Non Dominated Sorting Genetic Algorithm for Chance Constrained Supplier Selection Model with Volume Discounts

Remica Aggarwal[1] and Ainesh Bakshi[2]

[1] Department of Management, Birla Institute of Technology & Science, Pilani, India
[2] Department of Computer Science, Rutgers New Brunswick, USA

Abstract. This paper proposes a Stochastic Chance-Constrained Programming Model (SCCPM) for the supplier selection problem to select best suppliers offering incremental volume discounts in a conflicting multi-objective scenario and under the event of uncertainty. A Fast Non-dominated Sorting Genetic Algorithm (NSGA-II), a variant of GA, adept at solving Multi Objective Optimization, is used to obtain the Pareto optimal solution set for its deterministic equivalent. Our results show that the proposed genetic algorithm solution methodology can solve the problems quite efficiently in minimal computational time. The experiments demonstrated that the genetic algorithm and uncertain models could be a promising way to address problems in businesses where there is uncertainty such as the supplier selection problem.

Keywords: Supplier selection, Chance constrained approach, Incremental quantity discount model, Genetic algorithms.

1 Introduction

Today businesses run not only on a higher level of performance but also on maintaining cordial relationship with the clients. For a manufacturing firm , particularly , suppliers acts as a backbone of the business as the right choice of suppliers reduces costs, increases profit margins, improves component quality and ensures timely delivery and therefore choosing a few but superior suppliers becomes a very important strategic decision. Choice of suppliers depends on several dimensions such as price, delivery, quality, capacity etc. Selection of suppliers becomes more challenging when suppliers offer interesting deals such as better price and quality, incremental or all units quantity discounts etc. to attract and retain buyers for a longer period, to motivate them to procure larger quantities and to reduce cost of transportation per commodity. These deals and discounts could be based on the quantity of each product ordered from a supplier or based on the total value of all products ordered from a supplier. Therefore in general, the supplier selection problem is a multi-criteria problem based on joint consideration of purchasing cost, quantity discounts, order size restrictions, product quality and service levels, supplier capacity and lead time. Selecting an optimal supplier under such multiple conflicting criteria often gets complicated even for

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an experienced purchase manager because competing suppliers have different levels of achievement under these criteria.

However, in solving for practical supplier selection and purchasing plans, businesses are faced with some uncertain factors. In the event of uncertainty such as uncertain or fluctuating demand, changing supplier's capacity, supplier's unreliable lead time and varying quality, selection of suppliers becomes even more complex. Although the researches have been made in the field of selecting suppliers under uncertainty or under discount pricing and lot size restrictions, no research to the best of our knowledge has integrated quantity discounts model with uncertainty and lot size restrictions at a time.

Various multi-objective optimization techniques have already been established to solve a variety of deterministic supplier solution problems. However, when uncertain factors are explicitly considered in a supplier selection problem, it is hardly treated since the traditional mathematical modeling is difficult to deal with the uncertain programming problem. In such cases, where risk is a major part of the decision, it is imperative to capture the risk factors into a mathematical model. Chance-constrained programming that was pioneered by Charnes and Cooper [4] is one approach that can handle the uncertainty of the problem. Nature inspired / Evolutionary algorithms can be used as an alternative to obtain a global optimal solution to solve such Multi Objective Optimization problems. One of the most popular of these techniques is Genetic Algorithms (GA). GA is a stochastic search method for optimization problems based on the mechanics of natural selection and natural genetics (i.e., the principle of evolution—survival of the fittest). A Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) [7], a variant of GA, adept at solving Multi Objective Optimization, is used to obtain the Pareto optimal solution set for our problem statement.

