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Supplier Evaluation: Fuzzy Linguistic Preference Relations and Fuzzy C-Means Approach

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Abstract — One of the important areas of supply chain management is supplier evaluation which takes place in the purchasing department. Due to the complexity and multiple criteria involved, the problem of supplier evaluation has always received a great deal of attention among managers and researchers. In this study, the combination of fuzzy linguistic preference relations and fuzzy c-means (FCM) is proposed as a supplier evaluation method. The process begins by defining suppliers' criteria. Then, in order to estimate the weights of each criterion, the integration of analytic hierarchy process (AHP) and fuzzy linguistic preference relations is used. In the last step, fuzzy c-means clustering is applied to categorize the performance of suppliers. A numerical example composed of 21 suppliers and 15 criteria is studied, and the results show that the proposed methodology is suitable for supplier evaluation since the number of pair-wise comparison is reduced. In addition, it clusters all the suppliers with respect to their fuzzy similarity degrees.

Keywords — Supply chain management (SCM), Analytic hierarchy process (AHP), Fuzzy set, Fuzzy linguistic preference relations (LinPreRa), Fuzzy c-means (FCM)

1. INTRODUCTION

In supply chain management process (SCM), a series of actions need to take place in order for the firms to achieve their final goal, which is the dispersion of their products to the marketplace at the right time, right price, and right place. These actions include obtaining raw materials, transforming the raw materials into intermediate and finished goods, and finally distributing them to end consumers (Simchi-Levi et al. 2000, Si, et al. 2007). For companies desiring to be successful, the first step is to select and evaluate their suppliers (Gencer et al. 2007). Supplier selection is the process by which suppliers are reviewed, evaluated, and chosen to become part of the company's supply chain (Guneri et al. 2009).The performance and characteristics of suppliers in firms are so important that if not managed well, can bring profitability and reputation damage in its train(Araz et al. 2007). As a result, deciding how to manage suppliers is one of the principle decisions an enterprise should make. One of the main goals of supplier evaluation is to attain long term buyer-supplier relationship (Kang et al. 2010).

Supplier selection and evaluation has received considerable attention in the literature. Many research studies have been conducted to identify supplier criteria, and it was observed that hundreds of them have been proposed. The most popular ones are quality, delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment (Jain et al. 2014).In a very recent study, Ho et al. (2010) reviewed the literature related to supplier evaluation and selection models. Accordingly, the methods used for supplier selection can be categorized as linear weighting models like analytic hierarchy process (AHP), interpretive structural modeling (ISM), fuzzy set theory (FST); Total cost of ownership models; mathematical programming models such as linear programming (LP), mixed integer programming, goal programming, data envelopment analysis (DEA); statistical/probabilistic models and artificial intelligence models like case-based reasoning (CBR), genetic algorithm (GA), neural network(NN), expert systems (EX).

Due to the complexity of the problem, many researchers have focused on the integration of the above mentioned techniques. For example, Ferreira et al. (2012) proposed a method based on the integration of influence diagram and fuzzy logic to rank and evaluate suppliers. Sanayei et al. (2010) usedgroup decision-making process for supplier selection with VIKOR under fuzzy environment. Celebi and Bayraktar (2008) proposed a supplier evaluation method which integrates

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ANN and DEA. Guo et al. (2009) proposed a new support vector machine combined with decision tree to solve problems on supplier selection including feature selection and classification. Golmohammadi et al. (2009) presented a decision-making model to select suppliers using Neural Networks, while the genetic algorithm was applied to generate weights and network architecture. Amin et al. (2011) formulated fuzzy SWOT analysis and fuzzy linear programming model for supplier selection and order allocation. Chen et al. (2011) proposed an integrated model by combining K-means clustering, feature selection and the decision tree method into a single evaluation model to assess the performance of suppliers and simultaneously tackles the abovementioned shortcomings.

Although, all of the proposed supplier selection and evaluation models have useful principles, the majority of them neglect supplier clustering which can represent each supplier based on their similarity degree. As we have used AHP and clustering methodologies for supplier evaluation, our review of the literature is mostly related to this method and similar approaches. Some examples related to AHP and clustering are given as follows. Ghodsypour and O'Brien (1998) proposed an integration of an AHP and linear programming to consider both tangible and intangible factors in choosing the best suppliers. Kull and Talluri (2008) proposed a decision tool for supplier selection in the presence of risk measures and product life cycle, integrating AHP and goal programming. Razmi et al. (2009) developed a fuzzy analytic network process model to evaluate the potential suppliers and select the best one with respect to the vendor important factors, such as price, quality, finish time, company's rank, company's antecedents and company's economic status. Lee (2009) proposed a method that integrates fuzzy logic and AHP by taking opportunities, benefits, cost, and risk criteria into account. Ha and Krishnan (2008) developed a hybrid method, incorporating AHP, DEA, and ANN into the evaluation process. Mehdizadeh(2009) proposed a hybrid algorithm that combines FCM and particle swarm optimization (PSO) in order to cluster suppliers in fuzzy environment. Azadnia et al. (2011) used FCM to cluster suppliers into groups, and then they employed Elimination and Choice Expressing Reality (ELECTRE) to rank the suppliers. Khaleie et al. (2012) proposed a clustering method based on intuitionistic fuzzy value (IFS). In practice, decision making in supplier selection problem includes a high degree of fuzziness and uncertainties. Fuzzy set theory is one of the effective tools to handle uncertainty and vagueness.

This paper contributes to the supplier evaluation problem by presenting a novel approach that combines fuzzy linguistic Preference Relations based AHP and fuzzy c-means clustering. AHP is used to find the weights of risk criteria and the advantage of fuzzy linguistic preference relations(Fuzzy LinPreRa) is that the number of pair-wise comparison is reduced and also the consistency in fuzzy AHP method is improved. Fuzzy clustering is then used to compute the membership degrees of each supplier to all the clusters and based on that it categorizes suppliers to distinct groups.

