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An intelligent supplier evaluation, selection and development system

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ABSTRACT

Supplier evaluation and selection process has a critical role and significant impact on purchasing management in supply chain. It is also a complex multiple criteria decision making problem which is affected by several conflicting factors. Due to multiple criteria effects the evaluation and selection process, deciding which criteria have the most critical roles in decision making is a very important step for supplier selection, evaluation and particularly development. With this study, a hybridization of fuzzy *c*-means (FCM) and rough set theory (RST) techniques is proposed as a new solution for supplier selection, evaluation and development problem. First the vendors are clustered with FCM algorithm then the formed clusters are represented by their prototypes that are used for labeling the clusters. RST is used at the next step of modeling where we discover the primary features in other words the core evaluation criteria of the suppliers and extract the decision rules for characterizing the clusters. The obtained results show that the proposed method not only selects the best supplier(s), also clusters all of the vendors with respect to fuzzy similarity degrees, decides the most critical criteria for supplier evaluation and extracts the decision rules about data.

1. Introduction

A supply chain management (SCM) is a system consists of three key parts, which are: the supply focuses on obtaining raw materials to manufacturing, the manufacturing focuses on converting obtained raw materials into finished products and the distribution focuses on reaching these finished products to customers through distributors, warehouses and retailers. Supply chain activities begin with customer orders and end with customer satisfactions. Selection of suppliers plays a critical role in an organization because it heavily contributes to the overall performance of a supply chain system. Assessing suppliers and selecting suitable ones among them a complex and critical decision making problem due to considering several criteria such as quality, cost, service, production lead time and environmental impact [19]. Eventually firms should select the most appropriate suppliers, because significant supplier selection reduces the purchasing cost and improves corporate competitiveness however inaccurate selection of supplier may lead to problems of finance and operation.

In the literature, there are several approaches as linear weighting methods, total cost approaches, mathematical programming techniques, statistical methods and artificial intelligence approaches have been proposed for supplier selection and evaluation process, they mostly locks onto ranking the suppliers and selecting the most appropriate suppliers. However in this paper, all the vendors are clustered by similarity degrees among them so not only the most appropriate supplier is determined but also the supplier categories and the membership degrees to them are determined. With this aspect, the proposed approach makes the decision making process much more flexible. Furthermore, in the literature the majority of researches have focused on supplier selection or evaluation or development separately, but despite that, we focus on an integrated flexible and efficient decision making model for supplier selection, evaluation and development.

The proposed model can cope better with uncertainty than conventional methods because it is designed to be more like human decision making functioning by its clustering, rule induction and feature extraction modules. In the clustering module, suppliers are clustered with a fuzzy clustering algorithm – fuzzy *c* means (FCM) – to evaluate their performance and similarities degrees. For every vendor, the membership degrees to different clusters are calculated. Unlike traditional hard clustering schemes, such as *k*-means, that assign each data point to a specific cluster, the FCM algorithm employs fuzzy partitioning such that each data point belongs to a cluster to some degree specified by a membership grade [11]. If data groups are well-separated, the hard clustering approach can be a natural solution. However, if the clusters are overlapped and some of data belong partially to several clusters, then fuzzy

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clustering is a natural way to describe this situation. In this case, the membership degree of a data object to a cluster is a value from the interval [0, 1].

In terms of supplier selection, supplier can be described by large scaled attributes, which can be represented with features in the view of machine learning. Indeed the weights of these attributes considered differently while we are evaluating suppliers. So some intelligent methods should be used to determine the most critical and important supplier attributes. The feature extraction methods in machine learning are used to find which attributes are more efficient and important in a clustering or classification model. In the rule induction and feature extraction module of the proposed model, decision rules for these clusters are defined then the most efficient criteria in decision making process are discovered by a feature selection method based on RST and these criteria considered as the most important features for further supplier development process. This extraction would be also very valuable for the supplier firms. They can try to improve these attributes primarily to be preferred at the next time. A case study is conducted to illustrate the proposed system. The system can also be easily implemented with different real supplier selection problems.

