Fuzzy Inf. Eng. (2015) 7: 451–474

HOSTED BY ELSEVIER

Available online at www.sciencedirect.com
ScienceDirect
Fuzzy Information and Engineering
http://www.elsevier.com/locate/fiae

ORIGINAL ARTICLE

Multi-item Supplier Selection Model with Fuzzy Risk Analysis Studied by Possibility and Necessity Constraints

Kartik Patra · **Shyamal Kumar Mondal**

Received: 9 October 2014/ Revised: 12 May 2015/
Accepted: 15 October 2015/

Abstract Three different supplier selection models have been developed in crisp and fuzzy environments. Here two objective functions have been considered, profit and risk. In this paper, profit has been maximized and risk has been minimized with some constraints. Each supplier has an limited capacity. The purchasing cost of each item from different supplier as well as associative risk is known. The total space and budget of a retailer are constant. In Model I, all the parameters are considered as crisp. In Model II, the demand has been considered as fuzzy. In Model III, the risk values and demand have been considered as fuzzy. To defuzzyfy the fuzzy constraints, necessity and possibility have been introduced. To defuzzyfy the fuzzy objective, two different methods, credibility measure and α-cut method have been introduced. All the models have been illustrated numerically using multi-objective genetic algorithm (MOGA). Also a sensitivity analysis has been done taking different sets of risk values and a comparison result has been shown for credibility measure and α-cut method for Model III.

Keywords Supplier selection · Necessity · Possibility · Risk · Multi-objective genetic algorithm

Kartik Patra (✉) · Shyamal Kumar Mondal
Department of Applied Mathematics with Oceanology and Computer Programming, Vidyasagar University, Midnapore-721102, W.B., India
email: kpatrakp@gmail.com
Peer review under responsibility of Fuzzy Information and Engineering Branch of the Operations Research Society of China.

http://dx.doi.org/10.1016/j.fiae.2015.11.004

1. Introduction

In any business, selection of an appropriate supplier is a very difficult task. Nowadays, the supplier selection becomes one of the most widely researched areas in supply chain management. One of the most significant business decisions faced by a retailer in a supply chain is the selection of appropriate suppliers while trying to satisfy multi-criteria based on price, quality, demand and delivery. Hence supplier selection is a multi-criteria decision making problem. Supplier selection is the process by which retailers identify, evaluate, and contract with suppliers. The objective of supplier selection is to identify suppliers with the highest potential for meeting a retailer needs consistently. Different supplier selection models have been established by different researchers in different times in crisp or fuzzy environments. Lin [14] introduced an integrated model for supplier selection under a fuzzy situation. Arikan [1] presented a fuzzy solution approach for multi-objective supplier selection. Ruiz-Torres et al. [23] described a supplier selection model with contingency planning for supplier failures. Shirkouhi et al. [24] presented a supplier selection and order allocation problem using a two-phase fuzzy multi-objective linear programming. Kilic [13] presented an integrated approach for supplier selection in multi-item/multi-supplier environment. Rezaei and Davoodi [21] presented a multi-item inventory model with imperfect quality.

The fuzzy set theory is one of the best tools to handle impreciseness and vagueness. It was first introduced by Zadeh [30]. Goguen [10, 11] showed the intention of the authors to generalize the classical notion of a set. Zadeh [31] also introduced the concept of linguistic variable and its application to approximate reasoning. Dubois and Prade [6] presented theory and application on fuzzy set theory.

Just like in most real-world decision making problems, uncertainty is another important property of supplier selection problems. So risk is an important factor in any business. Different risk analysis problems have been introduced by different researchers. Chen et al. [3] introduced fuzzy risk analysis based on ranking generalized fuzzy numbers with different left and right heights. Chen and Wang [2] presented the ranking fuzzy number using α-cuts, belief feature and signal/noise ratio for risk analysis of a manufacturing system. Chen and Sanguansat [4] introduced a new fuzzy ranking of generalized fuzzy number for risk analysis. Patra and Mondal [20] presented a new ranking method of generalized trapezoidal fuzzy numbers and applied it to evaluate the risk in diabetes problems. Also there are some similarity measures methods to evaluate the risk. Wei and Chen [27] presented a new similarity measures of generalized trapezoidal fuzzy numbers to perform a fuzzy risk analysis using linguistic term values. In 2010, Xu et al. [29] also introduced a new similarity measures using center of gravity (COG) point of two linguistic valued trapezoidal fuzzy numbers and a new arithmetic operator of linguistic values trapezoidal fuzzy numbers. Wu et al. [28] presented risk analysis of corrosion failures of equipment in refining and petrochemical plants using fuzzy set theory. Markowski et al. [19] used fuzzy logic to explosion risk assessment.

In this paper, three different multi-objective and multi-items supplier selection models have been developed in crisp and fuzzy environments. All parameters have been considered as crisp in first model. In real world problems, the demand of a commodity is not always certain. Generally, it is vague in nature. So demand of the items has been considered as fuzzy in the second model. As a result, the constraints becomes fuzzy. As a fuzzy constraint represents a fuzzy event, it should be satisfied in some predefined possibility and necessity [7, 8, 15, 16]. Analogous to chance constrained programming with stochastic parameters, in fuzzy environment, it is assumed that some constraints will hold with a least possibility, η_1. Again some constraints may be satisfied with some predefined necessity, η_2. These possibility and necessity constraints may be imposed as per demand of the situation. Also the risk in any system are not always certain, so the risk and demand of the items are considered as fuzzy in the third model. The total available space and budget are constant for a retailer. Each items purchased from different suppliers have different risk depending on their purchasing cost, time of delivery etc. Now a retailer always wants to maximize their total profit and minimize their risk in the business. So in this paper, the profit function is maximized and risk is minimized for all the models. Also to convert the fuzzy objective to crisp objective, two different methods such as α-cut method and credibility measure method have been used in it.

To get the optimality of the proposed model, MOGA has been introduced. Genetic algorithm manipulates a family of solutions in the search of an optimal solution. So a retailer can take any optimal value from the set of solutions to buy an item from a supplier as per his/her need. Genetic algorithm approach was first proposed by Holland [12]. Because of its generality, it has been successfully applied to many optimization problems, for its several advantages over conventional optimization methods. There are several approaches using genetic algorithms to deal with the multi-objective optimization problems. These algorithms can be classified into two types: (i) non-elitist MOGA and (ii) elitist MOGA. Among non-elitist MOGA Fonseca and Fleming's MOGA [9], Srinivas and Deb's nondominated sorting genetic algorithm (NSGA) [25] enjoyed more attention. Two common features of all these algorithms are (i) assigning fitness to population members based on non-dominated sorting and (ii) preserving diversity among solutions of the same non-dominated front. Diversity is maintained using a sharing function depending on the problem. Among elitist MOGAs, one can refers Rudolph's elitist multi-objective evolutionary algorithm [22], Deb et al.'s [5] elitist non-dominated shorting MOGA. These algorithms normally select solution from parent population for cross-over and mutation randomly. After these operations parent and child population are combined together and among them better solutions are selected for next iteration.