The organization of this paper is as follows: Section 2 presents a description of the proposed method; Section 3 provides brief theoretical knowledge on Fuzzy Sets, Fuzzy linguistic Preference Relations (Fuzzy LinPreRa), and Fuzzy c-means (FCM); Section 4 applies the proposed methodology to a real case. The final section discusses the findings and also leaves a space for future research.

2. METHODOLOGY

This section describes the steps used in our methodology for assessing suppliers. In the first step, the decision criteria and their attributes need to be recognized. This paper uses the potential supply risk sources which have been extracted from previous research works by Kull and Talluri(2008). These risk sources are known as risk criteria $\left(C_1,\cdots,C_n\right)$ of the organization and a brief description of them are listed in Table 1. Then, in order to estimate the weights of each criterion $\left(w_1,\cdots,w_n\right)$, fuzzy linguistic preference relations based AHP is used. In this step, the decision makers $\left(DM_1,\cdots,DM_d\right)$ are asked to rate each criterion. Once, the criteria are rated, a decision maker is asked to assign scores to suppliers based on each criterion $\left(a_{i1},\cdots,a_{in}\right)$. The performance of each supplier in regard to each criterion is obtained using Eq. (1).

$$P_i = w_n a_{in} \tag{1}$$

Finally, to analyze the overall risk for each supplier, fuzzy c-means (FCM) algorithm which helps in categorizing suppliers based on their membership function is used. Fig. 1 also depicts an overview of the proposed model.

3. BASIC DEFINITIONS

In this section, we introduce some definitions and notations pertinent to our proposed methodology.

3.1 Fuzzy Set Theory

Most of the phenomena we experience in daily life are imprecise or ambiguous by nature. Zadeh(1965) introduced fuzzy set theory to overcome the uncertainty and vagueness. Since this paper uses triangular fuzzy number (TFN), the following definition is presented (Laarhoven et al. 1983):

A fuzzy number N on R is defined to be a TFN if its membership function $\mu_{\tilde{A}}(x): \mathbb{R} \rightarrow [0,1]$ is:

$$\mu_{\tilde{A}}(x) = \begin{cases} (x-l)/(m-l) & l \leq x \leq m \\ (u-x)/(u-m) & m \leq x \leq u \\ 0 & otherwise \end{cases} \tag{2}$$

where l and u are the lower and upper bounds of $\tilde{A}$ respectively, m is the median value.

Table 1. Supply base risks(Kull et al. 2008)

Risk Sources	Sub-Risks	Description
Delivery Failure	Capacity (C_1)	Supplier is near or at full capacity
	Material Availability (C_2)	Supplier's sources for raw material are unreliable
	Cycle Time (C_3)	Supplier has unreliable cycle time
	Logistics (C_4)	The logistics infrastructure from supplier is unreliable
	Geographical Location (C_5)	Supplier is prone to natural/political disaster
Cost Failure	Cost Management (C_6)	Supplier has poor cost management skills
	Market Strength (C_7)	Supplier has power in the marketplace to dictate pricing or is powerless to manage prices
Quality Failure	Legal Standards (C_8)	Supplier is unaware or unconcerned with legal or environmental standards
	Quality System (C_9)	Supplier's quality control methods are substandard
Flexibility Failure	R&D (C_{10})	Supplier has poor product development method
	Flexibility (C_{11})	Supplier has processes which do not allow significant changes in volume
	Information (C_{12})	Supplier's information systems are outdated or unreliable
Confidence Failure	Market Characteristics (C_{13})	The market in which the supplier operates is volatile
	Product Type (C_{14})	The supplier may not be able to handle the complexity of the product
	Relationship (C_{15})	The relations with the supplier are strained or difficult to manage

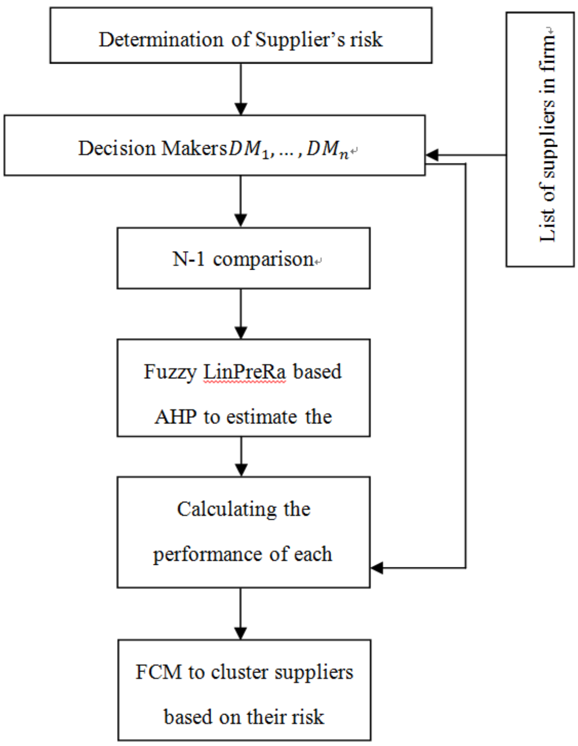

Figure 1. Flowchart of suppliers risk monitoring

The operational laws of two TFNs $A_1 = (l_1, m_1, u_1)$ and $A_2 = (l_2, m_2, u_2)$ are as follows:

Fuzzy number addition $\oplus$

$$\tilde{A}_1 \oplus \tilde{A}_2 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) \cong (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (3)$$

Fuzzy number multiplication $\otimes$

$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) \cong (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \quad (4)$$

Fuzzy number division (/)

$$\tilde{A}_1 (/) \tilde{A}_2 = (l_1, m_1, u_1)(/)(l_2, m_2, u_2) \cong \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right) \quad (5)$$