Although all of these proposed supplier selection models have useful and interesting principles, none of them is an integrated long-term relationship system as our system which presents the supplier evaluation rules due to fuzzy clusters and the attributes of suppliers due to their importance degrees. Therefore, there is a space for the development of new intelligent approaches toward effective support in the evaluation of suppliers, mainly for long-term relationships, characterized by the important supplier attributes. Beyond these, the classification methods must use the previous experiences to evaluate the performance levels of the available suppliers. However, if the supplier evaluation is realized due to a hard or fuzzy clustering algorithm, the past experiences are not required any more. This point is the one of the important reasons of selecting the FCM algorithm as a machine learning technique for this study. After the clusters are formed the second important point is to represent these clusters accurately. The rough set technique is generally used as a classifier and rule extractor in the literature. But it cannot be very sufficient to extract confident rules when it is used as a classifier method. On the other hand, rough set is a very robust rule and core attribute extractor. Therefore the rough set is applied on the clusters formed by FCM which is the most efficient fuzzy clustering algorithm. Briefly, this paper contributes to the state-of-art of the supplier selection problem, presenting a new and novel approach that integrates FCM and RST to construct a long-term relationship with suppliers.

The rest of the paper is organized as follows: Section 2 surveys relevant literature. Section 3 provides brief background knowledge about FCM and RST. The proposed system and obtained results from a sample supplier selection problem are presented in Section 4. The final section discusses the findings and concludes with a summary of this study and future directions.

2. Literature review

Extensive multi-criteria decision making approaches have been proposed in the literature for supplier selection and evaluation, such as the analytic hierarchy process (AHP), analytic network process (ANP), case-based reasoning (CBR), data envelopment analysis (DEA), multi-objective programming (MOP), fuzzy set theory, genetic algorithms (GA), mathematical programming models, simple multi-attribute rating technique (SMART), artificial neural networks (ANN) and the hybrid approaches. There are also journal articles reviewing the supplier evaluation and selection models in the literature [13,18].

It is difficult to find the best way to evaluate and select suppliers, so the companies use a variety of different methods to deal with it. Therefore, the most important issue in the process of supplier selection is to develop a suitable method to select the right supplier [9]. The proposed supplier evaluation and selection methods in the literature have been classified as linear weighted models, total cost models, mathematical programming models and artificial intelligent (AI) based techniques.

In linear weighted models, every criterion is being weighted and supplier's performance is multiplied by weights of criteria. The total performance of a supplier is calculated by the sum of these multiplications. Although it is a very simple method, it depends heavily on human judgment and also the criteria weighted equally, which rarely happens in practice. So the decisions by made these models are subjective. Categorical method, weighted point model (linear weighted model) and analytical hierarchy process (AHP) model are some of these models. Total cost models are complex methods which depend to cost. They consider not only the rate of product but also indirect item cost. The subjectivity cannot be removed by these models such as cost ratio method and ownership total cost model. Mathematical models are used to represent the complex structure of supplier selection and have been widely used for modeling selection and allocation problems. In multi-attribute-decision-making methods the ratings and weight of attributes must be known precisely, but in real applications judgments of the decision makers cannot be estimated by a certain numerical value. Linear programming, integer programming, mixed integer programming, multi criteria programming and goal programming are some of these models. Also the methods such as data envelopment analysis, neural networks, fuzzy set theory, and analytic network process and quality function deployment are used for supplier selection. Except these models, hybrid models such as using linear programming and analytic hierarchy process together are existed [22].

The AI techniques can accomplish better with multi-criteria, complex and uncertain problems than conventional techniques. There are several AI approaches have been proposed for supplier evaluation and selection problem in the literature in recent years, our study is also extends them. Therefore only artificial intelligence and machine learning techniques are analyzed in this section to guide readers which techniques are used successfully and which are not yet in SCM.

Ko et al. [23] summarized the findings by a review of research papers concerning the application of soft computing techniques to SCM and concluded that genetic algorithms and fuzzy logic approach are the most popular techniques adopted to solve supply chain management problems; neural networks are broadly used to improve sales forecasting performance.

Lee and Ou-Yang [27] developed an accurate artificial neural network-based predictive model can be applied for providing negotiation supports and recommendations to demander in supplier selection negotiation process. Wu [43] have presented a hybrid model that fist applies DEA and classifies suppliers into clusters based on the resulting efficiency scores, then utilizes firm performance-related data to train decision tree and neural networks model, finally apply the trained decision tree model to new suppliers. Last they achieved admissible classification and prediction accuracy rate. Vandani et al. [40], presented a more efficient AI approach than the existing AI approaches to predict the performance rating of the suppliers in cosmetics industry. The proposed model is trained by a locally linear model tree learning algorithm and demonstrated by multi-layer perceptron (MLP) neural network, radial basis function (RBF) neural network and least square-support vector machine (LS-SVM) techniques. Moghadam et al. [32] proposed a hybrid method which uses fuzzy neural network and GA for demand rate forecasting and selects the most appropriate supplier. Kuo et al. [25], tried to develop an intelligent supplier decision support system which is composed of collection of the quantitative factors, a fuzzy neural network (FNN) for handling qualitative data and a decision model. The fuzzy rules are generated by a proposed FNN with initial weights generated by particle swam optimization (PSO) algorithm; the decision integration model is realized through an ANN with back-propagation algorithm. Lam et al. [26] proposed a selection model based on Fuzzy Principal Component Analysis (PCA) for solving the material supplier selection problem.

