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ORIGINAL ARTICLE

Supplier selection for managing supply risks in supply chain: a fuzzy approach

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Abstract Supplier selection is one of the most important tasks for supply chain decision making, and there are many quantitative and qualitative factors that affect this process. This paper develops a simple and user-friendly supplier selection process for a supply chain which considers various selection criteria for managing supply risks. A rule-based fuzzy inference system (FIS) model is developed using the fuzzy logic toolbox in MATLAB R2012a to select the most excellent supplier by considering both quantitative and qualitative selection criteria. We identify a total of 18 selection criteria, of which four are quantitative and 14 qualitative. Risk factors are also incorporated in the model by developing fuzzy input and output criteria, and the best supplier is selected based on the aggregated supplier ranking index value. Finally, a numerical example presented to explain the usefulness of the developed model.

Keywords Supplier selection · Supply chain · Risk management · Fuzzy logic · Fuzzy inference system

1 Introduction

In the globally competitive business market, selecting a supplier is one of the most challenging tasks in a supply chain. Nowadays, strategic sourcing is one of the fastest growing areas of supply chain management; for example, raw materials and components are purchased from external suppliers. Appropriate supplier selection is important for any organization because it helps to achieve high-quality products at relatively lower costs with greater customer satisfaction and ultimately assists in increasing profitability. There are various quantitative and qualitative criteria that should be considered when selecting suppliers [3] which make ranking suppliers one of the most difficult tasks. As these criteria can also be uncertain, it is important to incorporate uncertainty in the selection process to manage supply risks which can be achieved by a fuzzy inference system (FIS) that can simultaneously consider multiple criteria.

Numerous studies of supplier selection have been performed over the past few years. Firstly, the benefits of a long-term relationship between a supplier and buyer were described by Spekman [22] using strategic supplier selection. Later, the advantages of a systematic approach for supplier selection decision making were studied by many researchers [27, 15, 25, 12, 13].

In recent years, some systematic approaches for supplier selection have been developed, with the analytical hierarchy process (AHP) one of the most dominant in this field. Muralidharan et al. [17] proposed an AHP-based five-step model for helping decision makers rate and select suppliers considering nine evaluation criteria. The AHP has also been successfully applied to select the best supplier by some other researchers [9, 24, 6, 14]. In 2003, a fuzzy characteristic was incorporated with the AHP to manage uncertainty in the selection process by Kahraman et al. [11] who selected the supplier firm of manufactured white goods in Turkey which provided the most satisfaction for the determined criteria. Recently, fuzzy AHPs were also applied in supplier selection by Benyoucef and Canbolat [4], Chan et al. [7] and Sultana et al. [23].

A new method proposed by Bevilacqua et al. [5] transferred the house of quality (HOQ) approach typical of quality function deployment (QFD) problems to the supplier selection

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process and also considered triangular fuzzy numbers to capture the vagueness of variables. Recently, an algorithm for a fuzzy hierarchical technique for ordering preferences by their similarities to the ideal solution in supplier selection was proposed by Wang et al. [26].

Its consideration of multiple criteria is one of the most important benefits of the AHP and is really vital for supplier selection. However, its limitations are that it only works on matrices that are all of the same mathematical form and becomes complex with increasing numbers of criteria and alternatives. The main objective of this paper is to develop a simple and uncomplicated supplier selection model which considers relevant criteria formanaging supply risks so that anyone can use it without difficulty. Eighteen selection criteria that have significant effects on supplier selection are identified and taken as input factors to the FIS to evaluate the supplier ranking index which is considered the output. Gaussian and triangular membership functions are considered for quantitative and qualitative criteria respectively, with some rules developed to relate all input criteria to the supplier ranking index. Finally, from the rule viewer, the ranking index for a specific supplier is calculated by entering the value of all the inputs of that supplier. The supplier with the highest ranking index is given the most preferences for selection.

The main contributions of this paper can be summarized as follows.

i. Identification of 18 quantitative and qualitative selection criteria
ii. Development of a rule-based FIS to select the best supplier
iii. Development of fuzzy input and output criteria to incorporate risk factors in the model

The remainder of this paper is organized as follows. In section 2, we briefly discuss the FIS and describe the problem and FIS for supplier selection in sections 3 and 4, respectively. A numerical example is presented in section 5 while section 6 presents the conclusions drawn from this study and the usefulness of the model.