The rest of the paper organized as follows. In Section 2, some preliminary ideas about triangular fuzzy number, α-cut of a fuzzy number have been described. Also possibility, necessity and credibility theory with some lemmas have been discussed in this section. In Section 3, multi-objective programming problems under possibility and necessity constraints have been shown. In Section 4, three different supplier selection models have been constructed in crisp and fuzzy environment. In Section 5, the procedure of multi-objective genetic algorithm has been given. In Section 6, a numerical example comes out with the results in both models and following Section 7 and 8 discussion and conclusion.

2. Preliminaries

2.1. Some Definitions

Triangular fuzzy number (TFN): A TFN $\widetilde{A}$ is specified by the triplet (a_1, a_2, a_3) and is defined by its continuous membership function $\mu_{\widetilde{A}}(x) : F \rightarrow [0, 1]$ as follows (Fig.1):

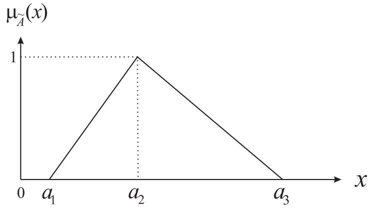

Fig. 1 Membership function of a TFN

$$\mu_{\widetilde{A}}(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1}, & \text{if } \ a_1 \le x \le a_2, \\ \dfrac{a_3 - x}{a_3 - a_2}, & \text{if } \ a_2 \le x \le a_3, \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

α-cut of fuzzy number: The α-cut / α - level set of a fuzzy number $\widetilde{A}$ is a crisp set defined as $\widetilde{A}_\alpha = \{x \in R \mid \mu_{\tilde{A}}(x) \ge \alpha\}$ where $\alpha \in [0, 1]$.

2.2. Possibility, Necessity and Credibility

Any fuzzy subset $\tilde{a}$ of R (where R represents a set of real numbers) with membership function $\mu_{\tilde{a}}(x) : R \rightarrow [0, 1]$ is called a fuzzy number. Let $\tilde{a}$ and $\tilde{b}$ be two fuzzy numbers with membership functions $\mu_{\tilde{a}}(x)$ and $\mu_{\tilde{b}}(x)$, respectively. According to Dubois and Prade [7, 8], Zadeh [32], Liu and Iwamura [15, 16],

$$Pos\left(\widetilde{a} * \widetilde{b}\right) = \{\sup(\min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y))), \ x, y \in R \text{ and } x * y\}, \tag{2}$$

$$Nes\left(\widetilde{a} * \widetilde{b}\right) = \{\inf(\max(1 - \mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y))), \ x, y \in R \text{ and } x * y\}, \tag{3}$$

where the abbreviation "Pos" and "Nes" represent possibility and necessity respectively. Also, $*$ is any of the the relations $>, <, =, \le, \ge$.

On the other hand, necessity measure of an event $\tilde{a} * \tilde{b}$ is a dual of possibility measure. The grade of necessity of an event is the grade of impossibility in the opposite event and is defined as

$$Nes(\tilde{a} * \tilde{b}) = 1 - Pos(\overline{\tilde{a} * \tilde{b}}).$$

Also necessity measures satisfy the condition

$$\mathrm{Min}(Nes(\tilde{a} * \tilde{b}), Nes(\overline{\tilde{a} * \tilde{b}})) = 0.$$

The relationships between possibility and necessity measures satisfy also the following conditions:

$$\begin{aligned} &Pos\left(\widetilde{a} * \widetilde{b}\right) \geq Nes\left(\widetilde{a} * \widetilde{b}\right), \quad Nes\left(\widetilde{a} * \widetilde{b}\right) > 0 \\ &\Rightarrow Pos\left(\widetilde{a} * \widetilde{b}\right) = 1 \text{ and } Pos\left(\widetilde{a} * \widetilde{b}\right) < 1 \\ &\Rightarrow Nes(\tilde{a} * \tilde{b}) = 0. \end{aligned}$$

If $\tilde{a}, \tilde{b} \in R$ and $\tilde{c} = f(\tilde{a}, \tilde{b})$ where $f : R \times R \to R$ is a binary operation, then membership function $\mu_{\tilde{c}}$ of $\tilde{c}$ is defined as

$$\mu_{\tilde{c}}(z) = \sup\{(\min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y))), \ x, y \in R \quad \text{and} \quad z = f(x, y) \forall z \in R\}.$$

Let $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ be two triangular fuzzy numbers. Then for these fuzzy numbers, following [16, 26] Lemmas 2.1, 2.2 can be derived.

Lemma 2.1 *$Pos(\tilde{a} \leq b) < \eta$ iff $\delta = \frac{b-a_1}{a_2-a_1} < \eta$ when b is a crisp number.*

Proof Let $Pos(\tilde{a} \leq b) < \eta$.

From Fig.2 it is clear that $Pos(\tilde{a} \leq b) = \frac{b-a_1}{a_2-a_1}$.
Therefore, $Pos(\tilde{a} \leq b) < \eta$ iff $\delta = \frac{b-a_1}{a_2-a_1} < \eta$.

Lemma 2.2 *$Pos(\tilde{a} \geq b) > \eta$ iff $\delta = \frac{a_3-b}{a_3-a_2} > \eta$ when b is a crisp number.*

Proof Let $Pos(\tilde{a} \geq b) > \eta$.

From Fig.2 it is clear that $Pos(\tilde{a} \geq b) = \frac{a_3-b}{a_3-a_2}$.
Therefore, $Pos(\tilde{a} \geq b) > \eta$ iff $\delta = \frac{a_3-b}{a_3-a_2} > \eta$.

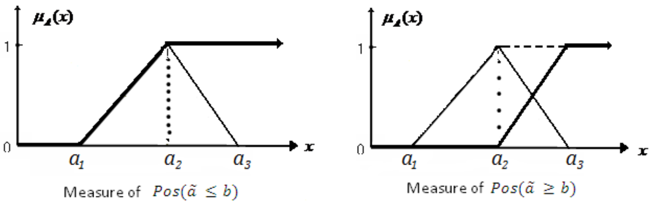

Fig. 2 Measure of $Pos(\tilde{a} \leq b)$ and $Pos(\tilde{a} \geq b)$

Based on possibility measure and necessity measure, the third set function Cr, called credibility measure, was analyzed by Liu and Liu [17], Maity et al. [18]. They defined the credibility measure in the following form

$$Cr(A) = [\rho Pos(A) + (1 - \rho)Nec(A)], \tag{4}$$

where A is a fuzzy subset of R and $0 < \rho < 1$.

