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A Fuzzy TOPSIS-Based Approach to Maintenance Strategy Selection: A Case Study

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Abstract: In this paper, the selection of maintenance strategies in Electerofan Company is studied. The evaluation of maintenance strategies for each piece of equipment is a multiple criteria decision-making (MCDM) problem. To deal with the uncertain judgment of decision makers, a fuzzy TOPSIS method is applied as an evaluation tool, where uncertain and imprecise judgments of decision makers are translated into fuzzy numbers. A specific example of selection of maintenance strategies in this company with the application of the proposed fuzzy TOPSIS method is given, showing that the Preventive maintenance strategy is the most suitable for equipment.

Key words: Maintenance strategies · Multiple criteria decision-making · Fuzzy logic · TOPSIS

INTRODUCTION

The importance of maintenance function has increased due to its role in keeping and improving the availability, product quality, safety requirements and plant cost-effectiveness levels. Maintenance costs constitute an important part of the operating budget of manufacturing firms. One of the main expenditure items for these firms is maintenance cost which can reach 15–70% of production costs, varying according to the type of industry [1]. On the other hand, maintenance plays an important role in keeping availability and reliability levels, product quality and safety requirements. Unfortunately, unlike production and manufacturing problems which have received tremendous interest from researchers and practitioners, maintenance received little attention in the past. This is one of the reasons that results in low maintenance efficiency in industry at present but today, research in this area is on the rise and research on maintenance represents an opportunity for making significant contribution by academics. This paper is organized as follows. Section 2 describes the possible alternative maintenance strategies in this study. In Section 3, the comparing criteria for the selection of maintenance strategies are presented. Section 4 introduces fuzzy set theory. Section 5 describes the basic concept of fuzzy TOPSIS. Section 6 describes the application of the proposed evaluation method for the selection of maintenance strategies in Electrofan Company and conclusion finally.

Alternative Maintenance Strategies: Five alternative maintenance policies are evaluated in this case study according to Bevilacqua *et al*. [1]. They are the following as:

- *Preventive maintenance.* Preventive maintenance is based on component reliability characteristics. This data makes it possible to analyze the behavior of the element in question and allows the maintenance engineer to define a periodic maintenance program for the machine. Preventive maintenance is effective in overcoming the problems associated with the wearing of components. It is evident that, after a check, it is not always necessary to substitute the component: maintenance is often sufficient.
- *Opportunistic maintenance.* The possibility of using opportunistic maintenance is determined by the nearness or concurrence of control or substitution times for different components on the same machine or plant. This type of maintenance can lead to the whole plant being shut down at set times to perform all relevant maintenance interventions at the same time.

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- *Corrective maintenance.* The main feature of corrective maintenance is that actions are only performed when a machine breaks down. There are no interventions until a failure has occurred.
- *Predictive maintenance.* Unlike the condition-based maintenance policy, in predictive maintenance the acquired controlled parameters data are analyzed to find a possible temporal trend. This makes it possible to predict when the controlled quantity value will reach or exceed the threshold values.
- *Condition-based maintenance.* A requisite for the application of condition-based maintenance is the availability of a set of measurements and data acquisition systems to monitor the machine performance in real time. The continuous survey of working conditions can easily and clearly point out an abnormal situation (e.g. the exceeding of a controlled parameter threshold level), allowing the process administrator to punctually perform the necessary controls and, if necessary, stop the machine before a failure can occur.

Comparing Criteria: Different manufacturing companies may have different maintenance goals.Accoding to Wang *et al*. [2], Bevilacqua *et al*. [1] and expert's opinion; these goals can be divided into four aspects analyzed as follows:

Added-value: A good maintenance program can induce added-value, including low inventories of spare parts, small production waste and Product quality.

Product Quality: Equipment failure can affect the quality of products which is produced. In fact, when the machin is in better condition and with greater reliability work, the quality of products will increase.

Production Waste: The failure of more important machines in the production line often leads to higher production loss cost. Selecting a suitable maintenance strategy for such machines may reduce production waste.

Spare Parts Inventories: Generally, corrective maintenance need more spare parts than other maintenance strategies.

Applicability: Applicability refers to the appropriate conditions for implementing the strategy.

Access to Equipment and Technology: One of the effective factors in selecting a strategy is access to equipment and technology needed to implement.

Technique Reliability: Still under development, condition-based maintenance and predictive maintenance may be inapplicable for some complicated production facilities.

