Computational Feedback Mechanisms for Iterative Multiunit Multiattribute Auctions

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ABSTRACT

Traditionally firms aiming to achieve competition among suppliers have used sealed bidding procedures in their procurement processes. However, the advances in computational technologies now allow companies to use different and more complex auction mechanisms for their sourcing needs. The multiattribute auction is a mechanism that allows negotiation over multiple characteristics of a contract including price as well as non-price attributes. Expected gains include faster negotiation, higher market transparency, and greater allocative efficiency. In this paper, we study the problem of improving information exchange in such auctions. We develop a model of a procurement auction in which the sales item is defined by multiple attributes. We consider the case of partial preference revelation where the buyer provides some feedback to the bidders to aid in their bid formulation but does not disclose her utility function in its entirety. We propose a feedback technique that is based on bid ranks and conduct laboratory experiments to explore the impact of such feedback on bidder strategies and performance. Based on our analysis of obtained experimental data, we propose additional advanced feedback metrics.

Keywords: Auctions, multiattribute auctions, feedback, experiments, bidder behavior.
I. Introduction

Traditional auction mechanisms have found widespread use in the last few years as tools for supporting and automating negotiations on the internet. Corporate procurement auctions often require the supplier to fulfill several required characteristics of a contract in addition to price. However, the negotiation allowed by the conventional auction mechanisms is based only on price. In other words, these auctions are not well suited for procurement problems (where commodities require detailed technical specifications), because they compel the buyers to commit to specific configurations of the product in advance. Multiattribute auctions alleviate this problem by allowing negotiation over price as well as non-price attributes. For example, in a procurement problem a multiattribute auction can allow different suppliers to compete over qualitative attributes, such as color, weight, and terms of delivery, in addition to price. In such cases, multiattribute auctions can achieve higher market efficiency through better information exchange of buyer’s preferences and suppliers’ capabilities, compared to price-only auctions. Other expected gains include faster negotiation and higher market transparency.

Since multiattribute procurement auctions are strategic in nature, the information exchange that takes place between the auctioneer (the buyer) and the bidders (suppliers) is of significant importance. A supplier may not want to reveal his cost function in order to maintain his margin, and the buyer would also not want to reveal her utility function in order to foster more competition. Thus, the nature of feedback provided to the bidders forms a critical element of multiattribute auctions. While a few researchers have looked at the problem of optimum information architecture in multiattribute auctions, almost all of them have only considered single-unit single-sourcing scenarios (Strecker 2003; Chen-Ritzo et al. 2005). We address a more complex problem, where the buyer requires multiple units of a commodity that he could
potentially source from multiple vendors. This is referred to as multiunit multiattribute auction with multiple sourcing.

In this paper, we investigate the effect of the current ranking of a bid as a feedback metric to aid bidders in such complex environments, through several lab experiments. Based on our analysis of the data from these experiments, we develop several additional computational feedback metrics that we believe will be more useful for the participants in such auctions. Our model consists of a buyer, who wants to procure a fixed number of identical units of a commodity with negotiable non-price attributes from multiple vendors. The buyer has her utility function that she uses to rank the bids, and the bidders have their own profit functions. The winners are determined by first-score, i.e., the bidders who win the auction are required to deliver the exact specifications mentioned in their respective bids. Under this scenario, we explore the following research questions: (a) What type of information should the buyer reveal in order to aid bidders in their bid formulation? (b) How do the suppliers interpret the feedback that they receive? (c) What is the likely bidding behavior of the suppliers? (d) How do the suppliers determine their best bids? In this paper, we provide results from several laboratory experiments, with human subjects, which were designed to study the impact of the rank feedback metric on the individual as well as aggregate bidding behavior of the suppliers. The empirical results provide insights for enhancing bidding and auction efficiency in multiunit multiattribute auction with multiple sourcing.

II. Related Work

Multiattribute auctions as models for procurement were first studied by Che (1993). He studied an auction protocol in which the negotiation was based on price as well as quality in a sealed-bid setting. He assumed that each seller was characterized by only one private cost parameter, which
the buyer was assumed to know. Branco (1997) extended this model by introducing cost correlation among bidding firms. Both Che and Branco assumed that the buyer has perfect knowledge of the bidders’ cost structures. Bichler et al. (1999) used a similar utility-function approach to study some internet-based implementations of multiattribute procurement auctions. They outlined some theoretical questions associated with multiattribute auctions and also described an implementation of the mechanism. Beil and Wein (2003) considered iterative multiattribute auctions where the buyer changed his scoring rule during the auction based on bids in the previous rounds. However, in this paper we consider multiattribute auctions that are based on an explicit model of buyer’s preferences.