Using this credibility, the expected value of any fuzzy number $\tilde{A} = (a_1, a_2, a_3)$ can be calculated as

$$E(\tilde{A}) = \frac{1}{2}[(1-\rho)a_1 + a_2 + \rho a_3]. \tag{5}$$

3. Multi-objective Programming under Possibility and Necessity Constraints

A general multi-objective mathematical programming problem with fuzzy parameters should have the following form:

$$\begin{aligned} &\max \ f_1(u,\xi) \\ &\min \ f_2(u,\xi) \\ &\text{s.t.} \quad g_j(u,\xi) \le b, \quad j = 1,2,\cdots,n, \end{aligned} \tag{6}$$

where u is a decision vector, ξ is a vector of fuzzy parameter, $f_1(u,\xi)$ and $f_2(u,\xi)$ are objective functions, $g_j(u,\xi)$ are constraint functions, $j = 1,2,\cdots,n$. To convert the fuzzy objectives and constraints to their crisp equivalents, Liu and Iwamura [16] proposed a method to convert the above problem into an equivalent fuzzy programming problem under possibility constraints. Similarly, we can convert the above problem to following fuzzy programming problem under possibility/necessity constraints

$$\begin{aligned} &\max \ f_1(u,\xi) \\ &\min \ f_2(u,\xi) \\ &\text{s.t.} \quad Nes\{\xi \mid g_j(u,\xi) \le b\} > \eta_{1j} \ \text{ and/or } \ Pos\{\xi \mid g_j(u,\xi) \le b\} > \eta_{2j}, \end{aligned} \tag{7}$$

where η_{1j} and η_{2j}, $j = 1,2,\cdots,n$, are predetermined confidence level for fuzzy constraints. $Nes\{\cdot\}$ denotes the necessity of the event in $\{\cdot\}$. So a point ξ is feasible if and only if necessity of the set $\{\xi \mid g_j(u,\xi) \le b\}$ is at least η_{1j}. $Pos\{\cdot\}$ denotes the possibility of the event in $\{\cdot\}$. So a point ξ is feasible if and only if possibility of the set $\{\xi \mid g_j(u,\xi) \le b\}$ is also at least η_{2j}, $j = 1,2,\cdots,n$.

4. Mathematical Formulation of a Supplier Selection Model in Crisp and Fuzzy Environment

4.1. Notations

To develop the proposed model, the next notations have been used.

- S_i: Selling price of i^{th} item.
- p_{ij}: The purchase cost of i^{th} item from j^{th} supplier.
- T_j: The transaction cost for j^{th} supplier.
- D_i: The demand of i^{th} item.
- r_{ij}: The risk value for i^{th} item supplies by j^{th} supplier.

- C_{ij}: The capacity of i^{th} item which can be supplied by j^{th} supplier.
- ω_i: A storage space needed by product i.
- W: Available total storage space.
- X_{ij}: Number of i^{th} items supplied from j^{th} supplier.
- TP: Total profit in the business.
- R: Total risk in the business.
- B: Available total budget of a retailer.

4.2. Assumptions

The proposed model have been formulated under the following assumptions.

- Shortages and backordering are not allowed.
- Each supplier has a limited capacity for each item.
- Available total storage space for a retailer is limited.
- Total budget of a retailer is limited.
- For each item a risk value has been considered for a supplier due to various factors such as (i) shipment in delay, (ii) purchasing cost, (iii) economic dealing.
- A supplier dependent transaction cost has been considered.
- Each item needs a storage space.

4.3. Proposed Supplier Selection Model in Crisp Environment: Model I

In this paper, a supplier selection model has been considered in which there are m different approved suppliers and each supplier may supply n different products with limited capacity. There exists a risk value r_{ij} for j^{th} supplier who supplies i^{th} product to a retailer whose demand (D_i) is known over a finite planing horizon. The retailer have a selling price S_i for i^{th} item. Here storage space and budget constraints have been considered for the retailer. The purchasing cost of each item varies from suppliers to suppliers. Also there exists different transaction cost for different suppliers. Now the retailer want to procure each required amount of item from a supplier such that the total profit of the retailer is maximum as well as total risk value is minimum.

To formulate the above problem it is supposed that the retailer procures i^{th} item of amount X_{ij} from j^{th} supplier. Therefore the total procurement cost (TC) for n items is given by

$$TC = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}p_{ij} + \sum_{j=1}^{m} T_jY_j, \tag{8}$$

where Y_j ($j = 1, 2, \cdots, m$) are calculated as follows:

$$Y_j = \begin{cases} 1, & \text{for } X_{ij} > 0, \\ 0, & \text{for } X_{ij} = 0. \end{cases}$$

The retailer sells these n items to the customers. After selling all items he/she collects the total revenue (TR) which is given by

$$TR = \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} S_i. \tag{9}$$

Therefore from this business the retailer earns the total profit (TP) that is given by

$$TP = \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} S_i - \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} p_{ij} - \sum_{j=1}^{m} T_j Y_j. \tag{10}$$

Simultaneously, the retailer wants to minimize the total risk to collect all these items from the suppliers. Now the total risk R is given by

$$R = \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} r_{ij} / \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij}. \tag{11}$$

Therefore, the above problem can be described in the following form in crisp environment:

$$\max\ TP = \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} S_i - \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} p_{ij} - \sum_{j=1}^{m} T_j Y_j$$

and

$$\min\ R = \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} r_{ij} / \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij}$$

subject to

$$\begin{cases} \sum_{j=1}^{m} X_{ij} - D_i \geq 0, \quad i = 1, 2, \cdots, n, \\ \sum_{i=1}^{n} \omega_i (\sum_{j=1}^{m} X_{ij} - D_i) \leq W, \\ 0 \leq X_{ij} \leq C_{ij}, \quad i = 1, 2, \cdots, n, \ \& \ j = 1, 2, \cdots, m, \\ Y_j = \begin{cases} 1, & \text{for } X_{ij} > 0, \\ 0, & \text{for } X_{ij} = 0, \quad j = 1, 2, \cdots, m, \end{cases} \\ \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} p_{ij} \leq B. \end{cases}$$

This is a multi objective decision making problem where a retailer wants to maximize the profit (TP) and minimize the risk (R). To solve the above problem MOGA has been applied. GA manipulates a family of solution in the search of an optimal solution. This is an advantage of GA which is better than another methods. So different retailers may have choose different optimal value as per their strategy in the business.

4.4. Proposed Supplier Selection Model in Fuzzy Environment: Model II

In this model, retailer's demand for each item has been considered fuzzy which is triangular. All other constraints are the same as in Model I. Therefore under this fuzzy environment, the model can be depicted as follows:

$$\max\ TP = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}S_i - \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}p_{ij} - \sum_{j=1}^{m} T_jY_j$$

and

$$\min\ R = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}r_{ij} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}$$

subject to

$$\begin{cases} \sum\limits_{j=1}^{m} X_{ij} - \tilde{D}_i \geq 0, \qquad i = 1, 2, \cdots, n, \\ \sum\limits_{i=1}^{n} \omega_i(\sum\limits_{j=1}^{m} X_{ij} - \tilde{D}_i) \leq W, \\ 0 \leq X_{ij} \leq C_{ij}, \qquad i = 1, 2, \cdots, n \ \&\ j = 1, 2, \cdots, m, \\ Y_j = \begin{cases} 1, & \text{for } X_{ij} > 0, \\ 0, & \text{for } X_{ij} = 0, \quad j = 1, 2, \cdots, m, \end{cases} \\ \sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m} X_{ij}p_{ij} \leq B. \end{cases}$$

where '$\sim$' indicates the fuzzyness of the parameter.

