An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management

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ABSTRACT

Supplier selection is an important issue in supply chain management. In recent years, determining the best supplier in the supply chain has become a key strategic consideration. However, these decisions usually involve several objectives or criteria, and it is often necessary to compromise among possibly conflicting factors. Thus, the multiple criteria decision making (MCDM) becomes a useful approach to solve this kind of problem. Considering both tangible and intangible criteria, this study proposes integrated fuzzy techniques for order preference by similarity to ideal solution (TOPSIS) and multi-choice goal programming (MCGP) approach to solve the supplier selection problem. The advantage of this method is that it allows decision makers to set multiple aspiration levels for supplier selection problems. The integrated model is illustrated by an example in a watch firm.

1. Introduction

Supplier selection is an important issue in supply chain management. Typically, manufacturer spends more than 60% of its total sales on purchased items, such as raw materials, parts, and components (Krajewski & Ritzman, 1996). In addition, manufacturer purchases of goods and services constitute up to 70% of product cost (Ghodsypour & O’Brien, 1998). Therefore, the selection of suppliers is an area of tremendous importance and should be considered a strategic issue in the effective management of a supply chain. Supplier selection and its related tasks are positioned at the front end in the supply chain process (see Fig. 1).

During the 1990s, many manufacturers sought to develop strategic alliances with suppliers in order to upgrade their management preference and competitiveness (Kumar, Vrat, & Shankar, 2006; Shin, Collier, & Wilson, 2000). While coordination between a manufacturer and its suppliers is typically an important and difficult link in the channel of distribution, many methods have been employed to evaluate and select supplier. Dickson (1966) identified 23 different criteria for supplier selection, based on which Weber, Current, and Benton (1991) suggested a number of selection criteria to measure supplier performance, such as price, delivery, quality, productive capability, location, technical capability, management organization, reputation, industry position, financial stability, performance history, and maintainability. Evans (1980) proposed that price, quality and delivery are key criteria for supplier evaluation in the industrial market. Shipley (1985) suggested that supplier selection involve three criteria, namely, quality, price and delivery lead time. Ellram (1990) suggested that in the supplier selection process, firms must to consider whether product quality, offering price, delivery time, and total service quality meet organizational demand. Tam and Tummala (2001) proposed an analytic hierarchy process (AHP) based model and adopted quality, cost, problem-solving capabilities, expertise, delivery lead time, response to customer requests, experience, and reputation in selecting telecommunications systems. Pi and Low (2005) suggested a method for supplier evaluation and selection based on quality, on-time delivery, price, and service quality.

Recently, the supplier selection process has received considerable attention in the marketing management literature. Chen et al. (2006) adopted a fuzzy decision making approach to address the supplier selection problem in the supply chain system. Five benefit criteria were considered, including the profitability of supplier, relationship closeness, technological capability, conformance...
quality, and conflict resolution. Lin and Chang (2008) claimed that communication, reputation, industry position, relationship closeness, customer responsiveness, and conflict-solving capabilities are important criteria in vendor selection. In addition, the role of organizational size in the supplier selection process has been addressed by Wang, Cheng, and Cheng (2009). Table 1 summarizes the criteria that have appeared in literature since 1966; most of the articles referenced above suggest that quality, price, and delivery performance are the most important supplier selection criteria.

Over the years, a number of techniques have been proposed to solve the supplier selection problem. The long list of approaches includes linear programming (LP), mathematical programming models, multiple-objective programming, statistical and probabilistic methods, data envelopment analysis (DEA), cost-based methods (CBM), case-based reasoning (CBR), neural networks (NN), AHP, analytic network process (ANP), fuzzy set theory, and techniques for order preference by similarity to ideal solution (TOPSIS). Recently, the integration of different methodologies to supplier selection process has received considerable attention in the supply chain management literature. Faez, Ghodsypour, and O'Brien (2009) presented an integrated fuzzy case-based reasoning and mathematical programming method. Ö nú t, Kara, and Isik (2009) developed a supplier evaluation approach based on the ANP and TOPSIS methods to help a telecommunication company in vendor selection. Ha and Krishnan (2008) developed a hybrid model that including AHP, DEA and NN approaches to the supplier selection problem. Most recently, Kokangul and Susuz (2009) integrated AHP and mathematical programming to consider both non-linear integer and multiple-objective programming under certain constraints to determine the best suppliers. The integrated model uses source data provided by a manufacturing firm to address a real-world supplier selection problem.

