International Journal of Industrial Engineering, 15(2), 155-165, 2008.

SIMULATED ANNEALING FOR SOLVING PIECEWISE LINEAR SUPPLIER SELECTION PROBLEM CONSIDERING QUANTITY DISCOUNTS

N. Arunkumar[1], L. Karunamoorthy[1], and N. Uma Makeshwaraa[2]

[1]Department of Mechanical Engineering,
Central Workshop Division,
Anna University, Chennai, India.

[2]Mechanical Engineering,
University of Texas at Austin,
Austin, TX, USA.

Corresponding author's e-mail: {N. Arunkumar, n.arunkumar@rediffmail.com}

Supplier selection problems are often complicated due to the conflicting objectives and constraints that need to be considered while selection. This problem becomes still more complicated with the inclusion of quantity discounts offered by the suppliers. A multi component multiple supplier selection model considering quantity discounts under incremental quantity discount scenario is proposed in this paper. The combinatorial nature of the supplier selection problem motivates to explore the use meta-heuristic algorithm for solving this complex problem. The proposed model is evaluated using simulated annealing in this article. The results were found to be near optimal along with the generation of alternate set of solutions. Such type of solutions will be very useful to manufacturing firm where the purchase manager would also like to look at options for alternative solutions.

Significance: This article considers the advantage of meta-heuristics like simulated annealing for solving hard combinatorial supplier selection problem. The results were found to be efficient when applied to a real case study – supplier selection in a textile machinery manufacturing company in India

Keywords: Supplier selection, Multi-objective, Combinatorial, Simulated annealing

(Received 4May 2006; Accepted in revised form 20 December 2007)

1. INTRODUCTION

In today's competitive operating environment it is impossible to successfully produce low cost, high quality products without satisfactory vendors. Thus, one of the important purchasing decisions is the selection and maintenance of a competent group of suppliers (Weber et al. 1991). The objective of supplier selection is to identify suppliers with the highest potential for meeting a firm's needs. The supplier selection decisions determine how many and which suppliers should be selected as supply sources and how order quantities should be allocated among the selected suppliers. According to Rajagopal and Bernard (1993), since an organisation is only as good as its sources of supply, decisions concerning the creation and management of the supplier base are among the most important and fundamental in the purchasing process.

Traditional supplier selection decisions are mostly based on procurement cost, product quality, delivery performance and supply capacity criteria. Supplier selection decision-making also involves trade-offs among multiple-criteria that involve both quantitative and qualitative factors, which may also be conflicting (Ghodsypour et al. 1998). The joint consideration of the above criteria complicates the selection decision even for experienced purchase managers, because competing vendors have different levels of achievement under these criteria. For example, the vendor with the least price in a given industry may not have the best delivery performance or product quality. In addition to the multi-objective nature of supplier selection, emergence of a discount pricing schedule becomes a major obstacle for procurement managers in finding the best purchasing strategy. In this environment, the supplier induces the buyer into making large purchases by offering discounts based on the quantity ordered for each product.

There exist a number of approaches of supplier selection considering various sets of criteria for selection. In this article, we present a model for supplier selection considering multiple components for multiple suppliers who offer quantity discounts. Trade-offs is considered when selecting suppliers using multiple criteria. The proposed supplier selection model is evaluated using simulated annealing (SA) for solving vendor selection problems. Simulated Annealing is been used for solving various problems in different domains (McKendall et al. 2006, Malmborg 2003). There is little evidence in the literature for using simulated annealing for supplier selection and order allocation problem.

2. LITERATURE SURVEY

A survey on the papers dealing with supplier or vendor selection problem was presented by Dickson (1966). At that time the most important criteria were quality of the product, on-time delivery, performance history and the warranty policy used by the suppliers. Due to industrial evolution, the relative importance of the criteria varied with the addition of new criteria such as quantity discounts.

According to the study by Hongwei Ding et al. (2003), the existing methods of solving the vendor selection problem can be classified into three principal categories. The various elementary methods presented below can also be combined.

1. Elimination Methods (Crow et al. 1980)
2. Optimization methods.
    - Without constraints: AHP approach (Golden et al. 1989)
    - Subject to a set of constraints: Mathematical programming approach (Weber et al. 1993, Ghodyspour et al. 1998)
3. Probabilistic methods (Soukup 1987).

The elimination models are simple to use, but the final choice is not made considering the total performance on all the criteria. Regarding Probabilistic methods, an optimal solution could not be found and is also not easy to analyze.

Cengiz Kahraman et al. (2003) Gary Teng (2005) proposes the use of the Analytic Hierarchy Process (AHP) to deal with imprecision in supplier choice. The AHP method relies on an inaccurate ratio scale. The scale directly limits the ability of decision-makers to express their real judgments, and easily results in undesirable criteria weights.

