Modified Fuzzy Logic Method for Materials Selection in Mechanical Engineering Design

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Title:

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Abstract:

Materials selection is one of the primary steps in designing products, including mechanical ones. As a result, researchers are continuously developing simple, accurate, and feasible techniques to enhance the performance of the designed component by selecting the optimum materials from a wide variety of candidate materials. In this research work, a modified fuzzy approach referred to as Modified Fuzzy Logic Method (MFLM) is proposed to provide some highly appreciated advantages besides resolving some of the substantial shortcomings of the existing solutions. Customizing the method based on the designer's knowledge and level of expertise, simultaneous consideration of qualitative and quantitative properties, and high accuracy in the ranking of candidate materials are some of the significant benefits of MFLM in comparison to the available alternative methods. While, complexity, high volume computational efforts, and more are amongst the resolved drawbacks. Moreover, the produced results show the power and simplicity of the technique in solving complex problems like materials selection for a gas turbine blade which involves a high range working temperature.

Keywords:

Fuzzy logic, Multi-criteria decision making, Materials selection, Materials Indices

1 Introduction

Multi-Criteria Decision-Making (MCDM) problems are frequent in human beings' daily life. Engineers also deal with these problems and consistently seek to find the optimum choices in different stages of the design cycle. In the meantime, materials selection is one of the most challenging steps, owing to the fact that a wide range of materials available coupled with various and sometimes hard-to-process criteria make it even more demanding. During the past decades, researchers have proposed several strategies for materials selection to face the difficulties. Ashby [1–4] by utilizing materials selection charts as well as multi-objective optimization method, and Farag [5] and Manshdi [6] by introducing weighted property method (WPM) and modified digital logic (MDL), respectively, are amongst the pioneers who tried to simplify the procedure of materials selection.

Furthermore, Shanian [7] has proposed the TOPSIS method, a simple and recognized technique by active researchers in this field. Analytical hierarchy process [8] (AHP) is also another admired approach. Among newfound methods, Electre [9] by pairwise comparison of candidate materials, Z-transformation [10] by using statistical operators, and Jahan's technique [11] by applying ordinal data strived to enhance the procedure of materials selection. Moreover, many of the criteria weighting techniques [12–14] have provided subjective and objective weighting coefficients for different attributes.

In more recent attempts, due to advancements in computing techniques, several researchers have investigated the use of relevant Machine Learning (ML) methods to assist the manufacturing process by adopting the most suitable materials for the assumed applications according to their properties and in-service operation. Under this focus, both supervised and unsupervised learning models can perform classifications and regressions on materials data [15–19]. These computing systems are robust in learning complex non-linear functions and

extracting information from large datasets; nevertheless, they require preliminary training and can be computationally demanding. Also, hyperparameters tuning is an inevitable and challenging part of applying any ML algorithm.

To be noted, as another related direction, some researchers have developed various strategies for multi-material (hybrid) design of components to select the proper materials for their intended functions [20–24]. These systems endeavor to select the discrete variables (i.e., material types) and optimize the continuous parameters like components' geometry to simultaneously achieve multiple objectives, such as satisfying structural performance, low cost, and lightweight. Solving such multi-objective optimization (MOO) problems is challenging due to the presence of various variables and goals, as well as highly nonlinear constraints [25]. Therefore, some recent works have employed metaheuristic (nature-inspired) optimization approaches like Genetic Algorithms [25, 26], Simulated Annealing [26], and Bat Algorithm [27] to find the ideal solutions based on the presumed constraints and defined objective functions. These algorithms are proven to be powerful in minimizing the cost functions and detecting global optima [28, 29]; however, when more than one objective is targeted, metaheuristic approaches should be supported with a multi-criteria decision analysis approach. MCDM methods provide a systematic trade-off between the assumed targets, and help one form proper objective functions. As an instance, Zhang [25] applied the well-known TOPSIS decision-making technique [7] to optimize concrete mixture proportions based on metaheuristic and ML algorithms.

The above-said MCDM methodologies work well when reliable, accurate, and adequate numerical data is at hand, an assumption that is not well-fitted with the vague and uncertain nature of materials selection problems. Data acquisition can become a time-consuming, expensive, and sometimes infeasible task. Accordingly, many material attributes are described either with ranges of numbers rather than precise amounts or with linguistic terms. With this in mind, also add the fact that variations in the working environments of components can cause the properties of their constituent materials to change. In this sense, having a concrete way of modeling uncertainties can ease the decision-making process and enhance the reliability of

outputs. The fuzzy logic concept [30], which provides us with the formal principles of approximate reasoning, has been widely used for materials selection in the past two decades. Rao [31] employed Graph theory in the fuzzy space. Sarfaraz [32] utilized fuzzy membership functions and tried to select the optimum materials based on defined IF-THEN rules. Moreover, Babu [33] proposed a similar work using the Grey relational analysis concept in the fuzzy environment. However, the high complexity of these methods in defining IF-THEN rules prevents their extensive application. Some researchers have also tried to implement conventional numerical methods in the fuzzy scope. Rathod [34] and Mayyas [35] separately modified the TOPSIS technique to apply it in the fuzzy environment, taking into account the fuzzy membership functions for materials properties and the weighting coefficients of the criteria, as well as using a few simple operators. Reddy [36] also ranked the materials by presenting a TOPSIS-based framework in the fuzzy space while considering a combination of subjective and objective weighting values for the criteria. Gul [37] implemented the Promethee method in the fuzzy space by defining a set of operators for trapezoidal membership functions. Applying the mentioned approaches is not recommended while only dealing with measurable attributes because the fuzzy functions cannot correctly differentiate the properties of the materials. Consequently, the accuracy of the ranking system deteriorates.

Efforts have not been limited to employing conventional approaches in the fuzzy environment; some researchers strived to introduce the principles of axiomatic design (i.e., independence and information axioms) to the field of multi-attribute decision-making based on vague and uncertain data. Kulak [38] developed a Fuzzy multi-attribute selection approach by combining the concept of axiomatic design with the analytic hierarchy process [8]. Cieck [39] modified the fuzzy axiomatic design-model selection interface (FAD-MSI) [40] to make it compliance with the nature of the materials selection scheme. Khandekar [41] also offered an axiomatic design-based approach considering triangular fuzzy membership functions for the design ratings, materials properties, and weighting coefficients of attributes. However, in many cases, the fuzzy membership functions of the design ratings stand far from the functions of materials properties, and the proper evaluation cannot be obtained.

In the following, an easily programmed fuzzy logic-based method for materials selection is proposed to remove the aforesaid drawbacks and reduce the computational efforts. Also, the capabilities of the method are examined using common problems in mechanical engineering design.

2 Method description

MFLM falls under the weighted property category of materials selection methodologies [5]. It means that it is a form of criteria weighting technique combined with a ranking system that usually converts crisp data into normalized values. In the following, the step-by-step procedure of the MFLM is explained.

2.1 Step 1: Parametric study of the problem to specify the constraints and performance requirements of the component

In materials selection schemes, choosing either materials properties or materials indices is the first move of the process. In mechanical cases where extraction of materials indices is applicable, authors prefer to employ them, as long as the correlations between indices are considered in the criteria weighting process (see reference [14]). However, in many other applications, such as resin selection for a mechanical composite part, it is not pragmatic to practice materials indices. Therefore, materials properties can be considered for these types of applications. Of Note, in the proposed method, there are no limits in choosing either of the said criteria; thus, the decision-maker can use any of them based on conditions of the problem and availability of the required information. Materials properties or indices are assumed either beneficial or cost, meaning that their higher or lower values are more favorable for the application, respectively.

2.2 Step 2: Formation of the matrix of attributes

In this step, a matrix consisting of the properties or indices of the candidate materials should be formed as shown below;

$$D = \begin{matrix} & C_1 & \cdots & C_j & \cdots & C_m \\ \begin{matrix} Y_1 \\ \vdots \\ Y_i \\ \vdots \\ Y_n \end{matrix} & \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n1} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \end{matrix}_{n \times m}$$

where Y_i is the i^{th} candidate material, C_j represents the j^{th} attribute, and x_{ij} is the numerical value of j^{th} attribute corresponding to i^{th} material. Also, n and m are the total numbers of considered materials and attributes, respectively. Even though a large number of candidate materials does not affect the originality and performance of the method, the decision-maker is advised to primarily eliminate the unsatisfying candidates using materials screening procedures like Ashby's method [1–4] to decrease the volume of calculations.