Bichler (2000) compared the efficiencies of multiattribute and price-only auctions through laboratory experiments and he found no significant difference. In these experiments, Bichler revealed the entire scoring function used by the buyer. Strecker (2003) conducted two sets of English auction experiments with two qualitative attributes, where the buyer’s scoring function was fully revealed in one of the auctions and not revealed at all in the other. He found full revelation to increase both allocative and Pareto efficiency of the auction. Similarly, in several experimental studies, Koppius and Heck (2003) found that revealing more information about buyer’s preferences improved the auction performance in terms of Pareto efficiency. However, according to Pinker et al. (2003), these results may not be practical, given that most firms seek to maximize their own utility rather than achieve economic efficiency for a market, and given that firms may also be reluctant to directly reveal their utility functions to competitors.

So, with more practical auctions in mind, we study cases where the buyer does not reveal her scoring function but provides several other pieces of information that would help the bidder in his bid formulation. The impact of this kind of feedback has recently been experimentally
studied by Chen-Ritzo et al. (2005). They found their restrictive feedback mechanism to increase both buyer utility and supplier profits compared to price-only mechanisms. In the single-unit sole-sourcing scenario studied by Chen-Ritzo et al., sellers were provided binary responses of whether their bids are winning or not, whereas in this paper we consider multiunit auctions with multiple sourcing, where we believe a relative ranking of the bids is a more appropriate form of feedback since multiple bidders might be winning at a given point in time.

III. Multiattribute Auction Environment

We simulate a multiunit multiattribute bidding scenario with \( m \) suppliers, a single buyer, and \( k \) identical units of a commodity defined by a quality attribute \( q \) in addition to its unit price \( p \). The quality attribute has hundred discrete abstract levels, denoted by \( q \in Q = \{0.01, 0.02, \ldots, 1.00\} \).

Since the buyer requires multiple units of the commodity which she can choose to source from any number of suppliers, quantity of the commodity is also negotiable along with the price and quality. In other words, a supplier’s bid in this auction consists of specifications for quality level, per-unit price, and quantity.

We use a standard non-linear valuation function for the buyer that monotonically increases in quality. This function is given by \( v(q) = A_0 q^{\alpha_0} \), where \( A_0 > 0 \) and \( \alpha_0 > 0 \) are quality-related constants for the buyer. The utility score function of the buyer is derived from the valuation function by subtracting the weighted price of the commodity. The utility of a bid non-linearly increases with quantity because typically the buyer prefers to buy as many units from a supplier as possible in order to minimize the transaction cost of procurement. The utility function is thus:

\[
U(p, q, n) = \left( A_0 q^{\alpha_0} - Bp^\beta \right) C n^\gamma,
\]
where $B > 0$ and $0 \leq \beta \leq 1$ are price-related constants and $C > 0$ and $\gamma \geq 1$ (since the marginal value of quantity is increasing) are quantity-related constants. Similar functions have been used by Chen-Ritzo et al. (2005) in their experimental environment.

The utility function translates the values of the attributes into a “utility score” that can be used to compare bids that are vectors of the three relevant attributes (i.e., quality, quantity, price). We allow partial bid fulfillment, which means that the suppliers can offer to supply any number of commodities $n \in N = \{1, \ldots, k\}$, but the buyer will make a decision on the number of units to procure from each of the winning sellers based on her utility function. We assume that the supplier will be ready to supply a partial order at the same unit price that he has quoted in his bid, which allows us to calculate the maximum per-unit utility that each bid generates and then rank bids accordingly. Without this assumption, winner determination would entail solving a combinatorial problem. The outcome of the auction consists of a list of winning suppliers along with the final quality level, the final price that each of them quoted, and the number of units of commodity the buyer decides to procure from each of the winners, based on his per-unit utility.

Each supplier’s production function is a standard non-linear function, monotonically increasing in quality. We model the cost function as $c_i(q) = A_{1i}q^{\alpha_{1i}}$, where $A_{1i} > 0$ and $\alpha_{1i} > 1$ are quality-related constants for the $i^{th}$ supplier. Each supplier is technologically equipped to produce any quality level from set $Q$. Since higher quality product requires higher effort and resources, the maximal quantity of production is dependent on the quality of produced goods according to the production function: $n_i(q) = D - A_{2i}q^{\alpha_{2i}}$, where $A_{2i} > 0$ and $\alpha_{2i} > 1$ are quality-related constants for the supplier and $D > 0$ is a threshold stipulating the maximum units of the commodity technologically possible to produce. The profit function of the suppliers who are awarded a contract is given by
\[ \pi_i(p,q) = \left( p - c_i(q) \right) n_i(q) = \left( p - A_i q^{\alpha_i} \right) \left( D - A_2 q^{\alpha_2} \right). \]

Note that the number of units that a supplier is capable of producing depends on the chosen quality level and hence the quantity term does not explicitly appear in the profit function.