2 Fuzzy inference system

The FIS is an optimization technique which considers different inputs and relates those inputs to the output according to some rules [19]. The output is optimized based on these relationships and the final output obtained from the aggregated optimized result from of individual rules. The fuzzy set theory was originally presented by Zadeh [28], and later, fuzzy logic was developed from it, primarily to handle uncertain and vague information and, secondarily, to represent knowledge in an operationally powerful form [8]. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic which then provides a basis from which decisions can be made and/or patterns discerned.

There are two types of FISs that can be implemented in the fuzzy logic toolbox in MATLAB, Mamdani and Sugeno, which vary somewhat in the way their outputs are determined. Because of its multidisciplinary nature, a FIS has a number of names, such as a fuzzy rule-based system, fuzzy expert system, fuzzy modeling, fuzzy associative memory, fuzzy logic controller and, simply (and ambiguously), fuzzy system. Mamdani's FIS is the most commonly seen fuzzy methodology and was among the first control systems built using fuzzy set theory. It was proposed by Mamdani and Assilian [16] as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani-type inference, as defined for the fuzzy logic toolbox, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible and, in many cases, much more efficient to use a single spike rather than a distributed fuzzy set as an output membership function. This type of output is sometimes known as a singleton output membership function and can be thought of as a pre-defuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which integrates across the two-dimensional function to find the centroid, by using the weighted average of a few data points as in Sugeno-type systems. In general, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant. Perfilieva and Močkoř [21] discussed the mathematical principles of fuzzy logic and provided a systematic study of the formal theory of fuzzy logic. Their book presents fuzzy logic as the mathematical theory of vagueness, as well as the theory of common-sense human reasoning, based on the use of natural language, the distinguishing feature of which is the vagueness of its semantics. Gottwald [10] developed the mathematical formulation of fuzzy logic known as mathematical fuzzy which is considered an approximate fuzzy logic reasoning technique.

In the fuzzy logic toolbox, the fuzzy inference process has five parts: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the antecedents, implication from the antecedents to consequents, aggregation of the consequents across the rules and defuzzification. These sometimes cryptic and odd names have very specific meanings, as defined in the following steps.

2.1 Step I: fuzzification of inputs

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via

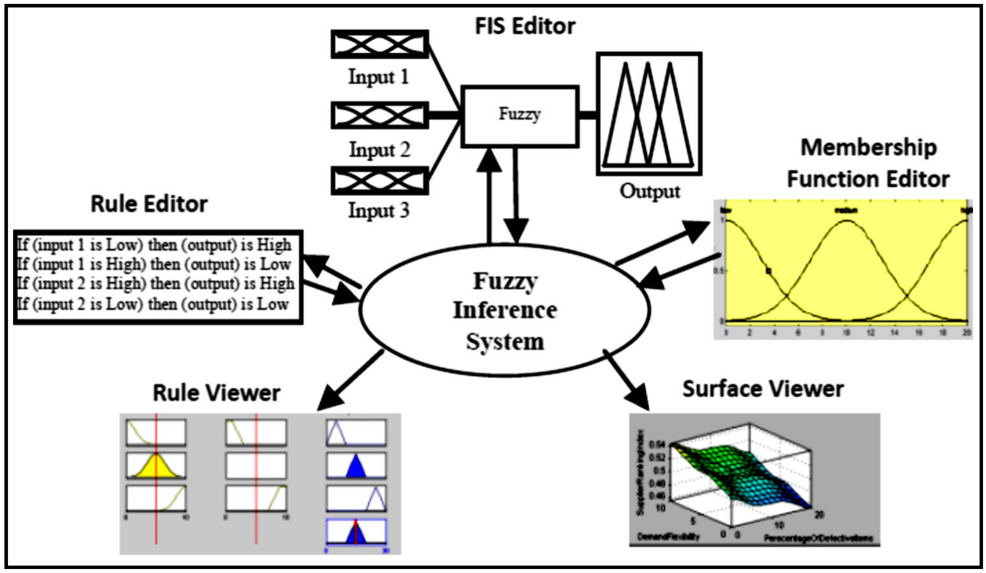

Fig. 1 Diagram of a FIS

membership functions. In the fuzzy logic toolbox, an input is always a crisp numerical value limited to the universe of discourse of the input variable and the output a fuzzy degree of membership in the qualifying linguistic set.