2.3 Step 3: Definition of a set of fuzzy membership functions for each criterion

In this step, specifying a set of membership functions is first explained for quantitatively stated criteria and then for qualitatively expressed ones. For the former, two options for mapping interval of functions are in service; either a design span, which is defined subjectively or the range of materials properties (i.e., distance from max to min). One can avoid the influences of materials properties outside of the desired span by mapping proper fuzzy functions in the design interval. In this sense, no matter how extreme the properties are, if they exceed the limit values (design range borders), their normalized quantities will be the same. This data treatment enables the system to neglect the superiority of out-of-the-box materials over one another. On the other hand, in the absence of enough design knowledge, the method still maintains its

efficiency, and sets of functions can be in the distance from maximum to minimum of materials properties. A linguistic term is also assigned to each membership function that shows the assumed qualitative perspective.

For qualitatively stated criteria, fuzzy membership functions are defined based on the assigned linguistic terms of candidate materials. Each linguistic term demands a membership function, and all groups of functions are mapped between zero and one. A comprehensive explanation about fuzzy logic and implementation of fuzzy set theory in materials selection is presented in reference [32]. As an example, the triangular membership functions considered for the cost criterion are shown in Fig. 1.

Fig. 1 Fuzzy membership functions for cost criterion

2.4 Step 4: Determination of an equivalent value for each fuzzy membership function

In this step, the considered linguistic terms of the functions are converted into equivalent values. Functions with more desirable positions in the assumed range receive higher values than the rest. Calculation of equivalent values is inspired by Rao's works [13, 31, 42]. Unfortunately, the articles published by Rao do not mention how exactly these values are obtained. However, by a close analysis of the geometry of membership functions and employing the trial and error approach, the formulas were extracted. The equivalent value is a dimensionless quantity between zero and one, which is defined by Eq. (1) according to Fig. 2;

$$\begin{cases} U_{f_i} = \frac{1 + (Z_{Mi} - Z_{Gi})}{2} & \text{for beneficial criteria} \\ U_{f_i} = \frac{1 - (Z_{Mi} - Z_{Gi})}{2} & \text{for cost criteria} \end{cases} \quad (1)$$

where U_{f_i} is the equivalent value and Z_{Mi} and Z_{Gi} depend on the geometrical status of the membership function. Z_{Mi} and Z_{Gi} are the measuring tools for the right and left branches of a triangular function and help the designer to identify the location of a membership function in the defined scope and assign a numerical value to each one. To elaborate on Eq. (1), consider shifting the membership function in Fig. 2 to the right side of the design span. As it goes further, Z_{Mi} increases and Z_{Gi} decreases, meaning that the equivalent value for a function corresponding to a beneficial criterion rises. In other words, for a beneficial criterion, as a membership function approaches the maximum value of the design range (x_{max}), its equivalent value increases. Eventually, if the decision-maker considers an “exactly equal to” type function, in which a_i , b_i , and c_i happen to be equal to the value of x_{max} , the equivalent value for that function would be one which is the maximum number that a function can receive. Note that vice versa of the above applies to cost criterion functions.

Fig. 2 Calculation of equivalent values for membership functions

This value should be calculated for all membership functions. For triangular functions, the values of Z_{Mi} and Z_{Gi} are calculated using Eq. (2);

$$\begin{aligned}
Z_{Mi} &= \frac{(c_i - x_{min})}{((x_{max} - x_{min}) - (b_i - c_i))} \\
Z_{Gi} &= \frac{(x_{max} - a_i)}{((x_{max} - x_{min}) + (b_i - a_i))}
\end{aligned} \tag{2}$$

x_{min} and x_{max} determine the presumed scope; while, a_i , b_i , and c_i fully identify the position of the function, and all of them are geometrically shown in Fig. 2. Eq. (2) is obtained by calculating the intersection values of the function and its crossing lines.

2.5 Step 5: Normalizing the attributes matrix [D] using fuzzy membership functions and their equivalent values

Given the matrix of attributes [D] and sets of membership functions as input data, the normalized values of candidate materials for different criteria can be calculated. For example, assuming x_{ij} is the cost of i^{th} material. The normalized value of x_{ij} is calculated based on Eq. (3) and Fig. 3:

$$r_{ij} = \frac{1}{2} \left[\frac{(f_{i+1}(x_{ij}) - f_i(x_{ij})) \times (U_{f_{i+1}} - U_{f_i})}{(1 - \min(f_{i+1}(x_{ij}), f_i(x_{ij})))} + (U_{f_{i+1}} + U_{f_i}) \right], \quad b_i \leq x_{ij} \leq b_{i+1} \tag{3}$$

Fig. 3 Normalizing the crisp data of candidate materials

In order to understand the logic behind the suggested normalization approach, consider that x_{ij} happens to be b_i or b_{i+1} . According to Eq. (3), r_{ij} for these points are found to be equal to U_{f_i} and $U_{f_{i+1}}$, respectively. It means that for the crisp values which belong entirely to a membership function (degree of membership is one), that function's equivalent value is considered as the normalized number. However, if x_{ij} happens right at the intersection of two surrounding membership functions (point G in Fig. 3) and equally belongs to both functions, r_{ij} would be $(U_{f_{i+1}} + U_{f_i})/2$. Based on the above explanation, Eq. (3) converts material properties or indices into the normalized values using a linear combination of the equivalent values of the surrounding membership functions. Also, notice that candidate materials with properties out of the design scope of each criterion receive the equivalent values of the closest membership functions as their normalized amounts.

The procedure is much more straightforward for qualitatively stated criteria, and the equivalent values of defined membership functions are considered as their normalized numbers. For example, consider that "High", "Medium", and "Low" are three linguistic terms describing the shock resistance property of candidate materials. First, one should map a set of three membership functions for shock resistance criterion based on step 3 and then calculate the corresponding equivalent values according to step 4. Candidate materials that demonstrate high shock resistance receive the equivalent value of "High" membership function as their normalized amounts. The same applies to the remaining functions. Finally, the input matrix [D] is converted into the normalized matrix [R] as shown in the following;

$$R = \begin{bmatrix} r_{11} & \dots & r_{1j} & \dots & r_{1m} \\ \dots & \dots & \dots & \dots & \dots \\ r_{i1} & \dots & r_{ij} & \dots & r_{im} \\ \dots & \dots & \dots & \dots & \dots \\ r_{n1} & \dots & r_{nj} & \dots & r_{nm} \end{bmatrix}_{n \times m}$$

2.6 Step 6: Calculation of the weighting vector

In this step, a coefficient between zero and one is assigned to each criterion which shows the importance of attributes in satisfying the desired purposes of the application. These values can be obtained utilizing objective, subjective, or integrated weighting methods [12–14]. In the present research work, MDL [6] is applied to calculate the weighting coefficients. The weighting vector would be as follows:

$$\mathbf{W} = [w_1 \quad w_2 \quad \dots \quad w_j \quad \dots \quad w_m]^T_{m \times 1}$$

where m is the number of criteria.

2.7 Step 7: Determination of performance indices of materials and extracting the final ranking

The performance index vector is obtained as shown in Eq. (4);

$$\begin{bmatrix} r_{11} & \dots & r_{1j} & \dots & r_{1m} \\ \dots & \dots & \dots & \dots & \dots \\ r_{i1} & \dots & r_{ij} & \dots & r_{im} \\ \dots & \dots & \dots & \dots & \dots \\ r_{n1} & \dots & r_{nj} & \dots & r_{nm} \end{bmatrix}_{n \times m} \times \begin{bmatrix} w_1 \\ \dots \\ w_j \\ \dots \\ w_m \end{bmatrix}_{m \times 1} = \begin{bmatrix} \gamma_1 \\ \dots \\ \gamma_i \\ \dots \\ \gamma_n \end{bmatrix}_{n \times 1} \quad (4)$$

Arrays of this matrix multiplication represent each candidate material's performance in fulfilling the goals of the application. Materials with higher performance indices are more favorable and stand in better ranks. Lastly, Fig. 4 displays the step-by-step comparison between MFLM and the Conventional Fuzzy Logic Method [32]. In contrast to the traditional fuzzy approach, MFLM necessitates neither an enormous number of IF-THEN rules nor fuzzification and defuzzification interfaces.