Guo et al. [17] have proposed a new support vector machine combined with decision tree to solve problems on supplier selection including feature selection and classification. Chen and Lin [10] have developed an SVM based risk hedging prediction model for construction material suppliers.

Ferreira and Borenstein [16] criticized the presented studies in the literature in terms of neglecting learning and adaptation. First, they specified the attributes for supplier performance such as delivery lead time, compliance with promised quality, compliance with the due date, supplying costs, and service level. For every attribute they formed different fuzzy membership functions and the rating of each criterion was represented by the following the linguistic terms: extremely low (EL), very low (VL), low (L), average (A), high (H), very high (VH) and extremely high (EH). They calculated the ratings of each criteria and the supplier performance using an algorithm based on probabilistic learning through Bayesian learning. Wu [42] considered the process capability estimating problem using Bayesian approach. The posterior probability of unseen process is derived to judge whether the investigating process is capable of satisfying the preset capability requirement. Dogan and Aydin [14] proposed a method Bayesian Networks and total cost. With their approach they modeled total cost and evaluated the supplier performances by probability distributions over different cost items and selection criteria.

Chang and Hung [6] proposed a RST model that provide effective and distinct supplier classification method among subjects of supplier selection. They aims to differentiate the suppliers as class 1 (excellent firms), class 2 (common firms), and class 3 (disappointed firms). The classification rules for this aim are created by rough set theory (RST) so the suppliers could be selected by decision-makers practically. As one of the conclusions of the study, they reflect that the classification capability of RST is not as good as learning machines and it must be applied with other methods to promote performance. Bai and Sarkis [2] proposed a method relying on gray system theory and based a performance evaluation technique on rough set theory. First they defined the importance of each decision maker such as "important", "moderately important" and "very important" and then they determined the performance of suppliers by a rough set classifier. At the end of steps of the algorithm they arrived at a number of rules related with supplier performances. Bai and Sarkis are also used RST in their two similar work [3,4].

After the studies in the literature are examined, it can be concluded that, the classification techniques which are one of the machine learning fields are broadly applied in SCM however the clustering techniques are not such a broad techniques.

The Adaptive Resonance Theory (ART) neural network model is firstly used for supplier evaluation and selection as a new and promising clustering technique by [22]. Che and Wang [7] clustered the suppliers due to a proposed hybrid KSACPSO approach which is combines k-means, simulated annealing algorithm (SA), convergence factor particle swarm optimization (CPSO), and the Taguchi method to avoid the disadvantages of k means algorithm. Che [8] proposed two models for clustering suppliers. The first model clusters the suppliers due to production cost, product quality and production time by a method integrates k-means and a simulated annealing algorithm with the Taguchi method (TKSA). Model 2 uses the supplier clusters obtained in model 1 to determine the appropriate suppliers by weighing every factor then using a simulated annealing algorithm with the Taguchi method (ATSA). Khaleie et al. [21] proposed a clustering method based on intuitionistic fuzzy value (IFS) in order to show opinions of the decision makers. Also an intuitionistic fuzzy weighted geometric (IFWG) is applied to aggregate the obtained clusters. Azadnia et al. [1] used FCM in order to cluster suppliers and then applied the Elimination and Choice Expressing Reality (ELECTRE) to rank the clusters. Esmaeil Mehdizadeh [15] proposed a hybrid algorithm named FPSO that combines FCM and particle swarm optimization (PSO) in order to cluster suppliers optimally.

3. Background knowledge

In this section, the brief overviews of relevant concepts such as FCM and RST with the proposed system are provided.

3.1. Fuzzy c means

The fuzzy c-means (FCM) clustering, proposed by Bezdek [5] is the widely used and discussed algorithm in fuzzy clustering literature. Unlike assigning each data object to a specific cluster as in traditional hard clustering schemes, the FCM employs fuzzy partitioning such that each data object belongs to a cluster to some degree specified by a membership grade. If the dataset is well separated a hard clustering method can be a sufficient solution. However, if the clusters are overlapped and some data belong to several clusters partially, then fuzzy clustering is a sufficient way to solve the problem. In fuzzy clustering the membership degree of each data object to each cluster is a value from the interval [0, 1].