3.2 Fuzzy linguistic preference relations

AHP was designed to solve complex problems involving multiple criteria by Saaty (1980). It helps decision makers specify their preferences using a linguistic scale. This scale can be very useful in helping a group or an individual make a fuzzy decision.Fuzzy AHP is the extension of the conventional AHP, which can solve imprecise hierarchical problems (Laarhoven et al. 1983). In fuzzy AHP, a comparison matrix $\widetilde{P}$ needs to be constructed in which each element $\tilde{p}_{ij}$ shows the preference of the i^{th} criterion over j^{th} criterion.

$$\tilde{P} = \begin{bmatrix} \tilde{p}_{11} & \cdots & \tilde{p}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{p}_{n1} & \cdots & \tilde{p}_{nn} \end{bmatrix}$$

The main drawback to use fuzzy method is that ensuring consistency in pair-wise comparison is difficult and it requires $\frac{n(n-1)}{2}$ judgements for a level with *n* number of criteria (Wang et al. 2008). In order to alleviate this problem, Wang and Chen (2008) have developed fuzzy linguistic preference relations which reduces the number of pair-wise comparison to $n-1$ and results in consistent fuzzy ranking. They proved the following statements to ensure the consistency of a fuzzy positive reciprocal matrix:

Proposition 1: For a fuzzy reciprocal linguistic preference relation, $\widetilde{P} = (\tilde{p}_{ij})$ with $\tilde{p}_{ij} \in [0,1]$; verifies the additive reciprocal, then, the following statements are equivalent.

$$P_{ij}^{L} + P_{ji}^{R} = 1 \quad (6)$$

$$P_{ij}^{M} + P_{ji}^{M} = 1 \quad (7)$$

$$P_{ij}^{R} + P_{ji}^{L} = 1 \quad (8)$$

Proof: See(Wang et al. 2008).

Proposition 2: For a reciprocal fuzzy linguistic preference relation $\widetilde{P} = \widetilde{P}_{ij} = (p_{ij}^{L}, p_{ij}^{M}, p_{ij}^{R})$ to be consistent, verifies the additive consistency, then, the following statements must be equivalent.

$$P_{ij}^{L} + P_{ik}^{L} + P_{ki}^{R} = \frac{3}{2} \ \forall i < j < k \quad (9)$$

$$P_{ij}^{M} + P_{jk}^{M} + P_{ki}^{M} = \frac{3}{2} \ \forall i < j < k \quad (10)$$

$$P_{ij}^{R} + P_{jk}^{R} + P_{ki}^{L} = \frac{3}{2} \ \forall i < j < k \quad (11)$$

$$P_{i(i+1)}^{L} + P_{(i+1)(1+2)}^{L} + \ldots + P_{(j-1)j}^{L} + P_{ji}^{R} = \frac{j-i+1}{2} \forall i < j \quad (12)$$

$$P^M_{i(i+1)} + P^M_{(i+1)(i+2)} + \ldots + P^M_{(j-1)j} + P^M_{ji} = \frac{j-i+1}{2} \forall i < j \tag{13}$$

$$P^R_{i(i+1)} + P^R_{(i+1)(i+2)} + \ldots + P^R_{(j-1)j} + P^L_{ji} = \frac{j-i+1}{2} \forall i < j \tag{14}$$

Proof: See (Wang et al. 2008).

3.3 Fuzzy c-means

Clustering techniques attempt to find grouping of the objects such that objects in a group are similar to each other and dissimilar to objects in other groups. The primary purpose of clustering is to find high-quality clusters with an increase in intra-cluster similarity and a decrease in inter-cluster similarity. Clustering is an unsupervised learning task and has been widely used in several domains such as machine learning (Alpaydin 2004), pattern recognition (Webb 2002), and data mining (Tan et al. 2005).

In the fuzzy clustering literature, fuzzy c-means (FCM) algorithm, first developed by Dunn(1973) and further improved by Bezdek(1981), is by far the most popular approach used in different areas. Unlike hard clustering, in which the clusters are mutually exclusive, in FCM, each data object belongs to more than one cluster. To put it another way, each data object can belong to several groups with the degree specified by membership grades between 0 and 1. Based on a defined similarity measures, data objects that are close to each other will be grouped in one cluster. The primary goal of FCM is to minimize the following objective function:

$$F\left(U, c\right) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} \left\| x_j - c_i \right\|^2 \tag{15}$$

where $U_{c\times n}$ is the membership matrix, c_i is the cluster centre of the fuzzy group i, μ_{ij} is between 0 and 1, $\|*\|$ is the Euclidean norm expressing the distance between ith cluster centre and jth data object, and m is the weighting exponent which must be greater than one $m > 1$.

Fuzzy clustering is done through an iterative optimization of the objective function in Eq. (15) with the update of μ_{ij} and c_i as follows:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - c_i \right\|}{\left\| x_j - c_k \right\|} \right)^{\frac{2}{m-1}}} \tag{16}$$

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{17}$$

In this method, there is an important constraint that must be imposed in the beginning of the algorithm, that is, the sum of the membership degrees of each data object to all clusters must be equal to one:

$$\sum_{i=1}^{c} \mu_{ij} = 1, \qquad j \in \left\{1, \cdots, c\right\} \tag{18}$$

A step by step procedure of the FCM algorithm is as follows:

FCM Algorithm:

Step 1: Set $m > 1$; $2 < c < n-1$; $\varepsilon > 0$; and choose an initial fuzzy c-partition matrix U^0.

Step 2: Calculate the fuzzy cluster centroid c_i for $i = 1, \cdots, c$ using Eq. (17).

Step 3: Apply Eq. (16) to update μ_{ij}.

Step 4: If $f(U, c) \le \varepsilon$, halt; otherwise go to step 2.