Fig. 4 Step-by-step comparison between MFLM and the Conventional Fuzzy Logic Method

Supplementary notes

A Matlab code is developed to execute the method. This code performs all of the computational steps (i.e., steps 4 to 7) of the proposed technique. It receives a matrix of attributes [D], a matrix of fuzzy functions, a vector that specifies the number of functions for each criterion, and finally, a binary vector that separates cost and beneficial criteria as input data. Then, utilizing the defined functions calculates the performance indices and final ranking of materials. Since the offered ranking system is based on simple algebraic equations, there is no major computational hurdle that must be tackled.

Indeed, the only challenge of applying the presented technique is defining the characteristics of fuzzy membership functions, including their number, mapping interval, and location (i.e., step 3). These functions inform the system of how accurate our data is and how the data should be normalized by dividing the considered range of materials properties into some groups. In other words, sets of fuzzy membership functions capture the qualitative viewpoint of the designer and apply it to simplify the procedure of decision-making based on uncertainties. Some of the fuzzy-based approaches have tried to limit the functions to certain ones with fixed locations to reduce the difficulties of function mapping [31, 42]. However, by doing so, functions lose their flexibility to represent unclear data. MFLM offers designers the chance to map their tailored fuzzy membership functions and customize the selection scheme. Bear in mind that, in many other fuzzy-based ranking systems such as the Conventional Fuzzy Logic method [32], which formed the foundation of the current research, the nomination of functions is left to designers' hands. MFLM, similar to other existing approaches, guarantees reliable results unless the functions are not well-fitted to the data. Consequently, decision-makers are not advised to apply MFLM if either precise numerical data is available or satisfying function mapping is beyond reach.

3 Verification of the proposed method

In this section, MFLM has been applied to three standard mechanical design cases, and the final rankings are compared with some reliable methods such as TOPSIS [7], Z-transformation [10], and the conventional Fuzzy Logic [32].

3.1 Cryogenic Storage tanks

Liquid hydrogen, oxygen, nitrogen, and liquefied natural gas (LNG) are among the gases stored at cryogenic temperature for various applications such as fuel cell, power generation, etc. [43]. Consequently, candidate materials for a cryogenic storage tank should possess adequate specific strength, specific stiffness, and toughness at the operating temperature. Satisfying weldability and processability, and good heat insulation are among other necessities. The requirements mentioned above lead the decision-maker to choose the proper cost and beneficial criteria for the materials selection procedure.

3.1.1 Step 1 & 2:

Density, specific heat, thermal expansion coefficient, and thermal conductivity are among the cost properties, and toughness, stiffness, and strength are the beneficial properties considered as criteria. Candidate materials and their corresponding properties are listed in Table 1.

Table 1 Properties of candidate materials for a cryogenic storage tank

Materials	Toughness index ^a	Yield strength (Mpa)	Young's modulus (Gpa)	Density (g/m^3)	Thermal expansion ^b	Thermal conductivity ^c	Specific heat ^d
Al 2024-T6	75.5	420	74.2	2.80	21.4	0.370	0.16
Al 5052-O	95	91	70	2.68	22.1	0.330	0.16
SS 301-FH	770	1365	189	7.90	16.9	0.040	0.08
SS 310-3AH	187	1120	210	7.90	14.4	0.030	0.08
Ti-6Al-4V	179	875	112	4.43	9.4	0.016	0.09
Inconel-718	239	1190	217	8.51	11.5	0.310	0.07
70Cu-30Zn	273	200	112	8.53	19.9	0.290	0.06

^a Toughness index, T, is based on UTS, yield strength YS, and ductility e, at -196 °C. $T = (UTS + YS)e/2$.

^b Thermal expansion coefficient is given in $10^{-6}/^{\circ}C$. The values are averaged between RT and -196 °C.

^c Thermal conductivity is given in $10^6 \text{ cal/cm}^2/\text{cm}/^{\circ}C/\text{s}$.

^d Specific heat is given in $\text{cal/g}/^{\circ}C$. The values are averaged between RT and -196 °C.

3.1.2 Step 3 & 4:

In this step, a set of triangular fuzzy membership functions for each attribute is defined. Also, the equivalent values of the functions are calculated by applying Eqs. (1), (2). These values are shown in Table 2.

Fig. 5 Defined fuzzy membership functions for a cryogenic storage tank

Table 2 Equivalent values of fuzzy membership functions for a cryogenic storage tank

Membership functions	Toughness Index	Yield strength	Young's modulus	Density	Thermal expansion	Thermal conductivity	Specific heat
Low	0.125	0.111	0.204	0.857	0.833	0.875	0.821
Medium	0.5	0.518	0.561	0.571	0.5	0.525	0.462
High	0.875	0.889	0.882	0.143	0.167	0.125	0.091

3.1.3 Step 5 & 6 & 7:

The crisp data of candidate materials (Table 1) are converted into normalized values using Eq. (3). The obtained normalized matrix is listed in Table 3. The weighting vector is also calculated based on MDL [6] method, and the values are as in Table 4.

Table 3 Normalized values of the candidate materials for a cryogenic storage tank

Materials	Toughness index	Yield strength	Young's modulus	Density	Thermal expansion	Thermal conductivity	Specific heat
Al 2024-T6	0.125	0.131	0.204	0.587	0.167	0.125	0.091
Al 5052-O	0.125	0.111	0.204	0.599	0.167	0.125	0.091
SS 301-FH	0.875	0.889	0.673	0.143	0.218	0.569	0.611
SS 310-3AH	0.217	0.889	0.839	0.143	0.273	0.656	0.611
Ti-6Al-4V	0.192	0.584	0.287	0.376	0.521	0.834	0.518
Inconel-718	0.414	0.889	0.87	0.143	0.441	0.125	0.725
70Cu-30Zn	0.466	0.111	0.287	0.143	0.168	0.125	0.785

Table 4 Application of modified digital logic method to the cryogenic storage tank

Materials Properties	Number of possible decisions																					Positive	Weighting
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	decisions	Coefficient
Toughness index	3	3	3	3	3	3																18	0.214
Yield strength	1						3	1	2	3	3											13	0.155
Young modulus		1					1					1	1	3	3							10	0.119
Density			1					3				3				3	3	3				16	0.19
Thermal expansion				1					2				3			1			3	3		13	0.155
Thermal conductivity					1					1				1			1		1		2	7	0.083
Specific heat						1					1				1			1		1	2	7	0.083

Finally, the performance indices for the candidate materials are obtained using Eq. (4). The final ranking of the candidate materials by the proposed method and other conventional ranking approaches are listed in Table 5.

Table 5 Performance indices and ranking of candidate materials for a cryogenic storage tank

Materials	MFLM		TOPSIS [2]		Z-transformation [10]		Conventional Fuzzy [32]	
	γ	Rank	γ	Rank	γ	Rank	γ	Rank
SS 301-FH	0.564	1	0.748	1	0.78	1	50.00	1
Inconel-718	0.496	2	0.344	3	0.27	3	43.83	2
SS 310-3AH	0.459	3	0.300	4	0.26	4	35.74	4
Ti-6Al-4V	0.430	4	0.348	2	0.39	2	38.42	3
70Cu-30Zn	0.280	5	0.252	7	-0.49	5	16.14	6
Al 2024-T6	0.227	6	0.259	5	-0.56	6	17.58	5
Al 5052-O	0.227	7	0.258	6	-0.65	7	16.10	7

According to Table 5, TOPSIS and Z-transformation methods allocate the second rank to Ti-6Al-4V; however, based on MFLM and Conventional Fuzzy ranking results, Inconel-718 stands in second place. Ti-6Al-4V demonstrates an extraordinarily low thermal conductivity compared to other candidate materials, and its density is less than Inconel-718. Nevertheless, its performance corresponding to all other beneficial criteria is weaker than Inconel-718 and even SS 310-3AH. TOPSIS and Z-transformation methods cannot identify a design scope

corresponding to each criterion for the application; as a result, materials with only one or two exceptional property values would earn better rankings. It is also the case for the third and fourth ranks of the Conventional Fuzzy method. This major flaw is resolved in MFLM by mapping the membership functions in each criterion's favorable design interval. To elaborate on this, see the set of membership functions for the Thermal conductivity property in Fig. 5. Values of candidate materials corresponding to this property range from 0.016 to 0.370; however, the design span for this criterion in which membership functions are mapped is from 0 to 0.12. It allows the decision-maker to balance the adverse influences of a material with an extraordinary property on the overall ranking results. Note that the final ranking would be much closer to the results of the mentioned methods if the set of fuzzy functions were defined in the total interval values of candidate materials.