In this paper, an attempt has been made to present a mathematical model for supplier selection supplying multiple products to a buyer under uncertain scenario incorporating incremental quantity discounts on lot sizes of multiple products to be supplied by multiple suppliers. Uncertainty in model parameters such as capacity, lead time and demand uncertainty is handled through the Chance constraints approach [4-6]. These uncertainties are captured by probability distribution of capacity, demand, cost and lead time. A stochastic chance-constrained programming model for the supplier selection problem is transformed into the deterministic equivalent mathematical programming model which is then solved using fast non dominated genetic algorithm (NSGAII). Our results show that the proposed genetic algorithm solution methodology can solve the problems quite efficiently in minimal computational time. The experiments demonstrated that the genetic algorithm and uncertain models could be a promising way to address problems in businesses where there is uncertainty such as the supplier selection problem.

The paper is structured as follows. Section 2 presents a review of the relevant literature on supplier selection and use of genetic algorithms to solve such problems. Section 3 formulates the Stochastic Chance-Constrained Programming Model (SCCPM) for the supplier selection problem with uncertain cost, quality and lead time. Section 4 explains the SVGAII algorithm to solve the formulated problem.

A case example has been presented in section 5 to validate the proposed model. Details of how SVGA applied to the case problem is presented in section 6 .Section 7 conclude the paper with future directions for research.

2 Literature Review

Although the process of supplier selection has been studied extensively, the problem of supplier selection under multi-supplier with quantity discounts has received attention quite recently. A weighted fuzzy multi-objective model for the supplier selection under price breaks or quantity discounts environment in a supply chain is proposed by [2]. Xia and Wu [16] propose a multi-objective optimization problem, where one or more buyers order multiple products from different vendors in a multiple sourcing network using using business volume discounts. Ebrahim et al. [8] uses a scatter search algorithm for supplier selection and order lot sizing under multiple price discount environment.

Alonso Ayuso et al. [1] proposed a two-phase stochastic program where they considered plant selection, product allocation and supplier selection under uncertain costs, product prices and demand. Burke et al. [3] also developed a supplier selection model with demand uncertainty and unreliable suppliers. These researches has not explored uncertainties related to demand, capacity and lead time at a time and also lack the concept of quantities discounts on the part of supplier.

Application of genetic algorithms is gaining momentum in a variety of industrial applications [9,10,11,12,15]. Rezaei and Davoodi [12] who formulated a fuzzy mixed integer programming model of a multi-period inventory lot sizing problem with supplier selection. The problem is converted to equivalent crisp decision making problems and solved by using a genetic algorithm that determines what items to order in what quantities from each supplier in which periods. But this paper however lacks the concept of uncertainty which prevails in the real business scenario.

Present paper integrates the concept of incremental quantities discounts and lot size restrictions offered by multiple suppliers in the event of uncertain demand, supplier's capacity and lead time. A stochastic chance-constrained programming model for the supplier selection problem is transformed into the deterministic equivalent mathematical programming model which is then solved using fast non dominated genetic algorithm (NSGAII) [7].

3 Problem Formulation

This section formulates a Stochastic Chance-Constrained Programming Model (SCCPM) for the supplier selection problem. Following **notations** are used to formulate the model.

j $1,2,\ldots,J$ suppliers
k $1,2,\ldots K$ products

x_{jk} 1 if supplier j is assigned as supplier of product k, 0 otherwise

h_{jk} The amount of product *k* shipped from supplier *j*

D_k Demand for product *k*

Cap_{jk} Capacity at supplier *j* for product *k*

m_{jk} middle order quantity to be supplied from supplier j of product k

u'_{jk} k[th] product unit cost incurred on buyer from j[th] supplier if order quantity $\leq m_{jk}$

u''_{jk} k[th] product unit cost incurred on buyer from j[th] supplier if order quantity $> m_{jk}$

$\bar{u}_{jk}$ Aggregate unit cost incurred when order quantity $\geq m_{jk}$

F_j Fixed cost of operating with supplier *j*

Q_{jk} Percentage of good quality items of product *k* procured from supplier *j*

L_{jk} Lead time of product *k* from supplier *j*

q_j Minimum order quantity to be supplied from supplier *j*

L_{jk} Lead time of product *k* from supplier *j*

μ_{ljk} Mean lead time of product *k* from supplier *j*

α_k Level of probability that units supplied satisfies the demand of k^{th} product