Safety: Safety levels required are often high in many manufacturing factories, especially in industry companies. The relevant factors describing the Safety are:

Facilities: For example, the sudden breakdown of pump can result in serious damage in this plant.

Personnel: The failure of many machines can lead to serious damage of personnel on site.

Environment: The failure of equipment with poisonous liquid or gas can damage the environment.

Cost: Different maintenance strategies have different expenditure of hardware, software and Specialist employee.

Hardware: For condition-based maintenance and predictive maintenance, a number of sensors and some computers are indispensable.

Specialist Employee Required: To implement each strategy, the specialist force is required that the number and type according to the chosen strategy will change. These forces can be absorbed from outside organizations, or individuals within the organization with the training they provide.

Software: Software is needed for analyzing measured parameters data when using condition-based maintenance and predictive maintenance strategies.

Fuzzy Sets and Fuzzy Numbers: Fuzzy set theory, which was introduced by Zadeh [3] to deal with problems in which a source of vagueness is involved, has been utilized for incorporating imprecise data into the decision framework. A fuzzy set $\tilde{A}$ can be defined mathematically by a membership function $\mu_{\tilde{A}}(X)$, which assigns each element x in the universe of discourse X a real number in

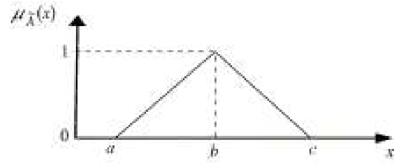

Fig 1. A triangular fuzzy number $\tilde{A}$

the interval [0,1]. A triangular fuzzy number $\tilde{A}$ can be defined by a triplet (a, b, c) as illustrated in Fig 1.
The membership function $\mu\tilde{A}(X)$ is defined as

$$\mu\tilde{A}(x)=\begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{x-c}{b-c} & \mathrm{b} \le x \le c \\ 0 & oterwise \end{cases} \tag{1}$$

Basic arithmetic operations on triangular fuzzy numbers A1 $\le$ (a_1,b_1,c_1), where $a_1 \le b_1 \le c_1$ and $A_2 \le (a_2,b_2,c_2)$, where $a_2 \le b_2 \le c_2$, can be shown as follows:

Additions:

$$A_1 \oplus A_2 = (a_1 + a_2, b_1 - b_2, c_1 + c_2) \tag{2}$$

Subtraction:

$$A_1 \ominus A_2 = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \tag{3}$$

Multiplication: if k is a scalar

$$k \otimes A_1 = \begin{cases} (ka_1, kb_1, kc_1), & k > 0 \\ (kc_1, kb_1, ka_1), & k < 0 \end{cases}$$

$$A_1 \otimes A_2 \approx (a_1a_2, b_1b_2, c_1c_2)$$

$$\text{if } a_1 \ge 0, a_2 \ge 0 \tag{4}$$

$$\text{Division: } A_1 \varnothing A_2 \approx \left(\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2}\right),$$

$$\text{if } a_1 \ge 0, a_2 \ge 0 \tag{5}$$

Although multiplication and division operations on triangular fuzzy numbers do not necessarily yield a triangular fuzzy number, triangular fuzzy number approximations can be used for many practical applications [4]. Triangular fuzzy numbers are appropriate for quantifying the vague information about most decision problems including personnel selection (e.g. rating for creativity, personality, leadership, etc.). The primary reason for using triangular fuzzy numbers can be stated as their intuitive and computational-efficient representation [5].

A linguistic variable is defined as a variable whose values are not numbers, but words or sentences in natural or artificial language. The concept of a linguistic variable appears as a useful means for providing approximate characterization of phenomena that are too complex or ill defined to be described in conventional quantitative terms [6].

The Fuzzy Topsis Method: This study uses this method to select the best maintenance strategy. TOPSIS views a MADM problem with m alternatives as a geometric system with m points in the n-dimensional space. The method is based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. TOPSIS defines an index called similarity to the positive-ideal solution and the remoteness from the negative-ideal solution. Then the method chooses an alternative with the maximum similarity to the positive-ideal solution [7]. It is often difficult for a decision-maker to assign a precise performance rating to an alternative for the attributes under consideration. The merit of using a fuzzy approach is to assign the relative importance of attributes using fuzzy numbers instead of precise numbers. This section extends the TOPSIS to the fuzzy environment [8]. This method is particularly suitable for solving the group decision-making problem under fuzzy environment. We briefly review the rationale of fuzzy theory before the development of fuzzy TOPSIS. The mathematics concept borrowed from Ashtiani [7, 9, 10].

