MODELLING A DECISION APPROACH OF GEAR MATERIAL SELECTION BY FUZZY BASED OPTIMIZATION

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ABSTRACT

This research ventures one of the major concerns in the field of decision engineering as well as selection management on the inspection environment. Determination the accuracy of material selection by fuzzy method for better decision. The article is presented the results of the decision management of the dynamics the change of values of the parameters of the internal selection criteria. The choice of stronger material parameters may allow the choice of better geometrical parameters. This project addresses modeling a hierarchy methodology for gear selection.

Keywords: *Selection parameters, decision making,, fuzzy ,gear material*

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1. Introduction

A gear is a rotating machine part having cut teeth, or cogs, which mesh with another toothed part in order to transmit torque [1]. There are other too many devices by which power can also transmit from one shaft to another like belt drive, chain drive, rope drive, cam, linkage etc. But when power transmits by these devices slip can occur, also the space occupied by these devices may be large. In precision machines, in which a definite velocity ratio is of importance (as in watch mechanism), the only positive drive is by gears. A gear drive is also provided, when the distance between the driver and the follower is very small and a large amount of power transmission required. Because of these reasons though the manufacturing cost of gear is very high, it is very popular device for transmit motion from one shaft to another [2].

Selection of the most appropriate material for a gear drive is one of the primary challenges often faced by the designers. As gear drive transmit large amount of power, the teeth should have sufficient strength so that they will not fail under static loading or dynamic loading during normal running conditions. While selecting materials for gear drive, various material properties, like surface hardness, core hardness, surface fatigue limit, bending fatigue limit etc. are to be taken into consideration. The present study involve fuzzy TOPSIS and fuzzy AHP method as mathematical tool to select the most appropriate gear material from a given set of alternatives.

2.Fuzzy numbers

In this section, some basic definitions of fuzzy sets and fuzzy numbers are reviewed from Kaufmann and Gupta [3] and Miranda et. al [4]. Below, the basic definitions and notations of fuzzy sets and fuzzy numbers arepresented which are applied throughout this paper until otherwise stated.

Definition 1. A fuzzy set $\tilde{A}$ in a universe of discourse X is characterized by a membership function $\mu_{\tilde{A}}(x)$which associates with each element x in X a real number in the interval [0,1] . The function value is$\mu_{\tilde{A}}(x)$ termed the grade of membership x of in$\tilde{A}$.

Definition2. The triangular fuzzy numbers can be denoted as $\tilde{A}= (a_1,a_2,a_3)$, the membership function ofthe fuzzy number$\tilde{A}$ is defined as follows:

$$\mu\tilde{A}(x) = \begin{cases} 0 & x < a_1 \\ \dfrac{x-a_1}{a_2-a_1} & a_1 \leq x \geq a_2 \\ \dfrac{a_3-x}{a_3-a_2} & a_2 \leq x \geq a_3 \\ 0 & x > a_3 \end{cases}$$

Definition 3. A non-fuzzy number R can be expressed as (r_1, r_2, r_3). The fuzzy sum $\oplus$ and fuzzy Subtraction $\ominus$ ofany two triangular fuzzy numbers are also triangular fuzzy numbers; however, the multiplication $\otimes$ of any twotriangular fuzzy numbers is only an approximate triangular fuzzy number. Given any two positive triangular fuzzy numbers, $\tilde{A}_1= (a_1,a_2,a_3)$, $\tilde{A}_2= (b_1,b_2,b_3)$ and a positive real number r, some main operations of fuzzynumbers $\tilde{A}_1$ and$\tilde{A}_2$ can be expressed as follows:

$\tilde{A}_1 \oplus \tilde{A}_2= (a_1+b_1, a_2+b_2, a_3+b_3)$

$\tilde{A}_1 \ominus \tilde{A}_2= (a_1-b_1, a_2-b_2, a_3-b_3)$

$\tilde{A}_1 \otimes r = (a_1r, a_2r, a_3r)$

$\tilde{A}_1 \otimes \tilde{A}_2= (a_1b_1, a_2b_2, a_3b_3)$

3.TOPSIS Method

The TOPSIS (technique for order preference by similarity to ideal solution) method, first introduced by Hwang and Yoon [5], is a multi-criteria decision-making (MCDM) approach based on the theory that the best alternative should be as close as possible to the positive- ideal solution and the farthest from the negative-ideal solution. The distances are to be estimated in the sense of Euclidean geometry. In this proposed work, an attempt is made to implement a fuzzy TOPSIS method for selecting the most suitable materials for gear.