Table 1

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1, Dickson (1966); 2, Evans (1980); 3, Shipley (1985); 4, Ellram (1990); 5, Weber et al. (1991); 6, Tam and Tummala (2001); 7, Pi and Low (2005); 8, Chen et al. (2006); 9, Lin and Chang (2008); 10, Wang et al. (2009).
In real life, the modeling of many situations may not be sufficient or exact, as the available data are inexact, vague, imprecise and uncertain by nature (Sarami, Mousavi, & Sanaye, 2009). Moreover, the decision making processes that take place in such situations are also based on uncertain and ill-defined information. In the real practice of supplier selection, firms usually confronts with a high degree of uncertainties and fuzziness. Fuzzy set theory is considered the most effective methods in managing vagueness and uncertainty problems. The concept of fuzzy sets was introduced by Zadeh (1965) to mathematically represent data and information possessing non-statistical uncertainties and to provide formalized tools for dealing with imprecision intrinsic to many problems (Kahraman, Cevik, Ates, & Güfer, 2007). In order to model such situations, fuzzy set theory was introduced to express the linguistic terms of decision marking processes.

In addition, TOPSIS is a classical MCDM method, and as such it may provide the basis for developing supplier selection models that can effectively handle uncertainty properties. This approach is based on the idea that a chosen alternative should be the shortest distance from the positive-ideal solution and the farthest distance from the negative-ideal solution. Chen et al. (2006) applied linguistic value to measure the ratings and weights of supplier selection criteria and then used a MCDM model based on fuzzy set theory to analyze a supply chain management case. However, their model is only suitable for single-sourcing problems. In the single sourcing scenario, one supplier presumably will satisfy the buyer’s needs; such that the decision must be made on which supplier is the best. In the multi-sourcing case, no supplier can satisfy all the buyer’s requirements, and so more than one supplier can be selected (Ghodsypour & O’Brien, 1998).

In this study, an integrated fuzzy TOPSIS and MCGP model is developed to solve multi-sourcing supplier selection problems. First, linguistic values expressed in trapezoidal fuzzy numbers are applied to assess weights and ratings of supplier selection criteria. Second, a hierarchy multi-model based on fuzzy set theory is expressed and fuzzy positive and negative-ideal solutions are used to find each supplier’s closeness coefficient. Finally, a MCGP model based on the tangible constrains regarding the buyer and its suppliers is constructed and solved to assign order qualities to each supplier.

The paper is organized as follows. The next section introduces the basic definitions and notations of fuzzy numbers and linguistic variables. Section 3 presents both the GP and MCGP approaches. Section 4 presents the analytical procedure of the proposed integrated approach. In Section 5, the proposed method is illustrated using a watch company as an example. The finally section presents conclusions and suggestions for future research.

2. Basic definitions and notation

Some basic concepts of fuzzy numbers and linguistic variables are now defined.

**Definition 2.1.** A positive trapezoidal fuzzy number \( \tilde{n} \) can be defined as \( (n_1, n_2, n_3, n_4) \) as shown in Fig. 2. The membership function \( u_n(x) \) is defined as follows:

\[
\begin{align*}
    u_n(x) = \begin{cases} 
        0, & x < n_1, \\
        x - n_1/n_2 - n_1, & n_1 \leq x < n_2, \\
        1, & n_2 \leq x < n_3, \\
        x - n_2/n_3 - n_4, & n_3 \leq x < n_4, \\
        0, & x > n_4.
    \end{cases}
\end{align*}
\]

For a trapezoidal fuzzy number \( \tilde{n} = (n_1, n_2, n_3, n_4) \), when \( n_2 = n_3 \), the number is called a triangular fuzzy number. A crisp number \( k \) can be expressed as \( (k, k, k, k) \).

**Definition 2.2.** A matrix \( \tilde{D} \) is called a fuzzy matrix, if it contains at least an entry in \( \tilde{D} \) is a fuzzy number (Buckley, 1985).

**Definition 2.3.** Let \( \tilde{m} = (m_1, m_2, m_3, m_4) \) and \( \tilde{n} = (n_1, n_2, n_3, n_4) \) be two triangular fuzzy numbers. Then the distance between them can be calculated using the vertex method (see Chen, 2000; Chen et al., 2006):

\[
d(\tilde{m}, \tilde{n}) = \sqrt{(1/4)[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2 + (m_4 + n_4)^2]}.\]

In this study, the importance weights of various criteria and the ratings of qualitative criteria are considered linguistic variables. Because linguistic assessments approximate the subjective judgment of DMs, we consider linear trapezoidal membership functions adequate for capturing the vagueness of these linguistic assessments. These linguistic variables can be expressed in positive trapezoidal fuzzy numbers, as shown in Figs. 3 and 4. In the proposed integrated model, the DMs use the linguistic variables to evaluate the importance of criteria and the ratings of alternative suppliers with respect to each selection criterion.