Given the economic importance and inherent complexity of the supplier selection process, it is surprising that little research has been devoted to developing a mathematical programming technique for this problem. A review of supplier selection criteria and methods (Weber et al. 1991) identifies ten such approaches. Mathematical programming models include Linear programming, Mixed-integer programming, Dynamic programming, Goal Programming and others (Weber et al. 1993, Das et al. 1994, and Buffa et al. 1983, Marvin et al. 2004). Once the criteria are decided, the mathematical programming model allows the decision-maker to formulate the decision problem in terms of a mathematical objective function. This then subsequently needs to be maximized (e.g. maximize profit) or minimized (e.g. minimize cost) by varying the values of the variables in the objective function. Mathematical programming models are most useful in repetitive, high volume-supply situations.

Mathematical programming techniques have frequently been applied to purchasing issues, mainly in the domain of determining order quantities, specifically in environments where supplier offers complex discounts. Sadrian et al. (1994) presented a mathematical formulation of the single item procurement decision problem under two different business volume discount schedules. Chaudhry et al. (1993) developed a mixed integer programming approach to situations involving the sourcing of a single product from vendors offering price breaks, which depend on the magnitude of the order quantity.

In this article, we consider a mathematical programming model considering multi-objectives for determining the best set of vendors offering price breaks due to the quantity discount model. During selections, multiple criteria and trade-offs are introduced to arrive at the final solution. Existing supplier selection models do not consider the defectives present in the supply and only give that order quantity to each vendor which will sum up to exact demand. The model used in this article considers defectives during order allocation so that the exact demand will always be met.

2.1 Motivation for this research

Most of the researchers have used conventional optimization techniques for solving vendor selection problems. These methods don't fare well over a broad spectrum of problem domains and are not efficient when the practical search space is too large. Meta-heuristics can fare well even when the search space is too large. The following important supplier selection factors motivate the proposed meta-heuristics for solving the multi-objective supplier selection problem.

1. The supplier selection criteria are multi-objective in nature, both qualitative and quantitative, and are conflicting.
2. Other problem parameters and market behaviors are mostly uncertain. The intervention of various industrial and social constraints related to manufacturer and suppliers, such as limited capacity of the supplier, minimum and maximum order quantity accepted by suppliers, quality, delivery time and price, complicate the development of an efficient approach (Hongwei Ding et al., 2003).
3. In addition to the constraints indicated above, the proposed research also includes price breaks due to quantity discounts offered by the suppliers. Often complicating the selection process for the buyer is the presence of price breaks, offered by vendors that depend on the size of the order quantity placed. This paper addresses quantity discounts under an incremental discount scenario.

The buyers should consider the tradeoffs between the costs and the benefits resulting from larger orders and come up with reasonable purchasing decisions. When the presence of price breaks is combined with capacity or rationing constraints of the vendors and quality and delivery requirements of the buyer, vendor selection can be extremely complex for the buyer to perform (Pirkul and Aras, 1985).

3. MODEL DEVELOPMENT

Consider a manufacturing company, which has a pool of ‘j’ vendors who are supplying ‘i’ components. The objective for the manufacturing company is to choose the best set of vendors satisfying their objective and to allocate order quantities for each of the vendors. Figure 1 indicates the model indicating the manufacturer and vendor constraints.

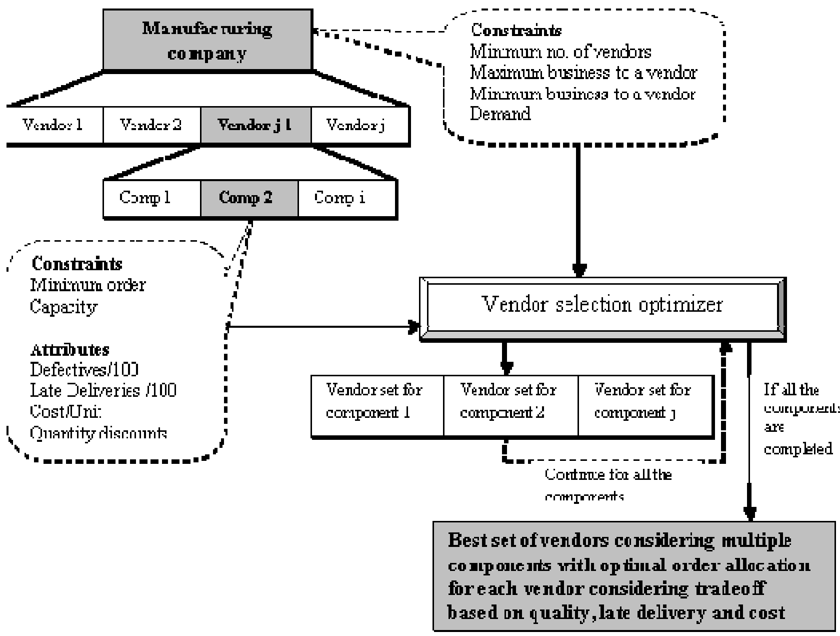

Figure 1. Model for multiple components multiple supplier selection

3.1 Model

The objectives indicated are subject to constraints placed by the manufacturer, the vendor as well as the trade-off values that are proposed by the manufacturer for the objectives. Let us consider Z1, Z2 and Z3 representing the quality, delivery and cost objectives.

