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Supplier selection using integrated fuzzy TOPSIS and MCGP: a case study

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Abstract

This study provides an overview of the fuzzy TOPSIS and Multi-Choice Goal Programming (MCGP) methods for Multi-Criteria Decision-Making (MCDM) problem under uncertain environments. Supplier selection is mostly a complex multi-criteria problem which consists of qualitative and quantitative criteria. Those criteria should be considered advertently as a final decision in comprehensive and objective supplier selection as well. This study deal with the optimum decision making for selecting supplier and allocating order by applying the proposed method of integrated fuzzy TOPSIS and MCGP (Multi-Choice Goal Programming). To deal with the uncertain and imprecise judgment of decision makers, a Fuzzy TOPSIS is utilized to express it by triangular fuzzy numbers. The final supplier selection and order allocation are obtained by integrating the closeness coefficients to the MCGP model. A numerical example is given to clarify the main results developed in this paper.

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Keywords: MCDM, Supplier Selection, Fuzzy TOPSIS, MCGP;

1. Introduction

Supplier selection is one of the critical activities for firms to gain competitive advantage and achieve the objectives of the whole supply chain. It is likely that the manufacturer allocates more than 60% of its total sales on purchased items, such as raw materials, parts, and components (Krajewsld & Ritzman, 1996). Moreover, material cost is up to 70 % of finished good product cost (Ghodsypour & O'Brien, 1998). Selecting the right suppliers and determining the appropriate orders from them can bring significant benefit in the reduction in purchasing cost, decrease in supplying risk and improved product quality. Therefore, by selecting appropriate supplier thoroughly, it can contribute success advantages to the manufacturing organization in confronting competitive environment (Liu & Hai, 2005).

There are various criteria to be considered when selecting the appropriate supplier. Dickson (1996) proposed 23 supplier selection criteria. But, it's not permanently judged that all the criteria must be included into a final decision making because each firm has a different strategy in the supply chain in terms of the characteristics of the product. As remark, in the case study of this paper, the Dickson's criteria will be the point to be adopted according to the preferences of the decision makers in the company.

Basically there are two kinds of supplier selection problem. In the first kind of supplier selection, one supplier can satisfy all the buyer's needs (single sourcing). The management needs to make only one decision: which supplier is the best. In the second type (multiple sourcing), no supplier can satisfy all the buyer's requirements. In

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many cases, organizations usually choose more than one supplier for their products, until facing with non-competence of one supplier to ensure continuity of supply. Sometimes, The firms are confronted with some problems such as delay in delivery time and supply capacity of supplier. Hence, by taking the second type namely multiple sourcing, the firm can utilize the business process as well and overcome the unpredicted supply when one of the suppliers does not meet the requirement related to delivery, quality, and quantity. In other words, it can be complemented by other suppliers.

It is not easy for the decision maker to select appropriate supplier who satisfies the entire requirement among various criteria. Moreover, supplier selection is a multiple criteria decision-making (MCDM) problem which is affected by several conflicting factors and it consists of both qualitative and quantitative factors. There are many methods for supplier selection problems including analytic hierarchy process (AHP), analytic network process (ANP), data envelopment analysis (DEA), fuzzy sets theory (FST), genetic algorithm (GA), goal programming (GP), simple multi-attribute rating technique (SMART), and other methods (Dahel, 2003). We classify some of these techniques in three groups: qualitative factor approach, quantitative factor approach, and integrated factor approach (quantitative and qualitative) (table 1). Kumar and Roy (2010), presented a hybrid model using analytic hierarchy process (AHP) and neural networks (NNs) theory to vendor selection. Asamoah et al. (2012) applied AHP Approach for Supplier Evaluation and Selection in a Pharmaceutical Manufacturing Firm in Ghana. Based on the method which is studied by Kumar and Roy (2010) and Asamoah et al. (2012), the study only represents qualitative factors in the procedure to obtain appropriate supplier. Some studies proposed the approach method to supplier selection which takes into account both factors. Such a study which is proposed by Jadidi et al. (2008) applied TOPSIS and fuzzy multi-objective model integration for supplier selection problem. Wang et al. (2004) suggested an integrated analytic hierarchy process (AHP) and preemptive goal programming (PGP) to supplier selection.

According to the review of 170 articles published during 2000 to 2010 about supplier selection which is presented by Setak et al. (2012), there are about 40% of the papers use hybrid methods. Multi Choice Goal Programming (MCGP) proposed by Chang (2007). The fundamental of the method is to emphasize that the decision when multi aspiration level existed cannot be solved by Goal Programming model (Chang, 2007). Chang (2008) elaborated the previous work into Revised Multi Choice Goal Programming to ease understanding for industrial participants and solving by ordinary linear programming solver. Another related work proposed is integrated Fuzzy TOPSIS and MCGP with trapezoidal fuzzy number (Liao & Kao, 2011). Liao and Kao (2011) adopted that method for selecting supplier in the company which engaged in watch manufacturing. This paper intends to adopt the hybrid method by using Fuzzy TOPSIS with triangular fuzzy number and MCGP for supplier selection and allocation order in the Fertilizer and Chemicals Company.

Table 1. Supplier selection approach

Category	Method	Author	Category	Method	Author
qualitative factor approach	AHP	Chan and Chan (2004)	**Quantitative factor approach**	GP	Karpak et. al (2001)
		Liu and Hai (2005)		LP	Talluri&Narasimhan (2005)
		Ho et. al (2010)		MOP	Dahel (2003)
		Asamoah et. al (2012)			Narasimhan et. al (2006)
	Fuzzy, AHP	Kharaman et. al (2003)		GA	Ding et al. (2005)
		Chan and Kumar (2007)	**Integrated factor approach**	AHP, GP	Wang et. al (2004)
	Fuzzy, TOPSIS	Shahanaghi and Yazdian (2009)			Kull and Talluri (2008)
		Mehralian et. al (2012)		AHP, MOP	Xia and Wu (2007)
	AHP, NNs	Kumar and Roy (2010)		DEA, MOP	Talluri et. al (2008)
	ANP	Sarkis and Talluri (2002)		DEA, MOMIP	Songhori (2010)
	SMART	Barla (2003)		TOPSIS, FMOMI	Jadidi et. al (2008)
		Huang and Keska (2007)		Fuzzy TOPSIS, MCGP	Liao and Kao (2011)
	Fuzzy, SMART	Kwong et. al (2002)			
		Chou and Chang (2008)			
	DEA	Weber (1996)			
		Wu et. al (2007)			

2. Fuzzy TOPSIS

The fuzzy theory was introduced by Zadeh (1965) as an extension of the classical notion of set. Among the various shapes of fuzzy number, triangular fuzzy number (TFN) is the most popular one. TFN is a fuzzy number represented with three points as follows: $\tilde{\boldsymbol{A}} = (l, m, u)$ which can be drawn in figure 1. This representation is interpreted as membership functions and holds the following conditions:

a) l to m is increasing function
b) m to u is decreasing function
c) $l \leq m \leq u$

$$\mu_{\tilde{A}}(x)=\begin{cases} 0 & for\ x < l\ ;\ x > u \\ \frac{x-l}{m-l} & for\ l \leq x \leq m \\ \frac{u-x}{u-m} & for\ m \leq x \leq u \end{cases}$$