For example, referring to Fig. 3, “Medium” can be represented as \((0.4, 0.5, 0.6, 0.7)\); it has the following membership function:

\[
u_{\text{Medium}}(x) = \begin{cases} 
    0, & x < 0.4, \\
    x - 0.4/0.5 - 0.4, & 0.4 \leq x \leq 0.5, \\
    1, & 0.5 \leq x \leq 0.6, \\
    x - 0.7/0.6 - 0.7, & 0.6 \leq x \leq 0.7, \\
    0, & x > 0.7.
\end{cases}
\]
As stated in Definition 2.2, a supplier selection problem can be expressed in a matrix as follows (Chen et al., 2006):

\[
\hat{X} = \begin{bmatrix}
\hat{x}_{11} & \hat{x}_{12} & \cdots & \hat{x}_{1n} \\
\hat{x}_{21} & \hat{x}_{22} & \cdots & \hat{x}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\hat{x}_{m1} & \hat{x}_{m2} & \cdots & \hat{x}_{mn}
\end{bmatrix}, \quad W = [\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n],
\]

(8)

where \(\hat{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})\) and \(\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}, w_{j4})\); \(i = 1, 2, 3, \ldots, m, j = 1, 2, 3, \ldots, n\).

According to the briefly-summarized discussion of fuzzy set theory, the normalized fuzzy decision matrix can be represented as:

\[
\tilde{R} = [\tilde{r}_{ij}], \quad i = 1, 2, 3, \ldots, m, \quad j = 1, 2, 3, \ldots, n.
\]

(9)

where the \(\tilde{r}_{ij}\) is the normalized value of \(\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})\), which be calculated as follows:

If the \(j\)th criterion is a benefit, then:

\[
\tilde{r}_{ij} = (a_{ij}/d_j, b_{ij}/d_j, c_j/d_j, d_j/d_j),
\]

(10)

where \(d_j = \max a_{ij}\).

If the \(j\)th criterion is a cost, then:

\[
\tilde{r}_{ij} = (a_{ij}/d_j, a_j/c_j, a_j/b_j, a_j/a_j),
\]

(11)

where \(d_j = \min a_{ij}\).

A weighted normalized fuzzy-decision matrix can be constructed according to the normalized fuzzy-decision matrix as follows:

\[
\tilde{V} = [\tilde{v}_{ij}]_{m \times n},
\]

(12)

where \(\tilde{v}_{ij} = \tilde{x}_{ij} \odot \tilde{w}_j, \quad i = 1, 2, 3, \ldots, m, \quad j = 1, 2, 3, \ldots, n\).

After constructing a weighted normalized fuzzy-decision matrix, the fuzzy positive-ideal solution (FPIS), \(S^+\), and the fuzzy negative-ideal solution (FNIS), \(S^-\), can be calculated as follows:

\[
S^+ = \{(\max_i \tilde{v}_{ij} | j \in J), (\min_i \tilde{v}_{ij} | j \in J^c)\} = (\tilde{v}_{i1}^+, \tilde{v}_{i2}^+, \ldots, \tilde{v}_{in}^+),
\]

(13)

\[i = 1, 2, \ldots, m, \quad j = 1, 2, 3, \ldots, n\]

and

\[
S^- = \{(\min_i \tilde{v}_{ij} | j \in J), (\max_i \tilde{v}_{ij} | j \in J^c)\} = (\tilde{v}_{i1}^-, \tilde{v}_{i2}^-, \ldots, \tilde{v}_{in}^-),
\]

(14)

\[i = 1, 2, \ldots, m, \quad j = 1, 2, 3, \ldots, n\]

where \(\tilde{v}_{ij}^+ = \max_i \tilde{v}_{ij}\) and \(\tilde{v}_{ij}^- = \min_i \tilde{v}_{ij}\). In addition, \(J\) is associated with benefit criteria, while \(J^c\) is associated with cost criteria.

The distance of each alternative from \(S^+\) and \(S^-\) can be calculated as:

\[
d_j^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}^+, \tilde{v}_{ij}^-), \quad i = 1, 2, \ldots, m,
\]

(15)

\[
d_j^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}^+, \tilde{v}_{ij}^-), \quad i = 1, 2, \ldots, m,
\]

(16)

where \(d(\cdot, \cdot)\) represents the distance measurement between two fuzzy numbers.

Finally, the closeness coefficients of each supplier according to distance from the fuzzy positive-ideal solution (FPIS), \(S^+\) and the fuzzy negative-ideal solution (FNIS), \(S^-\), can be calculated as:

\[
CC_i = d_j^+ / (d_j^+ + d_j^-), \quad i = 1, 2, \ldots, m.
\]

(17)

where \(CC\) range belongs to the closed interval [0, 1] and \(i = 1, 2, \ldots, m\).
3. Multi-choice goal programming

Goal programming (GP) is an analytical multiple objectives decision making approach designed to address decision-marking problems in which targets have been assigned to all attributes and where the decision makers are interested in minimizing the non-achievement of a particular goal (Liao, 2009). The model can take into account many simultaneous objectives as a decision maker seeks the best solution from among a set of feasible solutions. GP was first introduced by Charnes and Cooper (1961), and has been further developed by Ignizio (1976), Zimmermann (1978), Tamiz, Jones, and Romero (1998), Romero (2001), Chang (2007) and Liao (2009), and so on.