This method is suitable for solving the group decision-making problems under fuzzy environment. The steps of fuzzy TOPSIS method are given as below:

Step 1: Choose the linguistic rating ($\tilde{x}_{ij}$, i = 1, 2…, m) for the alternatives with respect to the considered criteria and the appropriate linguistic variables ($\tilde{w}_j$, j = 1, 2,…, n) for the criteria weights.

Step 2: Normalize the decision matrix to obtain dimensionless criteria values.

In order to transform the performance ratings into fuzzy linguistic variables [6], the performance ratings are first normalized into a range of (0,1) using the following equations for beneficial and non-beneficial criteria respectively.

$$r_{ij} = [x_{ij} – \min(x_{ij})]/[\max(x_{ij}) – \min(x_{ij})] \quad (1)$$

$$r_{ij} = [\max(x_{ij}) – x_{ij}]/[\max(x_{ij}) – \min(x_{ij})] \quad . \quad (2)$$

Then, these normalized values are converted into triangular fuzzy numbers using fuzzy membership functions. This transformation is also applied to the criteria weight values.

Step 3: Construct the weighted normalized fuzzy decision matrix. The weighted normalized value $\tilde{v}$ is calculated by multiplying the fuzzy normalized matrix by the corresponding fuzzy criteria weight values.

Step 4: Identify the positive-ideal (A*) and the negative-ideal (A^-) solutions. The fuzzy positive- ideal solution (FPIS, A*) and the fuzzy negative-ideal solution (FNIS, A^-) are given as below [4]:

$$A^* = (\tilde{v}^*_1, \tilde{v}^*_2, \tilde{v}^*_3, \ldots, \tilde{v}^*_n)$$

$$= \{ \min_i v_{ij}, \quad for\ i = 1,2,\ldots,m\ and\ j = 1,2,\ldots,n\} \quad (4)$$

$A^{-} = (\tilde{v}^{-}_{1}, \tilde{v}^{-}_{2}, \tilde{v}^{-}_{3}, \ldots, \tilde{v}^{-}_{n})$

$$= \{ \max_{i} v_{ij}, \quad for\ i = 1,2,\ldots,m\ and\ j = 1,2,\ldots,n \} \tag{3}$$

Step 5: Calculate the separation measures. The distance of each alternative from A* and A^{-} can be calculated using the following equations:

$$D_i^{*} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}^{*}_{j}) \quad i = 1,2,\ldots,m \tag{5}$$

$$D_i^{-} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}^{-}_{j}) \tag{6}$$

Step 6: The similarity to the positive-ideal solution or a closeness coefficient of each alternative is defined to determine the ranking order of all the alternatives. This step computes the similarities to the positive-ideal solution applying the following equation:

$$CC_i = \frac{D_i^{-}}{D_i^{-} + D_i^{*}} \tag{7}$$

Step 7: According to the preference order, choose the best alternative having the maximum CCi value.

4. Fuzzy AHP Method

The Analytic hierarchy process (AHP) [7] presents an approach for the situations in which ideas; feeling and emotions are quantified to provide a numeric scale for prioritizing decision alternatives. AHP is a decision support procedure that deals with complex unstructured and multiple criteria decisions. To provide some structures on a decision-making process the AHP is used in various applications.

