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A Fuzzy Synthesis Approach for Hierarchical Decision Analysis to Select Optimum Repair Technique

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Abstract

Selecting the best remanufacturing or repair strategy for engineering equipment/component is a complex task, partly due to the many factors affecting the decision as well as the high uncertainty associated with these factors. The challenge facing decision makers is to find an effective and reliable approach that supports their decisions regarding the best remanufacturing or repair technique that extends the service life of an equipment and keep it in operation from failures. This paper presents an innovative fuzzy-based approach for modelling the selection of optimum remanufacturing/repair technique for engineering equipment. The proposed fuzzy synthesis approach allows analysing hierarchical multi-criteria decision-making (MCDM) problems using a simplified and effective method for supporting the elicitation and processing of expert judgements. This approach is tested in a case study of selecting the optimum repair techniques for aero engine component and obtained good model performance in comparison with other alternative MCDM model, which shows the plausibility of applying the approach to domains that are based on human expertise.

Keywords: Circular Economy; Fuzzy Numbers; Fuzzy Synthesis; Multi-Criteria Decision Making; Remanufacturing; Repair

1. Introduction

Decision making is a process aiming to find a proper answer to the question "*Which the best course of action should I choose from a set of finite feasible alternatives such that it satisfies certain criteria of the goal to be achieved*?". In real-world applications, many decision problems can be regarded as Multi-Criteria Decision Making (MCDM) problems where the traditional model for analysing decision making is based on decision maker(s), identified criteria and alternatives, and constructing a decision matrix through decision makers estimations for the performance of alternatives in respect to criteria. Identifying the best alternative is then taken based on the decision rules applied.

There are many methods for solving MCDM problems. Among the most widely used methods are Weighted Sum Method (WSM) [1], Weighted Product Method (WPM) [2], Analytic Hierarchy Process (AHP) [3], Technique for the Order of Preference by Similarity to the Ideal Solution (TOPSIS) [4], Elimination and Choice Translating Reality (ELECTRE) [5], Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE) [6], and Case-Based Reasoning (CBR) [7]. Domains where these methods have been applied include financial management [8] and stock trading [9], supplier selection applications [10], software development strategy selection [11], material handling equipment selection [12], flood risk management [13] and water management problems [14], healthcare sector; including selection of an optimal medical imaging system [15], medical waste disposal [16] and supporting clinical decisions [17], selection of maintenance and repair strategy for engineering systems [18-22], and many more.

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Nowadays, the selection problem of remanufacturing and repair technology for engineering equipment is one of the domains where MCDM approach receives a growing attention. However, analysing such problems is associated with uncertainties related to time, cost and quality of repair that need to be appropriately accommodated to obtain reliable results. For example, the repair of aero engine component consists of several stages including *Cleaning, Welding, Machining, Heat Treatment, Coating*, and *Inspection*, with several techniques available to carry out repair task at each stage mentioned above, in which optimum repair techniques need to be selected. These techniques are summarised in Table 1.

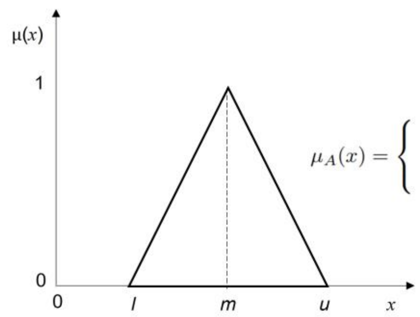
Therefore, the main motivation of this paper is to introduce an intermediate method that is turning the available knowledge about the problem into a mathematical or logical formalism. A fuzzy system based on fuzzy sets theory [23] is an appropriate means to perform this task.

This paper introduces an innovative fuzzy synthesis approach (FSA) for hierarchical decision analysis. It is highly suited for problems in which decision data is linguistically formulated and based on human judgment as well as objective data characterized with uncertainty. It requires less information to elicit from the decision maker compared to other MCDM methods. Furthermore, it provides a consistent way of representing decision maker estimations of the relevant data where uncertainty about estimations is precisely maintained during information processing into the decision model. The rest of the paper is organised in the following sections: Section 2 provides overview of fuzzy numbers and linguistic values. Section 3 presents the development steps of the FSA approach. Section 4 presents the application of the FSA approach in a case study of the selection of best repair technique for aero-engine component. Finally, the conclusion is drawn in section 5.

