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Optimization Based e-Sourcing

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1. Introduction

Sourcing or procurement is the process by which a company obtains goods and services for its manufacturing and operations. The materials procured could range from raw materials, components, and sub-assemblies, to office supplies and furniture. The services procured can be as vital as design and R&D to daily operations like IT and logistics. e-Sourcing or e-procurement refers to *online* procurement of the above direct and indirect inputs by an industrial buyer. The other predominantly used terms for this process are *procurement auctions*, *reverse auctions*, and *e-auctions*. We use the above terms in this chapter with the following definition of Minahan (2001): *the process of utilising Web-based technologies to support the identification, evaluation, negotiation, and configuration of optimal groupings of trading partners into a supply chain network, which can then respond to changing market demands with greater efficiency*.

e-Sourcing of production and non-production goods and services has been in practice since early 1990s, especially among the *Fortune 2000* companies. It was widely accepted then that web based sourcing can provide following advantages (Minahan 2001):

- Identify and negotiate with a broad range of qualified suppliers;
- Reduce process costs for sourcing engagements;
- Shorten sourcing cycles by 25% to 30%;
- Reduce time-to-market cycles by 10% to 15%;
- Negotiate an average of 5% to 20% unit price reductions;
- Extend strategic sourcing to a wider range of products and services; and
- Enhance collaboration and knowledge sharing.

The market analysts' predictions about the worth of online business transactions were in trillions of USD by 2003/4. However, the e-bust that happened in 2000, followed by the market studies of the real world implementations showed that these figures are indeed exaggerated and overstated, if not false (Emiliani & Stec, 2004; 2005). Irrespective of the figures projected and achieved, the use of e-sourcing is growing with steady incremental gains rather than abrupt exponential profits.

- Ariba[1], a leading provider of online spend management solutions, has enabled sourcing of USD 250 Billion worth of goods and services till date, using its *Ariba Sourcing Solution*. The total annual savings generated is over USD 15 Billion (Ariba, 2007).

[1] http://www.freemarkets.com

Source: Supply Chain, The Way to Flat Organisation, Book edited by: Yanfang Huo and Fu Jia,
ISBN 978-953-7619-35-0, pp. 404, December 2008, I-Tech, Vienna, Austria

- GlaxoSmithKline achieved a 5,452% annualized return-on-investment using Emptoris[2] (another leader in providing sourcing solutions and a pioneer in the use of optimization for strategic sourcing in industry).
- Motorola received the prestigious Franz Edelman Award for Achievement in Operations Research and the Management Sciences in 2004 for the application of optimization bid analysis with Emptoris to save USD 600 million.
- More than 60 Fortune 500 companies use CombineNet[3] for their most advanced strategic sourcing activities, with greater than 45x average return on investment.
- Volume-discount and combinatorial auctions benefited Mars Inc. and its suppliers (Hohner et al., 2003).
- Chilean government used combinatorial auctions to assign catering contracts for the supply of school meals to children and resulted in a 22% cost savings (Epstein et al., 2002).

In this chapter, we present different optimization based e-sourcing auctions from the literature and industry best practices. We also extend how these mechanisms could be used in global sourcing and the future research to include risk mitigation.

Auction is a market mechanism with well-defined set of rules for determining the terms of an exchange of something for money (McAfee & McMillan, 1987). Procurement auctions are *reverse* auctions in the sense that the buyer is the auctioneer and the sellers (suppliers) are the bidders. Traditionally, auctions for procurement at the industrial scale were mainly used by government for purchasing goods and services. The main reasons are openness and fairness of auctions, and till today, government purchasing happens through auctions. However, for many years, auctions played a relatively minor role in industrial procurement (Rothkopf & Whinston, 2007).

The industrial approach to procurement was to develop long-term cooperative relationships with few suppliers. The advent of Internet and the advancement of e-commerce changed this approach radically. The long term strategic partnerships with suppliers are still prevalent for sourcing of custom designed goods and services. On the other hand, for sourcing of commoditized goods and services, e-sourcing through auctions are being increasingly used by industries (Kouvelis et al., 2006). Also among the academics, there is a recent growing interest in this Internet based business process that led to new generation of procurement techniques like *combinatorial* (Cramton et al., 2006), *volume discount* (Eso et al., 2005) and *multi-attribute* (Bichler et al., 1999; Kameshwaran et al., 2007).

e-Sourcing and in general, e-auctions, are being studied by scholars from different disciplines such as economics, operations research, management science, information systems, and computer science (Rothkopf & Whinston 2007). Many works from operations research and management science community approach e-sourcing from the perspective of solving a *supply chain optimization* problem. This chapter also adopts the same perspective and other economic issues like *information asymmetry*, *adverse selection*, and *moral hazards* (McAfee & McMillan, 1987) are not addressed here.

The chapter is organized as follows. Section 2 describes the dynamics of the sourcing process, briefly outlines the design issues, and introduces the three different sourcing formats considered in this chapter. The three sourcing techniques are presented in detail in

[2] http://www.emptoris.com
[3] http://www.combinenet.com

sections 3 to 5. For each of the techniques, the mathematical programming formulation is presented. Sourcing based on volume discounts, one of earliest formats in business tradition, is presented in Section 3. The more recent and popular combinatorial sourcing is described in Section 4. Multi-attribute sourcing and its extension configurable bids are discussed in Section 5. Section 6 is devoted to global sourcing, where the traditional industrial procurement format of a single buyer with multiple suppliers is extended to multiple factories of the same organization procuring from multiple suppliers. Section 7 discusses the robustness approach to e-sourcing to design a risk-tolerant sourcing network that will operate at acceptable levels under a wide range of pre-identified random scenarios. Final notes are given in Section 8 and references are listed in Section 9.

2. Dynamics, design issues, and taxonomy

2.1 Dynamics

The overall industrial sourcing dynamics can be described as a standard three-step process: (1) Pre-auction stage, (2) auction stage, and (3) post-auction stage. This is adapted from the three-step process described in Caplice & Sheffi (2007) for procurement of transportation services.

Pre-auction stage

The buyer forecasts the demand for the planning horizon and determines which suppliers to invite for the sourcing auction. Common practice is to retain most incumbents (to maintain long term buyer-supplier relationship) and invite some new suppliers. A set of mandatory supplier selection criteria (Weber et al. 1991) is used to identify these potential suppliers. The buyer also decides the format of the auction and bid structure (to be described in detail).

Auction stage

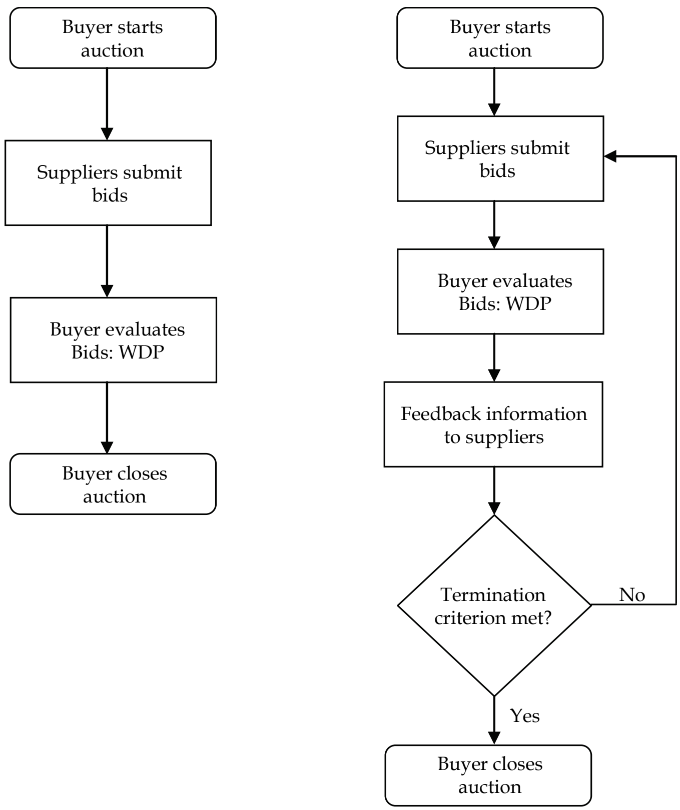
The demand, auction format, and the bid structure are communicated to the pre-selected suppliers in the form of RFQ or RFP through the use of faxed lists, spreadsheets, online web pages, email, or direct EDI connections. The suppliers conduct their own analysis and prepare the bid according the required format. The bidding phase in the auction could be *single round* or *multiple rounds* (see Figure 1). Once the bids are received, the buyer solves the *winner determination problem* (WDP), where the bids are evaluated to determine the winning the suppliers (also known as *bid evaluation problem*). In the single round auction, the auction closes after this stage and the suppliers are intimated of their status. In multi-round auctions, the winners determined are provisional winners and the suppliers are given feedback information, using which they can resubmit bids. Once a termination criterion is met the auction is closed. The criterion could be that no new bids from suppliers or the upper bound on the number of rounds reached.