α_{jk} Level of probability that $h_{jk} \leq cap_{jk} x_{jk}$

α_l Level of risk for the calculated value of lead time to be greater than aspired level

$F_{D_k}^{-1}$ Constant inverse probability distribution function for random demand

$F_{cap_{jk}x_{jk}}^{-1}$ Constant inverse probability distribution function for random capacity

$F_{A_1}^{-1}(\alpha_l)$ Constant inverse probability distribution function for random lead time

3.1 Stochastic Chance-Constrained Programming Model (SCCPM)for the Supplier Selection Problem with Uncertain Cost, Quality and Lead Time

A stochastic chance-constrained programming model for the supplier selection problem integrating incremental quantity discounts and lot size restrictions can be written as:

$$\text{Minimize } Z_1 = \sum_{j=1}^{J}\sum_{k=1}^{K} u_{jk} h_{jk} x_{jk} + \sum_{j=1}^{J}\sum_{k=1}^{K} F_j x_{jk} \tag{1}$$

$$\text{Maximize } Z_2 = \sum_{j=1}^{J}\sum_{k=1}^{K} Q_{jk} h_{jk} x_{jk} \tag{2}$$

$$\text{Minimize } Z_3 = \sum_{j=1}^{J}\sum_{k=1}^{K} L_{jk} h_{jk} x_{jk} \tag{3}$$

Subject to

$$P\left(\sum_{j=1}^{J} h_{jk} \geq D_k\right) \geq \alpha_k, \quad \forall k \in K \tag{4}$$

$$P\left(h_{jk} \leq cap_{jk} x_{jk}\right) \geq \alpha_{jk}, \quad \forall j \in J, k \in K \tag{5}$$

$$P\left(\sum_{j=1}^{J} \sum_{k=1}^{K} \mu_{l_{jk}} h_{jk} x_{jk} \geq A_1\right) \geq \alpha_l \tag{6}$$

$$\sum_{k=1}^{K} h_{jk} x_{jk} \geq q_j \ ,\forall j \in J \ ,\forall k \in K \tag{7}$$

$$x_{jk} \in [0,1] \ \forall j \in J \ ,\forall k \in K \tag{8}$$

$$h_{jk} \geq 0 \ ,\forall j \in J \ ,\forall k \in K \tag{9}$$

$$u_{jk} = u'_{jk} \quad if \ h_{jk} \leq m_{jk} \tag{10}$$

$$u_{jk} = \bar{u}_{jk} = u'_{jk} * m_{jk} + (h_{jk} - m_{jk})u''_{jk} \ , if \ h_{jk} > m_{jk} \tag{11}$$

Objective function Z_1 minimizes the total cost incurred by the buyer. Objective function Z_2 maximizes the total quality of purchased products. Objective function Z_3 minimizes the total lead time. Constraint given by equation (4) ensures that shipments from the suppliers cover the entire demand for each product. Equation (5) restricts the amount shipped from the suppliers to their capacity. Constraint (6) ensures the lead time of suppliers .Constraint (7) provides the lot size restriction on different products. Constraints in equation (8) and equation (9) enforce binary and non-negativity condition in the decision variables respectively. Constraints (10) and (11) indicates the incremental quantities discount provided by the j^{th} supplier for k^{th} product based on the number of components ordered.