4. EXPERIMENTAL RESULTS

In order to examine the proposed method, the suppliers' data information is gathered from a cement company named ShoaeBetonShargh. To construct the comparison matrix $\widetilde{P}$, fifteen risk criteria were selected (Table 1), and four decision makers $DM = \{1, \cdots, d\}$ were asked to rate the importance of each risk criterion based on their impacts on the company. A decision maker is also asked to rate the suppliers based on their risk impact (Table 7).

Since in this paper, fuzzy Linguistic Preference Relations (LinPreRa) is applied, fuzzy linguistic assessment variables shown in fig. 2 and Table 2 are used. Therefore, the decision makers only required $n-1$ pair-wise comparisons to fill the matrix (Tables 3-6). After making the comparison by each decision maker, the aggregation of the four decision makers' opinion is first obtained using Eq. (19). Then, the rest of the cells of the matrix $\widetilde{P}$ are completed using Eqs. ((6)-(14)). It is worth mentioning that each index of the matrix $\widetilde{P}$ has three elements and they are shown as P^L, P^M and P^R, therefore; for better visibility, P^L, P^M and P^R are shown in three separate tables (8-10) respectively.

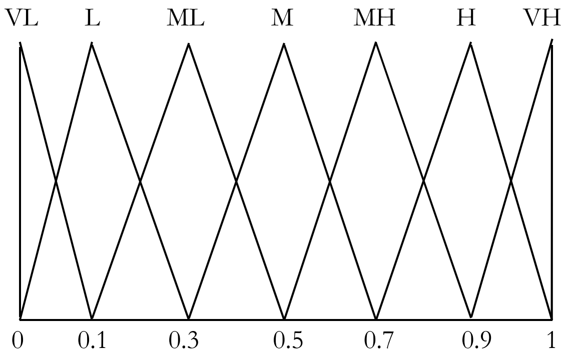

Figure 2. Fuzzy linguistic assessment variables

Table 2. Fuzzy Pair-wise Comparison of Risk Criteria

Linguistic Variables	Triangular Fuzzy Numbers
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)
Very High (VH)	(0.9, 1, 1)

$$\tilde{P}_{ij} = \frac{\sum_{k=1}^{d} \tilde{P}_{ij}}{d} \tag{19}$$

After obtaining the elements of the matrix $\widetilde{P}$, some may be in the range $[-c, 1+c]$, instead of $[0,1]$. As a result, a transformation function is required so as to preserve reciprocity and additive consistency (Wang et al. 2008). Eqs. ((20)-(22)) are used to do the transformation function. Tables (11-13) show the result of the transformation matrix for P^L, P^M and P^R respectively.

$$f\left(X^L\right) = \frac{X^L + c}{1+2c} \tag{20}$$

$$f\left(X^M\right) = \frac{X^M + c}{1+2c} \tag{21}$$

$$f\left(X^R\right) = \frac{X^R + c}{1+2c} \tag{22}$$

The weights of the criteria are then calculated using Eq. (23).

$$\tilde{w}_i = \frac{\tilde{g}_i}{\tilde{g}_1 \oplus \cdots \oplus \tilde{g}_n} \tag{23}$$

where $\tilde{g}_i$ is the mean of fuzzy comparison value of criterion i to every other criteria in the i_{th} row.

$$\tilde{g}_i = \frac{1}{n}\left[\tilde{p}_{i1} \oplus \cdots \oplus \tilde{p}_{in}\right] \tag{24}$$

Fig. 3 presents the defuzzified weight of each criterion. Using Eq. (1), the performance of suppliers based on the risk criteria is calculated. By applying FCM to the result of the previous step, suppliers are clustered. In this paper, the cluster number is set to four. Therefore, four types of suppliers are obtained in which the first cluster shows the suppliers with best performance or negligible risks and the fourth cluster shows the suppliers with worst performance or extreme risks. For instance, the best supplier of the first cluster is S_{16} with membership value of 0.6858. Table 14 represents the final result of the suppliers' categorization. It is worth noting that computations are performed in MATLAB 7.2.

Table 3. Fuzzy pair-wise comparison of fifteen risk criteria by decision maker DM_1

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1		ML													
C_2			H												
C_3				MH											
C_4					H										
C_5						H									
C_6							VH								
C_7								L							
C_8									ML						
C_9										H					
C_{10}											ML				
C_{11}												VH			
C_{12}													VH		
C_{13}														VL	
C_{14}															VH
C_{15}															

Table 4. Fuzzy pair-wise comparison of fifteen risk criteria by decision maker DM_2

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1		VL													
C_2			H												
C_3				M											
C_4					H										
C_5						H									
C_6							H								
C_7								ML							
C_8									M						
C_9										MH					
C_{10}											ML				
C_{11}												H			
C_{12}													VH		
C_{13}														VL	
C_{14}															MH
C_{15}															

Table 5. Fuzzy pair-wise comparison of fifteen risk criteria by decision maker DM_3

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1		L													
C_2			VH												
C_3				VH											
C_4					VH										
C_5						H									
C_6							VH								
C_7								VL							
C_8									VL						
C_9										VH					
C_{10}											VL				
C_{11}												VH			
C_{12}													VH		
C_{13}														M	
C_{14}															VH
C_{15}															

Table 6. Fuzzy pair-wise comparison of fifteen risk criteria by decision maker DM_4

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1		ML													
C_2			H												
C_3				H											
C_4					VH										
C_5						H									
C_6							VH								
C_7								VL							
C_8									L						
C_9										MH					
C_{10}											L				
C_{11}												VH			
C_{12}													VH		
C_{13}														L	
C_{14}															VH
C_{15}															