Initially, the GP was expressed as follows:

\[(GP \text{ model})\]
\[
\begin{align*}
\text{Min} & \sum_{i=1}^{n} |f_i(X) - g_i| \\
\text{s.t.} & \quad X \in F \quad (F \text{ is a feasible set}),
\end{align*}
\]

where \(f_i(X)\) is the linear function of the \(i\)th goal, and \(g_i\) is the aspiration level of the \(i\)th goal.

The above minimization process can be accomplished using the weighted GP (WGP) model as follows:

\[(WGP \text{ model})\]
\[
\begin{align*}
\text{Min} & \sum_{i=1}^{n} (x_i d^+_i + \beta_i d^-_i) \\
\text{s.t.} & \quad f_i(X) + d^+_i - d^-_i = g_i, \quad i = 1, 2, \ldots, n, \\
& \quad d^+_i, d^-_i \geq 0, \quad i = 1, 2, \ldots, n, \\
& \quad X \in F \quad (F \text{ is a feasible set}),
\end{align*}
\]

where parameters \(x_i\) and \(\beta_i\) are the weights reflecting preferential and normalizing purposes attached to positive and negative deviations of \(i\)th goal, respectively; \(d^+_i = \max(0, g_i - f_i(X))\) and \(d^-_i = \max(0, f_i(X) - g_i)\) are, respectively, under- and over-achievements of the \(i\)th goal, \(f_i(X)\) and \(g_i\) are defined as above in the GP model (Ignizio, 1976).

GP approaches have been applied to solve many real-world problems. However, many multiple-choice aspiration levels may exist, such as “something more/higher is better” or “something less/lower is better” (Chang, 2007). These typical multiple choice GP cannot be solved using a traditional GP approach. Chang (2007) presented a MCGP method to solve these types of problems, and it can be expressed as follows:

\[(MCGP \text{ model})\]
\[
\begin{align*}
\text{Min} & \sum_{i=1}^{n} (x_i d^+_i + \beta_i d^-_i) \\
\text{s.t.} & \quad f_i(X) - d^+_i + d^-_i = g_{i1} \text{ or } g_{i2} \text{ or } g_{i3} \text{ or } \cdots \text{ or } g_{im}, \\
& \quad d^+_i, d^-_i \geq 0, \quad i = 1, 2, \ldots, n, \\
& \quad X \in F \quad (F \text{ is a feasible set}),
\end{align*}
\]

where \(g_{ij}\) (\(i = 1, 2, \ldots, n\) and \(j = 1, 2, \ldots, m\)) is the \(j\)th aspiration level of the \(i\)th goal, \(g_{i1} \leq g_{i2} \leq \ldots \leq g_{im}\) are defined as in WGP.

Below we present two examples of MCGP model that have certain goals and constraints, while they cannot be solved by traditional GP approaches.

**Example 1**

Goals: \((G_1)\) 2.5\(x_1 + x_2 + 2x_3 = 90\) or 120, \((G_2)\) 3\(x_1 + 2x_2 + x_3 = 100\), \((G_3)\) 3.5\(x_1 + x_2 + 3x_3 = 75\), \(90\) or 110.

Constraints: \(x_1 + x_2 + x_3 \geq 17\), \(x_2 + x_3 \geq 12\), \(x_2 \geq 5\).

where the coefficients of decision variables denote product prices; \(x_1\), \(x_2\), and \(x_3\) represents three products, and target values (e.g., 90, 100, and 110) are three profit goals, respectively.

Using a MCGP method, this problem can be expressed as the following program:

\[
\begin{align*}
\text{Min} & \quad z = d^+_1 + d^+_2 + d^+_3 + d^-_1 + d^-_2 + d^-_3 \\
\text{s.t.} & \quad 2.5x_1 + 3x_2 + 2x_3 - d^+_1 - d^-_1 = 90b_1 + 120(1 - b_1), \\
& \quad 3x_1 + 2x_2 + x_3 - d^+_2 - d^-_2 = 80b_2 + 100(1 - b_2), \\
& \quad 3.5x_1 + x_2 + 3x_3 - d^+_3 - d^-_3 = 75b_3 + 90b_3(1 - b_4) + 110(1 - b_3)b_4, \\
& \quad x_1 + x_2 + x_3 \geq 17, \\
& \quad x_2 + x_3 \geq 12, \\
& \quad x_2 \geq 5. \\
& \quad d^+_i, d^-_i \geq 0, \quad i = 1, 2, 3.
\end{align*}
\]

where \(b_1\), \(b_2\), \(b_3\) and \(b_4\) are binary variables, and \(d^+_i\) and \(d^-_i\) are the positive and negative deviations of \(i\)th goal, respectively.

This problem can be solved using the existing optimization software LINGO (Schrage, 2002) to obtain the optimal solutions (\(x_1\), \(x_2\), \(x_3\) = \(15, 17, 5\), 0). From these results, we see that goal \(G_1\) reaches the aspiration level 90 at 90; goal \(G_2\) reaches the aspiration level 80 at 80; and goal \(G_3\) reaches the aspiration level 110 at 108.99.