3.2 Stochastic Chance-Constrained Programming Model (SCCPM) for the Supplier Selection with Deterministic Equivalents

Stochastic chance-constrained programming model (SCCPM) for the supplier selection with its deterministic equivalents is described from equation (12) to equation (17) as follows [4]:

$$\text{Minimize } Z_1 = \sum_{j=1}^{J} \sum_{k=1}^{K} u_{jk} h_{jk} x_{jk} + \sum_{j=1}^{J} \sum_{k=1}^{K} F_j x_{jk} \tag{12}$$

$$\text{Maximize } Z_2 = \sum_{j=1}^{J} \sum_{k=1}^{K} Q_{jk} h_{jk} x_{jk} \tag{13}$$

$$\text{Minimize } Z_3 = \sum_{j=1}^{J} \sum_{k=1}^{K} \mu_{l_{jk}} h_{jk} x_{jk} \tag{14}$$

Subject to

$$\sum_{j=1}^{J} h_{jk} = F_{D_k}^{-1}(\alpha_k) \quad \forall k \in K \tag{15}$$

$$h_{jk} \le F_{cap_{jk} x_{jk}}^{-1}(1 - \alpha_{jk}) \quad \forall j \in J, k \in K \tag{16}$$

$$\sum_{j=1}^{J} \sum_{k=1}^{K} \mu_{l_{jk}} h_{jk} x_{jk} \ge F_{A_l}^{-1}(\alpha_l) \tag{17}$$

Constraints (7)-(11)

4 Solution Methodology: Fast Non Dominated Sorting Genetic Algorithm (NSGAII)

In GA terminology, a solution vector is called an individual or a chromosome. In the modern implementations of GA, chromosomes can be real numbers, strings, matrices and other data structures. For the purpose of Multi Objective Optimization, GA provide a Pareto set of final solutions to the given problem. The set of all feasible non-dominated solutions in X is referred to as the Pareto optimal set, and for a given Pareto optimal set, the corresponding objective function values in the objective space is called the Pareto front. For many problems, the number of Pareto optimal solutions is enormous, sometimes even infinite. Thus the eventual goal of a multi-objective optimization algorithm, such as ours, is to closely approximate solutions in the Pareto optimal set. Therefore, a more pragmatic approach is followed in which the best known Pareto set is investigated as much as possible.

Pareto-ranking approaches explicitly utilize the concept of Pareto dominance in evaluating fitness or assigning selection probability to solutions. Initially, a random parent population P_0 is created. The population is sorted based on the non-domination. Each solution is assigned a fitness equal to its non-domination level. At first, the usual binary tournament selection, recombination, and mutation operators are used to create an offspring population Q_0 of size N. A combined population $\mathbf{R}_t = \mathbf{P}_t \cup \mathbf{Q}_t$ is formed. The population $\mathbf{R}_t$ is of size 2N and is sorted according to non-domination thereby ensuring non domination. Solutions belonging to the best non dominated set $\mathbf{F}_1$ are of best solutions in the combined population and must be emphasized more than any other solution in the combined population. If the size of $\mathbf{F}_{t+1}$ is smaller than N we definitely choose all members of the above set for the new population $\mathbf{P}_{t+1}$. The remaining members of the population $\mathbf{P}_{t+1}$ are chosen from subsequent non dominated fronts in the order of their ranking. Thus, solutions from the set $\mathbf{F}_2$ are chosen next, followed by solutions from the set $\mathbf{F}_3$ and so on. Crowding distance approaches (Rajagopalan et al. [11]) aim to obtain a uniform spread of solutions along the best11 known Pareto front without using a fitness sharing parameter.

Step 1. Rank the population and identify non-dominated fronts $\mathbf{F}_1, \mathbf{F}_2, \ldots \mathbf{F}_R$ .For each front *j=1 ... R* repeat Steps 2 and 3.

Step 2. For each objective function k, sort the solutions in **F j**$\boldsymbol{F_j}$ in the ascending order. Let l = $|F_j|$ and $x_{[i,k]}$ represent the i^{th} solution in the sorted list with respect to the objective function k. Assign $cd_k(\boldsymbol{x}_{[1,k]}) = \infty$ ∞ and $cd_k(\boldsymbol{x}_{[l,k]}) = \infty$ ∞ and

for i =2 … l assign

$$cd_k(x_{[i,k]}) = [z_k(x_{[i+1,k]}) - z_k(x^k_{[i-1,k]})]/[z_k^{max} - z_k^{min}] \quad (18)$$

Step 3. To find the total crowding distance cd(x) of a solution x, sum the solution crowding distances with respect to each objective, i.e. $cd(\boldsymbol{x}) = \sum_k cd_k(\boldsymbol{x})$(x).