2. Overview of fuzzy numbers and linguistic variables

2.1. Fuzzy numbers

Fuzzy sets, which has been founded by Zadeh [23], can be regarded as fuzzy numbers (see Figure 1) that represent the concept of approximate numbers or intervals. They allow gradual degrees of membership between 0 and 1 for elements into a set. This solves many real-life application problems where crisp membership cannot provide enough description to the sets. They also allow better (intuitive) representation of linguistic/inexact variables than ordinary numbers and provide a suitable means of transforming a fuzzy (vague) environment into a mathematical model [23,24].



$$\mu_A(x) = \begin{cases} \frac{x-l}{m-l}, & \text{for} \quad l \le x \le m \\ \frac{u-x}{u-m}, & \text{for} \quad m \le x \le u \\ 0, & \text{for} \quad otherwise \end{cases}$$

Fig. 1. Illustration of triangular fuzzy number.

2.2. Linguistic variables

The concept of linguistic variables plays a fundamental role in modelling fuzzy systems. It provides good means of describing the behavior of complex systems by representing uncertain variables in terms of propositions that the human use and understand. These propositions expressed in natural language are then converted into fuzzy meaning (e.g., fuzzy numbers) for processing using fuzzy mathematics [24]. Figure 2 shows an example of a linguistic variable expressed as five linguistic values (also called linguistic terms or linguistic labels). These linguistic values are represented by specific fuzzy numbers defined on the base variable universe.

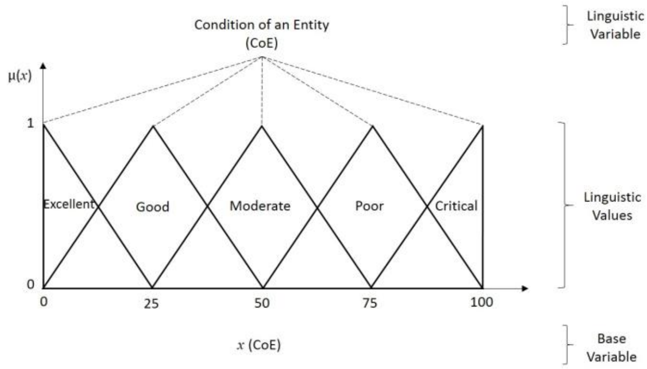


Fig. 2. Illustration of linguistic variable.

3. Proposed fuzzy synthesis approach

The proposed FSA approach uses a full fuzzy processing environment to rank candidate alternatives of the solution and select the best one. The first step is to identify the hierarchy structure of the problem. The second step includes calculating fuzzy weights (FW) for all criteria. In step three, we determine the triangular fuzzy numbers (TFNs) scale for the overall objective, and fuzzy influence (FI) scale of criterion's values on their associated overall objective. Then, in step four, combined fuzzy influence (CFI) of criteria on the overall objective is computed. In step five, the CFI is mapped onto the TFNs scale of the overall objective to determine global score (g) for each candidate alternative, and the alternative with highest global score is selected as best solution (i.e., decision) to the problem. Description of the method is presented next.

3.1. Identify problem structure

The hierarchy structure of the MCDM problem to be solved is defined, i.e., the overall objective is in the top followed by a set of criteria that affect the objective, and then a set of alternatives. Figure 3 shows the structure of MCDM problems.

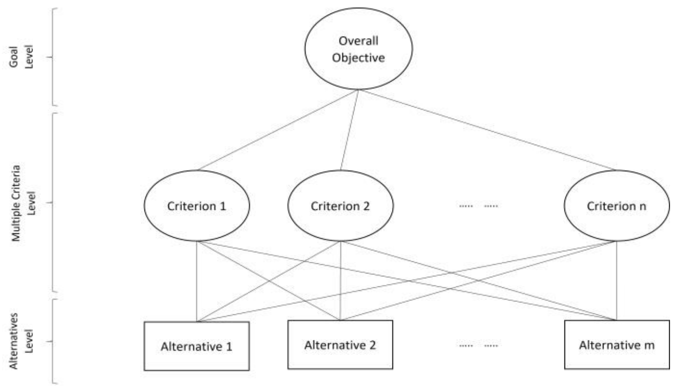


Fig. 3. MCDM problem typical structure.