2.2 Step II: application of fuzzy operator

After the inputs are fuzzified, the degree to which each rule's antecedent is satisfied is known. If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents its result which is then applied to the output function. The input to the fuzzy operator is two or more membership values from the fuzzified input variables and the output a single truth value. Any number of well-defined methods can fill in for the AND or OR operations while the fuzzy logic toolbox supports two in-built AND methods, min (minimum) and prod (product), and two in-built OR methods, max (maximum) and probor (probabilistic OR).

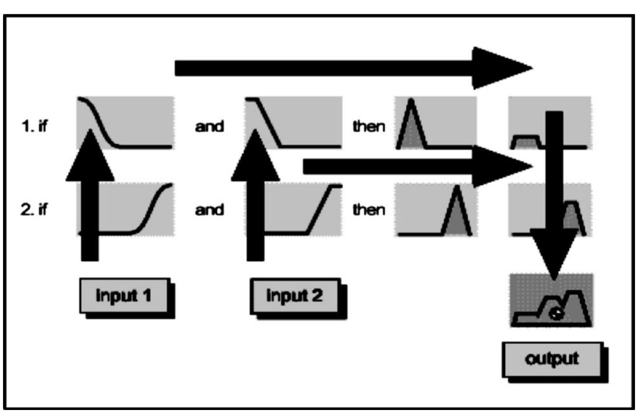

Fig. 2 Rule-based FIS

2.3 Step III: implication method

Before applying the implication method, each rule's weight, which is between 0 and 1, is determined and applied to the number given by its antecedent. Generally, as this weight is 1, it has no effect on the implication process. From time to time, one may want to weight one rule relative to the others by changing its weight value to something other than 1. After proper weighting is assigned to each rule, the implication method is implemented. A consequent is a fuzzy set represented by a membership function which appropriately weights the linguistic characteristics attributed to it and is then re-shaped using a function associated with its antecedent (a single number). The input to the implication process is a single number given by the antecedent and the output a fuzzy set, with implication implemented for each rule. Two in-built methods, which are the same functions used by the AND method, that is, min which truncates the output fuzzy set and prod which scales the output fuzzy set, are supported.

2.4 Step IV: aggregation of all outputs

Because decisions are based on the testing of all the rules in a FIS, these rules must be combined in some manner in order to make a decision. Aggregation is the process by which the fuzzy sets that represent the outputs from each rule are combined into a single fuzzy set and occurs only once for each

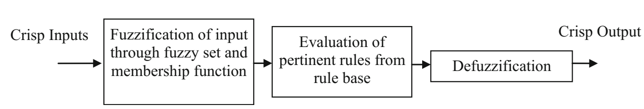

Fig. 3 General depiction of fuzzy expert system [1]