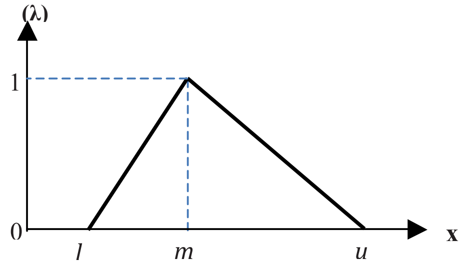

Figure 1. Triangular fuzzy number

The TOPSIS (technique for order preference by similarity to an ideal solution) was first developed by Hwang & Yoon (1981). In this method two artificial alternatives are defined as positive-ideal and negative-ideal solution. The positive-ideal solution is a solution that maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Wang & Elhag, 2006). In short, the positive-ideal solution is the one which has the best level for all attributes considered, whereas the negative ideal solution is the one which has the worst attribute values. TOPSIS selects the alternative that is the closest to the positive ideal solution and farthest from negative ideal solution.

The steps of fuzzy TOPSIS algorithm can be constructed in details as follows:

1) Generating feasible alternatives, determining the evaluation criteria, and setting a group of decision makers. Assume that there are m alternative, n evaluation criterion, and k decision maker.
2) Choose the appropriate linguistic variables for the importance weight of the criteria ($\tilde{w}_j = l_{ij}, m_{ij}, u_{ij}$) and the linguistic ratings for alternatives with respect to criteria ($\tilde{x}_{ij}$) as TFN.
3) Aggregate the weight of criteria to get the aggregated fuzzy weight $\tilde{w}_j$ of criterion C_j, and obtain the aggregated fuzzy rating $\tilde{x}_{ij}$ of alternative A_i under criterion C_j evaluated by expert.

$$\tilde{x}_{ij} = \frac{1}{k}\left[\, \tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \ldots + \tilde{x}_{ij}^{k} \,\right] \qquad ; i = 1,2, \ldots, m \ ; j = 1,2, \ldots, n \tag{1}$$

$$\tilde{w}_j = \frac{1}{k}\left[\, \tilde{w}_j^{1} + \tilde{w}_j^{2} + \ldots + \tilde{w}_j^{k} \,\right] \qquad ; j = 1,2, \ldots, n \tag{2}$$

4) Construct the fuzzy decision matrix.

$$\tilde{D} = \begin{matrix} & C_1 & C_2 & \cdots & C_n \\ A_1 & \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ A_2 & \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_m & \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{matrix} \quad ; \qquad \tilde{W} = [\, \tilde{w}_1, \tilde{w}_2, \ \ldots, \tilde{w}_n] \tag{3}$$

i = 1,2, …, m ; j = 1,2, …, n

5) Normalize fuzzy decision matrix.
The normalized fuzzy decision matrix denoted by $\tilde{R}$ is obtained by formula as follows:

$$\tilde{\mathbf{R}} = [\tilde{r}_{ij}]_{mxn} \quad , i = 1,2,\ldots, m ; \quad j = 1,2,\ldots, n \tag{4}$$

The formula above can be calculated as details:

$\tilde{r}_{ij} = \left(\frac{l_{ij}}{U_j^*}, \frac{m_{ij}}{U_j^*}, \frac{u_{ij}}{U_j^*}\right)$, where $U_j^* = \max u_{ij}$ (5)

6) Construct the weighted normalized fuzzy decision matrix.
In order to the different importance of each criterion, we can construct the weighted normalized fuzzy decision matrix as:
$\tilde{\mathbf{V}} = [\tilde{v}_{ij}]_{mxn}$, i = 1,2,…, m ; j = 1,2,…, n (6)
Where $\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j$, i = 1,2,…, m ; j = 1,2,…, n (7)

7) Determine the fuzzy positive-ideal solution (FPIS) S^+ and fuzzy negative-ideal solution (FNIS) S^-. The calculation can be obtained as follows:
$S^+ = (\tilde{v}_1^+ , \tilde{v}_2^+ , \ldots, \tilde{v}_n^+)$ (8)
$S^- = (\tilde{v}_1^- , \tilde{v}_2^- , \ldots, \tilde{v}_n^-)$ (9)
where $\tilde{v}_j^+ = \max \{v_{ij3}\}$ and $\tilde{v}_j^- = \min \{v_{ij1}\}$ since $\tilde{v}_j$ is weighted normalized TFNs
i = 1,2,…, m ; j = 1,2,…, n

8) Calculate the distance of each alternative from FPIS (d^+) and FNIS (d^-) .
According to the vertex method, the distance between two triangular fuzzy numbers A_1 (l_1, m_1, u_1) and A_2 (l_2, m_2, u_2) is calculated as:

$$d(A_1, A_2) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]}$$

$d_i^+ = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^+\right)$, i = 1,2,…, m (10)
$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right)$, i = 1,2,…, m (11)

9) Calculate the closeness coefficient (CC_i) and rank the order of alternatives according to the coefficient.
After we obtain the distance d^+ and d^-, we calculate the closeness coefficient of each alternative using the formula bellow:
$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}$, i = 1,2,…, m (12)
Based on the value of closeness coefficient of each alternative, we determine the ranking order of all alternatives from the highest closeness coefficient to the lowest. The alternative with the highest closeness coefficient is obviously considerable.

There are a number of specific procedures that can be used for Step 2 (developing weights), and for Step 8 (distance measures) (Olson, 2004). Additionally, different conventions can be applied to define the FPIS and FNIS (Olson, 2004).

3. Multi-Choice Goal Programming

The MCGP is an analytical method devised to address decision-making of multi-criteria aspiration levels problems. Chang (2007) has proposed a new method namely multi-choice goal programming (MCGP) for multiple decision variables coefficients problems, which allows DMs to set multi-segment aspiration levels (MSAL) selection for each goal to avoid underestimation of decision-making. The proposed idea for solving the MCDM problem with MSAL is very different from GP using membership function to manage the MCDM problem with imprecise aspiration levels of the decision variables coefficients. In order to solve the problem of MSAL, the DMs attempt to set a goal to get the acceptable solutions in which DMs would interest to minimize the deviations between the achievements of goal and their aspiration levels of decision variable coefficients.

The study-comparison between MCGP and several methods by using Weighted GP, Minmax GP, Lexicographic GP methods and FGP shows that MCGP can extend the feasible set and find the optimal solutions closer to the target value. Whereas, the several methods compared only give the solutions within smaller feasible region far from the target value (Chang, 2007).

