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Full Length Research Paper

Applying fuzzy-MSGP approach for supplier evaluation and selection in food industry

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Supplier selection is an important issue in food supply chain management (SCM). In previous research, the food industry generally lacks a formal reference approach for supplier's selection in agricultural products. The key purpose of this study is to develop an integrated fuzzy multiple criteria decision-making (MCDM) model to select supplier. The advantage of this method is its consideration of both qualitative and quantitative criteria, which allows decision makers (DMs) to set multiple segment aspiration levels for supplier selection. In addition, this method will guide DMs to evaluate supplier by taking into account the tangible and intangible resource under firm purchase strategy. A numerical illustration of application is also presented by using a food manufacturer.

Key words: Techniques for order preference by similarity to ideal solution (TOPSIS), multi-segment goal programming (MSGP), supplier selection, supply chain management (SCM), food industry.

INTRODUCTION

Supplier selection is an important issue in food supply chain management (SCM). The evaluation and selection procedure is a critical activity for a firm seeking to obtain competitive advantage and achieve its objectives. Food SCM involves the integration of suppliers, manufacturers, distributors, and customers to meet consumer needs and expectations efficiently and effectively (Cox, 1999). In the context of the food supply chain, many studies have already been conducted with different approaches, all focusing on enhancing the food supply chain's efficiency (Zarei et al., 2011). Selecting the right agricultural products suppliers significantly decreases purchasing costs, improves competitive advantage and enhances customer satisfaction. Therefore, selecting the best foodstuffs supplier in the food supply chain has become a key strategic consideration for many firms.

This selection procedure is essentially considered as a multiple criteria decision-making (MCDM) problem which is affected by different tangible and intangible criteria such as quality, price, delivery time (e.g., JIT), service, warranty, technical capability, and execution time. Typically, manufacturer spends more than 60% of its total sales on purchased items, such as raw materials, parts, and components (Krajewsld and Ritzman, 1996). In addition, purchases of goods and services by manufacturers constitute up to 70 to 80% of total product cost (Ghodsypour and O'Brien, 1998; Guneri et al., 2009). Hence, the selection of suppliers is an area of tremendous importance and should be considered a strategic topic in the effective management of a food supply chain.

Over the years, many firms sought to develop strategic alliances with suppliers in order to promote their management preference and competitiveness (Kumar et al., 2006; Shin et al., 2000). While the coordination between a manufacturer and its suppliers is typically an important and difficult link in the channel of distribution, many methods have been adopted for supplier selection using rather simplistic perceptions of the decision making process (Chen et al., 2006). However, decision makers

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(DMs) need to consider various criteria and attributes when selecting suppliers.

Since 1991, many criteria have been employed to evaluate supplier selection. Weber et al. (1991) suggested a number of selection criteria to measure supplier performance including price, delivery, quality, productive capability, technical capability, reputation, financial stability, performance history, and maintainability. 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 the selection of telecommunications systems. Pi and Low (2005) suggested a method for supplier evaluation and selection based on quality, on-time delivery, price, and service quality. Cakravastia and Takahashi (2004) proposed an integration model for supplier selection and negotiation in a make-to-order environment.

In recent years, the food industry faced various multiple criteria decision-making (MCDM) problems in agricultural products. However, the food company generally lacks a formal reference framework for supplier selection (Bevilacqua et al., 2004). Therefore, this paper is proposed a fuzzy MCDM approach to evaluate and select the best supplier. The advantage of this method is its consideration of both qualitative (e.g., quality, service and reputation) and quantitative criteria (e.g., hours, dollars and volumes) which allows DMs to set multiple segment aspiration levels for supplier selection. To the best of our knowledge, this integrated method has not been discussed in the food SCM literature.

LITERATURE REVIEW

Recently, the supplier selection issue has received considerable attention in the academic literature. Chen et al. (2006) adopted a fuzzy decision making approach to address the supplier selection problem in the supply chain system using five benefit criteria such as the profitability of supplier, relationship closeness, technological capability, conformance quality, and conflict resolution. Lin and Chang (2008) claimed that industry position, relationship closeness, communication, reputation, customer responsiveness, and conflict-solving capabilities are all important criteria for vendor selection. In addition, Wang et al. (2009) address the role of organizational size (e.g., sales force) in the supplier selection process. Guneri et al. (2009) proposed that relationship closeness, reputation and position in industry, performance history, conflict solving capability and delivery time are key criteria for supplier evaluation in Textile Company. Önüt et al. (2009) suggested that supplier selection involves six criteria, quality, price, delivery lead time, institutionally and execution time. Liao and Kao (2010) suggested that in the supplier selection process, firms must consider whether product quality, offering price, delivery time, and total service quality meet organizational demand. Lin et al. (2011) proposed that price, quality, service satisfaction, trust, and delivery are key criteria for supplier evaluation in the electronics industrial market. Table 1 summarizes the criteria from updated Liao and Kao (2011) that have appeared in literature since 1991.

A number of techniques have been proposed to solve the supplier selection problem. These approaches including techniques for order preference by similarity to ideal solution (TOPSIS), linear programming (LP), data envelopment analysis (DEA), cost-point methods (CPM), analytical hierarchy process (AHP), analytic network process (ANP) and fuzzy set theory. Recently, the use of different methodologies in the supplier selection process has received considerable attention in the SCM literature. Önüt et al. (2009) developed a supplier evaluation approach based on the ANP and TOPSIS methods to help a telecommunication company in vendor selection. Faez et al. (2009) presented an integrated fuzzy case-based reasoning and mathematical programming method. Ha and Krishnan (2008) developed a hybrid model that included 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. Wu and Blackhurst (2009) showed an augmented DEA approach to supplier evaluation and selection. Liao and Kao (2010) integrated the Taguchi loss function, AHP and multi-choice goal programming (MCGP) model for solving the supplier selection problem. Liao and Kao (2011) developed an integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management. This integrated model uses source data provided by a firm to address a real-world supplier selection problem.

However, the modeling of many situations may not be sufficient or accurate as the available data are inaccurate, vague, imprecise and uncertain by nature in real life (Sarami et al., 2009). Furthermore, the decision making in such situations is also based on uncertain and ill-defined information. For supplier selection, firms are usually confronted with a high degree of uncertainty and fuzziness in practice. Fuzzy set theory is considered the most effective methods to manage uncertainty and vagueness in decision making. The concept of fuzzy sets was introduced by Zadeh (1965) as a mathematical representation of data and information possessing non-statistical uncertainties, which gives formalized tools for dealing with the intrinsic imprecision of many problems (Kahraman et al., 2007). To model such situations, fuzzy sets were introduced to express the linguistic terms of decision making problems.

