



Neutrosophic MCDM Methodology to Select Best Industrial Arc Welding Robot

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Abstract

Industrial robots have made it possible for industrial companies to make goods of a good quality at lower costs. As a result, industrial robots are an integral component of sophisticated manufacturing systems. Industrial robots may be programmed to do a wide variety of tasks, including welding, painting, construction, and debugging. All of the elements are completed with an exceptional level of endurance, swiftness, and accuracy. The efficiency of industrial robots is governed by a number of different factors, some of which are in direct opposition to one another; for a strong choice approach, all of these criteria must be examined concurrently. For the purpose of selecting an industrial robot for the arc soldering process, a straightforward multi-criteria decision-making (MCDM) approach that is VIKOR method will be described in this research. The VIKOR method used to rank the robots. The results of the VIKOR methodology are provided here in the form of a priority of rating. The findings demonstrated that the MCDM strategies are highly helpful when selecting robots to utilize.

Keywords: Neutrosophic Sets; MCDM; Welding Robot; VIKOR; Selection Problem.

1. Introduction

An industrial robot is a programmed device that can perform a variety of tasks and has particular anthropometrical characteristics. Its robot arm is the anthropometrical element that is considered to be the most crucial and essential. Other less key parts, such as its decision-making abilities, ability to react to numerous sensory inputs, and the ability to interact with other devices, make it a useful element for a variety of industrial apps, such as handling of materials, construction, completing, device loading, painting swastikas, and welding [1], [2]. When choosing an industrial robot for a specific app, the most crucial determinants to take into account are the robot's control decision, correctness, consistency, programming adaptability, maximum tip quickness, large memory, and the reliability of the provider's service. These factors that go into deciding which robot to use may be divided into two categories: those that are objective and those that are subjective, as well as those that are advantageous and those that are not beneficial. Objective qualities, like the price and load carrying capability of a robot, etc., are amenable to being specified using numerical values. In contrast hand, subjective qualities are qualitative in nature, such as the quality of a user's service or the adaptability of a robot's programming, among other examples [3]–[5]. The helpful characteristics are those whose greater amounts are always preferred; for example, load bearing capacity and programming flexibility [6], [7]. On the other hand, the non-benefit characteristics are those whose smaller values are desirable; for example, price and repetition. When choosing an industrial robot for a certain usage, the person making the selection has to take into account all of these features, and in some cases, strike a compromise between those features and the performance metrics of the robot [8]–[10]. Previous researchers have indeed come up with a number of different strategies for

selecting robots, some of which involve the use of multi-criteria decision-making (MCDM) techniques, manufacturing systems performance optimization techniques, computer-assisted modeling techniques, and mathematical analysis[11]–[13].

This study employ the MCDM under neutrosophic environment. The study used the VIKOR method to rank and select best robot from various robots. The VIKOR technique is an excellent tool in the process of making decisions based on several criteria, especially in circumstances in which the decision maker is unable to communicate his or her choice at the beginning of the process of system design or is unaware of how to do so[14]–[16]. The reached compromise solution has the potential to be approved by the decision makers since it offers the "majority" the most possible group benefit while the "opponents" express the least amount of individual regret possible. The alternatives that represent a compromise might serve as the starting point for negotiations, with the decision-makers' preferences being weighted according to the criteria[17]–[19]. The outcome of the VIKOR test is contingent on the optimal solution, which is valid only for the options that have been provided. The inclusion (or omission) of a particular alternative in the new set of options may have an effect on the VIKOR rating of those options. By presenting both the best and the worst possible values, it would be possible to prevent this effect; but, doing so would require the decision-maker to come up with a definitive perfect option[20]–[23].

1.1 Arc welding

Arc welding is now one of the most significant welding methods in contemporary welding production, and it is extensively used in the automotive processing industry, in construction, and in engineering. There have been several phases of development for the arc welding technique. Welding was done by hand by welders in the initial phases, hence the strength of the weld was greatly reliant on the welder's conceptual underpinnings and operational experience. Because of this, there were issues with the welded structural elements having an unstable condition and being non-uniform. The use of industrial welding robots started to progressively digitalize welding in welding manufacturing as robotic technology advanced. This transition constituted the second phase of automated welding and was initiated by industrial welding robotics. The use of industrial robotic welding allows for successful welding to be performed in locations that are impossible to human welders, as well as for overall improvements to be made to welding quality, flexibility, and productivity improvement. However, the "training and playback" option is still the predominant way of operation for most welding robots. Off-line programmed welding depending on computer-aided design (CAD) can only handle circumstances in which previous information about the modeling approach is given. This limits its applicability. Despite this, there remains a possibility of significant placement mistakes. Due to the inevitability of assembly mistakes, pre-processing problems, and disturbances during the well-meant, ecological work piece recognition and defect detection must still rely on human observation and ongoing re-training[24], [25].

