e-Procurement Using Goal Programming*

S. Kameshwaran and Y. Narahari

eEnterprises Laboratory, Department of CSA
Indian Institute of Science
Bangalore-560012, India
{kameshn,hari}@csa.iisc.ernet.in
http://lcm.csa.iisc.ernet.in

Abstract. e-Procurement is an Internet-based business process for obtaining materials and services and managing their inflow into the organization. In this paper we develop multiattribute e-Procurement systems with configurable bids and formulate the bid evaluation problem as a linear integer multiple criteria optimization problem. Configurable bids allow multiple values for each attribute and for each value the bidder can specify price as a piecewise linear function of quantity. The suppliers can express volume discount bargaining strategy and economies of scale, using the above price function. The buyer can include several business rules and purchasing policies as side constraints in the optimization problem to evaluate the winning bids. We propose the use of goal programming techniques to solve the bid evaluation problem.

1 Introduction

The Internet and Internet-based technologies are impacting businesses in many ways. With the increasing pressure that companies are experiencing as markets become more global, Internet continues to play a critical role to speed up operations and to cut costs. e-Procurement is an Internet-based business process for obtaining materials and services and managing their inflow into the organization. This involves identifying, evaluating, negotiating and configuring optimal groupings of suppliers' bids, which are received in response to the buying organization's Request-for-Quote (RFQ).

The business logic used in current e-Procurement systems can be broadly categorized as: *reverse auctions*, *multiattribute auctions*, *optimization techniques*, and *configurable bids*. Reverse auctions select the supplier with the lowest bid price. They are simple, inexpensive and many commercial systems like SpeedBuy (http://www.edeal.com) can be deployed within hours. Though reverse auctions are successful in various cases [7], competing on price alone make the suppliers feel de-branded and commoditized. Moreover, as sourced goods increase in complexity, several aspects of supplier performance, such as quality, lead time, on-time delivery, etc. also need to be addressed.

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Multiattribute auctions based on multiattribute utility theory (MAUT) [8] for e-Procurement were first proposed in [1]. Multicriteria decision analysis techniques like MAUT are also used in bid analysis products from Frictionless Commerce (http://www.frictionless.com) and Moai Technologies (http://www.moai.c̃om). The buyer assigns weights to the attributes indicating their relative importance and has a scoring function for each attribute. A bid is scored by combining the weights and the scoring function in the weighted additive fashion [1, 3] and the bids are ranked according to their score. IBM Research's ABSolute decision engine [5] provides to buyers, in addition to standard scoring mechanisms, an interactive visual analysis capability that enable buyers to view, explore, search, compare and classify submitted bids. An English auction protocol for multiattribute items was proposed in [3], which again uses a weighted additive scoring function to rank the bids. *Multicriteria auction* proposed in [4] is an iterative auction which allows incomparability between bids and the sellers *increment* their bid value by bidding *more* in at least one attribute. To automate negotiations in multiattribute auctions, *configurable bids* were proposed in [2]. In configurable bids of [2], bidders can specify multiple values for each attribute and price markups for each attribute value, and the buyer can configure the bid optimally by choosing appropriate values for the attributes.

e-Procurement systems that promise a productive strategic sourcing should also take into account various business rules and purchasing policies like *exclusion constraints* (e.g. goods of supplier X cannot be received from location A), *aggregation constraints* (e.g. at least two and at most five winning suppliers), *exposure constraints* (e.g. at most forty percentage of total business to any supplier), *business objective constraints* (e.g. overall quality factor must at least be seven), etc. The above mentioned multiattribute auction mechanisms cannot handle such policies. Many commercial bid analysis products from companies like Emptoris (http://www.emptoris.com), Rapt (http://www.rapt.com), and Mindflow (http://www.mindflow.com) use optimization techniques like linear programming and constraint programming, where the business rules are added as constraints to the optimization problem. However, they are limited by their inability to express multiple objectives of the buyer in the bid evaluation process. The general objective considered in these models is *minimizing cost*, whereas other possible objectives like *minimizing lead time*, *maximizing on-time delivery*, and *minimizing part failure rate* are not considered.