Table 1. Summary of repair techniques.

Cleaning	Welding	Machining	Heat Treatment	Coating	Inspection
Chemical	Metal Inert Gas	Computer numerical control	Vacuum furnace	Electron beam physical vapour deposition	Visual
Ultrasonic	Tungsten Inert Gas	Electrical discharge	Argon oven	Air plasma spraying	Magnetic particle
Waterjet	Electron beam	Electrochemical	Local heat treatment	High velocity oxy-fuel coating spray	Laser techniques
Abrasive	Resistive spot	Photochemical		Electrostatic spray assisted vapour deposition	Acoustic mission
Manual	ElectroSlag	Ultrasonic		Direct Vapour Deposition	Eddy current

3.2. Compute criteria fuzzy weights

The FSA approach employs the Fuzzy Analytic Hierarchy Process (FAHP) to calculate FWs of criteria. The process of calculation is similar to the AHP technique [3], however; it uses an improved scale of triangular fuzzy numbers for pairwise comparisons, as shown in Table 2, which is better representing the comparison rations in case of equal importance criteria. Also, the approach uses the Fuzzy Row Means of Normalized Columns with Geometric Fuzzy Division Normalization (FRM-GFD) for calculating the normalized FW (Equations (1) and (2)) where it has been proved very effective in representing the comparison ratios given by the decision maker(s) [25].

Table 2. The fuzzy scale for pairwise comparisons.

Intensity of Importance, c_{ij}	Definition
(1/3,1,3)	Equally important
(1,3,5)	Moderately more important
(3,5,7)	Strongly more important
(5,7,9)	Very strongly more important
(7,9,9)	Extremely more important

3.3. Determine TFNs scale of objective and criteria influence

The FSA approach suggests a distribution method to generate the TFNs scale of the overall objective and the fuzzy influence scale of the criteria on the overall objective. It is possible to automate due to the simple way used in eliciting information required from the decision maker(s).

<u>Determining the TFNs Scale of the Overall Objective:</u>

1. Ask the decision maker to determine how many candidate alternatives to solve the overall objective (i.e., the linguistic values associated with the objective).
2. Ask the decision maker to rank them from least to most based on their preference to the overall objective.
3. Each alternative is represented by TFN. The lower, middle, and upper values for each TFN are determined automatically by assigning 0 to the middle of least preferred one and 100 to most preferred one. The middle values of intervening alternatives are determined as:

$$\frac{100}{number\ of\ alternatives - 1}$$

4. An evenly distributed TFNs scale for alternatives associated with the overall objective is generated such that total membership grades across all mapped alternatives added up to 1. Figure 4 shows TFNs scale generated by the proposed method for Overall Objective that has five alternatives of the solution.

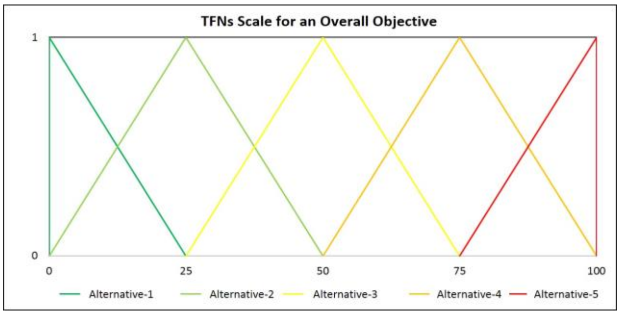


Fig. 4. Illustration of the TFNs scale for an overall objective.

<u>Determining the TFNs Scale of the Influence of Criteria:</u>

1. Ask the decision maker to divide the criterion into categories that encompass the meaningful range of the criterion. Each category is represented by a TFN.
2. Ask the decision maker to determine which criterion's categories that link to first and last alternatives of the overall objective (i.e., categories that are mapped to first and last alternatives of the overall objective).
3. The TFNs of criterion influence on the overall objective is automatically generated by dividing 100 on the number of intervening categories we need to calculate for the criterion plus 1, as seen below:

$$\frac{100}{number\ of\ intervening\ categories + 1}$$

4. The TFNs are evenly distributed across the scale, such that the lines of the TFN for both sides are extended to the middle values of the neighbouring TFN giving a half-way overlapping between adjacent TFNs. Figure 5 shows an example explains how the influence scale is generated.