Notations:

N	Total number of vendors
n	Total number of components
λ_{ij}	Percentage Defective of i^{th} component produced by vendor j
β_{ij}	Percentage late delivery for i^{th} component produced by vendor j
η_{ij}	Cost per unit for i^{th} component produced by vendor j
X_{ij}	Number of components of type i that are to be purchased from vendor j.
$\eta 1_{ij}$	Cost per unit for i^{th} component produced by vendor j without discount
$\eta 2_{ij}$	Cost per unit for i^{th} component produced by vendor j with discount
m_{ij}	Middle order quantity for the i^{th} component of vendor j
ϕ_i	Upper limit desired by the purchase manager for number of defectives for i^{th} component

ω_i	Upper limit desired by the purchase manager for number of late deliveries for i^{th} component.
B_{ij}	Minimum Business for the vendor j for the ith component
M_{ij}	Maximum Business for the vendor j for the ith component
D_i	Total Demand for component i
$\xi_{ij} \in (0,1)$	Selection of Vendor j for supplying i^{th} component 0 – vendor has not been selected 1- Vendor has been selected
C_{ij}	Capacity of the vendor j for the ith component
Q_{ij}	Minimum order quantities the vendor j will supply for the ith component

Objectives:

[Quality Objective] *Minimize* $$Z_{i1} = \sum_{j=1}^{N} \lambda_{ij} \times X_{ij} \qquad \ldots \quad \ldots. (1)$$

i=1, 2…..n

[Delivery Objective] *Minimize* $$Z_{i2} = \sum_{j=1}^{N} \beta_{ij} \times X_{ij} \qquad \ldots \quad \ldots. (2)$$

i=1, 2…..n

[Cost Objective] *Minimize* $$Z_{i3} = \sum_{j=1}^{N} \eta_{ij} \times X_{ij} \qquad \ldots \quad \ldots. (3)$$

i=1, 2…..n

One of the criteria considered in this model is the quantity discount. The vendors provide price breaks based on the number of components ordered. This is determined considering the middle order quantity as indicated below. If the quantity exceeds 'm', then the total cost incurred by the manufacturer for buying the i^{th} component from a particular vendor is

$$\eta_{ij} = \eta 1_{ij} \quad \forall X_{ij} \le m_{ij}$$

$$\eta_{ij} = (\eta 1_{ij} \times m_{ij}) + (\eta 2_{ij} \times (X_{ij} - m_{ij})) \quad \forall X_{ij} > m_{ij}$$

This type of discount model is termed as incremental quantity discount models. The cost objective (3) considers the above said incremental discounts when solving the model.

Constraints:

To arrive at the minimization of cost objective, the trade-off values for quality and delivery should be considered. This model follows a step by step approach, where each criterion is evaluated in turn. Hence, the first objective is quality and the next one is delivery. They are represented as below

Minimize Z_{i2} (Delivery) subject to $$\sum_{j=1}^{N} \left(\lambda_{ij} \times X_{ij}\right) \le \phi_i \qquad \ldots \quad \ldots.(4)$$

i=1, 2…..n

Minimize Z_{i3} (Cost) Subject to $$\sum_{j=1}^{N} \left(\lambda_{ij} \times X_{ij}\right) \le \phi_i, \ \sum_{j=1}^{N} \left(\beta_{ij} \times X_{ij}\right) \le \omega_i \qquad \ldots \quad \ldots. (5)$$

i=1, 2…..n

In the above model, ϕ_i and ω_i are the user input based on the trade-off values. For example, though the model is able to get a minimum defective (best value) of 58, the user may relax it to 75 to get a different solution. So ϕ_i is equal to 75 and the problem is then solved. ϕ_i and ω_i may be fixed by the purchase manager based on the company policy. Similarly for cost calculation, the trade-off value is input considering defectives and late deliveries. The following constraints indicate the common constraints of the manufacturing company in order to meet the above said objectives

Common constraint 3 (Minimum business) $X_{ij} \geq (B_{ij} \times \xi_{ij})$ ... .*(6)*

$\forall$ *i=1, 2… n*
j=1, 2… N

Common constraint 4 (Maximum business) $X_{ij} \leq (M_{ij} \times \xi_{ij})$ ... .*(7)*

$\forall$ *i=1, 2… n*
j=1, 2… N

Common Constraint 5 (Demand) $\sum_{j=1}^{N} X_{ij} \geq D_i$ ....*(8)*

i=1, 2… N

The vendor constraints also influence the selection of the vendors. They are indicated as given below

Common constraint 1 (Capacity) $X_{ij} \leq (C_{ij} \times \xi_{ij})$ ... .*(9)*

$\forall$ *i=1, 2… n*
j=1, 2… N

Common constraint 2 (Minimum Quantity) $X_{ij} \geq (Q_{ij} \times \xi_{ij})$ ... .*(10)*

$\forall$ *i=1, 2… n*
j=1, 2… N

4. SOLUTION METHODOLOGY

4.1 Overview of the proposed approach

Three different aspects characterize the supplier selection problem

1. The first aspect is the determination of the number of suppliers.
2. The second aspect is the selection of suppliers based on the constraints and objectives specified.
3. The third aspect is the allocation of order quantities for each of these vendors.

