the industry grows, business partners are concerned with how they will influence previously established business relationships. We propose a model that exploits the advantages auctions bring to buyers, while decreasing the disadvantages they bring to sellers. The buyer calculates seller's reputations from a combination of different attributes, such as the quality of items the supplier offers, the volume of all transactions conducted with the supplier, and the financial damages caused by the supplier's late delivery of purchased items. We conducted several experiments and focused our analysis on auctions that have different outcomes depending on whether they took reputation into account or not. From those experiments, we can see that the reputation tracking reverse auction model achieves savings

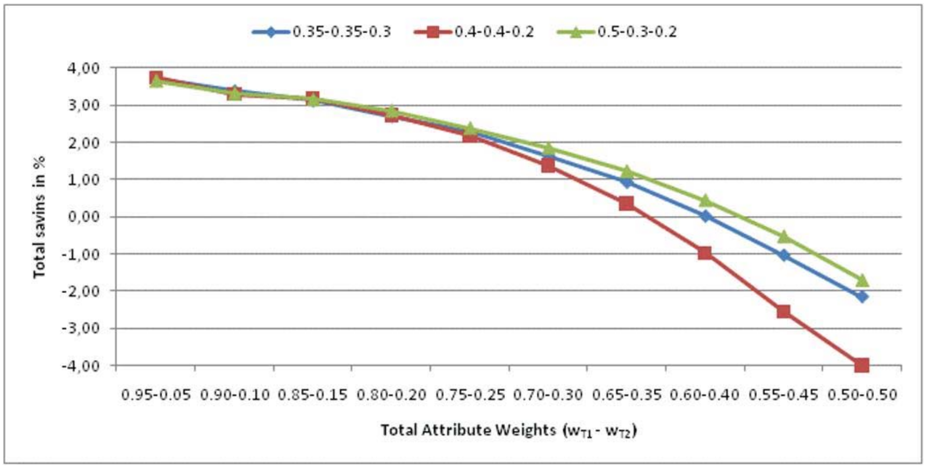

Fig. 2. Total savings compared with the value of all auctions

for the buyer only when the weight of seller reputation in the decision making process is less than 35%.

For future work, we plan the upgrade our supplier model with attributes modeling a supplier's willingness to make dedicated investments towards the buyer, as well as improving the way sellers make offers to their significant buyers. Furthermore, we plan to model the indirect financial damage caused to the buyer by late delivery of purchased items.

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References

1. Dou, W., Chou, D.C.: A structural analysis of business-to-business digital markets. Industrial Marketing Management **31**(2) (February 2002) 165–176
2. Pressey, A.D., Ashton, J.K.: The antitrust implications of electronic business-to-business marketplaces. Industrial Marketing Management **In Press, Corrected Proof** (2008) –
3. Shaw, M.: Electronic commerce: State of the art. In Shaw, M., Blanning, R., Strader, T., Whinston, A., eds.: Handbook on Electronic Commerce. Springer-Verlag New York, Inc., Secaucus, NJ, USA (2000) 3–24
4. Jap, S.D., Haruvy, E.: Interorganizational relationships and bidding behavior in industrial online reverse auctions. Journal of Marketing Research **45**(5) (October 2008) 550–561

5. He, S., Cattelan, R.G., Kirovski, D.: Modeling viral economies for digital media. In Sventek, J.S., Hand, S., eds.: EuroSys, ACM (2008) 149–162
6. Maes, P., Guttman, R.H., Moukas, A.: Agents that buy and sell. Communications of the ACM **42**(3) (1999) 81–91
7. Wurman, P.R., Wellman, M.P., Walsh, W.E.: Specifying rules for electronic auctions. AI Magazine **23**(3) (2002) 15–24
8. He, M., Jennings, N.R., Leung, H.F.: On agent-mediated electronic commerce. IEEE Transactions on Knowledge and Data Engineering **15**(4) (2003) 985–1003
9. Carter, C.R., Kaufmann, L., Beall, S., Carter, P.L., Hendrick, T.E., Petersen, K.J.: Reverse auctions–grounded theory from the buyer and supplier perspective. Transportation Research Part E: Logistics and Transportation Review **40**(3) (2004) 229 – 254
10. Smeltzer, L.R., Carr, A.S.: Electronic reverse auctions: Promises, risks and conditions for success. Industrial Marketing Management **32**(6) (2003) 481 – 488
11. Jap, S.D.: The impact of online reverse auction design on buyersupplier relationships. Journal of Marketing **71**(1) (January 2007) 146–159
12. Jap, S.D.: An exploratory study of the introduction of online reverse auctions. Journal of Marketing **67**(3) (July 2003) 96–107
13. Engelbrecht-Wiggans, R., Haruvy, E., Katok, E.: A comparison of buyer-determined and price-based multiattribute mechanisms. Marketing Science **26**(5) (2007) 629–641
14. Do, V.T., Halatchev, M., Neumann, D.: A context-based approach to support virtual enterprises. Hawaii International Conference on System Sciences **6** (2000) 6005
15. Bichler, M., Kalagnanam, J.: Configurable offers and winner determination in multi-attribute auctions. European Journal of Operational Research **160**(2) (2005) 380–394
16. Grey, W., Olavson, T., Shi, D.: The role of e-marketplaces in relationship-based supply chains: A survey. IBM Systems Journal **44**(1) (2005) 109–124
17. Arunachalam, R., Sadeh, N.M.: The supply chain trading agent competition. Electronic Commerce Research and Applications **4**(1) (2005) 66 – 84
18. Podobnik, V., Petric, A., Jezic, G.: An agent-based solution for dynamic supply chain management. Journal of Universal Computer Science **14**(7) (2008) 1080–1104
19. Tassabehji, R., Taylor, A., Beach, R., Wood, A.: Reverse e-auctions and supplier-buyer relationships: an exploratory study. International Journal of Operations & Production Management **26**(2) (2006) 166 – 184
20. Bichler, M.: An experimental analysis of multi-attribute auctions. Decision Support Systems **29**(3) (2000) 249–268
21. Vulkan, N., Jennings, N.R.: Efficient mechanisms for the supply of services in multi-agent environments. Decision Support Systems **28**(1-2) (2000) 5–19
22. Tong, H., Zhang, S.: A fuzzy multi-attribute decision making algorithm for web services selection based on qos. In: APSCC '06: Proceedings of the 2006 IEEE Asia-Pacific Conference on Services Computing, Washington, DC, USA, IEEE Computer Society (2006) 51–57
23. Bellosta, M.J., Kornman, S., Vanderpooten, D.: An agent-based mechanism for autonomous multiple criteria auctions. In: IAT, IEEE Computer Society (2006) 587–594
24. Bui, T., Yen, J., Hu, J., Sankaran, S.: A multi-attribute negotiation support system with market signaling for electronic markets. Group Decision and Negotiation **10**(6) (November 2001) 515–537