Consider the following multiple-objective decision-making problems, modified slightly from Example 1.

**Example 2**

Goals: \((G_1)\) 2.5\(x_1 + x_2 + 2x_3 = 90\), \((G_2)\) 3\(x_1 + 2x_2 + x_3 = 80\), \((G_3)\) 3.5\(x_1 + x_2 + 3x_3 = 90\).

Constraints: \(x_1 + x_2 + x_3 \geq 17\), \(x_2 + x_3 \geq 12\), \(x_2 \geq 5\).

where the coefficients of decision variables and target values are defined as in Example 1.

Again, this problem can be solved using optimization software LINGO (Schrage, 2002) to obtain the optimal solutions (\(x_1\), \(x_2\), \(x_3\) = \(15, 17.5, 0\), 0). From these results, we see that goal \(G_1\) reaches the aspiration level 90 at 90; goal \(G_2\) reaches the aspiration level 80 at 80; and goal \(G_3\) has a positive value +15 over aspiration level 90.

According to the above examples, Example 1 is better than Example 2 for the decision maker, as the solution to Example 1 is perfectly balanced across the three goals. In other words, the more the aspiration levels there are, the better are the solutions generated by this proposed MCGP method. This configuration forces an optimized consensus by minimizing total deviation (Chang, 2007).

In addition, to reduce the binary variables, the MCGP can be reformulated as the following two alternative MCGP achievement functions (Chang, 2008).

Type 1: “the more the better” case:

\[
\begin{align*}
\text{Min} & \quad \sum_{i=1}^{n} [w_i(d^+_i + d^-_i) + \alpha(e^+_i + e^-_i)] \\
\text{s.t.} & \quad f_i(X) - d^+_i + d^-_i = y_i, \quad i = 1, 2, \ldots, n, \\
& \quad y_i - e^+_i + e^-_i = g_{i,\text{max}}, \quad i = 1, 2, \ldots, n, \\
& \quad g_{i,\text{min}} \leq y_i \leq g_{i,\text{max}}, \\
& \quad d^+_i, d^-_i, e^+_i, e^-_i \geq 0, \quad i = 1, 2, \ldots, n, \\
& \quad X \in F \quad (F \text{ is a feasible set.} \ X \text{ is unrestricted in sign}),
\end{align*}
\]
positive and negative deviations corresponding to \(|y_i - g_{1\text{max}}| \) in Eq. (21); and \(x_i\) is the weight attached to the sum of the deviation of \(|y_i - g_{1\text{max}}|\). Other variables are defined as in MCGP.

Type 2: “the less the better” case:

\[
\text{Min} \sum_{i=1}^{n} \left[ w_i (d_i^+ + d_i^-) + x_i (e_i^+ + e_i^-) \right] 
\]

\[\text{s.t.} \quad f_j(X) - D_i^+ + D_i^- = y_i, \quad i = 1, 2, \ldots, n, \]

\[y_i - e_i^+ + e_i^- = g_i, \quad i = 1, 2, \ldots, n, \]

\[g_{1\text{min}} \leq y_i \leq g_{1\text{max}}. \]

\[d_i^+, \quad d_i^-, \quad e_i^+, \quad e_i^- \geq 0, \quad i = 1, 2, \ldots, n. \]

\[X \in F \quad (F \text{ is a feasible set, } X \text{ is unrestricted in sign}). \]

where \(d_i^+\) and \(d_i^-\) are the positive and negative deviations corresponding to the \(i\)th goal \(f_j(X) - y_i\) in Eq. (23); \(e_i^+\) and \(e_i^-\) are the positive and negative deviations corresponding to \(|y_i - g_{1\text{max}}|\) in Eq. (24); and \(x_i\) is the weight attached to the sum of the deviation of \(|y_i - g_{1\text{max}}|\). Other variables are defined as in MCGP.

4. The proposed method

The proposed method not only considers DM’s preference and experience for supplier selection criteria, but also includes various tangible constraints, for example, the buyer’s budget, suppliers’ capacities, and delivery time. On the other hand, fuzzy TOPSIS approach helps to convert DMs’ preference and experience to meaningful results by applying linguistic values to assess each criterion and alternative suppliers. Integration with MCGP enables to assign order quantities to each supplier by considering the total value created from the procurement. According to Chang (2007), MCGP allows DMs to set multi-choice aspiration levels (MCAL) for each goal (i.e., one goal mapping multiple aspiration levels) to avoid underestimation or overestimation of decision making. The MCAL on a single attribute can be seen in the following three scenarios (Chang, 2008):

1. As a type of uncertainty/imprecision where a DM considers only that his/her aspiration level lies in a certain range, in which the aspiration level can be represented by a range of interval values.

