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A multiobjective optimization model for optimal supplier selection in multiple sourcing environment

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Abstract

Supplier selection is an important concern of a firm's competitiveness, more so in the context of the imperative of supply-chain management. In this paper, we use an approach to a multiobjective supplier selection problem in which the emphasis is on building supplier portfolios. The supplier evaluation and order allocation is based upon the criteria of expected unit price, expected score of quality and expected score of delivery. A fuzzy approach is proposed that relies on nonlinear S-shape membership functions to generate different efficient supplier portfolios. Numerical experiments conducted on a data set of a multinational company are provided to demonstrate the applicability and efficiency of the proposed approach to real-world applications of supplier selection.

Key words: Multiobjective optimization, Fuzzy supplier selection, Nonlinear optimization, Membership functions.

MSC 2010: 90C30, 90C70.

1 Introduction

Supplier selection or vendor selection is a multi-criteria decision making (MCDM) problem. One of the well known studies on supplier selection by Dickson [10] discusses 23 important evaluation criteria for supplier selection. It has been pointed out that quality, delivery, and performance history are the three most important criteria. Other important studies that highlights the importance of evaluation criteria for supplier selection includes the works of Ghodsypour and O'Brien [13], Ho et al. [16], Weber et al. [35]. Many authors have discussed optimization models of supplier selection problem. Parthiban et al. [26] developed an integrated model based on 10 criteria including quality, delivery, productivity, service, costs for the supplier selection problem. Punniyamoorthy et al. [27] applied 10 criteria for supplier evaluation including quality, technical capability, financial position. Karpak et al. [19] used a goal programming model to minimize costs and maximize delivery reliability and quality in supplier selection when assigning order quantities to each supplier. Weber and Current [36] used multi-objective linear programming for supplier selection to systematically analyze the trade-off between conflicting factors. Recently, Feng et al. [12] proposed a multiobjective model to select desired suppliers and also developed a multiobjective algorithm based on Tabu search for solving it. Reviews of supplier selection criteria and methods can be found in studies carried out by Aissaoui et al. [1] and Chai et al. [8].

In real-world, for supplier selection problem, decision makers do not have exact and complete information related to various input parameters. In such cases the fuzzy set theory (FST) [38] is considered one of the best tools to handle uncertainty. The supplier selection formulations have benefited greatly from the FST in terms of integrating quantitative and qualitative information, subjective preferences and knowledge of the decision maker. A review of literature on applications of FST in supplier selection shows that a variety of approaches are being used. Kumar et al. [20] presented fuzzy goal programming models to capture uncertainty related to the supplier selection problem. Amid et al. [2, 3] developed a weighted additive fuzzy model for supplier selection problem. Bayrak et al. [6] presented a fuzzy multi-criteria group decision making approach to supplier selection based on fuzzy arithmetic operation. Chen et al. [9] extended the concept of TOPSIS method to develop a methodology for solving supplier selection problems in fuzzy environment. Erol et al. [11] and Li et al. [24] discussed the applications of FST in supplier selection. Kwang et al. [21] introduced a combined scoring method with fuzzy expert systems approach for determination of best supplier. Kahraman et al. [18] developed a fuzzy AHP model to select the best supplier firm providing the most satisfaction for the criteria determined. Shaw et al. [30] proposed an integrated approach that combines fuzzy AHP and fuzzy multiobjective linear programming for selecting the appropriate supplier. Toloo and Nalchigar [32] proposed a new integrated data envelopment analysis model which is able to identify most appropriate supplier in presence of both cardinal and ordinal data. Tsai and Hung [33] proposed a fuzzy goal programming approach that integrates activity-based costing and performance evaluation in a value-chain structure for optimal green supply chain supplier selection and flow allocation. Yücel and Güneri [37] developed a weighted additive fuzzy programming approach for multi-criteria supplier selection. Recently, Amid et al. [4] developed a weighted maxmin fuzzy model to handle effectively the vagueness of input data and different weights of criteria in a supplier selection problem. Arikan [5] proposed a fuzzy mathematical model and a novel solution approach to satisfy the decision maker's aspirations for fuzzy goals.