3.2 Gas turbine blades

3.2.1 Step 1 & 2:

Unlike the previous example, materials indices are considered as criteria to show the capability of the proposed method in solving problems under different circumstances. Materials indices that are obtained based on operating conditions and also fatigue requirements-are as follows: $M_1 = \left(\frac{\sigma_y}{\rho}\right)^{0.5}$, $M_2 = \left(\frac{E}{\rho}\right)$, $M_3 = \sigma_y$, $M_4 = \left(\frac{E}{\rho}\right)^{0.5}$, $M_5 = \left(\frac{\sigma_y}{E\alpha}\right)$, $M_6 = \left(\frac{k}{\rho c}\right)$, M_7 : Creep rupture stress, $M_8 = (\text{elongation} \times \frac{(\sigma_y + \sigma_{ut})}{2})$, $M_9 = T_m$, M_{10} : Oxidation resistance, M_{11} : Corrosion resistance, where σ_y , σ_{ut} , ρ , E , α , k , c , and T_m are yield stress, ultimate tensile stress, density, Young's modulus, thermal expansion coefficient, thermal conductivity, specific heat, and melting temperature, respectively. Details of extracting these indices can be found in reference [14]. Since a turbine blade experiences a wide temperature range in its working environment, accurate properties of the candidate materials at different temperature points should be considered. Over the past two decades, the working temperature of gas turbines has risen from 1000-1300 °F to 1300-1800 °F. Also, the non-operating temperature is assumed to be 70 °F.

Table 6 provides the selected material indices and their values for screened candidate materials, respectively.

Table 6 Indices of candidate materials at different temperature points for a gas turbine blade

Superalloys		M1-70	M1-1000	M1-1200	M1-1400	M1-1600	M1-1800	M2-70	M2-1000	M2-1200	M2-1400	M2-1600	M2-1800	M3-70	M3-1000	M3-1200	M3-1400	M3-1600	M3-1800	M4-70	M4-1000	M4-1200	M4-1400	M4-1600	M4-1800	M5-1000
Hastelloy S		15.02	12.84	12.71	12.17	11.31	7.34	103.7	88.89	84.85	81.14	76.09	70.71	67	49	48	44	38	16	10.18	9.428	9.211	9.008	8.723	8.409	0.221
Hastelloy X		13.19	11.53	10.52	10.37	9.413	6.414	94.3	81.65	78.16	73.73	70.25	64.56	55	42	35	34	28	13	9.711	9.036	8.841	8.587	8.382	8.035	0.22
Haynes HR-120		12.52	9.398	9.25	9.343	9.632	8.165	98.28	81.1	77.32	73.2	68.73	64.6	45.6	25.7	24.9	25.4	27	19.4	9.914	9.006	8.793	8.555	8.29	8.038	0.121
Haynes HR-160		12.5	9.345	9.382	9.197	8.7	6.082	104.8	87.67	83.56	78.42	74.32	67.81	45.6	25.5	25.7	24.7	22.1	10.8	10.24	9.363	9.141	8.856	8.621	8.235	0.12
Haynes 230		13.72	11.65	11.6	12.03	10.23	7.495	94.44	81.48	78.09	74.38	71.3	67.59	61	44	43.6	46.9	33.9	18.2	9.718	9.027	8.837	8.625	8.444	8.221	0.219
Haynes 282		18.65	17.73	17.64	17.45	15.73	7.972	105.4	90.97	86.96	82.61	76.59	68.9	104	94	93	91	74	19	10.26	9.538	9.325	9.089	8.751	8.3	0.461
Haynes 625		15.26	13.43	13.31	12.8	9.918	6.273	99.02	83.93	79.67	74.75	69.51	61.31	71	55	54	50	30	12	9.951	9.162	8.926	8.646	8.337	7.83	0.265
Inconel 600		12.65	11.72	11	9.218	7.231	5.113	101.6	87.25	83.33	79.41	74.51	68.63	49	42	37	26	16	8	10.08	9.341	9.129	8.911	8.632	8.284	0.187
Inconel 601		10.93	9.05	9.599	9.776	7.838	6.127	102.4	86.69	82.25	76.79	69.97	62.8	35	24	27	28	18	11	10.12	9.311	9.069	8.763	8.365	7.925	0.111
Inconel 625		15.58	14.03	14.26	14.03	11.59	8.098	98.69	84.92	80.98	76.39	70.16	63.93	74	60	62	60	41	20	9.934	9.215	8.999	8.74	8.376	7.996	0.297
Inconel 718		24.07	22.73	22.32	20.18	12.58	8.308	97.64	83.5	79.8	75.08	68.01	58.59	172	153.5	148	121	47	20.5	9.881	9.138	8.933	8.665	8.247	7.654	0.764
Haynes 556		14.33	10.86	10.7	10.54	9.881	7.34	100	77.78	73.4	73.4	70.37	67.68	61	35	34	33	29	16	10	8.819	8.567	8.567	8.389	8.227	0.172
Incoloy 800		11.2	11.04	10.56	8.755	6.858	4.939	98.95	81.53	77.7	73.52	69.69	65.51	36	35	32	22	13.5	7	9.948	9.03	8.815	8.574	8.348	8.094	0.159
Incoloy 800H		11.04	7.919	7.696	7.919	7.696	6.73	98.95	81.53	77.7	73.52	69.69	65.51	35	18	17	18	17	13	9.948	9.03	8.815	8.574	8.348	8.094	0.082
Incoloy 800HT		11.04	7.919	7.696	7.919	7.696	6.73	98.95	81.53	77.7	73.52	69.69	65.51	35	18	17	18	17	13	9.948	9.03	8.815	8.574	8.348	8.094	0.082
Haynes 188		14.41	11.39	11.07	10.96	10.53	7.658	85.19	80.86	76.85	72.84	68.83	64.81	67.3	42	39.7	38.9	35.9	19	9.23	8.992	8.767	8.535	8.296	8.051	0.208
Haynes 25 (L-605)		14.46	10.44	12.06	11.15	10.44	7.385	98.48	78.18	73.64	69.09	64.85	60.3	69	36	48	41	36	18	9.924	8.842	8.581	8.312	8.053	7.766	0.174
MAR-M-247		19.98	20.86	20.94	21.01	20.23	18.02	64.94	56.17	53.25	50.32	47.4	44.81	123	134	135	136	126	100	8.058	7.495	7.297	7.094	6.885	6.694	0.922
CMSX-4		20.7	21.33	21.8	21.18	19.88	17.48	119.6	116.3	113.3	109.6	106.3	102.3	129	137	143	135	119	92	10.94	10.78	10.64	10.47	10.31	10.12	0.483