From the above discussion, we can infer that the important requirements of an e-Procurement system are: (1) allowing bidders to bid on *multiple attributes*, (2) a rich bidding language like *configurable bids* to automate negotiations across multiple bids, (3) flexibility for allowing *business rules* and *purchasing logic* in bid evaluation, and (4) bid evaluation using *multiple criteria*. The current solutions satisfy only some of the above requirements. Bid optimization and analysis tool from Perfect (http://www.perfect.com) provides flexibility for incorporating business rules and uses multicriteria decision analysis technique for handling multiple attributes, whereas the multiattribute auctions proposed in [2] uses in addition configurable bids. In this paper, we develop an e-Procurement system for trading multiple units of a single good (not combinatorial) that meets all the above requirements. Our proposal differs from the current approaches in the following ways: (1) the configurable bids are more general, namely piecewise linear functions of price on quantity for each value of each attribute, (2) the bid evaluation problem is modeled as a multiple criteria optimization problem, and (3) the use of goal programming (GP) techniques for bid evaluation.

2 The Model

The e-Procurement system considered in this paper consists of the following phases: (1) *RFQ generation* and distribution by the buyer, (2) sealed *bid submission* by the suppliers during a predefined bidding interval, and (3) *bid evaluation* by the buyer (after the expiration of the bidding interval) to determine the winning bids and their optimal configuration. To illustrate the practical applicability of the model, we will use the procurement of single lens reflexive cameras as an example procurement scenario.

2.1 RFQ Generation

The RFQ consists of two parts: the header and the feature [5]. The header part contains relevant information such as an identifier, product name, issue date, quote due date, and the buyer information. The feature part specifies the set of attributes U and the admissible domain of E_u of each attribute $u \in U$.

RFQ Notation

$[\underline{b}, \overline{b}]$	Requested quantity range ($\underline{b} \leq \overline{b}$)
U	Set of attributes
E_u	Admissible domain of values for attribute $u \in U$

The attributes can consist of product features (like lens focus, flash), service features (like lead time, warranty), and supplier features (like stock values, manufacturing capacity). We allow for goods to be sourced from multiple suppliers. The domain E_u of attribute u can be either discrete (like varieties of flashes) or continuous (like on-time delivery probability).

2.2 Bid Submission

Configurable bids proposed in [2] allow bidders to specify multiple values for each attribute and markup prices (unit price) for each attribute value. The buyer can configure the product by choosing appropriate attribute values that suits his interests and demand. In this paper we consider configurable bids of following nature: for each attribute u, the bid j can specify a set of values $W_u \subseteq E_u$ and

