Supplier selection: A hybrid approach using ELECTRE and fuzzy clustering

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Supplier Selection: A Hybrid Approach Using ELECTRE and Fuzzy Clustering

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Abstract. Vendor selection is a strategic issue in supply-chain management for any organization to identify the right supplier. Such selection in most cases is based on the analysis of some specific criteria. Most of the researches so far concentrate on multi-criteria decision making (MCDM) analysis. However, it incurs a huge computational complexity when a large number of suppliers are considered. So, data mining approaches would be required to convert raw data into useful information and knowledge. Hence, a new hybrid model of MCDM and data mining approaches was proposed in this research to address the supplier selection problem. In this paper, Fuzzy C-Means (FCM) clustering as a data mining model has been used to cluster suppliers into groups. Then, Elimination and Choice Expressing Reality (ELECTRE) method has been employed to rank the suppliers. The efficiency of this method was revealed by conducting a case study in an automotive industry.

Keywords: Supplier selection, Multiple Criteria Decision Making, ELECTRE, Fuzzy Analytical Hierarchy Process, Fuzzy C-Means clustering.

1 Introduction

An important concern in supply-chain management is supplier selection. Normally, above 60% of a manufacturer's total sales are spent on purchased items, such as components, parts and raw materials [1]. Moreover, purchases of goods and services by the manufacturer constitute up to 70% of product price [2]. So, selection of suppliers has gained an enormous extent of importance as a tactical issue in the area of supply-chain management.

Che and Wang [3] declared that enterprises must make an important decision regarding the selection and evaluation of suppliers in order to collaborate with qualified suppliers and eliminate those unqualified ones. Establishing a long-term cooperation with qualified suppliers can lead to rapid exchange of information which can provide beneficial support for supply-chain management. Lin *et al.* [4] mentioned that performance of outsourcing operations is greatly affected by vendor selection activities. Mafakheri *et al.* [5] pointed out that costs reduction and quality improvement

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of end products is highly dependent on choosing the appropriate supplier. Consequently, considerable amount of interests exist in development of suitable frameworks to evaluate and select suppliers. He *et al.* [6] suggested that selecting the suitable suppliers based on the characteristics of market and product features is a key factor in achieving good supply-chain management.

In order select a supplier, some different alternative suppliers should be evaluated according to different criteria. According to Degraeve and Roodhoft [7], price considerations in supplier evaluation were the main focus in supplier selection. Later, companies realized that being dependent on this single criterion in supplier selection could be harmful to their performance. A list of 23 criteria was indentified for supplier evaluation and selection process by a study done by Dickson [8]. In another study, Weber *et al.* [9] identified that the decisions to select the suppliers are influenced by some key factors. These key factors were derived from reviewing 74 related papers that appeared after Dickson's [8] distinguished research work. According to this well established review in the area of supplier selection, it was disclosed that price, quality and delivery performance are the most important factors to be considered in solving the problem of supplier selection.

Multi criteria decision-making (MCDM) is involved with the process of supplier selection. This process is mainly influenced by different intangible and tangible criteria such as price, quality, technical capability, delivery performance, etc. [10,11]. Many researchers solved the problem of supplier selection by different approaches which include linear programming (LP), integer non-linear programming, mixed-integer linear programming (MILP), analytic network process (ANP), multiple-objective programming, neural networks (NN), goal programming, data envelopment analysis (DEA), simple multi-attribute rating technique (SMART), analytic hierarchy process (AHP), cost-based methods (CBM), genetic algorithm, techniques for order preference by similarity to ideal solution (TOPSIS) and Elimination and Choice Expressing Reality (ELECTRE) methods [12-26].