2. These aspiration levels indicate different levels of optimism, which can happen when maximizing or minimizing attribute values. For example, a DM who claims “I expect nothing less than 95, would be content with 115, and would be very happy with 130”.

3. Conservative policies are usually adopted by the decision maker to avoid a negative effect. For example, the DM may claim, “Under company’s resource limitations and the incompleteness of available information, I suggest that 120 million should be our initial aspiration levels for the goal this year, then, in the future for higher the aspiration levels. It will be in the long run if we have more available resources”.

The algorithm of the multi-person multi-criteria decision-making with fuzzy TOPSIS and MCGP method for dealing with the supplier selection is given as follows:

Step 1. Choose the appropriate linguistic variables for the importance weight of selection criteria and the linguistic ratings for suppliers.

Step 2. Aggregate the weight \(w_j\) of criterion \(C_j\) and pool the DMs’ ratings to get the aggregated fuzzy rating \(x_i\) of supplier \(S_i\) under criterion \(C_j\).

Step 3. Construct the fuzzy-decision matrix and normalize the matrix.


Step 5. Determine FPIS and FNIS.

Step 6. Calculate the distance of each supplier from FPIS and FNIS, respectively.

Step 7. Calculate the closeness coefficient (CC) of each supplier.

Step 8. According to the closeness coefficients obtained from Step 7 for each supplier, build the integrated model to find the best suppliers and their optimum order quantities. In order to find the best order quantities, the total value created from the procurement (TVP) should be maximized.

The final model (FTM model) which integrates fuzzy TOPSIS and MCGP can be shown as:

\[
\text{Min} \sum_{i=1}^{n} (d_i^+ + d_i^-) 
\]

\[\text{s.t.} \quad \text{Goal and systems constraints} \]

\[\sum_{i=1}^{n} C_{i1} X_i - d_i^+ + d_i^- \geq g_{1\text{min}} \quad \text{(TVP goal)} \]

\[\sum_{i=1}^{n} \text{price}_i X_i - d_i^+ + d_i^- \geq g_{2\text{min}} \quad \text{or} \quad \leq g_{2\text{max}} \quad \text{(Budget constraint)} \]

\[\sum_{i=1}^{n} \text{time}_i X_i - d_i^+ + d_i^- \geq g_{3\text{min}} \quad \text{or} \quad \leq g_{3\text{max}} \quad \text{(Delivery time constraint)} \]

\[\sum_{i=1}^{n} X_i - d_i^+ + d_i^- = D \quad \text{(Demand constraint)} \]

\[X_i \leq \text{Cap}_i \quad \text{(Suppliers capacity constraints)} \]

\[X_i, \quad d_i^+, \quad d_i^- \geq 0, \quad i = 1, 2, \ldots, n. \]

\[X \in F \quad (F \text{ is a feasible set, } X \text{ is unrestricted in sign}) \]

where \(CC\) is the closeness coefficient of the \(i\)th supplier, and \(\text{price}_i\) is the sale price of the \(i\)th supplier, and \(\text{time}_i\) is the delivery time level of the \(i\)th supplier. Then \(D\) represent the total purchase from \(X_i\), and \(\text{Cap}_i\) is the capacity of the \(i\)th supplier. Other variables are defined as in MCGP.

5. Case study

The company Formosa Watch Co., Ltd. (FWCL) is a large, well-known manufacturer that sells watches in its own chain stores in Asia. For developing new products, its board of directors wishes to select material suppliers to purchase key components in order to find the best order quantities, the total value created from the procurement (TVP) should be maximized.

Step 1. Choose the appropriate linguistic variables for the importance weight of selection criteria and the linguistic ratings for suppliers.

Step 2. Aggregate the weight \(w_j\) of criterion \(C_j\) and pool the DMs’ ratings to get the aggregated fuzzy rating \(x_i\) of supplier \(S_i\) under criterion \(C_j\).

Step 3. Construct the fuzzy-decision matrix and normalize the matrix.


Step 5. Determine FPIS and FNIS.

Step 6. Calculate the distance of each supplier from FPIS and FNIS, respectively.

Step 7. Calculate the closeness coefficient (CC) of each supplier.

Step 8. According to the closeness coefficients obtained from Step 7 for each supplier, build the integrated model to find the best suppliers and their optimum order quantities. In order to find the best order quantities, the total value created from the procurement (TVP) should be maximized.