Data objects which are close to each other according to a defined similarity measure should be mapped to the same cluster and also clusters should be labeled to indicate a particular semantic meaning pertaining to all data objects mapped to that cluster. In clustering analysis clusters are mostly represented and labeled by their prototypes which are usually their centroids.

FCM aims to find fuzzy partitioning of a given training set, by minimizing of an objective function as in Eq. (1) for a predefined number of clusters:

$$f(u, c_1, \ldots, c_c) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\|x_j - c_i\|^2 \tag{1}$$

$$\sum_{i=1}^{c} u_{ij} = 1, \quad \forall j = 1, \ldots, n \tag{2}$$

where $U = (u_{ij})_{c\times n}$ is the membership matrix, $u_{ij} \in [0, 1]$, c_i is the center of the cluster i, ${u_{ij}}^m$ is the fuzzy membership degree of supplier j (denoted by x_j) in the cluster i, m is a weighting exponent on each fuzzy membership that defines the fuzziness of the resulting partitions, c and n are total number of clusters and suppliers respectively. The sum of the membership degrees to all clusters has to be 1 for each datum as stated in Eq. (2).

Fuzzy clustering is provided through an iterative optimization of the objective function shown in Eq. (1), with the update of membership u_{ij} and the cluster centers c_i by Eqs. (3) and (4). The iterations stop when the difference between the fuzzy partition matrices in two following iterations is lower than a predefined error rate [31]. Namely, this iteration will stop when $f(u, c_1, \ldots, c_c)^{\text{new}} \leq \varepsilon$, where ε is a termination criterion between 0 and 1, whereas k is the iteration steps.

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{3}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\|x_j - c_i\| / \|x_j - c_k\| \right)^{-2/(m-1)}} \quad (4)$$

The steps of FCM clustering algorithm is as follows:

Input: Supplier dataset, number of clusters to be formed.
Output: Clustered data, membership matrix.
Step 1 – Initialization: The membership degrees of each supplier data to all clusters are initialized in the range [0, 1] and stored in membership matrix U.
Step 2 – Calculating fuzzy cluster centers: Calculate the cluster centers c_i, $i = 1, \ldots, c$ using Eq. (3).
Step 3: Compute objective function: Compute the mean-square error as an objective function using Eq. (1).
Step 4: Evaluation of objective function: If it is under a certain tolerance value then stop the algorithm. If $f(u, c_1, \ldots, c_c)^{\text{new}} \leq \varepsilon$ then break. Else compute a new membership matrix U using Eq. (4).
Step 5: Go to step 2 of the algorithm and iterate the algorithm stopping criterion ε is met.

3.2. Rough set theory

3.2.1. Basic concepts

The rough set theory was proposed by Pawlak [34] and it has been studied by many researchers. Rough set theory is a mathematical approach to managing uncertain data or problems of the information systems, indiscernibility relations and classification; attribute dependence and approximation accuracy; reduct sets and core attributes; and the decision rules [12]. Rough set theory requires no external parameters and uses only the information presented in the given data.

Due to the advantages of the rough set theory, rough set based decision support systems has been applied in many problems in financial analysis, marketing analysis, gene analysis, banking, industrial management, business intelligence, engineering, medicine, pattern recognition and linguistics. The main advantage of rough set theory is that it requires no external parameters and does not need any preliminary information about data like probability in statistics. For the rest, it provides algorithms for extracting hidden patterns in data; identifies relationships that could not be found by statistical methods; finds the core attributes or minimal sets of data, evaluates the importance of attributes; reduce all redundant objects; generates decision rules about data [35].

In RST a data set is represented as a table called information system, where each row correspond to a case, an event or simply an object and each column correspond to an attribute such as a variable, an observation or a property that can be measured for each object [24].

3.2.2. Indiscernibility relation and discernibility matrix

In RST, an information system is denoted by $I = \{U, A, C, D\}$; where $U = \{x_1, x_2, \ldots, x_n\}$ is non-empty called universe and a finite set of cases, $A = \{a_{1,}, a_2, \ldots, a_n\}$ is a non-empty set of attributes, C is a set of condition attributes, D is a set of decision attributes and $C, D \subset A$.

The P-indiscernibility relation is defined by $IND(P) = \{(x, y) \in U \times U : \forall a \in P, a(x) = a(y)\}$; where (x, y) is a pair of cases, $a(x)$ is the value of attribute for case x. If $(x, y) \in IND(P)$ then (x, y) are indiscernible with respect to P [35].