The analytic hierarchy process (AHP) method plays a major role in MCDM methods which is based on pairwise comparisons as it was firstly developed by Saaty [27,28] but AHP would encounter difficulties in calculating the pairwise comparison matrix when there is a large amount of data. Likewise, Wang and Triantaphyllou [40] declared that ranking irregularities related to the AHP was found as a weak point in the TOPSIS method. Consequently, ELECTRE method was selected to perform the supplier ranking. This method plays a prominent role in the group of MCDM models which is based on the concept of appropriate employment of outranking relations [19]. It is obvious that MCDM methods have been widely used in order to solve the supplier selection problems but due to the huge amount of suppliers' information, analyzing the data using MCDM methods has become difficult. In order to lessen these problems, data mining techniques are being widely used by researchers to convert data into useful information and knowledge. Generally, digging out useful information from huge quantities of data is conceived as data mining [29]. Hidden patterns and relationships can help decision makers to perform better. Basically, this goal can be achieved by discovering those hidden patterns. Consequently, data mining techniques are utilized to address this issue [30]. One of the most popular techniques of data mining is clustering. It mainly focuses on constructing several clusters by dividing a great amount of raw data based on assessment rules. The outcome of this process can be helpful decision-making information for managers [3]. K-means [31], Fuzzy C-Means [32,33], Hierarchical clustering [34], Mixture of Gaussian [35] and Artificial neural network Self-Organization Maps (SOM) [36,37] are five of the most used clustering algorithms. In this research, Fuzzy C-Means (FCM) algorithm has been utilized which allows objects to belong to more than one cluster. This feature makes FCM more flexible than *K*-means method [38]. Also, in this research activity, Fuzzy AHP was used to weight the criteria. Then, FCM was utilized in order to cluster suppliers into clusters. After that, ELECTRE method was applied to rank the clusters. The final step was constituted of ranking the suppliers within the best cluster by means of ELECTRE method.

2 Basic Definitions and Notations

2.1 Fuzzy C-Means for Supplier Clustering

Fuzzy C-Means (FCM) clustering algorithm was firstly proposed by Dunn [33]. This algorithm has been further developed by Bezdek [32]. FCM algorithm allows objects to belong to more than one cluster with different membership degrees. As the core basis of this method, the following objective function should be minimized:

$$j_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m \left\| x_i - c_j \right\|^2 \quad 1 < m < \infty \tag{1}$$

Where, N and c are respectively the number of data and clusters. x_i is the i^{th} datum, m is any real number greater than 1, c_j is the center of the j^{th} cluster, u_{ij} is the membership degree of x_i belonging to the cluster j and ||*|| is the Euclidean vector norm expressing the distance between j^{th} cluster's center and i^{th} datum. Fuzzy clustering is done throughout an iterative optimization of the j_m, with the update of u_{ij} and c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \quad , \quad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{2}$$

If $\|U^{k+1} - U^k\| < \delta$, then the iteration will be discontinued, where δ is a prescribed accuracy level between 0 and 1, while k is the iteration step. This procedure converges to a local minimum or a saddle point of j_m. The algorithm steps are as follows [33]:

i) Initialize $U = [U_{ij}]\ matrix, U^{(0)}$
ii) At k-step: calculate the center vectors

$$C^k = [c_j]\ with\ U^{(k)}, c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{3}$$

iii) Update $U^{k+1}, U^k, u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$

iv) If $\|U^{k+1} - U^k\| < \delta$ then stop; Otherwise return to step ii

2.2 Elimination and Choice Expressing Reality (ELECTRE) Method for Ranking Suppliers

In this research, ELECTRE as a MCDM model has been used to rank the suppliers. Roy [19] firstly developed ELECTRE in order to solve the problem of insufficiency of existing decision making solution methods. Basically, two core actions are embedded in ELECTRE methods. First, one or several outranking relation(s) will be constructed [41]. After that, an exploitation process will be performed. Considering $A_1, A_2, \ldots, A_m$ are possible alternatives , $C_1, C_2, \ldots, C_n$ are criteria with which performances of alternatives are measured, x_{ij} is the rating of alternative A_i with respect to criteria C_j. Consequently, the steps of ELECTRE for ranking the clusters of suppliers are described as follows [19]:

1) Obtain the weights, w_j of criteria, using AHP.

2) Establish the data matrix $[x_{ij}]$ which shows the average score of suppliers in each cluster based on the criteria.