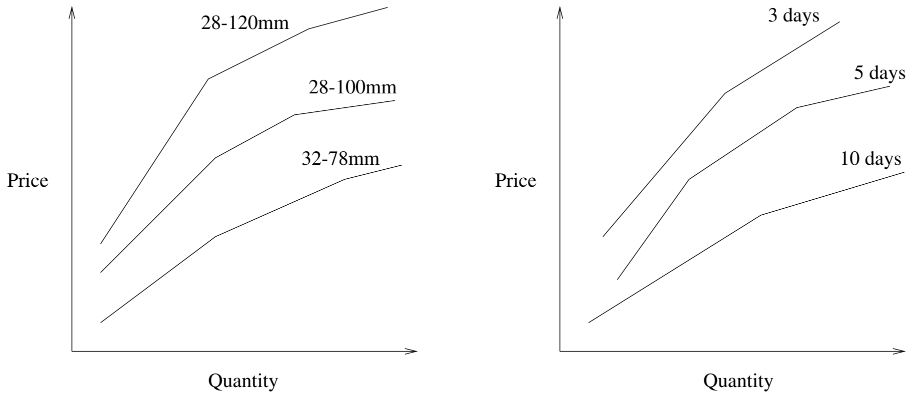

Fig. 1. Configurable bids for attributes *Lens Focus* and *Lead Time*

a continuous piecewise linear price function Q_{juw} defined over quantity range $[\underline{a}_{juw}, \overline{a}_{juw}]$ for each value $w \in W_u$. In [2] the price function of any attribute is linear with quantity, whereas we generalize it to piecewise linear. This generalization is reasonable as the cost structure of product features like accessories (lens focus and flash) and service features like lead time (transportation mode) depend on quantity. The supplier can easily express the volume discount bargaining strategy and the economies of scale using the above structure. Figure 1 illustrates the possible cost functions for attributes lens focus and lead time, for the camera procurement example.

Notation for Bid *j*

W_u	Set of values for each attribute $u \in U$
$[\underline{a}_{juw}, \overline{a}_{juw}]$	Supply quantity range available for attribute u with value w
Q_{juw}	Piecewise linear cost function for attribute u with value w defined over $[\underline{a}_{juw}, \overline{a}_{juw}]$
Q_{juw}	$\equiv ((\delta^0_{juw}, \ldots, \delta^{l(juw)}_{juw}), (\beta^1_{juw}, \ldots, \beta^{l(juw)}_{juw}), n_{juw})$
$l(juw)$	Number of piecewise linear segments in Q_{juw}
δ^*_{juw}	Breakpoints at which the slope of Q_{juw} changes
β^s_{juw}	Slope of Q_{juw} on $(\delta^{s-1}_{juw}, \delta^s_{juw})$
n_{juw}	Price at $\underline{a}_{juw}$

The price function Q_{juw} shown in Figure 2 is the total price (not the unit price) at which the bidder is willing to trade as the function of quantity. The function shown in the figure can be compactly represented by tuples of break points and slopes $((\delta^0_{juw}, \ldots, \delta^{l(juw)}_{juw}), (\beta^1_{juw}, \ldots, \beta^{l(juw)}_{juw}), n_{juw})$ where $l(juw)$ is the number of linear segments and n_{juw} is the price at $\delta^0_{juw} = \underline{a}_{juw}$. The break points $\delta^0_{juw}(= \underline{a}_{juw}), \delta^1_{juw}, \ldots, \delta^{l(juw)}_{juw}(= \overline{a}_{juw})$ denote the points where the slope

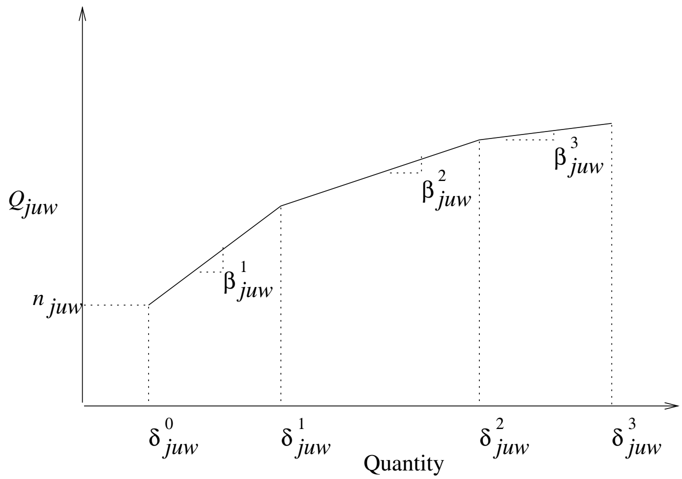

Fig. 2. Piecewise linear price function Q_{juw}

changes and the corresponding slopes are $\beta^1_{juw}, \ldots, \beta^{l(juw)}_{juw}$. The set W_u is assumed to be always finite even if the domain E_u is infinite. For example the attribute *on-time delivery probability* can have $E_u = [0.8, 1]$, but the bidder can specify only finite possible values $W_u = \{0.8, 0.85, 0.9\}$. The Q_{juw} shown in Figure 2 is for only one value w of attribute u. The bidder specifies such function for each $w \in W_u$ as shown in Figure 1. If the buyer configures the bid j with q_{juw} units for $w \in W_u$ and $u \in U$, then the total cost of procurement from bid j is:

$$Cost_j = \sum_{u \in U} \sum_{w \in W_u} Q_{juw}(q_{juw}) \tag{1}$$

The implicit assumption in the above cost structure is that the attributes are independent of each other except with the quantity procured.