The final model (FTM model) which integrates fuzzy TOPSIS and MCGP can be shown as:

\[
\text{Min} \sum_{i=1}^{n} (d_i^+ + d_i^-) 
\]

\[\text{s.t.} \quad \text{Goal and systems constraints} \]

\[\sum_{i=1}^{n} C_{i1} X_i - d_i^+ + d_i^- \geq g_{1\text{min}} \quad \text{(TVP goal)} \]

\[\sum_{i=1}^{n} \text{price}_i X_i - d_i^+ + d_i^- \geq g_{2\text{min}} \quad \text{or} \quad \leq g_{2\text{max}} \quad \text{(Budget constraint)} \]

\[\sum_{i=1}^{n} \text{time}_i X_i - d_i^+ + d_i^- \geq g_{3\text{min}} \quad \text{or} \quad \leq g_{3\text{max}} \quad \text{(Delivery time constraint)} \]

\[\sum_{i=1}^{n} X_i - d_i^+ + d_i^- = D \quad \text{(Demand constraint)} \]

\[X_i \leq \text{Cap}_i \quad \text{(Suppliers capacity constraints)} \]

\[X_i, \quad d_i^+, \quad d_i^- \geq 0, \quad i = 1, 2, \ldots, n. \]

\[X \in F \quad (F \text{ is a feasible set, } X \text{ is unrestricted in sign}) \]

where \(CC\) is the closeness coefficient of the \(i\)th supplier, and \(\text{price}_i\) is the sale price of the \(i\)th supplier, and \(\text{time}_i\) is the delivery time level of the \(i\)th supplier. Other variables are defined as in MCGP.

5. Case study

The company Formosa Watch Co., Ltd. (FWCL) is a large, well-known manufacturer that sells watches in its own chain stores in Asia. For developing new products, its board of directors wishes to select material suppliers to purchase key components in order to achieve the competitive advantage in the market. A decision committee including three DMs (D1, D2, D3) has been formed to select a supplier from four qualified suppliers (S1, S2, S3, S4). From a complete set of criteria, FWCL chooses five supplier selection criteria for the present case:

(1) Relationship closeness (C1).

(2) Quality of product (C2).

(3) Delivery capabilities (C3).

(4) Warranty level (C4).

(5) Experience time (C5).

In this study, the hierarchy structure of the decision problem is shown in Fig. 5. The integrated fuzzy TOPSIS and MCGP method is
applied to solve this problem, and the computational procedure is summarized as follows:

Step 1. Three DMs use the linguistic variables shown in Fig. 3 to assess the importance weight of each supplier criterion; the results of the weights are presented in Table 2.

Step 2. Three DMs use the linguistic variables shown in Fig. 4 to rate suppliers with respect to each criterion; the results of the ratings are shown in Table 3.

Step 3. The linguistic evaluations shown in Tables 2 and 3 are converted into trapezoidal fuzzy numbers to construct a fuzzy-decision matrix and determine the fuzzy weight of each criterion, as shown in Table 4.

Step 4. Table 4 is used to construct a normalized fuzzy-decision matrix. Using the normalized fuzzy decision matrix in Table 5, a weighted normalized fuzzy decision matrix is constructed as shown in Table 6.

Step 5. FPIS and FNIS are determined as follows:


Step 6. Calculate the distance of each supplier from FPIS and FNIS with respect to each criterion, respectively, as shown in Tables 7 and 8.

Step 7. Calculate the closeness coefficients of each supplier, as per Table 9: \( CC_1 = 0.558 \), \( CC_2 = 0.502 \), \( CC_3 = 0.516 \), \( CC_4 = 0.476 \).

Step 8. According to the closeness coefficients \((CC_i, i = 1, 2, 3, 4)\) obtained from Step 7 for each supplier, build the MCGP model to identify the best suppliers and optimum order qualities. Similar to Ghodsypour and O’Brien (2001) and Guneri, Yucel, and Ayyildiz (2009), supplier weights (or priority values) are used as closeness coefficients in an objective function to allocate order quantities among suppliers such that the total value of procurement (TVP) is maximized.

According to the sales record in the last 5 years and the sales forecast by FWCL, the CEO and top managers of FWCL have established four goals as follows:

1. The TVP of at least 3500 units from procurement; and the more the better.
2. The total cost of procurement of less than 53,200 thousand dollars; and the less the better.
3. For achieving the procurement levels, the delivery time (per batch) from supplier is set between 4 and 7 days; the less the better.
4. For seeking differentiation strategy (i.e., quality leadership), maintain the current procurement level of less than 5000 units.

In addition, the coefficients of variables in model are given by FWCL’s database calculated from the last 5 years record. The unit material cost for suppliers \( S_1, S_2, S_3, \) and \( S_4 \) are \$12, \$9, \$15, and \$6, respectively, and the capacities of the four candidate suppliers \( S_1, S_2, S_3, \) and \( S_4 \) are 2700, 3500, 2300, and 3100 units, respectively. Furthermore, the delivery time levels of the four candidate suppliers are 2.5, 4, 6, and 3 days, respectively. The functions and parameters related to FWCL’s supplier selection problem are listed below:

\[
f_1(X) = 0.558x_1 + 0.502x_2 + 0.516x_3 + 0.476x_4 \\
\geq 3500 \quad \text{(TVP goal; the more the better)}
\]

\[
f_2(X) = 12x_1 + 9x_2 + 15x_3 + 6x_4 \geq 46000 \quad \text{and}
\]

\[
\leq 53200 \quad \text{(procurement cost goal; the less the better)}
\]

\[
f_3(X) = 2.5x_1 + 4x_2 + 6x_3 + 3x_4 \geq 4 \quad \text{and}
\]

\[
\leq 7 \quad \text{(delivery time goal; the less the better)}
\]

\[
f_4(X) = x_1 + x_2 + x_3 + x_4 \leq 5000 \quad \text{(procurement level goal)}.
\]
The problem can be formulated as follows:

Computation of $d^*_i$, $d^+_i$ and $CC_i$.