Here the two fuzzy constraints actually stand for fuzzy relation. There are several representations of fuzzy relation. Here these relations are interpreted in the form of possibility theory in which fuzzy numbers are interpreted by a degree of uncertainty. It is considered that there are n items that are supplied by m suppliers. According to Liu and Iwamura [15], first two constraints reduce to following respective necessary and possibility constraints. There may be two different combinations of the fuzzy constraints depending on the different scenarios such as

Scenario 1:

$$\begin{aligned}
&Nes\{\tilde{D}_1 > \sum_{j=1}^{m} x_{1j}\} < \eta_{11},\\
&Nes\{\tilde{D}_2 > \sum_{j=1}^{m} x_{2j}\} < \eta_{12},\\
&\quad\vdots\\
&Nes\{\tilde{D}_n > \sum_{j=1}^{m} x_{nj}\} < \eta_{1n},\\
&Nes\{(\sum_{i=1}^{n}\sum_{j=1}^{m} \omega_i x_{ij} - W) < \sum_{i=1}^{n} \omega_i \tilde{D}_i\} > \eta_{1,n+1}.
\end{aligned} \tag{12}$$

Scenario 2:

$$\begin{aligned}
&Pos\{\tilde{D}_1 \geq \sum_{j=1}^{m} x_{1j}\} < \eta_{11},\\
&Pos\{\tilde{D}_2 \geq \sum_{j=1}^{m} x_{2j}\} < \eta_{12},\\
&\quad\vdots\\
&Pos\{\tilde{D}_n \geq \sum_{j=1}^{m} x_{nj}\} < \eta_{1n},\\
&Pos\{(\sum_{i=1}^{n}\sum_{j=1}^{m} \omega_i x_{ij} - W) \leq \sum_{i=1}^{n} \omega_i \tilde{D}_i\} > \eta_{2,n+1}.
\end{aligned} \tag{13}$$

4.4.1. Equivalent Crisp Representation of Model

Let $\tilde{D}_i = (D_{i1}, D_{i2}, D_{i3})$ be a triangular fuzzy number represented in Fig.1. So $\sum_{i=1}^{m} \omega_i \tilde{D}_i = (D'_1, D'_2, D'_3)$ is also a triangular fuzzy number by it's properties. Therefore on the basis of Lemmas 2.1, 2.2, the fuzzy Model II reduces to following multi objective crisp model:

$$\max\ TP = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}S_i - \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}p_{ij} - \sum_{j=1}^{m} T_j Y_j$$

and

$$\min\ R = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}r_{ij} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}$$

subject to constraint for all scenarios

$$\begin{cases} 0 \le X_{ij} \le C_{ij} \qquad i = 1, 2, \cdots, n \;\&\; j = 1, 2, \cdots, m, \\ Y_j = \begin{cases} 1, & \text{for } X_{ij} > 0, \\ 0, & \text{for } X_{ij} = 0, \end{cases} \qquad j = 1, 2, \cdots, m, \\ \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} p_{ij} \le B \end{cases}$$

and
Scenario 1:

$$\begin{aligned} &\frac{(\sum_{j=1}^{m} x_{1j} - D_{11})}{(D_{12} - D_{11})} > (1 - \eta_{11}), \\ &\frac{(\sum_{j=1}^{m} x_{2j} - D_{21})}{(D_{22} - D_{21})} > (1 - \eta_{12}), \\ &\qquad\vdots \\ &\frac{(\sum_{j=1}^{m} x_{nj} - D_{n1})}{(D_{n2} - D_{n1})} > (1 - \eta_{1n}), \\ &\frac{(\sum_{i=1}^{n} \sum_{j=1}^{m} \omega_i x_{ij} - W) - D'_1}{(D'_2 - D'_1)} < (1 - \eta_{1,n+1}). \end{aligned} \tag{14}$$

Scenario 2:

$$\begin{aligned} &\frac{(D_{13} - \sum_{j=1}^{m} x_{1j})}{(D_{13} - D_{12})} < \eta_{11}, \\ &\frac{(D_{23} - \sum_{j=1}^{m} x_{2j})}{(D_{23} - D_{22})} < \eta_{12}, \\ &\qquad\vdots \\ &\frac{(D_{n3} - \sum_{j=1}^{m} x_{nj})}{(D_{23} - D_{22})} < \eta_{1n}, \\ &\frac{D'_3 - (\sum_{i=1}^{n} \sum_{j=1}^{m} \omega_i x_{ij} - W)}{(D'_3 - D'_2)} > \eta_{2,n+1}. \end{aligned} \tag{15}$$

4.5. Proposed Supplier Selection Model with Fuzzy Risk: Model III

Here the risk value of each item supplied from each supplier has been considered as fuzzy which are taken as a triangular fuzzy number, i.e., $\tilde{r}_{ij} = (r_{ij1}, r_{ij2}, r_{ij3})$ and demand is also taken as fuzzy as in Model II. Therefore the proposed model can be described as follows

$$\max\ TP = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}S_i - \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}p_{ij} - \sum_{j=1}^{m} T_jY_j$$

and

$$\min\ \tilde{R} = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}\tilde{r}_{ij} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}$$

subject to

$$\begin{cases} \sum_{j=1}^{m} X_{ij} - \tilde{D}_i \geq 0, \quad i = 1,2,\cdots,n, \\ \sum_{i=1}^{n} \omega_i(\sum_{j=1}^{m} X_{ij} - \tilde{D}_i) \leq W, \\ 0 \leq X_{ij} \leq C_{ij}, \quad i = 1,2,\cdots,n, \ \& \ j = 1,2,\cdots,m, \\ Y_j = \begin{cases} 1, & \text{for } X_{ij} > 0, \\ 0, & \text{for } X_{ij} = 0, \end{cases} \quad j = 1,2,\cdots,m, \\ \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}p_{ij} \leq B. \end{cases} \tag{16}$$

Lemma 4.1 *Since all the risk values ($\tilde{r}_{ij}$) are triangular fuzzy numbers so the total risk $\tilde{R}$ is also a triangular fuzzy number such that*

$$\begin{aligned} \tilde{R} &= \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}\tilde{r}_{ij} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij} \\ &= (\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}r_{ij1} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}r_{ij2} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}r_{ij3} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}) \\ &= (R_1, R_2, R_3), \end{aligned}$$

where $R_k = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}r_{ijk} / \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}, k = 1,2,3.$

Since one of the objective functions is fuzzy in nature, hence to solve the model the fuzzy objective function converted into the crisp objective functions. Here two methods for defuzzyfications of the objective function have been given as follows:

4.5.1. α-Cut Method

Now the fuzzy objective function is converted to a crisp objective function using the α-cut of the objective function. Let $(\tilde{R})_\alpha = [R^L_\alpha, R^R_\alpha]$. Now we aim to minimize both the R^L_α and R^R_α and maximize TP with the given constraints. Here the fuzzy constraints are converted to crisp constraints using necessity measure as given in the previous model. So the problem becomes

$$\begin{aligned}
&\max\ TP = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}S_i - \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}p_{ij} - \sum_{j=1}^{m} T_jY_j \\
&\min\ R_\alpha^L = R_1 + \alpha(R_2 - R_1) \qquad (17) \\
&\min\ R_\alpha^R = R_3 - \alpha(R_3 - R_2)
\end{aligned}$$

subject to

$$\begin{cases}
\dfrac{(\sum\limits_{j=1}^{m} x_{ij} - D_{11})}{(D_{i2} - D_{i1})} > (1-\eta_{1i}), \qquad i = 1, 2, \cdots, n, \\
\dfrac{(\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m} \omega_i x_{ij} - W) - D_1'}{D_2' - D_1'} < (1-\eta_{1,n+1}), \\
\sum\limits_{i=1}^{n} \omega_i(\sum\limits_{j=1}^{m} X_{ij} - \tilde{D}_i) \le W, \\
0 \le X_{ij} \le C_{ij}, \qquad i = 1, 2, \cdots, n,\ \&\ j = 1, 2, \cdots, m, \\
Y_j = \begin{cases} 1, & \text{for } X_{ij} > 0, \\ 0, & \text{for } X_{ij} = 0, \qquad j = 1, 2, \cdots, m, \end{cases} \\
\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m} X_{ij}p_{ij} \le B.
\end{cases}$$