Chang (2008) has revised MCGP to reduce the extra binary variables used in the left-hand side. Following the idea of FGP model, a new idea of upper (G_i,max) and lower (G_i,min) bound of the ith aspiration level, y_i is introduced to the MCGP-achievement and y_i is the continuous variables, G_i,min ≤ y_i ≤ G_i,max (Chang,2008). Therefore, the MCGP can be resumed as the following two alternative types of revised MCGP-achievement functions:

Type 1: ''the more the better'' case:

$$\text{Max} \sum_{i=1}^{n}[w_i\,(d_i^+ + d_i^-) + \alpha(e_i^+ + e_i^-)] \quad (13)$$

$$\text{s.t. } f_i\,(X) - d_i^+ + d_i^- = y_i \;,\; i = 1,2, \ldots, n \quad (14)$$

$$y_i - e_i^+ + e_i^- = G_i,\text{max} \;,\; i = 1,2, \ldots, n \quad (15)$$

$$G_{i,min} \le y_i \le G_{i,max}$$

$$d_i^+,\; d_i^-,\; e_i^+,\; e_i^- \ge 0 \;,\; i = 1,2, \ldots, n$$

X ∈ F (F is a feasible set, X is unrestricted in sign)

where d_i^+ and d_i^- are the positive and negative deviation corresponding to the *i*-th goal $|f_i\,(X) - y_i|$. Then, e_i^+ and e_i^- are the positive and negative deviations corresponding to $|y_i - G_{i,max}|$; and α_i is the weight attached to the sum of the deviation of $|y_i - G_{i,max}|$. Other variables are defined as in MCGP.

Type 2: ''the less the better'' case:

$$\text{Min} \sum_{i=1}^{n}[w_i\,(d_i^+ + d_i^-) + \alpha(e_i^+ + e_i^-)] \quad (16)$$

$$\text{s.t. } f_i\,(X) - d_i^+ + d_i^- = y_i \;,\; i = 1,2, \ldots, n \quad (17)$$

$$y_i - e_i^+ + e_i^- = G_{i,min} \;,\; i = 1,2, \ldots, n \quad (18)$$

$$G_{i,min} \le y_i \le G_{i,max}$$

$$d_i^+,\; d_i^-,\; e_i^+,\; e_i^- \ge 0 \;,\; i = 1,2, \ldots, n$$

X ∈ F (F is a feasible set, X is unrestricted in sign)

where d_i^+ and d_i^- are the positive and negative deviation corresponding to the *i*-th goal $|f_i\,(X) - y_i|$. Then, e_i^+ and e_i^- are the positive and negative deviations corresponding to $|y_i - G_{i,min}|$; and α_i is the weight attached to the sum of the deviation of $|y_i - G_{i,min}|$. Other variables are defined as in MCGP.

4. Solution Methodology

The approach to solve the problem adopts Fuzzy TOPSIS and integrates with MCGP. It uses two phase solution, first phase will come up with finding the best supplier based on the criteria by using Fuzzy TOPSIS, and second phase will incorporate both the qualitative factors which assess suppliers respect to the criteria and the quantitative factors by using MCGP. By applying closeness coefficient as coefficient of an objective function in MCGP, the order allocation can be determined to select the best fit supplier with expecting least number of suppliers to achieve maximum efficiency. The steps of integrated Fuzzy TOPSIS and MCGP can be shown in figure 2 in terms of supplier selection.

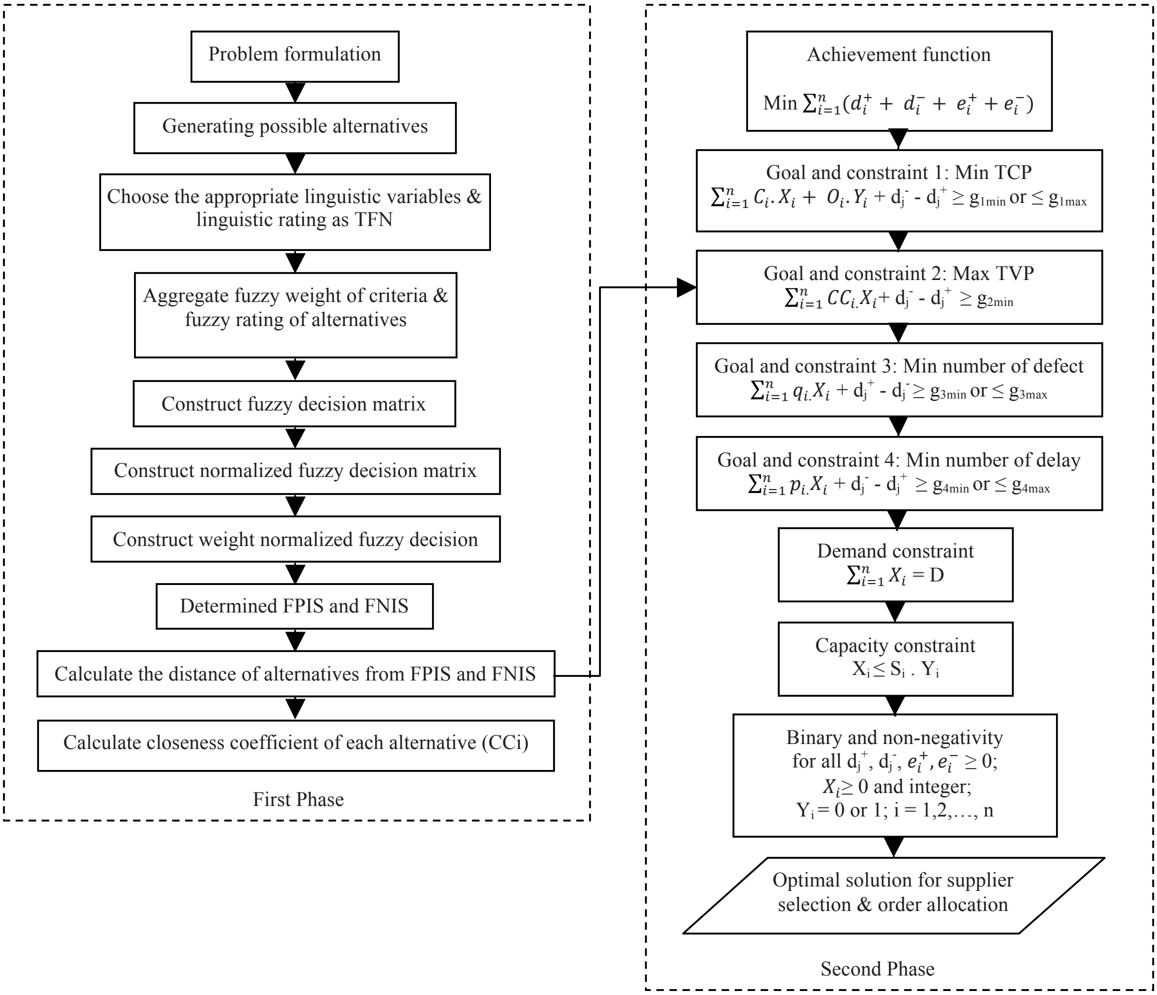

Figure 2. An integrated Fuzzy TOPSIS and MCGP steps for supplier selection problem

5. A Case Study

The paper intends to suggest the best suppliers for a stated owned company. The company produces several kinds of fertilizers such as urea, ZA, SP-36, PHONSKA, ZK and etc. One of the products of fertilizer "PHONSKA" needs to be supplied by one of the raw material namely white clay. The supplier selection is dealing with the multiple sourcing of white clay. Based on the literature reviews and experts' opinions, we finally collected 17 criteria of supplier selection. The criteria of supplier selection are defined as supply capacity (C1), production capacity (C2), response time (C3), production technology (C4), price (C5), warranty (C6), procedural compliance (C7), purchase transaction (C8), communication system (C9), quality (C10), completed shipping document (C11), quantity (C12), On time delivery (C13), financial position (C14), location (C15), reputation (C16), management and organization (C17). The hierarchy of criteria and alternatives is constructed as figure 3.