2.3 Bid Evaluation

Multiple attributes can be used both in bid definition and bid evaluation. Multiple attributes in bid definition (or RFQ) provides a means to specify complex product or service. In bid evaluation, the buyer can use multiple attributes to select the winning bidders. We will use the phrases *criteria* for bid evaluation and *attributes* for bid definition. In our camera procurement example, the *attributes* defined in the RFQ are like lens focus, flash, lead time, and warranty, and the *criteria* used by the buyer for evaluating the bids can be like total cost, lead time and supplier credibility. With the above norm established, a criterion for evaluating the bids may consist of zero, one or many attributes defined in the RFQ. For example, the criterion that the winning supplier should have high *credibility*, is not an attribute defined in the RFQ but a private information known to the buyer. On the other hand, minimizing cost of procurement is a function of many attributes defined in the RFQ.

Evaluating the bids by taking into account different factors is a multiple criteria decision making (MCDM) problem. MCDM has two parts: *multiattribute decision analysis* and *multiple criteria optimization*. Multiattribute decision analysis techniques like MAUT [8] are often applicable to problems with a small number of alternatives that are to be ordered according to different attributes. In MAUT, a multiattribute utility function representing the preferences of the decision maker is elicited and is used to order the set of feasible alternatives. When the decision space has very large or infinite number of alternatives, the practical possibility of obtaining a reliable representation of the decision maker's multiattribute utility function is limited. Multiple criteria optimization [10] techniques are used in such scenarios where explicit knowledge of the utility function is not available. The bid evaluation problem of [1, 3] to rank the bids was solved by MAUT of multiattribute decision analysis. In our case, the decision space is large (many winning bids and multiple possible configurations for each winning bid) and it is difficult for the buyer to explicitly specify his utility function over such a large space. We model the bid evaluation problem as a linear integer multiple criteria optimization problem.

Decision Variables in Bid Evaluation

- $x^s_{juw} \in \mathcal{Z}^+$, amount of goods bought from bid j with value w for attribute u with unit cost β^s_{juw}
- $X_j \in \mathcal{Z}^+$, amount of goods bought from bid j
- $z_j \in \{0,1\}$, indicator variable that selects/rejects bid j
- $d^s_{juw} \in \{0,1\}$, binary variable that assumes 1 if goods are bought from linear segment s of Q_{juw}
- $D_{juw} \in \{0,1\}$, indicator variable for choosing value w for attribute u of bid j

Constraints We first formulate the constraints in configuring the bids. The amount of goods from bid j with value w for attribute u has to be chosen considering the price function Q_{juw}. As shown in Figure 1, this function can be nonlinear. Using the piecewise linear nature, we can represent them using linear inequalities. The quantity range $[\underline{a}_{juw}, \overline{a}_{juw}]$ is split into $l(juw)$ segments, where the quantity range in segment s is $[0, \delta^s_{juw} - \delta^{s-1}_{juw}]$. For the above conversion to make sense, whenever $x^s_{juw} > 0$, then $d^{s'}_{juw} = 1$ and $x^{s'}_{juw} = \delta^{s'}_{juw} - \delta^{s'-1}_{juw}$ for $s' < s$. The following are the set of linear constraints that handle the quantity selection:

$$x^s_{juw} \leq d^s_{juw}\ (\delta^s_{juw} - \delta^{s-1}_{juw}) \quad s = 1, \ldots, l(juw) \tag{2}$$

$$x^s_{juw} \geq d^{s+1}_{juw}\ (\delta^s_{juw} - \delta^{s-1}_{juw}) \quad s = 1, \ldots, l(juw) - 1 \tag{3}$$