3) Normalize the data matrix

$$R = [r_{ij}]_{m*n} \quad ,rij = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1,\ldots,\mathrm{m};\ j = 1,\ldots,\mathrm{n} \tag{4}$$

4) Establish weighted matrix

In this step, the weights of the criteria are taken into consideration. The weighted matrix, V, is calculated by multiplying the normalized rates by the relevant weights. Therefore, the weighted matrix is configured to be:

$$V = [v_{ij}]_{m*n}, \ v_{ij} = [w_j r_{ij}] \tag{5}$$

5) Establish Concordance and Discordance Sets

For each pair of alternatives A_p and A_q (p,q=1,2,…,m and p≠q), the set of attributes is divided into two different subsets. The concordance set, which consists of all attributes for which alternative A_p is preferred to alternative A_q can be written as:

$$C\ (p,q) = \{j, Vpj\ \geq Vqj\} \tag{6}$$

In the above equation V_{pj} is a weighted score of alternative A_p with regard to the j^{th} attribute. *C (p,q)* is the set of attributes where A_p is better than or equal to A_q. The discordance set which is the complement of $C\ (p,q)$, contains all attributes for which A_q is better than A_p. This can be shown as:

$$D\ (p,q) = \{j, Vpj\ < Vqj\} \tag{7}$$

6) Calculate Concordance and Discordance Indices

The relative power of each concordance set is measured by means of the concordance index. The concordance index C_{pq} represents the degree of confidence in the pair wise judgments of (A_p,A_q). The concordance index of $C\ (p,q)$ is defined as:

$$Cpq = \sum_{j^*} W_{j^*} \tag{8}$$

Where j^* are attributes which belong to concordance set $C\ (p,q)$. On the other hand, the discordance index, measures the power of $D\ (p,q)$. The discordance index of $D\ (p,q)$, which indicates the degree of disagreement in (A_p,A_q), can be defined as:

$$Dpq = \frac{max|Vpj - Vqj|, j \in D\ (p,q)}{\delta} \tag{9}$$

Where Vpj indicates the performance of alternative A_p in terms of criterion C_j , Vqj indicates the performance of alternative A_q in terms of criterion C_j, and $\delta = \max|Vpj - Vqj|, j = 1,2,3, \ldots, n$.

7) Determine the threshold value

In this step, two thresholds should be determined. Consequently, C^* and D^* as identified thresholds represent the average of C_{pq} and D_{pq} of suppliers, respectively.

8) Determine outranking relationships

The dominance relationship of alternative A_p over alternative A_q becomes stronger with a higher concordance index C_{pq} and a lower discordance index D_{pq}. The method defines that A_p outranks A_q when $C_{pq} \geq C^*$ and $D_{pq} \leq D^*$.

3 Proposed Method

In this section, a hybrid approach of clustering method and MCDM have been proposed to deal with supplier selection problem. This problem would be intensified in the case of computational complexity when a large number of alternatives and criteria are considered. Moreover, wrong selection might be generated due to computational error. To address these limitations, a novel model namely supplier selection using Fuzzy C-Means algorithm and ELECTRE method is presented in this paper by integrating the Fuzzy C-Means (FCM) algorithm, Fuzzy Analytic Hierarchy Process (FAHP) and ELECTRE. The proposed method mainly uses FAHP, FCM and ELECTRE for solving the problem of supplier selection. The procedures of the proposed method are listed step by step as follows:

- **Step1:** Criteria selection. In this step, criteria for selecting the suppliers are selected based on the product and decisions of the company's experts.
- **Step 2:** Weighting selected criteria. FAHP is applied in order to perform the weightings.
- **Step 3:** Normalizing and weighting suppliers' data.
- **Step 4:** Clustering the suppliers based on their weighted normalized data in each criterion using FCM.
- **Step 5:** Ranking suppliers' clusters using ELECTRE method and identifying the best cluster.
- **Step 6:** Ranking suppliers in the best cluster using ELECTRE method.

4 Case Study

To illustrate the model, a case study was conducted. An automotive manufacturing company which is located in Iran was selected. G.G.S Company is a leading spare parts manufacturer in the automotive industry. This company supplies various components for the two great car manufacturers in Iran (SAIPA and IRANKHODRO). The aforementioned company utilizes an outsourcing policy for producing the components. In order to run its business, the company works with several small and medium automotive part manufacturers. Decision makers within the company wanted to ensure that the right manufacturers are selected to supply the fuel filter. For this study, 37 manufacturers of fuel filter were selected. Managers of the company wanted to select the best suppliers based on the four criteria (product price, quality, technical capability and delivery). They wanted to divide suppliers into four clusters based on their strategies. From the company's ISO 9001:2000 documents and suppliers' historical records, the data sets for suppliers' performance scores and products prices were collected.