In all the studies mentioned thus far, supplier selection is driven by non-portfolio based approaches only. This type of framework is restrictive as it does not provide the decision maker with an opportunity to leverage the supplier diversity with reference to preferences in respect of cost, quality and delivery. Recently, Guu et al. [15] discussed supplier selection problem with interval coefficients using portfolio based approach. In this paper, we consider three supplier's selection criteria, namely, expected unit price, expected score of quality and expected score of delivery. The proposed fuzzy optimization model simultaneously minimize the expected unit cost and maximize the expected score of quality and expected score of delivery. The model is constrained by several realistic constraints, namely, demand constraint, maximal and minimal fraction of the total order allocation to a single supplier, number of suppliers held in the portfolio. Note that in comparison to the approach used in Guu et al. [15], the proposed approach is capable of generating many efficient supplier portfolios using different shape parameters of the nonlinear S-shape membership functions from which the decision maker may choose the one according to his/her preferences.

The paper is organized as follows. In Section 2, we present multiobjective programming model of supplier selection based on portfolio theory. In Section 3, we present fuzzy optimization models of supplier selection using nonlinear S-shape fuzzy membership functions. The proposed models are test-run in Section 4. This section also includes a discussion of the results obtained. Finally in Section 5, we submit our concluding observations.

2 The supplier selection problem

Here, we assume that the decision maker allocate orders among n suppliers offering different price, quality and delivery. We use the following variables and parameters in the supplier selection model:

x_i: the proportion of total order allocated to i-th supplier,

p_i: the per unit net purchase price from i-th supplier,

q_i: the percentage of quality level of i-th supplier,

d_i: the percentage of on-time-delivery level of i-th supplier,
y_i: the binary variable indicating whether the i-th supplier is contained in the supplier portfolio or not, i.e.,

$$y_i = \begin{cases} 1, & \text{if } i\text{-th supplier is contained in the supplier portfolio,} \\ 0, & \text{otherwise,} \end{cases}$$

u_i: the maximal fraction of the total order allocated to the i-th supplier,
l_i: the minimal fraction of the total order allocated to the i-th supplier.

2.1 Objectives

• **Expected unit price**
The expected unit cost is the weighted average of the prices quoted by different suppliers, the fractions of the overall quantity ordered to them serving as the respective weights. Here, we consider the overall demand as 1 which overcomes the dependence of supplier selection problem on the units of measurement of the commodities [15].
The expected unit price of the supplier portfolio is expressed as

$$f_1(x) = \sum_{i=1}^{n} p_i x_i \,.$$

• **Expected score of quality**
Quality of the supplies is measured in terms of the extent of satisfaction (fraction) with quality. We use the expected score of quality which in effect is the average of the satisfaction of the established standards by different suppliers as an objective of supplier selection [15]. The expected score of quality of the supplier portfolio is expressed as

$$f_2(x) = \sum_{i=1}^{n} q_i x_i \,.$$

• **Expected score of delivery**
A supplier's compliance (fraction of 1) with on-time-delivery schedule is regarded as his/her score of delivery. Using the fraction of quantity allocated to different suppliers as weight [15], the expected score of delivery of the supplier portfolio is expressed as

$$f_3(x) = \sum_{i=1}^{n} d_i x_i \,.$$

2.2 Constraints

• Total order constraint on the suppliers:

$$\sum_{i=1}^{n} x_i = 1\,.$$

• Maximal fraction of the total order that can be allocated to a single supplier:

$$x_i \leq u_i y_i\,, \quad i = 1, 2, \ldots, n\,.$$

• Minimal fraction of the total order that can be allocated to a single supplier:

$$x_i \geq l_i y_i\,, \quad i = 1, 2, \ldots, n\,.$$

The constraints corresponding to lower bounds l_i and upper bounds u_i on the allocation to individual suppliers ($0 \leq l_i, u_i \leq 1$, $l_i \leq u_i\,, \forall i$) are included to avoid a large number of very small allocations (lower bounds) and at the same time to ensure a sufficient diversification of the allocation (upper bounds) [15].

• Number of suppliers held in a supplier portfolio:

$$\sum_{i=1}^{n} y_i = h$$

where h is the number of suppliers that the decision maker chooses to include in the supplier portfolio [15]. Of all the suppliers from a given set, the decision maker would pick up the ones that are likely to yield the desired satisfaction of his/her preferences. It is not necessary that all the suppliers from a given set may configure in the supplier portfolio as well.