Superalloys	M5-1200	M5-1400	M5-1600	M5-1800	M6-70	M6-1000	M6-1200	M6-1400	M6-1600	M6-1800	M7-1200	M7-1400	M7-1500	M7-1600	M7-1800	M8	M9-70	M9-1000	M9-1200	M9-1400	M9-1600	M9-1800	M10-1800	M10-2000	M11
Hastelloy S	0.221	0.207	0.187	0.083	2587	4011	4261	4339	4274	4521	58	24.5	16	11.8	5.2	2300	4728	4025	4208	4580	2088	1054	0.5	1.3	29.5
Hastelloy X	0.186	0.182	0.152	0.074	1719	3311	3438	3479	3449	3352	48	22.5	14.3	10.6	3.7	2435	3652	3060	3186	2677	2117	1268	0.9	2.7	29.5
Haynes HR-120	0.12	0.126	0.139	0.104	2393	3411	3580	3798	3890	4002	47	21.6	14.9	10.3	4.4	2375	3790	3224	2937	2235	1913	1920	3.7	7.7	0.9
Haynes HR-160	0.122	0.121	0.111	0.057	2335	3626	3674	3834	3863	4019	34	13	9.9	6.8	3.5	2360	5331	4077	3553	3168	2567	1404	5.9	10.3	1.1
Haynes 230	0.213	0.234	0.171	0.093	2014	3665	3409	3616	3810	4094	56	27	19	13.7	6	2375	4392	3942	4013	3809	2948	1080	0.7	1.3	12.6
Haynes 282	0.459	0.455	0.371	0.099	2315	3640	3918	3946	3958	4134	85	57	38	23	6.2	2370	4050	4046	3798	2365	2418	1562	1.8	10.9	2.2
Haynes 625	0.265	0.252	0.154	0.067	3186	3924	4028	4206	4401	4616	77	29	16.2	8.6	2.7	2350	4949	5163	4592	3631	2160	792	0.7	4.8	13.7
Inconel 600	0.169	0.12	0.077	0.041	2382	3245	3401	3479	3591	3674	23	8.4	6.3	4.8	2.8	2470	3020	2313	2639	2025	1197	650	0.9	1.6	12.5
Inconel 601	0.126	0.135	0.092	0.061	3208	3882	4011	4100	4209	4283	33	10.6	7.3	4.9	2.3	2375	3535	2725	2401	2720	1767	1260	1.3	2.6	2.9
Inconel 625	0.306	0.303	0.218	0.114	2911	3536	3655	3786	3906	4016	77	29	16.2	8.6	2.7	2350	5350	4656	3111	3150	5125	3020	0.72	4.8	1.7
Inconel 718	0.743	0.617	0.25	0.12	2636	3173	3298	3367	3430	3488	76.1	26.4	14.2	6.9	1.7	2300	3610	2877	2928	2846	2990	3465	0.5	1	0.2
Haynes 556	0.173	0.165	0.148	0.084	2427	3833	4051	4315	4449	4512	53	25	17	11.5	4.8	2425	4230	3456	3146	2575	2014	1408	1.1	2.6	3.8
Incoloy 800	0.149	0.105	0.066	0.035	2534	3510	3653	3830	4017	4575	24	9.5	6	4.4	1.9	2475	2684	2071	2139	2044	1344	810	1.4	8.2	0.4
Incoloy 800H	0.079	0.086	0.083	0.066	2534	3510	3653	3830	4017	4575	22.5	9.4	6.1	3.9	1.7	2475	3207	2160	1731	1088	1755	1296	1.8	7.4	11
Incoloy 800HT	0.079	0.086	0.083	0.066	2534	3510	3653	3830	4017	4575	22.5	9.4	6.1	3.9	1.7	2475	3207	2160	1731	1088	1755	1296	1.7	7.1	16
Haynes 188	0.194	0.194	0.183	0.099	2291	3491	3694	3935	3949	4167	72	37	17.5	11.6	4.3	2240	5419	4590	4219	4057	3069	1599	0.6	1.3	3.3
Haynes 25 (L-605)	0.241	0.209	0.185	0.096	2141	3497	3726	3968	4242	4523	69	36	24.7	17.5	7.2	2425	5483	4484	4680	2814	2160	936	0.7	10.2	1.8
MAR-M-247	0.823	0.713	0.591	0.429	1743	3571	3732	3816	3944	4058	127	90.6	72	53	28	2400	1676	1465	1446	1371	1420	1748	0.5	1.1	2.1
CMSX-4	0.477	0.46	0.387	0.293	2161	4972	5287	5478	5596	5157	145	130	113	82	42	2901	1587	1358	1444	1770	2080	2024	0.7	1.3	3

3.2.2 Step 3 & 4:

Here, five triangular fuzzy membership functions are mapped in the interval defined by the minimum and maximum values of each material index of candidate materials. Fig. 6 shows the membership functions for the strength index at 1600 °F (i.e., M3-1600). The remaining sets of membership functions are similar and not repeated here. In addition, the equivalent values are obtained according to Eqs. (1), (2). These values for M3-1600 °F membership functions are as follows: $U_{VL} = 0.134, U_L = 0.357, U_M = 0.532, U_H = 0.706, U_{VH} = 0.897$. The rest of the values is calculated likewise.

Fig. 6 Defined fuzzy membership functions of M3-1600 for a gas turbine blade

3.2.3 Step 5:

In this step, crisp numbers of Table 6, which gives the values of indices for candidate materials at different temperatures, are normalized by Eq. (3) and presented in Table 7.

Table 7 Normalized indices of candidate materials at different temperature points for a gas turbine blade

Superalloys		M1-70	M1-1000	M1-1200	M1-1400	M1-1600	M1-1800	M2-70	M2-1000	M2-1200	M2-1400	M2-1600	M2-1800	M3-70	M3-1000	M3-1200	M3-1400	M3-1600	M3-1800	M4-70	M4-1000	M4-1200	M4-1400	M4-1600	M4-1800	M5-1000
Hastelloy S		0.333	0.349	0.359	0.339	0.35	0.264	0.68	0.522	0.512	0.509	0.495	0.475	0.293	0.291	0.294	0.287	0.285	0.163	0.695	0.554	0.54	0.536	0.517	0.5	0.249
Hastelloy X		0.255	0.297	0.271	0.265	0.269	0.182	0.518	0.456	0.448	0.427	0.419	0.36	0.229	0.259	0.218	0.216	0.206	0.135	0.542	0.486	0.482	0.47	0.466	0.424	0.248
Haynes HR-120		0.194	0.166	0.174	0.175	0.28	0.299	0.579	0.448	0.434	0.416	0.381	0.36	0.145	0.129	0.132	0.133	0.192	0.213	0.627	0.481	0.473	0.463	0.444	0.425	0.123
Haynes HR-160		0.191	0.163	0.185	0.163	0.218	0.154	0.691	0.511	0.502	0.488	0.479	0.433	0.145	0.128	0.136	0.129	0.144	0.12	0.703	0.538	0.526	0.51	0.503	0.475	0.122
Haynes 230		0.282	0.301	0.307	0.332	0.301	0.272	0.519	0.454	0.447	0.439	0.439	0.429	0.268	0.27	0.277	0.298	0.262	0.193	0.544	0.484	0.481	0.477	0.478	0.473	0.247
Haynes 282		0.554	0.646	0.661	0.686	0.647	0.292	0.696	0.546	0.533	0.522	0.498	0.452	0.501	0.532	0.547	0.59	0.518	0.206	0.707	0.594	0.574	0.557	0.522	0.486	0.476
Haynes 625		0.347	0.395	0.413	0.39	0.291	0.169	0.598	0.482	0.468	0.446	0.4	0.317	0.305	0.31	0.315	0.309	0.23	0.127	0.641	0.503	0.494	0.481	0.456	0.349	0.285
Inconel 600		0.21	0.303	0.289	0.164	0.113	0.106	0.654	0.507	0.5	0.496	0.481	0.448	0.169	0.259	0.236	0.137	0.11	0.104	0.677	0.533	0.523	0.518	0.504	0.484	0.201
Inconel 601		0.1	0.144	0.208	0.221	0.141	0.157	0.665	0.503	0.493	0.473	0.412	0.334	0.1	0.122	0.144	0.151	0.119	0.121	0.684	0.526	0.513	0.498	0.463	0.378	0.116
Inconel 625		0.371	0.446	0.474	0.481	0.372	0.296	0.589	0.49	0.482	0.468	0.417	0.349	0.316	0.332	0.36	0.374	0.298	0.221	0.635	0.51	0.504	0.495	0.465	0.409	0.302
Inconel 718		0.9	0.9	0.9	0.857	0.46	0.303	0.565	0.478	0.47	0.451	0.367	0.296	0.9	0.9	0.9	0.797	0.324	0.228	0.613	0.5	0.495	0.484	0.431	0.314	0.733
Haynes 556		0.304	0.274	0.278	0.274	0.289	0.264	0.623	0.378	0.352	0.42	0.421	0.431	0.268	0.201	0.207	0.203	0.219	0.163	0.657	0.436	0.407	0.466	0.468	0.474	0.175
Incoloy 800		0.109	0.281	0.272	0.134	0.1	0.1	0.596	0.455	0.441	0.423	0.405	0.378	0.103	0.201	0.185	0.116	0.1	0.1	0.64	0.485	0.477	0.467	0.459	0.443	0.158
Incoloy 800H		0.104	0.1	0.1	0.1	0.133	0.217	0.596	0.455	0.441	0.423	0.405	0.378	0.1	0.1	0.1	0.1	0.114	0.135	0.64	0.485	0.477	0.467	0.459	0.443	0.1
Incoloy 800HT		0.104	0.1	0.1	0.1	0.133	0.217	0.596	0.455	0.441	0.423	0.405	0.378	0.1	0.1	0.1	0.1	0.114	0.135	0.64	0.485	0.477	0.467	0.459	0.443	0.1
Haynes 188		0.306	0.293	0.292	0.291	0.311	0.28	0.393	0.445	0.425	0.407	0.383	0.364	0.294	0.259	0.256	0.259	0.274	0.206	0.441	0.478	0.468	0.458	0.446	0.429	0.234
Haynes 25 (L-605)		0.308	0.253	0.324	0.297	0.308	0.266	0.583	0.387	0.356	0.336	0.323	0.308	0.299	0.212	0.294	0.272	0.275	0.19	0.631	0.443	0.413	0.38	0.357	0.334	0.179
MAR-M-247		0.668	0.797	0.839	0.895	0.9	0.9	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.624	0.774	0.834	0.9	0.9	0.9	0.1	0.1	0.1	0.1	0.1	0.9
CMSX-4		0.698	0.839	0.883	0.9	0.889	0.88	0.9	0.9	0.9	0.9	0.9	0.9	0.666	0.805	0.882	0.896	0.867	0.848	0.9	0.9	0.9	0.9	0.9	0.9	0.49