The complete procedure of AHP method is as follows:

Step 1. Construct a pair-wise comparison matrix using a scale of relative importance. Let C={C_j | j= 1,2,….,n} be the set of criteria. The result of the pair wise comparison on n criteria can be summarized in an (n x n) evaluation matrix A. The every element a_{ij} (i,j = 1, 2,…,n) denotes the comparative importance of criteria i with respect to j. A criteria compared with itself is always assigned the value 1 so the main diagonal entries of the pair wise comparison matrix are all 1.

$$A = \begin{bmatrix} 1 & a_{12} & \ldots & a_{1n} \\ a_{21} & 1 & \ldots & a_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ a_{n1} & a_{n2} & \ldots & 1 \end{bmatrix} \qquad a_{ji} = 1/a_{ij}, \quad a_{ij} \neq 0 \tag{1}$$

Step 2. Find the relative normalized weight (W_i) of each criterion by calculating the geometric mean of ith row and normalizing the geometric means of rows in the comparison matrix.

$$GM_i = \{a_{i1} \text{ x } a_{i2} \text{ x } a_{i3} \text{ x } \ldots \text{x } a_{ij}\}^{1/n} \tag{2}$$

$$W_i = \frac{GM_i}{\sum_{j=1}^{j=n} GM_i} \tag{3}$$

Step 3. Obtain matrix X which denote an n-dimensional column vector describing the sum of

the weighted values for the importance degrees of alternatives, then $X = A * W$ where
$W = [W_1, W_2, W_3 \ldots W_n]^T$ (4)

$$X = A * W = \begin{bmatrix} 1 & a_{12} & \ldots & a_{1n} \\ a_{21} & 1 & \ldots & a_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ a_{n1} & a_{n2} & \ldots & 1 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ \ldots \\ W_n \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \ldots \\ c_n \end{bmatrix} \quad (5)$$

Step 4. Calculate the consistency values (*CV*) for the cluster of alternatives represented by the vector

$$CV_i = \frac{c_i}{W_i} \quad (6)$$

Step 5. Find out the maximum Eigen value λ_{max} that is the average of the consistency values.
Step 6. Calculate the consistency index (CI) = (λ_{max}- n) / (n - 1). It should be noted that the quality of the output of the AHP is strictly related to the consistency of the pair-wise comparison judgments.
Step 7. Obtain the random index (RI) for the number of criteria used in decision making from a standard table.
Step 8. Calculate the consistency ratio CR = CI/RI. The number 0.1 is the accepted upper limit for CR. If the final consistency ratio exceeds this value, the evaluation procedure has to be repeated to improve consistency. The measurement of consistency can be used to evaluate the consistency of decision makers as well as the consistency of overall hierarchy.

5. Gear Material Selection

Cast iron is an alloy of iron and carbon, containing more than 2% of carbon. In addition to carbon, cast iron contains other elements like silicon, manganese, sulfur and phosphorus. While most varieties of cast iron are brittle, ductile iron is much more flexible and elastic, due to its nodular graphite inclusions. A typical chemical analysis of this material includes iron, carbon 3.3 to 3.4%, silicon 2.2 to 2.8%, manganese 0.1 to 0.5%, magnesium 0.03 to 0.05%, phosphorus 0.005 to 0.04%, sulfur 0.005 to 0. S. G Iron is an abbreviation for spheroidal graphite cast iron. As the name implies, graphite is present in spheroidal form instead of flakes and compared with grey cast Iron it has higher mechanical strength, ductility and increased shock resistance. Cast high alloy steels are widely used for their corrosion resistance in aqueous media at or near room temperature. Mechanical properties of these grades (for example, hardness and tensile strength) can be altered by suitable heat treatment. The cast high-alloy grades that contain more than 20 to 30% Cr+Ni. Through hardened alloy steel is basically a medium alloy steel. The through hardening process is used on medium and high carbon steels. Hardening occurs during heat treating when the steel (containing sufficient carbon) is cooled rapidly (quenched) from above its critical temperature. This temperature varies for different alloys but generally is in the range 1500F- 1900F. Surface hardened alloy steel is a surface hardening steel through heat treatment process. There are many different types of heat-treatment process used to modify the surface properties of steel components. The majority of these processes are used to produce harder, more wear and fatigue resistant surfaces than could be obtained from the base material. A component that has a tough and relatively ductile core with a hard wear resistant case is the result of heat treatment. Carburised steel is produced through heat treatment process in which iron or steel is heated in the presence of another material (in the range of 900 to 950°C (1,650 to 1,740 °F)) which liberates carbon as it decomposes. Depending on the amount of time and temperature, the affected area can vary in carbon content. Nitride Steel is produced through nitrogen implantation, the change in hardness and wear depends on the nitrogen dose. Under the best implantation conditions, the hardness was increased by about 60% and the wear rate reduced by five times [8]. Nitriding involves nitrogen diffusing into the surface of certain steels and forming compounds. It then deforms the steel structure at the surface putting the atomic bonds into tension. This makes the surface very hard. Through hardened carbon steel is a medium carbon steel. If this steel is subsequently quenched it will harden the surface layer, also known as the case, -hence "case hardening". The case depth will generally be from two thousandths of an inch up to one hundred and fifty thousandths of an inch.