The use of TOPSIS is the logical, straightforward, and simple mathematical way to solve MCDM problems, and as such it may provide the basis for developing supplier

Table 1. Supplier selection criteria literature review (Update from Liao and Kao, 2011).

Selection criteria	a	b	c	d	e	f	g	h	i	j	k
Price /cost	•		•	•	•	•		•			
Product quality	•		•	•	•	•	•	•	•		
Delivery capabilities (JIT)	•	•	•	•	•	•		•			•
Warranty level	•			•							
After sales service							•				
Technical support/expertise							•				
Attitude/trust					•						
Service satisfaction				•	•			•			
Experience time (years)	•	•	•	•		•	•				
Financial stability				•		•			•		•
Location						•					
Relationship closeness	•	•							•	•	
Management and organization						•					
Conflict/problem solving capability		•					•		•	•	
Information sharing										•	
Technical/R&D capability						•			•		
Production capability	•					•					
Reputation in industry		•				•	•			•	•

[a]Liao and Kao (2011); [b] Guneri et al. (2009); [c]Önüt et al. (2009); [d]Liao and Kao (2010); [e]Lin et al. (2011); [f]Weber et al. (1991); [g]Tam and Tummala (2001); [h]Pi and Low (2005); [i] Chen et al. (2006); [j]Lin and Chang (2008); [k]Wang et al. (2009).

selection models that effectively handle uncertain properties. Chen et al. (2006) applied a 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. 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 (Liao and Kao, 2011). However, in the multi-goal case, no supplier can satisfy all of the buyer's requirements, and therefore more than one supplier can be selected (Ghodsypour and O'Brien, 1998).

In this paper, an integrated fuzzy TOPSIS and MSGP model is developed to solve supplier selection problems in a multiple goal scenario. First, linguistic values expressed in triangular 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 MSGP model based on the tangible constrains regarding the buyer and its suppliers is constructed and applied to assign order qualities to each supplier. The integrated process is shown in Figure 1, and presented a comparison of this proposed and the others techniques are show in Table 2.

In previous research, much has been said on the subject of supplier evaluation and selection. Most of these models finalize the supplier selection decision-making process based on a set of supplier performance criteria (Youssef et al., 1996; Pi and Low, 2005; Liao, 2010; Liao and Kao, 2010), which are summarized as in the following subsections.

Cost-point method

There are two styles of cost-point methods for supplier selection. First, the cost-ratio method evaluates the cost of each attribute as a percentage of the total purchase for the suppler. By summing these percentages and adding to the price percentage, DMs can obtain the total price of the purchasing parts. Nevertheless, this approach has difficulty in developing cost accounting systems (Tam and Tummala, 2001). Next, in the cost-based method the suppliers' performance evaluation system reflects the actual total cost of doing business with suppliers. Liao and Kao (2010) recognized that material price is only a fraction of the cost of the purchased material in this model. They developed two performance indexes, the service factor rating and the supplier performance index. Before calculating these two indexes, the evaluated items and performance parameters should be identified.

Youssef et al. (1996) recognized the cost-point method

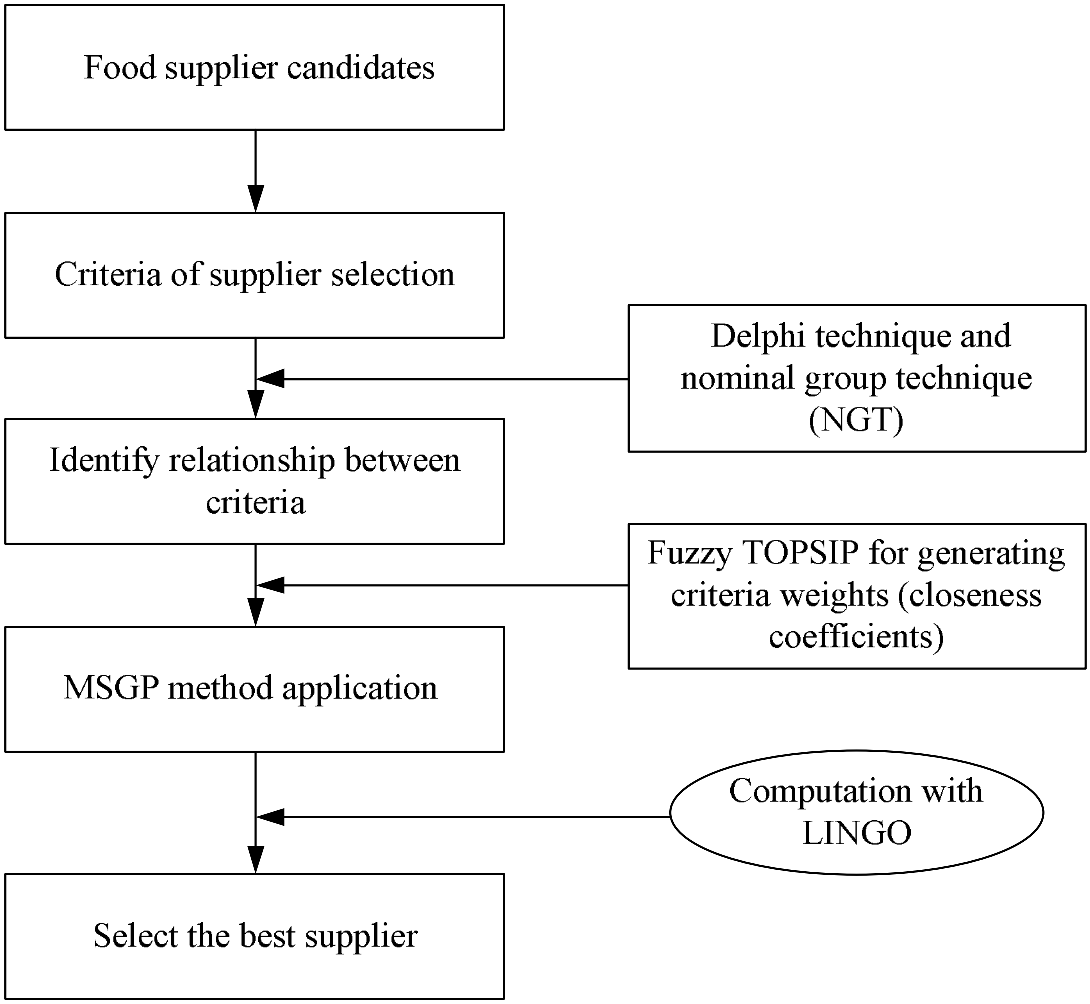

Figure 1. The integration procedure.