If the values of two objects are different in at least one attribute than they are discernible. Skowron and Rauszer [37] proposed a matrix representation called discernibility matrix for sets of attributes that discern pairs of object. Both the rows and columns of the matrix correspond to the data objects. The elements of the matrix are sets of condition attributes that discern the corresponding data objects, namely, in discernibility matrix, every entry represents a set consist of all attributes discerning two objects [45]. If an entry consists of only one attribute then this attribute must be a member of set of core attributes. The shorter entries are more significant than longer ones. If the times of appearance of an attribute are more than the others in the same entry, then this attribute may contribute more classification power to reduct [28]. A discernibility matrix can be used to find the reducts of attributes. In our proposed model, the discernibility matrix that has the dimension $n \times n$, where n is the number of all suppliers and its elements are defined as the set of all condition attributes is used to find core attributes.

3.2.3. Lower and upper approximations

The two main concepts of the RST are lower and upper approximation set definitions which refer the data object that belong definitely to the set and the data object that possibly belong to the set respectively [6]. Any subset $X \subseteq U$ in RST may be represented by its lower and upper approximations.

The lower approximation set of X presented as $\underline{P}X = \cup\{Y \in U : Y_{IND(P)} \subseteq X\}$, is the complete set of cases of U which can be unambiguously classified as belonging to the target set X. The lower approximation set of X is also called P-positive region of X and denoted by $POS_B(P) = \underline{P}x$. This set contains the data objects which can be certainly classified in it.

The upper approximation set of X presented as $\bar{P}X = \cup\{Y \in U : Y_{IND(P)} \cap X \neq \varnothing\}$, is the set of objects of U that are possibly in X. The upper approximation set of X is also called P-negative region of X and denoted by $NEG_B(P) = U - \underline{P}x$. This set contains the data objects which can be possibly classified in it [41].

P-boundary region of X is presented as $Bnd(X) = \bar{P}X - \underline{P}X$ consists of data objects that can neither be ruled in nor ruled out as members of the set X.

3.2.4. Reducts of attributes and core

An important feature of RST is its capability of shrinking the size of the dataset, since it considers only the data really useful for finding out the supplier evaluation. In fact, some records of the dataset may be redundant, and some of the features may not be useful for determining the value of the decision attribute. RST is very effective in eliminating these redundant data [30].

Feature selection process refers to choosing optimal subset of attributes from the set of original attributes that satisfy a given criteria. The purpose of the feature selection is to identify the significant features, eliminate the irrelevant of dispensable features and build a good learning model [39].

A subset of condition attributes $R \subset C$ is called reduct in RST. C may have any reducts and $IND(R) = IND(C)$. $R_{\text{all}}(C)$ denotes the set of all reducts of C. The core of C is intersections of all reducts and denoted as $CORE(C) = \cap R_{\text{all}}(C)$. The core set cannot be eliminated when reducing the attributes [36].

Many feature selection algorithms are shown to work effectively on discrete data or even more strictly on binary data. In order to deal with numeric attributes, a common practice for those algorithms is to discretize the data before conducting feature selection [29]. In this study, the global discretization of the continuous attributes of suppliers is realized and then the discernibility matrix search is used in order to determine the core attributes of the clustered data. Discernibility search strategies can find optimal reduct in most cases.

Discretization of real value attributes is an important task in data mining, particularly for the classification problem. Empirical results are showing that the quality of classification methods depends on the discretization algorithm used in preprocessing step. In general, discretization is a process of searching for partition of attribute domains into intervals and unifying the values over each interval. Hence discretization problem can be defined as a problem of searching for a suitable set of cuts (i.e. boundary points of intervals) on attribute domains.

A global discretization method uses the whole instances to discretized, while a local method would discretize only a subset of instances. A local method is usually associated with a dynamic discretization method in which discretization is more specific for particular situations, but taking into consideration only a part of the data set [33].

3.2.5. Decision rules

Another important feature of RST is to get decision rules which maintain the underlying semantics of the feature set, from the knowledge of given problem. The rule induction stage reads feature patterns and outputs a set of if–then rules connecting features and their implied classes from a decision table.

An information system can be assumed as a decision table and denoted by $I = \{U, A, C, D\}$, U is non-empty set called universe, A is non-empty set of attributes, C is called conditional attributes or simply conditions, D is called decision attributes, $C \cap D = \varnothing$ and $C, D \subset A$. A decision table expresses the information model and unfortunately can be unnecessarily large because the indiscernible data objects may be represented several times.

In the information system $B \subseteq A$ is and an equivalence relation is $IND_A(B)$, called B-indiscernibility relation. a_i is an attribute and $a_i \subseteq B$.

If a_i exerts no influence on the lower approximations set of D then it is D-superfluous, in other saying $POS_B(D) = POS_{(B-a_i)}(D)$. Else a_i is D-indispensable in A. The set of all D-indispensable attributes in A is called the D-core of A.