• No negative proportions of total orders:

$$x_i \geq 0\,, \quad i = 1, 2, \ldots, n\,.$$

2.3 The decision problem

The mixed-integer model for purchasing a single item in multiple sourcing networks is presented as follows:

$$
\begin{aligned}
\text{(P1)} \qquad & \min f_1(x) = \sum_{i=1}^{n} p_i x_i \\
& \max f_2(x) = \sum_{i=1}^{n} q_i x_i \\
& \max f_3(x) = \sum_{i=1}^{n} d_i x_i \\
& \text{subject to} \\
& \sum_{i=1}^{n} x_i = 1\,, && (1)\\
& \sum_{i=1}^{n} y_i = h\,, && (2)\\
& x_i \le u_i y_i\,, \quad i = 1,2,\ldots,n\,, && (3)\\
& x_i \ge l_i y_i\,, \quad i = 1,2,\ldots,n\,, && (4)\\
& x_i \ge 0\,, \quad i = 1,2,\ldots,n\,, && (5)\\
& y_i \in \{0,1\}\,, \quad i = 1,2,\ldots,n\,. && (6)
\end{aligned}
$$

It may be noted that the basic framework of the supplier selection model (P1) is similar to the one used in [15]; however, instead of using interval coefficients for an uncertain environment as in [15], we rely on fuzzy membership functions to generate supplier selection strategies that meets the preferences of the decision maker.

3 Supplier portfolio selection models based on fuzzy set theory

Operationally, formulating an supplier portfolio requires estimation of distributions of price, quality and delivery for the various suppliers. Distributed randomly as they are over the chosen time horizon, such estimates, at best, represent decision maker's subjective interpretation of the information available at the time of decision making. Note that the same information may be interpreted differently by different decision makers. Under such circumstances, the issue of constructing a supplier portfolio becomes the one of a choice from a 'fuzzy' set of subjective interpretations, the term 'fuzzy' being suggestive of the diversity of both the decision maker's objective functions as well as that of the constraints.

Here, we formulate fuzzy multiobjective supplier portfolio selection problem based on vague aspiration levels of decision makers to determine a satisfying supplier portfolio selection strategy. We assume that decision makers indicate aspiration levels on the basis of their prior experience and knowledge. As the aspiration levels are vague, we may refer to the fuzzy membership functions, for example, linear [39, 40], piecewise linear [17], exponential [23], tangent [22]. A linear membership function is most commonly used because it is simple and it is defined by fixing two points: the upper and lower levels of acceptability. However, there are some difficulties in using linear membership functions as pointed out by Watada [34]. Further, if the membership function is interpreted as fuzzy utility of the decision maker, describing the behavior of indifference, preference or aversion towards uncertainty, then a nonlinear membership function provides a better representation. It may also be noted that nonlinear membership functions are much more desirable for real-world decision making, as unlike linear membership functions, for nonlinear membership functions, the marginal rate of increase (or decrease) of membership values as a function of model parameters is not constant-a technique that reflects reality better than the linear case.

In this paper, we use logistic function [34], i.e., a nonlinear S-shape membership function to express vague aspiration levels of decision makers. This function has several advantages over other nonlinear membership functions and is considered an appropriate choice in portfolio selection, see Gupta et al. [14].

We now define the following nonlinear S-shape membership function of the goal of net price:

- $$\mu_p(x) = \frac{1}{1 + \exp\left(\alpha_p\left(\sum_{i=1}^{n} p_i x_i - p_m\right)\right)},$$

where p_m is the mid-point (middle aspiration level for the net price) at which the membership function value is 0.5 and α_p is provided by decision makers based on their degree of satisfaction of the goal (see Fig. 1).

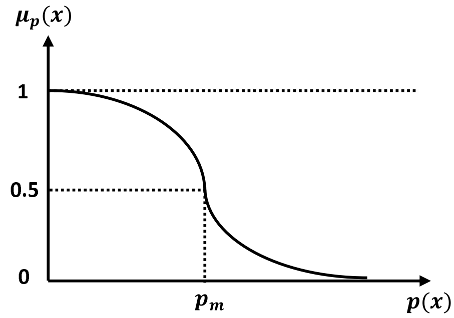

Figure 1. Membership function of the goal of net price

The membership function of the goal of quality is given by

- $$\mu_q(x) = \frac{1}{1 + \exp\left(-\alpha_q\left(\sum_{i=1}^{n} q_i x_i - q_m\right)\right)},$$

where q_m is the mid-point and α_q is provided by decision makers based on their degree of satisfaction regarding the level of quality (see Fig. 2).