The above set of constraints are for each $w \in W_u$ of every attribute $u \in U$ of every bid j. Following constraints handle the consistency and logical relationships among the variables, and the demand requirements:

$$\sum_{s=1}^{l(juw)} d_{juw}^s \leq l(juw)\ D_{juw}\ \forall w \in W_u,\ \forall u \in U,\ \forall j \tag{4}$$

$$\sum_{w \in W_u} D_{juw} = z_j \qquad \forall u \in U,\ \forall j \tag{5}$$

$$\sum_{w \in W_u} \sum_{s=1}^{l(juw)} x_{juw}^s = X_j\ \ \forall u \in U,\ \forall j \tag{6}$$

$$\underline{b} \leq \sum_j X_j \leq \overline{b} \tag{7}$$

There may be several business rules and purchasing policies like restriction on the number of suppliers, allowable quantity in a single shipment, homogeneity of attributes [2], etc. Such business rules can be added as side constraints. Furthermore, we have not considered any interaction effects between the attributes for simplicity. There may be logical restrictions on the allowable combination of the attribute values and the supplier may give special discounts on certain attribute combinations. These logical constraints were modeled as linear constraints in [2] which can be added with the above set of constraints.

Objectives Let $\mathbf{X}$ denote the vector of decision variables. Then the bid evaluation problem is the following multiple criteria optimization problem with G linear objectives:

$$\begin{aligned}
&\min\ \{\mathbf{c_1X} = f_1\}\\
&\min\ \{\mathbf{c_2X} = f_2\}\\
&\vdots\\
&\min\ \{\mathbf{c_GX} = f_G\}\\
&\text{s.t.}\quad \mathbf{X} \in F
\end{aligned}$$

where F is the set of feasible solutions defined by the constraints. Without loss of generality all the objectives considered were of minimization type. The objectives of the buyer can be like *minimize total-cost*, *minimize lead-time*, *maximize on-time-delivery probability*, etc. For example, the objective of minimizing total cost is:

$$\min\ \sum_j \sum_{u \in U} \sum_{w \in W_u} (n_{juw}\ D_{juw} + \sum_{s=1}^{l(juw)} \beta_{juw}^s\ x_{juw}^s)$$

3 Bid Evaluation Using Goal Programming

Multiple criteria optimization problems can be solved using various techniques like GP, vector maximization, and compromise programming [9, 10]. The idea of GP is to establish a goal level of achievement for each criterion. For example, the cost minimization criterion can be converted to the goal: *cost* $\leq \$20,000$, where $\$20,000$ is the target or aspiration level. When the target levels are set for all criteria, GP finds a solution that simultaneously satisfies all the goals as *closely* as possible: it is more of a *satisficing* technique than an *optimizing* technique. The goal g can be any of the following types: *greater than or equal to* $(\geq t_g)$, *less than or equal to* $(\leq t_g)$, *equality* $(= t_g)$, and *range* $(\in [\underline{t}_g, \overline{t}_g])$, where t_g's are the target or aspiration levels. Without loss of generality let us assume the *less than or equal to* goal structure for the procurement problem:

$$\begin{aligned} &\text{goal } \{\mathbf{c_1 X} = f_1\} \qquad (f_1 \leq t_1) \\ &\vdots \\ &\text{goal } \{\mathbf{c_G X} = f_G\} \qquad (f_G \leq t_G) \\ &\text{s.t.} \quad \mathbf{X} \in F \end{aligned} \tag{8}$$

For each goal, there will be a deviational variable that measures the deviation from the target level and these give rise to new goal constraints:

$$\begin{aligned} &\mathbf{c_1 X} - \gamma_1 \;\leq\; t_1 \\ &\vdots \\ &\mathbf{c_G X} - \gamma_G \;\leq\; t_G \\ &\gamma_g \;\geq\; 0 \;\; g = 1, \ldots, G \end{aligned} \tag{9}$$

The γ_g measures the deviation away from the goal g. The above goal constraints do not restrict the original feasible region F. In effect, they augment the feasible region by casting F into a higher dimensional space [10]. The GP techniques vary by the way the deviational variables are used to find the final solution. We present in this paper three popular GP techniques for solving the bid evaluation problem.