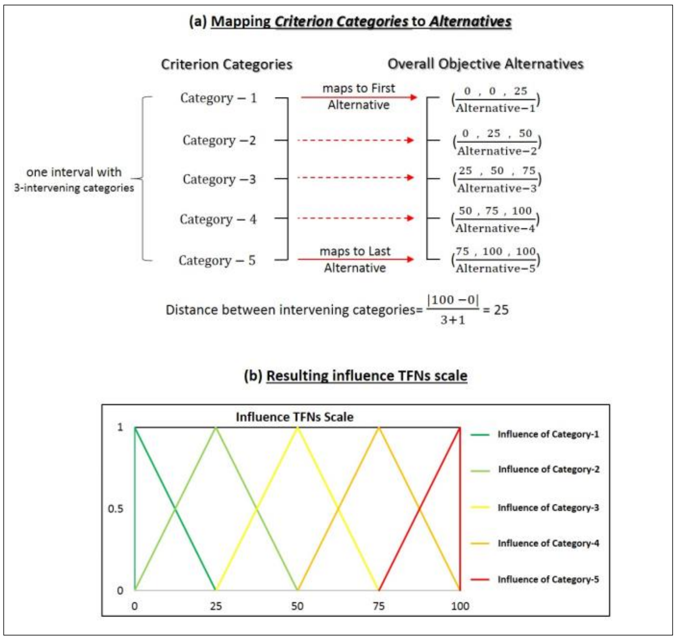


Fig. 5. Illustration of the Influence Scale of the Criterion.

Rules Applied to the TFNs Scale Generation Method:

All TFNs scales generated for the overall objective and criteria are always evenly distributed across the x-axis. This means that the linguistic values have the following constraints:

- middle of lower linguistic value maps to lower of next higher linguistic value.
- upper of lower linguistic value maps to middle of next higher linguistic value.

3.4. Combining the influence of the criteria

The combined influence of criteria is computed by multiplying the criterion FW and its fuzzy influence. This is done for every criterion using Equation (3). The aggregation of the multiplication would result in CFI of the criteria on the overall objective, represented as TFN. The CFI for the criteria values is then calculated case by case in the same way.

3.5. Determine the global score of alternatives

Determining the global scores of alternatives is performed by mapping the TFN of the CFI onto TFNs scale of the overall objective. This produces a set of intersection points between the CFI of the criteria and candidate alternatives. The highest intersection point for every alternative is then interpreted as the global score, g, of the alternative. Consequently, the resulting global scores for alternatives are ranked and the alternative with the highest global score is selected as best alternative solution. Equation (4) illustrates the logical expression of how the highest global score, g^*, is determined among m alternatives.

$$g^* = max \bigcup_{i=1}^{m} g \qquad (4)$$

Figure 6 shows the mapping of the CFI on a certain overall objective scale consists of five candidate alternatives. It provides a graphical interpretation to the extent of the combined influence of criteria on the overall objective represented by the global scores, g^1, g^2, g^3, g^4, and g^5. Accordingly, the second alternative is selected in this case as it has the highest score, $g^*=g^2$. This mapping operation is carried out for every criteria input to obtain the corresponding best alternative solution.

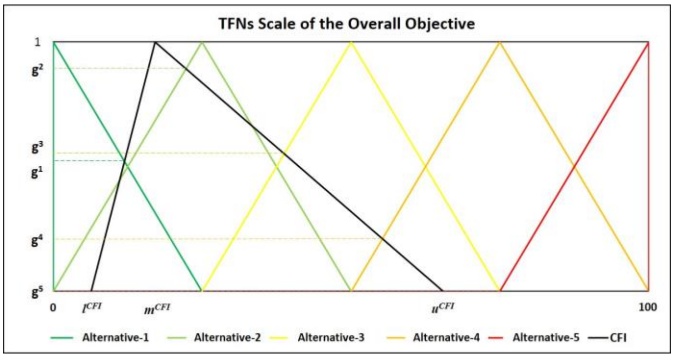


Fig. 6. Mapping of combined fuzzy influence on the overall objective scale.

4. Case study

4.1. Introduction

The case study selected is to apply the FSA approach in selecting the best repair technique for an aero-engines component, Nozzle Guide Vanes (NGV). The information on this case study was collected from [26].