Table 7. Measures of Suppliers

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
S_1	3	4	4	3	4	4	4	4	3	4	3	4	3	4	3
S_2	3	4	4	3	4	3	3	2	3	4	3	3	4	2	3
S_3	3	4	3	2	4	3	4	2	4	3	4	3	4	3	4
S_4	2	3	2	3	2	2	2	1	3	3	2	3	1	3	2
S_5	2	2	3	2	3	2	2	1	3	2	3	2	3	3	3
S_6	2	3	4	3	4	4	4	5	4	3	4	3	4	4	5
S_7	3	4	3	2	2	2	2	1	3	3	3	1	2	2	1
S_8	3	2	2	3	2	3	3	2	3	4	4	3	2	2	3
S_9	3	4	3	4	4	3	2	2	4	3	2	2	3	3	2
S_{10}	2	2	2	3	4	3	2	4	4	3	2	3	2	3	2
S_{11}	3	4	2	1	1	2	3	1	4	3	3	2	2	2	3
S_{12}	2	4	2	1	1	2	3	1	4	3	3	2	2	2	3
S_{13}	3	2	2	1	1	2	3	2	2	3	4	2	3	2	3
S_{14}	4	4	2	3	4	3	4	4	4	3	4	4	3	3	4
S_{15}	3	4	4	4	4	3	3	4	2	2	4	2	3	3	3
S_{16}	4	4	3	3	2	4	4	5	4	3	3	4	4	4	5
S_{17}	3	4	3	2	2	3	3	4	3	3	4	4	3	4	4
S_{18}	3	4	2	3	2	3	4	4	5	4	4	4	3	4	4
S_{19}	2	3	2	2	3	3	3	4	3	3	4	3	3	2	3
S_{20}	4	5	3	4	3	4	5	5	5	4	2	5	4	4	5
S_{21}	3	2	2	3	2	3	4	3	4	3	2	3	4	3	3

Table 8. Fuzzy linguistic preference relations matrix for the risk criteria (P^L)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0.5	0	0.2	0.3	0.65	0.85	1.2	0.7	0.3	0.45	-0.05	0.3	0.7	0.2	0.5
C_2	0.7	0.5	0.7	0.8	1.15	1.35	1.7	1.2	0.8	0.95	0.45	0.8	1.2	0.7	1.0
C_3	0.2	0	0.5	0.6	0.95	1.15	1.5	1.0	0.6	0.75	0.25	0.6	1.0	0.5	0.8
C_4	-0.2	-0.4	0.1	0.5	0.85	1.05	1.4	0.9	0.5	0.65	0.15	0.5	0.9	0.4	0.7
C_5	-0.7	-0.9	-0.4	0	0.5	0.7	1.05	0.55	0.15	0.3	-0.2	0.15	0.55	0.05	0.35
C_6	-1.2	-1.4	-0.9	-0.5	0	0.5	0.85	0.35	-0.05	0.1	-0.4	-0.05	0.35	-0.15	0.15
C_7	-1.7	-1.9	-1.4	-1.0	-0.5	0	0.5	0	-0.4	-0.25	-0.75	-0.4	0	-0.5	-0.2
C_8	-1.45	-1.65	-1.15	-0.75	-0.25	-0.25	0.75	0.5	0.1	0.25	-0.25	0.1	0.5	0	0.3
C_9	-1.35	-1.55	-1.05	-0.65	-0.15	0.35	0.85	0.6	0.5	0.65	0.15	0.5	0.9	0.4	0.7
C_{10}	-1.8	-2.0	-1.5	-1.1	-0.6	-0.1	0.4	0.15	0.05	0.5	0	0.35	0.75	0.25	0.55
C_{11}	-1.65	-1.85	-1.35	-0.95	-0.45	0.05	0.55	0.3	0.2	0.65	0.5	0.85	1.25	0.75	1.05
C_{12}	-2.15	-2.35	-1.85	-1.45	-0.95	-0.45	0.05	-0.2	-0.3	0.15	0	0.5	0.9	0.4	0.7
C_{13}	-2.65	-2.85	-2.35	-1.95	-1.45	-0.95	-0.45	-0.7	-0.8	-0.35	-0.5	0	0.5	0	0.3
C_{14}	-2.45	-2.65	-2.15	-1.75	-1.25	-0.75	-0.25	-0.5	-0.6	-0.15	-0.3	0.2	0.7	0.5	0.8
C_{15}	-2.92	-3.12	-2.62	-2.22	-1.72	-1.22	-0.72	-0.97	-1.07	-0.62	-0.77	-0.27	0.23	0.03	0.5

Table 9. Fuzzy linguistic preference relations matrix for the risk criteria (P^M)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0.5	0.1	0.5	0.7	1.1	1.5	1.97	1.57	1.29	1.61	1.28	1.75	2.25	1.9	2.32
C_2	0.9	0.5	0.9	1.1	1.5	1.9	2.37	1.97	1.69	2.01	1.68	2.15	2.65	2.3	2.72
C_3	0.5	0.1	0.5	0.7	1.1	1.5	1.97	1.57	1.29	1.61	1.28	1.75	2.25	1.9	2.32
C_4	0.3	-0.1	0.3	0.5	0.9	1.3	1.77	1.37	1.09	1.41	1.08	1.55	2.05	1.7	2.12
C_5	-0.1	-0.5	-0.1	0.1	0.5	0.9	1.37	0.97	0.69	1.01	0.68	1.15	1.65	1.3	1.72
C_6	-0.5	-0.9	-0.5	-0.3	0.1	0.5	0.97	0.57	0.29	0.61	0.28	0.75	1.25	0.9	1.32
C_7	-0.97	-1.37	-0.97	-0.77	-0.37	0.03	0.5	0.1	-0.18	0.14	-0.19	0.28	0.78	0.43	0.85
C_8	-0.57	-0.97	-0.57	-0.37	0.03	0.43	0.9	0.5	0.22	0.54	0.21	0.68	1.18	0.83	1.25
C_9	-0.29	-0.69	-0.29	-0.09	0.31	0.71	1.18	0.78	0.5	0.82	0.49	0.96	1.46	1.11	1.53
C_{10}	-0.61	-1.01	-0.61	-0.41	-0.01	0.39	0.86	0.46	0.18	0.5	0.17	0.64	1.14	0.79	1.21
C_{11}	-0.28	-0.68	-0.28	-0.08	0.32	0.72	1.19	0.79	0.51	0.83	0.5	0.97	1.47	1.12	1.54
C_{12}	-0.75	-1.15	-0.75	-0.55	-0.15	0.25	0.72	0.32	0.04	0.36	0.03	0.5	1.0	0.65	1.07
C_{13}	-1.25	-1.65	-1.25	-1.05	-0.65	-0.25	0.22	-0.18	-0.46	-0.14	-0.47	0	0.5	0.15	0.57
C_{14}	-0.9	-1.3	-0.9	-0.7	-0.3	0.1	0.57	0.17	-0.11	0.21	-0.12	0.35	0.85	0.5	0.92
C_{15}	-1.32	-1.72	-1.32	-1.12	-0.72	-0.32	0.15	-0.25	-0.53	-0.21	-0.54	-0.07	0.43	0.08	0.5