Post-auction stage

Once the auction is closed, the results of the WDP are uploaded to the downstream planning, execution, auditing, and payment systems.

2.2 Design issues

The sourcing process with RFX generation and bidding by suppliers is inherently based on auctions and hence the design principles for sourcing generally follow auction design. As mentioned above, auctions can be categorized based on the dynamics as: (1) *single-round or one-shot* auctions and (2) *multiple-round* or *progressive* or *iterative* auctions. Single-round auctions are sealed bid auctions. Multi-round auctions can be sealed bid or open bid, but has



(a) Single-round auction (b) Multi-round auction

Fig. 1. Single-round and multi-round auction dynamics

multiple rounds of bidding phases. At the end of each bidding phase, there will be flow of information from the auctioneer to the bidders. This will help the bidders to prepare their bids for the next bidding phase. The design parameters of single-round auctions are *bid structure*, *winner determination policy*, and *pricing policy*. The bid structure specifies the format of bids, the winner determination policy describes the technique to determine the winners, and the pricing policy determines the price(s) of the winning good(s).

On the other hand, design of multi-round auctions is relatively non-trivial, which includes the specification of bid structure, winner determination technique at each bidding round, information exchange at the end of each round, termination condition, and the pricing policy. Multi-round auction has many advantages over its one-shot counterpart (Cramton 1998), especially in sourcing (Parkes & Kalagnanam 2005). There are many design methodologies for multi-round auctions for sourcing (Bikhchandani & Ostroy 2006, Kameshwaran et al. 2005, Parkes & Kalagnanam 2005).

The sourcing process with the RFX and the bidding, only borders on auctions and are indeed less formally structured than auctions. The auction design is generally based on the

principles of *mechanism design*. Mechanism design (Mas-Colell et al., 1995) is the sub-field of microeconomics and game theory that considers how to implement good system-wide solutions to problems that involve multiple self interested agents, each with private information about their preferences. The mechanism design methodology has also been found useful in designing e-markets (Varian, 1995). One of the main assumptions in mechanism design is that the rules of the auction are a common knowledge to all the participating agents. In sourcing, though the rules of bid submission are common knowledge, rules of winner determination may not be revealed to the suppliers. The purchasing manager may take into account several business rules and purchasing logic in winner determination, which are not generally revealed to the suppliers. Moreover, the criteria and the constraints can be modified by the auctioneer (buyer), based on the received bids. Here, we do not follow the mechanism design approach.
Pricing policy is another design issue, which dictates the price to be paid to the winning suppliers for the supply of the winning goods. The commonly used pricing policy in current e-sourcing systems is the *pay-as-bid* or *first price* policy where the suppliers are paid the cost quoted in their respective bids. There are non-trivial pricing policies such as VCG (Ausubel & Milgrom, 2006), where the price is function of the price quoted by the other suppliers. Though this pricing policy has certain desirable economic features, it is not widely used in practice.

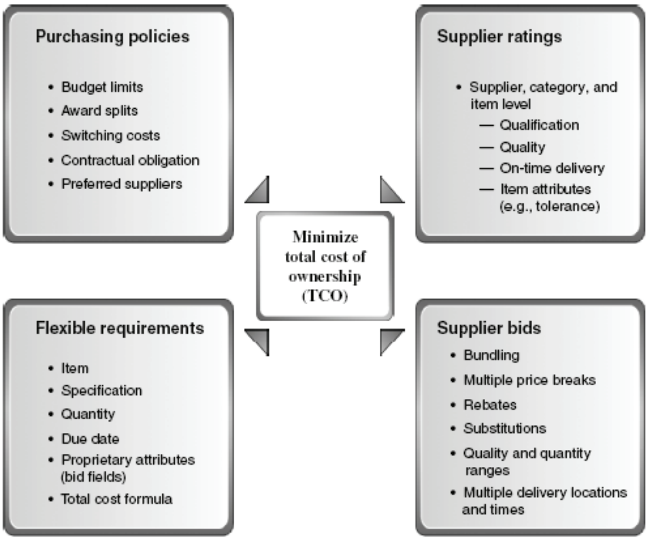


Fig. 2. Factors considered by Motorola in awarding business to suppliers (Source: Metty et al. (2005))

2.2 Bid structure and winner determination

We consider only the design issues related to bid structure and winner determination technique, from the perspective of the buying organization (auctioneer). The bid structure dictates how a bid is defined. For example, it could be as simple as a unit price for an item or set of attributes like unit price, lead time, quantity, etc. A *rich* bid structure is advantageous to both the buyer and suppliers. The buyer has more negotiating parameters rather than just unit price and hence can optimize the total cost or procurement. Suppliers, on the other hand, can differentiate themselves from their competitors with value added services rather than competing on just cost. The earlier e-sourcing techniques achieved cost reduction to buyers by squeezing the profit margins of the competing suppliers. Many historical and incumbent suppliers did not prefer the online sourcing as they felt that the buyers used it to wring price concessions from them in the presence of new suppliers (Jap, 2002). However, e-sourcing evolved with a rich set of bid structures, providing a win-win situation to both the buyers and sellers, and thereby achieving overall supply chain efficiency. Figure 2 shows the factors considered by Motorola to minimize the total cost of ownership while awarding business to the suppliers (Metty et al., 2005).

The winner determination problem faced by the buyer at the end of the bidding phase (or at the end of every bidding phase in progressive auctions) is an optimization problem. The problem is to determine the set of winning suppliers and their respective winning items, such that the total procurement cost is minimized subject to various business constraints and purchasing policies. Indeed, one of the earliest applications of linear programming is winner determination (also referred as bid evaluation) (Gainen et al., 1954). Many commercial bid analysis products from companies like Emptoris, and CombineNet use optimization techniques like linear programming, combinatorial optimization, and constraint programming. Optimization also allows for addition of business constraints and purchasing logic as side constraints in winner determination, which is a new development in sourcing auctions (Rothkopf & Whinston, 2007). Some of the commonly used business rules are:

- Limiting the number of winning suppliers in a given range;
- Limiting the business awarded (in terms of quantity or worth) to a winning supplier in a given range;
- Guaranteeing a minimum amount of business to incumbent suppliers;

Note that the above business rules need not be disclosed to the suppliers and often many of them are experimented with WDP like analyzing *what-if* scenarios.

2.3 Taxonomy

We categorize the e-sourcing techniques based on the bid structure and the winner determination policy, which also implicitly depends on the number of goods purchased and their respective quantities. We broadly classify e-sourcing under three categories: (a) Volume discount sourcing, (b) Combinatorial sourcing, and (c) Multi-attribute and multi-criteria sourcing. We describe each of the above in detail in the following sections.

3. Volume discount sourcing

Volume or quantity discounts in sourcing is a long established business tradition. Buyers expect discounts for buying large quantities and the suppliers provide discounts to price discriminate from the competing suppliers. Studies by Lippman (1969), Prikul & Aras (1985), Jucker & Rosenblatt (1985), and Dolan (1987) focus on how buyers determine the economic order quantities with quantity discounts. On the other hand, Crowther (1964), Monahan (1984), Lee & Rosenblatt (1986), and Kim & Hwang (1988) focus on the supplier's perspective of formulating the form of quantity discount pricing schedule.