Hardness of a gear material is the measure of how resistant solid matter is to various kinds of permanent shape change when a force is applied.The resistance of the surface of a hardened mortar to indentation by a loaded steel ball. Core hardness is the measurement of the hardness of the center of the wall of a gear material. The ability of a core of a gear material to resist scratching or abrasion. Surface fatigue limit of a gear material is the maximum fluctuating stress in a surface of a gear material can endure for an infinite number of cycles. It is usually determined from an S-N diagram. Bending fatigue limit of a gear material is the maximum fluctuating stress in the core of a material can endure for an infinite number of cycles. It is usually determined from an S-N diagram. Ultimate tensile strength of a gear material is the maximum stress that a gear material can withstand while being stretched or pulled before necking, which is when the specimen's cross-section starts to significantly contract.

In order to show the applicability and potentiality of the fuzzy TOPSIS method, gear material selection problem is considered here. The example deals with the selection of the most appropriate material for a gear. The gear material selection problem[9] contains nine alternative materials, i.e. Cast Iron (A_1), Ductile Iron (A_2), S. G Iron (A_3), Cast Alloy Steel (A_4), Through Hardened Alloy Steel (A_5), Surface Hardened Alloy Steel (A_6), Carburised Steel (A_7), Nitrided Steel (A_8) and Through Hardened Carbon Steel (A_9) and five criteria, like surface hardness (B_1), core hardness (B_2), surface fatigue limit (B_3), bending fatigue limit (B_4) and ultimate tensile strength (B_5). Gear material selection problem is given in Table 1 which is converted into Table 2 using fuzzy number. The criteria weights are given as w_{SH} = 0.15, w_{CH} = 0.05, w_{SFL}= 0.4, w_{BFL}= 0.3 and w_{UTS} = 01. Now, the normalized and the weighted normalized decision matrices are obtained before calculating the fuzzy positive-ideal solution (FPIS) and the fuzzy negative-ideal solution (FNIS) values. The criteria values of the gear material selection problem are first normalized using Eqn. (1) or (2), as shown in Table 3. Then, the fuzzy weighted normalized decision matrices are derived, as given in Table 4.

Now, the fuzzy positive-ideal solution (FPIS, A^*) and the fuzzy negative-ideal solution (FNIS, A^-) are $\tilde{v}_j^* = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$ respectively. The distances of each alternative material from A^* and A^- are calculated using Eqns. (5) and (6) respectively. Now, the similarities to the positive-ideal solution of the alternative gear materials are calculated using Eqn. (7).Tables 5 shows the results of the fuzzy TOPSIS method-based analyses with FPIS and FNIS values along with the corresponding closeness coefficients and ranking of the alternatives for the considered gear material selection problem. Finally, the gear materials are arranged in descending order, according to the closeness coefficient values. In the gear material selection problem, the final ranking of the alternatives is obtained as A_7-A_8-A_6-A_5-A_4-A_9-A_3-A_2-A_1. Nemes et al. [9] obtain the ranking of alternative as A_7-A_8-A_6-A_5-A_4-A_9-A_3-A_2-A_1 which is exactly matches with the proposed fuzzy TOPSIS methods. For the gear material selection problem, the best choice is carburised steel and worst choice is cast iron. Hence; the obtained rankings prove the applicability of the fuzzy TOPSIS method for solving the gear material selection problem.