Table 2. The comparison of supplier selection methods.

Methods	**Selection criria**		**Multiple segment aspiration levels**
	Qualitative	**Quantitative**	
Cost-point method	No	Yes	No
Weighted-point method	Yes	No	No
Supplier profile analysis	No	Yes	No
Dimensional analysis	Yes	No	No
Categorical models	Yes	No	No
Taguchi loss function	No	Yes	No
TOPSIS	Yes	No	No
LP	No	Yes	No
DEA	No	Yes	No
CPM	No	Yes	No
AHP	Yes	No	No
ANP	Yes	No	No
ANP+TOPSIS	No	Yes	No
AHP+MCGP	Yes	Yes	No
This proposed (Fuzzy TOPSIS+MSGP)	Yes	Yes	Yes

has three advantages. First, it allows for qualitative and quantitative evaluation criteria. Second, the evaluation on qualitative criteria is done by those who have direct contact with suppliers. Third, the two indexes are complementary to each other, and if integrated properly, they would make this model superior to other available models. However, with this and other models, the process of evaluation is still subjective.

Weighted-point method

The weighted-point method which can be expressed as $V_j = \sum_{i}^{n} w_i p_{ij}$, where V_i is the summated score representing the total performance expected from vendor j ; w_i is the importance weight attached to evaluative criteria i ; p_{ij} denotes the performance rating on evaluative criteria i for supplier j ; and n is the number of evaluative criteria (Thompson, 1990; Liao and Kao, 2010). When using the weighted-point method that the criteria of supplier evaluation must be identified and the weight point assigned in the beginning (Willis and Houston, 1990). Then the purchaser will rate the supplier's performance using intuitive judgment. Thompson (1990) pointed out the underlying mathematics weighting the point decision. However, weighted point models also have some disadvantages. One major disadvantage is the limitations associated with scaling techniques (Pi and Low, 2005).

Provider profile analysis

Provider profile analysis is a modified weighted-point method (Thompson, 1990) that can be expressed as $V_{jk} = \sum_{i}^{n} w_i p_{ijk}$, where V_{ik} is the summated score for provider j on iteration k of the simulation; w_i is the importance weight attached to evaluative criteria i ; p_{ijk} denotes the performance rating on evaluative criteria i for provider j during iteration k from simulation; and n is the number of evaluative criteria (Liao and Kao, 2010). In this model, the Monte Carlo Simulation (MCS) technique is used for modeling the uncertainty associated with predicting provider performance against the evaluative criteria, rather than a rating based on human intuitive judgment (Liao, 2010). The simulation algorithm randomly samples values p_{ijk} from within each estimated performance range and then combines these values with importance weights in accordance with linear compensatory rules to produce a distribution of ummated scores. Each computer generated V_{jk} amounts to a single iteration of the simulation process (Pi and Low, 2005). The approach of MCS simplifies the DMs' input to the model evaluation and provides output that includes more information for making purchase decisions than do standard weight point decision models (Liao, 2010). This process is repeated up to several thousand times for each provider.

The dimensional analysis

The evaluation process of the dimensional analysis ratio (DAR) (Youssef et al., 1996) for supplier involves a series of one-on-one comparisons: only two suppliers can be compared at a time with dimensional analysis (Liao and Kao, 2010). The DAR can be obtained from Equation 1:

$$DAR = \prod_{i=1}^{n} \left(\frac{x_{\mathrm{i}}}{y_i} \right)^{R_i} \tag{1}$$

Where x_i and y_i represent i th attribute score of entity x and y , respectively, and R_i is a relative importance assigned to attribute i ; $i = 1, 2, \cdots, n$ th attribute. For the values of DAR there are three conditions: $DAR > 1$, $DAR = 1$ and $DAR < 1$. For example, in the first case, the denoted ranks vendor A higher than vendor B , and so on (Liao and Kao, 2010). In addition, Youssef et al. (1996) indicated two disadvantages of this model. First, a value of $DAR = 1$ will cause the DM to be indifferent about which vendor to chose. Second, the process becomes very tedious and time consuming if a large number of vendors can be selected.

The categorical models

Willis and Houston (1990) proposed the categorical model based on each criteria, such as quality, cost, and speed of delivery. The suppliers were evaluated and classified as good-, fair-, or bad-level, and were assigned a (+), (0) or (−) for each level, respectively. The supplier with the most (+) will be determined to be the best. Based on the total score, suppliers then can be ranked and the supplier with the highest score will be selected (Liao and Kao, 2010). The limitation of this model is that all the attributes are weighted equally. Distinctly, this method is intuitive, subjective, and simplistic in nature but is easy to use. Youssef et al. (1996) suggested that the model can be useful if a weight is assigned to each attribute and the (+), (0) and (−) are replaced with (+1), (0) and (−1), respectively.

Taguchi loss functions

Liao (2010) proposed a supplier evaluation and selection method via a modified Delphi technique, AHP and Taguchi loss functions to increase the decision-making efficiency. In addition, Liao and Kao (2010) integrated the Taguchi loss functions, AHP and MCGP models for solving the supplier selection problem. The advantage of this proposed method is that it allows DMs to set multiple aspiration levels for the decision criteria. The performance of each criterion for each supplier has been transferred to quality loss by using Taguchi loss functions. The results guide the DMs to select the best supplier among the candidates.

METHODOLOGY

Fuzzy TOPSIS

In real life, the modeling process of many phenomena may not be performed sufficiently and exactly because the available information is vague, imprecise, inexact, and uncertain by nature (Sarami et al., 2009). In this paper, fuzzy set theory is introduced to express the linguistic terms of the supplier selection processes. In the following section, some basic definitions of fuzzy sets theory will be reviewed from Chen et al. (2006), Önüt and Soner (2008), Önüt et al. (2009) and Sarami et al. (2009). Some basic concepts of fuzzy numbers and linguistic variables will now be defined next.