Superalloys	M5-1200	M5-1400	M5-1600	M5-1800	M6-70	M6-1000	M6-1200	M6-1400	M6-1600	M6-1800	M7-1200	M7-1400	M7-1500	M7-1600	M7-1800	M8	M9-70	M9-1000	M9-1200	M9-1400	M9-1600	M9-1800	M10-1800	M10-2000	M11
Hastelloy S	0.269	0.271	0.291	0.193	0.55	0.484	0.493	0.481	0.421	0.631	0.319	0.211	0.16	0.168	0.153	0.157	0.729	0.676	0.771	0.9	0.29	0.226	0.9	0.886	0.1
Hastelloy X	0.226	0.237	0.247	0.165	0.1	0.144	0.139	0.127	0.104	0.1	0.28	0.187	0.145	0.152	0.125	0.322	0.514	0.473	0.518	0.478	0.293	0.286	0.858	0.746	0.1
Haynes HR-120	0.128	0.134	0.22	0.257	0.477	0.211	0.224	0.278	0.282	0.379	0.275	0.177	0.15	0.149	0.137	0.278	0.536	0.496	0.482	0.346	0.263	0.476	0.441	0.341	0.889
Haynes HR-160	0.13	0.129	0.151	0.129	0.447	0.301	0.268	0.287	0.275	0.392	0.16	0.118	0.117	0.117	0.122	0.262	0.882	0.684	0.635	0.562	0.365	0.308	0.1	0.132	0.886
Haynes 230	0.261	0.294	0.274	0.23	0.274	0.31	0.129	0.189	0.258	0.445	0.31	0.237	0.195	0.201	0.174	0.278	0.686	0.66	0.721	0.713	0.472	0.236	0.883	0.886	0.544
Haynes 282	0.504	0.554	0.548	0.246	0.434	0.304	0.333	0.311	0.298	0.464	0.504	0.433	0.324	0.298	0.181	0.273	0.611	0.679	0.69	0.386	0.332	0.342	0.704	0.1	0.862
Haynes 625	0.3	0.306	0.25	0.147	0.894	0.451	0.388	0.43	0.474	0.675	0.472	0.252	0.162	0.132	0.111	0.25	0.783	0.9	0.888	0.69	0.298	0.125	0.883	0.587	0.519
Inconel 600	0.192	0.128	0.109	0.106	0.472	0.119	0.126	0.127	0.142	0.26	0.102	0.1	0.101	0.105	0.112	0.364	0.389	0.3	0.391	0.308	0.1	0.1	0.858	0.868	0.547
Inconel 601	0.133	0.146	0.125	0.135	0.9	0.426	0.377	0.364	0.378	0.507	0.152	0.108	0.105	0.105	0.106	0.278	0.5	0.378	0.322	0.485	0.228	0.285	0.769	0.755	0.842
Inconel 625	0.328	0.362	0.318	0.275	0.725	0.276	0.261	0.274	0.286	0.389	0.472	0.252	0.162	0.132	0.111	0.25	0.884	0.788	0.506	0.557	0.9	0.758	0.881	0.587	0.874
Inconel 718	0.825	0.762	0.367	0.284	0.587	0.1	0.1	0.1	0.1	0.143	0.467	0.231	0.144	0.118	0.1	0.157	0.508	0.433	0.48	0.501	0.479	0.9	0.9	0.9	0.9
Haynes 556	0.202	0.2	0.239	0.197	0.489	0.388	0.405	0.474	0.487	0.625	0.3	0.217	0.17	0.164	0.144	0.314	0.66	0.526	0.512	0.458	0.28	0.308	0.82	0.755	0.803
Incoloy 800	0.16	0.114	0.1	0.1	0.523	0.266	0.26	0.286	0.309	0.659	0.105	0.104	0.1	0.103	0.102	0.373	0.314	0.267	0.283	0.311	0.118	0.129	0.75	0.31	0.897
Incoloy 800H	0.1	0.1	0.115	0.145	0.523	0.266	0.26	0.286	0.309	0.659	0.1	0.103	0.1	0.1	0.1	0.373	0.449	0.281	0.155	0.1	0.224	0.291	0.704	0.371	0.61
Incoloy 800HT	0.1	0.1	0.115	0.145	0.523	0.266	0.26	0.286	0.309	0.659	0.1	0.103	0.1	0.1	0.1	0.373	0.449	0.281	0.155	0.1	0.224	0.291	0.713	0.413	0.481
Haynes 188	0.238	0.254	0.288	0.246	0.414	0.259	0.274	0.308	0.296	0.476	0.438	0.294	0.175	0.165	0.135	0.1	0.893	0.766	0.775	0.767	0.49	0.354	0.892	0.886	0.827
Haynes 25 (L-605)	0.285	0.272	0.289	0.238	0.315	0.261	0.284	0.316	0.4	0.632	0.407	0.29	0.257	0.256	0.217	0.314	0.9	0.74	0.9	0.498	0.298	0.168	0.883	0.139	0.872
MAR-M-247	0.9	0.9	0.9	0.9	0.107	0.287	0.286	0.283	0.295	0.423	0.77	0.658	0.588	0.606	0.636	0.297	0.11	0.113	0.1	0.148	0.129	0.421	0.9	0.896	0.865
CMSX-4	0.516	0.562	0.581	0.638	0.323	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.1	0.1	0.1	0.272	0.289	0.495	0.883	0.886	0.838

3.2.4 Step 6:

This step aims to provide the equivalent weighting coefficients for each one of the material index-temperature point pairs. First, weighting factors for material indices should be determined. This task can be done using MDL [6], QFD [14], or other weighting methods. However, since equal weighting coefficients for the material indices are taken into account by TOPSIS and Z-transformation methods, for a more meaningful comparison of the results with outputs of the named techniques, equal values are considered for eleven material indices. It means that the weighting coefficient for each material index is assumed to be 1/11. Second, the weighting factors for temperature points should be calculated. This step could be quickly done by the MDL method, see Table 8. Now with having weighting coefficients of material indices (α_m) and also point to point temperature weighting factors (α_T), equivalent weighting numbers can be defined by the following equation:

$$\alpha_{eq} = \alpha_m \times \alpha_T \quad (5)$$

It can be inferred from Eq. (5) that the changes in the working environment, like temperature fluctuations, which may cause variation in material indices, dictates the equivalent weighting coefficients (α_{eq}) to consist of proper weighting factors for all the influential working parameters. Here, in order to demonstrate the importance of each material index-temperature point pair, Eq. (5) first enables the decision-maker to consider materials data in a wide range of working temperatures (α_m), and second, value the material indices at more important temperature points (α_T). Note that since the materials data are not available at all temperature points, the points with available information are employed for some indices. For example, for the corrosion resistance index (M10), material indices are not presented in a broad range of working temperatures. As a result, materials data at 1800 and 2000 °F are considered for evaluation. The equivalent weighting coefficients for each material index-temperature point are listed in Table 9.