The remaining portion of the article is structured as follows: Section 2 discusses neutrosophic MCDM methodology, followed by the presentation results in Section 3. Section 4 provides summary and conclusions.

2. Materials and Methods

Even though there are several theories for working with ambiguous knowledge and information, like the fuzzy set (FS), the intuitionistic FS, and the rough set theory, these theories can only tackle a portion of the ambiguous situations that occur in the actual world. Smarandache accomplished this goal by combining a non-standard analysis with a tri-component set, which was the beginning of neutrosophic set theory. A NS is made up of three membership functions, which are the truth-membership function, the indeterminacy-membership feature, and the falsity-membership function. Each function value is either a real standard or non-standard fraction of the nonstandard unit interval, which ranges from 0 to 1.

By streamlining NSs, Wang et al. offered SVNSs as an alternative. SVNSs may also be seen as an extension of intuitionistic FS. In this kind of FS, the function values of the three membership factors are not connected to one another, and they all fall inside the same closed interval. SVNS have given rise to a brand new pressing research problem.

In this section, the single value neutrosophic sets (SVNSs) presented to select best robot. The VIKOR approach was initially presented to the scientific community for the very first time in 2004 by Opricovic and Tzeng. The product's guiding idea is to choose the option that best fits the requirements at hand by placing the available options in descending order according to a set of criteria that is mutually exclusive. In the course of the sorting and selecting that has to be done, reaching a consensus is the objective of the procedure.

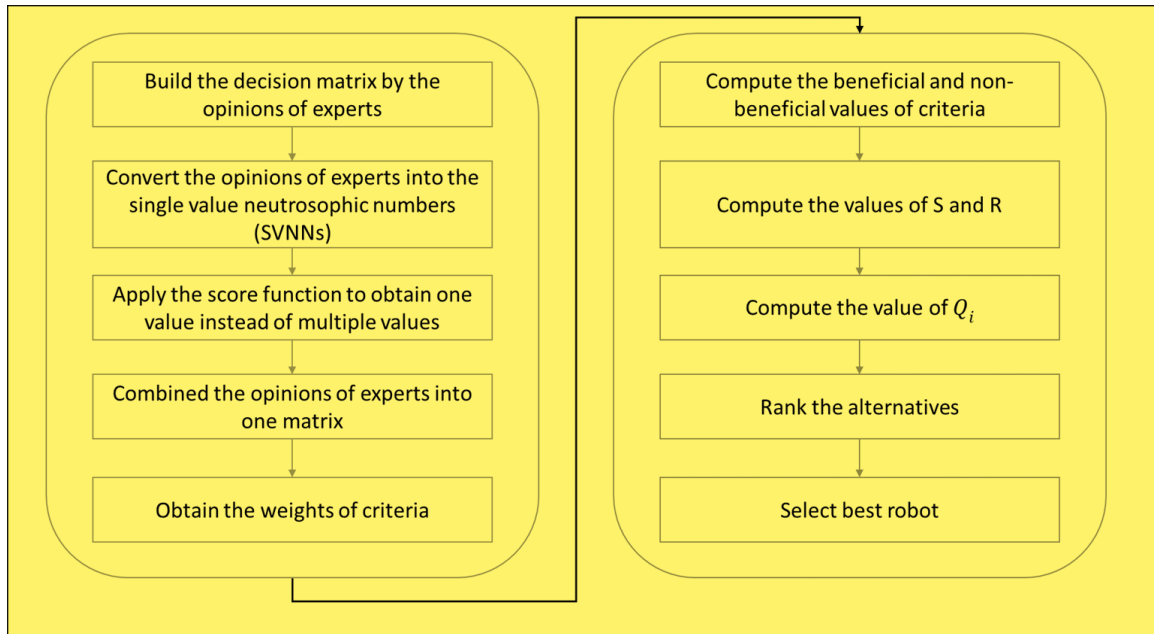


Figure 1: The Steps of VIKOR method.