A real fuzzy number A is described as a fuzzy subset of the real number x with member function $u_{\tilde{n}}(x)$ that representing uncertainty. A positive triangular fuzzy number $\tilde{n}$ can be defined as (n_1, n_2, n_3), as shown in Figure 2. The membership function $u_{\tilde{n}}(x)$ is defined as follows (Liao and Kao, 2011):

$$u_{\tilde{n}}(x) = \begin{cases} 0, & x \le n_1 \\ \dfrac{x-n_1}{n_2-n_1}, & n_1 \le x \le n_2 \\ \dfrac{n_3-x}{n_3-n_2}, & n_2 \le x \le n_3 \\ 0, & x \le n_3 \end{cases} \tag{2}$$

Given any two positive triangular fuzzy numbers $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ and a positive number k, some main operations of fuzzy numbers $\tilde{m}$ and $\tilde{n}$ can be expressed as follows:

$$\tilde{m}(+)\tilde{n} = (m_1 \oplus n_1, m_2 \oplus n_2, m_3 \oplus n_3) \tag{3}$$

$$\tilde{m}(-)\tilde{n} = (m_1 \Theta n_3, m_2 \Theta n_2, m_3 \Theta n_1) \tag{4}$$

$$\tilde{m}(\times)\tilde{n} = (m_1 \otimes n_1, m_2 \otimes n_2, m_3 \otimes n_3) \tag{5}$$

$$\tilde{m}(\div)\tilde{n} = (m_1 \div n_3, m_2 \div n_2, m_3 \div n_1) \tag{6}$$

$$k\ (\times)\tilde{n} = (k \otimes n_1, k \otimes n_2, k \otimes n_3) \tag{7}$$

The concept of a linguistic variable is useful in dealing with situations that are too complex or not well defined enough to be reasonably described in conventional quantitative expressions (Zimmermann, 1991). For instance, "weight" is a linguistic variable with values that are very low, low, medium, high, or very high. Fuzzy numbers can also represent these linguistic variables. Let $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ be two triangular fuzzy numbers. Then the distance between them can be calculated using the vertex method (Chen et al., 2006):

$$d(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1-n_1)^2 + (m_2-n_2)^2 + (m_3-n_3)^2]}. \tag{8}$$

The problem can be described by following sets:

(a) a set of k DMs called $A = (A_1, A_2, \ldots, A_k)$;

(b) a set of m possible candidates called $S = (S_1, S_2, \ldots, S_m)$;

(c) a set of n criteria called $C = (C_1, C_2, \ldots, C_n)$;

(d) a set of performance ratings of $A_i (i = 1,2,\ldots,m)$ with respect to criteria $C_j = (j = 1,2,\ldots,n)$ called $\tilde{X} = \{\tilde{x}_{ij}, i = 1,2,\ldots,m,\ j = 1,2,\ldots,n\}$, with a set of importance weights of each criterion $w_i (i = 1,2,\ldots,n)$.

As stated earlier, a decision-making problem matrix can be expressed as follows:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad \tilde{W} = [\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n], \tag{9}$$

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

Let the fuzzy rating and importance weight of the *k*th DM be $\tilde{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk})$ and $\tilde{w}_{jk} = (\tilde{w}_{jk1}, \tilde{w}_{jk2}, \tilde{w}_{jk3})$, Where $i = 1,2,\cdots,m$, $j = 1,2,3,\ldots,n$, respectively. Therefore, the aggregated fuzzy ratings, $\tilde{x}_{ij}$, of alternatives with respect to each criterion can be calculated as $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$; where $a_{ij} = \min_k \{a_{ijk}\}$, $b_{ij} = 1/K \sum_{K=1}^{K} b_{ijk}$, and $c_{ij} = \max_k \{c_{ijk}\}$, and the aggregated fuzzy weights, $\tilde{w}_j$, of each

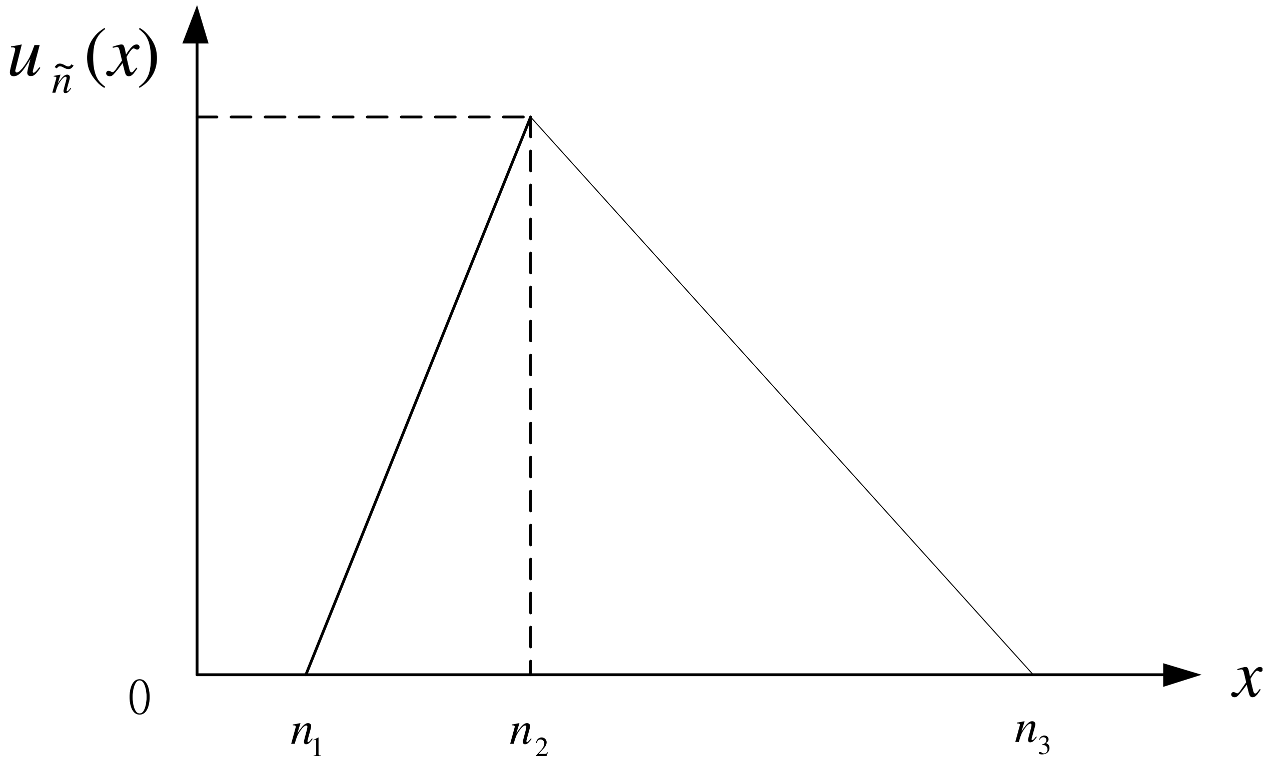

Figure 2. A triangular fuzzy number.

criterion can be calculated as $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$; where $w_{j1} = \min_k \{w_{jk1}\}$, $w_{j2} = 1/K \sum_{K=1}^{K} w_{jk2}$, and $w_{j3} = \max_k \{w_{jk3}\}$ (Chen et al., 2006).