Step 1: Determine the weighting of evaluation criteria.

A systematic approach to extend the TOPSIS is proposed to selecting best maintenance strategy under a fuzzy environment in this section. In this paper the importance weights of various criteria and the ratings of qualitative criteria are considered as linguistic variables (Table 1) [11].

Step 2: Construct the fuzzy decision matrix and choose the appropriate linguistic variables for the alternatives with respect to criteria.

Table 1: Linguistic scales for the importance of each criterion

Linguistic variable	Corresponding triangular fuzzy number
Very low (VL)	(0.0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very high (VH)	(0.7, 0.9, 1.0)

$$\tilde{D}= \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_M \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_N \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{n1} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array}$$

i = 1,2,...,m; j=1,2,...,n

$$\tilde{x}_{ij} = \frac{1}{2}(\tilde{x}_{ij} + \tilde{x}_{ij}^2 + \ldots \tilde{x}_{ij}^k) \tag{6}$$

Where $\tilde{x}_{ij}^k$ is the rating of alternative A_i with respect to criterion C_j evaluated by K expert and

$\tilde{x}_{ij}^k = (a_{ij}^k,\ b_{ij}^k,\ c_{ij}^k)$

Step 3: Normalize the fuzzy decision matrix.

The normalized fuzzy decision matrix denoted by $\tilde{R}$ is shown as following formula:

$$\tilde{R}=\left[\tilde{r}_{ij}\right]_{m\times n},$$

i = 1,2,...,m; j=1,2,...,n (7)

Then the normalization process can be performed by following formula:

Where $\tilde{r}_{ij} = (\frac{a_{ij}}{c_j}, \frac{b_{ij}}{c_j}, \frac{c_{ij}}{c_j})\ c_j^+ = \max_i c_{ij}$

The normalized $\tilde{r}_{ij}$ are still triangular fuzzy numbers. For trapezoidal fuzzy numbers, the normalization process can be conducted in the same way. The weighted fuzzy normalized decision matrix is shown as following matrix $\tilde{V}$:

$$\tilde{v}=[\tilde{v}_{ij}]_{m\times n},$$

i = 1,2,...,m; j=1,2,...,n (8)

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \tag{9}$$

Step 4: Determine the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS).

According to the weighted normalized fuzzy decision matrix, we know that the elements $\tilde{V}_{ij}$ are normalized positive TFNs and their ranges belong to the closed interval [0, 1]. Then, we can define the FPIS A^+ and FNIS A^- as following formula:

$$A^+ = (\tilde{V}_1^+,\ \tilde{V}_2^+,\ldots,\tilde{V}_n^+) \tag{10}$$

$$A^- = (\tilde{V}_1^-,\ \tilde{V}_2^-,\ldots,\tilde{V}_n^-) \tag{11}$$

Where $\tilde{V}_j^+$ =(1,1,1) and $\tilde{V}_j^-$ =(0,0,0) j=1,2,…,n

Step 5: Calculate the distance of each alternative from FPIS and FNIS

The distances (d_i^+ and d_i^-) of each alternative A^+ from and A^- can be currently calculated.

$$d_i^+ = \sum\nolimits_{j=1}^n d(\tilde{v}_{ij}, \tilde{V}_j^+),$$

$$i = 1,2,\ldots..,m \quad j = 1,2,\ldots..n \tag{12}$$

$$d_i^+ = \sum\nolimits_{j=1}^n d(\tilde{v}_{ij}, \tilde{V}_j^-), \tag{13}$$

$$i = 1,2,\ldots..,m \quad j = 1,2,\ldots..n$$

Step 6: Obtain the closeness coefficient (CC) and rank the order of alternatives

The CC_i is defined to determine the ranking order of all alternatives once the d_i^+ and d_i^- of each alternative have been calculated. Calculate similarities to ideal solution. This step solves the similarities to an ideal solution by formula:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{14}$$

$$i = 1,2,\ldots.m$$

According to the CC_i, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives.