3.1 Weighted GP

Weighted GP (WGP) or *Archimedean* GP uses weights, given by the decision maker, to penalize the *undesirable* deviational variables. The GP [8] will then be the following single objective programming problem:

$$\begin{aligned} \min \; &\textstyle\sum_g w_g \gamma_g \\ \text{s.t.} \;\; &[9] \;\; \text{and} \;\; \mathbf{X} \in F \end{aligned} \tag{10}$$

The goals are generally incommensurable (for example, cost minimization is measured in currency whereas minimizing lead time is measured in days) and the above objective function is meaningless as the weighted summation includes different units. The most intuitive and simplest way would be to express γ_g as percentage rather than as absolute value [9]. For e-Procurement, the buyer can specify minimum and maximum deviations allowed for a goal and then use the percentage of deviation in the objective function.

3.2 Lexicographic GP

In lexicographic GP (LGP) or *preemptive* GP, the goals are grouped according to priorities. The goals at level l are considered to be infinitely more important than the goals at level $l+1$. First the problem is solved only for the goal(s) at the highest level (if there are more than one goal at a level, then they are aggregated as in WGP). If there are alternate optimal solutions, then the next level goals are optimized over the alternate optimal solutions. This procedure stops when all levels are optimized or at some level which has no alternate optimal solutions. Unlike WGP, LGP requires several iterations.

3.3 Interactive Sequential GP

The main aim of multiple criteria optimization techniques is to work without the explicit knowledge of the utility function and to search the *space of trade-offs* among the conflicting objectives. The *interactive procedures* that involve human intervention have proven to be most effective in searching trade-off space for a final solution [10]. Interactive sequential GP (ISGP), proposed in [6], combines and extends the attractive features of both GP and interactive solution approaches. ISGP is based on the implicit assumption that the decision maker can adjust the desired goals through an iterative learning process based on information in a set of solutions. The information provided in each iteration is contained in a current best compromise solution (solution provided by GP solved using the goals given in previous iteration), and a set of alternate solutions which are compromise solutions obtained if each goal is satisfied serially. Using this information, the decision maker can set new goal levels. The algorithm terminates when a satisfactory solution is found. If the goal levels are changed in a consistent manner then the number of iterations is expected to be small (refer to [6] for a detailed algorithm).

4 Conclusions and Future Work

e-Procurement is an Internet-based business process for obtaining materials and services and managing their inflow into the organization. In this paper we proposed an e-Procurement system with the following properties: (1) allowing the bidders to bid on multiple attributes, (2) a rich bidding language to automate negotiations across multiple bids, (3) flexibility for allowing business rules and purchasing logic in bid evaluation, and (4) bid evaluation using multiple criteria. The proposed piecewise linear cost structure of the configurable bids allows bidders to specify price functions that closely capture their volume discount bargaining strategy and also the economies of scale. The bid evaluation problem is formulated as a multiple criteria linear integer programming problem, where the criteria for bid evaluation are formulated as objectives and the business rules can be included as side constraints. We proposed the use of goal programming to solve the above optimization problem. The approach is practically appealing as it does not demand explicit knowledge of utility functions but simple aspiration or target levels for each criterion. Moreover, the GP techniques proposed can be solved using the existing commercial integer optimization solvers. The immediate requirement is the investigation of computational complexity and implementation feasibility of the above system. Another prospective research direction is the use of game theoretic and experimental analysis to determine whether the information about goal levels, allowable deviations, and weights for the different criteria should be disclosed by the buyer.

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