We proposed an integrated fuzzy TOPSIS and MCGP to gain the appropriate suppliers and determine order allocation of each appropriate supplier. The model will combine qualitative and quantitative criteria by integrating the closeness coefficient of each alternative obtained from fuzzy TOPSIS method to the MCGP model. In the MCGP model, there will be constructed four goal functions and one of the goal function which maximize the total value of purchasing is relating the closeness coefficient of each alternative in the model for making a comprehensive decision based on intangible in view of achieving a high efficiency.

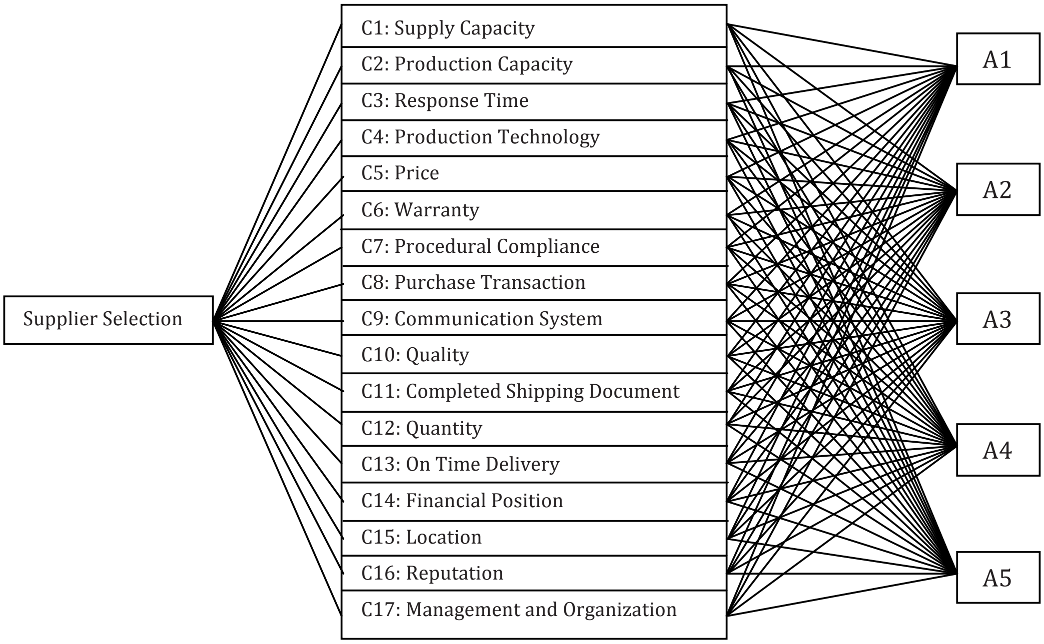

Figure 3. The hierarchical structure

Step 1, Generating feasible alternatives, determining the evaluation criteria, and setting a group of decision makers.

Based on the data collection, there are 5 alternatives, 17 evaluation criteria, and 2 decision makers. The generation of criteria is adopted from the Dickson's criteria (1996) which are evaluated by decision makers to match between the preferences and literatures.

Step 2, Choose the appropriate linguistic variables for the importance weight of the criteria and the linguistic variables for ratings of alternatives with respect to criteria as TFN.

The DMs choose linguistic variables for both the importance weight of the criteria and alternatives with respect to criteria in 7 scales because of ease to understand and apply. We define it as TFN which is shown in tables 2 and 3 (Chen, 2000).

Table 2. Linguistic variables for the importance weight of the criteria

Linguistic Variable	Corresponding Triangular Fuzzy Number
Very Low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium Low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium High (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1.0)
Very High (VH)	(0.9, 1.0, 1.0)

Table 3. Linguistic variables for the ratings

Linguistic Variable	Corresponding Triangular Fuzzy Number
Very Poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium Poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium Good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very Good (VG)	(9, 10, 10)

Step 3, Aggregate the weight of criteria to get the aggregated fuzzy weight of criterion, and obtain the aggregated fuzzy rating of alternative under criterion evaluated by expert.

Step 4, Construct the fuzzy decision matrix as shown in table 4.

Table 4. Fuzzy decision matrix

Weight	A1	A2	A3	A4	A5
C1 (0.2, 0.4, 0.6)	(6, 8, 9.5)	(4, 6, 8)	(2, 4, 6)	(3, 5, 7)	(2.5, 4, 6)
C2 (0.3, 0.5, 0.7)	(4, 6, 8)	(4, 6, 8)	(1.5, 3, 5)	(3, 5, 7)	(2, 4, 6)
C3 (0.5, 0.7, 0.9)	(5, 7, 8.5)	(4, 6, 8)	(3, 5, 7)	(3, 5, 7)	(2.5, 4, 6)
C4 (0.3, 0.5, 0.7)	(5,7,9)	(5, 7, 8.5)	(2.5, 4, 6)	(4, 6, 8)	(2.5, 4, 6)
C5 (0.5, 0.7, 0.9)	(2, 4, 6)	(2.5, 4, 6)	(6, 8, 9.5)	(1.5, 3, 5)	(4, 6, 8)
C6 (0.6, 0.8, 0.95)	(2.5, 4,6)	(1,3,5)	(5,7,9)	(4, 6, 8)	(3,5,7)
C7 (0.1, 0.3, 0.5)	2.5, 4,6)	(2, 4, 6)	(7, 9, 10)	(3,5,7)	(1,3,5)
C8 (0.1, 0.3, 0.5)	(5, 7, 9)	(3,5,7)	(4, 6, 8)	(2.5, 4, 6)	(2.5, 4, 6)
C9 (0.1, 0.3, 0.5)	(4, 6, 8)	(4, 6, 7.5)	(5, 7, 9)	(2, 4, 6)	(1, 2, 4)
C10 (0.8, 0.95, 1)	(2, 4, 6)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(2, 4, 6)
C11 (0.3, 0.5, 0.7)	(7, 9, 10)	(3,5,7)	(5, 7, 9)	(4, 6, 8)	(3,5,7)
C12 (0.4, 0.6, 0.8)	(4, 6, 7.5)	(2, 4, 6)	(4, 6, 8)	(1, 3, 5)	(3, 5, 7)
C13 (0.4, 0.6, 0.8)	(6, 8, 9.5)	(2, 4, 6)	(7, 9, 10)	(2, 4, 6)	(5, 7, 9)
C14 (0.8, 0.95, 1)	(7, 9, 10)	(5, 7, 9)	(3, 5, 7)	(5, 7, 8.5)	(4, 6, 8)
C15 (0.2, 0.4, 0.6)	(4, 6, 8)	(3,5,7)	(7, 9, 10)	(2.5, 4, 6)	(2, 4, 6)
C16 (0.9, 1, 1)	(6, 8, 9.5)	(5, 7, 8.5)	(4, 6, 7.5)	(5, 7, 9)	(5, 7, 9)
C17 (0.1, 0.3, 0.5)	(4, 6, 7.5)	(5, 7, 8.5)	(5, 7, 9)	(3,5,7)	(3,5,7)