4.5.2. Credibility Measure Method

On the basis of credibility measure, (Liu and Iwamura [15, 16], Maity et al. [17]) the expected value of fuzzy risk objective $\tilde{R}$ is given by

$$E(\tilde{R}) = \frac{1}{2}((1-\rho)R_1 + R_2 + \rho R_3), \ \text{ where } 0 < \rho < 1.$$

5. Solution Methodology: Multi-objective Genetic Algorithm (MOGA)

In this paper, the proposed supplier selection model has been developed with multi-objective problem. This multi-objective problem is solved with the MOGA. The MOGA is illustrated as follows.

We assume that there are M objective functions. In order to cover both minimization and maximization of objective functions, we use the operators between two solutions and as to denote that solution is better than the one on a particular objective. Similarly, for a particular objective implies that solution is worse than the one on this objective. For example, if an objective function is to be minimized, the operator would mean the < operator, whereas if the objective function is to be maximized, the operator would mean the > operator. The following definition covers mixed problems with minimization of some objective functions and maximization of the rest of them.

Definition 5.1 *A solution X_1 is said to dominate the other solution X_2 if the following both conditions* (i) *and* (ii) *are true:* (i) *The solution X_1 is no worse than X_2 in all objectives, or for all $j = 1, 2, \cdots, M$.* (ii) *The solution X_1 is strictly better than X_2 in at least one objective, or for at least one $j = 1, 2, \cdots, M$. If any of the above condition is violated, the solutions X_1 does not dominate the solution X_2. If X_1 dominates the solution X_2, it is also customary to write any of the following:*

(i) *X_2 dominated by X_1;*

(ii) *X_1 non-dominated by X_2;*

(iii) *X_1 non-inferior to X_2.*

It is intuitive that if a solution X_1 dominates another one X_2, the solution X_1 is better than X_2 in the parlance of multi-objective optimization. Since the concept of domination allows a way to compare solutions with multiple objectives, most multi-objective optimization methods use this domination concept to search for non-dominated solution.

Crowding distance

Crowding distance of a solution is measured using the following rule.

Step 1: Sort the population set according to every objective function values in ascending order of magnitude.

Step 2: For each objective function, the boundary solutions are assigned an infinite distance value. All other intermediate solutions are assigned a distance value equal to the absolute normalized difference in the function values of two adjacent solutions. This calculation is continued with other objective functions.

Step 3: The overall crowding distance value is calculated as the sum of individual distance values corresponding to each objective.

Each objective function is normalized before calculating the crowding distance. Following algorithm is used for this purpose.

set k = number of solutions in F
for each k
{
set $F[k]_{distance} = 0$
}
for each m
{
sort F, in ascending order of magnitude of m-th objective
set $F[1]_{distance} = F[m]_{distance} = M$ where M is a large number
for $i = 2$ to $k - 1$
{
$F[i]_{distance} = F[i]_{distance} + (F[i+1]_m - F[i-1]_m)/(f_m^{max} - f_m^{min})$
}
}.

Here, $F[i]_m$ refers to the m-th objective function value of $F[i]$. f_m^{max} and f_m^{min} are the maximum and minimum values of the m-th objective function.

Non-dominated sorting of a population

In this case, first, for each solution we calculate two entities: 1) domination count n_p, the number of solutions which dominate the solution p, and 2) S_p, a set of solutions that the solution p dominates. All solutions in the first non-dominated front will have their domination count as zero. Now, for each solution p with $n_p = 0$, we visit each member (q) of its set S_p and reduce its domination count by one. In doing so, if for any member q the domination count becomes zero, we put it in a separate list Q. These members belong to the second non-dominated front. Now, the above procedure is continued with each member of Q and the third front is identified. This process continues until all fronts are identified.

Parameters

Firstly, we set the different parameters on which this GA depends. These are maximum number of generation ($MAXGEN$), population size ($POPSIZE$), probability of crossover ($PXOVER$), probability of mutation (PMU). There is no clear indication as to how large a population should be. If the population is too large, there may be difficulty in storing the data, but if the population is too small, there may not be enough string for good crossovers. In our problem, $POPSIZE = 100$, $PXOVER = 0.7$, $PMU = 0.3$ and $MAXGEN = 5000$.

Chromosome representation

An important issue in applying a GA is to design an appropriate chromosome representation of solutions in the problem together with genetic operators. Traditional binary vectors used to represent the chromosome are not effective in many non-linear physical problems. Since the proposed problem is non-linear, hence to overcome this difficulty, a real-number representation is used in this problem.

Evaluation

Evaluation function plays the same role in GA as the environment plays in natural evolution. To this problem, the evaluation function means

$$eval(V_i) = objective\ \ function\ \ value$$

By roulette wheel selection method, the batter chromosome are selected from the population to generate the next improved chromosomes. Now new chromosomes are produced by arithmetic crossover and uniform mutation. Next comes the general outline of the algorithm:

```
    begin
t ← 0
initialize Population(t)
evaluate Population(t)
while(not terminate-condition)
```

{
$t \leftarrow t$+1
select Population(t) from Population(t-1)
alter(crossover and mutate) Population(t)
evaluate Population(t)
}
Print Optimum Result
end.

Procedure of MOGA

Step 1: Generate initial population P_1 of size N.

Step 2: $i \leftarrow 1$ [i represent the number of current generation.]

Step 3: Select solution from P_i for crossover.

Step 4: Made crossover on selected solution to get child set C_1.

Step 5: Select solution from P_i for mutation.

Step 6: Made mutation on selected solution to get solution set C_2.

Step 7: Set $P_i' = P_i \bigcup C_1 \bigcup C_2$.

Step 8: Partition P_i' into subsets $F_1, F_2, \cdots, F_k$, such that each subset contains non-dominated solutions of P_i' and every solutions of F_i dominates every solutions of F_{i+1} for $i = 1, 2, \cdots, k-1$.

Step 9: Select largest possible integer l, so that none of solutions in the set $F_1 \bigcup F_2 \bigcup \cdots \bigcup F_l \leq N$.

Step 10: Set $P_{i+1} = F_1 \bigcup F_2 \bigcup \cdots \bigcup F_l$.

Step 11: Sort F_{l+1} in decreasing order by crowding distance.

Step 12: Set M = number of solutions in P_{i+1}.

Step 13: Select first $N - M$ solutions from set F_{l+1}.

Step 14: Insert these solution in solution set P_{i+1}.

Step 15: Set $i \leftarrow i + 1$.

Step 16: If termination condition does not hold, goto Step 3.