In the last years, some fuzzy TOPSIS methods were developed in the different applied field. Lin and Chang [12] adopted fuzzy TOPSIS for order selection and pricing of manufacturer (supplier) with make-to-order basis when

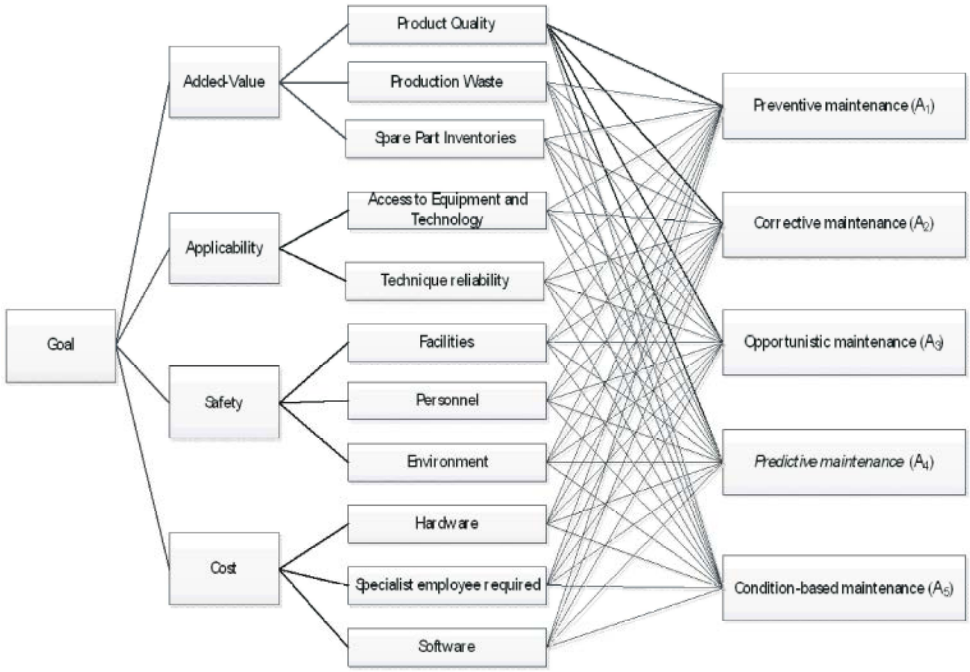

Fig. 2: Research framework

orders exceed production capacity. Chen and Tsao [13] are to extend the TOPSIS method based on interval-valued fuzzy sets in decision analysis. Ashtiani *et al*. [9] used interval-valued fuzzy TOPSIS method is aiming at solving MCDM problems in which the weights of criteria are unequal, using interval-valued fuzzy sets concepts. Mahdavi *et al*. [14] designed a model of TOPSIS for the fuzzy environment with the introduction of appropriate negations for obtaining ideal solutions. Büyüközkan *et al*. [10] identified the strategic main and sub-criteria of alliance partner selection that companies consider the most important through Fuzzy AHP and Fuzzy TOPSIS model and achieved the final partner-ranking results. Abo-Sinna *et al*. [15] focused on multi-objective large-scale non-linear programming problems with block angular structure and extended the technique for order preference by similarity ideal solution to solve them. Wang and Chang [7] applied fuzzy TOPSIS to help the Air Force Academy in Taiwan choose optimal initial training aircraft in a fuzzy environment. Li [16] developed a compromise ratio (CR) methodology for fuzzy multi-attribute group decision making (FMAGDM), which is an important part of decision support system. Wang and Lee [17] generalized TOPSIS to fuzzy multiple-criteria group decision-making (FMCGDM) in a fuzzy environment. Kahraman *et al*. [18] proposed a fuzzy hierarchical TOPSIS model for the multi-criteria evaluation of the industrial robotic systems. Benı´tez *et al*. [19] presented a fuzzy TOPSIS approach for evaluating dynamically the service quality of three hotels of an important corporation in Gran Canaria island via surveys. Wang and Elhag [20] proposed a fuzzy TOPSIS method based on alpha level sets and presents a non-linear programming solution procedure. Chen *et al*. [11] applied fuzzy TOPSIS approach to deal with the supplier selection problem in supply chain system.

Case Study: The Electrofan Company is a large, well known manufacturer that Working in LPG and CNG industry in Iran. In this research, 12 experts and managers were invited to survey five alternatives using the research framework shown in Fig 2. This research framework includes 11 evaluation criteria, such as Product Quality (C_1), Production waste (C_2), Spare part inventories (C_3), Access to Equipment and Technology (C_4), Technique reliability (C_5), Facilities (C_6), Personnel (C_7), Environment (C_8), Hardware (C_9), Specialist employee required (C_{10}) and Software (C_{11}). In addition, there are five alternatives.