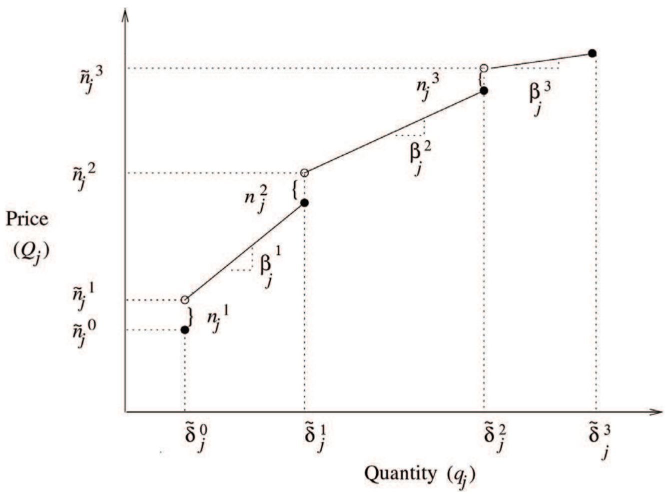


Fig. 3. Piecewise linear cost function as bid

According to Sadrian & Yoon (1994), the rationale behind quantity discount models is derived from the numerous economic advantages gained from buyers ordering larger quantities of products. With larger orders, both the supplier and the buyer should be able to reduce their order processing costs. These might include packaging and handling costs, administrative costs, and shipping costs. However, the major benefits come from the savings in the supplier's manufacturing costs. A supplier that produces the item itself for these larger orders will require fewer manufacturing setups and have larger production runs. These savings are especially significant if the supplier experiences high product-specific setup costs. On the other hand, increased order size results in a higher inventory holding cost for the buyer. Therefore, the supplier should compensate for this extra cost with an attractive quantity discount pricing schedule to induce buyers to increase their order size.

Munson and Rosenblatt (1998) provided a classification of different quantity discounts. The form of discount could be *all-units* or *incremental*. In all-units form, the discount is applicable to all the units purchased, whereas in incremental, the discount is applicable only to the additional units that has crossed the break-up point. The *item aggregation* describes whether the discount applies to one or multiple products (bundling). A *business volume discount* represents item aggregation where the price breakpoints are based on the total dollar volume of business across all products purchased from the supplier. The *time aggregation* describes whether the discounts apply to individual purchases or multiple purchases over a given time frame. Finally, the number of price breakpoints may be one, multiple, or infinite (as represented by a continuous price schedule). In this section, we present incremental discount form applied to sourcing of multiple units of a single item (Kameshwaran & Narahari, 2009b). Our focus here is on solving the WDP faced by the buyer, when the suppliers submit non-convex piecewise linear quantity discount price functions.

3.1 Sourcing of multiple units of a single item

Consider an industrial procurement of multiple units of a single item. The demanded item can be a raw material or a sub-component and let the demanded number of units be B. Let N

be the number of potential suppliers, out of whom the winning suppliers have to be selected. Usually, the buyer prefers multi-sourcing as the supply failure in a single supplier scenario will be disruptive. Further, the demand B could be formidably large for a single supplier. With multi-sourcing, the buyer needs to determine the winning suppliers and also their winning quantity. This provides an additional negotiable parameter to the suppliers in addition to unit price. The bid thus is a price function defined over quantity. The price function that is commonly used in industry for long-term strategic sourcing is *piecewise linear* (Davenport & Kalagnanam, 2002).

3.2 Piecewise linear bid

The bid submitted by supplier j is a cost function Q_j defined over the supply quantity $[a_j, z_j]$. Q_j is piecewise linear and nonconvex, as shown in Figure 3. It can be represented compactly by tuples of break points, slopes, and costs at break points: $Q_j \equiv ((\tilde{\delta}_j^0 = a_j, ..., \tilde{\delta}_j^{l_j} = z_j), (\beta_j^1, ..., \beta_j^{l_j}), (\tilde{n}_j^0, ..., \tilde{n}_j^{l_j}))$. For notational convenience, define $\delta_j^s \equiv \tilde{\delta}_j^s - \tilde{\delta}_j^{s-1}$ and n_j^s as the jump cost associated with linear segment s. Note that, by this definition, $n_j^0 = \tilde{n}_j^0$.

Notations

$[a_j, z_j]$	Supply range
Q_j	Cost function defined over $[a_j, z_j]$
l_j	Number of piecewise linear segments in Q_j
β_j^s	Slope of Q_j on $(\tilde{\delta}_j^{s-1}, \tilde{\delta}_j^s)$
δ_j^s	$\equiv \tilde{\delta}_j^s - \tilde{\delta}_j^{s-1}$
n_j^s	Fixed cost associated with segment s
$\tilde{n}_j^s$	$Q_j(\tilde{\delta}_j^s) + n_j^s$
Q_j	$\equiv ((\tilde{\delta}_j^0 = a_j, ..., \tilde{\delta}_j^{l_j} = z_j), (\beta_j^1, ..., \beta_j^{l_j}), (\tilde{n}_j^0, ..., \tilde{n}_j^{l_j}))$

The function is assumed to be strictly increasing, but not necessarily marginally decreasing as shown in the figure. The assumed cost structure is generic enough to include various special cases: *concave, convex, continuous,* and $a_j = 0$. The cost structure enables the suppliers to express their *volume discount* or *economies of scales* and/or the production and logistics constraints. The volume discount strategy, which is *buy more and pay less* can be expressed with marginally decreasing cost functions. The discontinuities with jump costs in the cost structure can capture the production and transportation constraints.

3.3 Winner determination problem

Let J be the set of N suppliers. The index j denotes a supplier from set J. As each supplier can only submit one bid, we use the index j to denote both the supplier and his bid. The winner determination problem (WDP) faced by the buyer is to minimize the total cost of procurement with the following decisions: (1) select a set of winning bidders $J' \subseteq J$ and (2) determine the trading quantity q_j for each winning bid $j \in J'$. The above decisions are to be made subject to the following constraints:

- *Supply Constraint:* For every winning bid $j \in J'$, $q_j \in [a_j, z_j]$, and for losing bids, $q_j = 0$.
- *Demand Constraint:* The total quantity procured should satisfy the demand of the buyer: $\sum_{j \in J'} q_j \geq B$.

The WDP is a nonconvex piecewise linear knapsack problem (Kameshwaran & Narahari, 2009a), which is *NP*-hard. It is a minimization version of a nonlinear knapsack problem with a demand of B units. Each bid corresponds to an *item* in the knapsack. Unlike traditional knapsack problems, each item *j* can be included in the knapsack in a pre-specified range $[a_j, z_j]$ and the cost Q_j is a function of quantity included.

The cost function Q_j of Figure 3 is nonlinear but due to the piecewise linear nature, the WDP can be modelled as the following MILP.

$$\min \sum_{j \in J} \left(n_j^0 d_j^0 + \sum_{s=1}^{l_j} \left(n_j^s d_j^s + \beta_j^s \delta_j^s x_j^s \right) \right) \tag{1}$$

subject to

$$d_j^1 \leq d_j^0 \quad \forall j \in J \tag{2}$$

$$x_j^s \leq d_j^s \quad \forall j \in J; 1 \leq s \leq l_j \tag{3}$$

$$x_j^s \geq d_j^{s+1} \quad \forall j \in J; 1 \leq s < l_j \tag{4}$$

$$\sum_{j \in J} \left(a_j d_j^0 + \sum_{s=1}^{l_j} \delta_j^s x_j^s \right) \geq B \tag{5}$$

$$d_j^s \in \{0,1\} \quad \forall j \in J; 0 \leq s \leq l_j \tag{6}$$

$$x_j^s \in [0,1] \quad \forall j \in J; 1 \leq s \leq l_j \tag{7}$$

The decision variable x_j^s denotes the fraction of goods chosen from the linear segment s of bid j. For this setup to make sense, whenever $x_j^s > 0$ then $x_j^{s-1} = 0$, for all s. To enable this, binary decision variable d_j^s is used for each segment to denote the selection or rejection of segment s of bid j. The winning quantity for bid j is $a_j d_j^0 + \sum_{s=1}^{l_j} \delta_j^s x_j^s$ with cost $n_j^0 d_j^0 + \sum_{s=1}^{l_j} \left(n_j^s d_j^s + \beta_j^s \delta_j^s x_j^s \right)$. The binary decision variable d_j^0 is also used as an indicator variable for selecting or rejecting bid j, as $d_j^0 = 0$ implies that no quantity is selected for trading from bid j.