The main steps of a decision table analysis is as follows:

1. Construction of object sets in D-space.
2. Calculation of upper and lower approximations of the object sets in D.
3. Finding D-core and D-reducts of A attributes [41].

The decision rules can be derived from decision table. And the decision table can also be regarded as decision rules. The attribute reduction simply means reduction of unnecessary conditions in the decision rules. It is also known as the generation of decision rules from the data.

A decision rule can be regarded as "If $a_i = k$ then $d = j$". Where a_i is a condition attribute that takes value k and d is a decision attribute takes value j [41].

4. Computational results

To test the contribution of the proposed system, a supplier dataset adopted from Talluri and Narasimhan [38] is used. Wu [43] tested their model with the same dataset as well. This dataset is referred as TN data and is derived from multinational telecommunications company which is a global design, production and marketing leader of communication systems. It operates production plants, research and development facilities, and distribution systems globally.

TN data contains capabilities and performance outcomes of the suppliers as the attribute set. Talluri and Narasimhan [38] developed two separate questionnaires to assess supplier capabilities and to assess supplier performance. The eleven attributes were measures with a composite score between 0 and 1 and they are shown in Table 1. The scores were computed as ratio of "yes" answers to other individual questionnaire items in the category and these attribute values are shown in Table 2.

Table 1
Attributes and descriptions.

Number	Criteria	Description
1	QMP	Quality management practices and systems
2	SA	Self-audit
3	PMC	Process/manufacturing capability
4	MGT	Management of the firm
5	DD	Design and development capabilities
6	CR	Cost reduction capability
7	Quality	Quality performance
8	Price	Price performance
9	Delivery	Delivery performance
10	CRP	Cost reduction performance
11	Other	Other

The basic framework of the proposed system is reflected in Fig. 1. The first module of the system is clustering the suppliers and analyzing their performance ratings by FCM algorithm. The second module of the system is identifying the decisions regarding suppliers' development by an attribute reduction method based upon RST and determining the decision rules to evaluate suppliers.

An empirical case study used to exemplify the proposed framework is as follows. The FCM algorithm is executed using the TN data contains 23 suppliers with 11 defined evaluation criteria. FCM clustered these suppliers into 3 clusters with regard to their similarity degrees. The clustering process stops when the objective function improvement between two consecutive iterations is less than the improvement threshold value specified as 0.00001.

Table 3 shows the formed clusters with their labels, memberships of these clusters, definitions and the calculated priority measures. The underlined suppliers are the representatives of the clusters.

In cluster analysis, clusters are represented by their prototypes. In fuzzy clustering, the member who represents the cluster best has the highest membership degree in that cluster. The priority measures in Table 3 are determined via computing the mean attribute values of the best representative supplier in each cluster. The prototype of cluster 1 is the 23rd member which has maximum membership degree (0.8919) among the others, the prototype of cluster 2 is the 14th member which has maximum membership degree (0.9037) and the prototype of cluster 3 is the 17th member which has maximum membership degree (0.9444).

According to priority measures the three formed clusters are labeled. This process aimed to differentiate cluster 1 (best performers), cluster 2 (must improve their performances), and cluster 3 (must be pruned) from vendors to evaluate the suppliers. As it is seen from Table 3, the distribution of suppliers among these clusters is as follows. S4, S6, S7, S15, S22, S23 are the best performers. S1, S5, S8, S12, S13, S14, S19, S20 must improve their performances. S2, S3, S9, S10, S11, S16, S17, S18, S21 which are members of cluster 3 must be pruned from the supply base.

The suppliers who are the members of cluster 1 are the suppliers that the company management can choose any one/s of them to build long-term relationship. The suppliers who are the members of cluster 2 should be considered as potential recommended candidates for supplier development. If they make some improvements especially on their features determined as the core attributes they could be in the preferred cluster. And finally the suppliers belong to cluster 3 are potential candidates for pruning.

A global discretization of the continuous attributes of suppliers is realized and then the discernibility matrix search is used in order to determine the core attributes of the suppliers. In consequence of these methods, the process/manufacturing capability (PMC), the quality and the cost reduction performance (CRP) attributes are defined as the core attributes. The suppliers who are potential candidates for pruning can make improvements on their PMC, quality

Table 2
Candidate suppliers and their grades according to evaluation criteria.