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

$$\tilde{R} = [\tilde{r}_{ij}],\ i = 1,2,3,\ldots m,\quad j = 1,2,3,\ldots,n, \tag{10}$$

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

If the *j*th criterion is a benefit, then:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \tag{11}$$

Where $c_j^* = \max c_{ij}$.

If the *j*th criterion is a cost, then:

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right) \tag{12}$$

Where $a_j^- = \min a_{ij}$.

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

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m \times n}, \tag{13}$$

Where $\tilde{v}_{ij} = \tilde{x}_{ij} \otimes \tilde{w}_j,\ i = 1,2,3,\ldots m,\ \ j = 1,2,3,\ldots,n$.

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:

$$S^* = \left\{ \left(\max_i \tilde{v}_{ij} \middle| j \in J\right), \left(\min_i \tilde{v}_{ij} \middle| j \in J'\right) \right\}$$

$$= (\tilde{v}_1^*, \tilde{v}_2^*, \cdots, \tilde{v}_n^*),\ i = 1,2,\cdots,m,\ \ j = 1,2,3,\ldots,n, \tag{14}$$

And

$$S^- = \left\{ \left(\min_i \tilde{v}_{ij} \middle| j \in J\right), \left(\max_i \tilde{v}_{ij} \middle| j \in J'\right) \right\}$$

$$= (\tilde{v}_1^-, \tilde{v}_2^-, \cdots, \tilde{v}_n^-),\ i = 1,2,\cdots,m,\ \ j = 1,2,3,\ldots,n, \tag{15}$$

Where $v_j^* = \max\{v_{ij3}\}$ and $\tilde{v}_j^- = \min\{v_{ij1}\}$. In addition, J is associated with benefit criteria, but J' is associated with cost criteria.

The distance of each alternative from S^* and S^- can be calculated as:

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*), \quad i = 1,2,\cdots,m, \tag{16}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \quad i = 1,2,\cdots,m, \tag{17}$$

Where $d(\cdot,\cdot)$ represents the distance measured between two fuzzy numbers.

Finally, the closeness coefficients (CC_i) 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:

$$CC_i = \frac{d_i^-}{(d_i^* + d_i^-)}, \quad i = 1,2,\cdots,m, \tag{18}$$

Where CC_i range belongs to the closed interval [0, 1] and $i = 1,2,\cdots,m$.

Multi-segment goal programming (MSGP)

The goal programming (GP) is an important technique to find a set of satisfying solutions to MCDM problems (Liao and Kao, 2010). GP is a multi-objectives analytical approach devised to address decision-making problems in which targets have been assigned to all attributes and where the decision makers are interested in minimizing the non-achievement of the corresponding goal (Liao, 2009). This model can take into account many simultaneous objectives as a decision maker seeks the best solution from a set of feasible options. GP was first introduced by Charnes and Cooper (1961) and has been further developed by Ignizio (1976), Zimmermann (1978), Tamiz et al. (1998), Romero (2001), Chang (2007) and Liao (2009). However, many multiple-segment aspiration levels may exist such as “something more/higher is better” or “something less/lower is better.” These typical multiple segment GP problems cannot be solved using a traditional GP approach.

Liao (2009) proposed a MSGP method to solve multi-segment aspiration levels (MSAL) problems in which decision makers can set multiple aspiration levels to each segment level and the achievement function of MSGP as follows:

$$\text{Min } Z = \sum_{i=1}^{n} w_i (d_i^+ + d_i^-) \tag{19}$$

$$\text{s.t. } f_i(x) + d_i^+ - d_i^- = g_i, \; i = 1,2,....,n, \tag{20}$$

$$f_i(x) = \sum_{j=1}^{m} s_{ij} B_{ij}(b) \cdot x_i$$

$$s_{ij} B_{ij}(b) \in R_i(x), \quad i = 1,2,....,n, \quad j = 1,2,....,m, \tag{21}$$

$$d_i^+, d_i^- \geq 0, \quad i = 1,2,....,n,$$

$X \in F$ (F is a feasible set).

Where w_i represents the weight attached to the deviation, and d_i is the deviation from the target value g_i, are denoted under- and over-achievements of the i th goal, respectively.

$$d_i^+ = \max\,(0, f_i(x) - g_i) \tag{22}$$

And

$$d_i^- = \max\,(0, \; g_i - f_i(x)) \tag{23}$$

s_{ij} is a decision variable coefficients that represents the multi-segment aspiration levels of j th segment of i th goal, and $B_{ij}(b)$ represents a function of a binary serial number, and $R_i(x)$ is the function of resource limitations.

The MSGP model can then be reformulated by the following MSGP achievement type (Liao, 2011):

$$\text{Min } S = w_i(d_i^+ + d_i^-), w_i(e_i^+ + e_i^-) \tag{24}$$

$$\text{s.t. } \sum_{j=1}^{m} s_{ij} B_{ij}(b) \cdot x_i + d_i^+ - d_i^- = g_i \quad i = 1,2,....,n, \tag{25}$$

$$\frac{1}{L_i}(b_i s_{ij}^{\max} + (1-b_i) s_{ij}^{\min}) - e_i^+ + e_i^-,$$

$$= 1 + \frac{(s_{ij}^{\max} \; or \; s_{ij}^{\min})}{L_i}, \quad i = 1,2,....,n, \tag{26}$$

$$s_{ij} B_{ij}(b) \in R_i(x), \quad i = 1,2,....,n, \quad j = 1,2,....,m, \tag{27}$$

$$b_i \in \{0,1\}, \quad i = 1,2,....,n \tag{28}$$

$$d_i^+, d_i^-, e_i^+, e_i^- \geq 0 \quad i = 1,2,....,n \tag{29}$$

$$X \in F \quad (F \text{ is a feasible set}) \tag{30}$$

Where $L_i = s_{ij}^{\max} - s_{ij}^{\min}$, and all other variables are defined as in the MSGP model.

The proposed method

The proposed method not only considers DMs’ preference and experience for supplier selection criteria but also includes various tangible constraints including the buyer’s budget, suppliers’ capacity and delivery time. Additionally, the 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 MSGP enables the assignment of ordered quantities to each supplier by considering the total value created from the procurement. According to Liao (2009), MSGP allows DMs to set MSAL for each segment goal to avoid underestimation or overestimation of decision-making.

The algorithm of the multi-segment decision-making with fuzzy TOPSIS and MSGP 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 $\tilde{w}_j$ of criterion C_j and pool the DMs' ratings to get the aggregated fuzzy rating $\tilde{x}_{ij}$ of supplier S_i under criterion C_j.