The n options that are being considered are going to be denoted as $Robot_1, Robot_2, \dots, Robot_n$, the evaluation attribute is going to be denoted as F_1, F_2, \dots, F_n , and the rating of each alternative ($j = 1, \dots, n$) with regard to attribute ($i = 1, \dots, m$). After that, the VIKOR method's compromise ranking algorithm is broken down into the following phases. Figure 1 shows the steps of the methodology.

Step 1: Build the decision matrix by the opinions of experts

Step 2: Convert the opinions of experts into the single value neutrosophic numbers.

Step 3: Apply the score function to obtain one value instead of multiple values.

$$Score = \frac{2+T-I-F}{3}$$

Where T, I, F refers to the truth, indeterminacy and falsity membership degrees.

Step 4: Combined the opinions of experts into one matrix.

Step 5: Obtain the weights of criteria.

The weights of criteria are obtained by the average method.

Step 6: Compute the beneficial and non-beneficial values of criteria

$$B_i^+ = \max_j A_{ij} \tag{1}$$

$$B_i^- = \min_j A_{ij} \tag{2}$$

$$B_i^+ = \min_j A_{ij} \tag{3}$$

$$B_i^- = \max_j A_{ij} \tag{4}$$

Step 7: Compute the values of S and R.

$$S_i = \sum_{i=1}^n \frac{w_i(B_i^+ - B_{ij})}{(B_i^+ - B_i^-)} \tag{5}$$

$$R_i = \max_i \left(\frac{w_i(B_i^+ - B_{ij})}{(B_i^+ - B_i^-)} \right) \tag{6}$$

Step 8: Compute the value of Q_i .

$$Q_i = \alpha \frac{(S_j - S^+)}{(S^- - S^+)} + (1 - \alpha) \frac{(R_j - R^+)}{(R^- - R^+)} \tag{7}$$

Step 9: Rank the alternatives

Rank the alternatives according to minimum value of Q_i .

3. Results

Because there is such a wide variety of options available for industrial arc welding robots, increased product quality criteria should be able to drive it at a lower cost while still producing a solid weld. There is a

wide selection of robots available to buy from a variety of various manufacturers. These machines come with a large number of innovative and diverse capabilities, but the major differentiating factor is determining which one is the best based on basic characteristics. The VIKOR approach is used in this research project in order to investigate the choice of industrial robots for arc welding operations. The information for arc welding robots were gathered to apply to ten distinct robots, each of which had six controllable axes and various controllers that were manufactured by their own individual firms. There are five characteristics or criteria that are attributed to these ten robots. After evaluating the numerous data files that were supplied by firms that manufacture robots in order to give information about their goods, the choice feature were taken into consideration. In addition to that, the views of industry specialists are taken into consideration. Following the conversation that took place among the study group and the expert in the field, the choice feature were determined[26]–[28]. It was decided to analyze the combined choice reached by both groups, and the important characteristics held by every robot were taken into consideration as factors for an assessment in the ultimate decision matrix. When it comes to making decisions, the term "useful criteria" almost often refers to a greater value, such as the payload capacity of a robot. The non-beneficial rules are applied to a lesser value, such as the amount of electricity that the robot consumes. The following is a description of the 5 main factors that were taken into consideration throughout the process of selecting an arc welding robot:

Weight of the robot's moving parts, measured in kilograms: It is referring to the actual weight of the robot. Since a customer would often choose a robot that has a lower weight, this criteria is not considered to be advantageous. Predictive validity in millimeters: This presents the capacity of the robot to do an action in a manner that is identical to previous iterations. Because reproducibility is a favorable characteristic, it is typically preferable for there to be more of it. Payload capability of the robot in kilograms: This refers to the greatest amount of combined weight that a robot can lift in a single rotation. As a result, this is a helpful criteria since it is often desired to be greater. Maximum range of the robot in millimeters: This term refers to the average of the greatest vertical and horizontal distances up to which a robot may extend its arm in order to complete the task at hand. Being more is a desirable trait in most people, which is why this is a good criteria. The robot's kilowatt-hourly power usage on average: It is a reference to the standard number of power units that are used by the robot on a regular basis. It is a cost criteria since it is often desirable for a robot to have minimal energy usage; nevertheless, this is not a need [29], [30].

Step 1: Build the decision matrix by the opinions of experts

This study used three experts to evaluate the five criteria and ten alternatives. The three experts build three decision matrices. The three experts have experience in the industrial robot arc welding.

Step 2: Convert the opinions of experts into the single value neutrosophic numbers (SVNNs). The SVNNs show in Table 1.

The opinions of experts are converted to the SVNNs as shown in Tables A.1-A.3 in appendix A.

Table 1: The SVNNs.