Table 10. Fuzzy linguistic preference relations matrix for the risk criteria (P^R)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0.5	0.3	0.8	1.2	1.7	2.2	2.7	2.45	2.35	2.8	2.65	3.15	3.65	3.45	3.92
C_2	1.0	0.5	1.0	1.4	1.9	2.4	2.9	2.65	2.55	3.0	2.85	3.35	3.85	3.65	4.12
C_3	0.8	0.3	0.5	0.9	1.4	1.9	2.4	2.15	2.05	2.5	2.35	2.85	3.35	3.15	3.62
C_4	0.7	0.2	0.4	0.5	1.0	1.5	2.0	1.75	1.65	2.1	1.95	2.45	2.95	2.75	3.22
C_5	0.35	-0.15	0.05	0.15	0.5	1.0	1.5	1.25	1.15	1.6	1.45	1.95	2.45	2.25	2.72
C_6	0.15	-0.35	-0.15	-0.05	0.3	0.5	1.0	0.75	0.65	1.1	0.95	1.45	1.95	1.75	2.22
C_7	-0.2	-0.7	-0.5	-0.4	-0.05	0.15	0.5	0.25	0.15	0.6	0.45	0.95	1.45	1.25	1.72
C_8	0.3	-0.2	0	0.1	0.45	0.65	1.0	0.5	0.4	0.85	0.7	1.2	1.7	1.5	1.97
C_9	0.7	0.2	0.4	0.5	0.85	1.05	1.4	0.9	0.5	0.95	0.8	1.3	1.8	1.6	2.07
C_{10}	0.55	0.05	0.25	0.35	0.7	0.9	1.25	0.75	0.35	0.5	0.35	0.85	1.35	1.15	1.62
C_{11}	1.05	0.55	0.75	0.85	1.2	1.4	1.75	1.25	0.85	1.0	0.5	1.0	1.5	1.3	1.77
C_{12}	0.7	0.2	0.4	0.5	0.85	1.05	1.4	0.9	0.5	0.65	0.15	0.5	1.0	0.8	1.27
C_{13}	0.3	-0.2	0	0.1	0.45	0.65	1.0	0.5	0.1	0.25	-0.25	0.1	0.5	0.3	0.77
C_{14}	0.8	0.3	0.5	0.6	0.95	1.15	1.5	1.0	0.6	0.75	0.25	0.6	1.0	0.5	0.97
C_{15}	0.5	0	0.2	0.3	0.65	0.85	1.2	0.7	0.3	0.45	-0.05	0.3	0.7	0.2	0.5

Table 11. Transformation matrix for (P^L)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0.5000	0.4309	0.4586	0.4724	0.5207	0.5483	0.5967	0.5276	0.4724	0.4931	0.4240	0.4724	0.5276	0.4586	0.5000
C_2	0.5276	0.5000	0.5276	0.5414	0.5898	0.6174	0.6657	0.5967	0.5414	0.5622	0.4931	0.5414	0.5967	0.5276	0.5691
C_3	0.4586	0.4309	0.5000	0.5138	0.5622	0.5898	0.6381	0.5691	0.5138	0.5345	0.4655	0.5138	0.5691	0.5000	0.5414
C_4	0.4033	0.3757	0.4448	0.5000	0.5483	0.5760	0.6243	0.5552	0.5000	0.5207	0.4517	0.5000	0.5552	0.4862	0.5276
C_5	0.3343	0.3066	0.3757	0.4309	0.5000	0.5276	0.5760	0.5069	0.4517	0.4724	0.4033	0.4517	0.5069	0.4378	0.4793
C_6	0.2652	0.2376	0.3066	0.3619	0.4309	0.5000	0.5483	0.4793	0.4240	0.4448	0.3757	0.4240	0.4793	0.4102	0.4517
C_7	0.1961	0.1685	0.2376	0.2928	0.3619	0.4309	0.5000	0.4309	0.3757	0.3964	0.3273	0.3757	0.4309	0.3619	0.4033
C_8	0.2307	0.2030	0.2721	0.3273	0.3964	0.4655	0.5345	0.5000	0.4448	0.4655	0.3964	0.4448	0.5000	0.4309	0.4724
C_9	0.2445	0.2169	0.2859	0.3412	0.4102	0.4793	0.5483	0.5138	0.5000	0.5207	0.4517	0.5000	0.5552	0.4862	0.5276
C_{10}	0.1823	0.1547	0.2238	0.2790	0.3481	0.4171	0.4862	0.4517	0.4378	0.5000	0.4309	0.4793	0.5345	0.4655	0.5069
C_{11}	0.2030	0.1754	0.2445	0.2997	0.3688	0.4378	0.5069	0.4724	0.4586	0.5207	0.5000	0.5483	0.6036	0.5345	0.5760
C_{12}	0.1340	0.1064	0.1754	0.2307	0.2997	0.3688	0.4378	0.4033	0.3895	0.4517	0.4309	0.5000	0.5552	0.4862	0.5276
C_{13}	0.0649	0.0373	0.1064	0.1616	0.2307	0.2997	0.3688	0.3343	0.3204	0.3826	0.3619	0.4309	0.5000	0.4309	0.4724
C_{14}	0.0925	0.0649	0.1340	0.1892	0.2583	0.3273	0.3964	0.3619	0.3481	0.4102	0.3895	0.4586	0.5276	0.5000	0.5414
C_{15}	0.0276	0	0.0691	0.1243	0.1934	0.2624	0.3315	0.2970	0.2831	0.3453	0.3246	0.3936	0.4627	0.4351	0.5000

