Solving a Seal-Bid Reverse Auction by Fuzzy Multiple objective programming

Chi-Bin Cheng
Dept. of Information Management, Tamkang Univ., 151 Ying-chuan Road, Tamsui, Taipei County, Taiwan
cbcheng@mail.tku.edu.tw

Yu-Ru Syau
Dept. of Information Management, National Formosa University, 64 Wunhua Rd., Huwei Township, Yunlin, Taiwan
yrsyau@nfu.edu.tw

Rung-Tsung Tzeng
Dept. of Information Management, National Formosa University, 64 Wunhua Rd., Huwei Township, Yunlin, Taiwan

Abstract

This study solves a sealed-bid and multiple issue reverse auction problem. At the supplier side, the bidding process is formulated as a fuzzy multiple objective programming to assist the supplier determining its optimum offer, while at the buyer side, the selection of the best offer from suppliers is considered as a multiple attribute decision making problem and is solved by the TOPSIS method. The solution to the supplier's fuzzy multiple objective problem is obtained by a heuristic algorithm that adjusts the production plan to fulfill the buyer's demand based on the information of current master production schedule and available-to-promise inventory.

Keywords: Reverse auctions, Electronic procurement, Available to promise, Fuzzy multiple objective programming, Multiple attribute decision making, TOPSIS.

1 Introduction

Within the B2B e-Commerce, many firms have recognized the opportunity of cost reduction via the use of online reverse auctions. Online reverse auctions, also called *electronic auctions* or simply *reverse auctions* [7], have become a common method to source goods and services by Fortune 2000 companies since 1995 [15]. Buyers believe that suppliers are motivated to use reverse auctions because of four benefits: the promise of increased business, market penetration, reduced cycle time between bidding and awarding of business, and better production scheduling and inventory management due to less time lost between the bid and the actual sale [12].

Reverse auctions are the traditional auctions in reverse [12]. In the traditional forward auctions, a seller offers a product for sale to the highest bidder, while in the reverse auctions a buyer offers a tender or contract for the supply of specific goods or service. In terms of the suppliers' authority to view their competitors' bids, there are two types of auction: sealed-bid and open-bid. Open- and sealed-bid auctions represent opposite ends of a spectrum of auctions: open-bid auctions have full price visibility, whereas sealed-bid auctions have no price visibility for bidders. Additional details of the online reverse auctions can be found in [5].

Reverse auctions have become a popular e-procurement mechanism for being a driver to bargain with suppliers to reduce the unit price of purchased products. Thus, most existing online auctions mainly focus on a single issue, namely price of the merchandise [9]. Despite report of million dollars of saving with reverse auctions by companies such as Quaker Oats and SmithKlineBeecham [2], the empirical study by Emiliani and Stec [8] on the aerospace industry pointed out that reverse auctions have failed to live up to expectations with regard to global sourcing and unit price reduction. Online reverse auctions, rooted in power-based price bargaining, offer no real benefits for buyers or sellers [6].

To maintain the efficiency of reverse auctions and to avoid its disadvantages due to sole price bargaining, the present study proposes a reverse auction framework with multiple issues. The multi-issue referred here means that the bid is represented by many attributes such as quality grade, warranty, product features, and

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terms of delivery and payment, etc., other than price. Previous research did not always make a distinction between issues and attributes [14]. In this paper we will use these two terms interchangeably. Price bargaining is a distributive bargaining, which involves the division of a fixed resource and results in a zero-sum situation. On the other hand, the use of multi-issue in a negotiation is referred to as an integrative bargaining [16], and it results in a variable-sum situation in which the negotiators cooperatively face a common problem. A multi-issue setting enables trade-offs between different issues, under the assumption of unequal weights between issues, such that both parties can reach a mutually beneficial agreement [3].

Teich et al. [14] argued that bidders in reverse auctions were in need of support regarding how low to bid; however, how to support bidders to make appropriate bids has not received much attention in the auction literature. Thus, the reverse auction framework proposed in this paper not only consider the winner determination problem but also comprises an optimization model to assist suppliers construct the bid that is most beneficial to themselves and, at the same time, most promising to win. Our framework is therefore consists of two separate models, a multiple attribute decision making (MADM) for the buyer to evaluate the bids submitted by suppliers, and a fuzzy multiple objective decision making (FMODM) for the suppliers to determine their bids. The two models are solved from the buyer and the supplier's perspectives, respectively, to optimize their own interests.