3.4 Business constraints

The business rules and purchasing logic can be added as side constraints to the WDP. For the above procurement scenario, the relevant business constraints are restricting the number of winning suppliers in a given range [*LB, UB*] and guaranteeing a minimum volume (or monetary business worth) *MIN_QTY* (*MIN_*VAL) for a set of incumbent suppliers $J' \subset J$.

$$LB \leq \sum_{j \in J} d_j^0 \leq UB \tag{8}$$

$$\sum_{j \in J'} \left(a_j d_j^0 + \sum_{s=1}^{l_j} \delta_j^s x_j^s \right) \geq MIN\_QTY \tag{9}$$

$$\sum_{j \in J'} \left(n_j^0 d_j^0 + \sum_{s=1}^{l_j} \left(n_j^s d_j^s + \beta_j^s \delta_j^s x_j^s \right) \right) \geq MIN\_VAL \tag{10}$$

The above constraints can be added as side constraints to the WDP. Usually one of the (9) or (10) is used. Business rule that limits the winning quantity or business value for a winning supplier can be implicitly included by suitably modifying the supply range $[a_j, z_j]$.

3.5 Algorithms

Dynamic programmic based exact and approximation algorithms were proposed in (Kameshwaran & Narahari, 2009a) and a Benders' decomposition based exact algorithm was proposed in (Kameshwaran & Narahari, 2009b) to solve the WDP formulated as (1)-(7). Similar procurement scenarios have been considered in the literature with various assumptions. Kothari et al. (2003) expressed the cost function using fixed unit prices over intervals of quantities (piecewise linear but continuous with no jump costs) and approximation algorithms based on dynamic programming were developed for solving the WDP. Procurement with nonconvex piecewise linear cost functions was considered by Kameshwaran & Narahari (2005) with the additional business constraint of restricting the number of winning suppliers. A Lagrangian based heuristic was proposed to solve the WDP. Eso et al. (2005) considered the quantity discount procurement of heterogeneous goods and column-generation based heuristic was proposed to solve the WDP.

3.6 Other discount based sourcing techniques

In the above, we briefly discussed about volume discounts offered while procuring multiple units of a single item. Eso et al. (2005) considered buying multiple items with volume discounts for each item. There are two kinds of discounts for procuring multiple units of multiple items: *Business volume discounts* (Sadrain & Yoon ,1994) and *total quantity discounts* (Goossens et al. 2007). In the business volume discounts, the discounts are based on the total monetary worth of the purchase rather than on the quantity. This discount structure is applicable in telecommunication sourcing. In total quantity discounts, discount is based on the total quantity of all items purchased. This discount is used in chemical and also in telecom capacity sourcing. Exact algorithms based on brand and bound were proposed in (Goossens et al., 2007) to solve this problem. For a special case with single unit demand for multiple items, a suite of branch-and-cut algorithms was proposed in (Kameshwaran et al., 2007).

4. Combinatorial sourcing

Consider a sourcing scenario where the buyer wants to buy a set of heterogeneous items. Two immediate approaches to procure them are in *sequence* (sequential procurement with one after another) and in *parallel* (all items are procured simultaneously by conducting a sourcing auction for each item separately). The third option is to conduct a *combinatorial auction* where the supplier can bid on a combination of items by providing a single bid price (Cramton, 2006). Thus the bid price is conditional on winning the entire combination of items. These auctions are ideal for scenarios in which synergies exist between the items. Suppose a supplier obtains more profit by selling a set of items together, then he can submit this *all-or-nothing* combinatorial bid by providing a discounted price on that entire package. The supplier can submit more than one bid and the items in different bids can be overlapping.

Combinatorial auctions were initially used in selling scenarios like airport slot allocation (Rassenti et al., 1982) and radio spectrum auctions (Rothkopf et al., 1998). The sourcing applications mainly include procurement of transportation services (Caplice & Sheffi, 2006), in addition to direct sourcing of industrial inputs (Hohner et al., 2003). In this following, we present various combinatorial bids and the respective WDP formulations.

4.1 Static package bids

Let the items to be procured be indexed by i, each with demand d_i. A bidder j bids on a *package* or *bundle* of items, providing a single bid price for that bundle. Let the package be indexed by k. As mentioned above, the bidder can submit different packages as bids with possibly overlapping items. The winner determination problem can be formulated as the following 0-1 integer program.

$$\min \sum_j \sum_k C_j^k y_j^k \tag{11}$$

subject to

$$\sum_j \sum_{k:i\in k} \delta_{ij}^k y_j^k = d_i \quad \forall i \tag{12}$$

$$y_j^k \in \{0,1\} \quad \forall j,k \tag{13}$$

where the notations are:

Indices

i Item identification

j Supplier identification

k Package identification

Decision variables

y_j^k = 1 if supplier j is assigned package k = 0, otherwise

Data

C_j^k Bid price for package k of supplier j

δ_{ij}^k Volume of item i as a part of package k for supplier j

The objective function (11) minimizes the total procurement cost. The constraint (12) enforces the demand requirements of the buyer. The above formulation allows for each supplier to win more than one package bids. This is *OR* bidding language (implying logical OR). Another popular bidding language used in practice is *XOR*, which allows at most one winning package bid for each supplier. For a more detailed discussion about the bidding languages, see Nisan (2000). The XOR constraint can be easily included as follows:

$$\sum_{k} y_j^k \leq 1 \quad \forall j \tag{14}$$

The above formulation is more appropriate for unit demand d_i=1 for each item i (hence $\delta_{ji}^k = 1$). For multi-unit demands, flexible package bids are beneficial, as the buyer can choose the winning quantity for each supplier.

4.2 Flexible package bids

With flexible package bids, supplier j can provide supply range $[LB_{ji}^k, UB_{ji}^k]$ for item i as a part of package k. The formulation for the WDP is as follows:

$$\min \sum_{j} \sum_{k} \sum_{i} C_{ij}^k x_{ij}^k \tag{15}$$

subject to

$$\sum_{j} \sum_{k:i \in k} x_{ij}^k = d_i \quad \forall i \tag{16}$$

$$LB_{ji}^k y_j^k \leq x_{ij}^k \leq UB_{ji}^k y_j^k \quad \forall i,k,j \tag{17}$$

$$y_j^k \in \{0,1\} \quad \forall j,k \tag{18}$$

$$x_{ji}^k \geq 0 \quad \forall i,k,j \tag{19}$$

where the additional decision variable and data are:

x_{ij}^k	Decision variable that denotes the winning quantity for item i from package k of supplier j
C_{ij}^k	Unit bid price for item i from package k of supplier j

4.3 Business constraints

Several business rules are used in combinatorial sourcing. We will need additional decision variables and data to add the business rules as side constraints to the WDP.