Linguistic Terms	SVNNs
Extremely Good	(0.9,0.1,0.2)
Very Very Good	(0.8,0.2,0.3)
Very Good	(0.7,0.3,0.4)
Good	(0.6,0.4,0.5)
Medium	(0.5,0.5,0.5)
Poor	(0.4,0.6,0.4)
Very Poor	(0.2,0.7,0.8)

Step 3: Apply the score function to obtain one value instead of multiple values.

The score function is used to convert three values in SVNNs into one number as shown in Tables A.4-A.6 in appendix.

Step 4: Combined the opinions of experts into one matrix

Apply the average method to combine the three decision matrices into one matrix as shown in Table 2.

Table 2: The combined values of experts.

	F ₁	F ₂	F ₃	F ₄	F ₅
Ro ₁	0.655556	0.522222	0.455556	0.533333	0.8
Ro ₂	0.566667	0.566667	0.466667	0.666667	0.233333
Ro ₃	0.533333	0.8	0.7	0.466667	0.6

Ro ₄	0.455556	0.8	0.588889	0.655556	0.666667
Ro ₅	0.733333	0.522222	0.766667	0.6	0.233333
Ro ₆	0.566667	0.6	0.766667	0.766667	0.8
Ro ₇	0.655556	0.7	0.866667	0.766667	0.466667
Ro ₈	0.566667	0.455556	0.766667	0.866667	0.233333
Ro ₉	0.466667	0.566667	0.533333	0.588889	0.6
Ro ₁₀	0.655556	0.766667	0.633333	0.733333	0.344444

Step 5: Obtain the weights of criteria

The decision makers emulate the five criteria. Then obtained three matrices. Then combined these values into one matrix. Then apply the average method to compute the weights of criteria. The weights of five criteria shown in Figure 2.

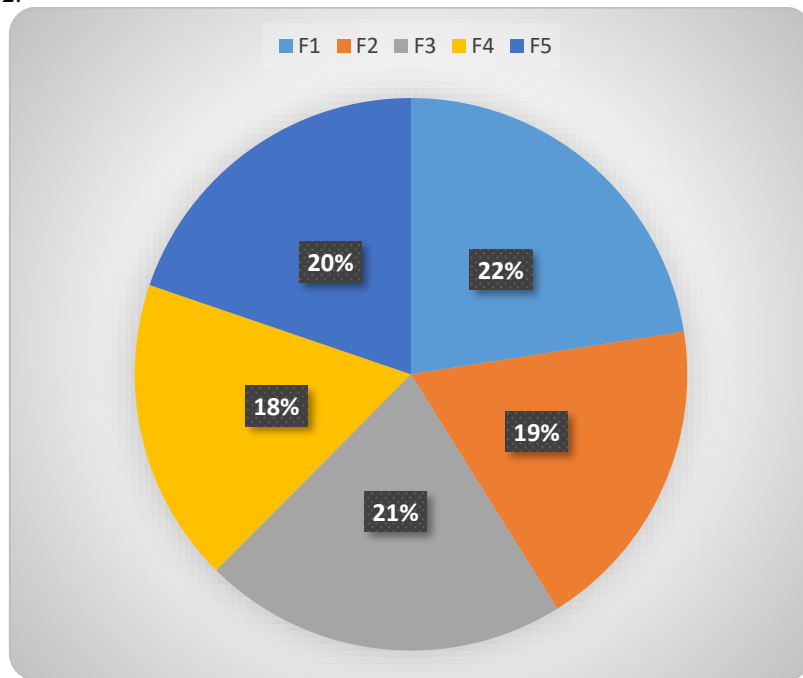


Figure 2: The weights of 5 factors.

Step 6: Compute the beneficial and non-beneficial values of criteria

Determine the positive and cost criteria. The power usage and weight is a cost criteria and all criteria are positive. The compute the maximum value of positive and cost criteria and minimum value of positive and cost criteria using Equations (1-4).

Step 7: Compute the values of S and R

The values of S and R are computed using Equations (5, 6) as shown in Table 3.

Table 3: The Values of S and R.