Step 17: Output P_i.

Step 18: End.

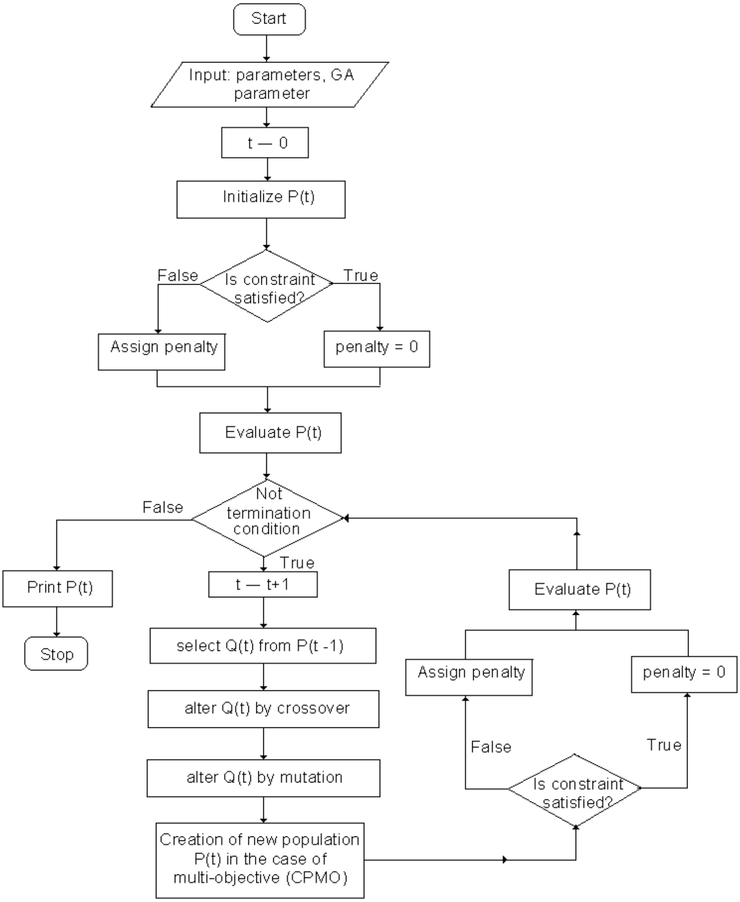

Fig. 3 Flow-chart of MOGA

6. Numerical Illustration

To illustrate Model I, Model II and Model III, it is considered that there are two suppliers who supply two different items. Now, a retailer has to decide what amount of items will be taken from which supplier such as the profit and risk will be optimized. To study the feasibility of all models, following three examples have been taken.

6.1. Example 1

In this example, to find an optimal profit and risk of Model I, following parametric values have been considered in crisp form:

$m = 2, n = 2, S_1 = 50\$, S_2 = 40\$, p_{11} = 25\$, p_{12} = 27\$,$
$p_{21} = 30\$, p_{22} = 32\$, r_{11} = 0.15, r_{12} = 0.1, r_{21} = 0.12, r_{22} = 0.18,$
$S_1 = 50\$, S_2 = 40\$, T_1 = 1000\$, T_2 = 700\$, w_1 = 0.2, w_2 = 0.18,$
$C_{11} = 150, C_{12} = 200, C_{21} = 100, C_{22} = 80, W = 200, B = 8000\$,$
$D_1 = 130, D_2 = 100.$

Using the above values of all parameters, the MOGA has been applied simultaneously to minimize the risk and maximize the profit of Model I whose some pareto optimal solution have been shown in Table 1.

Table 1: Solution set of Model I.

X_{11}	X_{12}	X_{21}	X_{22}	R	$TP(\$)$
4.31	177.69	92.06	8.72	0.1097	3485.41
14.34	171.04	89.75	10.27	0.1117	3572.36
16.43	169.03	89.75	10.26	0.1120	3578.36
40.86	141.0	72.74	28.08	0.1201	3585.75
61.31	122.5	67.83	34.74	0.1251	3606.63

From Table 1, it is observed that among these five optimal solutions, the minimum risk is 0.1097 and maintaining this minimum risk, optimum value is 3485.41\$. To obtain such risk and profit values, the retailer buys the item 1 and 2 of amount 4.31 and 92.06 respectively from supplier 1 and 177.69 and 8.72 from supplier 2 respectively. Again, it is also noticed that the maximum profit among these five is 3606.63\$ and at that time the risk is 0.1251. So, it is seen that if a retailer wants to get higher profit, then he/she has to take higher risk and if he/she wants little less risk, then he/she will have less profit.

6.2. Example 2

To illustrate the Model II, the demand of the items have been considered as a fuzzy variable. All other input values are same as in Example 1. So, here the demands of the items considered as triangular fuzzy number. Therefore, to study this fuzzy model the following parametric values have been taken

$\tilde{D}_1 = (110, 130, 150), \tilde{D}_2 = (90, 100, 110),$
$\eta_{11} = 0.95, \eta_{12} = 0.9, \eta_{13} = 0.7,$
$\eta_{21} = 0.15, \eta_{22} = 0.2, \eta_{23} = 0.8.$

Since $n = 2$, so the number of fuzzy constraints is 3. For two different scenarios, the results are discussed numerically as follows.
Scenario 1:

$$\frac{(\sum_{j=1}^{2} x_{1j} - D_{11})}{(D_{12} - D_{11})} > (1 - \eta_{11}),$$

$$\frac{(\sum_{j=1}^{2} x_{2j} - D_{21})}{(D_{22} - D_{21})} > (1 - \eta_{12}),$$
$$\frac{(\sum_{i=1}^{2}\sum_{j=1}^{2} \omega_i x_{ij} - W) - D'_1}{(D'_2 - D'_1)} < (1 - \eta_{13}). \qquad (18)$$

In this case, also optimal results of Model II are obtained by MOGA and the pareto optimal solution has been given in Table 2.

Table 2: Solution set of Model II in Scenario 1.

X_{11}	X_{12}	X_{21}	X_{22}	R	$TP(\$)$
39.35	73.97	48.50	46.87	0.1320	1845.29
39.35	73.97	48.22	48.04	0.1323	1851.79
39.35	73.97	48.22	47.46	0.1321	1847.18
39.35	73.97	48.22	47.61	0.1322	1848.39
39.35	73.97	49.85	42.07	0.1308	1820.36

From this table, it is observed that among these five optimal solutions, the minimum risk is 0.1308 and maintaining this minimum risk, the optimum value is 1820.36 $. To obtain such risk and profit values, the retailer buys the item 1 and 2 of amount 39.35 and 49.85 respectively from supplier 1 and 73.97 and 42.07 from supplier 2 respectively. Again, it is also noticed that the maximum profit among these five is 1851.79$ and at that time, the risk is 0.1323. So, it is seen that if a retailer wants to get higher profit, then he/she has to take higher risk and if he/she wants less risk, then he/she will have less profit.