Bid \( b \) consists of specifications for quality level, price, and quantity; i.e., \( b = (p, q, n) \) where \( p \in P, q \in Q, \) and \( n \in N. \) We developed a feedback metric called RANK to aid bidders in their bid formulation. Each submitted bid is evaluated by the buyer with the objective of maximizing her utility. Following this evaluation, the buyer ranks all bids in descending order of per-unit utility derived from each bid. This information, \( \text{RANK}(b) \), is then disclosed to each bidder in response to a bid submission. The higher the utility score per unit of provisionally allocated quantity, the higher the \( \text{RANK}(b) \). Since this is a multiunit auction with partial fulfillment possibility, multiple bidders can have the same rank if the per-unit utility scores of their last bid happen to be the same. Note that the bidders ranked second or lower do not necessarily lose the auction. If the highest-ranked supplier is unable to fulfill the entire order, the lower-ranked suppliers will win a portion of the order. Since this is a first-score auction (analogous to first-price auctions for price-only cases), the winner has to match the exact quality and price listed in his winning bid. So it might pay to win the auction ranked second or even lower because in that case the supplier needs to match lower levels of utility than the supplier(s) ranked higher.

IV. Experiments, Data, and Results

We conducted two experimental sessions: the first consisting of ten auctions and the second consisting of seven. Each session was conducted with the same set of bidders to study the learning effects of repeated auction participation on the bidder performance. Since this is a complex auction environment, we hypothesized that bidder performance would improve with experience. The bidders represented the suppliers, and a computer program, with a built-in
utility function for evaluating bids and providing appropriate feedback, played the role of a buyer. The supplier profit functions and the buyer utility functions were identical in the two sessions as was the number of units of the commodity (to be procured by the buyer) per supplier. This was done to ensure that the optimal allocation levels were equivalent in the two sessions for easier comparison of results. The subjects were MBA students whose participation in the auction was part of a project work for a class with the performance in the auction counting towards the final grade. The parameter values in our model were chosen as follows: $A_0 = 10$, $A_{1i} = 100$, $A_{2i} = 800$, $B = 2.4$, $C = 1$, $D = 1000$, $a_0 = 0.6$, $a_{1i} = 2$, $a_{2i} = 2$, $\alpha = 0.3$, $\gamma = 1.05$. These values were selected so as to provide the utility and cost functions their desired characteristics, as discussed above, and also to set the Pareto-optimal allocations at desired levels in order to accurately measure bidder performance. In particular, the parameters were chosen in such a way that the maximum possible profit margin for every supplier was 15%, beyond which buyer utility would be negative. More precisely, in both experimental sessions the Pareto-optimal profit was set at approximately $3,000, which could be earned if each supplier bid at the quality level of 1.00 and quantity level 200, with about 15% profit margin. This was Pareto optimal because no bidder could gain by deviating from these specifications without hurting another bidder’s earnings. However, myopic profits for each supplier could be maximized at a quality level around 0.80.

![Figure 1](image1.png)  ![Figure 2](image2.png)

**Figure 1.** Production functions of suppliers.  **Figure 2.** Utility & per-unit utility curves at 5% margin.
The supplier production functions in terms of cost, \( c_i(q) \), and quantity, \( n_i(q) \), are graphically represented in Figure 1. The downward-sloping quantity curve indicates that, as a supplier improves the quality of his product, he would be able to produce fewer units due to resource constraints. Figure 2 shows the total utility and per-unit utility curves for different quality levels with the price level chosen by the supplier so as to extract a 5% margin. The quantities were assumed to be the maximum that could be produced at each quality level. Notice that, unlike the total utility function, the per-unit utility function is monotonically increasing with quality due to the fact that fewer units could be produced at increasing levels of quality. This was the reason we chose to use per-unit (as opposed to total) utility as the determinant of rank.