After the construction of the hierarchy the different priority weights of each criteria, attributes and alternatives are calculated using the fuzzy TOPSIS approach. The comparison of the importance or preference of one criterion, attribute or alternative over another can be done with the help of the questionnaire. The method of calculating priority weights of the different decision alternatives is discussed following part.

Table 2: Weights of each criterion

		BNP	Rank
C_1	(0.58, 0.78, 0.93)	0.763	2
C_2	(0.55, 0.75, 0.90)	0.734	4
C_3	(0.32, 0.51, 0.70)	0.510	11
C_4	(0.64, 0.83, 0.95)	0.806	1
C_5	(0.54, 0.76, 0.83)	0.710	7
C_6	(0.38, 0.62, 0.80)	0.600	8
C_7	(0.54, 0.72, 0.89)	0.716	5
C_8	(0.32, 0.53, 0.74)	0.530	10
C_9	(0.53, 0.73, 0.88)	0.713	6
C_{10}	(0.58, 0.79, 0.89)	0.753	3
C_{11}	(0.34, 0.55, 0.72)	0.536	9

Table 3: Linguistic scales for the rating of each cluster policy

Linguistic variable	Corresponding triangular fuzzy number
Very poor (VP)	(0, 1, 3)
Poor (P)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Good (G)	(5, 7, 9)
Very good (VG)	(7, 9, 10)
Very poor (VP)	(0, 1, 3)

Step 1: Determine the linguistic weighting of each criteria

We adopt fuzzy TOPSIS method to evaluate the weights of different criteria for selecting the most efficient maintenance strategy. Following the construction of fuzzy TOPSIS model, it is extremely important that experts fill the judgment matrix. From the viewpoint of expert validity, the buildup of most of the operationalizations was based on the literature that caused them to have expert validity.

This research applies the COA method to compute the BNP value of the fuzzy weights of each dimension:
To take the BNP value of the weight of C_1 as an example, the calculation process is as follows:

$$BNP_{w1} = [(U_{w1}-L_{w1}) + (M_{w1}-L_{w1})]/3 + L_{w1}$$
$$= [(0.93-0.58)+(0.78-0.58)]/3+0.58=0.763 \quad (15)$$

Then, the weights for the remaining dimensions can be found as shown in Table 2. Table 2 shows the relative weight of criteria, which obtained by fuzzy TOPSIS method. The weights for each criterion are: C_1 (0.763), C_2 (0.734), C_3 (0.710), C_4 (0.806), C_5 (0.710), C_6 (0.600), C_7 (0.716), C_8 (0.530), C_9 (0.713), C_{10} (0.753) and C_{11} (0.536). From the fuzzy TOPSIS results, we can understand the first two important factors for selecting maintenance strategy are C_4 (0.806) and C_1 (0.763). Moreover, the less important factor is C_3 (0.510).

Step 2: Estimating the performance

This paper focus on determining the best maintenance strategy; so, we assume that questionnaire have collected completely and will start with building dataset that are collected. The evaluators have their own range for the linguistic variables employed in this study according to their subjective judgments [9].

For each evaluator with the same importance, this study employs the method of average value to integrate the fuzzy/vague judgment values of different evaluators regarding the same evaluation dimensions. The evaluators then adopted linguistic terms (Table 3), including “very poor”, “poor”, “fair”, “good” and “very good” to express their opinions about the rating of every person, based on the fuzzy data of the four person listed in Table 4.

Step 3: Normalize the fuzzy decision matrix

Using Eq. (7), we can normalize the fuzzy decision matrix as Table 5.

Table 4: Subjective cognition results of evaluators towards the five levels of linguistic variables