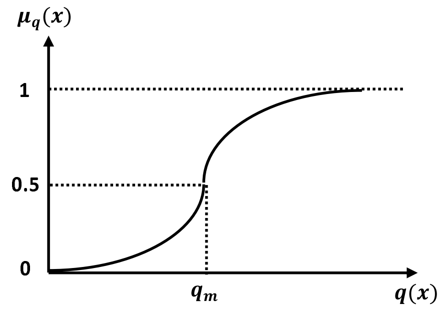

Figure 2. Membership function of the goal of quality

Similarly, we define membership functions of the goal of delivery as follows:

- $$\mu_d(x) = \frac{1}{1 + \exp\left(-\alpha_d\left(\sum_{i=1}^{n} d_i x_i - d_m\right)\right)},$$

where d_m is the respective mid-point and α_d is provided by decision makers. Note that the membership function of the goal of delivery as described above, have shape similar to that of the membership function defining the goal of quality.

Using Bellman and Zadeh's maximization principle [7] with the above defined fuzzy membership functions, the fuzzy supplier portfolio selection problem for selecting suppliers is formulated as follows:

$$
\begin{aligned}
\text{(P2)} \qquad & \max\ \eta \\
& \text{subject to} \\
& \eta \le \mu_p(x)\,, \\
& \eta \le \mu_q(x)\,, \\
& \eta \le \mu_d(x)\,, \\
& 0 \le \eta \le 1\,, \\
& \text{and Constraints } (1) - (6)\,.
\end{aligned}
$$

The problem (P2) is a nonlinear programming problem. It can be transformed into a linear programming problem by letting $\theta = \log \dfrac{\eta}{1-\eta}$, so that $\eta = \dfrac{1}{1+\exp(-\theta)}$. Since, the logistic function is monotonically increasing, hence, maximizing η makes θ maximize. Therefore, the problem (P2) can be transformed into the following equivalent linear programming problem:

$$
\begin{aligned}
\text{(P3)} \qquad & \max \theta \\
& \text{subject to} \\
& \theta \le \alpha_p \left(p_m - \sum_{i=1}^{n} p_i x_i \right)\,, \\
& \theta \le \alpha_q \left(\sum_{i=1}^{n} q_i x_i - q_m \right)\,, \\
& \theta \le \alpha_d \left(\sum_{i=1}^{n} d_i x_i - d_m \right)\,, \\
& \text{and Constraints } (1) - (6)\,.
\end{aligned}
$$

Note that $\theta \in]-\infty, +\infty[$. The fuzzy supplier portfolio selection problem (P2)/(P3) leads to a fuzzy decision that simultaneously satisfies all the fuzzy objectives. Then, we determine the maximizing decision as the maximum degree of membership for the fuzzy decision. In this approach, the relationship between various objectives in a fuzzy environment is considered fully symmetric [40], i.e., all fuzzy objectives are treated equivalent. This approach is efficient in computation but it may provide 'uniform' membership degrees for all fuzzy objectives even when achievement of some objective(s) is more stringently required. Therefore, we use the 'weighted additive model' proposed in [31] to incorporate relative importance of various fuzzy objectives in supplier portfolio selection. The weighted additive model of the fuzzy supplier portfolio selection problem is formulated as follows:

$$
\begin{aligned}
\text{(P4)} \qquad & \max \sum_{r=1}^{3} \omega_r \eta_r \\
& \text{subject to} \\
& \eta_1 \le \mu_p(x)\,, \\
& \eta_2 \le \mu_q(x)\,, \\
& \eta_3 \le \mu_d(x)\,, \\
& 0 \le \eta_r \le 1\,, \qquad r = 1,2,3 \\
& \text{and Constraints } (1) - (6)\,,
\end{aligned}
$$

where ω_r is the relative weight of the r-th objective given by decision makers such that $\omega_r > 0$ and $\sum_{r=1}^{3} \omega_r = 1$.