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

Step 4. Construct weighted normalized fuzzy decision matrix.

Step 5. Determine FPIS and FNIS.

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

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

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

Illustrative example

The supplier selection model is applied to a large-scale food company, Hunya Foods CO., LTD. (HFCL). HFCL is a well-known Taiwanese manufacturing firm that sells foods in its own chain stores. The chief executive officer (CEO) wishes to select a food material supplier to purchase key components for new products in order to more competitive in the Chinese market. However, the company lacks an objective way of selecting the most promising foodstuffs supplier. Therefore, a decision committee for supplier selection is assembled and includes the CEO, market manager and purchase manager.

Three DMs (D_1, D_2, D_3) has been formed to select a best supplier from four qualified suppliers (S_1, S_2, S_3, S_4) by applying the Delphi technique and nominal group technique (NGT) (Sarami et al., 2009). In addition, according to HFCL's purchasing strategic, the first task was to identify the factors affecting the success and performance of supplier selection. Base on the literature reviews, manager and experts' interviews, and data analysis, the five qualitative criteria for selecting the best supplier are financial stability (C_1), product quality (C_2), reputation in industry (C_3), R&D capability (C_4) and service quality (C_5) for the present case.

Fuzzy TOPSIS is employed to prioritize the relative importance of qualitative multiple evaluation criteria and the preference of candidates by DMs' opinions. In addition, three quantitative criteria of suppliers, that is, delivery time (in hours), procurement cost (in dollars) and production capacity (in volumes) are consideration. In this study, the hierarchy structure of the decision-making problem is shown in Figure 3.

The integrated fuzzy TOPSIS and MSGP method is applied to solve this problem, and the procedure is summarized as follows:

Step 1. Three DMs use the linguistic variables shown in Table 3 to assess the importance weight of each supplier criterion; the results of the weights are presented in Table 4.

Step 2. Three DMs use the linguistic variables shown in Table 5 to rate suppliers with respect to each criterion; the results of the ratings are shown in Table 6.

Step 3. The linguistic evaluations shown in Tables 4 and 6 are converted into triangular fuzzy numbers to construct a fuzzy decision matrix and determine the fuzzy weight of each criterion as shown in Table 7.

Step 4. Table 7 is used to construct a normalized fuzzy decision matrix. Using the normalized fuzzy decision matrix in Table 8, a weighted normalized fuzzy decision matrix is constructed as shown in Table 9.

Step 5. FPIS and FNIS are determined from Equations. (14) and (15) as follows:

$$S^* = [(0.9, 0.9, 0.9), (1,1,1), (1,1,1), (1,1,1), (0.9, 0.9, 0.9)],$$

$$S^- = [(0.25, 0.25, 0.25), (0.15, 0.15, 0.15, (0.25, 0.25, 0.25), (0.35, 0.35, 0.35), (0.25, 0.25, 0.25)].$$

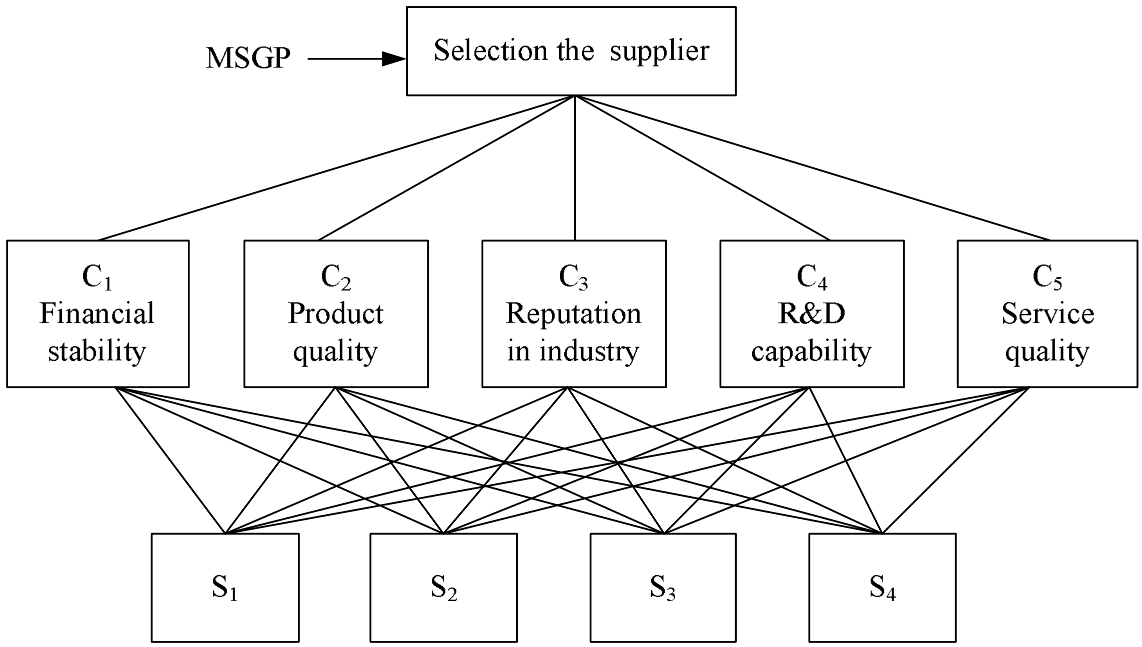

Figure 3. Hierarchy structure of decision making problem.

Table 3. Linguistic variables for the importance weight of each criterion.

Linguistic variables	Triangular fuzzy number
Very low	(0,0,0.1)
Low	(0,0.1,0.3)
Medium low	(0.1,0.3,0.5)
Medium	(0.3,0.5,0.7)
Medium high	(0.5,0.7,0.9)
High	(0.7,0.9,1)
Very high	(0.9,1,1)

Table 4. Importance weights of criteria for three DMs.

Criteria	D_1	D_2	D_3
C_1	(0.5,0.7,0.9)	(0.7,0.9,1)	(0.5,0.7,0.9)
C_2	(0.9,1,1)	(0.7,0.9,1)	(0.1,0.3,0.5)
C_3	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.9,1,1)
C_4	(0.9,1,1)	(0.9,1,1)	(0.7,0.9,1)
C_5	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.7,0.9,1)

Step 6. Calculate the distance of each supplier from FPIS and FNIS with respect to each criterion as shown in Tables 10.

Step 7. Calculate the closeness coefficients of each supplier obtained CC_1 = 0.586, CC_2 = 0.543, CC_3 = 0.555 and CC_4 = 0.546, as shown in Table 11.