4.1 Weighting Criteria Using FAHP

Product price, quality, technical capability and delivery were selected as the criteria for supplier evaluation based on the decision of experts within the company, ISO 9001:2000 documents and previous research activities in the literature. In this phase, FAHP has been used to weight the criteria. The steps of this phase are described as follows:

- *Step1*: *Pairwise comparisons.* In this step, using the fuzzy scale shown in Table 1, a group of three experts was asked to make pairwise comparison of the relative importance of the criteria. The group consisted of the owner, manager and chief executive officer of the company. The results are shown in Table 2.

- *Step 2*: *Calculating the weights of criteria*. In this step, Chang's FAHP [39] has been utilized for calculating the weights of criteria. The results are illustrated in Table 3.

Table 1. Triangular fuzzy scale

Triangular fuzzy scale	Linguistic scale
(1,1,1)	Just equal
(2/3, 1, 3/2)	Slightly more important
(3/2, 2, 5/2)	More important
(5/2, 3, 7/2)	Strongly more important
(7/2, 4, 9/2)	Very strongly more important

Table 2. Fuzzy pairwise comparison

	Price	Quality	Technical capability	Delivery
Price	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(2/3,1,3/2)
Quality	(2/3,1,3/2)	(1,1,1)	(2/3,1,3/2)	(2/5,1/2,2/3)
Technical capability	(2/5,1/2,2/3)	(2/3,1,3/2)	(1,1,1)	(2/7,1/3,2/5)
Delivery	(2/3,1,3/2)	(3/2,2,5/2)	(5/2,3,7/2)	(1,1,1)

Table 3. Weights

Criterion	Price	Quality	Technical capability	Delivery
Weight	0.316284	0.487303	0.057591	0.138822

4.2 Normalizing and Weighting Suppliers' Data

Suppliers' data are shown in Table 4. Data inputs are measured in different scales. Therefore, a normalization process is required to put the fields into comparable scales and guarantee that fields with larger values don't determine the solution. In this paper, min-max approach was used which recalled all record values in the range between

Table 4. Data matrix

Supplier ID	Price	Quality	Technical capability	Delivery
1	8485	6	6	9
2	5061	3	4	7
3	8571	6	8	5
4	9465	7	5	8
5	7919	4	3	7
.	.	.	.	
.	.	.	.	
35	6793	7	4	6
36	5550	4	5	5
37	6540	7	6	6
Max	9960	9	8	9
Min	5046	2	3	4

zero to one. For the benefit criteria (quality, technical capability, delivery) the normalized value is equal to (record value- min value of field)/(max value of field- min value of field) and for the cost criterion (price), it is equal to (max value of field- record value)/(max value of field- min value of field). The normalized data have been multiplied by the weight of each criterion for achieving the weighted normalized data. The results are shown in Table 5.

Table 5. Weighted normalized data matrix

Supplier ID	Price	Quality	Technical capability	Delivery
1	0.094937	0.278459	0.034555	0.138822
2	0.315318	0.069615	0.011518	0.083293
3	0.089401	0.278459	0.057591	0.027764
4	0.03186	0.348074	0.023037	0.111058
5	0.131366	0.139229	0	0.083293
.	.	.	.	
.	.	.	.	
35	0.20384	0.348074	0.011518	0.055529
36	0.283844	0.139229	0.023037	0.027764
37	0.220124	0.348074	0.034555	0.055529

4.3 Clustering of Suppliers

The idea behind this approach is that FCM can make effective clusters containing similar data. So, the vendors who have a little deviation in points were considered in the same cluster. Thus, FCM groups the vendors into different clusters such as best vendors, better vendors, moderate vendors, and the worst vendors. After clustering the vendors into four clusters, they were ranked which is discussed in the next section. MATLAB 7.10 has been utilized for performing Fuzzy C-Means clustering. The results of supplier clustering using Fuzzy C-Means are shown in Table 6. It indicates four clusters; each with the related number of suppliers and their average four criteria values. The last row in addition shows the total average of product price, quality, technical capability and delivery for all suppliers.