In this work, all these aspects of vendor selection are considered. A combinatorial approach is used to generate the set of vendors. The SA optimizer takes these vendor sets and the constraints as the input and produces the best set of vendors for each component along with their order allocation. The goal of determination of the number of vendors is implicitly achieved by selecting and allocating orders to be best set of vendors. Hence all three aspects defined above are satisfied in the final result obtained. Here a step-by-step process first generates an objective value based on constraints discussed in model. Then the objective value relaxed and added as another constraint for the next objective function based on the value found in the previous step. The purchase manager can decide on the relaxation of the quality and delivery constraint depending on the company policy. Thereby the purchase manager can choose from different possible selections of vendors.

4.2 Combinatorial approach

Combinatorial optimization problems are concerned with the efficient allocation of limited resources to meet desired objectives when the values of some or all of the variables are restricted to be integral. Constraints on basic resources restrict the possible alternatives that are considered feasible. Still, there are many possible alternatives to consider and one overall goal determines which of these alternatives is the best. Unlike other vendor selection approaches which focuses at the determination of only one vendor for a specific task this research focus is on the determination of a set of vendors that can collectively accomplish the objectives and constraints in an optimal manner. Therefore a combinatorial search for the optimal vendor selection is required. Here the objectives are applied on combination of suppliers rather than for just individual suppliers. SA is used for solving such combinatorial problem taking the vendor sets as the input for the SA optimizer. Simulated Annealing has its major advantage due to the relative ease of implementation and the ability to provide reasonably good solutions for many combinatorial problems. In the proposed supplier selection problem using combinatorial approach only the various combinations of vendor sets are determined and does not consider any constraints when determining these combinations. Constraints are applied by the SA optimizer when allocating orders.

4.3 Multi-objective supplier selection

This paper proposes a multi objective approach for supplier selection considering trade-offs among the relevant criteria. Multi-objective programming is been used for solving various problems in the manufacturing environment (Lashkari et. al., 2002). There exist various multi-objective techniques among which we propose multi-level programming to be suited for the proposed problem. Multilevel programming is a one-shot optimization technique and is intended to find just one optimal point. The first step in multilevel programming involves ordering the objectives in terms of importance. Next, it is needed to find the set of points for which the minimum value of the first objective function is attained. Then find the points in this set that minimize the second most important objective. The method proceeds recursively until all objectives have been optimized on successively smaller sets. Multilevel programming is a useful approach if the hierarchical order among the objectives is of prime importance This problem considers and prioritizes quality, late delivery and price as the three main objectives.

In the proposed algorithm, initially the optimal value of the first objective (quality) is determined say the value is 56. Then the quality is relaxed from this optimal value by increasing the number of defectives to be accepted. This relaxed value is input for calculating the second objective (late delivery). It would be found that relaxing the quality after a certain value does not give an appreciable difference in the value of late delivery. Hence based on these values, an upper limit for quality is fixed. Once the quality is fixed, the upper limit for late delivery is determined in a similar way by considering the third objective (cost). Here the cost objective is solved with a fixed upper limit on quality and relaxing the number of late deliveries. Once the upper limit for late deliveries is also fixed, these two tradeoff values for quality and late delivery forms the basis for solving final (best) value of cost.

4.4 Simulated annealing algorithm

SA is motivated by an analogy to annealing in solids. The algorithm starts by generating an initial solution (either randomly or heuristically constructed) and by initializing the so-called temperature parameter *T*. Then the following is repeated until the termination condition is satisfied: A solution s' from the neighborhood $N(s)$ of the solution s is randomly sampled and it is accepted as new current solution depending on $f(s)$, $f(s')$ and T. s' replaces s if $f(s') < f(s)$ or, in case $f(s') >= f(s)$, with a probability which is a function of T and $f(s') - f(s)$. The probability is generally computed following the Boltzmann distribution $exp\ (-(f(s') - f(s))/T)$. This completes an iteration of the SA procedure. The algorithm is terminated when sufficiently small temperature is obtained or when the system is "frozen" at the current temperature (that is, no better or worse moves are being accepted).

4.4.1 SA

Initial temperature:

Initial temperature is used to specify the temperature from which the annealing process is to be initiated. For this specific problem we have chosen to accept the inferior solution by 50% relative to the original solution with an associated probability of 0.7. Hence we arrive at the initial temperature setting as given below.

