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Chance Constraint based Multi-Objective Vendor Selection using NSGAII

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Abstract

Success of a buying firm depends largely on the suitable selection of its vendors as it ensures timely delivery of goods to support the firm's output. The paper presents a Stochastic Vendor Selection Problem (SVSP) in the presence of uncertainties associated with operational risks. The problem is modeled using Chance constraint approach and solved using NSGA II. A case example is presented as an illustration.

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Keywords: Vendor selection; Operational risks; Chance constrained approach; Genetic Algorithm

1. Introduction

Today buying firms are demanding a higher level of performance from their vendors in terms of timely delivery of goods, an increase in profit margins thereby increasing the output from firm's overall activities. Selection of vendors becomes more challenging when a firm has to deal with uncertain or fluctuating demand, changing vendor's capacity, vendor's unreliable lead time and varying quality. Therefore, in real scenario vendor selection under uncertain environment is stochastic in nature. In literature, work on such stochastic vendor selection is limited due to the involvement of difficult and complex mathematical modelling. Chance constrained programming [1,2,3] is one of the approach that can handle the uncertainty of the problem. Nature inspired algorithms such as GA can be used to obtain global optimal solution to solve such problems. GA are

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meta-heuristic methods based on the mechanics of natural selection and natural genetics.

Nomenclature	
GA	Genetic Algorithm
NSGAII	Fast Non Dominated Sorting Genetic Algorithm

NSGAII [4], a variant of GA, adept at solving Multi Objective Optimization, is used to obtain the Pareto optimal solution set for our problem statement. The results show that the proposed genetic algorithm solution methodology can solve the problems quite efficiently .

The paper is structured as follows. Section 2 presents a review of the relevant literature on vendor selection under uncertainty and on genetic algorithms to solve vendor selection problem. Section 3 presents model for deterministic version and stochastic version of the Multi-objective Vendor Selection Problem. Section 4 explains NSGAII to solve such problems. Section 5 presents a case problem to numerically demonstrate the proposed model.

2. Literature Review

Literature on vendor selection under uncertainties is quite recent, the prominent one being the vendor selection problems with uncertainty and unreliable suppliers [5] , the other category of vendor selection problems comes with various drivers of operational risk [6-9]. Theoretical aspects to deal with uncertain constraint to a deterministic one can be found from [1-3]. However application of chance constraint approach to the vendor selection is relatively new [10] . GA have been the most popular meta heuristic approach to Multi Objective Optimization. Recent applications of GA approach to vendor selection problems are addressed by [11-12]. Present paper presents a stochastic chance-constrained programming model for the vendor selection problem under uncertain scenario and then solves it using NSGAII [4].

3. Problem Formulation

Consider a single buyer multiple vendors supply chain management problem under conflicting objectives such as quality level maximization; total cost minimization and minimization of vendor's lead time under the usual constraints of limited demand and vendor's capacity. The problem is stochastic in nature since some of the parameters such as total cost, lead time, demand and capacity are not certain or deterministic rather stochastic or probabilistic in nature. This section formulates the required SVSP using following notations:

j 1,2,...,J vendors
k 1,2,...K products
b^{jk} 1 if vendor j is assigned as vendor of product k, 0 otherwise
q^{jk} The amount of product k shipped from vendor j
D^k Demand for product k
C^{jk} Capacity at vendor j for product k
c^{jk} Aggregate variable cost vendor j charges for product k
$\mu_{c^{jk}}$ Mean value of aggregate variable cost vendor j charges for product k
$\sigma^2_{c^{jk}}$ Variance of aggregate variable cost vendor j charges for product k
t^{jk} Unit transportation cost vendor j charges for shipping product k to the buyer
$\mu_{t^{jk}}$ Mean value of unit transportation cost vendor j charges for shipping product k
$\sigma^2_{t^{jk}}$ Variance of unit transportation cost vendor j charges for shipping product k

v^{jk} Other unit variable costs vendor j charges for product k

$\mu_{v^{jk}}$ Mean value of unit variable costs vendor j charges for product k

$\sigma^2_{v^{jk}}$ Variance of unit variable costs vendor j charges for product k