Table 6. Clusters created by Fuzzy C-Means

	Average in cluster				
Cluster no.	Price	Quality	Technical capability	Delivery	No. of suppliers
1	7561.25	6.083333	5.416667	6	12
2	5448.090909	3.363636	4.727273	6.363636	11
3	7128.142857	4.285714	5.142857	7	7
4	9300.285714	7.428571	5.142857	7.285714	7
Total average	7359.44237	5.29031	5.10741	6.66233	

4.4 Ranking Suppliers' Clusters Using ELECTRE and Identifying the Best Cluster

In this phase, ELECTRE method has been used to rank the clusters. The steps of ELECTRE method are detailed as follows:

- *Step 1: Normalizing the Data Matrix.* As shown in Table 7, the data were normalized based on Equation (4) and R matrix has been developed.

Table 7. Normalized data

	Price	Quality	Technical capability	Delivery
1	0.505027009	0.551048239	0.529659	0.448991
2	0.363886005	0.304689188	0.462248	0.476203
3	0.476099146	0.388214024	0.502885	0.523823
4	0.621179763	0.672904308	0.502885	0.545204

- *Step 2: Establishing weighted matrix.* The weighted rating matrix was calculated. It was constructed based on multiplying the rates by the relevant FAHP calculated weights of the criteria. Therefore, according to Equation (5), *V* matrix was calculated.

- *Step 3: Establishing Concordance and Discordance Sets.* In Table 8 and 9, Concordance set and Discordance set were determined using Equations (6) and (7). This was followed by calculating Concordance and Discordance indices, C_{pq} and D_{pq}, using Equations (8) and (9).

Table 8. Concordance set

	Concordance set	Concordance index
C(1,2)	2,3	0.544894
C(1,3)	2,3	0.544894
C(1,4)	1,3	0.373875
C(2,1)	1,4	0.455106
C(2,3)	1	0.316284
C(2,4)	1	0.316284
C(3,1)	1,4	0.455106
C(3,2)	2,3,4	0.683716
C(3,4)	1,3	0.373875
C(4,1)	2,4	0.626125
C(4,2)	2,3,4	0.683716
C(4,3)	2,3,4	0.683716

Table 9. Discordance Set

	Discordance set	*Discordance index*
D(1,2)	1,4	0.371845
D(1,3)	1,4	0.130918
D(1,4)	2,4	*1*
D(2,1)	2,3	*1*
D(2,3)	2,3,4	1
D(2,4)	2,3,4	1
D(3,1)	2,3	1
D(3,2)	1	0.871978
D(3,4)	2,4	1
D(4,1)	1,3	0.618671
D(4,2)	1	0.453529
D(4,3)	1	0.330761

- *Step 4: Determine the threshold values.* C^* and D^* were defined as thresholds which represent the average of C_{pq} and D_{pq} C^* is calculated as 0.504799 and D^* is equal to 0.731475.

- *Step 5: Detemine Outranking Relationships.* According to ELECTRE model, A_p outranks A_q when $C_{pq} \geq C^*$ and $D_{pq} \leq D^*$. As shown in Table 10, among C_{pq} indices C_{12}, C_{13}, C_{32}, C_{41}, C_{42}, C_{43} are more than C^* and among D_{pq} indices, D_{12}, D_{13}, D_{41}, D_{42}, D_{43} are less than D^*.

Table 10. Outranking relationships

		$\geq C^*$			$\leq D^*$	*Relations*
C_{12}	0.544894	✓	D_{12}	0.371845	✓	$A_1>A_2$
C_{13}	0.544894	✓	D_{13}	0.130918	✓	$A_1>A_3$
C_{14}	0.373875		D_{14}	1		
C_{21}	0.455106		D_{21}	1		
C_{23}	0.316284		D_{23}	1		
C_{24}	0.316284		D_{24}	1		
C_{31}	0.455106		D_{31}	1		
C_{32}	0.683716	✓	D_{32}	0.871978		
C_{34}	0.373875		D_{34}	1		
C_{41}	0.626125	✓	D_{41}	0.618671	✓	$A_4>A_1$
C_{42}	0.683716	✓	D_{42}	0.453529	✓	$A_4>A_2$
C_{43}	0.683716	✓	D_{43}	0.330761	✓	$A_4>A_3$
C^*	0.504799		D^*	0.731475		