2 Modeling of the Reverse Auction Problem

This study considers a sealed-bid reverse auction, where the bid is presented by multiple attributes other than price. The auction is one-sided (one buyer and multiple suppliers), and only one supplier can win the bidding, i.e. the entire demand is purchased from a single supplier. The proposed reverse auction process is illustrated in Figure 1, in which the steps are described as follows.

Step1. The buyer sends the request for quotation (RFQ) to qualified suppliers.

Step 2. Suppliers use a bid generation model to check their own production status and generate bids that they think are most beneficial and promising with respect to the buyer's RFQ. Bids are then submitted to the buyer.

Step 3. The buyer evaluates suppliers' bids by a multiple attribute decision making (MADM) method.

On receiving the bids from suppliers, the buyer can employ the MADM method to select the best bid according to the preference structure, e.g. weights of attributes, given by the buyer. The supplier will then check its production schedule, capacity constraints, and cost structure, and use the bid generation model to determine the optimum content of the bid. Though the present study suggests a common model for all suppliers, in the real-world practice each supplier of course can construct its own model and preference structure. The detailed models of the above auction process are discussed in the following subsections.

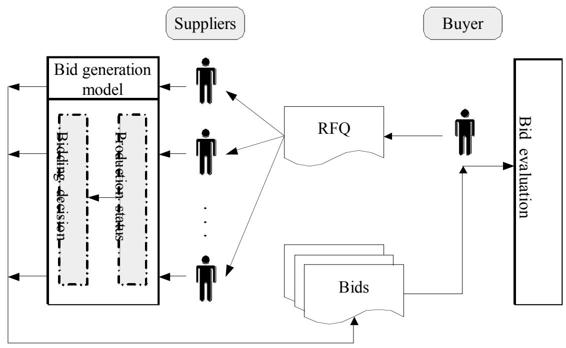

Figure 1: Reverse auction process

2.1 Buyer's decision-making model

For simplicity, the present study assumes two issues in the auction. Each bid from suppliers is represented by a pair, (unit price, delivery time). The adoption of these two issues are based on previous research on competitive bidding [4] that showed the best performance to win an order from a customer is related to two indicators: product price, and delivery lead time.

Let the returned bid of the i-th supplier be denoted by (p_i, t_i), where p_i is the unit price offered by the supplier and t_i is the promised time of delivery. When evaluating the bid, the delivery time, t_i, is converted to the difference between the supplier's delivery time and the buyer's request delivery time specified in the RFQ. For convenience, we define this difference as a delay and denote it by d_i. This conversion enables the comparison of bids on the same basis. Let e be the expected delivery time of the buyer, then the delay d_i is computed by the following equation.

$$d_i = \begin{cases} 0, & \text{if } t_i - e \geq 0 \\ t_i - e, & \text{otherwise.} \end{cases} \quad (1)$$

The presentation of the bid is now changed to (p_i, d_i).

Bid evaluation by the buyer is to choose the best bid among all suppliers. This therefore becomes a multiple attribute decision making problem. The present study employs the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to solve this MADM problem. The TOPSIS was developed by Hwang and Yoon [10], based on the concept that the chosen alternative should be the shortest distance from the ideal solution and the farthest from the negative-ideal solution.

The so-called ideal solution in TOPSIS is the combination of the best values of individual attributes among all alternatives. For example, there are three bids, ($100, 3 days), ($120, 0 days), and ($110, 1 days), then the ideal solution to the buyer is ($100, 0 days), while the negative-ideal solution is ($120, 3 days). The concept of ideal solution is analog to the enquiry behavior of buyer in real-world. The buyer generally uses the information from other vendors to bargain with a target supplier. In such a case, the buyer often picks up those issues that favor he/she by other vendors as chips to bargain with the target supplier.