Step 5, Construct a normalized fuzzy decision matrix as shown in table 5. The normalization is to transform different scales and units among various criteria into common measurable units to allow comparisons across the criteria.

Table 5. Normalized fuzzy decision matrix

	A1	A2	A3	A4	A5
C1	(0.63, 0.84, 1)	(0.42, 0.63, 0.84)	(0.21, 0.42, 0.63)	(0.32, 0.53, 0.74)	(0.26, 0.42, 0.63)
C2	(0.5, 0.75, 1)	(0.5, 0.75, 1)	(0.19, 0.38, 0.63)	(0.38, 0.63, 0.88)	(0.25, 0.5, 0.75)
C3	(0.59, 0.82, 1)	(0.47, 0.71, 0.94)	(0.35, 0.59, 0.82)	(0.35, 0.59, 0.82)	(0.29, 0.47, 0.71)
C4	(0.56, 0.78, 1)	(0.56, 0.78, 0.94)	(0.28, 0.44, 0.67)	(0.44, 0.67, 0.89)	(0.28, 0.44, 0.67)
C5	(0.21, 0.42, 0.63)	(0.26, 0.42, 0.63)	(0.63, 0.84, 1)	(0.16, 0.32, 0.52)	(0.42, 0.63, 0.84)
C6	(0.28, 0.44, 0.67)	(0.11, 0.33, 0.56)	(0.56, 0.78, 1)	(0.44 , 0.67, 0.89)	(0.33, 0.56, 0.78)
C7	(0.25, 0.4, 0.6)	(0.2, 0.4, 0.6)	(0.7, 0.9, 1)	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)
C8	(0.56, 0.78, 1)	(0.33, 0.56, 0.78)	(0.44, 0.67, 0.89)	(0.28, 0.44, 0.67)	(0.28, 0.44, 0.67)
C9	(0.44, 0.67, 0.89)	(0.44, 0.67, 0.83)	(0.56, 0.78, 1)	(0.22, 0.44, 0.67)	(0.11, 0.22, 0.44)
C10	(0.22, 0.44, 0.67)	(0.56, 0.78, 1)	(0.33, 0.56, 0.78)	(0.56, 0.78, 1)	(0.22, 0.44, 0.67)
C11	(0.7, 0.9, 1)	(0.3, 0.5, 0.7)	(0.5, 0.7, 0.9)	(0.4, 0.6, 0.8)	(0.3, 0.5, 0.7)
C12	(0.5, 0.75, 0.94)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.13, 0.38, 0.63)	(0.38, 0.63, 0.88)
C13	(0.6, 0.8, 0.95)	(0.2, 0.4, 0.6)	(0.7, 0.9, 1)	(0.2, 0.4, 0.6)	(0.5, 0.7, 0.9)
C14	(0.7, 0.9, 1)	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)	(0.5, 0.7, 0.85)	(0.4, 0.6, 0.8)
C15	(0.4, 0.6, 0.8)	(0.3, 0.5, 0.7)	(0.7, 0.9, 1)	(0.25, 0.4, 0.6)	(0.2, 0.4, 0.6)
C16	(0.63, 0.84, 1)	(0.53, 0.74, 0.89)	(0.42, 0.63, 0.79)	(0.53, 0.74, 0.95)	(0.53, 0.74, 0.95)
C17	(0.44, 0.67, 0.83)	(0.56, 0.78, 0.94)	(0.56, 0.78, 1)	(0.33, 0.56, 0.78)	(0.33, 0.56, 0.78)

Step 6, Construct the weighted normalized fuzzy decision matrix as shown in table 6.

Table 6. The weighted normalized fuzzy decision matrix

	A1	A2	A3	A4	A5
C1	(0.13, 0.34, 0.60)	(0.08, 0.25, 0.50)	(0.04, 0.17, 0.38)	(0.06, 0.21, 0.44)	(0.05, 0.17, 0.38)
C2	(0.15, 0.38, 0.70)	(0.15, 0.38, 0.70)	(0.06, 0.19, 0.44)	(0.11, 0.32, 0.62)	(0.08, 0.25, 0.53)
C3	(0.59, 0.57, 0.90)	(0.24, 0.50, 0.85)	(0.18, 0.41, 0.74)	(0.18, 0.41, 0.74)	(0.15, 0.33, 0.64)
C4	(0.17, 0.39, 0.70)	(0.17, 0.39, 0.66)	(0.08, 0.22, 0.47)	(0.13, 0.34, 0.62)	(0.08, 0.22, 0.47)
C5	(0.11, 0.29, 0.57)	(0.13, 0.29, 0.57)	(0.32, 0.59, 0.90)	(0.08, 0.22, 0.47)	(0.21, 0.44, 0.76)
C6	(0.17, 0.35, 0.64)	(0.07, 0.26, 0.53)	(0.34, 0.62, 0.95)	(0.26, 0.54, 0.85)	(0.20, 0.45, 0.74)
C7	(0.03, 0.12, 0.30)	(0.02, 0.12, 0.30)	(0.07, 0.27, 0.50)	(0.03, 0.15, 0.35)	(0.01, 0.09, 0.25)
C8	(0.06, 0.23, 0.50)	(0.03, 0.17, 0.39)	(0.04, 0.20, 0.45)	(0.03, 0.13, 0.34)	(0.03, 0.13, 0.34)
C9	(0.04, 0.20, 0.45)	(0.04, 0.20, 0.42)	(0.06, 0.23, 0.50)	(0.02, 0.13, 0.34)	(0.01, 0.07, 0.22)
C10	(0.18, 0.42, 0.67)	(0.45, 0.74, 1)	(0.26, 0.53, 0.78)	(0.45, 0.74, 1)	(0.18, 0.42, 0.67)
C11	(0.21, 0.45, 0.7)	(0.09, 0.25, 0.49)	(0.15, 0.35, 0.63)	(0.12, 0.30, 0.56)	(0.09, 0.25, 0.49)
C12	(0.20, 0.45, 0.75)	(0.10, 0.30, 0.60)	(0.20, 0.45, 0.8)	(0.05, 0.23, 0.50)	(0.15, 0.38, 0.70)
C13	(0.24, 0.48, 0.76)	(0.08, 0.24, 0.48)	(0.28, 0.54, 0.8)	(0.08, 0.24, 0.48)	(0.20, 0.42, 0.72)
C14	(0.56, 0.86, 1)	(0.40, 0.67, 0.90)	(0.24, 0.48, 0.70)	(0.40, 0.67, 0.85)	(0.32, 0.57, 0.80)
C15	(0.08, 0.24, 0.48)	(0.06, 0.20, 0.42)	(0.14, 0.36, 0.60)	(0.05, 0.16, 0.36)	(0.04, 0.16, 0.36)
C16	(0.57, 0.84, 1)	(0.48, 0.74, 0.89)	(0.38, 0.63, 0.79)	(0.48, 0.74, 0.95)	(0.48, 0.74, 0.95)
C17	(0.04, 0.20, 0.42)	(0.06, 0.23, 0.47)	(0.06, 0.23, 0.5)	(0.03, 0.17, 0.39)	(0.03, 0.06, 0.39)