Nearly 350 bids were placed in each auction on average. The data enables us to analyze the individual bidding behavior of each supplier as well as the aggregate behavior of the competing suppliers. We specifically wanted to observe the strategies followed by the suppliers as they developed an understanding of the environment and formulated bids in response to feedback. It was observed in both sessions that, as bidders gained experience with the setup, they converged towards the optimum in the later auctions. For example, the average quality level bid by the suppliers in the first auction was 0.82 whereas the average quality level in the last auction of both sessions was 0.98 (the optimum was 1.00). Moreover, the Euclidean distance from the optimum in terms of quantity allocation\(^1\) decreased by 91% between the first and the last auctions in the first session and by 54% in the second session. Thus, we find empirical evidence in support of our hypothesis that performance in multiattribute auction improves with experience.

A notable trend in our experiments was a significant increase in buyer utility over a series of auctions. In particular, the average buyer utility of the last three auctions was consistently higher

\[^1\] \[ \sqrt[1]{\sum_{i=1}^{m} (z - n_i)^2}, \] where \( z \) is the Pareto-optimal allocation and \( n_i \) is the final allocation for the \( i^{th} \) supplier.
than that of the first three. This came at the expense of seller profits as shown in Table 1. The bidders found it cognitively complex to optimize along multiple dimensions of the bid simultaneously – it was generally observed that in each auction bidders kept the quality constant and decreased the margin in order to improve their rank. This led to reduced margins in the later auctions in both sessions. This behavior was one of our main motivations for developing more sophisticated feedback mechanisms discussed in the next section.

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<th>Table 1. Bidding statistics</th>
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<td>Average quality levels</td>
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<td>Average buyer utility</td>
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<td>Average total sellers' profit</td>
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Since this was a first-score auction with multiple sourcing, the supplier ranked second or even third had a good chance of winning and earning potentially more profit than the top-ranked supplier. Therefore, we expected to see significant competition for the second or third ranks as that would have earned the most profits. Although some suppliers used this strategy, this was not a consistent pattern among all of them. One possible reason is that we only provided the rank information without any feedback on whether the suppliers were winning anything at that specified rank. So, the suppliers could only be sure of winning something when they were ranked first. Hence, RANK was not adequate to support competitive and transparent bidding in this kind of environment.

V. Advanced Computational Feedback

In light of our analysis of the data obtained from the experiments, we have developed several other feedback metrics that we think would be most effective in multiunit multiattribute auctions.
Specifically, we noticed that in every auction the bidders were iteratively trying to figure out the marginal bid to reach a winning position by making slight improvements to the previous bid. This proved to be a painstaking process for the suppliers with each of them placing more than 60 bids on average in each auction. So, we propose to provide vectors of marginal values for the three negotiable attributes to the suppliers in order to help them formulate their optimal bid at any given state of the auction. These are: (a) Price Update (PU) – a vector of possible prices to achieve each rank, where quality and quantity levels remain the same as in the last bid; (b) Quality Update (QU) – a vector of possible quality levels to achieve each rank, where price and quantity levels remain the same as in the last bid; and (c) Quantity Update (NU) – a vector of possible quantity levels to achieve each rank, where price and quality levels remain the same as in the last bid. Note that these feedback metrics provide personalized information – the above vectors would be tailored to the bid specifications of each supplier. Each supplier’s optimal strategy would be to weigh these three pieces of information against his own profit function and revise his bid accordingly so as to extract maximum profit. Both from theoretical and practical standpoints, it would be useful to study the impact of each additional piece of feedback on the utilities of the buyer and sellers as well as on the overall efficiency of the auction. Note that furnishing such real-time customized feedback is possible due to the largely improved computational techniques that we have at our disposal today.

VI. Conclusions

Multiattribute auctions form a promising extension to the standard auction framework. Such auctions can support efficient procurement of configurable goods and services through the use of more expressive bids and competition across suppliers. The characteristics of multiattribute auctions make it a very likely candidate for use in B2B marketplaces. In this paper we presented
some preliminary analysis towards our complete understanding of several central issues in the application of multiattribute auctions for procurement problems. Our research contribution is threefold: (1) an engineering contribution of developing decision support capabilities that can assist bidders in effectively evaluating the current state of multidimensional bidding environments, (2) an empirical contribution of testing the effectiveness of the decision support system using the test bed approach of experimental economics, and (3) a theoretical contribution of understanding the behavior of participants in complex auctions. The results from our experiments provide us valuable insights into bidder strategies and the nature of information that can help bidders in their bid formulation. Further experiments will allow us to statistically test our propositions comparing the results from multiattribute auctions with price-only auctions. Future research can build on these results to develop appropriate information architecture for specific auction objectives.

References