Additional decision variables

w_j^i	= 1 if supplier j supplies item i, = 0 otherwise
z_j	= 1 if supplier j is a winning supplier, = 0 otherwise

Additional data

L_i	Item limit of suppliers who can supply item i
$[S', S'']$	Range of number of overall winning suppliers

[*Min_Vol, Max_Vol*]	Minimum and maximum volume guarantee
[*Min_Val, Max_Val*]	Minimum and maximum business guarantee
M	A large constant
F_j	Fixed cost of developing supplier j
F_j^i	Fixed cost of developing supplier j for item i

To limit the number of suppliers at the item level and at the whole sourcing level, following side constraints can be added:

$$x_{ij}^k \le M\ w_j^i \quad \forall i,k,j \tag{20}$$

$$y_j^k \le M\ z_j \quad \forall k,j \tag{21}$$

$$\sum_j w_j^i \le L_i \quad \forall i \tag{22}$$

$$S' \le \sum_j z_j \le S'' \tag{23}$$

$$w_j^i \in \{0,1\} \quad \forall j,i \tag{24}$$

$$z_j \in \{0,1\} \quad \forall j \tag{25}$$

Minimum and maximum volume (business) guarantees can be enforced with the following constraints:

$$Min\_Vol\ z_j \le \sum_k \sum_i x_{ij}^k \le Max\_Vol\ z_j \quad \forall j \tag{26}$$

$$Min\_Val\ z_j \le \sum_k \sum_i C_{ij}^k x_{ij}^k \le Max\_Val\ z_j \quad \forall j \tag{27}$$

Including new suppliers into the sourcing network may incur extra fixed costs. This cost is associated with developing and maintaining a long-term relationship with a new supplier. This is due to the joint technology transfer, engineering, and quality programs with the supplier to enable him to meet the buyer's business and product and requirements. Sometimes the fixed cost could at product level. The fixed cost business constraints, however, need to be added at the objective function.

$$\min \sum_j \sum_k C_{ij}^k x_{ij}^k + \sum_j \sum_i F_{ij} w_j^i + \sum_j F_j z_j \tag{28}$$

4.4 Algorithms

Winner determination problems for combinatorial bids are well studied among the current bid structures. As noted in (Sandholm et al., 2005), three different approaches have been pursued in literature: (1) algorithms that find a provable optimal solution but the computational time dependent on problem instances (Sandholm, 2006), (2) algorithms that are fast with guaranteed computational time but can only find a feasible, not necessarily an optimal solution (Lehmann et al., 2002), and (3) restricting the bundles on which bids can be submitted so that the problem can be solved optimally and provably fast (Rothkopf et al., 1998; Muller, 2006). Combinatorial sourcing are supported and conducted by many commercial providers like CombineNet, Manhattan Associates, JDA, NetExchange, and Trade Extensions.

5. Multi-attribute and multi-criteria sourcing

In industrial procurement, several aspects of the supplier performance, such as quality, lead time, delivery probability, etc have to be addressed, in addition to the qualitative attributes of the procured item. A multi-attribute bid has several dimensions and this also allows the suppliers to differentiate themselves, instead of competing only on cost. Multi-attribute auctions deal with trading of items which are defined by multiple attributes. They are considered to play significant role in the commerce conducted over the WWW (Teich et al., 1999; Bichler, 2001). A multi-attribute auction as a model for procurement within the supply chain was studied in (Che, 1993). It is a one-shot auction in which the suppliers respond to the scoring function provided by the buyer. Multi-attribute auction for procurement proposed in (Branco, 1997) has two stages: A supplier is chosen in the first stage and the buyer bargains with the chosen supplier in the second stage to adjust the level of quality. The other approach in designing multi-attribute auctions is combining multi-criteria decision analysis and single-sided auction mechanisms.

5.1 Scoring function

Evaluating the bids by taking into account different factors is a multi-criteria decision making (MCDM) problem. MCDM has two parts: *multi-attribute decision analysis* and *multiple criteria optimization*. Multi-attribute decision analysis techniques are often applicable to problems with a small number of alternatives that are to be ordered according to different attributes. Two commonly used multi-attribute decision techniques (Belton 1986) are *multi-attribute utility/value theory* (MAUT) (Keeney & Raiffa, 1976) and the *analytic hierarchy process* (AHP) (Saaty, 1980). They use different techniques to elicit the scores or weights, which denote the relative importance among the attributes. MAUT allows one to directly state the scores or estimate as a utility function identified through risk lotteries. AHP uses paired comparisons of hierarchical attributes to derive weights as ratio-scale measures. An insightful comparison of both techniques is presented in (Belton 1986). For a comprehensive study of different multi-attribute decision analysis techniques the reader is referred to (Olson 1996).

Multi-attribute decision analysis has been used in traditional supplier/vendor selection problems (Ghodsypour & O'Brien, 1998; Benyoucef et al., 2003). Multi-attribute auction based on MAUT for e-procurement was proposed in (Bichler et al., 1999). The bids submitted by the suppliers are in the form of (attribute, value) pairs. Each attribute has a set of possible values. Thus a bid is an ordered tuple of attribute values.

Indices

i Attribute identification

K_i Set of possible values for attribute i
j Supplier identification
Multi-attribute bid from j
V_j $(v_{1j}, \ldots, v_{ij}, \ldots)$ where $v_{ij} \in K_i$

The buyer assigns weights to the attributes indicating their relative importance and has a scoring function for each attribute. The scoring functions essentially convert each attribute value to a virtual currency, so that all attribute values can be combined into a single numerical value that quantifies the bid. The combination rule generally used is the weighted additive combination.
Scores and weights
S_i Scores for values of attribute *i*: $S_i(v_{ij}) \in \mathrm{R}$
w_i Weight for attribute *i*
Additive scoring function for bid V_j
$$\sum_i w_i S_i(v_{ij})$$
The above weighted scoring function implicitly assumes *preferential independence of all attributes* (Olson 1996). In other words, the preference for any value of an attribute is independent of any value of any other attribute. However, in many real world applications, interactions exist between attribute values. Such preferential dependencies require non-linear scoring functions, which are seldom used in practice. For a more comprehensive study on the design of multi-attribute auctions see (Bichler, 2001). IBM Research's ABSolute decision engine (Lee et al., 2001) provides buyers, in addition to standard scoring mechanisms, an interactive visual analysis capability that enables buyers to view, explore, search, compare, and classify submitted bids.
An iterative auction mechanism to support multi-attribute procurement was proposed in (Beil & Wein, 2003). The buyer uses an additive scoring function for non-price attributes and announces a scoring rule at the beginning of each round. Through inverse optimization techniques, the buyer learns his optimal scoring rule from the bids of the suppliers. The mechanism is designed to procure a single indivisible item. An English auction protocol for multi-attribute items was proposed in (David et al., 2002), which again uses weighted additive scoring function to rank the bids. All the above mechanisms solve the incomparability between the bids, due to multiple attributes, by assigning a single numerical value to each bid and then ranking the bids by these values. Multi-criteria auction proposed in (Smet, 2003) is an iterative auction which allows incomparability between bids and the sellers increment their bid value by bidding more in at least one attribute. Iterative multi-attribute auctions for procurement were proposed in (Parkes & Kalagnanam, 2005) for procuring a single item. The bid consists of a price for each attribute and the iterative format provides feedback to the suppliers to update their bid prices.

5.2 Multi-criteria optimization for bid evaluation

In multiple criteria decision making situations with large or infinite number of decision alternatives, where the practical possibility of obtaining a reliable representation of decision maker's utility function is very limited, multiple criteria optimization techniques are useful approaches. Multiple attributes can be used both in bid definition and bid evaluation (winner determination). In the following, we describe the use of multiple criteria in bid evaluation using *goal programming* (adapted from Kameshwaran et al. (2007)). In (Beil &

Weun, 2003), the attributes are distinguished as *endogenous* (bidder controllable) and *exogenous* from the bidders' perspective. Attributes in bid definition (or RFQ) provide a means to specify a complex product or service, whereas in bid evaluation, the buyer can use multiple attributes to select the winning bidders. Therefore in bid definition, all attributes should be endogenous for the bidders, whereas in bid evaluation, the buyer can use some exogenous attributes to select the winners. In the MCDM literature, the words criteria and attribute are used interchangeably, and are defined as descriptors of objective reality which represent values of the decision makers (Zeleny, 1982).

We associate the word attribute with the RFQ and bids i.e. the buyer declares in the RFQ various attributes of the goods. We use the word criteria to indicate the objectives defined by the buyer for evaluating the bids. For example, if the attributes defined in the RFQ are cost, delivery lead time, and delivery probability, and then the criteria used by the buyer for evaluating the bids can be total cost, delivery 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 private information known to the buyer. On the other hand, minimizing cost of procurement is a function of many attributes defined in the RFQ. Thus criterion is used here in the sense of an objective.