The max-min approach used in the formulation of the problems (P2)/(P3) and (P4) possesses good computational properties. However, the approach does not ensure fuzzy-efficient solution. To ensure efficiency of the solution, we take recourse to the two-phase approach proposed in [25]. As a result, it becomes possible to choose explicitly a minimum degree of satisfaction (taken to be equal to the solution of the max-min approach) for each fuzzy objective function and examine whether the same can be improved upon or not. Hence, we solve the problems (P5) and (P6) corresponding to the problems (P3) and (P4) respectively in the second-phase.

$$
\begin{aligned}
\text{(P5)} \qquad & \max \sum_{r=1}^{3} \omega_r \theta_r \\
& \text{subject to} \\
& \log \frac{\mu_p(x^*)}{1-\mu_p(x^*)} \le \theta_1 \le \alpha_p \left(p_m - \sum_{i=1}^{n} p_i x_i \right)\,, \\
& \log \frac{\mu_q(x^*)}{1-\mu_q(x^*)} \le \theta_2 \le \alpha_q \left(\sum_{i=1}^{n} q_i x_i - q_m \right)\,, \\
& \log \frac{\mu_d(x^*)}{1-\mu_d(x^*)} \le \theta_3 \le \alpha_s \left(\sum_{i=1}^{n} d_i x_i - d_m \right)\,, \\
& \text{and Constraints } (1) - (6)\,,
\end{aligned}
$$

where x^* is an optimal solution of (P3), $\omega_1 = \omega_2 = \omega_3$, $\omega_r > 0$, $\sum_{r=1}^{3} \omega_r = 1$ and $\theta_r \in]-\infty, +\infty[\ r = 1,2,3$.

$$
\begin{aligned}
\text{(P6)} \qquad & \max \sum_{r=1}^{3} \omega_r \eta_r \\
& \text{subject to} \\
& \mu_p(x^{**}) \leq \eta_1 \leq \mu_p(x)\,, \\
& \mu_q(x^{**}) \leq \eta_2 \leq \mu_q(x)\,, \\
& \mu_d(x^{**}) \leq \eta_3 \leq \mu_d(x)\,, \\
& 0 \leq \eta_r \leq 1\,, \qquad r = 1, 2, 3 \\
& \text{and Constraints } (1) - (6)\,,
\end{aligned}
$$

where x^{**} is an optimal solution of (P4), ω_r is the relative weight of the r-th objective given by decision makers such that $\omega_r > 0$ and $\sum_{r=1}^{3} \omega_r = 1$.

The problems (P3) and (P5) are linear programming problems which can be solved using the LINDO software [28]. The problems (P4) and (P6) are nonlinear programming problems. Although, for medium or large-sized problems, one may suspect that solving these nonlinear programming problems could be computationally difficult, this is not the case, as many excellent softwares are available to solve them. We can use LINGO [29] to solve (P4) and (P6).

4 Numerical illustration

In this section, we present an illustration of the developed supplier portfolio selection decision procedure for a multinational company. The purchasing manager of the company have identified 10 potential suppliers. The manager will select the most favorable suppliers(s) and allocate various proportion of total order among selected suppliers(s) such that to minimize the net price of purchasing and to maximize total quality and delivery level of purchased items.

4.1 Supplier allocation

The 10 suppliers form the population from which we attempt to construct a supplier portfolio comprising 5 suppliers. The suppliers profiles shown in Table 1 represents the estimated values of their net price (p_i), quality level (q_i) and delivery level (d_i) along with the estimated values of lower and upper bounds.

Table 1 Input data of suppliers

	Price (Rs.)	Quality (%)	Delivery (%)	Lower bound (l_i)	Upper bound (u_i)
Supplier 1	13	0.82	0.80	0.03	0.22
Supplier 2	12.5	0.78	0.75	0.06	0.33
Supplier 3	11.5	0.70	0.80	0.03	0.20
Supplier 4	14	0.88	0.90	0.027	0.22
Supplier 5	15	0.84	0.92	0.2	1.17
Supplier 6	16	0.95	0.88	0.06	0.27
Supplier 7	14.5	0.80	0.78	0.05	0.4
Supplier 8	15.5	0.92	0.84	0.017	0.17
Supplier 9	13.5	0.85	0.85	0.03	0.25
Supplier 10	12	0.75	0.78	0.06	0.30