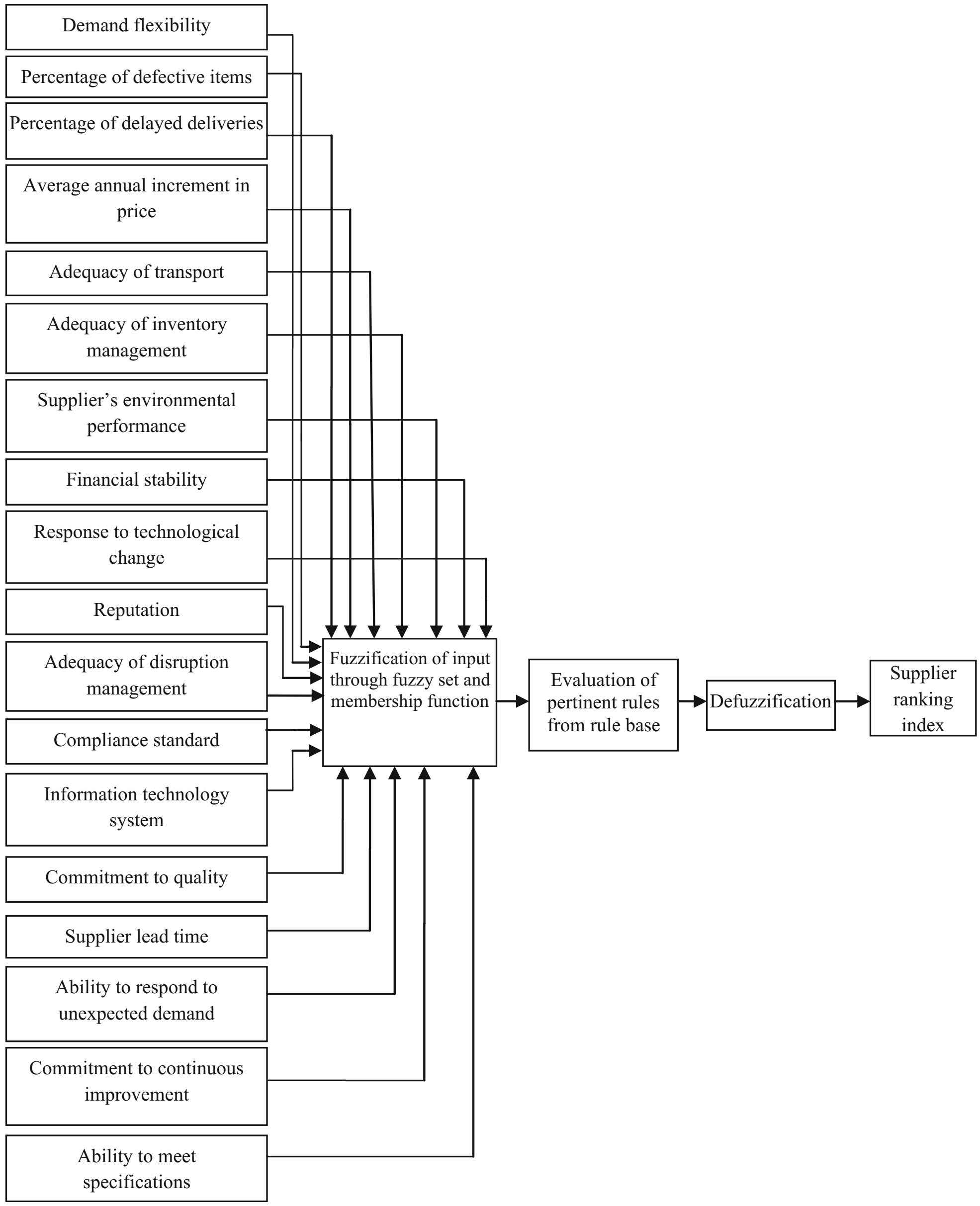

Fig. 4 Proposed FIS for supplier selection

output variable, just prior to the fifth and final step, defuzzification. The input to the aggregation process is the list of truncated output functions returned by the implication process for each rule and its output one fuzzy set for each output variable. As long as the aggregation method is commutative (which it always should be), the order in which the rules are executed is unimportant. Three in-built methods, max (maximum), probor (probabilistic OR) and sum (simply the sum of each rule's output set), are supported.

2.5 Step V: defuzzification

The input to the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and, while fuzziness helps rule evaluation during the intermediate steps, the final desired output for each variable is generally a single number. However, as the aggregate of a fuzzy set encompasses a range of output values, it must be defuzzified in order to obtain a single output value.

The most popular defuzzification method is the centroid calculation which returns the centre of the area under the

Name	: 'Supplier_Selection'
Type	: 'mamdani'
And method	: 'min'
Or method	: 'max'
Defuzzification method	: 'centroid'
Implication method	: 'prod'
Aggregation method	: 'sum'
Input	: 18
Output	: 1

Fig. 5 FIS properties for supplier selection

Table 1 Linguistic variables for input criteria

Input criteria	Type	Low	Medium	High
Demand flexibility	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Percentage of defective items	Quantitative	[3, 0]	[3, 10]	[3, 20]
Percentage of delay delivery	Quantitative	[5, 0]	[5, 20]	[5, 40]
Average annual increment in price	Quantitative	[8, 0]	[8, 25]	[8, 50]
Adequacy of transport	Qualitative	[0, 0, 3]	[2, 5, 8]	[7, 10, 10]
Adequacy of inventory management	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Supplier environmental performance	Qualitative	[0, 0, 4]	[1, 5, 9]	[6, 10, 10]
Financial stability	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Response to technological change	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Reputation	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Adequacy of disruption management	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Compliance standard	Qualitative	[0, 0, 3.5]	[2, 5, 8]	[6.5, 10, 10]
Information technology system	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Commitment to quality	Qualitative	[0, 0, 5]	[2, 5, 8]	[5, 10, 10]
Supplier lead time	Quantitative	[3, 10]	[3, 20]	[3, 30]
Ability to respond to unexpected demand	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Commitment to continuous improvement	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]
Ability to meet specifications	Qualitative	[0, 0, 4]	[2, 5, 8]	[6, 10, 10]