Multiple criteria optimization problems can be solved using various techniques like goal programming, vector maximization, and compromise programming (Steuer, 1986; Romero, 1991). We describe here the use of (goal programming) GP to solve the bid evaluation problem. Unlike many multiple criteria optimization techniques which require special software tools, GP can be handled by commercial linear and nonlinear optimization software packages with minimal modifications. In GP, the criteria are given as goals and the technique attempts to simultaneously achieve all the goals as closely as possible. 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 ($=t_g$)
- range ($\in [t'_g, t''_g]$)

The t_g's are the target or aspiration levels. Without loss of generality let us assume the following goal structure for the procurement problem:

$$
\begin{array}{ll}
\text{goal } \{\mathbf{c}_1\mathbf{X} = f_1\} & (f_1 \geq t_1) \\
\text{goal } \{\mathbf{c}_2\mathbf{X} = f_2\} & (f_2 \leq t_2) \\
\text{goal } \{\mathbf{c}_3\mathbf{X} = f_3\} & (f_3 = t_3) \\
\vdots & \\
\text{goal } \{\mathbf{c}_G\mathbf{X} = f_G\} & (f_G \in [t'_G, t''_G])
\end{array}
\tag{29}
$$

$$
\text{subject to} \quad \mathbf{X} \in F \tag{30}
$$

The $\mathbf{X}$ is the vector of decision variables belonging to the feasible set F. The constraint set $\mathbf{X} \in F$ can be explicitly defined by linear inequalities. For brevity, we will use the above implicit representation. To convert the above GP to a single objective mathematical program, a deviational variable is defined for each goal. It essentially measures the deviation of the respective goal from its target value. Following goal constraints are added to the constraint set (30):

$$\begin{gathered}
\mathbf{c}_1\mathbf{X} + \gamma_1^+ \geq t_1 \\
\mathbf{c}_2\mathbf{X} - \gamma_2^- \leq t_2 \\
\mathbf{c}_3\mathbf{X} + \gamma_3^+ - \gamma_3^- = t_3 \\
\vdots \\
\mathbf{c}_G\mathbf{X} + \gamma_G^+ \geq t_G^{'} \\
\mathbf{c}_G\mathbf{X} - \gamma_G^- \leq t_G^{''} \\
\text{all } \gamma \geq 0
\end{gathered} \tag{31}$$

The range goal gives rise to two constraints but the other goals lead to only one each. The γ_g^+ measures the deviation away from the goal in the positive direction and γ_g^- is for the negative direction. 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 (Steuer, 1986). The GP techniques vary by the way the deviational variables are used to find the final solution. We present here the weighted GP technique for solving the bid evaluation problem.

Weighted GP (WGP) or *Archimedian* GP uses weights, given by the buyer, to penalize the undesirable deviational variables. The buyer specifies the weight $\kappa_g^{+/-}$ for goal *g*. The weights measure the relative importance of satisfying the goals. The GP (29) will then be the following single objective programming problem:

$$\min \sum_g \kappa_g^{+/-} \gamma_g^{+/-} \tag{32}$$

subject to

$$(31) \text{ and } \mathbf{X} \in F \tag{33}$$

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 *g* as percentage rather than as absolute value (Romero, 1991). For e-sourcing, the buyer can specify maximum deviation allowed for a goal and then use the percentage of deviation in the objective function.

The multi-attribute sourcing techniques described in this section are extremely useful for sourcing complex goods and services, but they are not wide spread in practice as one would expect. The main hurdle is the lack of exposition of the purchase managers and vendors to these techniques. It is only a matter of time till they are convinced of the profitability of these techniques at the cost of the high complexity, like in the case of combinatorial and volume discount auctions.

5.3 Configurable bids

Configurable bids are used for trading complex configurable products and services like computer systems, automobiles, insurances, transportation, and construction (Bichler et al., 2002). Configurable bids are an extension of multi-attribute bids. A multi-attribute bid is a set of attribute-value pairs, where each pair denotes the value specified by the bidder for the corresponding attribute. In a configurable bid, the bidder can specify multiple values for an attribute. The buyer can configure the bid optimally by choosing an appropriate value for each of the attributes.

Indices

i Attribute identification

k Value identification

j Supplier identification

Configurable bid from j

$\{c_{ij}^k\}_{i,k}$ where c_{ij}^k is the cost of value k for attribute i

Decision variables

x_{ij}^k = 1 if value k is chosen for attribute i for supplier j

The above bid structure implicitly assumes that the total cost is the sum of the individual costs incurred for each attribute. This may not be realistic but on the other hand, defining a cost function over a space of attribute-value pair is pragmatically impossible for the buyer. For example, a bid for 10 attributes with 5 values for each should consider a space of 9.7 million possible configurations. The additive cost structure generally works fine, except for certain constraints. For example, while configuring a computer system, a particular operating system may require a minimum amount of memory but not vice versa. Such logical constraints are not uncommon. Also, such logical constraints can be used to model non-additive cost structures like discounts and extra costs. The logical constraints can be converted into linear inequalities (probably with additional binary variables) and hence can be added to the winner determination problem. Buyer's constraints like homogeneity of values for a particular attribute in multi-sourcing can also be added as constraints to the optimization problem.

The configurable bids and in general, multi-attribute sourcing is not widely used in practice despite the theoretical popularity. Even the laboratory experiments showed encouraging results. Multi-attribute auctions with three different settings were experimented in laboratories: (1) with buyer's scoring function fully revealed for two attributes (Bichler, 2000), (2) with buyer's scoring function not revealed for three attributes (Strecker, 2003), and (3) with partial revelation of the scoring function for three attributes (Chen-Ritzo et al., 2005). All the three showed that multi-attribute auction formats outperform single attribute auctions. Though rarely used in practice currently, one can expect to see its wide spread usage in near future.

6. Global sourcing

Advent of global markets enhanced the emergence of global firms which have factories in different countries. Manufacturers typically set up foreign factories to benefit from tariff and trade concessions, low cost direct labor, capital subsidies, and reduced logistics costs in foreign markets (Ferdows, 1997). Global sourcing is used as a competitive strategy by firms to face the international competition, where suppliers located worldwide are selected to meet the demands of the factories, which are also located internationally (Gutierrez & Kouvelis, 1995; Velarde & Laguna, 2004). The main reasons are lower costs, improved quality, operational flexibility, and access to new technology.

Global sourcing is also used synonymously with outsourcing by some authors. In this chapter, global sourcing is used to denote *international sourcing* or *international purchasing*. In particular, we define global sourcing as procuring from a set of suppliers located worldwide to meet the demands of a set of factories, which are also located worldwide. Thus, there is no single buyer, but a set of buyers (factories belonging to the same company). Consider a company with many factories located domestically in a region. The purchasing department usually aggregates the demands of all the factories (to gain volume discount) and conducts e-sourcing auction for procurement. There is no distinction between the different factories from the suppliers' perspective, as usually they belong to the same region. Consider a multinational company with a set of factories located worldwide. The classical way of managing a multinational is to operate each firm as a domestic firm in its respective country. In the last two decades, global firms started adopting integrated management strategies, which blurs the national borders and treat the set of factories from different countries as a part of the same supply chain network. Global sourcing is one such integrated strategy, where suppliers located worldwide are selected to meet the demands of the factories, which are also located internationally. In this section, we present the design of *global sourcing network*, which is the equivalent to the winner determination problem in the global sourcing scenario.

Global sourcing network (GSN) is a set of suppliers in various countries to support the demands of the firm's international factory network. There are two kinds of decisions that are made in the design of GSN:

- *Supplier selection*: The subset of suppliers to be included in the sourcing network. This is a strategic investment decision that is made at the beginning of planning horizon, which incurs the one-time supplier development costs to the firm.
- *Order allocation*: The allocation of orders from the selected suppliers to the factories to meet the demand at the factories. This is a tactical decision, influenced by the procurement costs.

The first decision is implemented before the planning horizon and the second is implemented during it. This is a single-period problem as there is only one order allocation. The supplier selection decision is assumed fixed and irreversible during the planning horizon i.e. no new suppliers can be added once the decision is made. Each supplier has a fixed development cost, which is the cost of including the supplier in the network. The objective is to minimize the total procurement cost that includes both the supplier development costs and the order allocation costs. Hence, both the decisions are contingent on each other and are made in tandem. In addition to the suppliers, we consider two other sources of supply: *Redundant inventory* and *spot purchase*. Redundant inventory is a part of strategic decision, which once invested incurs a fixed cost irrespective of whether it is used or not. Thus it has a fixed cost and a maximum capacity associated with it. Spot purchase is another option that has no strategic component. If all other sources are unavailable, the organization can always go for this sure but costlier option. We assume that the capacity is infinite. The cost incurred due to lost in sales or unmet demand can also be modelled using this option. It essentially has the same characteristics: *No fixed cost*; *no upper limit*; *sure but costlier option*. All the above can be summarized as follows.