We now present the computational results.
Corresponding to $p_m = 13.3$, $q_m = 0.83$ and $d_m = 0.82$, we obtain supplier portfolio selection strategy by solving the problem (P3). To check efficiency of the solution obtained, we use the two-phase approach and solve the problem (P5). If the purchasing manager is not satisfied with the supplier portfolio obtained, more supplier portfolios can be generated by varying the values of the shape parameters in the problem (P3). The computational results summarized in Table 2 are based on three different sets of values of the shape parameters. Note that all the three solutions obtained are efficient, i.e., their criteria vector are nondominated. Table 3 presents proportions of the total order allocated to suppliers in obtained supplier portfolios

Table 2 Summary results of supplier portfolio selection

Shape parameters & variables					Net price	Quality level	Delivery level
η	θ	α_p	α_q	α_d			
0.85900	1.80700	200	600	600	13.29095	0.83301	0.84703
0.58128	0.32803	100	100	100	13.29671	0.83328	0.84720
0.52087	0.08353	6	30	30	13.28609	0.83278	0.84688

Table 3 The proportions of the total order allocated to suppliers in obtained supplier portfolios

Shape parameters			Suppliers									
α_p	α_q	α_d	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
200	600	600	0.22	0.27635	0	0.22	0	0	0	0.03365	0.25	0
100	100	100	0.22	0.27443	0	0.22	0	0	0	0.03557	0.25	0
6	30	30	0.22	0.27797	0	0.22	0	0	0	0.03203	0.25	0

Next, we present computational results considering preferences of the purchasing manager for the three objectives.

• **Case 1**

We consider the following weights of the fuzzy goals of expected net price (ω_1), expected quality level (ω_2) and expected delivery level (ω_3): $\omega_1 = 0.6$, $\omega_2 = 0.25$, $\omega_3 = 0.15$. Corresponding to $p_m = 13.3$, $q_m = 0.81$ and $d_m = 0.88$, we obtain supplier portfolio selection strategy by solving the problem (P4). The efficiency of the solution is verified by solving the problem (P6) in the second phase. The corresponding computational results are listed in Tables 4-5. The achievement levels of the various membership functions are $\eta_1 = 0.95744$, $\eta_2 = 0.41261$, $\eta_3 = 0.31576$. Note that these achievement levels are consistent with the purchasing manager preferences, i.e., ($\eta_1 > \eta_2 > \eta_3$) agrees with ($\omega_1 > \omega_2 > \omega_3$).

• **Case 2**

Here, we consider the weights as $\omega_1 = 0.15$, $\omega_2 = 0.6$, $\omega_3 = 0.25$. By taking $p_m = 13.3$, $q_m = 0.81$ and $d_m = 0.88$, we obtain supplier portfolio selection strategy by solving the problem (P4). The solution is verified for efficiency. The corresponding computational results are listed in Tables 4-5. The achievement levels of the various membership functions are $\eta_1 = 0.00023$, $\eta_2 = 0.90362$, $\eta_3 = 0.70285$ which are consistent with the purchasing manager preferences.

• **Case 3**

As performed above in case 1 and case 2, corresponding to the weights $\omega_1 = 0.15$, $\omega_2 = 0.2$, $\omega_3 = 0.65$ and $p_m = 13.3$, $q_m = 0.81$, $d_m = 0.88$, we obtain portfolio selection strategy by solving the problem (P4). The solution is found to be efficient. The corresponding computational results are listed in Tables 4-5. The achievement levels of the various membership functions are $\eta_1 = 0.00028$, $\eta_2 = 0.77664$, $\eta_3 = 0.78516$ which are consistent with the purchasing manager preferences.

Table 4 Summary results of supplier portfolio selection incorporating purchasing manager preferences

Case	Shape parameters			Price	Quality level	Delivery level
	α_p	α_q	α_d			
Case 1	6	30	30	12.78110	0.79823	0.85422
Case 2	6	30	30	14.69752	0.88460	0.90870
Case 3	6	30	30	14.66650	0.85154	0.92320

Table 5 The proportions of the total order allocated to suppliers in obtained supplier portfolios incorporating purchasing manager preferences

Class	Suppliers									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Class 1	0.0661	0	0.2	0.22	0	0	0	0	0.25	0.2639
Class 2	0	0	0	0.22	0.21496	0.27	0	0.04504	0.25	0
Class 3	0	0	0	0.027	0.646	0.06	0	0.017	0.25	0

The foregoing analysis of the various decision situations from the stand point of decision makers preferences demonstrates that the supplier portfolio selection models developed in this paper discriminate among decision makers. Thus, it is possible to construct efficient portfolios with reference to the diversity of decision maker preferences.