Table 8 Weighting coefficients of temperature points for a gas turbine blade

Temp. °F	Number of possible decisions															Positive decisions	Coefficient α_T
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		
70	1	1	1	1	1											5	0.083
1000	3					1	1	1	1							7	0.117
1200		3				3				1	1	1				9	0.150
1400			3				3			3			1	1		11	0.183
1600				3				3			3		3		1	13	0.217
1800					3				3			3		3	3	15	0.250

Table 9 Equivalent weighting factors of the material indices for a gas turbine blade

Material Index	Value	Material Index	Value	Material Index	Value	Material Index	Value	Material Index	Value
M1-70	0.007545	M2-1600	0.019727	M4-1200	0.013636	M6-1000	0.010636	M8	0.090909
M1-1000	0.010636	M2-1800	0.022727	M4-1400	0.016636	M6-1200	0.013636	M9-70	0.007545
M1-1200	0.013636	M3-70	0.007545	M4-1600	0.019727	M6-1400	0.016636	M9-1000	0.010636
M1-1400	0.016636	M3-1000	0.010636	M4-1800	0.022727	M6-1600	0.019727	M9-1200	0.013636
M1-1600	0.019727	M3-1200	0.013636	M5-1000	0.009090	M6-1800	0.022727	M9-1400	0.016636
M1-1800	0.022727	M3-1400	0.016636	M5-1200	0.013636	M7-1200	0.009090	M9-1600	0.019727
M2-70	0.007545	M3-1600	0.019727	M5-1400	0.018181	M7-1400	0.013636	M9-1800	0.022727
M2-1000	0.010636	M3-1800	0.022727	M5-1600	0.022727	M7-1500	0.018181	M10-1800	0.045454
M2-1200	0.013636	M4-70	0.007545	M5-1800	0.027272	M7-1600	0.022727	M10-2000	0.045454
M2-1400	0.016636	M4-1000	0.010636	M6-70	0.007545	M7-1800	0.027272	M11	0.090909

3.2.5 Step 7:

By multiplying the normalized matrixes ($R_{19 \times 50}$) with the weighting vector ($W_{50 \times 1}$), the performance index vector and final ranking of the candidate materials can be extracted. The number 19 represents the number of candidate materials, and 50 indicates the number of material index-temperature point pairs. Table 10 presents the final ranking of the proposed method and the results obtained by the Z-transformation, QFD, and TOPSIS methods. As it is seen, there is extensive compatibility between the results obtained by different methods, and it proves the claim made earlier in this research work on the accuracy of the Modified Fuzzy Logic Method. Also, some minor discrepancies can be seen in the results. According to the TOPSIS method, candidate materials are ranked based on their distances from ideal and non-ideal solutions [7], meaning that materials are ranked relative to each other. Data dependency can adversely affect the results, especially when the designer faces candidate materials with low or high exceptional properties. These materials extend the range of property values and do not allow the decision-maker to differentiate the materials with close property values correctly. It is

the case for TOPSIS rankings of materials Hastelloy S (rank 18) and Haynes 625 (rank 15). Surprisingly, although material indices of Haynes 25 (L-605) are so close to Hastelloy S, TOPSIS allocates the seventh place to this candidate material. MFLM resolved this major flaw by using its unique normalizing technique. Here, the defined sets of membership functions and their corresponding equivalent values act as auxiliary tools for accurately assessing the properties of materials and extracting their performance indices. Additionally, the poor performance of Haynes 188 corresponding to some material indices like corrosion resistance forced the QFD method to disregard its other valuable capabilities. On the other hand, MFLM can notice the requirements and objectives of the application and appreciate all of the favorable characteristics of different alternatives.

This example illustrates the power of the method in solving complex and hard-to-process problems. The enormous number of criteria (i.e., 50) makes it extremely time-consuming for conventional fuzzy logic-based approaches to provide the final ranking. For example, having 50 criteria and a set of 5 fuzzy membership functions leads to 5^{50} IF-THEN rules (before reduction) in the Conventional Fuzzy Logic method [32], making it inefficient while facing such elaborate problems. However, the proposed method allows us to confront complicated problems, besides giving us the undeniable advantages of the fuzzy environment.

Table 10 Performance indices and ranking of candidate materials for a gas turbine blade

Materials	MFLM		TOPSIS [7]		Z-transformation [10]		QFD method [14]	
	γ	Rank	γ	Rank	γ	Rank	γ	Rank
CMSX-4	0.794	1	0.833	1	2.0786	1	2.038503	1
MAR-M-247	0.546	2	0.792	2	0.4076	2	0.437551	2
Inconel 718	0.498	3	0.630	3	0.2856	4	0.268965	4
Haynes 282	0.473	4	0.582	6	0.290	3	0.401309	3
Inconel 625	0.459	5	0.598	4	0.1763	5	0.135930	5
Haynes 188	0.421	6	0.586	5	-0.066	7	0.14546-	11
Haynes 556	0.416	7	0.563	8	-0.013	6	0.07022-	7
Haynes 230	0.407	8	0.500	12	-0.090	10	0.14345-	10
Haynes 625	0.403	9	0.463	15	-0.072	8	0.09228-	8
Haynes 25 (L-605)	0.401	10	0.571	7	-0.092	11	0.06205-	6
Hastelloy S	0.388	11	0.353	18	-0.080	9	0.12437-	9
Inconel 601	0.377	12	0.547	9	-0.178	12	0.23988-	13
Haynes HR-120	0.355	13	0.526	11	-0.315	15	0.25074-	14
Incoloy 800	0.347	14	0.539	10	-0.307	13	0.28666-	15
Inconel 600	0.344	15	0.463	14	-0.311	14	0.34051-	16
Haynes HR-160	0.334	16	0.473	13	-0.362	16	0.23915-	12
Incoloy 800H	0.320	17	0.438	16	-0.418	17	0.38783-	17
Hastelloy X	0.314	18	0.324	19	-0.473	19	0.45904-	19
Incoloy 800HT	0.311	19	0.382	17	-0.461	18	0.42858-	18

3.3 Thermal barrier coatings (TBCs)

3.3.1 Introduction to TBCs:

Superalloys experience mechanical and chemical degradations at high temperatures. In such cases, knowledge of surface engineering must be used to protect the parts. Tribology suggests using proper coatings to assure materials properties remain stable. All coatings applied to turbine blades should preserve the surface from the destructive effects of high-temperature corrosion, erosion, and oxidation due to combustion products. High strength under static and dynamic stresses, chemical inertness, and proper adhesion to the substrate are among other essential characteristics. Fig. 7 shows the flowchart of selecting an optimum material as a coating for gas turbine blades.

Fig. 7 Flowchart of material selection for coatings of gas turbine blades

The application of thermal barrier coatings (TBCs) in turbine engines is quite common [44]. In this type of coatings, a ceramic layer is applied on the surface of the superalloy. Ceramics, due to their low thermal conductivity, provide thermal insulators that keep the temperature of sublayers much lower than the operating temperature of the engine. Perforated TBCs with $300\ \mu m$ thickness can cause temperature differences of up to hundreds of degrees of Celsius between the hot gas and the blade superalloy [45]. New TBC generations mostly made up of YSZ are used for turbine blades, nozzles, and some parts of the combustion chamber.

Unfortunately, YSZ and many other coatings cannot prevent the penetration of oxygen, so the underlying layer is exposed to oxidation. In addition, the difference between thermal expansion coefficients of coatings and superalloys can lead to thermal stresses and eventually spallation of coatings. A layer called bond coating is applied to superalloy prior to the ceramic coating to reduce these adverse effects.