Parameters

- *International factory network*: The number of factories and their locations are assumed to be known and fixed. Index i is used as the factory identifier.
- *Potential suppliers*: The potential global suppliers are assumed to be known and their locations are fixed. Suppliers are identified by index j.
- *Demand*: The demand for the item to be sourced at factory i is d_i.
- *Supply*: The available supply quantity from supplier j is given as range $[a_j, z_j]$, which denotes the minimum and maximum quantity that can be procured from the supplier.
- *Supplier development costs*: The fixed cost of developing supplier j is Fc_j if he is accepted in the sourcing network.
- *Procurement costs*: Unit cost of procurement from supplier j for factory i is c_{ij}.
- *Redundant inventory*: A possible investment in redundant inventory for each factory i with capacity r_i and total cost Ic_i. It is more realistic to assume different levels of investments with varying capacity and cost $\{(r_i^l, Ic_i^l)\}$. For the sake of brevity, we assume only one level of investment for each factory. The proposed model can be easily extended to include various levels.
- *Spot purchase*: For each factory i, there is a sure source of supply with unit cost Sc_i and infinite capacity. Penalty incurred due to lost sales of unmet demand can also be modelled similarly. We have just restricted to one option of this kind per factory for the sake of brevity.

The design of GSN involves identifying an optimal set of suppliers, order allocation from the winning suppliers, investments in the redundant inventories, and the quantity to be spot purchased for the factory network, such that the total cost of procurement is minimized.

Decision variables

x_i = 1 if supplier j is included in the network, = 0 otherwise

y_{ij} Quantity supplied from supplier j to factory i

u_i = 1 if investment is made for redundant inventory at factory i

w_i Spot purchase quantity at factory i

MILP formulation

$$\min \sum_j Fc_j x_j + \sum_i \sum_j c_{ij} y_{ij} + \sum_i Ic_i u_i + \sum_i Sc_i w_i \tag{34}$$

subject to

$$\sum_j y_{ij} + w_i + r_i u_i \geq d_i \quad \forall i \tag{35}$$

$$a_j x_j \leq \sum_i y_{ij} \leq z_j x_j \quad \forall j \tag{36}$$

$$x_j \in \{0,1\} \quad \forall j \tag{37}$$

$$y_{ij} \geq 0 \quad \forall i, j \tag{38}$$

$$u_i \in \{0,1\}, w_i \geq 0 \quad \forall i \tag{39}$$

The above problem is the same as the capacitated version of the well studied *facility location* problem (Drezner & Hamacher, 2002) with the suppliers as the facilities and the factories as the markets with demands. The developing cost of a supplier is the fixed cost associated with opening of a new facility. Many of the algorithms for facility location problem can be adapted for solving the design of GSN problem.

7. Robust e-sourcing

Current supply chains are characterized by leanness and JIT principles for maximum efficiency, along with a global reach. This makes the supply chain highly vulnerable to exogenous random events that create deviations, disruptions, and disasters.

- A strike at two GM parts plants in 1998 led to the shutdowns of 26 assembly plants, which ultimately resulted in a production loss of over 500,000 vehicles and an $809 million quarterly loss for the company.
- An eight-minute fire at a Philips semiconductor plant in 2001 brought its customer Ericsson to a virtual standstill.
- Hurricanes Katrina and Rita in 2005 on the U.S. Gulf Coast forced the rerouting of bananas and other fresh produce.
- In December 2001, UPF-Thompson, the sole supplier of chassis frames for Land Rover's Discovery vehicles became bankrupt and suddenly stooped supplying the product.

Much writings in the recent past as white papers, thought leadership papers, and case studies on supply chain risk management have emphasized that redundancy and flexibility are pre-emptive strategies that can mitigate loses under random events. But this is against the leanness principles and increases the cost. It is required to trade-off between the leanness under normal environment and robustness under uncertain environments. It is in this context; this section briefly introduces *robustness*, a characteristic of winner determination that is almost neglected in current e-sourcing. Caplice & Sheffi (2006), who were directly involved in managing more than hundred sourcing auctions for procuring transportation services, emphasize on the significance of robustness in bid evaluation. The supplier bankruptcy, transportation link failure, change in demand are common sources of uncertainties that are need to be taken into account during bid evaluation.

7.1 Deviations and disruptions

The uncertainties in supply chains might manifest in the form of *deviations*, *disruptions*, or *disasters* (Gaonkar & Viswanadham, 2004). The deviations refer to the change in the certain parameters of the sourcing network like the demand, supply, procurement cost, and transportation cost. The deviations may occur due to macroeconomic factors and the default sourcing strategies may become inefficient and expensive under deviations. Disruptions change the structure of the supply network due to the non-availability of certain production, warehousing and distribution facilities or transportation options due to unexpected events caused by human or natural factors. For example, Taiwan earthquake resulted in disruption of IC chip production and the foot-and-mouth disease in England disrupted the meat supply. Under such structural changes, the normal functioning of supply chain will be momentarily disrupted and can result in huge losses. The third kind of risk is a disaster, which is a temporary irrecoverable shut-down of the supply chain network due to unforeseen catastrophic system-wide disruptions. The entire US economy was temporarily shutdown due to the downturn in consumer spending, closure of international borders and shut-down of production facilities in the aftermath of the 9/11 terrorist attacks. In general, it is possible to design supply chains that are robust enough to profitably continue operations

in the face of expected deviations and disruptions. However, it is impossible to design a supply chain network that is robust enough to react to disasters. This arises from the constraints of any system design, which is limited by its operational specification.
First, we characterize the deviations and disruptions that can happen in a sourcing network. The three parameters that influence the sourcing decision are: *Demand*, *supply*, and *procurement cost*. The demand is the buyer's parameter, whereas the supply and the cost are given in the bids by the suppliers. In terms of bid evaluation as a mathematical program, the objective coefficients are the costs and the demand-supply parameters are the right hand side constants of the constraints. The optimal solution to the above mathematical program obviously depends on the three parameters. However, all the three are subject to deviations:

- *cost deviation* due to macroeconomic change or exchange rate fluctuations
- *supply disruption* due to supplier bankruptcy
- transportation link failure due to natural calamity or port strike, leading to *supply disruption*
- *supply deviation* due to upstream supply default
- *demand deviation* due to market fluctuation

The above deviations and disruptions are realized after the bid evaluation but before the physical procurement. Thus, these deviations can render the optimal solution provided by the bid evaluation costly and inefficient, and even sometimes infeasible and inoperable. To handle unforeseen events in sourcing network or in general, supply chain network, there are two obvious approaches: (1) to design networks with built in risk-tolerance and (2) to contain the damage once the undesirable event has occurred. Both of these approaches require a clear understanding of undesirable events that may take place in the network and also the associated consequences and impacts from these events. We show here how we can design a risk-tolerant sourcing network by taking into account the uncertainties in bid evaluation.