curve. Five in-built methods, the centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum and smallest of maximum [20], are supported. Figure 1 illustrates a FIS.

This fuzzy inference diagram is the composite of all the smaller diagrams presented so far in this section and simultaneously displays all parts of the fuzzy inference process. Information that flows through it is shown in Fig. 2 in which the flow proceeds up from the inputs in the lower left, across each row or rule and then down the rule output to finish in the lower right. This compact flow shows every process at once, from linguistic variable fuzzification through to defuzzification of the aggregate output ([18]).

3 Problem description

There are both quantitative and qualitative factors in the supplier selection process, and we identify 18 different ones, a supplier's demand flexibility, percentage of defective items, percentage of delayed deliveries, average annual increment in price, adequacy of transport, adequacy of inventory management, environmental performance, financial stability, response to technological change, reputation, adequacy of disruption management, compliance standards, information technology system, commitment to quality, lead time, ability to respond to unexpected demand, commitment to continuous improvement and ability to meet specifications, with the output from the selection process the supplier ranking index. The percentages of defective items and delayed deliveries, average annual price increment and lead time are quantitative variables and the rest qualitative criteria quantified (0–10 scale) using a Likert scale [2]. Gaussian and triangular membership functions are considered for these quantitative and qualitative variables respectively. A rule-based FIS is developed considering all the input variables related to the supplier ranking index to manage the risks involved in the selection process. A supplier is selected based on its supplier ranking index value, with higher values given greater priority.

4 FIS for supplier selection

During generation of the FIS's linguistic variables, 18 major supplier selection criteria are identified, for each of which three linguistic variables are developed and used to evaluate

Table 2 Linguistic variables for output

Output	Very low	Low	Medium	High	Very high
Supplier ranking index	[0, 0.1, 0.2]	[0.2, 0.3, 0.4]	[0.4, 0.5, 0.6]	[0.6, 0.7, 0.8]	[0.8, 0.9, 1]

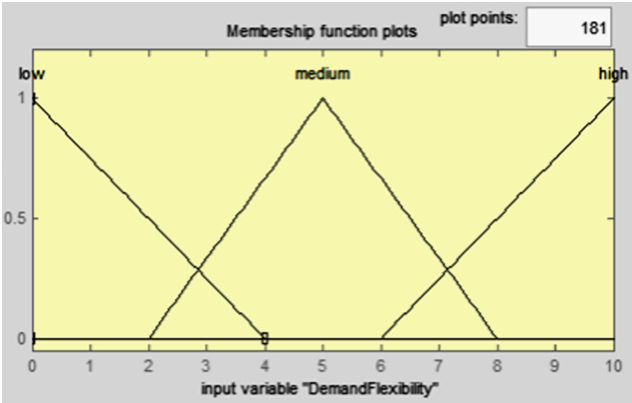

Fig. 6 Membership functions for demand flexibility

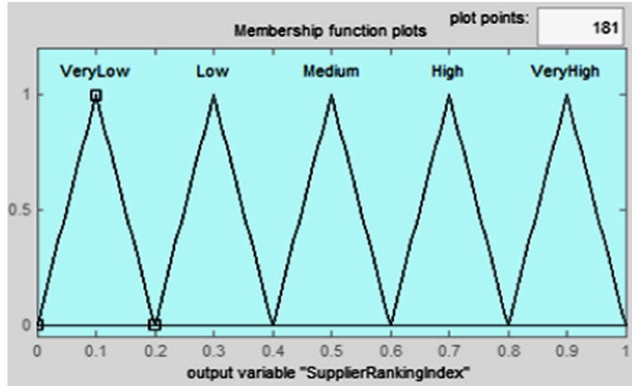

Fig. 8 Membership functions for output supplier ranking index

the supplier ranking index. For all these inputs to the model, the linguistic variables are 'low', 'medium' and 'high' and, for the output, the 'supplier ranking index', 'very low', low, medium, high and 'very high'.