Step 8. Next, according to the closeness coefficients

Table 5. Linguistic variables for the ratings.

Linguistic variable (benefit /cost criteria)	Triangular fuzzy number
Very poor/very low	(0,0,1)
Poor/low	(0,1,3)
Medium poor/medium low	(1,3,5)
Fair/ medium	(3,5,7)
Medium good/ medium high	(5,7,9)
Good/ high	(7,9,10)
Very good/very high	(9,10,10)

Table 6. Ratings of four candidates by decision-makers according to five criteria.

Criteria	Supplier	Decision-makers		
		D_1	D_2	D_3
C_1	S_1	(7,9,10)	(7,9,10)	(7,9,10)
	S_2	(5,7,9)	(5,7,9)	(7,9,10)
	S_3	(9,10,10)	(9,10,10)	(7,9,10)
	S_4	(7,9,10)	(7,9,10)	(7,9,10)
C_2	S_1	(7,9,10)	(7,9,10)	VG
	S_2	(7,9,10)	(7,9,10)	(7,9,10)
	S_3	(9,10,10)	(9,10,10)	(9,10,10)
	S_4	(7,9,10)	(5,7,9)	(9,10,10)
C_3	S_1	(9,10,10)	(9,10,10)	(5,7,9)
	S_2	(7,9,10)	(7,9,10)	(7,9,10)
	S_3	(5,7,9)	(5,7,9)	(5,7,9)
	S_4	(5,7,9)	(5,7,9)	(7,9,10)
C_4	S_1	(9,10,10)	(9,10,10)	(9,10,10)
	S_2	(7,9,10)	(5,7,9)	(9,10,10)
	S_3	(9,10,10)	(7,9,10)	(7,9,10)
	S_4	(7,9,10)	(7,9,10)	(7,9,10)
C_5	S_1	(9,10,10)	(9,10,10)	(7,9,10)
	S_2	(7,9,10)	(7,9,10)	(5,7,9)
	S_3	(5,7,9)	(5,7,9)	(7,9,10)
	S_4	(5,7,9)	(5,7,9)	(7,9,10)

($CC_i, i = 1,2,3,4$) obtained from Step 7 for each supplier, build the MSGP model to identify the best suppliers and optimum order qualities. Similar to Liao and Kao (2011), supplier weights (or priority values) are used as closeness

Table 7. Fuzzy decision matrix and fuzzy weights of four candidates.

Supplier	C_1	C_2	C_3	C_4	C_5
S_1	(7,9,10)	(7,9.3,10)	(5,9,10)	(9,10,10)	(7,9.7,10)
S_2	(5,7.7,10)	(7,9,10)	(7,9,10)	(5,8.7,10)	(5,8.3,10)
S_3	(7,9.7,10)	(9,10,10)	(5,7,9)	(7,9.3,10)	(5,7.7,10)
S_4	(7,9,10)	(5,8.7,10)	(5,7.7,10)	(7,9,10)	(5,7.7,10)
Weights	(0.5,0.77,0.9)	(0.3,0.8,1.0)	(0.5,0.87,1.0)	(0.7,0.97,1.0)	(0.5,0.83,1.0)

Table 8. The normalized decision matrix.

Supplier	C_1	C_2	C_3	C_4	C_5
S_1	(0.7,0.9,1)	(0.7,0.93,1)	(0.5,0.9,1)	(0.9,1,1)	(0.7,0.97,1)
S_2	(0.5,0.77,1)	(0.7,0.9,1)	(0.7,0.9,1)	(0.5,0.87,1)	(0.5,0.83,1)
S_3	(0.7,0.97,1)	(0.9,1,1)	(0.5,0.7,0.9)	(0.7,0.93,1)	(0.5,0.77,1)
S_4	(0.7,0.9,1)	(0.5,0.87,1)	(0.5,0.77,1)	(0.7,0.9,1)	(0.5,0.77,1)

Table 9. The weighted normalized decision matrix.

Supplier	C_1	C_2	C_3	C_4	C_5
S_1	(0.35,0.69,0.9)	(0.21,0.75,1)	(0.25,0.78,1)	(0.63,0.97,1)	(0.35,0.81,1)
S_2	(0.25,0.59,0.9)	(0.21,0.72,1)	(0.35,0.78,1)	(0.35,0.84,1)	(0.25,0.69,1)
S_3	(0.35,0.74,0.9)	(0.27,0.8,1)	(0.25,0.61,0.9)	(0.49,0.9,1)	(0.25,0.64,1)
S_4	(0.35,0.69,0.9)	(0.15,0.69,1)	(0.25,0.66,1)	(0.49,0.87,1)	(0.25,0.64,1)

Table 10. Distances between FPIS (and FNIS) and suppliers' ratings.

		C_1	C_2	C_3	C_4	C_5
FPIS	$d(S_1, S^*)$	0.34	0.48	0.45	0.21	0.33
	$d(S_2, S^*)$	0.42	0.48	0.40	0.39	0.40
	$d(S_3, S^*)$	0.33	0.44	0.49	0.30	0.41
	$d(S_4, S^*)$	0.34	0.52	0.47	0.30	0.41
FNIS	$d(S_1, S^-)$	0.40	0.60	0.53	0.54	0.54
	$d(S_2, S^-)$	0.42	0.59	0.53	0.47	0.50
	$d(S_3, S^-)$	0.47	0.62	0.43	0.50	0.49
	$d(S_4, S^-)$	0.46	0.58	0.49	0.49	0.49

Table 11. The results of CC_i.

Supplier	d_i^*	d_i^-	$d_i^* + d_i^-$	CC_i
S_1	1.81	2.56	4.37	0.586
S_2	2.08	2.47	4.55	0.543
S_3	1.97	2.46	4.43	0.555
S_4	2.05	2.46	4.51	0.546

coefficients in an objective function to allocate order quantities among suppliers such that the total value of procurement (TVP) is maximized.

Moreover, from the sales record in the last six years and the sales forecast by HFCL, the CEO, market manager and purchase manager of HFCL have established four goals are to maximize the satisfaction of the airline such as the selection highest TVP of supplier (G_1), delivery time (G_2), budget cost (G_3), and procurement demand level (G_4). The MSGP model for the supplier selection problem is set next:

G_1 : $f_1(x) \geq$ 2,000 is to maximize the TVP of suppliers;

G_2 : $f_2(x) \leq$ 130 hours per year, and is to minimize delivery time of suppliers;

G_3 : $f_3(x) \leq$ 53,200 thousand dollars, and is to minimize the total cost of procurement;

G_4 : $f_4(x) =$ 4,000 unit, and is maintain the current procurement demand level.