F^j Fixed cost of operating with vendor j

Q^{jk} Percentage of good quality items of product k procured from vendor j

L^{jk} Lead time of product k from vendor j

$\mu_{L^{jk}}$ Mean lead time of product k from vendor j

α^k Level of probability that units supplied satisfies the demand of kth product

α^{jk} Level of probability that units supplied for kth product from jth vendor are less than capacity at j[th] vendor

α^l Level of risk (0.05 say) for the calculated value of lead time to be greater than the aspired level

$F^{-1}_{D^k}$ Constant inverse probability distribution function for random demand for given α^k

$F^{-1}_{C^{jk}b^{jk}}$ Constant inverse probability distribution function for random capacity for given α^{jk}

$F^{-1}_{A_1}(\alpha^l)$ Constant inverse probability distribution function for random lead time for given α^l

3.1. Deterministic model

Multi-objective problem involving multi-vendor supplying multiple products with deterministic demand, lead time, capacity and variable costs can be written as [13]:

$$\text{Minimize } Z_1 = \sum_{j=1}^{J}\sum_{k=1}^{K} c^{jk} q^{jk} b^{jk} + \sum_{j=1}^{J}\sum_{k=1}^{K} F^j b^{jk}$$

$$\text{Maximize } Z_2 = \sum_{j=1}^{J}\sum_{k=1}^{K} Q^{jk} q^{jk} b^{jk}$$

$$\text{Minimize } Z_3 = \sum_{j=1}^{J}\sum_{k=1}^{K} L^{jk} q^{jk} b^{jk}$$

Subject to (P1)

$$\sum_{j=1}^{J} q^{jk} = D^k, \forall k \in K$$

$$q^{jk} \le C^{jk} b^{jk}, \forall j \in J, \forall k \in K$$

$$b^{jk} \in [0,1] \ \forall j \in J, \forall k \in K$$

$$q^{jk} \ge 0, \forall j \in J, \forall k \in K$$

3.2. Stochastic Model

Applying chance constraint approach [1-3], the deterministic model (P1) is converted to stochastic form (P2):

$$\text{Minimize} Z_1 = \sum_{j=1}^{J}\sum_{k=1}^{K} \mu_{c^{jk}} q^{jk} b^{jk} + \sum_{j=1}^{J}\sum_{k=1}^{K} F^j b^{jk} = \sum_{j=1}^{J}\sum_{k=1}^{K} (\mu_{t^{jk}} + \mu_{v^{jk}}) q^{jk} b^{jk} + \sum_{j=1}^{J}\sum_{k=1}^{K} F^j b^{jk}$$

$$\text{Maximize } Z_2 = \sum_{j=1}^{J}\sum_{k=1}^{K} Q^{jk} q^{jk} b^{jk}$$

$$\text{Minimize } Z_3 = \sum_{j=1}^{J}\sum_{k=1}^{K} \mu_{L^{jk}} q^{jk} b^{jk}$$

Subject to (P2)

$$\sum_{j=1}^{J} q^{jk} = F_{D^k}^{-1} \quad \forall k \in K$$

$$q^{jk} \le F_{C^{jk}b^{jk}}^{-1}\left(1-\alpha^{jk}\right) \quad \forall j \in J, k \in K$$

Where

$$\sum_{j=1}^{J}\sum_{k=1}^{K} \mu_{L^{jk}} q^{jk} b^{jk} \ge F_{A_1}^{-1}\left(\alpha^{l}\right)$$

$$b^{jk} \in [0,1] \ \forall j \in J \ , \forall k \in K$$

$$q^{jk} \ge 0 \ , \forall j \in J \ , \forall k \in K$$

4. Solution Methodology

4.1. *NSGA-II* [4,7]