After examining the linguistic variables, the membership functions are determined. The general FIS for the input and output variables is shown in Fig. 3 and that for the proposed model for supplier selection in Fig. 4 in which the input variables are shown on the left and the output variable on the right.

The membership functions and linguistic variables of the input and output variables are entered in MATLAB's fuzzy logic toolbox's membership function editor. Gaussian and triangular membership functions are considered for the quantitative and qualitative variables respectively, with the FIS properties for supplier selection presented in Fig. 5.

Gaussian and triangular membership functions are considered for the quantitative and qualitative criteria, respectively. The former are presented as [std, mean] and the latter as a triplet [a, b, c]. Tables 1 and 2 list the linguistic variables of the input criteria and output index respectively.

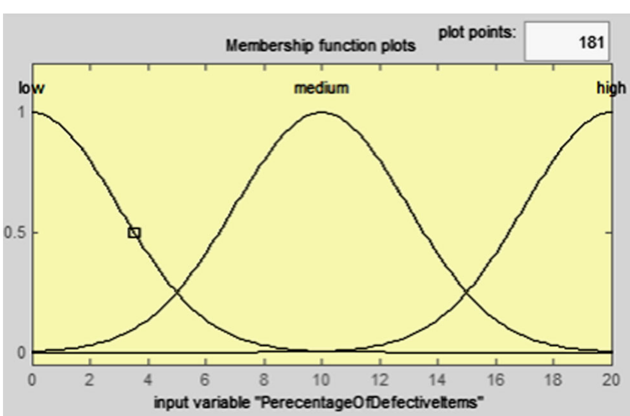

Fig. 7 Membership functionsfor percentage of defective items

Figure 6 presents the triangular membership functions for the qualitative input variable 'demand flexibility' and Fig. 7 the gaussian membership functions for the quantitative input variable 'percentage of defective items' which, together with the other qualitative and quantitative input variables, are entered in the FIS. The triangular membership functions for the output variable, supplier ranking index, are presented in Fig. 8.

A total of 168 rules is developed to relate all the inputs to the output; for example, (i) if the demand flexibility is high, the supplier ranking index is very high, and (ii) if the percentage of defective items is high, the supplier ranking index is very low.

5 Numerical example

A numerical example considering hypothetical data for five different suppliers (S1, S2, S3, S4 and S5) is presented. Each supplier has different values of the input criteria, as shown in Table 3.

The input data are entered in the rule viewer of the developed FIS to obtain the supplier ranking index value for each supplier; for example, the rule viewer for supplier 'S5' is shown in Fig. 9. The results obtained from the FIS are shown in Table 4 in which the supplier obtaining the highest ranking index, S5, is ranked 1 in the selection process, that is, it is the

Table 3 Data for five suppliers

Supplier	Input value [input1, input2,………,input18]
S1	[6, 15, 10, 30, 6, 8, 4, 7, 4, 6, 5, 6, 7, 4, 10, 5, 8, 8]
S2	[8, 5, 6, 5, 7, 8, 6, 4, 6, 8, 7, 10, 9, 5, 15, 7, 9, 9]
S3	[5, 15, 30, 35, 5, 4, 3, 6, 7, 8, 6, 5, 8, 5, 25, 6, 4, 7]
S4	[4, 20, 30, 40, 4, 2, 3, 6, 6, 7, 6, 6, 5, 4, 30, 5, 3, 6]
S5	[7, 2, 5, 3, 8, 8, 9, 7, 5, 8, 5, 9, 9, 5, 10, 8, 8, 9]