The NGVs are static components that are commonly used in the turbine of a gas turbine engine, where they direct the flow of incoming exhaust gasses onto rotating turbine blades maximizing downstream blade performance. Figure 7 shows the structure of NGVs.

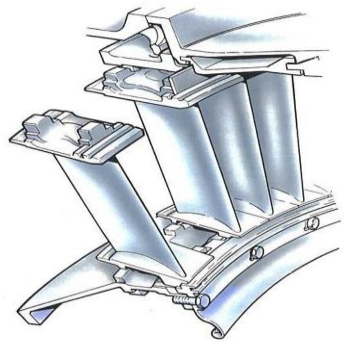


Fig. 7. Nozzle Guide Vanes [27].

4.2. Data for NGVs case study

The data in this case study of FSA approach is based on the data used in the case study of FAHP-TOPSIS approach used in [26]. The study is particularly scoped on *Cleaning* stage, where there are 3 types of cleaning techniques (Table 3).

Table 3. Selected cleaning techniques.

Repair Stage	Technique
Cleaning	Chemical cleaning
	Ultrasonic cleaning
	Waterjet cleaning

4.3. Applying FSA approach

The FSA approach has been applied to take a decision regarding the best cleaning technique by evaluating three potential alternatives of cleaning techniques (see Table 3) against three decision criteria (quality, cost and time).

Applying FSA approach we obtain the fuzzy weights of the criteria, the TFNs scale of the overall objective, and the TFNs scales of the influence of the criteria on the alternatives, based on information shown below that has been extracted from [26].

1. Fuzzy Weights of the Criteria: Based on the criteria comparisons, the matrix of pairwise comparison rations has been built and fuzzy wights for criteria were calculated, as presented in Table 4. The pairwise comparisons of criteria used are:
   - Quality has *Moderate Importance* than Cost
   - Quality has *Extreme Importance* than Time
   - Cost has *Strong Importance* than Time

$$GF = \left(l_{ij}^{GF}, m_{ij}^{GF}, u_{ij}^{GF}\right) = \left(\frac{l_{ij}}{\left(\sum_{i=1}^{n} l_{ij} \sum_{i=1}^{n} u_{ij}\right)^{1/2}}, \frac{m_{ij}}{\left(\sum_{i=1}^{n} m_{ij}\right)^{1/2}}, \frac{u_{ij}}{\left(\sum_{i=1}^{n} l_{ij} \sum_{i=1}^{n} l_{ij}\right)^{1/2}}\right) \quad (1)$$

$$FW_i = \left(l_{ij}^{FW}, m_{ij}^{FW}, u_{ij}^{FW}\right) = \left(\frac{\sum_{j=1}^{n} l_{ij}^{GF}}{n}, \frac{\sum_{j=1}^{n} m_{ij}^{GF}}{n}, \frac{\sum_{j=1}^{n} u_{ij}^{GF}}{n}\right) \quad (2)$$

$$CFI = \left(l^{CFI}, m^{CFI}, u^{CFI}\right) = \left(\sum_{i=1}^{n} l_{i}^{FW} \times l_{ij}^{FI}, \sum_{i=1}^{n} m_{ij}^{FW} \times m_{ij}^{FI}, \sum_{i=1}^{n} u_{ij}^{FW} \times u_{ij}^{FI},\right) \quad (3)$$

where, l_{ij}, m_{ij} and u_{ij} are lower, middle, and upper-bound of TFN of fuzzy comparison ratios, respectively. *GF* is the matrix of normalized comparison ratios using geometric fuzzy division.

Table 4. Fuzzy comparisons matrix and weights

Criteria	*Quality*	*Cost*	*Time*	Fuzzy Weight
Quality	(1,1,1)	(1,3,5)	(7,9,9)	(0.460,0.669,0.871)
Cost	(1/5,1/3,1)	(1,1,1)	(3,5,7)	(0.203,0.267,0.460)
Time	(1/9,1/9,1/7)	(1/7,1/5,1/3)	(1,1,1)	(0.059,0.064,0.083)

2. The TFNs Scale of the Overall Objective: The TFNs scale of the cleaning techniques was generated based on method proposed in (3.3) and information in Table 5.

Table 5. Information for TFNs scale of the cleaning techniques.