	F ₁	F ₂	F ₃	F ₄	F ₅	S	R
Ro ₁	0.063083	0.149815	0.213439	0.148221	0	0.574558	0.213439
Ro ₂	0.135178	0.125845	0.20767	0.088933	0.197628	0.755254	0.20767
Ro ₃	0.162213	0	0.086529	0.177866	0.069751	0.496359	0.177866
Ro ₄	0.225296	0	0.144215	0.093874	0.046501	0.509886	0.225296
Ro ₅	0	0.149815	0.051918	0.118577	0.197628	0.517938	0.197628
Ro ₆	0.135178	0.107867	0.051918	0.044466	0	0.339429	0.135178
Ro ₇	0.063083	0.053933	0	0.044466	0.116252	0.277735	0.116252
Ro ₈	0.135178	0.185771	0.051918	0	0.197628	0.570495	0.197628
Ro ₉	0.216285	0.125845	0.173058	0.123518	0.069751	0.708457	0.216285
Ro ₁₀	0.063083	0.017978	0.121141	0.059289	0.158878	0.420368	0.158878

Step 8: Compute the value of Q_i

By using Equation (7), the value of Q_i is computed.

Step 9: Rank the alternatives

Rank the alternatives according to minimum value of Q_i as shown in Figure 3.

From Figure 2 the Robot-7 is the best alternative and Robot-2.

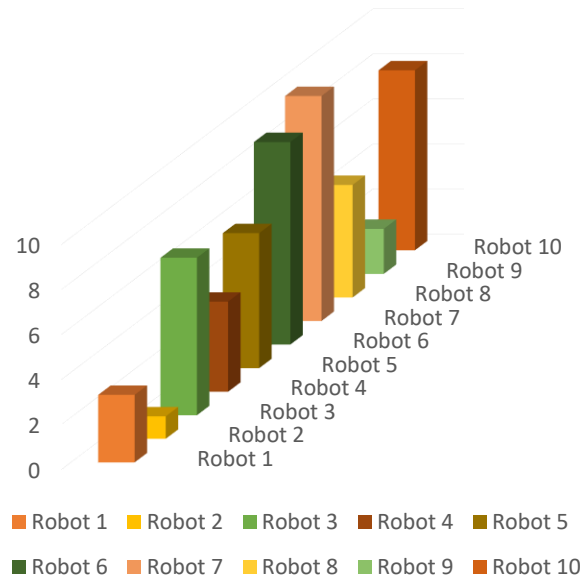


Figure 3: The ordering of ten alternatives.

4. Conclusions

The purpose of this investigation is to determine which kind of industrial robot is best suited for arc welding. In order to make a selection, we considered a total of ten different options based on five different characteristics or criteria. The VIKOR method is used in order to determine which robot is the most suitable for a given set of requirements. By applying the average method, the objective weights of importance that are given to the traits and criteria are determined. According to the results, the VIKOR method has been used to choose the Robot-7 machine as the first candidate. The VIKOR methodology is statistically simpler, and it has the potential to provide more accurate findings. Additionally, the Robots product line may be extended to include other choices and characteristics. The significance weights that are assigned may be examined using both objective and subjective weights in the same manner.

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Appendix A

Table A.1. The opinions of first expert.

	F ₁	F ₂	F ₃	F ₄	F ₅
RO ₁	(0.9,0.1,0.2)	(0.2,0.7,0.8)	(0.6,0.4,0.5)	(0.4,0.6,0.4)	(0.9,0.1,0.2)
RO ₂	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.4)	(0.6,0.4,0.5)	(0.2,0.7,0.8)
RO ₃	(0.4,0.6,0.4)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.4,0.6,0.4)	(0.6,0.4,0.5)
RO ₄	(0.4,0.6,0.4)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.6,0.4,0.5)
RO ₅	(0.9,0.1,0.2)	(0.2,0.7,0.8)	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.2,0.7,0.8)
RO ₆	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.9,0.1,0.2)
RO ₇	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.4,0.6,0.4)
RO ₈	(0.6,0.4,0.5)	(0.2,0.7,0.8)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.2,0.7,0.8)
RO ₉	(0.4,0.6,0.4)	(0.6,0.4,0.5)	(0.4,0.6,0.4)	(0.8,0.2,0.3)	(0.6,0.4,0.5)
RO ₁₀	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.2,0.7,0.8)

Table A.2. The opinions of second expert.