Step 7, Determine the fuzzy positive-ideal solution S^+ (FPIS) and fuzzy negative-ideal solution S^- (FNIS) as follows:

S^+ = [(0.6, 0.6, 0.6), (0.7, 0.7, 0.7), (0.9, 0.9, 0.9), (0.7, 0.7, 0.7), (0.9, 0.9, 0.9), (0.95, 0.95, 0.95), (0.5, 0.5, 0.5), (0.5, 0.5, 0.5), (0.5, 0.5, 0.5), (1,1,1), (0.7, 0.7, 0.7), (0.8, 0.8, 0.8), (0.8, 0.8, 0.8), (1,1,1), (0.6, 0.6, 0.6), (1,1,1), (0.5, 0.5, 0.5)]

S^- = [(0.04, 0.04, 0.04), (0.06, 0.06, 0.06), (0.15, 0.15, 0.15), (0.08, 0.08, 0.08), (0.08, 0.08, 0.08), (0.07, 0.07, 0.07), (0.01, 0.01, 0.01), (0.03, 0.03, 0.03), (0.01, 0.01, 0.01), (0.18, 0.18, 0.18), (0.09, 0.09, 0.09), (0.05, 0.05, 0.05), (0.08, 0.08, 0.08), (0.24, 0.24, 0.24), (0.04, 0.04, 0.04), (0.38, 0.38, 0.38), (0.03, 0.03, 0.03)]

Step 8, Calculate the distance of each alternative from FPIS (d^+) and FNIS (d^-) with respect to each criterion as shown in tables 7 and 8.

Table 7. Distance between FPIS, FNIS and alternative ratings.

	FPIS					FNIS				
	A1	**A2**	**A3**	**A4**	**A5**	**A1**	**A2**	**A3**	**A4**	**A5**
C1	0.31	0.37	0.43	0.40	0.42	0.37	0.29	0.20	0.25	0.21
C2	0.37	0.37	0.50	0.41	0.45	0.42	0.42	0.23	0.36	0.29
C3	0.26	0.45	0.51	0.51	0.56	0.56	0.45	0.37	0.37	0.30
C4	0.35	0.36	0.47	0.39	0.47	0.40	0.38	0.31	0.35	0.31
C5	0.61	0.60	0.38	0.66	0.49	0.31	0.31	0.57	0.24	0.45
C6	0.60	0.69	0.40	0.47	0.53	0.37	0.29	0.62	0.54	0.45
C7	0.37	0.37	0.28	0.35	0.40	0.18	0.18	0.32	0.21	0.15
C8	0.29	0.34	0.30	0.36	0.36	0.30	0.22	0.26	0.19	0.19
C9	0.30	0.32	0.29	0.36	0.41	0.28	0.26	0.31	0.20	0.13
C10	0.61	0.35	0.52	0.35	0.61	0.32	0.59	0.40	0.59	0.32
C11	0.32	0.45	0.38	0.41	0.45	0.41	0.25	0.35	0.30	0.25
C12	0.40	0.51	0.40	0.57	0.45	0.47	0.35	0.49	0.28	0.42
C13	0.37	0.56	0.34	0.56	0.41	0.46	0.25	0.51	0.25	0.42
C14	0.27	0.40	0.56	0.40	0.48	0.68	0.46	0.33	0.44	0.38
C15	0.37	0.40	0.29	0.43	0.43	0.28	0.24	0.38	0.20	0.20
C16	0.26	0.34	0.43	0.34	0.34	0.46	0.37	0.28	0.39	0.39
C17	0.32	0.30	0.29	0.34	0.34	0.25	0.28	0.29	0.22	0.21

Table 8. The distance of each alternative d^+ and d^-

	d^+	d^-
A1	6.38	6.52
A2	7.18	5.59
A3	6.77	6.22
A4	7.31	5.38

Step 9, calculate the closeness coefficient (CC_i) and rank the order of alternatives according to the coefficient. The result is shown in table 9.

Table 9. Rank of alternatives according and its closeness coefficient

	CC_i	Rank
A1 (LH)	0.51	1
A2 (AK)	0.44	3
A3 (PCS)	0.48	2
A4 (KI)	0.43	4
A5 (SBT)	0.40	5

After the closeness coefficients (CC_i) of each alternative are obtained, we define MCGP model according to the goals considered which are as follows:

Goal 1: Minimize total cost of purchasing (TCP)

$$\text{Min } Z_1 = \sum_{i=1}^{n} C_i.X_i + O_i.Y_i \qquad , \quad i = 1,2,\ldots n$$

Based on the regulation, the head of procurement estimates to delimit the total cost of purchasing should not exceed 200.000.000,- and the most desirable is 190.000.000,-. Based on the record, the unit material cost for supplier A1, A2, A3, A4, and A5 respectively are 440.000,- , 465.000,- , 450.000,-, 550.000,-, 465.000,-. In addition, order cost will apply in order to procure material from each supplier in which the amount of cost per order is 850.000,-.

Goal 2: Maximize total value of purchasing (TVP)

$$\text{Max } Z_2 = \sum_{i=1}^{n} CC_i.X_i \qquad , \quad i = 1,2,\ldots n$$

Goal 3: Minimize total amount due to delivery defects (disadvantages in materials)

$$\text{Min } Z_3 = \sum_{i=1}^{n} q_i.X_i \qquad , \quad i = 1,2,\ldots n$$

By considering the historical experience in delivery defects rate of supplier, the delivery defects rate is set between 2% and 3%. The database records that defects rate of supplier A1, A2, A3, A4, and A5 are 4 %, 2%, 3%, 2%, 3% respectively.