Table 1. Data for gear material selection problem[9]

Alternative Materials	Hardness		surface fatigue limit	Bending Fatigue limit	UTS
	surface	core			
A_1	200	200	330	100	380
A_2	220	220	460	360	880
A_3	240	240	550	340	845
A_4	270	270	630	435	345
A_5	270	270	670	540	1190
A_6	585	240	1160	680	1580
A_7	700	315	1500	920	2300
A_8	750	315	1250	760	1250
A_9	185	185	500	430	635

Table 2. Fuzzy decision matrix of gear material selection

Sl. No.	B_1	B_2	B_3	B_4	B_5
A_1	(180,200,220)	(180,200,220)	(297,330,363)	(90,100,110)	(342,380,418)
A_2	(198,220,242)	(198,220,242)	(414,460,506)	(324,360,396)	(792,880,968)
A_3	(216,240,264)	(216,240,264)	(495,550,605)	(306,340,374)	(761,845,929)
A_4	(243,270,297)	(243,270,297)	(567,630,693)	(392,435,478)	(311,345,379)
A_5	(243,270,297)	(243,270,297)	(603,670,737)	(486,540,594)	(1071,1190,1309)
A_6	(527,585,643)	(216,240,264)	(1044,1160,1276)	(612,680,748)	(1422,1580,1738)
A_7	(630,700,770)	(284,315,346)	(1350, 1500,1650)	(828, 920,1012)	(2070,2300,2530)

A_8	(675,750,825)	(284,315,346)	(1125, 1250, 1375)	(684,760,836)	(1125, 1250, 1375)
A_9	(167,185,203)	(167,185,203)	(450,500,550)	(387,430,473)	(572,635,698)

Table 3. Fuzzy normalized decision matrix for gear material selection

Sl. No.	B_1	B_2	B_3	B_4	B_5
A_1	(.025,.026,.027)	(.888,.884,.881)	(0,0,0)	(0,0,0)	(.017,.017,.018)
A_2	(.061,.612,.063)	(.735,.730,.727)	(.111,.111,.111)	(.317,.317,.317)	(.273,.273,.273)
A_3	(.096,.097,.098)	(.581,.576,.573)	(.188,.188,.188)	(.292,.292,.292)	(.255,.255,.255)
A_4	(.149,.150,.151)	(.350,.346,.342)	(.256,.256,.256)	(.409,.408,.408)	(0,0,0)
A_5	(.149,.150,.151)	(.350,.346,.342)	(.290,.290,.290)	(.536,.536,.536)	(.432,.432,.432)
A_6	(.709,.708,.707)	(.581,.576,.573)	(.709,.709,.709)	(.707,.707,.707)	(.631,.631,.631)
A_7	(.911,.912,.912)	(0,0,0)	(1,1,1)	(1,1,1)	(1,1,1)
A_8	(1,1,1)	(0,0,0)	(.786,.786,.786)	(.804,.804,.804)	(.462,.462,.463)
A_9	(0,0,0)	(1,1,1)	(.145,.145,.145)	(.402,.402,.402)	(.148,.148,.148)