5 Conclusions

This paper proposed a flexible approach to multiobjective supplier selection problems. We used the criteria of expected unit price, expected score of quality and expected score of delivery for supplier evaluation and order allocation. Further, the benefits of supplier diversification using trade-offs among the three chosen criteria have been achieved. The upper bounds and lower bounds are used for fractions of order that may be assigned to a particular supplier in order to ensure supplier diversification as well as to avoid the situations where very small fractions of the ordered quantity are obtained. Recognizing that supplier selection involves MCDM in an environment that befits more fuzzy approximation than deterministic formulation, we have transformed the supplier portfolio selection model into a fuzzy model using nonlinear S-shape fuzzy membership functions. Numerical illustrations based on 10-supplier universe have been presented to illustrate the effectiveness of the proposed models. The efficiency of the obtained solutions was verified using the two-phase approach.

The main advantage of the proposed models is that if decision maker is not satisfied with any of the supplier portfolios, more portfolios can be generated by varying the values of the shape parameters. These parameters may be configured to suit decision makers preferences. Thus, the fuzzy supplier portfolio selection models proposed in this paper can provide satisfying portfolio selection strategies according to vague aspiration levels, degrees of satisfaction and relative importance of the various objectives.

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References

[1] N. Aissaoui, M. Haouari and E. Hassini, *Supplier selection and order lot sizing modeling: a review*, Computers and Operations Research 34 (2007), 3516-3540.

[2] A. Amid, S. H. Ghodsypour and C. O'Brien, *Fuzzy multiobjective linear model for supplier selection in a supply chain*, International Journal of Production Economics 104 (2006), 394-407.

[3] A. Amid, S. H. Ghodsypour and C. O'Brien, *A weighted additive fuzzy multiobjective model for the supplier selection problem under price breaks in a supply Chain*, International Journal of Production Economics 121 (2009), 323-332.

[4] A. Amid, S. H. Ghodsypour and C. O'Brien, *A weighted maxmin model for fuzzy multi-objective supplier selection in a supply chain*, International Journal of Production Economics 131 (2011), 139-145.

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

[6] M. Y. Bayrak, N. Çelebi and H. Taskin, *A fuzzy approach method for supplier selection*, Production Planning and Control: The Management of Operations 18 (2007), 54-63.

[7] R. Bellman and L. A. Zadeh, *Decision making in a fuzzy environment*, Management Science 17 (1970), 141-164.

[8] J. Chai, J. N. K. Liu and E. W. T. Ngai, *Application of decision-making techniques in supplier selection: a systematic review of literature*, Expert Systems with Applications 40 (2013), 3872-3885.

[9] C. T. Chen, C. T. Lin and S. F. Huang, *A fuzzy approach for supplier evaluation and selection in supply chain management*, International Journal of Production Economics 102 (2006), 289-301.

[10] G. W. Dickson, *An analysis of vendor selection systems and decisions*, Journal of Purchasing 2 (1966), 5-17.

[11] I. Erol, G. William and Jr. Ferrel, *A methodology for selection problems with multiple, conflicting objectives and both qualitative and quantitative criteria*, International Journal of Production Economics 86 (2003), 187-199.

[12] B. Feng, Z. Fan and Y. Li, *A decision method for supplier selection in multi-service outsourcing*, International Journal of Production Economics 132 (2011), 240-250.

[13] S. H. Ghodsypour and C. O'Brien, *The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint*, International Journal of Production Economics 73 (2001), 15-27.

[14] P. Gupta, M. K. Mehlawat and A. Saxena, *Asset portfolio optimization using fuzzy mathematical programming*, Information Sciences 178 (2008), 1734-1755.

[15] S.M. Guu, M. Mehlawat and S. Kumar, *A multiobjective optimization framework for optimal selection of supplier portfolio*, Optimization 63 (10) (2014), DOI:10.1080/02331934.2014.917306.

[16] W. Ho, X. Xu and P. K. Dey, *Multi-criteria decision making approaches for supplier evaluation and selection: a literature review*, European Journal of Operational Research 202 (2010), 16-24.