	A_1	A_2	A_3	A_4	A_5
C_1	(4.21, 6.21, 8.21)	(3.56, 6.45, 7.46)	(2.92, 4.84, 6.84)	(3.00, 5.00, 7.00)	(2.00, 4.00, 6.00)
C_2	(5.17, 7.17, 9.00)	(2.45, 4.45, 6.45)	(1.80, 3.65, 5.65)	(3.48, 5.76, 7.76)	(4.02, 6.00, 7.96)
C_3	(5.11, 7.11, 9.16)	(4.52, 6.50, 8.56)	(3.50, 5.50, 7.50)	(3.86, 5.86, 7.86)	(3.18, 5.18, 7.18)
C_4	(4.68, 6.68, 8.56)	(4.65, 6.65, 8.65)	(4.00, 6.00, 8.00)	(2.06, 4.00, 6.00)	(2.19, 4.19, 6.19)
C_5	(4.33, 6.35, 8.35)	(4.11, 6.00, 7.89)	(3.86, 5.86, 7.86)	(2.44, 4.46, 6.48)	(2.53, 4.53, 6.53)
C_6	(4.23, 6.32, 8.46)	(3.00, 5.00, 7.00)	(3.85, 5.85, 7.64)	(4.50, 6.50, 8.50)	(3.17, 5.17, 7.17)
C_7	(4.46, 6.52, 8.58)	(2.08, 4.00, 6.00)	(2.45, 4.45, 6.45)	(3.50, 5.50, 7.50)	(1.75, 3.50, 5.50)
C_8	(4.33, 6.33, 8.33)	(1.70, 3.52, 5.52)	(1.67, 3.56, 5.56)	(1.67, 3.50, 5.50)	(4.08, 6.00, 7.83)
C_9	(2.36, 4.42, 6.42)	(4.50, 6.50, 8.42)	(2.67, 4.67, 6.67)	(3.00, 5.00, 7.00)	(3.24, 5.24, 7.38)
C_{10}	(2.46, 4.38, 6.38)	(4.86, 6.84, 8.78)	(2.67, 4.67, 6.67)	(3.50, 5.50, 7.50)	(3.20, 5.20, 7.20)
C_{11}	(1.67, 3.56, 5.56)	(5.17, 7.17, 9.00)	(4.33, 6.33, 8.25)	(4.00, 6.00, 8.00)	(1.67, 3.56, 5.56)

Table 5: Normalized fuzzy decision matrix

	A_1	A_2	A_3	A_4	A_5
C_1	(0.46, 0.68, 0.90)	(0.39, 0.70, 0.81)	(0.32, 0.53, 0.75)	(0.33, 0.55, 0.76)	(0.22, 0.44, 0.66)
C_2	(0.56, 0.78, 0.98)	(0.27, 0.49, 0.70)	(0.20, 0.40, 0.62)	(0.42, 0.63, 0.85)	(0.44, 0.66, 0.87)
C_3	(0.56, 0.78, 1.00)	(0.49, 0.71, 0.93)	(0.33, 0.60, 0.82)	(0.42, 0.64, 0.86)	(0.35, 0.57, 0.78)
C_4	(0.51, 0.73, 0.93)	(0.51, 0.73, 0.94)	(0.44, 0.66, 0.87)	(0.22, 0.44, 0.66)	(0.24, 0.46, 0.68)
C_5	(0.47, 0.69, 0.91)	(0.45, 0.66, 0.86)	(0.42, 0.64, 0.86)	(0.27, 0.49, 0.71)	(0.28, 0.49, 0.71)
C_6	(0.46, 0.69, 0.92)	(0.33, 0.55, 0.76)	(0.42, 0.64, 0.83)	(0.49, 0.71, 0.93)	(0.35, 0.56, 0.78)
C_7	(0.49, 0.71, 0.94)	(0.23, 0.44, 0.66)	(0.27, 0.49, 0.70)	(0.38, 0.60, 0.82)	(0.19, 0.38, 0.60)
C_8	(0.47, 0.69, 0.91)	(0.19, 0.38, 0.60)	(0.18, 0.39, 0.61)	(0.18, 0.38, 0.60)	(0.45, 0.66, 0.85)
C_9	(0.26, 0.48, 0.70)	(0.49, 0.71, 0.92)	(0.29, 0.51, 0.73)	(0.33, 0.55, 0.76)	(0.35, 0.57, 0.81)
C_{10}	(0.27, 0.48, 0.70)	(0.53, 0.75, 0.96)	(0.29, 0.51, 0.73)	(0.38, 0.60, 0.82)	(0.35, 0.57, 0.79)
C_{11}	(0.18, 0.39, 0.61)	(0.56, 0.78, 0.98)	(0.47, 0.69, 0.90)	(0.44, 0.66, 0.87)	(0.18, 0.39, 0.61)