<table>
<thead>
<tr>
<th></th>
<th>$d^*_i$</th>
<th>$d^+_i$</th>
<th>$d^*_i + d^+_i$</th>
<th>$CC_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>1.86</td>
<td>1.48</td>
<td>3.34</td>
<td>0.558</td>
</tr>
<tr>
<td>$S_2$</td>
<td>1.58</td>
<td>1.57</td>
<td>3.14</td>
<td>0.502</td>
</tr>
<tr>
<td>$S_3$</td>
<td>1.65</td>
<td>1.55</td>
<td>3.20</td>
<td>0.516</td>
</tr>
<tr>
<td>$S_4$</td>
<td>1.55</td>
<td>1.71</td>
<td>3.27</td>
<td>0.476</td>
</tr>
</tbody>
</table>

Using an integrated fuzzy TOPSIS and MCGP approach, this problem can be formulated as follows:

$$
\text{Min } z = d^*_i + d^+_i + d^*_j + d^+_j + d^*_k + d^+_k + e_i^* + e_j^* + e_k^* + e_1^* + e_2^* + e_3^* + e_4^* \\
\text{s.t. } 0.558x_1 + 0.502x_2 + 0.516x_3 + 0.476x_4 - d^*_i + d^*_j > 3500 \\
(\text{TVP goal; the more the better})
$$

$$
12x_1 + 9x_2 + 15x_3 + 6x_4 - d^*_j + d^*_j = y_1 \\
(\text{procurement cost; the less the better})
$$

$$
y_1 - e_i^* - e_j^* = 46000 \text{ for } y_1 - s_{1,\text{min}} \\
46000 \leq y_1 \leq 53200 \text{ for bound of } y_1
$$

$$
2.5x_1 + 4x_2 + 6x_3 + 3x_4 - d^*_i + d^*_j = y_2 \text{ for delivery time goal}
$$

$$
y_2 - e_i^* + e_j^* = 4 \text{ for } y_2 - s_{2,\text{min}} \\
4 \leq y_2 \leq 7 \text{ for bound of } y_2
$$

$$
x_1 + x_2 + x_3 + x_4 - d^*_i + d^*_j \leq 5000 \text{ for procurement level}
$$

$$
x_1 \leq 2700 \text{ for the capacity bound of } S_1
$$

$$
x_2 \leq 3500 \text{ for the capacity bound of } S_2
$$

$$
x_3 \leq 2300 \text{ for the capacity bound of } S_3
$$

$$
x_4 \leq 3100 \text{ for the capacity bound of } S_4
$$

$$
x_i \geq 0, \quad i = 1, 2, 3, 4.
$$

where all decision variable coefficients are defined as in FTM model.

These models can be solved using LINGO (Schrage, 2002) to obtain optimal solutions. The best suppliers and their optimum quantities are calculated as follows: $S_1(x_1 = 2700)$, $S_2(x_2 = 907)$, $S_3(x_3 = 0)$, and $S_4(x_4 = 0)$ with TVP = 8608.82.

6. Conclusion

Supplier selection is one of the critical decision-making activities for firms to obtain competitive advantage. To achieve this goal, DMs should apply an effective method and select suitable criteria for supplier selection. Taking both tangible and intangible criteria into account, this paper proposed a novel method, which integrates fuzzy TOPSIS and MCGP, to evaluate suppliers.
In a decision-making process, the use of linguistic variables in decision problems is highly beneficial when performance values cannot be expressed by means of numerical values. In general, supplier evaluation and selection problems are vague and uncertain, and so fuzzy set theory helps to convert DM preferences and experiences into meaningful results by applying linguistic values to measure each criterion with respect to every supplier. Employing MCGP enables us to assign order quantities to each supplier and thus maximize the total value of procurement. Given that many multi-choice aspiration levels may exist, a multiple choice method is most appropriate for this type of decision-making. In addition, this integrated method allows for the vague aspirations of DMs to set multiple aspiration levels for supplier selection problems. The integrated advantage of this method is that it allow for the vague aspirations of DMs to set multiple aspiration levels for supplier selection problems in which “the more/higher is better” (e.g., benefit criteria) or “the less/lower is better” (e.g., cost criteria).

Furthermore, the proposed method may be useful for various MCDM problems, such as management problems (e.g., project management and location selection) and marketing problems (e.g., new products development and promotion activities) when available data are inexact, vague, imprecise and uncertain by nature.

References