Supplier/criteria	QMP	SA	PMC	MGT	DD	CR	Quality	Price	Delivery	CRP	Other
S1	0.9662	0.9742	1.0385	1.0808	1.1417	0.7839	0.6211	0.8922	0.1284	1.2107	0.6359
S2	0.7054	1.0438	0.7500	0.8782	0.0000	0.8750	0.6932	0.8922	0.3855	0.0000	0.3179
S3	0.5611	0.8947	0.7789	0.7205	0.8372	0.7404	1.0205	0.4341	1.5420	0.0000	1.2719
S4	1.1272	1.0438	0.9520	0.9607	0.9661	1.1402	1.6639	1.1333	1.5420	1.2107	1.8019
S5	1.1272	1.0438	1.1251	1.0808	1.2560	1.2115	0.9983	1.3503	1.1565	1.2107	0.9540
S6	0.9877	1.0438	0.9376	1.0808	1.0466	0.9422	1.0426	1.3263	1.7990	2.4214	1.2719
S7	0.8051	0.8351	1.0385	0.9607	1.2560	1.0768	1.2201	1.2056	0.7710	2.4214	1.2719
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
S19	1.0735	1.0438	1.1251	0.9007	1.1593	0.9422	1.1647	0.8922	1.4135	1.2107	1.0599
S20	1.0735	1.0438	1.1251	1.0808	0.6762	1.1442	0.8429	1.0550	1.4135	1.2107	1.4839
S21	1.2346	1.0438	1.1251	1.0133	1.2560	1.2115	0.7764	0.8922	1.0279	0.0000	0.9540
S22	1.2346	1.0438	0.9520	1.0808	1.0466	1.2115	1.4642	1.3263	1.7990	2.4214	1.4839
S23	1.0735	1.0438	1.0385	1.0172	0.8695	1.0768	1.2423	1.3503	1.2849	2.4214	1.5900

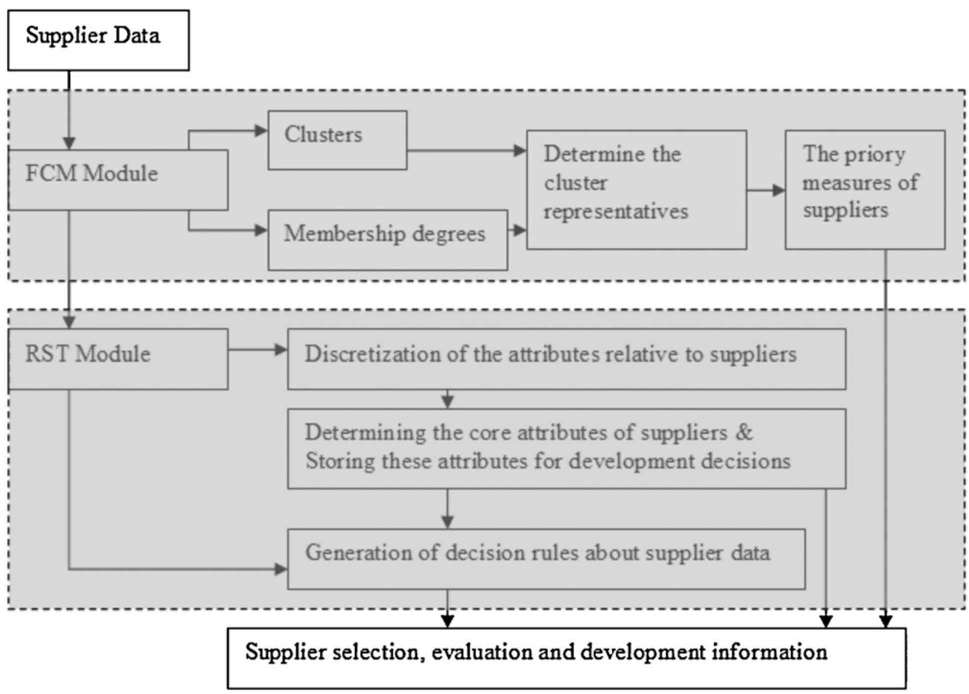

Fig. 1. Basic framework of the proposed system.

and CRP features not to be pruned. In summary the managerial implications are that, the suppliers in clusters 2 and 3 must improve their performances with respect to PMC, quality and CRP.

The core attributes is the key issue at development stage of the proposed system. The suppliers defined as "must improve their performance" must improve all or some of the evaluating criteria. The core attributes detect the primary criteria that must be improved. The core attributes obtained from current clustering indicate the criteria that have strong effect on supplier evaluation and selection. Therefore if the rise of the suppliers' performance is expected, then the conditions related with the critical criteria must be improved primarily. At the current study, if one of the S1, S5, S8, S12, S13, S14, S19, S20 suppliers wants to make a performance development plan then they must improve their PMC, Quality and CRP features primarily.