Goal 4: Minimize total amount due to delivery delay number

$$\text{Min } Z_4 = \sum_{i=1}^{n} p_i.X_i \qquad , \quad i = 1,2,\ldots n$$

The maximum rate of delivery delay number is between 5%-10%. The delay sometimes occurs in order shipping in terms of the quantity order due to unavoidable internal condition of supplier and the approximate rate are 0, 15%, 5%, 10%, and 5% respectively for supplier A1, A2, A3, A4, and A5.

There are several constraints that need to be taken into account:

1. Total demand
   $\sum_{i=1}^{n} X_i = D$; $i = 1,2,\ldots n$
   The average monthly demand of white clay is 415 tons
2. Supplier capacity
   $X_i \le S_i \cdot Y_i$; $i = 1,2,\ldots n$
   Each supplier has a different ability of production in which high number of production impresses high capacity of supply. The capacity of supplier A1, A2, A3, A4, and A5 are 100 tons, 400 tons, 600 tons, 160 tons, 100 tons respectively.
3. Non-negativity and binary constraint
   $X_i \ge 0$ and integer ; $i = 1,2,\ldots n$
   $Y_i = 0$ or 1 ; $i = 1,2,\ldots n$

The following notations are defined to formulate the model:

Indices:

i	= 1,2,…, n	index of suppliers;
j	= 1,2,…, J	index of deviation corresponding to the goals
t	= 1,2,…., T	index of deviation corresponding to the multi-criteria

Parameters:

C_i	= Cost of material of supplier –i
O_i	= Order cost of supplier –i
CC_i	= Coefficient correlation of supplier –i
V	= Value of purchasing
d_j^+, d_j^-	= Maximum and minimum deviation of goal –j
e_t^+, e_t^-	= Maximum and minimum deviation of $\lvert y_t - G_{i,max/min} \rvert$
q_i	= Rate of delivery defects of supplier –i
p_i	= Rate of delivery delay number of supplier –i
Q	= Maximum acceptable rate of delivery defects
P	= Maximum acceptable rate of delivery delay number
D	= Demand
S_i	= Capacity of supplier –i

Decision variables:

X_i = Order quantity of supplier –i

Y_i = *Binary integer* $\begin{cases} 1 - \text{If the order is supplied by supplier} -i \\ 0 - \text{otherwise} \end{cases}$

Using MCGP model, this problem can be formulated as follows:

$$\text{Min } Z = d_1^+ + d_1^- + d_2^+ + d_2^- + d_3^+ + d_3^- + d_4^+ + d_4^- + e_1^+ + e_1^- + e_2^+ + e_2^- + e_3^+ + e_3^-$$

s.t

$\Rightarrow \sum_{i=1}^{n} C_i.X_i + O_i.Y_i + d_j^- - d_j^+ = y_t$

$440000.X_1 + 850000.Y_1 + 465000.X_2 + 850000.Y_2 + 450000.X_3 + 850000.Y_3 + 550000.X_4 + 850000.Y_4 + 465000.X_5 + 850000.Y_5 + d_1^- - d_1^+ = y_1$

- $y_1 - e_1^+ + e_1^- = 190000000$
- $1900000000 \le y_1 \le 200000000$

$\Rightarrow \sum_{i=1}^{n} CC_i.X_i + d_j^- - d_j^+ \ge V$

$0.51.\ X_1 + 0.44.\ X_2 + 0.48.\ X_3 + 0.43.\ X_4 + 0.40.\ X_5 + d_2^- - d_2^+ \ge 195$

$\Rightarrow \sum_{i=1}^{n} q_i.X_i + d_j^+ - d_j^- = y_t$

$0.04.\ X_1 + 0.02.\ X_2 + 0.03.\ X_3 + 0.02.\ X_4 + 0.03.\ X_5 + d_3^- - d_3^+ = y_2$

- $y_t - e_t^+ + e_t^- = Q_{min}.D$
  $y_2 - e_2^+ + e_2^- = 0{,}02.\ 415$
- $Q_{min}.D \le y_2 \le Q_{max}.D$
  $0{,}02.415 \le y_2 \le 0{,}03.415$

$\Rightarrow \sum_{i=1}^{n} p_i.X_i + d_j^- - d_j^+ = y_t$

$0.\ X_1 + 0.15.\ X_2 + 0.05\ X_3 + 0.1.\ X_4 + 0.05.\ X_5 + d_4^- - d_4^+ = y_3$

- $y_t – e_t^+ + e_t^- = P_{min}.D$
  $y_3 – e_3^+ + e_3^- = 0{,}05.\ 415$
- $P_{min}.D \le y_3 \le P_{max}.D$
  $0{,}05.415 \le y_3 \le 0{,}1.415$

$\Rightarrow \sum_{i=1}^{n} X_i = D$
$X_1 + X_2 + X_3 + X_4 + X_5 = 415$

$\Rightarrow X_i \le S_i\ .\ Y_i$
$X_1 \le 75.\ Y_1;\ X_2 \le 150.\ Y_2;\ X_3 \le 200.\ Y_3;\ X_4 \le 120.\ Y_4;\ X_5 \le 80.\ Y_5$

$\Rightarrow X_1, X_2, X_3, X_4, X_5 \ge 0$ and integer
$\Rightarrow Y_1, Y_2, Y_3, Y_4, Y_5 = 0$ or 1
$\Rightarrow d_1^+ , d_2^+, d_3^+, d_4^+, d_1^- , d_2^-, d_3^-, d_4^- \ge 0$
$\Rightarrow e_1^+, e_2^+, e_3^+, e_1^-, e_2^-, e_3^- \ge 0$

The model is solved by using LINGO 8 software. The optimal solution is obtained as: X_1 (LH) = 75, X_2 (AK) = 140, X_3 (PCS) = 200, X_4 (KI) = 0, X_5 (SBT) = 0. The achievement of each goal is satisfied by the total amount for goal 1, the total cost of purchasing is 190.650.000; goal 2, the total value of purchasing is 195.85 units; goal 3, total amount due to delivery defects is 11.8 ton; goal 4, total amount due to delivery delay number is 31 ton.

6. Conclusion

This paper presents a hybrid method for supplier selection and allocation order. The model integrates Fuzzy TOPSIS and MCGP to avoid the thoughtlessness in decision making because the judgment of decision making likely contains uncertainty and vagueness. The Fuzzy TOPSIS is applied to make a judgment about the intangible criteria of suppliers so it can be considered as parameters to measure the eligibility of each supplier. Based on the intangible criteria, the appropriate supplier can be represented by the best ranking associating with the closeness coefficient. The supplier who has the top ranking is definitely most considered. But in this case, the supplier selection is dealing with the multiple-sourcing because of the inability of each supplier to satisfy all the needs of the buyer. Hence, The MCGP is intended to perform the integration of intangible and tangible criteria with multi-choice aspiration levels. It allows for the vague aspirations of DMs to set multiple aspiration levels for supplier selection problems. By relating the closeness coefficient which is derived from fuzzy TOPSIS to the MCGP model with respect to the goal of maximum total value of purchasing, we can obtain the advantages corresponding criteria of supplier if we hold a business with the selected supplier.