In the NSGA-II, this crowding distance measure is used as a tie-breaker as in the selection phase that follows. Randomly select two solutions x and y; if the solutions are in the same non dominated front, the solution with a higher crowding distance wins. Otherwise, the solution with the lowest rank is selected.

Deb also proposed the constrain-domination concept and a binary tournament selection method based on it, called a constrained tournament method. A solution x is said to constrain-dominate a solution y if either of the following cases are satisfied:

Case 1: Solution x is feasible and solution y is infeasible.
Case 2: Solutions x and y are both infeasible; however, solution x has a smaller constraint violation than y.
Case 3: Solutions x and y are both feasible, and solution x dominates solution y.

In the constraint tournament method in NSGA-II, first non-constrain-dominance fronts $\boldsymbol{F_1 F_2 \ldots F_R}$ **F** $_{\mathbf{R}}$ are identified by using the constrain-domination criterion. In the constraint tournament selection, two solutions x and y are randomly chosen from the population. If solutions x and y are both in the same front, then the winner is decided based on crowding distances of the solution.

5 Numerical Illustration : (5*3 Test Problem; Three Objectives)

Consider Five suppliers (S1, S2, S3, S4, S5) supplying three different products (P1, P2, P3) to the buyer. Stochastic data corresponding to the capacity, minimum order, middle order quantities, demand, unit cost, fixed cost, quality levels and stochastic lead time are given from Table 1 to Table 6. All data are randomly generated. The reliability level for the capacity is set at $\alpha_{jk} = 0.95 \ \forall j = 1,2,\ldots 5; k = 1,2,3$ meaning that at least 95% of demand should be met. The risk level is set at $\alpha_k, \alpha_l = 0.05$.

We begin with developing the NSGA-II algorithm framework and subsequently approach the given problem from a GA viewpoint. From the equations formulated above it is inferred that there are 15 independent real variables (h_{jk}) and 15 binary variables (x_{jk}) involved in the optimization problem, the values of which need to be determined. The feature vector for each individual in the population thus consists of 30 variables. The problem is to be optimized with respect to 3 objective functions and is subject to 6 constraints. The 15 intermediate variables (u_{jk}) are introduced in the problem formulation according to the given data. The genetic algorithm is initialized with a random starting population of 100 individuals. The probability for crossover is 0.75 and that for mutation is 0.05. The termination condition is set at 250 generations.

Table 1. Stochastic capacity data and lot size restriction (in units)

	P1	P2	P3	Min. order
S 1	N(50,6.25)	N(45, 5)	N(100,25)	100
S 2	N(90, 20)	N(100,25)	N(20,1)	100
S 3	N(70,12)	N(50,6.25)	N(150,56)	100
S 4	N(80, 6)	N(200,100)	N(50,6.25)	100
S 5	N(70,12)	N(100,25)	N(70,12.25)	100

Table 2. Stochastic demand data (in units)

P1	P2	P3
N(210,36)	N(250,49)	N(250,64)

Table 3. Fixedcost data (in dollars)

S 1	S 2	S 3	S 4	S 5
100	200	150	150	120

Table 4. Unit cost data (in dollars)

	Without discount				With discount			
	Ranges	P1	P2	P3	Ranges	P1	P2	P3
S 1	$30 \leq h \leq 50$	15	10	8	h>50	12	9	6
S 2	$30 \leq h \leq 60$	10	8	10	h>60	8	7	9
S 3	$30 \leq h \leq 50$	6	5	9	h>50	5	4	7
S 4	$30 \leq h \leq 60$	5	9	7	h>60	4	8	6
S 5	$30 \leq h \leq 60$	7	7	10	h>60	5	6	8