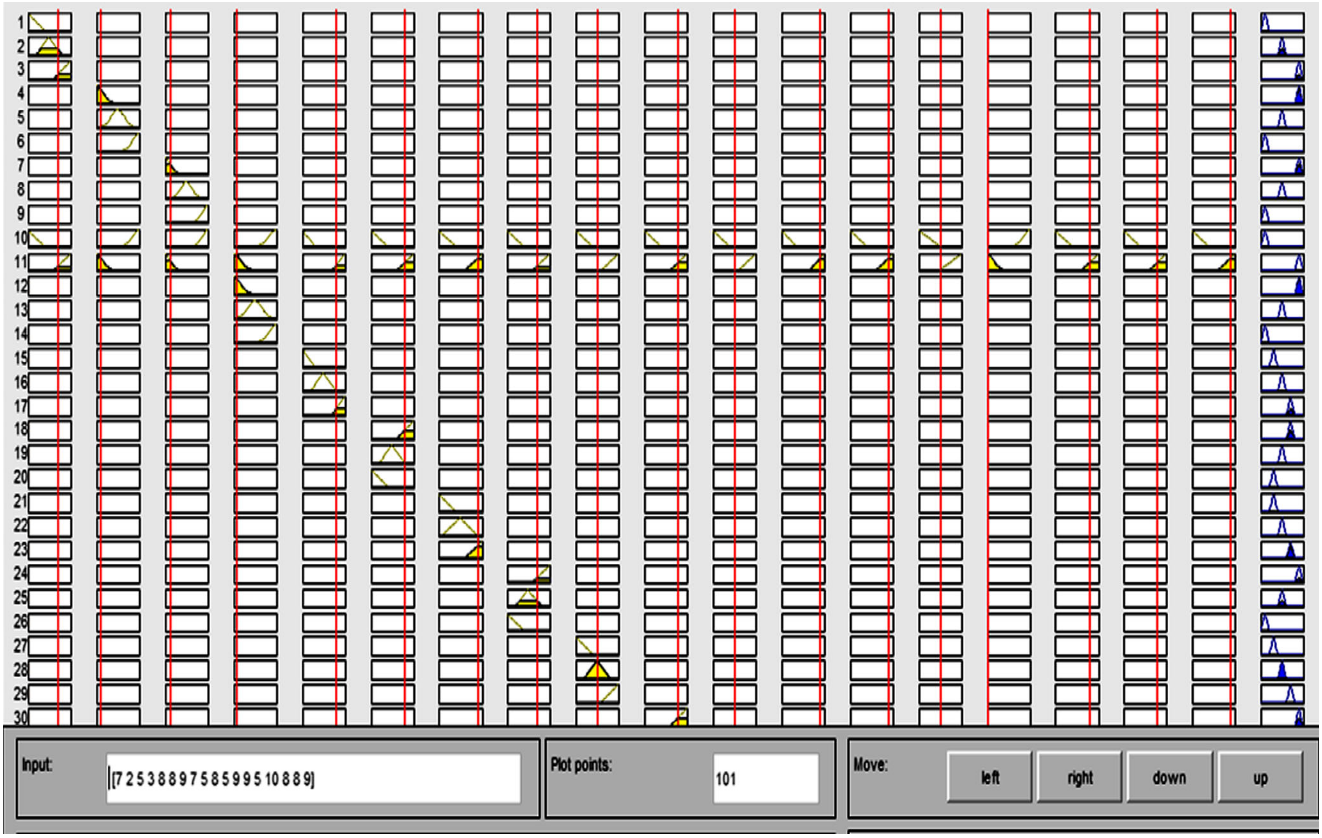

Fig. 9 Rule viewer of FIS for supplier 'S5'

best selection among the suppliers. If any organization wants an alternative supplier, supplier 'S2' should be the first choice because it obtains the second-highest ranking index.

To judge the ability of our FIS model, we have generated 100 random test scenarios within the range of data provided in Table 1 and solved those problems by using the proposed model, which confirms the ability of the model to solve all type of scenarios.

6 Conclusions

The main objective of this paper was to develop a simple and straightforward supplier selection model by considering relevant criteria for managing supply risks. Both qualitative and quantitative criteria were taken into consideration while developing the model and 18 different selection criteria used to determine the supplier ranking index. A FIS was applied to obtain aggregated optimized results based on some developed rules. Risks due to uncertainty were also incorporated in this model by considering triangular and gaussian membership functions for the input and output variables. Anyone can easily use this model to select the best supplier by entering the collected input data in the rule viewer of the developed FIS, and it can be applied in any manufacturing or service supply chain organization to select the most suitable suppliers.

Table 4 FIS results and supplier rankings

Supplier	Supplier ranking index	Ranking
S1	0.558	3
S2	0.673	2
S3	0.502	4
S4	0.405	5
S5	0.709	1

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