Scenario 2:

$$\frac{(D_{13} - \sum_{j=1}^{2} x_{1j})}{(D_{13} - D_{12})} < \eta_{11},$$
$$\frac{(D_{23} - \sum_{j=1}^{2} x_{2j})}{(D_{23} - D_{22})} < \eta_{12}, \qquad (19)$$
$$\frac{D'_3 - (\sum_{i=1}^{2}\sum_{j=1}^{2} \omega_i x_{ij} - W)}{(D'_3 - D'_2)} > \eta_{23}.$$

In this scenario, the optimal results of Model II are obtained by MOGA which is given in Table 3 as follows:

Table 3: Solution set of Model II in Scenario 2.

X_{11}	X_{12}	X_{21}	X_{22}	R	$TP(\$)$
121.72	25.29	60.03	48.06	0.1436	2909.71
121.72	25.29	60.03	48.51	0.1437	2913.37
121.72	25.29	60.03	48.94	0.1438	2916.80
121.72	25.29	59.32	50.29	0.1440	2920.57
120.95	26.07	60.02	47.97	0.1435	2907.55

From this table, it is observed that among these five optimal solutions, the minimum risk is 0.1435 and maintaining this minimum risk, the optimum value is 2907.55$. To obtain such risk and profit values, the retailer buys the item 1 and 2 of amount 120.95 and 60.02 respectively from supplier 1 and 26.07 and 47.97 from supplier 2 respectively. Again, it is also noticed that the maximum profit among these five is 2920.57$ and at that time the risk is 0.1440. So, it is seen that if a retailer wants to get higher profit, then he/she has to take higher risk and if he/she wants lesser risk, then he/she will have less profit.

6.3. Example 3

To illustrate Model III, the risk values are considered as fuzzy which are triangular. All other parameters remain the same as in the previous Example 2. So, to study the feasibility of Model III, following parametric values have been considered

$$\tilde{r}_{11} = (0.1, 0.15, 0.2), \tilde{r}_{12} = (0.07, 0.1, 0.13),$$
$$\tilde{r}_{21} = (0.08, 0.12, 0.16), \tilde{r}_{22} = (0.14, 0.18, 0.21).$$

Here, two different methods have been applied to illustrate this model: One is α-cut method and the other is credibility measure method. The results obtained by these two methods are discussed as follows.

(i) Using α-Cut Method

Considering different α-cut of the fuzzy risk, the obtained optimized results are given in the following Fig.4.

From Figures 4 (a, b, c, d), it's very easy to obtain the amount of risk and profit as well as the amount of items collected from supplier 1 and supplier 2 for any α-cut. For example, when $\alpha = 0.5$, at that time the minimum risk value lies in the interval [0.1049, 0.1110] along with the maximum profit 1805.02$, also the amount of item purchased from supplier 1 and supplier 2 are 92.02 and 110.58 respectively.

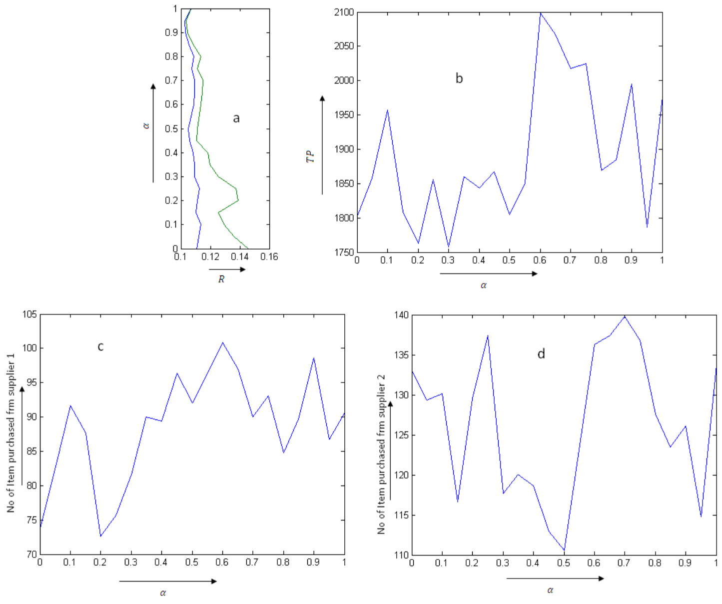

Fig. 4 Risk, Profit, Number of item purchased from different suppliers with different α-cuts

(ii) Using Credibility Measure Method

Now, the optimal result of Model III has been obtained using the credibility measure of the fuzzy risk objective function taking the value of $\rho = 0.5$. Here the maximum profit is 1708.95$ and the minimum risk is 0.1051 when the amount of items purchased from supplier 1 is 39.29 and 45.42 respectively and the amount of items purchased from supplier 2 is 74.04 and 33.65 respectively.

7. Discussion

From the result in Section 6, following managerial insights have been drawn

- If a retailer wants to get higher profit, then he/she has to take higher risk and if he/she wants lesser risk, then he/she will have less profit.

- Also a sensitivity analysis has been made on the objective functions due to the different risk values associated with the system which is shown in Fig.5. The changes in one risk value has been considered when other three risk values remain same. For four different risk values, four studies have been taken.

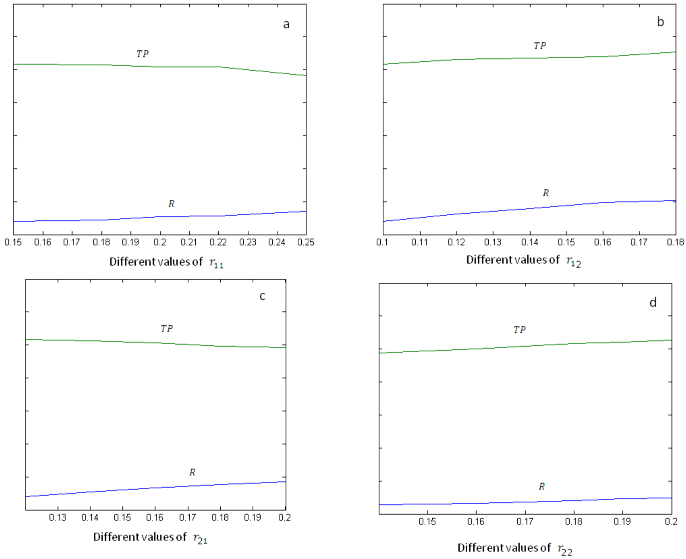

Fig. 5 Change of profit and risk with different values of r_{ij}

From Figures 5 (a,b,c,d), it is seen that when any one of the risk values increases, then the total risk of the system also increases for all the cases. But the total profit decreases for first and third case whereas profit increases for second and fourth case. Since, the purchasing cost for both items are lower for the first supplier than second supplier, when risk values are increased for the first supplier, then retailer wants to purchase more things from second supplier as much as possible to minimize the total risk value. For this reason, the total profit decreases. On the other hand, when risk values are higher for the second supplier, then a retailer wants to purchase more amount of items from first supplier. Due to the low purchasing price of first supplier total profit will be more.

- From the consideration of necessity and/or possibility constraints in two different scenarios of Model II, it is observed that the total demand for a planning horizon for Scenarios 1 and 2 belongs to $[D_{i1}, D_{i2}]$ and $[D_{i2}, D_{i3}]$ respectively. From these, it may be concluded that necessity and possibility constraints demand the lower and upper range of the values of demand respectively. Hence, if a decision maker desires to impose the demand constraints in possibility sense, he/she should be expected to happen the imprecise demand at higher level (i.e., $[D_{i2}, D_{i3}]$). On the other hand, for necessary constraint, he/she will expect the demand at lower level. This feature is reflected from the results of Scenarios 1 and 2.