2.2 Supplier's decision-making model

The supplier's primary objective of course is to win the contract. The probability of winning the contract is definitely associated with the content of the bid. When the unit price is lower and the delay is smaller, then the probability to win the contract is greater. However, lower price and shorter lead-time often imply increasing costs and shrinking profit. For the supplier to maintain its competitiveness, it must also watch the profit margin when striving to obtain the contract. Thus, the present study considers the bidding decision as a trade-off between the supplier's profit and the possibility to win the contract. This results in a multi-objective formulation. The notations used in the model are:

Objectives:

π: the gross profit generated from the bid.

d: the delay; that is, difference between the supplier's proposed delivery time and that specified in the buyer's RFQ.

Decision variables:

y_k: the quantity that is acquired from the k-th production method, k =1, 2, 3, 4 where y_1 is the inventory, y_2 is the current MPS; y_3 means new production lots that uses the regular capacity will be added; and y_4 denotes a crash production using overtime.

p: the unit price to bid the contract.

Parameters:

τ: total production cost of the bid.

c_k: the unit cost associated with the k-th production method, k =1, 2, 3, 4.

$\tilde{u}$: the upper bound of the unit price that the suppler considers the bid is hopeless if he/she proposes a unit price greater then $\tilde{u}$; since it is difficult to give a precise value, this parameter is defined as a fuzzy set.

$\delta(\cdot)$: this notation indicates that the resultant delivery time is a function of the production plan.

Q: the demanded quantity specified in the RFQ.

The mathematical model for the supplier to determine the bid is then formulated as: (FMODM)

$$\text{Maximize } \pi \quad (2)$$

$$\text{Minimize } d \quad (3)$$

Subject to:

$$p \leq \tilde{u} \quad (4)$$

$$\pi = p - (\tau/Q) \quad (5)$$

$$\tau = c_1\, y_1 + c_2\, y_2 + c_3\, y_3 + c_3\, y_4 \quad (6)$$

$$d = \delta\,(y_1, y_2, y_3, y_4) \quad (7)$$

$$y_1 + y_2 + y_3 + y_4 = Q \quad (8)$$

$$y_1, y_2, y_3, y_3, p \geq 0 \quad (9)$$

The constraint (4) presents the supplier's belief regarding the chance of wining the contract with different prices. It is difficult to give a precise value to elicit such belief. On the other hand, fuzzy sets are suitable to model this subjective judgment. Thus, constraint (4) is described by a membership function as depicted in Figure 2(a), where the membership

$\mu_{\text{price}}(p)\in[0, 1]$ expresses the supplier's belief of the possibility to win the contract with price p. The values of p^{inf} and p^{sup} in Figure 2(a) are assigned by the decision-maker. The gradual transition of the belief defined in Figure 2(a) alleviates the difficulty of subjective judgment.

The fuzzy constraint in the above model results in a fuzzy multiple objective decision making problem. A simple and commonly used method for fuzzy decision-making is the max-min approach suggested by Bellman and Zadeh [1]. To use this approach we first define the satisfactory degree of the objectives by membership functions. The membership functions defined for π and d are shown in Figures 2(b) and 2(c), respectively. Again, Figure 2(c) is interpreted as the possibility of wining the contract with different d. It is noted that if the membership function in Figure 2(b) is defined on the profit rate (i.e. π/p) rather than on the profit itself, it would be more convenient for the decision maker to express his/her judgment. However, for simplicity we still define the membership function on the profit directly. The parameters in these two membership functions are given by the decision maker, too.

The fuzzy decision-making of Bellman and Zadeh [1] is introduced as follows. Let G_i, i=1,…, m, be the m fuzzy goals and L_j, j=1,…,n, be the n constraints defined on the decision space Z. The satisfactory degree or the membership value of the fuzzy decision D is defined as a conjunction of individual satisfaction (also defined through membership functions) of all fuzzy goals and constraints. That is,

$$\mu_D(z) = \mu_{G_1}(z)\otimes\mu_{G_2}(z)\otimes\cdots\otimes\mu_{G_m}\otimes\mu_{L_1}(z)\otimes\mu_{L_2}(z)\otimes\cdots\otimes\mu_{L_n}(z),$$