7.2 Bid evaluation under uncertainty

Bid evaluation problem is an optimization problem and hence we can draw upon the optimization techniques that can handle randomness in data. The decision-making environments can be divided into three categories (Rosenhead et al., 1972): certainty, risk, and uncertainty. In *certainty* situations, all parameters are deterministic and known, whereas risk and uncertainty situations involve randomness. In *risk* environments, there are random parameters whose values are governed by probability distributions that are known to the decision maker. In *uncertainty* environments, there are random parameters but their probability distributions are unknown to the decision maker.
The random parameters can be either continuous or discrete scenarios. Optimization problems for risk environments are usually handled using stochastic optimization and that for uncertain environments are solved using robust optimization. The goal of both the stochastic optimization and robust optimization is to find a solution that has acceptable level of performance under any possible realization of the random parameters. The acceptable level is dependent on the application and the performance measure, which is part of the modelling process.
Stochastic optimization problems (Birge & Louveaux, 1997; Kall & Wallace, 1994) generally optimize the expectation of the objective function like minimizing cost or maximizing profit. As probability distributions are known and expectation is used as the performance measure,

the solution provided is ex-ante and the decision maker is risk neutral. Robust optimization (Kouvelis & Yu, 1994) is used for environments in which the probability information about the random events is unknown. The performance measure is hence not expectation and various robustness measures have been proposed. The two commonly used measures are minimax cost and minimax regret. The minimax cost solution is the solution that minimizes the maximum cost across all scenarios, where a scenario is a particular realization of the random parameters. The minimax regret solution minimizes the maximum regret across all scenarios. The regret of a solution is the difference (absolute or percentage) between the cost of that solution in a given scenario and the cost of the optimal solution for that scenario. Both the approaches have been used to solve the sourcing problem with randomness.
A robust optimization based approach for uncapacitated version of the sourcing problem with exchange rate uncertainty (cost deviation) was considered in (Gutierrez & Kouvelis, 1995; Kouvelis & Yu, 1997). The uncertainties were modelled using discrete scenarios and minimax regret criterion was used to determine the robust solution. In (Velarde & Laguna, 2004), the deviations in both demand and exchange rates were considered. The randomness was modelled using discrete scenarios with probabilities. The objective function had two components: expected cost and variability (that measures the risk). In the following we outline a robust optimization based approach to solve the bid evaluation problem.

7.3 Robustness approach to bid evaluation

The objective here is to propose a robust optimization methodology to design a sourcing network that is risk-tolerant. The choice of robust optimization is due to the fact that managers are more concerned about the outcome of a random event than its probability of occurrence (March & Shapira, 1987). Hence, the optimization of expected cost approach, which implicitly assumes the decision maker to be risk neutral, is not directly applicable. It was also noted by Gutierrez & Kouvelis (1995) that decisions of the managers are not evaluated by their long term expected outcome but by their annual or half-yearly performance. Hence, robust optimization that directly works with the outcome of the random events, rather than probability and long-run expected outcomes, is more appropriate for e-sourcing.
In the proposed methodology, the randomness is modelled via discrete scenarios. The advantage with discrete scenarios is that one need not concern about the source of the scenario, but rather work with the scenario directly. For example, a supplier might get disrupted due to several reasons: Bankruptcy, transportation link failure, upstream supply failure, etc. The buyer needs to only concern about the scenario of a particular supplier failing rather than the sources that would cause it. Working at the level of scenarios is complicated for probability models, as one has to derive the probability of a scenario from the probabilities of the random events that are responsible for that scenario. With no probability information required for robust information, discrete scenario modelling is more appropriate for sourcing. In the following, we abstract the bid evaluation problem to be an optimization problem without specifying the bid structure and the business constraints.
Indices
s Scenario identifier
Data
D^s Demand vector in scenario s
A^s Supply vector in scenario s

C^s Cost vector in scenario s

Notation

X A solution vector to the bid evaluation problem

X^s Optimal solution vector to bid evaluation in scenario s

X^R Robust solution vector

$Z^s(\cdot)$ Cost of solution $(\cdot)$

A scenario s is characterized by a 3-tuple of vectors: $\{D^s, A^s, C^s\}$. Thus, any change in demand or supply or cost or their combinations represents a scenario. By definition, any two scenarios will differ in at least one of the *D*, *A*, *C* vectors. Let s=0 denote the default or unperturbed scenario. The lowest cost L^s for scenario s is its optimal cost:

$$L^s = Z^s(X^s) \tag{40}$$

From the optimality of X^s, it follows that for any solution X, $L^s \le Z^s(X)$. The relative regret of solution X for scenario s is:

$$r^s(X) = \frac{Z^s(X) - L^s}{L^s} \tag{41}$$

Let U^s denote the maximum cost that will be incurred for scenario s. If $U^s - L^s$ is negligible, then the scenario is not sensitive to the solution. On the other hand if $U^s >> L^s$, the scenario s has to be judiciously handled, even if it is a low probable event, as it might end up with huge increase in the cost. The objective function is robust optimization is a robustness measure. The two commonly used measures are *minimax cost* and *minimax regret*. The minimax cost solution is the solution that minimizes the maximum cost across all scenarios, where a scenario is a particular realization of the random parameters. The minimax regret solution minimizes the maximum regret across all scenarios. The minimax regret objective is given by:

$$\min_X \max_s r^s(X) \tag{42}$$

In general, the minimax versions are overly conservative as the emphasis is on the worst possible scenario, which may occur very rarely in practice. Hence, a solution that is good with respect to the worst-case scenario may perform poorly on the other commonly realizable scenarios. Another measure of robustness is to constrain the regret within pre-specified value $p^s : r^s(X) \le p^s$ (Snyder & Daskin, 2006). Small values of p^s make the solution X to perform close to that of the optimal solution X^s for scenario s. Thus, by judiciously selecting p^s, the buyer can characterize the importance of scenario s. To implement the above, the following constraints are included in the formulation for robust design.

$$Z^s(X) \le (1 + p^s)L^s \qquad \forall s \tag{43}$$

Note that L^s is the optimal cost for scenario s, and hence for robust design, one needs to solve the bid evaluation problem for each of the scenarios. For any solution X, $L^s \le Z^s(X) \le U^s$. Combining with constraint (43), one can derive the maximum value for p^s:

$$p^s \leq \frac{U^s}{L^s} - 1 \qquad \forall s \tag{44}$$

The $\{p^s\}$ are the input parameters to be provided by the buyer to define the *acceptable levels* of operation for different scenarios. Determining U^s will aide the buyer in choosing an appropriate value for p^s. Let X^R be a robust solution that satisfies the constraints (xx). Then,

$$r^s(X^R) \leq p^s \qquad \forall s \tag{45}$$

Given a set of robust solutions $\{X^R\}$, the buyer can choose the best one based on different business criteria. The robust solution ensures that the sourcing network operates at the predetermined operating levels under a wide range of pre-identified scenarios. Thus, the usefulness of the approach clearly depends on the number and the nature of the representative scenarios identified. However, constraint set (43) requires that the winner determination problem needs to be solved for every scenario. As noted in the previous sections, winner determination problems are computationally challenging for complex bid structures and in the presence of business constraints. Thus, the need for solving it for each of the scenarios limits the number of scenarios that can be considered in the robust design.

8. Final notes

This chapter was devoted to optimization based e-sourcing models. It reviewed three popular e-sourcing techniques with their underlying mathematical programming models that are used to solve the winner determination problems. The volume discount and combinatorial sourcing are actively used in business-to-business commerce saving billions of dollars annually. The multi-attribute sourcing technique is yet to catch up, but one can expect increased use in near future given its popularity in literature and encouraging results in laboratory experiments.

All the three techniques reviewed in the chapter are provided commercially as e-sourcing tools by many vendors. We also presented in this chapter two future directions, which are inevitable in the evolution of e-sourcing techniques and tools. One is global sourcing, which connects multiple suppliers with multiple factories, all located internationally. The second is the robust sourcing that takes into account deviations and disruptions, which can render the solution provide by traditional e-sourcing tools inefficient and costly. We presented both the above in the framework of optimization based e-sourcing and hence the currently available methodologies and tools can be adapted to include them.

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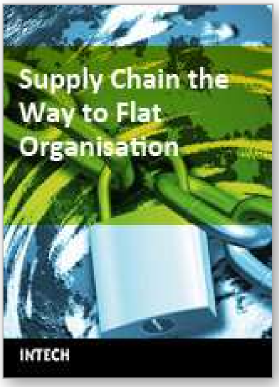

Supply Chain the Way to Flat Organisation
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With the ever-increasing levels of volatility in demand and more and more turbulent market conditions, there is a growing acceptance that individual businesses can no longer compete as stand-alone entities but rather as supply chains. Supply chain management (SCM) has been both an emergent field of practice and an academic domain to help firms satisfy customer needs more responsively with improved quality, reduction cost and higher flexibility. This book discusses some of the latest development and findings addressing a number of key areas of aspect of supply chain management, including the application and development ICT and the RFID technique in SCM, SCM modeling and control, and number of emerging trends and issues.