Table 4. Fuzzy weighted normalized decision matrix for gear material selection

Sl. No.	B_1	B_2	B_3	B_4	B_5
A_1	(0.00,0.00,0.00)	(0.04,0.04,0.04)	(0.00,0.00,0.00)	(0.00,0.00,0.00)	(0.00,0.00,0.00)
A_2	(0.01,0.01,0.01)	(0.04,0.04,0.04)	(0.04,0.04,0.04)	(0.1,0.1,0.1)	(0.03,0.03,0.03)
A_3	(0.01,0.01,0.01)	(0.03,0.03,0.03)	(0.08,0.08,0.08)	(0.09,0.09,0.09)	(0.03,0.03,0.03)
A_4	(0.02,0.02,0.02)	(0.02,0.02,0.02)	(0.1,0.1,0.1)	(0.12,0.12,0.12)	(0.00,0.00,0.00)
A_5	(0.02,0.02,0.02)	(0.02,0.02,0.02)	(0.12,0.12,0.12)	(0.16,0.16,0.16)	(0.04,0.04,0.04)
A_6	(0.11,0.11,0.11)	(0.03,0.03,0.03)	(0.28,0.28,0.28)	(0.21,0.21,0.21)	(0.06,0.06,0.06)
A_7	(0.14,0.14,0.14)	(0.00,0.00,0.00)	(0.4,0.4,0.4)	(0.3,0.3,0.3)	(0.1,0.1,0.1)
A_8	(0.15,0.15,0.15)	(0.00,0.00,0.00)	(0.31,0.31,0.31)	(0.24,0.24,0.24)	(0.05,0.05,0.05)
A_9	(0.00,0.00,0.00)	(0.05,0.05,0.05)	(0.06,0.06,0.06)	(0.12,0.12,0.12)	(0.01,0.01,0.01)

Table 5. Results for gear material selection

Sl. No.	D_i*	D_i^-	CC_i	Rank
A_1	4.9500	0.0500	0.0100	9
A_2	4.7872	0.2128	0.0426	8
A_3	4.7680	0.2320	0.0464	7
A_4	4.7350	0.2650	0.0530	5
A_5	4.6397	0.3603	0.0721	4
A_6	4.3058	0.6942	0.1388	3
A_7	4.0633	0.9367	0.1873	1
A_8	4.2477	0.7523	0.1505	2
A_9	4.7563	0.2437	0.0487	6

For solving the gear material selection problem using fuzzy AHP method the decision matrix of Table 1 which is converted into Table 2 using fuzzy number. Now a pair-wise comparison matrix between alternative is developed for importance of different criteria, corresponding priority vector is calculated are shown in Table

6, Table 7, Table 8, Table 9 and Table 10 respectively. Table 11 represents a pair-wise comparison matrix between criteria. Finally, the global priority was calculated and shown in Table 12. The alternatives are arrange in descending order according to the values of global priority, the ranking of alternatives as A_7-A_8–A_6–A_5–A_3–A_4–A_2-A_9–A_1. Nemes et al. [9] obtain the ranking of alternative as A_7-A_8-A_6-A_5-A_4-A_9-A_3-A_2-A_1.

Table 6. Pair-wise comparison of importance of 'surface hardness' on the alternatives

Sl.No	Priority vector	Defuzzified priority vector
A_1	(0.083090,0.083146,0.083149)	0.083128
A_2	(0.093836.0.093899,0.093902)	0.093879
A_3	(0.103415,0.103484,0.103488)	0.103462
A_4	(0.116575,0.116653,0.116657)	0.116628
A_5	(0.117375,0.117454,0.117454)	0.117429
A_6	(0.112355,0.112431,0.112435)	0.112407
A_7	(0.147435,0.147321,0.147326)	0.147367
A_8	(0.144496,0.144367,0.144412)	0.144412
A_9	(0.081407,0.081245,0.081248)	0.081300

Table 7. Pair-wise comparison of importance of 'core hardness' on the alternatives

Sl. No.	Priority vector	Defuzzified priority vector
A_1	(0.082681,0.083146,0.083122)	0.082982794
A_2	(0.093374,0.093899,0.093959)	0.093743767
A_3	(0.102905,0.103484,0.103549)	0.103313005
A_4	(0.116001,0.116653,0.116726)	0.116460057
A_5	(0.116797,0.117454,0.117528)	0.117259347
A_6	(0.111802,0.112431,0.112501)	0.112244632
A_7	(0.146727,0.147321,0.147225)	0.147091084
A_8	(0.143785,0.144367,0.144272)	0.144141299
A_9	(0.085929,0.081245,0.081118)	0.082764016

Table 8. Pair-wise comparison of importance of 'surface fatigue limit' on the alternatives