$P=\exp(-\Delta/T)$, i.e., $0.7 = \exp(-50/T)$, Hence $T \approx 140$

In order to obtain an efficient initial temperature setting, a few trial runs were made with starting temperature in the neighborhood of 140. The results were best with the initial temperature setting of 150 during the trial runs

Temperature step:

The way in which the temperature decremented is critical to the success of the algorithm. The temperature is decremented using the below given method

$T_{i+1} = \alpha T_i \qquad 0< \alpha<1$

Where i is the step number and starts from 1. α usually be between 0.8 and 0.99, with better results being found in the higher end of the range. Of course, the higher the value of α, the longer it will take to decrement the temperature to the stopping criterion. The value chosen for this problem is 0.986. Hence the temperature step value is 2 degree

Number of iterations:

Enough iteration should be allowed at each temperature so that the system stabilizes at that temperature. According to the literature, a suitable value of number of iterations can be chosen (20-100) depending on the available computing resource and the solution time (Kalyanmoy Deb 2002). It was found that with a size of 50 and above, same 'vendor set' (1:2:5:6) were chosen and also resulted in very minute difference in objective values. Hence the number of iterations performed at each temperature is chosen to be 50 in this problem.

Minimum temperature:
The minimum temperature determines when the search can be halted. The search can be halted when it ceases to make progress. Lack of progress is no improvement (i.e. no new best solution) being found during the search at one temperature. Based on many trial runs, the final temperature is fixed to be 50, as it makes sure that the algorithm runs for 50 temperature settings, with a temperature step as 2, which is found to be a good balance between computational effort and solution quality in the trial runs. The termination of SA algorithm is done when the temperature is less than or equal to 50. This is done because the chances of obtaining further good solutions appear to be diminishing and hence we terminate the search process.

4.4.2 The proposed SA algorithm and its steps for vendor selection

Step 1: Obtain the combination of vendors using combinatorial approach

Step 2: For each vendor combination generated by the combinatorial approach, SA allocates the order randomly. This vendor set along with their order allocation is termed as 'vendor_alloc'. For example V1, V2, V5 and V6 with their allocation as 600, 351, 651, and 464 are a 'vendor_alloc' 600:351:651:464.

Step 3: The 'vendor_alloc' is then tested for the feasibility of the constraints in this problem. This is done because only the feasible and viable solution is taken to the search space.

Step 4: Initialize the initial temperature T=150, Count =0, n= 50.

Step5: The feasible solution during the first iteration of maximum temperature is considered as the best and stored in memory. Say its energy function value is 25J. The energy function is evaluated considering all the objectives.

Step 6: If current temperature = minimum temperature
Go to step 10:
Else
Proceed to step 7

Step 7: Increase the iteration counter.

Step 8: Take the adjacent 'vendor_alloc' and evaluate its energy function. Say if the energy during the second iteration is 21J. Then if this is less than the solution stored in memory this is considered as best. As the iteration is increased the next feasible solution from the random order allocator is tested. This is repeated for each iteration, until the number of iterations reaches 'n'. If number of iteration is less than 'n' then go to Step 7.

Step 9: Decrease the temperature by one step. Reset the iteration counter. Go to Step 7. As the temperature is decreased the search space decreases and the solution converges. For each iteration in a step, one 'vendor_alloc' is selected and its energy calculated using its energy function. The near optimal solution is generated using these 'vendor_alloc's and its calculated energy function

Step 10: If the temperature is less than 50 and the number of iterations 'n' is 50, then stop. When the iterations are over the best feasible solution for each vendor combination is compared using the constraints and the final (best) solution is given.

For this problem, if the temperature step is chosen as two then the number of steps is 50 and number of iterations 'n' per step is 50. Hence here the total number of iterations per 'vendor combination' is 50 * 50 = 2500. Since for each iteration one 'vendor_alloc' is generated, there would be 2500 'vendor_alloc' for one vendor combination.

5. COMPUTATIONAL RESULTS AND DISCUSSIONS

To demonstrate the applicability of multiobjective programming to the supplier selection problem the case of a leading textile machinery manufacturing company in India is considered. This company manufactures draw texturising machine and spinning machines. It requires wide variety of material like castings, machined components, plastics, sheet metals, ceramic guides, etc to make the machines. The model is evaluated considering seven vendors and the data for seven vendors are indicated in Table 1. The purchasing department also sets the minimum and maximum order quantities that can be placed for each vendor. Here the minimum and maximum business constraints for each vendor considered are 100 and 1200 respectively. The demand to be met is 2000.

As the model is first solved for quality objective, the near optimal objective value of quality is 56.The second objective considered here is minimization of late deliveries. The near optimal value of quality is taken as basis, and the procedure is repeated by increasing the value of defectives from this optimal value of quality, and the number of late deliveries for each quality value is as obtained in Table 2. From Table 2 it is found that there is no appreciable decrease in late deliveries when quality is relaxed beyond 75. Hence this value of defectives is fixed as the upper limit for quality.