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 (or rank) equal to its non-domination level. Thus, minimization of fitness is assumed. At first, the usual binary tournament selection, recombination, and mutation operators are used to create an offspring population Q_0 of size N. Since elitism is introduced by comparing current population with previously found best non dominated solutions a separate procedure is followed for the initial population. A combined population $R_t = P_t \cup Q_t$ is formed. The population 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 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 F_1 is smaller than N we definitely choose all members of the above set for the new population P_{t+1}. The remaining members of the population P_{t+1} are chosen from subsequent non dominated fronts in the order of their ranking. Thus, solutions from the set F_2 are chosen next, followed by solutions from the set F_3 and so on. This procedure is continued until no more sets can be accommodated. Say that the set F_l is the last non dominated set beyond which no other set can be accommodated. In general, the count of solutions in all sets would be larger than the population size. To choose exactly N population members, we sort the solutions of the last front using the crowded-comparison operator α_n in descending order and choose the best solutions needed to fill all population slots.

Crowding distance approaches aim to obtain a uniform spread of solutions along the best 11 known Pareto front without using a fitness sharing parameter.

Step 1. Rank the population and identify non-dominated fronts $F_1\ F_2 \dots F_R$. For each front j=1, ..., R repeat Steps 2 and 3.

Step 2. For each objective function k, sort the solutions in F_j 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 $cd_k(x_{[1,k]}) = \infty$ and $cd_k(x_{[l,k]}) = \infty$ and for i =2 … l assign

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

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. $cd(x) = \sum_k cd_k(x)$. (2)

In the NSGA-II [4,7], 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.

5. Numerical Illustration

Consider a supplier selection problem involving five vendors (V1,V2,V3,V4,V5) supplying three different products (Pr1, Pr2, Pr3) to the buyer. Stochastic data corresponding to the capacity, demand, transportation cost, variable cost, quality levels and stochastic lead time are given from table 1to table6. All data are randomly generated; inflation and deflation against assignment levels are also randomly calculated. Fixed cost for in dollars are 100,200,150,150,120 for V1,V2,V3,V4,V5 respectively. The reliability level for the capacity is set at $\alpha^{jk}=0.95 \ \forall j=1,2,...5; k=1,2,3$ .The risk level is set at $\alpha^k, \alpha^l = 0.05$.Results are presented in Table 7 &Table 8.

Table 1. Stochastic capacity data (in units)

	Pr1	Pr2	Pr3		Pr1	Pr2	Pr3
V1	N(50,6.25)	N(45, 5)	N(100,25)	V4	N(80, 6)	N(200,100)	N(50,6.25)
V2	N(90, 20)	N(100,25)	N(20,1)	V5	N(70,12)	N(100,25)	N(70,12.25)
V3	N(70,12)	N(50,6.25)	N(150,56)				

Table 2. Stochastic demand data (in units)

Pr1	Pr2	Pr3
N(210,36)	N(250,49)	N(250,64)

Table 3. Transportation cost data (in dollars)

	Pr1	Pr2	Pr3		Pr1	Pr2	Pr3
V1	N(15, $\sigma^2_{t^{11}}$)	N(5, $\sigma^2_{t^{12}}$)	N(8, $\sigma^2_{t^{13}}$)	V4	N(5, $\sigma^2_{t^{41}}$)	N(9, $\sigma^2_{t^{42}}$)	N(5, $\sigma^2_{t^{43}}$)
V2	N(10, $\sigma^2_{t^{21}}$)	N(4, $\sigma^2_{t^{22}}$)	N(3, $\sigma^2_{t^{23}}$)	V5	N(4, $\sigma^2_{t^{51}}$)	N(4, $\sigma^2_{t^{52}}$)	N(10, $\sigma^2_{t^{53}}$)
V3	N(6, $\sigma^2_{t^{31}}$)	N(5, $\sigma^2_{t^{32}}$)	N(3, $\sigma^2_{t^{33}}$)				

Table 4. Variable cost data (in dollars)