Sl.No	Priority vector	Defuzzified priority vector
A_1	(0.046809,0.046809,0.046809)	0.046809
A_2	(0.065248,0.065248,0.065248)	0.065248
A_3	(0.078014,0.078014,0.078014)	0.078014
A_4	(0.089362,0.089362,0.089362)	0.089362
A_5	(0.095035,0.095035,0.095035)	0.095035
A_6	(0.164539,0.164539,0.164539)	0.164539
A_7	(0.212766,0.212766,0.212766)	0.212766
A_8	(0.177305.0.177305,0.177305)	0.177305
A_9	(0.070922,0.070922,0.079022)	0.070922

Table 9. Pair-wise comparison of importance of ‘bending fatigue limit’ on the alternatives

Sl.No	Priority vector	Defuzzified priority vector
A_1	(0.021903,0.021906,0.021908)	0.021906
A_2	(0.078851,0.078861,0.078869)	0.078860
A_3	(0.074471,0.074480,0.074487)	0.074479
A_4	(0.095400,0.095290,0.095200)	0.095297
A_5	(0.118277,0.118291,0.118303)	0.118290
A_6	(0.148941,0.148959,0.148974)	0.148958
A_7	(0.201509,0.201533,0.201553)	0.201532
A_8	(0.166464,0.166484,0.166501)	0.166483
A_9	(0.094183,0.094195,0.094204)	0.094194

Table 10. Pair-wise comparison of importance of ‘UTS’ on the alternatives

Sl.No	Priority vector	Defuzzified priority vector
A_1	(0.040397,0.040404,0.040410)	0.040404
A_2	(0.093551,0.093567,0.093581)	0.093566
A_3	(0.089889,0.089846,0.089811)	0.089848
A_4	(0.076735,0.036683,0.036640)	0.036686
A_5	(0.126506,0.126528,0.126547)	0.126527
A_6	(0.167966,0.167996,0.168020)	0.167994
A_7	(0.244507,0.244551,0.244586)	0.244548
A_8	(0.132884,0.132908,0.132927)	0.132907
A_9	(0.067564,0.067517,0.067479)	0.067520

Table 11**.** Pair wise comparison matrix between criteria

Criteria	SH	CH	SFL	BFL	UTS	PV
SH	1.00	0.33	2.67	2.00	0.67	0.1568
CH	3.00	1.00	8.00	6.00	2.00	0.4705
SFL	0.38	0.13	1.00	0.75	0.25	0.0588
BFL	0.50	0.17	1.33	1.00	0.33	0.0784
UTS	1.50	0.50	4.00	3.00	1.00	0.2352

Table 12**.** Composite weight matrix and calculation of global weight.

Criteria Weight	0.1568	0.4705	0.0588	0.0784	0.2352		
Sl. No.	SH	CH	SFL	BFL	UTS	Global priority	Rank
A_1	0.0831	0.0830	0.0468	0.0219	0.0404	0.0661	9
A_2	0.0939	0.0937	0.0652	0.0789	0.0936	0.0909	7
A_3	0.1035	0.1033	0.0780	0.0745	0.0898	0.0964	5
A_4	0.1166	0.1165	0.0894	0.0953	0.0367	0.0944	6
A_5	0.1174	0.1173	0.0950	0.1183	0.1265	0.1182	4
A_6	0.1124	0.1122	0.1645	0.1490	0.1680	0.1313	3

A_7	0.1474	0.1471	0.2128	0.2015	0.2445	0.1781	1
A_8	0.1444	0.1441	0.1773	0.1665	0.1329	0.1452	2
A_9	0.0813	0.0828	0.0709	0.0942	0.0675	0.0791	8

6. Conclusions

This fuzzy MCDM method considers both the quantitative and qualitative material selection criteria, and their interrelationships to achieve the best decision and helps in selecting the most suitable gear materials from the existing list of alternatives. The results reveal that this method is a potential approach for solving the gear material selection problems. When the performance ratings are indistinct and imprecise, it is the most suitable technique to implement. Thus, it can help and guide the designers to select the best material for the given engineering applications.

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