Table 12. Transformation matrix for (P^M)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0.5000	0.4448	0.5000	0.5276	0.5829	0.6381	0.7030	0.6478	0.6091	0.6533	0.6077	0.6727	0.7417	0.6934	0.7514
C_2	0.5552	0.5000	0.5552	0.5829	0.6381	0.6934	0.7583	0.7030	0.6644	0.7086	0.6630	0.7279	0.7970	0.7486	0.8066
C_3	0.5000	0.4448	0.5000	0.5276	0.5829	0.6381	0.7030	0.6478	0.6091	0.6533	0.6077	0.6727	0.7417	0.6934	0.7514
C_4	0.4724	0.4171	0.4724	0.5000	0.5552	0.6105	0.6754	0.6202	0.5815	0.6257	0.5801	0.6450	0.7141	0.6657	0.7238
C_5	0.4171	0.3619	0.4171	0.4448	0.5000	0.5552	0.6202	0.5649	0.5262	0.5704	0.5249	0.5898	0.6588	0.6105	0.6685
C_6	0.3619	0.3066	0.3619	0.3895	0.4448	0.5000	0.5649	0.5097	0.4710	0.5152	0.4696	0.5345	0.6036	0.5552	0.6133
C_7	0.2970	0.2417	0.2970	0.3246	0.3798	0.4351	0.5000	0.4448	0.4061	0.4503	0.4047	0.4696	0.5387	0.4903	0.5483
C_8	0.3522	0.2970	0.3522	0.3798	0.4351	0.4903	0.5552	0.5000	0.4613	0.5055	0.4599	0.5249	0.5939	0.5456	0.6036
C_9	0.3909	0.3356	0.3909	0.4185	0.4738	0.5290	0.5939	0.5387	0.5000	0.5442	0.4986	0.5635	0.6326	0.5843	0.6423
C_{10}	0.3467	0.2914	0.3467	0.3743	0.4296	0.4848	0.5497	0.4945	0.4558	0.5000	0.4544	0.5193	0.5884	0.5401	0.5981
C_{11}	0.3923	0.3370	0.3923	0.4199	0.4751	0.5304	0.5953	0.5401	0.5014	0.5456	0.5000	0.5649	0.6340	0.5856	0.6436
C_{12}	0.3273	0.2721	0.3273	0.3550	0.4102	0.4655	0.5304	0.4751	0.4365	0.4807	0.4351	0.5000	0.5691	0.5207	0.5787
C_{13}	0.2583	0.2030	0.2583	0.2859	0.3412	0.3964	0.4613	0.4061	0.3674	0.4116	0.3660	0.4309	0.5000	0.4517	0.5097
C_{14}	0.3066	0.2514	0.3066	0.3343	0.3895	0.4448	0.5097	0.4544	0.4157	0.4599	0.4144	0.4793	0.5483	0.5000	0.5580
C_{15}	0.2486	0.1934	0.2486	0.2762	0.3315	0.3867	0.4517	0.3964	0.3577	0.4019	0.3564	0.4213	0.4903	0.4420	0.5000

Table 13. Transformation matrix for (P^R)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0.5000	0.4724	0.5414	0.5967	0.6657	0.7348	0.8039	0.7693	0.7555	0.8177	0.7970	0.8660	0.9351	0.9075	0.9724
C_2	0.5691	0.5000	0.5691	0.6243	0.6934	0.7624	0.8315	0.7970	0.7831	0.8453	0.8246	0.8936	0.9627	0.9351	1.0000
C_3	0.5414	0.4724	0.5000	0.5552	0.6243	0.6934	0.7624	0.7279	0.7141	0.7762	0.7555	0.8246	0.8936	0.8660	0.9309
C_4	0.5276	0.4586	0.4862	0.5000	0.5691	0.6381	0.7072	0.6727	0.6588	0.7210	0.7003	0.7693	0.8384	0.8108	0.8757
C_5	0.4793	0.4102	0.4378	0.4517	0.5000	0.5691	0.6381	0.6036	0.5898	0.6519	0.6312	0.7003	0.7693	0.7417	0.8066
C_6	0.4517	0.3826	0.4102	0.4240	0.4724	0.5000	0.5691	0.5345	0.5207	0.5829	0.5622	0.6312	0.7003	0.6727	0.7376
C_7	0.4033	0.3343	0.3619	0.3757	0.4240	0.4517	0.5000	0.4655	0.4517	0.5138	0.4931	0.5622	0.6312	0.6036	0.6685
C_8	0.4724	0.4033	0.4309	0.4448	0.4931	0.5207	0.5691	0.5000	0.4862	0.5483	0.5276	0.5967	0.6657	0.6381	0.7030
C_9	0.5276	0.4586	0.4862	0.5000	0.5483	0.5760	0.6243	0.5552	0.5000	0.5622	0.5414	0.6105	0.6796	0.6519	0.7169
C_{10}	0.5069	0.4378	0.4655	0.4793	0.5276	0.5552	0.6036	0.5345	0.4793	0.5000	0.4793	0.5483	0.6174	0.5898	0.6547
C_{11}	0.5760	0.5069	0.5345	0.5483	0.5967	0.6243	0.6727	0.6036	0.5483	0.5691	0.5000	0.5691	0.6381	0.6105	0.6754
C_{12}	0.5276	0.4586	0.4862	0.5000	0.5483	0.5760	0.6243	0.5552	0.5000	0.5207	0.4517	0.5000	0.5691	0.5414	0.6064
C_{13}	0.4724	0.4033	0.4309	0.4448	0.4931	0.5207	0.5691	0.5000	0.4448	0.4655	0.3964	0.4448	0.5000	0.4724	0.5373
C_{14}	0.5414	0.4724	0.5000	0.5138	0.5622	0.5898	0.6381	0.5691	0.5138	0.5345	0.4655	0.5138	0.5691	0.5000	0.5649
C_{15}	0.5000	0.4309	0.4586	0.4724	0.5207	0.5483	0.5967	0.5276	0.4724	0.4931	0.4240	0.4724	0.5276	0.4586	0.5000