Now the next objective considered is minimization of cost. From Table 2, it is found that there is no appreciable difference in cost when late delivery is relaxed beyond 55 with a fixed value of quality as 75. Hence the late delivery is fixed to be 55, with a quality of 75. Now these trade-off values of quality and late delivery forms the basis for determining the cost. This would be helpful for scenarios, where if the company can permit a certain amount of defectives and late deliveries in order to reduce the cost and also keep an eye on quality and late deliveries. This upper limit of the objective values and their trade-offs will be more helpful in practical scenarios

Table 1 Vendor details

Vendors	Vendor's Min. order	Vendor's Max. capacity	Percentage defectives	Cost 1* ($\eta 1$) before discount	Percentage late deliveries	Cost 2 * ($\eta 2$) after discount	Middle order (m) in quantities
V1	100	600	2.5	10	3.25	9	299
V2	200	750	4.5	11.5	5.25	10	499
V3	250	800	5	12	6.25	11	499
V4	350	750	3.5	9.5	15	9	549
V5	100	700	1.5	10.5	0.2	10	399
V6	300	950	6	12.25	2.5	11.5	599
V7	250	1000	5.8	15	2.35	14	649

**Cost in US $*

Table 2 Data to fix the trade off values for quality and late delivery

Iterations for quality and delivery		**Iterations for quality, delivery and cost**		
Quality (Number of defectives)	Late deliveries (near optimal)	Quality (Number of defectives)	Late deliveries	Cost*
≤ 65	63.42	75	≤ 47	23641
≤ 70	55.53	75	≤ 50	23526
≤ 75	**47.50**	**75**	**≤ 55**	**22094**
≤ 80	46.32	75	≤ 60	22053
≤ 85	45.20	75	≤ 65	22043
≤ 90	44.98	75	≤ 70	21995

**Cost in US $*

The quantity discount model includes price breaks as in Table 1when determining the cost objective. The final results obtained using SA optimizer is as indicated in Table 3.

Figures 2 and Figure 3 shows the various alternate selection groups generated using SA considering quantity discounts for quality vs. cost and delivery objectives vs. cost. Here the vendor set V1, V2, V5, and V6 is represented as 1:2:5:6. From the figures, there are two possible vendor sets 1:2:5:7 and 1:2:5:6 which satisfy the quality and delivery objectives and their upper limit value. Among which 1:2:5:6 produces the better objective value for cost as is evident from Figure 5 and hence this combination forms the optimal selection of vendors.

Table 3 Vendor selection with quantity discounts using SA

Vendor number	**Order**	**Number of defectives**	**Number of late deliveries**	**Middle Order**	**Cost***
V1	565	14	18	299	5384
V2	506	22	26	499	5808
V5	665	10	1	399	6860
V6	330	20	8	599	4042
Total	2066	66	53		22094
Order – Defectives = 2066 – 66= 2000 = Demand					

*Cost in US $

5.1 Comparison of vendor selection between ILP and SA

As discussed through this paper, this research proposes a new method of using meta-heuristic for the supplier selection for the incremental quantity discount scenario. There is no evidence for a multi component supplier selection model which considers incremental quantity discounts and the objectives and constraints used in this research. There exists one paper on single component multiple supplier selection model which uses ILP with all unit quantity discounts (Arunkumar et al. 2006). All the constraints and objectives considered are the same in this paper when compared to the proposed research except that they differ in the discount scenario. Hence to validate the results of the proposed method considering only a single component, the objective values of quality and delivery obtained in this method is fixed as trade off values for the ILP method which uses LINGO. This ensures both the model having same constraints and tradeoff values. The results are then compared.