So, the determination of outranking relationships was illustrated. Five outranking relations are described as follows:

1. Cluster 1 outranks cluster 2
2. Cluster 1 outranks cluster 3
3. Cluster 4 outranks cluster 1
4. Cluster 4 outranks cluster 2
5. Cluster 4 outranks cluster 3

According to these relations, it can be understood that cluster 4 is the best cluster followed by cluster 1 but the ranking of clusters 2 and 3 cannot be determined. Consequently, the threshold should be changed in order to reveal the ranking orders of clusters 2 and 3. So, the D^* has been changed to 0.9 which leads to a new determination of outranking relationships that are shown in Table 11. So, according to Table 11, six outranking relations are determined as follows:

1. Cluster 1outranks cluster 2
2. Cluster 1 outranks cluster 3
3. Cluster 4 outranks cluster 1
4. Cluster 4 outranks cluster 2
5. Cluster 4 outranks cluster 3
6. Cluster 3 outranks cluster 2

Table 11. New outranking relationshipsï

		$\geq C^*$			$\leq D^*$	*Relations*
C_{12}	0.544894	✓	D_{12}	0.371845	✓	$A_1>A_2$
C_{13}	0.544894	✓	D_{13}	0.130918	✓	$A_1>A_3$
C_{14}	0.373875		D_{14}	1		
C_{21}	0.455106		D_{21}	1		
C_{23}	0.316284		D_{23}	1		
C_{24}	0.316284		D_{24}	1		
C_{31}	0.455106		D_{31}	1		
C_{32}	0.683716	✓	D_{32}	0.871978	✓	$A_3>A_2$
C_{34}	0.373875		D_{34}	1		
C_{41}	0.626125	✓	D_{41}	0.618671	✓	$A_4>A_1$
C_{42}	0.683716	✓	D_{42}	0.453529	✓	$A_4>A_2$
C_{43}	0.683716	✓	D_{43}	0.330761	✓	$A_4>A_3$
C^*	0.504799		D^*	0.9		

Consequently, the ranking of the clusters is 4, 1, 3 and 2. It means that cluster 4 is the best cluster, cluster 1 is the better cluster, cluster 3 is the moderate and cluster 2 is the worst cluster of suppliers.

4.5 Ranking Suppliers in the Best Cluster Using ELECTRE

In this step, seven suppliers from the best cluster have been ranked by ELECTRE method. The suppliers' information is shown in the Table 12. The process of outranking suppliers in the best cluster is the same as the previously done process for outranking the clusters. For summarization purposes, the final results of outranking suppliers are shown in Table 13.

Table 12. Suppliers' information

Supplier no.	Product price	Quality	Technical	Delivery	Cluster
4	9465	7	5	8	4
8	9960	8	3	6	4
13	8193	7	7	9	4
14	9692	6	7	9	4
27	8766	7	7	7	4
29	9670	9	3	4	4
33	9356	8	4	8	4

Table 13. Outranked suppliers

Rank	Supplier no.
1	33
2	29
3	8
4	13
5	27
6	4
7	14

5 Conclusion

In this paper, a new hybrid method based on clustering method and MCDM methods was proposed. It is shown that the new method can deal with supplier selection problem when the amount of suppliers' data increased. FAHP was employed to weight the criteria. After that, FCM clustering was used to group suppliers into four predefined clusters. Then, ELECTRE method as one of the MCDM methods has been used to outrank the clusters. From the best cluster, seven suppliers have been outranked by ELECTRE. A case study in an automotive manufacturing company was carried out to demonstrate the employment of the proposed model. The main contributions of this study are described as follows:

1. A new method of decision support system for supplier selection has been developed.
2. The pre-processing of suppliers' data is facilitated.
3. FCM integrated with FAHP has been used to cluster the suppliers.
4. FCM has been integrated with ELECTRE to solve the problem of MCDM when there are huge amount of data.

In spite of the fact that a large numbers of suppliers generate difficulties in the process of decision making; the proposed approach has overcome this problem by employing data mining methods to transfer the data into useful information. As a result, managers can benefit from the major advantage of the proposed method.

For future work it can be a good opportunity to combine other data mining approaches such as unsupervised methods with MCDM methods. Also, the resource allocation to suppliers could be considered by mathematical models.

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