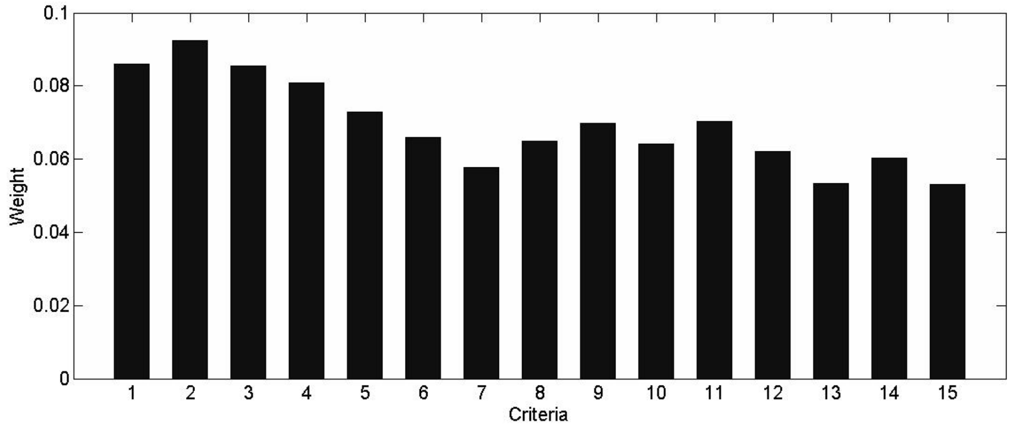

Figure 2. Defuzzified weight of each criterion

Table 14. Supplier categorization

Cluster Number	Supplier Number
1	14, 16, 17, 18, 20
2	1, 2, 3, 6, 9, 15
3	4, 5, 8, 10, 19, 21
4	7, 11, 12, 13

Table 15. List of suppliers based on their risk levels

Supplier	TWP	Supplier with low level risk (descending order)
S_1	3.7429	S_{20}
S_2	3.3604	S_{16}
S_3	3.4410	S_6
S_4	2.3894	S_1
S_5	2.4783	S_{14}
S_6	3.8025	S_{18}
S_7	2.4587	S_3
S_8	2.8221	S_{15}
S_9	3.1253	S_{17}
S_{10}	2.8264	S_2
S_{11}	2.5149	S_9
S_{12}	2.4290	S_{21}
S_{13}	2.3790	S_{19}
S_{14}	3.6608	S_{10}
S_{15}	3.3881	S_8
S_{16}	3.8275	S_{11}
S_{17}	3.3664	S_5
S_{18}	3.6230	S_7
S_{19}	2.9398	S_{12}
S_{20}	4.2571	S_4
S_{21}	2.9768	S_{13}

5. CONCLUSION

The rapid march of globalization has caused the number of suppliers and the risks associated with them to increase and this, in turn, can be one of the main factors to increase supply chain vulnerability. Due to this reason, the main objective of this paper is to develop a methodology which can identify and assess suppliers based on their risk levels.

In the proposed method, the risk criteria are first given weights using fuzzy LinPreRa approach. Given n risk criteria, fuzzy linguistic preference relation (fuzzy LinPreRa) requires only $n-1$ pair-wise comparisons, which provides greater flexibility. It also avoids consistency checking which is done in AHP method.

The contribution of the proposed method is the clustering technique used to categorize suppliers based on their similarity degrees. On the contrary, other conventional methods used to categorize vendors based on aggregated value.For instance, total weight performance (TWP) can be inaccurate as each criterion's effect may be neglected. In addition, one needs to assign a threshold value when classifying suppliers (Keskin et al. 2010). In the proposed method, however, the suppliers are categorized with the help of fuzzy c-means clustering technique. In fuzzy clustering, a data point may belong to several clusters with different degree of memberships. Therefore, membership values for a data point will represent the degree to which that point belongs to a particular cluster. For instance, S_{17} belongs to the first cluster. However, if we use TWP to categorize suppliers, S_{17} will not be among the potential suppliers with lower risk levels. Table 15 represents the list of suppliers based on their TWP in descending order.

For future work, we expect to apply the proposed method to a larger number of data so as to check the speed and accuracy of the method in depth. Developing an Internet-based system that can handle supplier clustering is another direction because of the pervasiveness of the Internet. With the help of this system, supplier clusters can be updated regularly due to any changes in their performance and can therefore reduce supplier risk. In addition, other clustering methods can be applied as FCM has some drawbacks. For instance, it may trap into a local optimum especially when then data set is very high dimensional.

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