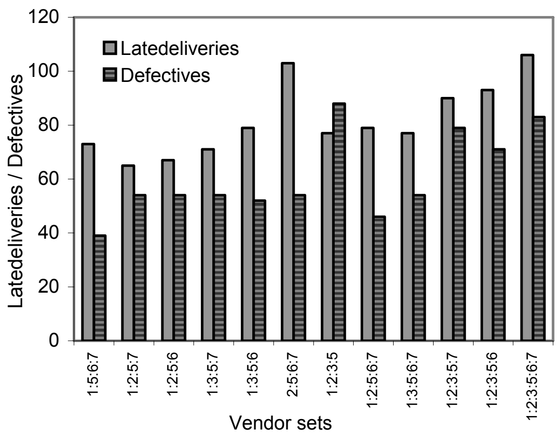

Figure 2 Alternate vendor sets with their quality and delivery objective

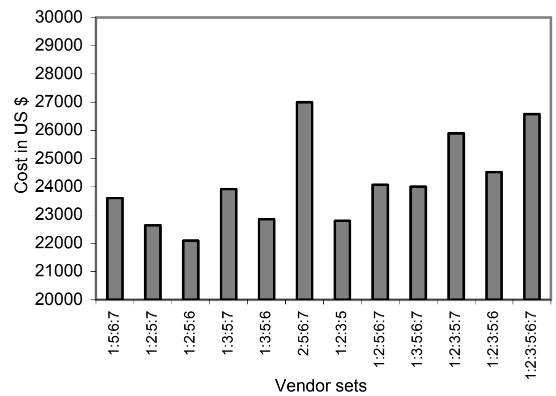

Figure 3 Alternate vendor sets with their cost objective

5.1.1 Solution methodology using ILP

Under all unit quantity discount scenario, the ILP method solves supplier selection as follows. Consider each range of discount offered by a vendor as an additional vendor with same quality and delivery. For this particular problem since there are 7 vendors with each offering 2 price breaks, we get 7 * 2= 14 vendors. The corresponding additional vendors are V1-V8, V2-V9, V3-V10, V4-V11, V5-V12, V6-V13, and V7-V14. The constraints then become minimum quantity for V1 as 100 and V8 as 300, capacity for V1 as 299 and V8 as 600. Using this approach either V1 or V8 and similarly for other vendors would be chosen. Hence due to this the price would then be calculated for the total order allocated using that price break. Say if V8 has an order allocation of 500, then the price would be 500 * 9.

5.1.2 Discussion on the results

Table 4 indicate the final vendors selected and their order allocation using the same input parameters using ILP. It is evident from Table 3 and Table 4 that both the approaches select V1:V2:V5:V6 as the best vendors. There are differences in order allocation due to the difference in the discounting model and also the cost is lesser in case of ILP method than SA due to the all-unit quantity discount. Through ILP, it is very difficult to achieve good results for such kind of incremental discounts. Whereas SA can be used effectively for incremental quantity discounts. If the order allocated for V1 is 500, then the price calculated would be (299*10) + (201 * 9).

Table 4 Vendor selection with quantity discounts using ILP

Vendor number	Order	Number of defectives	Number of late deliveries	Middle Order	Cost*
V1 (V8)	599	15	19	299	5391
V2	462	21	24	499	5313
V5 (V12)	690	11	2	399	6900
V6	315	19	8	599	3859
Total	2066	66	53		21463
Order – Defectives = 2066 – 66 = 2000 = Demand					

**Cost in US $*

Although there is difference in the quantity discount model, one similarity between the ILP method and SA method is that with the same constraints and tradeoff values considered, both result in the same set of vendors, order allocations differing only due to the discount method considered. One of the advantages of SA is that it is more suitable for scenarios considering incremental quantity discounts. Also by using SA it is possible to obtain alternate solutions apart from the best solution which is useful for some practical scenarios.

7. CONCLUSIONS AND SCOPE OF FUTURE RESEARCH

This article describes a model for multi-component, supplier selection by considering each component step by step. The major advantage of this model is that when trying to get the best solution, the purchase manager is given visibility to frame constraints for subsequent objectives i.e. the tradeoff between quality and delivery can be set. This enables the purchase manager to control the objectives that can be better applied practically. This article also introduced the use of SA for solving this problem. Among the advantages of SA are the relative ease of implementation and the ability to provide reasonably good solutions for many combinatorial problems. The results of this research should be of interest to the researches for using SA for supplier selection and order allocation mainly in the incremental quantity discount scenario. This approach provides a way of getting the next set of vendors and hence this will be very helpful to the purchase manager who also would like to find the alternate set of suppliers.

There are several possible extensions of this work that are left for future research. Methods to improve the computational time and reduce complexity due to tradeoffs can be some of the areas of research. Also there are various discount models. This article describes a model where the suppliers offer discounts based on the quantity ordered for each item. There is also another model where the supplier offers discounts based on the total volume of business given to the supplier. This is called volume discount model. This is another area where future research can be made applying SA for such kind of problem