Table 5. Quality data (% of good items)

	P1	P2	P3
S 1	0.95	0.95	0.93
S 2	0.95	0.97	0.99
S 3	0.9	0.9	0.9
S 4	0.9	0.93	0.9
S 5	0.9	0.92	0.97

Table 6. Stochastic lead time data (days)

	P1	P2	P3
S 1	N(10,6)	N(9, 5)	N(1,0)
S 2	N(5, 2)	N(2,1)	N(8,1)
S 3	N(8,2)	N(3,1)	N(9,2)
S 4	N(3,1)	N(4,2)	N(6,2)
S 5	N(8,2)	N(2,1)	N(4,1)

Table 7. Results in terms of cost, quality and lead time

	NSGA-II (Population1)	NSGA-II (Population2)	NSGA-II (Population3)
Cost	8736.04	9023.806	8709.357
Quality	687.4363	689.433	685.5609
Lead time	3671.174	3742.611	3652.361

Table 8. Number of units supplied from each supplier

NSGA II Population1				NSGA II Population 2				NSGA II Population 3			
x_{11}	1	h_{11}	26.2	x_{11}	1	h_{11}	26.79	x_{11}	1	h_{11}	24.07
x_{12}	1	h_{12}	38.2	x_{12}	1	h_{12}	40.93	x_{12}	1	h_{12}	38.25
x_{13}	1	h_{13}	62.4	x_{13}	1	h_{13}	59.59	x_{13}	1	h_{13}	62.48
x_{21}	1	h_{21}	78.4	x_{21}	1	h_{21}	80.08	x_{21}	1	h_{21}	78.42
x_{22}	1	h_{22}	45.8	x_{22}	1	h_{22}	45.95	x_{22}	1	h_{22}	45.84
x_{23}	0	h_{23}	0.00	x_{23}	1	h_{23}	0.00	x_{23}	0	h_{23}	0.00
x_{31}	0	h_{31}	0.00	x_{31}	0	h_{31}	0.00	x_{31}	0	h_{31}	0.00
x_{32}	1	h_{32}	37.2	x_{32}	1	h_{32}	35.22	x_{32}	1	h_{32}	37.22
x_{33}	1	h_{33}	101.9	x_{33}	1	h_{33}	104.9	x_{33}	1	h_{33}	101.8
x_{41}	1	h_{41}	54.9	x_{41}	1	h_{41}	49.64	x_{41}	1	h_{41}	54.97
x_{42}	1	h_{42}	45.9	x_{42}	1	h_{42}	45.89	x_{42}	1	h_{42}	45.98
x_{43}	1	h_{43}	40.8	x_{43}	1	h_{43}	40.40	x_{43}	1	h_{43}	40.05
x_{51}	1	h_{51}	59.9	x_{51}	1	h_{51}	63.66	x_{51}	1	h_{51}	60.89
x_{52}	1	h_{52}	91.9	x_{52}	1	h_{52}	92.00	x_{52}	1	h_{52}	91.98
x_{53}	1	h_{53}	58.2	x_{53}	1	h_{53}	58.99	x_{53}	1	h_{53}	58.17

6 Interpretation of Results

Results in terms of objective function values for cost, quality and lead time corresponding to different Pareto optimal solutions obtained from SVGAII is given in Table 7. Although many optimal solution were obtained from the algorithm (which is the distinct advantage of this algorithm), three have been shown. Although these solutions are not necessarily optimal and are almost near-optimal, it can be possible for decision maker select one of them that matches with the real world condition.

7 Conclusions and Future Directions

Fast non dominated Sorting NSGA II algorithm has been used to solve the multi-objective optimization model related to supplier selection with incremental quantities discount and lot size restrictions under uncertainties in demand, capacity and lead time associated with supplier. Model is validated using a case problem. The problem can be extended to include the cases of multiple buyers, business volume discounts and all unit discounts as well. Other costs such as transportation costs and variable costs can also be included as a part of total costs.

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