Least Preferred Alternative	Most Preferred Alternative	No. of Alternatives
Ultrasonic	Water Jet	3

3. The TFNs Scale of the Criteria's Influence: Similarly, the TFNs scales of the influence of criteria on cleaning techniques have been generated based on the method proposed in (3.3) using information presented in Table 6. These TFNs scales are equivalent to the performance matrix of the cleaning techniques with respect to criteria (quality, cost and time) used in TOPSIS method [26].

Table 6. TFNs scales of criteria influence on cleaning techniques

Criteria	Categories	Category Maps to first Alternative	Category Maps to last Alternative
Quality	Min. Importance	Min. Importance	Max. Importance
	Low Importance		
	Moderate Importance		
	High Importance		
	Max. Importance		
Cost	Min. Importance	Min. Importance	Max. Importance
	Low Importance		
	Moderate Importance		
	High Importance		
	Max. Importance		
Time	Min. Importance	Min. Importance	Max. Importance
	Low Importance		
	Moderate Importance		
	High Importance		
	Max. Importance		

4.4. Results and Discussions

The FSA approach has analysed a case study where input values of criteria were: *Maximum Importance* for Quality, *Moderate Importance* for Cost and *Minimum Importance* for Time. A VBA-Excel computational model has been developed for implementation. First, we calculate the FWs of criteria. Then, we obtain the CFI by multiplying the FW of the criterion by the fuzzy influence corresponding to its input value. This is done for every criterion and the aggregate multiplications (i.e., CFI) is mapped onto the cleaning techniques scale to determine the appropriate cleaning technique for NGVs.

To investigate the performance of the FSA approach, the results of the case study example were compared with those of the alternative MCDM method in [26]. This method was a combination of Fuzzy AHP and TOPSIS methods, where Fuzzy AHP is used to create the weights of criteria, and TOPSIS is used as ranking system for alternatives. Table 7 presents the performance matrix of cleaning techniques that were elicited from an expert and used in TOPSIS method where 10 is the most preferred and 1 is the least preferred. The preference judgments of the criteria used in Fuzzy-TOPSIS were the same as those used in the FSA approach.

Table 7. Performance score of cleaning techniques (alternatives).

Cleaning Techniques	Quality Preference	Cost Preference	Time Preference
Chemical Cleaning	8	4	6
Ultrasonic Cleaning	5	5	6
Water Jet	9	3	4

The outcomes of both methods were compared, as seen in Tables 8. It can be noticed that they have given the same ranking of cleaning techniques, i.e., *Water Jet* is the best option, followed by *Chemical*, and then *Ultrasonic*. The consistency between the results of the two methods indicates promising use of the proposed FSA to solve similar MCDM problems. The FSA preserves fuzziness information throughout the process of computations allowing natural representation of expert judgements. It also solves the problem of loss of fuzziness in multi-level system structure, in which it enables information to propagate in its fuzzy format throughout the hierarchy structure. Accordingly, the proposed FSA approach is expected to perform better than other alternative methods that use defuzzification of values during computations. This will be more emphasised when applying the method for all repair stages, which is considered as a future step. Furthermore, the input variables and parameters in the FSA approach are fully represented by linguistic values (propositions) that support its applicability to any domain with high uncertainty requiring human expertise to input data and explain decisions.

Table 8. Comparison of Results.

Cleaning Techniques	Proposed FSA Global Score (g*)	FAHP-TOPSIS Index of Closeness
Chemical Cleaning	0.666	0.271
Ultrasonic Cleaning	0.115	0.777
Water Jet	0.789	0.223

5. Conclusion

This paper has described an innovative fuzzy synthesis approach for analyzing MCDM problems with hierarchical structure. It employs fuzzy numbers and linguistic values for transforming and combining experts' opinions where fuzziness is maintained throughout the whole process, such that there is no loss of uncertainty information. The FSA approach has been applied in a case study of repair technique selection for an aero-engines component where inputs are associated with uncertainty. Outcomes obtained from the FSA were compared with an alternative MCDM method (combined FAHP-TOPSIS) [26], which showed consistent results. Among the advantages of the FSA approach, it uses full fuzzy computational environment that allows natural representation of expert judgments leads to a good model performance. Future work will include applying the proposed model of FSA on a large-scale problem structure, for example, the full structure of repair stages for the NGVs component. This is suitable for further testing of model efficacy where the input data are based on human judgments associated with high uncertainty.

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