where $z\in Z$ and $\otimes$ is a conjunction operator. The problem is then becomes to maximize $\mu_D(z)$. If there exists a z^* such that $\mu_D(z^*) = \max_z\{\mu_D(z)\}$, then z^* is the optimum solution of the decision D. When the conjunction operator in the above equation is defined as a min operator, then the solution is in fact obtained by a max-min approach. Consequently, by applying the max-min approach to the FMODM problem, the optimum solution is obtained as

$$\mu_{\text{FMODM}}(\text{y}^*) = \max_{\text{y}}\{\min\{\mu_{\text{profit}}(\pi), \mu_{\text{delay}}(d), \mu_{\text{price}}(p)\}\} \tag{10}$$

where y = [y_1, y_2, y_3, y_4, p] and y satisfies constraints (4) ~ (9). The solution obtained by Equation (10) provides a compromise among objectives and constraints.

Since it is difficult to obtain an explicit function for the constraint (7) in the FMODM formulation, we are unable to solve the problem directly. Instead, a heuristic algorithm is formulated in the next section to solve this FMODM problem.

3 Heuristics for solving the FMODM

The first objective in the FMODM is to maximize the gross profit, which is associated with the price and the production decisions. Two ways to raise the profit is to set a higher price and/or to find a production plan with lower cost. However, a higher price may reduce the chance to win the contract, and a lower cost production plan often implies less effort in meeting the buyer's demand of delivery time, which in turn also decreases the winning chance. The two objectives are apparently conflict in nature. Thus, the most appropriate bid is the one that make compromise between the two objectives. This observation is coincided with Equation (10). The algorithm developed to solve the FMODM is based on such a concept. The flow chart of the proposed algorithm is illustrated in Figure 3.

In the algorithm, each generated proposal (i.e. production plan and price) is evaluated through the membership functions of profit, delay, and price. At the stage of price determination, since the production plan has been determined, the maximization of μ_{FMODM}(y) is in fact equivalent to

$$\mu_{\text{FMODM}}(p^*) = \max_{p}\{\min\{\mu_{\text{profit}}(\pi), \mu_{\text{delay}}(d), \mu_{\text{price}}(p)\}\}$$

The newly generated proposal and its corresponding μ_{FMODM}(y) are recorded. The algorithm continues seeking feasible proposals until no more such proposals will be generated, then all the generated proposals will be compared according to their values of μ_{FMODM}(y). The one with the greatest μ_{FMODM}(y) value is selected and proposed to the buyer. The question now is how to generate production plans? We have limited our production to three methods, namely by the current plan, changing the production plan with available capacity, and a crash production with overtime capacity. The first method is most economic, because nothing needs to be changed. The second one will cost more, because not only changing the planned production but also requiring additional setup costs for new production. The last method is most expensive, since the regular hour capacity is not enough and it has to use the overtime for setting up new production. The buyer's demand, Q, is thus fulfilled by the combination of previous inventory and the three production methods.

The present study adopts the concept of Available to Promise (ATP) inventory to find possible production plans. ATP is the uncommitted portion of a company's inventory and planned production, maintained in the master schedule to support customer order promise.

The ATP calculation used here is the look-ahead procedure, which involves summing booked customer orders period by period until (but not including) a period in which there is a Master Production Schedule (MPS) amount. The MPS is a schedule to indicate the quantity and timing of planned production. The concept of ATP is introduced next.

3.1 Available to promise

Considering a master schedule for the next eight weeks indicates the quantity and delivery times for a product as shown in Table 1, in which the schedule shows the forecasted demand and real customer orders (i.e. committed orders). The initial inventory prior to the schedule is 100 units. Let I_k be the projected on-hand inventory at the k-th week, and F_k be the forecasted demand and O_k be the committed customer order at the k-th week, respectively. The projected on-hand inventory is calculated by:

$$I_k = I_{k\text{-}1} - \max\{F_k, O_k\}.$$

Projected on-hand inventories are shown in Table 1 for the first four weeks until the projected on-hand amount becomes negative.