	F ₁	F ₂	F ₃	F ₄	F ₅
RO ₁	(0.2,0.7,0.8)	(0.7,0.3,0.4)	(0.2,0.7,0.8)	(0.4,0.6,0.4)	(0.7,0.3,0.4)
RO ₂	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.4)	(0.6,0.4,0.5)	(0.2,0.7,0.8)
RO ₃	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.4,0.6,0.4)	(0.4,0.6,0.4)	(0.7,0.3,0.4)
RO ₄	(0.2,0.7,0.8)	(0.7,0.3,0.4)	(0.2,0.7,0.8)	(0.2,0.7,0.8)	(0.6,0.4,0.5)
RO ₅	(0.4,0.6,0.4)	(0.4,0.6,0.4)	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.2,0.7,0.8)
RO ₆	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.7,0.3,0.4)
RO ₇	(0.2,0.7,0.8)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.4,0.6,0.4)
RO ₈	(0.6,0.4,0.5)	(0.4,0.6,0.4)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.2,0.7,0.8)
RO ₉	(0.4,0.6,0.4)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.2,0.7,0.8)	(0.7,0.3,0.4)
RO ₁₀	(0.2,0.7,0.8)	(0.8,0.2,0.3)	(0.4,0.6,0.4)	(0.8,0.2,0.3)	(0.2,0.7,0.8)

Table A.3. The opinions of third expert.

	F ₁	F ₂	F ₃	F ₄	F ₅
Ro ₁	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.9,0.1,0.2)
Ro ₂	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.4)	(0.9,0.1,0.2)	(0.2,0.7,0.8)
Ro ₃	(0.4,0.6,0.4)	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.4,0.6,0.4)	(0.6,0.4,0.5)
Ro ₄	(0.7,0.3,0.4)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.9,0.1,0.2)
Ro ₅	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.2,0.7,0.8)
Ro ₆	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.9,0.1,0.2)
Ro ₇	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.4,0.6,0.4)
Ro ₈	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.2,0.7,0.8)
Ro ₉	(0.4,0.6,0.4)	(0.6,0.4,0.5)	(0.4,0.6,0.4)	(0.8,0.2,0.3)	(0.6,0.4,0.5)
Ro ₁₀	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.6,0.4,0.5)

Table A.4. The score valued of first expert.

	F ₁	F ₂	F ₃	F ₄	F ₅
Ro ₁	0.866667	0.233333	0.566667	0.466667	0.866667
Ro ₂	0.566667	0.566667	0.466667	0.566667	0.233333
Ro ₃	0.466667	0.766667	0.766667	0.466667	0.566667
Ro ₄	0.466667	0.866667	0.766667	0.866667	0.566667
Ro ₅	0.866667	0.233333	0.766667	0.566667	0.233333
Ro ₆	0.566667	0.566667	0.766667	0.766667	0.866667
Ro ₇	0.866667	0.766667	0.866667	0.766667	0.466667
Ro ₈	0.566667	0.233333	0.766667	0.866667	0.233333
Ro ₉	0.466667	0.566667	0.466667	0.766667	0.566667
Ro ₁₀	0.866667	0.766667	0.866667	0.766667	0.233333

Table A.5. The score values of second expert.

	F ₁	F ₂	F ₃	F ₄	F ₅
Ro ₁	0.233333	0.666667	0.233333	0.466667	0.666667
Ro ₂	0.566667	0.566667	0.466667	0.566667	0.233333
Ro ₃	0.666667	0.766667	0.466667	0.466667	0.666667
Ro ₄	0.233333	0.666667	0.233333	0.233333	0.566667
Ro ₅	0.466667	0.466667	0.766667	0.566667	0.233333
Ro ₆	0.566667	0.666667	0.666667	0.766667	0.666667
Ro ₇	0.233333	0.766667	0.866667	0.766667	0.466667
Ro ₈	0.566667	0.466667	0.766667	0.866667	0.233333
Ro ₉	0.466667	0.566667	0.666667	0.233333	0.666667
Ro ₁₀	0.233333	0.766667	0.466667	0.766667	0.233333

Table A.6. The score values of third expert.

	F ₁	F ₂	F ₃	F ₄	F ₅
Ro ₁	0.866667	0.666667	0.566667	0.666667	0.866667
Ro ₂	0.566667	0.566667	0.466667	0.866667	0.233333
Ro ₃	0.466667	0.866667	0.866667	0.466667	0.566667
Ro ₄	0.666667	0.866667	0.766667	0.866667	0.866667
Ro ₅	0.866667	0.866667	0.766667	0.666667	0.233333
Ro ₆	0.566667	0.566667	0.866667	0.766667	0.866667
Ro ₇	0.866667	0.566667	0.866667	0.766667	0.466667
Ro ₈	0.566667	0.666667	0.766667	0.866667	0.233333
Ro ₉	0.466667	0.566667	0.466667	0.766667	0.566667
Ro ₁₀	0.866667	0.766667	0.566667	0.666667	0.566667