8. REFERENCES

1. Arunkumar, N., Karunamoorthy, L., Anand, S. and Ramesh Babu, T. (2006). Linear approach for solving a piecewise linear vendor selection problem of quantity discounts using lexicographic method. International Journal of Advanced Manufacturing Technology, 28(11): 1254-1260.
2. Buffa, F.P. and Jackson, W.M. (1983). A goal-programming model for purchase planning. Journal of Purchasing and Materials Management , 19(3): 27-34.
3. Chaudhry, S.S., Forst, F.G. and Zydiak,J.L. (1993). Vendor selection with price breaks. European Journal of Operational Research , 70: 52-66.
4. Cengiz Kahraman, Ufuk Cebeci and Ziya Ulukan (2003). Multi-criteria supply selection using fuzzy AHP. Logistics Information Management, 16(6): 382-394.
5. Crow, L.E., Olshavsky, R.W. and Summers J O (1980). Industrial Buyer Choice Strategies: A Protocol Analysis. Journal of Marketing Research, 17: 34-44.
6. Das, C. and Tyagi, R. (1994). Wholesaler: a decision support system for wholesale procurement and distribution. Intenational Journal of Physical Distribution and Logistics Management, 24(10): 4-12.
7. Dickson, G W (1966). An analysis of vendor selection systems and decisions, Journal of Purchasing, 2(1): 5-17.
8. Gary Teng, and Hector Jaramillo (2005). A model for evaluation and selection of suppliers in global textile and apparel supply chains. International Journal of Physical Distribution and Logistics Management, 35(7): 503-523
9. Ghodsypour, S.H. and O'Brien, C (1998). A decision support system for supplier selection using an integrated analytical hierarchy process and linear programming. International Journal of Production Economics 56(57): 199-212.
10. Golden, B.L., Wasil, E.A. and Harker P.T. (1989). The Analytical Hierarchy Process: Applications and Studies. New York, Springer Verlag.
11. Hongwei Ding, Lyes Benyoucef and Xiaolan Xie (2003). A simulation-optimization approach using Genetic Search for Supplier Selection. Proceedings of the 2003 Winter Simulation Conference.1260-1267.
12. Kalyanmoy Deb (2002). Optimization for Engineering Design: Algorithms and Examples. Prentice-Hall of India Private Limited. New Delhi. ISBN-81-203-0943-X.
13. Lashkari, R.S., Balakrishnan, B. and Dutta S.P. (2002). A multi-objective model for the allocation of pallets in a flexible manufacturing cell. International Journal of Industrial Engineering. 9(3): 287-300.
14. Malmborg, J. Charles. (2003), A simulated annealing algorithm for dynamic document retrieval. International Journal of Industrial Engineering, 10(2): 115-125
15. Marvin, E.Gonzalez and Giaconda Quesada and Carlo A Mora Monge (2004). Determining the importance of the supplier selection process in manufacturing: a case study. International Journal of Physical Distribution and Logistics Management, 34(6): 492-504.
16. McKendall, A.R., Shang, J., Noble, J.S. and Klein C.M.(2006). A Simulated Annealing Heuristics for a Crane sequencing problem, International Journal of Industrial Engineering, 13(1): 90-98
17. Pirkul, H. and Aras, O.A. (1985) .Capacitated multiple item ordering problem with quantity discounts. IIE Transactions 17(3): 206-211

18. Rajagopal, S. and Bernard, K.N. (1993). Strategic procurement and competitive advantage, InternationalJournal of Purchasing and Materials Management, Fall: 13-19
19. Sadrian,A.A. and Yoon,Y.S. (1994). A procurement decision support system in business volume discount environments. Operations Research, 42 (1): 14-23.
20. Soukup, W.R. (1987). Supplier Selection Strategies. Journal of Purchasing and Materials Management , 26(1): 7-12.
21. Weber, C.A., Current, J.R. and Benton, W.C. (1991). Vendor Selection Criteria and Methods. European Journal of Operational Research, 50: 2-18.
22. Weber, C.A. and Current, J.R. (1993). A Multi-Objective Approach to Vendor Selection, European Journal of Operational Research , 68: 173-184

BIOGRAPHICAL SKETCH

Dr. N. Arunkumar is Professor in the Mechanical Engineering department of St. Joseph's college of Engineering, Chennai, India. He completed his Bachelor of Engineering degree in Mechanical engineering from PSG College of Technology, Coimbatore in 1994 and holds a Master of Engineering degree in Production Engineering from the same institution. He holds a PhD in Mechanical Engineering from Anna University, Chennai, India. His research areas are production and industrial engineering. He is specialized in supply chain management. He has published papers in International and national journals and presented papers in International conferences. Some of the international journals in which papers are published include - International Journal of Advanced Manufacturing Technology, Journal of Industrial Engineering International, International Journal of Industrial and Systems Engineering.

Dr. L. Karunamoorthy is the Professor and Head for the Central Workshop Division in Anna University, Chennai, India. He has obtained ME Production Engineering Degree and PhD Degree from Anna University. He has 22 years of teaching and research experience. He has guided 8 PhD and currently guiding 5 PhD research scholars. He has 140 research publications in International and National Journals and conference proceedings. Some of the international journals in which his papers are published include International Journal of Materials and Design, International Journal of Advanced Manufacturing systems, International Journal of Robotics and Automation, International Journal of Advanced Manufacturing Technology, International Journal of Industrial and Systems Engineering. His current research interest includes metal cutting, automation, Mechatronics, and Supply Chain Management.

N. Uma Makeshwaraa is a research scholar. He completed his Bachelor of Engineering in Manufacturing Engineering from Anna University, Chennai, India in 2005 and holds Master of Science in Mechanical Engineering from the University of Texas at Austin. His research areas are in the area of rapid manufacturing and supply chain management. He has published papers in International and national journals and presented papers in International conferences.