Table 6: Weighted normalized fuzzy decision matrix

	A_1	A_2	A_3	A_4	A_5
C_1	(0.27, 0.53, 0.83)	(0.23, 0.55, 0.76)	(0.18, 0.41, 0.69)	(0.19, 0.43, 0.71)	(0.13, 0.34, 0.61)
C_2	(0.31, 0.59, 0.88)	(0.19, 0.36, 0.63)	(0.11, 0.30, 0.56)	(0.23, 0.47, 0.76)	(0.24, 0.49, 0.78)
C_3	(0.18, 0.40, 0.70)	(0.16, 0.36, 0.65)	(0.12, 0.31, 0.57)	(0.13, 0.33, 0.60)	(0.11, 0.29, 0.55)
C_4	(0.33, 0.61, 0.89)	(0.32, 0.60, 0.90)	(0.28, 0.54, 0.83)	(0.14, 0.36, 0.62)	(0.15, 0.38, 0.64)
C_5	(0.26, 0.53, 0.77)	(0.24, 0.50, 0.72)	(0.23, 0.49, 0.72)	(0.14, 0.37, 0.59)	(0.15, 0.38, 0.60)
C_6	(0.18, 0.43, 0.74)	(0.20, 0.34, 0.61)	(0.16, 0.40, 0.67)	(0.19, 0.44, 0.74)	(0.13, 0.35, 0.63)
C_7	(0.26, 0.51, 0.83)	(0.12, 0.31, 0.58)	(0.14, 0.35, 0.63)	(0.21, 0.43, 0.73)	(0.10, 0.28, 0.53)
C_8	(0.15, 0.37, 0.67)	(0.60, 0.20, 0.45)	(0.60, 0.21, 0.45)	(0.60, 0.20, 0.44)	(0.14, 0.35, 0.63)
C_9	(0.14, 0.35, 0.62)	(0.26, 0.52, 0.81)	(0.15, 0.37, 0.64)	(0.17, 0.40, 0.67)	(0.19, 0.42, 0.71)
C_{10}	(0.16, 0.38, 0.62)	(0.31, 0.59, 0.85)	(0.17, 0.40, 0.65)	(0.22, 0.47, 0.73)	(0.20, 0.45, 0.70)
C_{11}	(0.06, 0.21, 0.44)	(0.19, 0.43, 0.71)	(0.17, 0.38, 0.65)	(0.15, 0.36, 0.63)	(0.06, 0.21, 0.44)

Step 4: Establish the weighted normalized fuzzy decision matrix

The forth step in the analysis is to find the weighted fuzzy decision matrix and the resulting
Fuzzy weighted decision matrix is shown as Table 6.

Step 5: Determine the fuzzy positive and fuzzy negative-ideal reference points

Then we can define the fuzzy positive-ideal solution (FPIS) and the fuzzy negative-ideal solution (FNIS) as: $A^+$and A^-. This is the fifth step of the fuzzy TOPSIS analysis.

$$A^+ = [\ (1,1,1)]$$
$$A^- = [\ (0,0,0)]$$

Step 6: Ranking the alternatives

In order to calculate the closeness coefficients of each of the alternatives d_i^+ and d_i^- calculation is used as an example as follows.

Table 7: Closeness coefficients and ranking

	d_i^+	d_i^-	Cc_i	Rank
A_1	11.02	9.74	0.47	1
A_2	11.41	9.23	0.45	2
A_3	12.05	8.46	0.41	4
A_4	12.06	8.56	0.42	3
A_5	12.27	8.30	0.40	5

Once the distances of cluster policy from FPIS and FNIS are determined, the closeness coefficient can be obtained with Eq. (14). The index CC_1 of first alternative is calculated as:

$$d_i^+ = 11.02 \quad d_i^- = 9.74$$

From the alternative evaluation results in Table 7, the best person is P_2.

$$CC_i = \frac{9.74}{11.02 + 9.74} = 0.47$$

$$CC_1 > CC_2 > CC_4 > CC_3 > CC_5$$

CONCLUSION

This paper aims to evaluate different maintenance strategies for different equipment. The selection of maintenance strategies is a typical multiple criteria decision-making (MCDM) problem. Considering the imprecise judgments of decision makers, the fuzzy TOPSIS is used for the evaluation of different maintenance strategies. For making uniform consensus of the decision makers, we converted all pair-wise comparisons into triangular fuzzy numbers to adjust fuzzy rating and fuzzy attribute weight and used fuzzy operators to get to select the best alternative.

Finally, observing all these results, Fuzzy TOPSIS approach proposes preventive maintenance strategy (A_1) as the best choice.

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