The case study is a multiple-sourcing problem which is confronted by conflicting fitness between suppliers in which the one is better in quality but poor in capacity and the other one is conversely. Therefore, by taking into account the capacity and demand constraint to obtain the best suppliers, the MCGP model is constructed to determine the best suppliers and allocation order in reaching a comprehensive decision making with respect to the goals. In addition, multi-choice aspiration levels exist in this case. It was evident that the results of fuzzy TOPSIS only yield the decision making without considering the capacity. The final result shows that the powerful integrated methods can explore multi-criteria to be taken into account in determining order quantity.

The result can give a suggestion to DMs in the company when decide to select a supplier. The competitive advantages such as hold a good cooperation and conduct long term relations are achieved. It impacts the strength of supply chain since consolidation is easily afforded between supplier and company. The company is able to efficiently fulfill the continuity of supply of white clay.

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References

Asamoah, D., Annan, J., & Nyarko, S. (2012). AHP approach for supplier evaluation and selection in a pharmaceutical manufacturing firm in Ghana. *International Journal of Business and Management*, 7 (10), 49-62.

Chan, F.T.S., & Chan H.K. (2004). Development of the supplier selection model- A case study in the advanced technology industry. *Proceeding of the institution of Mechanical Engineers part B- J. Eng. Manufacture*. 21 (12), 1807-1824.

Chan, F.T.S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *OMEGA – Int. J. Manage. Sci*., 35 (4), 417-431.

Chang, C.T. (2004). On the mixed binary goal programming problems, *Applied Mathematics and Computation,* 159, 759-768.

Chang, C.T. (2007). Multi-choice goal programming. *Omega, The International Journal of Management Science,* 35, 389-396.

Chen, C.T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems,* 114, 1-9

Chou, S.Y., & Chang, Y.H. (2008). A decision support system for supplier selection based on a strategy-aligned fuzzy SMART approach. *Expert Syst. Appl*., 34 (4), 2241-2253.

Dahel, N.E. (2003). Vendor selection and order quantity allocation in volume discount environments. *Supply Chain Management: Int. J*., 8(4), 335-342.

Dickson, G.W. (1966). An analysis of vendor selection system and decisions. *J. Purchas*., 2(1), 28-41.

Ghodsypour, S.H., & O'Brin, C. (1998). A decision support system for supplier selection using an integrated analytic hierarchy process and linear programming. *Int. J. Product. Econ*., 56-57(1-3), 199-212.

Ho, W., Xu, X., & Dey, P.K. (2010). Multi-criteria decision making approach for supplier evaluation and selection: A literature review. *Eur. J. Oper. Res*., 202, 16-24.

Huang, S., & Keska, H. (2007). Comprehensive and configurable metrics for supplier selection. *Int. J. Product. Econ*., 105(2), 510-523.

Jadidi., O., Hong, T.S., Firouzi, F., Yusuff, R.M., & Zulkifli, N. (2008). TOPSIS and fuzzy multi-objective model integration for supplier selection problem. *Journal of Achievements in Materials and Manufacturing Engineering*: 31 (2), 762-769.

Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. *Logistics Inform. Manage*., 16, 382-394.

Karpak, B., Rammohan, K.G., & Kasuganti, R. 2001. Purchasing materials in the supply chain: managing a multi-objective task. *European Journal of Purchasing & Supply Management*, 7: 209-216.

Krajewsld, L.J., & Ritzman, L.P. (1996). *Operations management strategy and analysis*. London: Addison-Wesley Publishing CO.

Kull, T.J. & Talluri, S. 2008. A supply risk reduction model using integrated multicriteria Decision Making. *IEEE Transactions on Engineering Management*, 55(3), 409-419.

Kumar, J & Roy, N. (2010). A hybrid method for vendor selection using neural network. *International Journal of Computer Applications*, 11 (12), 35-40.

Kwong, C.K., Ip, W.H., & Chan, J.W.K. (2002). Combining scoring method and fuzzy expert systems approach to supplier assessment: A case study. *Integrated Manufacturing Systems*. 13, 512-519.

Liao, C.N. & Kao, H.P. (2011). An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management. *Expert Systems with Applications*, 38, 10803-10811.

Liu, F.H. & Hai, H.L. (2005). The voting analytic hierarchy process method for selecting supplier. *International Journal of Production Economics,* 97(3), 308-317.

Mehralian, G., Gatari, A.R., Morakabati, M., & Vatanpour, H. (2012). Developing a suitable model for supplier selection based on supply chain risks: an empirical study from Iranian Pharmaceutical Companies. *Iranian Journal of Pharmaceutical Research*, 11 (1), 209-219

Narasimhan, R., Talluri, S., & Mahapatra, S.M. (2006). Multiproduct, multi criteria model for supplier selection with product life-cycle considerations. *Decision Sciences*, 37(4), 577-603.

Olson, D.L. (2004). Comparison of weights in TOPSIS Models. *Mathematical and Computer Modelling*, 40, 721-727.

Sarkis, J. & Talluri, S. (2002). A Model for Strategic Supplier Selection. *The Journal of Supply Chain Management*, 38(1), 18-28.

Setak, M., Sharifi, S., & Almohammadin, A. Supplier selection and order allocation models in supply chain management: a review. *World Applied Sciences Journal*, 18 (1), 55-72

Shahanaghi, K. & Yazdian, S. A. (2009). Vendor selection using a new fuzzy group TOPSIS approach. *Journal of Uncertain Systems*, 3 (3), 221-231.

Songhori, J.M., Tavana, M., Azadeh, A., & Khakbaz, M.H. (2011). A supplier selection and order allocation model with multiple transportation alternatives. *Int. J. Adv. Manuf. Technol.,* 52, 365-376

Talluri, S., & Narasimhan, R. (2005). A note on a methodology for supply base optimization. *IEEE transactions on management*, 52(1), 130-139.

Talluri, S., Vickery, S.K., & Narayanan, S. (2008). Optimization models for buyer-supplier negotiations. *International Journal of Physical Distribution and Logistics Management*, 38(7), 551-561.

Wang, G., Huang, S.H., & Dismukes, J.P. (2004). Product-driven supply chain selection using integrated multi-criteriadecision-making methodology, *Int. J. Production Economics*, 91, 1-15.

Wang, Y. M., & Elhag, T. M. S. (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. *Expert Systems with Applications*, 31, 309–319.

Weber, C.A. (1996). A data envelopment analysis approach to measuring vendor performance. *Supply Chain Management*, 1(1), 28-39.

Wu, T., Shunk, D., Blackhurst, J., & Appalla, R. (2007). A methodology for supplier evaluation and selection in a supplier-based manufacturing environment. *Int. J. Manufacturing Technology and Management*, 11(2), 174- 192.
Xia, W., & Wu, Z. (2007). Supplier selection with multiple criteria in volume discount Environments. *Omega*, 35, 494-504.