When the projected on-hand inventory becomes negative, a planned production (i.e. MPS) is assigned. Assuming the production lot size is 60 units, the MPS for the master schedule of Table 1 is determined as shown in Table 2. The ATP appears in each interval between two consecutive MPS. The amount of the ATP is the initial inventory or the MPS deducts the cumulated customer orders before the next MPS as shown in Table 2. For instance, the ATP in Weeks 1~3 is 100-(20+20+5)=55, and is 60-(5+25)=30 in Weeks 4~5. If there is a new order with demand of 80 units coming in and requires the delivery by Week 5, the sales representative can promise the delivery immediately because the cumulative ATP is (55+30)>80. As additional orders are booked, they would be entered in the schedule and the ATP amounts would be updated. In case the order is 90 units in the aforementioned example, then either the sales representative asks the buyer extending the delivery to Week 6, or the production division will have to change the production plan.

Table 1: Master schedule and projected on-hand inventories

	Week							
	1	2	3	4	5	6	7	8
Forecast	10	30	30	30	30	60	30	30
Committed orders	20	20	5	5	25	15		
Predicted on-hand inventory	80	50	20	-10				

Table 2: MPS and ATP

	Week							
	1	2	3	4	5	6	7	8
Forecast	10	30	30	30	30	60	30	30
Committed orders	20	20	5	5	25	15		
Predicted on-hand inventory	80	50	20	50	20	20	50	20
MPS				60		60	60	
ATP	55			30		45	60	

Changes to the master production schedule can be disruptive particularly changes to the early portions of the schedule. Stability of the schedule is important, because turbulent changes imply additional costs and the nearer the change is the higher the cost. Thus, the changes to the earlier portions of the schedule are generally prohibited. Master production schedules are often divided into four phases referred to as the time fences, namely the frozen zone, the firm zone, the full zone, and the open zone [13, p.628]. The first phase usually contains the first few periods of the schedule. Once it is established, changes cannot be made without the permission from the highest levels in an organization. In the second phase, changes are still disruptive; management views the schedule as firm, and only exceptional changes are made. In the third phase, although changes do impact the schedule, their effect is less critical and they are made if there is a good reason of doing so. The final phase is considered as open, meaning that most of the capacity has not been allocated.

3.2 Production plan generation

The generation of production plans follows the following scenarios.

Case 1: If the current MPS is able to meet the buyer's demand, i.e. the cumulative ATPs prior to the delivery time requested by the buyer is greater than or equal to the buyer's demand, then nothing will be changed. Since this plan is the most economic one ever possible, the search of alternatives is terminated.

Case 2: If Case 1 is not existed, then one can still choose not to change the current MPS but extend the delivery time instead. This new delivery time is found by accumulating the ATPs until the period that the cumulative amount is greater than or equal to the buyer's demand.

Case 3: To explore more alternative plans, we can try to advance the delivery time one period ahead of the plan found in Case 2, and then consider if the available capacity is sufficient to carry out this trial plan.

Case 4: The feasibility of a trial plan is checked by the available capacity by the delivery time of the trial plan. If the capacity is enough to produce the deficiency of ATPs, i.e. the difference between the buyer's demand and the cumulative ATPs, then additional productions will be added to the original MPS; otherwise, Case 5 is applied. To continue exploring alternative plans, the delivery time of the newly generated plan is advanced one period ahead again, and its feasibility is checked in the same manner. Case 4 is repeated until the trial delivery time is earlier than the original delivery time requested by the buyer.

Case 5: When the capacity is insufficient, trial production plans can still be achieved by using overtime to compensate the deficiency of the regular hour capacity. Again, the delivery time of this newly generated plan is advanced one period ahead, and Case 4 is repeated.

4 Conclusions

This paper has presented a framework for sealed-bid-multi-issue reverse auctions. In this auction setting, one buyer sends the RFQ to many suppliers and suppliers then return the buyer with bids represented by two attributes, namely price and delivery time. Bids are only visible to the buyer and the winner is determined in one-shot. The decision-making problems of the supplier and the buyer are solved by two respective models. The supplier's decision is formulated as a fuzzy multiple objective decision making problem, in which the bid is determined with the considerations of the supplier's capacity constraints, production costs, profit margin, and the chance to win the contract. At the buyer side, the problem is to determine the winning bid, which is referred to as the winner determination problem. The multiple attribute decision making approach, TOPSIS, is used to solve the problem.

Previous approaches for solving reverse auctions mainly focused on the winner determination problem at the buyer side. In the present study, we have considered the situation that suppliers and the buyer pursuit their own interests in the reverse auction, and formulated the decision-making problems based on their respective aspects. Such formulations enable suppliers to propose the most beneficial offers to them conditioning to their production status.