[17] M. Inuiguchi, H. Ichihashi and Y. Kume, *A solution algorithm for fuzzy linear programming with piecewise linear membership functions*, Fuzzy Sets and Systems 34 (1990), 15-31.

[18] C. Kahraman, U. Cebeci and Z. Ulukan, *Multi-criteria supplier selection using fuzzy AHP*, Logistics Information Management 16 (2003), 382-394.

[19] B. Karpak, E. Kumcu and R. R. Kasuganti, *An application of visual interactive goal programming: a case in vendor selection decisions*, Journal of Multi-Criteria Decision Analysis 8 (1999), 93-105.

[20] M. Kumar, P. Vart and P. Shankar, *A fuzzy goal programming approach for supplier selection problem in a supply chain*, Computer and Industrial Engineering 46 (2004), 69-85.

[21] C. K. Kwang, W. H. Lp and J. W. K. Chan, *Combining scoring method and fuzzy expert systems approach to supplier assessment: a case study*, Integrated Manufacturing Systems 13 (2002), 512-519.

[22] H. Leberling, *On finding compromise solutions in multicriteria problems using the fuzzy min-operator*, Fuzzy Sets and Systems 6 (1981), 105-118.

[23] R. J. Li, and E. S. Lee, *An exponential membership function for fuzzy multiple objective linear programming*, Computers and Mathematics with Applications 22 (1991), 55-60.

[24] C. C. Li, Y. P. Fun and J. S. Hung, *A new measure for supplier performance evaluation*, IIE Transactions 29 (1997), 753-758.

[25] X. -Q. Li, B. Zhang and H. Li, *Computing efficient solutions to fuzzy multiple objective linear programming problems*, Fuzzy Sets and Systems 157 (2006), 1328-1332.

[26] P. Parthiban, H. A. Zubar and P. Katakar, *Vendor selection problem: a multi-criteria approach based on strategic decisions*, International Journal of Production Research 51 (2013), 1535-1548.

[27] M. Punniyamoorthy, P. Mathiyalagan and P. Parthiban, *A strategic model using structural equation modeling and fuzzy logic in supplier selection*, Expert Systems with Applications 38 (2011), 458-474.

[28] L. Scharge, *Optimization Modeling with LINDO*, Duxbury Press, CA, 1997.

[29] L. Scharge, *Optimization Modeling with LINGO, 6th edn.*, LINDO Systems Inc., Chicago, Illinois, 2006.

[30] K. Shaw, R. Shankar, S. S. Yadav and L. S. Thakur, *Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming for developing low carbon supply chain*, Expert Systems with Applications 39 (2012), 8182-8192.

[31] R. N. Tiwari, S. Dharmar and J. R. Rao, *Fuzzy goal programming-an additive model*, Fuzzy Sets and Systems 24 (1987), 27-34.

[32] M. Toloo and S. Nalchigar, *A new DEA method for supplier selection in presence of both cardinal and ordinal data*, Expert Systems with Applications 38 (2011), 14726-14731.

[33] W. Tsai and S. Hung, *A fuzzy goal programming approach for green supply chain optimisation under activity-based costing and performance evaluation with a value-chain structure*, International Journal of Production Research 47 (2009), 4991-5017.

[34] J. Watada, *Fuzzy portfolio selection and its applications to decision making*, Tatra Mountains Mathematical Publications 13 (1997), 219-248.

[35] C. A. Weber, J. R. Current and W. C. Benton, *Vendor selection criteria and methods*, European Journal of Operational Research 50 (1991), 2-18.

[36] C. A. Weber and J. R. Current, *A multiobjective approach to vendor selection*, European Journal of Operational Research 68 (1993), 173-184.

[37] A., Yücel and A. F. Güneri, *A weighted additive fuzzy programming approach for multi-criteria supplier selection*, Expert Systems with Applications 38 (2011), 6281-6286.

[38] L. A. Zadeh, *Fuzzy sets*, Information and Control 8 (1965), 338-353.

[39] H. -J. Zimmermann, *Description and optimization of fuzzy systems*, International Journal of General Systems 2 (1976), 209-215.

[40] H. -J. Zimmermann, *Fuzzy programming and linear programming with several objective functions*, Fuzzy Sets and Systems 1 (1978), 45-55.