In this paper the RST is also used to generate classification rules to underlie semantics of the feature set from the given supplier selection problem. Thus the formed supplier clusters will be labeled with the classification rules and the result of clustering can be storable for future decisions [20]. The attribute reduction is also provides reduction of unnecessary decision rules. After all considerable rules about clusters are created; the managers refer to these rules to evaluate and select the suppliers in their business area. The extracted rules are shown in Table 4. In the computational experiment, five rules extracted with their support degrees for all clusters.

Table 3
The cluster membership of the suppliers and the calculated priority measures.

Cluster labels	Suppliers	Cluster definitions	Priority measures
Cluster 1	S4, S6, S7, S15, S22, <u>S23</u>	Must be preferred as best performers	1.2735
Cluster 2	S1, S5, S8, S12, S13, <u>S14</u>, S19, S20	Must improve their performance	1.0325
Cluster 3	S2, S3, S9, S10, S11, S16, <u>S17</u>, S18, S21	Must be pruned	0.8803

Table 4
Rules for clusters.

Rule ID	Rule	Support degree
1	If CRP ≥ 1.81605 then cluster = 1	83.33%
2	If quality ≥ 1.45305 then cluster = 1	33.33%
3	If (quality < 1.03155) and (CRP ≥ 0.60535) then cluster = 2	87.50%
4	If (PMC ≥ 1.0818) and (QMP < 1.10035) then cluster = 2	37.50%
5	If CRP < 0.60535 then cluster = 3	100.00%

Once the rules where obtained, the validation of each rule ensured that the knowledge was correct. The goal is to find rules that are accurate representations of the data. The accuracy is calculated by dividing the support of the decision attributes by the support of the conditional attributes. We are looking for rules with relatively high support and high accuracy [44].

The 1st, 3rd, 5th rules have over 80% support degrees. So their accuracy degrees are over an acceptable threshold value, so these rules are deterministic for characterizing the clusters. The threshold value can be specified by the user of the proposed system.

5. Discussion and conclusions

Supplier evaluation and selection problems have been solved by several methods in literature such as linear weighting methods, total cost approaches, mathematical programming methods, statistical methods and AI methods. Through them, AI methods designed to be more like human judgment functioning and can cope better with the complexity.

This study presents an effective hybrid system by FCM and RST for solving supplier selection, evaluation and development problem. With the proposed system, the suppliers are clustered by FCM algorithm then as the result of the algorithm the fuzzy membership degrees of each vendor to these clusters are determined. Additionally, this system enables the decision makers to consider the most critical and important criteria of the suppliers which are effective at improving their own performances by using RST.

Supplier evaluation and selection involves ambiguous and imprecise appraisals by fuzzy nature. The proposed system is established to solve the supplier evaluation and selection problem in which all evaluation criteria ratings are taken into account separately for each supplier by fuzzy similarity degrees. In conventional methods; although, all evaluation criteria are rated separately, the categorization of the suppliers are done based only on an aggregated value, for example total weight point (TWP). The calculated TWP value is used to measure supply performance of the vendor. But two suppliers that have exactly the same TWP value can have totally different grades according to evaluation criteria. It means different suppliers that have the same TWP value can be dissimilar from the supply performance point of view. Oppositely, two vendors with different TWP can be in the same category of supply behavior. The aggregated TWP value can cause loss of all criteria's separated effects and failures in evaluation process [22]. At the proposed system all evaluation criteria ratings are regarded separately for each supplier to group them in a high degree of accuracy. So the system can adequately handle the imprecision of human judgment. This contribution of the proposed system is very important.

In the previous studies, the importance degree of evaluation criteria is neglected. The all evaluation criteria considered as they have an equal degree of importance. In this study the core evaluation criteria of the suppliers are determined by a feature selection method based on RST. The core evaluation criteria are the most important, critical an efficient features for supplier development. With the help of proposed system, decision makers are aware of which criteria are critical in supplier selection mainly. Additionally, the suppliers who are members of the cluster labeled as "Must improve their performance" or "Must be pruned" are aware of which of their features must be improved primarily. One of the new and useful contributions of this study is deciding the evaluation criteria which must be improved for a better evaluation performance.

Another contribution of the study is the decision rules which are used to characterize the supplier data and are provided to decision makers in an apparent form. According to these rules, the new supplier data can be grouped in one of the clusters without repeating the clustering process. These valid rules can be stored for future decisions about suppliers.

Consequently, the novel architecture of proposed system is very flexible and can be easily applied to other real supplier selection problems and also other multi-criteria decision making problems, such as personnel appraisal. Furthermore the system can be executed whatever how much the dataset size.

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