- Comparing the results of α-cut method and credibility measure method, it is seen that the risk calculated by the credibility measure is 0.1051 and it lies in the interval [0.1049, 0.1110] which is found by α-cut method. But, it is seen that the maximum profit in the α-cut method is more than the credibility measure method. So, the α-cut method gives the better solution than the credibility measure method.

8. Conclusion

In this paper, supplier selection by a retailer has been considered with respect to profit function and risk function. The selection has been done maximizing the profit and minimizing the risk. For this purpose, three different supplier selection models have been developed in different environment. In first model (Model I), all parameters associated with the suppliers and retailer have been considered as crisp in nature. Since in real world all parameters are not crisp in nature, hence in the second model (Model II), demands of the items for a retailer have been considered as fuzzy and in the third model (Model III), risk of taking an item from a supplier as well as demand of the items for a retailer have been considered also as fuzzy. Here in Model II, the fuzzy constraints are converted to crisp constraints using necessity and possibility measures. In Model III, the fuzzy objective function has been converted to crisp objective function using α-cut and credibility measure methods. The objective functions such as risk and profit for all models have been optimized using MOGA simultaneously minimizing risk maximizing profit of the models. Finally, three numerical examples have been given to illustrate all models.

Future Research Work

The such selection model may be further developed considering more constraints and the parameters involved in the model may be considered as fuzzy-rough, rough etc. Besides, these such concept in the paper may be applied in different multi-criteria decision making problem.

Acknowledgements

We are very grateful to the anonymous reviewers for their careful reading, constructive comments and helpful suggestions, which have helped us to improve the presentation of this work significantly.

References

[1] F. Arikan, A fuzzy solution approach for multi objective supplier selection, Expert Systems with Applications 40 (2013) 947-952.

[2] S.M. Chen, C.H. Wang, Fuzzy risk analysis based on ranking fuzzy numbers using α-cuts, belief features and signal/noise ratios, Expert Systems with Applications 36 (2009) 5576-5581.

[3] S.M. Chen, A. Munif, G.S. Chen, H.C. Liu, B.C. Kuo, Fuzzy risk analysis based on ranking generalized fuzzy numbers with different left heights and right heights, Expert Systems with Applications 39 (2012) 6320-6334.

[4] S.M. Chen, K. Sanguansat, Analyzing fuzzy risk based on a new fuzzy ranking method between generalized fuzzy numbers, Expert Systems with Applications 38 (2011) 2163-171.

[5] K. Deb, A. Pratap, S. Agarawal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation 6 (2002) 182-197.

[6] D. Dubois, H. Prade, Fuzzy Sets and Systems: Theory and Applications, Academic Press. Inc., New York, 1980.
[7] D. Dubois, H. Prade, Ranking fuzzy numbers in the setting of possibility theory, Information Sciences 30 (1983)183-224.
[8] D. Dubois, H. Prade, Possibility Theory, Academic Press, New York, London, 1988.
[9] C.M. Fonseca, P.J. Fleming, Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization, Proceedings of the Fifth International Conference on Genetic Algorithm, S.Forrest, Ed. San Mateo, CA: Morgan Kauffman, 1993, pp. 416-423.
[10] J.A. Goguen, L-fuzzy sets, JMAA 18 (1967) 145-174.
[11] J.A. Goguen, The logic of inexact concepts, Synthese 19 (1969) 325-373.
[12] H.J. Holland, Adaptation in Natural and Artificial Systems, University of Michigan, 1975.
[13] H.S. Kilic, An integrated approach for supplier selection in multi-item/ multi-supplier environment, Applied Mathematical Modelling 37 (2013) 7752-7763.
[14] R.H. Lin, An integrated model for supplier selection under a fuzzy situation, International Journal of Production Economics 138 (2012)55-61.
[15] B. Liu, K.B. Iwamura, Chance constraint programming with fuzzy parameters, Fuzzy Sets and Systems 94 (1998) 227-237.
[16] B. Liu, K.B. Iwamura, A note on chance constrained programming with fuzzy coefficients, Fuzzy Sets and Systems 100 (1998) 229-233.
[17] B. Liu, Y.K. Liu, Expected value of fuzzy variable and fuzzy expected value model, IEEE Transaction on Fuzzy systems 10(4) (2002) 445-450.
[18] A.K. Maity, K. Maity, M. Maity, A production recycling inventory system with imprecise holding costs, Applied Mathematical Modelling 32 (2008) 2241-2253.
[19] A.S. Markowski, M.S. Mannan, A. Kotynia, H. Pawlak, Application of fuzzy logic to explosion risk assessment, J Loss Prevent Proc. 24(6) (2011) 780-790.
[20] K. Patra, S.K. Mondal, Risk analysis in diabetes prediction based on a new approach of ranking of generalized trapezoidal fuzzy numbers, Cybernetics and Systems: An International Journal 43(8) (2012) 623-650.
[21] J. Rezaei, M. Davoodi, A deterministic multi item inventory model with supplier selection and imperfect quality, Applied Mathematical Modelling 32 (2008) 2106-2116.
[22] G. Rudolph, Evolutionary search under partially ordered fitness sets, Proceedings of the International Symposium on Information Science Innovations in Engineering of Natural and Artificial Intelligent Systems (ISI), 2001, pp. 818-822.
[23] A.J. Ruiz-Torres, F. Mahmoodi, A.Z. Zeng, Supplier selection model with contingency planning for supplier failures, Computers and Industrial Engineering 66 (2013) 374-382.
[24] S.N. Shirkouhi, H. Shakouri, B. Javadi, A. Keramati, Supplier selection and order allocation problem using a two-phase fuzzy multi-objective linear programming, Applied Mathematical Modelling 37 (2013) 9308-9323.
[25] N. Srinivas, K. Deb, Multi-objective optimization using nondominated sorting in genetic algorithms, Journal of Evolutionary Computation 2(3) (1994) 221-248.
[26] J. Wang, Y.F. Shu, Fuzzy decision modelling for supply chain management, Fuzzy Sets and Systems 150(2005) 107-127.
[27] S.H. Wei, S.M. Chen, A new approach for fuzzy risk analysis based on similarity measures of generalized fuzzy numbers, Expert System with Applications 36(1) (2009) 589-598.
[28] W. Wu, G. Cheng, H. Hu, Q. Zhou, Risk analysis of corrosion failures of equipment in refining and petrochemical plants based on fuzzy set theory, Engineering Failure Analysis 32 (2013) 23-34.
[29] Z. Xu, S. Shang, W. Qian, W. Shu, A method for fuzzy risk analysis based on the new similarity of trapezoidal fuzzy numbers, Expert System with Applications 37 (2010) 1920-1927.
[30] L.A. Zadeh, Fuzzy Sets. Information and Control 8 (1965) 338-356.
[31] L.A. Zadeh, The concept of linguistic variable and its application to approximate reasoning. I, II, III, Information Sciences 8 (1975) 199-249.
[32] L.A. Zadeh, Fuzzy sets as a basis of possibility, Fuzzy Sets and Systems 1 (1978) 3-24.