	Pr1	Pr2	Pr3		Pr1	Pr2	Pr3
V1	N(5, $\sigma^2_{v^{11}}$)	N(5, $\sigma^2_{v^{12}}$)	N(4, $\sigma^2_{v^{13}}$)	V4	N(10, $\sigma^2_{v^{41}}$)	N(7, $\sigma^2_{v^{42}}$)	N(4, $\sigma^2_{v^{43}}$)
V2	N(5, $\sigma^2_{v^{21}}$)	N(4, $\sigma^2_{v^{22}}$)	N(5, $\sigma^2_{v^{23}}$)	V5	N(2, $\sigma^2_{v^{51}}$)	N(4, $\sigma^2_{v^{52}}$)	N(8, $\sigma^2_{v^{53}}$)
V3	N(4, $\sigma^2_{v^{31}}$)	N(4, $\sigma^2_{v^{32}}$)	N(2, $\sigma^2_{v^{33}}$)				

Table 5. Quality data (in % of good items)

	Pr1	Pr2	Pr3		Pr1	Pr2	Pr3
V1	0.95	0.95	0.93	V4	0.9	0.93	0.9
V2	0.95	0.97	0.99	V5	0.9	0.92	0.97
V3	0.9	0.9	0.9				

Table 6. Stochastic lead time data (in days)

	Pr1	Pr2	Pr3		Pr1	Pr2	Pr3
V1	N(10,6)	N(9, 5)	N(1,0)	V4	N(3,1)	N(4,2)	N(6,2)

V2	N(5, 2)	N(2,1)	N(8,1)	V5	N(8,2)	N(2,1)	N(4,1)
V3	N(8,2)	N(3,1)	N(9,2)				

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

	NSGA-II(Population1)	NSGA-II (Population2)	NSGA-II(Population3)
Cost	9836.031	9613.193	9440.941
Quality	686.4054	687.1301	686.1239
Lead time	3258.965	3381.509	3293.947

Table 8. Number of units supplied from each vendor

NSGA II (Population1)				NSGA II (Population 2)				NSGA II (Population 3)			
x_{11}	0	n_{11}	0.0000	x_{11}	0	n_{11}	0.0000	x_{11}	0	n_{11}	0.0000
x_{12}	1	n_{12}	35.5839	x_{12}	1	n_{12}	35.6983	x_{12}	1	n_{12}	39.2049
x_{13}	1	n_{13}	78.0684	x_{13}	1	n_{13}	60.2617	x_{13}	1	n_{13}	76.9379
x_{21}	1	n_{21}	80.3158	x_{21}	1	n_{21}	80.3860	x_{21}	1	n_{21}	80.3141
x_{22}	1	n_{22}	46.0000	x_{22}	1	n_{22}	45.9976	x_{22}	1	n_{22}	46.0000
x_{23}	1	n_{23}	2.8747	x_{23}	1	n_{23}	16.7864	x_{23}	0	n_{23}	0.0000
x_{31}	0	n_{31}	0.0000	x_{31}	0	n_{31}	0.0000	x_{31}	0	n_{31}	0.0000
x_{32}	1	n_{32}	45.8086	x_{32}	1	n_{32}	45.6383	x_{32}	1	n_{32}	45.3821
x_{33}	1	n_{33}	118.5276	x_{33}	1	n_{33}	121.6435	x_{33}	1	n_{33}	122.5612
x_{41}	1	n_{41}	75.9904	x_{41}	1	n_{41}	75.9983	x_{41}	1	n_{41}	75.0808
x_{42}	1	n_{42}	40.0428	x_{42}	1	n_{42}	40.0273	x_{42}	1	n_{42}	36.8075
x_{43}	1	n_{43}	0.0000	x_{43}	0	n_{43}	0.0000	x_{43}	0	h_{43}	0.0000
x_{51}	1	n_{51}	63.0765	x_{51}	1	n_{51}	62.9965	x_{51}	1	h_{51}	63.9799
x_{52}	1	n_{52}	91.9551	x_{52}	1	n_{52}	91.9890	x_{52}	1	h_{52}	91.9594
x_{53}	1	n_{53}	63.2268	x_{53}	1	n_{53}	63.9858	x_{53}	1	h_{53}	63.1663

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