3.3.2 Materials selection for TBCs

Since the method description is fully clarified in the previous examples, the step-by-step explanation is skipped here. Thermal stresses caused by the difference in thermal expansion coefficients of the blade coating and superalloy substrate is calculated by Eq. (6) as follows;

$$\sigma = \frac{E_c(\alpha_T - \alpha_{Tc})(T - T_0)}{1 - \nu} \quad (6)$$

where E_c is the elastic modulus of coating, α_T and α_{Tc} are thermal expansion coefficients of superalloy and coating, respectively, ν is the Poisson's ratio of coating, T is the operating temperature of the turbine, and T_0 is the initial temperature. This stress should not exceed the yield stress of coating (σ_y). Hence, the first material index is obtained as;

$$M_1 = \frac{\sigma_y(1 - \nu)}{E_c(\alpha_T - \alpha_{Tc})} \quad (7)$$

The relatively large thickness of the applied ceramic coating can lead to high stresses due to centrifugal loads. Therefore, its specific strength, which is defined as $M_2 = \frac{\sigma_y}{\rho}$, is of great importance. Here, σ_y and ρ are the yield stress and density of the coating, respectively. The first two material indices are among the beneficial criteria. Also, smaller thermal conductivity and thermal expansion coefficient, higher melting point temperature, and good shock resistance are of interest. So, materials indices are defined as $M_3 = k$, $M_4 = \alpha$, $M_5 = T_m$, M_6 : *shock resistance*. Here, k is the thermal conductivity, α is the thermal expansion

coefficient, and T_m is the melting temperature point. Moreover, as all ceramics exhibit good oxidation and corrosion resistance, these properties have been neglected. The final candidate materials and their indices are listed in Table 11.

Table 11 Indices of candidate materials for TBCs

Materials	M1	M2	M3	M4	M5	M6
ZrO2	8.76	2.74	1.62	0.7	2973	High
3YSZ	5.353	1.658	1.23	0.58	2719	Very High
8YSZ	7.933	1.898	0.83	0.21	2973	Very High
Mullite	3.152	3.571	1.39	0.14	2123	Medium
Al2O3	35.09	2.71	5.8	0.47	2323	Low
CeO2	11.37	1.37	2.77	0.86	2873	Very High
La2Zr2O7	5.464	1.667	1.56	0.54	2573	High
BaZrO3	4.728	1.818	3.42	1.25	2963	High
TiO2	3.568	2.5	3.3	0.52	2098	Low
LaPO4	8.831	2.016	1.8	0.42	2343	High
60% Mullite-40% YSZ BC Alloy	4.142	2.66	1.31	0.39	2463	High

Similar to the gas turbine blade example, a set of five fuzzy membership functions is considered in the domain limited by the Min-Max values of each material index of candidate materials. Fig. 8 demonstrates membership functions for the thermal stress index (M_1).

Fig. 8 Defined fuzzy membership functions for M1 material index

The equivalent values are calculated according to Eqs. (1) and (2), and subsequently, the crisp data presented in Table 11 are converted into normalized values (see Table 12).

Table 12 Normalized indices of candidate materials for TBCs

Materials	M1	M2	M3	M4	M5	M6
ZrO ₂	0.258	0.596	0.757	0.498	0.9	0.7
3YSZ	0.138	0.209	0.853	0.571	0.681	0.9
8YSZ	0.233	0.296	0.9	0.866	0.9	0.9
Mullite	0.1	0.9	0.818	0.9	0.113	0.5
Al ₂ O ₃	0.9	0.577	0.1	0.677	0.303	0.3
CeO ₂	0.303	0.1	0.578	0.368	0.816	0.9
La ₂ Zr ₂ O ₇	0.141	0.215	0.77	0.621	0.521	0.7
BaZrO ₃	0.125	0.277	0.491	0.1	0.895	0.7
TiO ₂	0.105	0.506	0.501	0.641	0.1	0.3
LaPO ₄	0.259	0.321	0.728	0.699	0.314	0.7
60% Mullite-40% YSZ BC Alloy	0.114	0.552	0.837	0.711	0.45	0.7

Furthermore, material indices are considered equally important, so the weighting coefficient for each one of them would be $1/6$. The final ranking results offered by MFLM, TOPSIS, and Z-transformation methods are summarized in Table 13. As was mentioned earlier, 8YSZ material stands in the first place by all ranking methods, except for the TOPSIS method, which allocates the first rank to Al₂O₃. The compatibility of thermal expansion coefficients of Al₂O₃ and superalloy substrate provides a higher thermal stress index (M_1) for this coating. However, it does not justify the poor performance of Al₂O₃ in other indices compared to other candidates. Sacrificing other materials indices just because of one or two extraordinary characteristics is seen in the TOPSIS ranking. This flaw is prevented in the Modified Fuzzy Logic approach by mapping a suitable set of fuzzy membership functions in the design interval values of candidate materials.

Additionally, it can be inferred from Table 13 that the Z-transformation method does not notice the better shock resistance of 8YSZ and 60% Mullite-40% YSZ BC Alloy over Mullite material; thus, Mullite earned third place by this ranking method. According to the scaling technique of the Z-transformation method, criteria with more dispersed values of candidate materials have less influence on the final ranking. This approach can cause severe problems, especially when facing qualitatively stated properties. Values attributed to the materials corresponding to these criteria are so scattered; as a result, the Z-transformation method always underestimates these attributes against quantitatively stated criteria. In contrast, MFLM uses equivalent values of membership functions combined with a weighting technique to fairly evaluate the materials.

Table 13 Performance indices and ranking of candidate materials for TBCs

Materials	MFLM		TOPSIS [7]		Z-transformation [10]	
	γ	Rank	γ	Rank	γ	Rank
8YSZ	0.682	1	0.545	2	0.6506	1
ZrO ₂	0.618	2	0.472	6	0.3879	2
60% Mullite–40% YSZ BC Alloy	0.561	3	0.479	5	0.2306	4
3YSZ	0.559	4	0.465	7	0.1595	5
Mullite	0.555	5	0.5	3	0.2744	3
CeO ₂	0.511	6	0.416	9	-0.059	8
LaPO ₄	0.504	7	0.488	4	0.0214	6
La ₂ Zr ₂ O ₇	0.495	8	0.446	8	-0.059	7
Al ₂ O ₃	0.476	9	0.579	1	-0.063	9
BaZrO ₃	0.431	10	0.274	11	-0.456	10
TiO ₂	0.359	11	0.353	10	-0.58	11

4 Conclusion

The vast range of alternatives, inadequate data, dual qualitative and quantitative nature of criteria, measurements inaccuracy, and occasionally conflicting attributes add up a great deal of uncertainty and vagueness to the selection scheme. In this sense, applying conventional weighted methods leaves the designer with imprecise and unreliable results. Generally, a fuzzy environment offers indisputable advantages to MCDM problems and aids the designer in deciding based on ambiguous and uncertain data. Nevertheless, the complexity and inaccuracy of conventional fuzzy logic approaches sometimes discourage one to practice these methods. MFLM endows the decision-maker with the opportunity to employ his/her knowledge and preferences by mapping a few simple fuzzy functions in the desired range and normalize the crisp data without struggling with any complicated IF-THEN rules or fuzzy operators. The significant advantages and highlights of the proposed fuzzy technique are summarized as follows;

- 1) MFLM exploits the newfound concept of the linear combination of equivalent values of surrounding membership functions as its novel normalizing technique.

- 2) It passes the data through the filter of fuzzy membership functions to add the effects of uncertainties; thus, the produced rankings are more trustworthy than traditional numerical approaches.
- 3) MFLM is able to sense the presence of a specified design interval for each criterion and subsequently undermine the remarkable influences of out-of-box characteristics of materials on final rankings.
- 4) It can simultaneously incorporate both quantitative and qualitative criteria.
- 5) Depending on the application and availability of required knowledge, both materials properties and indices can be used as criteria.
- 6) This method does not require any complex IF-THEN rules or fuzzy operators.
- 7) The ranking results are independent of candidate materials.
- 8) The method is straightforward and can be programmed with a few lines of code.
- 9) Although this technique is particularly developed to facilitate the procedure of materials selection, it can be employed to other MCDM problems as well.
- 10) Remarkably, MFLM outperforms the existing complicated techniques in terms of accuracy, efficiency, and reliability.

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