The proposed decision-making model of the supplier is solved by a heuristic algorithm based on the concepts of master production schedule and available-to-promise inventories. The master production schedule and available-to-promise inventories are commonly used in practice to handle customer orders. They are frequently updated by companies to reflect current production and inventory status. The use of these tools in our solution procedure provides the supplier an accurate estimation of his/her production costs and the delivery date to promise, and hence enables the supplier to construct bids that are profitable as well as probable to obtain the contract.

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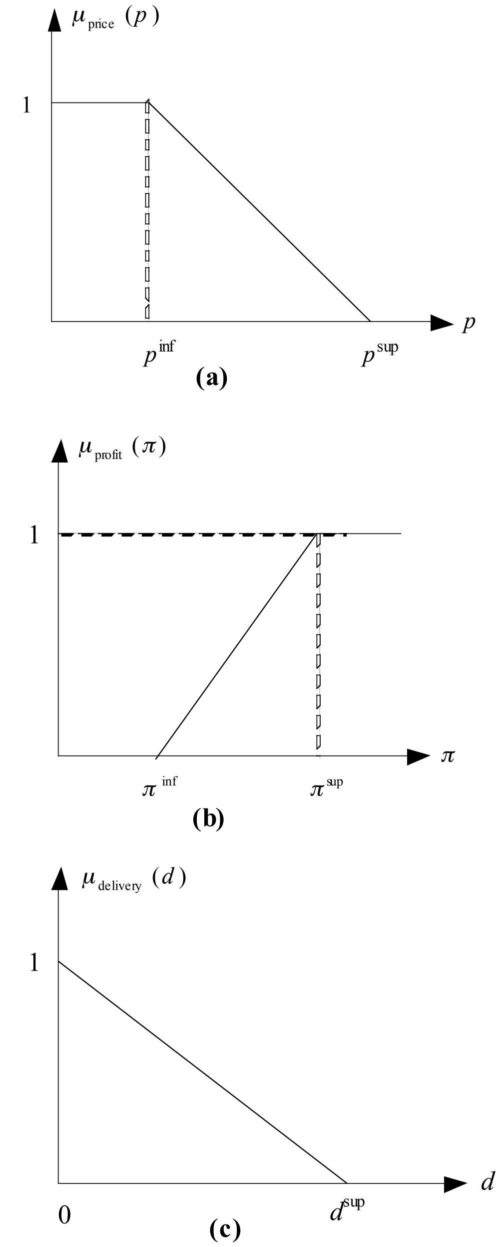

Figure 2: Membership functions of (a) *price*, (b) *profit*, and (c) *delay*

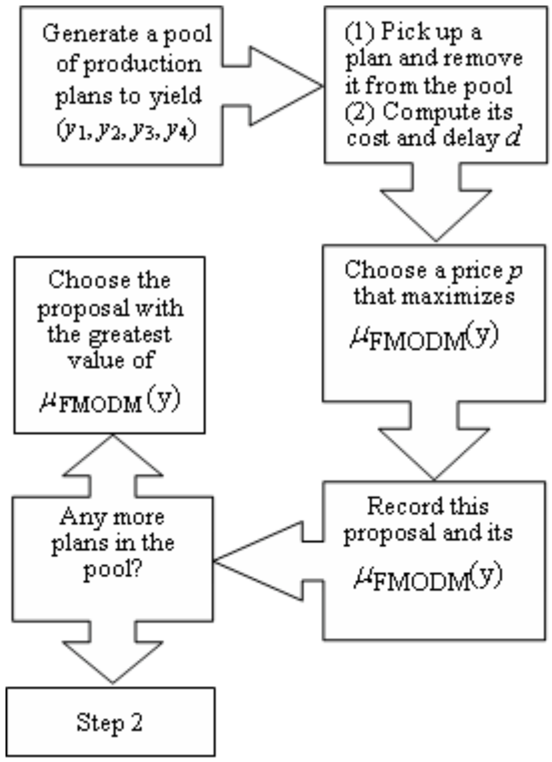

Figure: 3 Flow chart of the algorithm