In addition, the coefficients of variables in the model are given by HFCL's database calculated from the last six years' records. The capacities of the four suppliers S_1, S_2, S_3, and S_4 are 2600, 3600, 2400, and 3200 units, respectively, and unit material costs are \$10~\$12, \$9, \$15, and \$6~\$8, respectively. Then, the delivery time levels of the four candidate suppliers are 0.025, 0.04~0.048, 0.06~0.072, and 0.03 days per time, respectively. The functions and parameters related to HFCL's supplier selection problem are listed:

TVP goal: $f_1(X) = 0.586x_1 + 0.543x_2 + 0.555x_3 + 0.546x_4 \geq$ 20 00

Delivery time goal: $f_2(X) = 0.025x_1 + [0.04, 0.048]x_2 + [0.06, 0.073]x_3 + 0.03x_4 \leq 130$

Total cost of procurement goal: $f_3(X) = [10, 12]x_1 + 9x_2 + 15x_3 + [6, 8]x_4 \leq$ 53,200

Procurement demand level goal: $f_4(X) = x_1 + x_2 + x_3 + x_4 =$ 4,000.

Using afore-mentioned goal and data are given by HFCL, and then a fuzzy-GP model and its description can be formulated as follows (Fuzzy TOPSIS MSGP-achievement):

Min Z = $d_1^+ + d_1^-$ + $d_2^+ + d_2^-$ + $d_3^+ + d_3^-$ + $d_4^+ + d_4^-$ + $e_1^+ + e_1^- + e_2^+ + e_2^- + e_3^+ + e_3^- + e_4^+ + e_4^-$

Satisfy all obligatory goal .

s.t. 0.586 x_1 + 0.543 x_2 +0.555 x_3 +0.546 x_4 $- d_1^+ + d_1^- \geq$ 2,000

For weighted of suppliers goal.

0.025 x_1 + (0.048 b_1 +0.04 $(1-b_1)$) x_2 + (0.073 b_2 +0.06 $(1-b_2)$) x_3 +0.03 x_4 $- d_2^+ + d_2^- \leq$ 130

For delivery time goal.

(1/0.008)(0.048 b_1 +0.04 $(1-b_1)$) $- e_1^+ + e_1^-$ = 626

For minimize delivery time goal of x_2.

(1/0.013)(0.073 b_2 +0.06 $(1-b_2)$) $- e_2^+ + e_2^-$ = 356

For minimize delivery time goal of x_3.

(12 b_3 +10 $(1-b_3)$) x_1 +9 x_2 +15 x_3 + (8 b_4 +6 $(1-b_4)$) x_4 $- d_3^+ + d_3^- \leq$ 53,200

For procurement cost goal.

(1/2) (12 b_3 +10 $(1-b_3)$) $- e_3^+ + e_3^-$ = 6

For minimize procurement cost goal of x_1.

(1/2) (8 b_4 +6 $(1-b_4)$) $-e_4^+ + e_4^-$ = 4

For minimize procurement cost goal of x_4.

$x_1 + x_2 + x_3 + x_4 - d_4^+ + d_4^- =$ 4,000

For procurement level goal.

$x_1 \leq$ 2,600

For the capacity bound of S_1.

$x_2 \leq$ 3,600

For the capacity bound of S_2.

$x_3 \leq$ 2,400

For the capacity bound of S_3.

$x_4 \leq$ 3,200

For the capacity bound of S_4.

$b_i \in \{0, 1\}$, $i = 1, 2, \ldots, 4$,

Represent binary number

$d_i^+, d_i^- \geq 0$, $i = 1, 2, \ldots, 4$,

Deviation for the target.

$e_i^+, e_i^- \geq 0$, $i = 1, 2, \ldots, 4$.

Deviation for the target.

All variables are non-negative.

This supplier selection problem (Fuzzy TOPSIS MSGP-achievement) of HFCL can be solved using LINGO (Schrage, 2002) to obtain optimal solutions. The result of the ranking of suppliers $S_4 > S_2 > S_1 = S_3$, and their optimum quantities are calculated as S_1 ($x_1 = 0$), S_2 ($x_2 = 800$), S_3 ($x_3 = 0$), S_4 ($x_4 = 3{,}200$). Therefore, in the best interest of the HFCL, 800 units should be purchased from supplier 2 and 3,200 units from supplier 4 with an obtained TVP of 2181.60.

Conclusion

Supplier selection is one of the critical decision-making activities for firms seeking to obtain competitive advantage. To achieve this goal, DMs should apply an effective method and select suitable criteria for supplier selection. In the food industry the lack of a formal reference framework for selecting the most suitable supplier of agricultural products (e.g., foodstuffs) has not been discussed in the literature. This paper proposes a novel integration technique using TOPSIS and MSGP to evaluate and select the best foodstuffs supplier.

In a decision-making process, the use of linguistic variables in decision-making problems is highly beneficial when performance values cannot be expressed using numerical values. In general, supplier evaluation and selection problems are vague and uncertain, so fuzzy set theory helps to convert DMs preferences and experiences into meaningful results by applying linguistic values to measure each criterion with respect to every supplier. Employing MSGP enables us to assign order quantities to each supplier and thus maximize the total value of purchasing. Given that many multi-segment aspiration levels may exist, a multiple-segment method is the most appropriate for this type of decision-making. In addition, this integrated method allows DMs to set multiple segment aspiration levels for supplier selection problems. The integrated advantage of this method is that it considers both tangible (qualitative) and intangible (quantitative) criteria for supplier selection problems for which "the more/higher is better" (e.g., benefit criteria) or "the less/lower is better" (e.g., cost criteria). The contribution of this paper is proposed an easy and effective approach to help a firm to select the best supplier in practice.

The explicit consideration of this study has yielded a number of meaningful managerial implications in practice as follows:

(a) In practice, expect the qualitative criteria that the quantitative criteria such as hours, dollars and volumes of foodstuffs supplier's selection need be considered;
(b) The model illustrated two simple computational procedure can be easily applied to multiple sourcing supplier selection problems;
(c) Also the integrated method can be extended to the analysis of other management decision problems.

Furthermore, the proposed method may be useful for various MCDM issues such as logistics problems (e.g., using fuzzy MCDM approach to evaluate logistics service providers (Ding, 2011) for foodstuffs) and marketing problems (e.g., new products development and R&D project) or consideration to the negotiation problems (Wu and Blackhurst, 2009; Cakravastia and Takahashi, 2004), when available data are inexact, vague, imprecise and uncertain by nature.

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