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Material Selection for Tool Holder using MCDM Methods

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ABSTRACT

Due to different properties, cost and specific requirement of materials in different manufacturing processes, material selection becomes an important task for an engineer. Material selection for any engineering material or manufacturing process is one of the difficult or complex problem. For tool holder material selection, the quantitative or qualitative or both the attributes should be identified and taken into account. In this research paper, Grey Relational Analysis (GRA) and Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method, both, have been used for tool holder material selection working under hard milling conditions. The weight of all the six attributes have been taken with the help of Entropy method. The ranking of all the available nine materials have been done by arranging grey relational grade and priority in descending order in GRA and MOORA method respectively. The results obtained from two different MCDM methods have compared to conclude the effects of different MCDM methods on ranking of materials. Among all the nine alternatives, Fe-5Cr-Mo-V was found as the best material in both the MCDM methods. Thus, Fe-5Cr-Mo-V can be selected as best material for tool holder material working under hard milling conditions.

Index Terms – GRA Method, Material Selection, MCDM, MOORA Method, Tool Holder.

1. INTRODUCTION

Due to continuous advancement in technologies, the materials are developed or manufactured which have different applications, advantages, limitations and the most important is the characteristics. The structure, strength and functionality of the product depends on the materials. These days, researchers or scientists are preferring newly developed materials instead of traditionally made materials to overcome the problem of inferior performance, high cost and high weight [1], [2]. Development of the novel materials having properties of high strength but low density is very important which do not only reduces weight of transportation vehicles but, also fuel efficiency is enhanced due increase in operating temperature [3]. Material selection for specific application is tough process and it requires not only the enough knowledge and time, but also expertise in this field [4]. Selection of the best material for desired application cannot be compromised which may directly or indirectly affects the performance of the product and may result in early failure also [5]. These types of problems can affect the progress and reputation of the industry or the organization. To avoid these kinds of situations, it becomes important and essential to select the best or optimum material which are desired for required applications and should have improved performance than other materials. In the past years, composites of the aluminium metal alloy have been widely used due to the reason that composites of aluminium metal alloy are used in automobile, aircraft, defense and marine areas. The reason of the wide applications of these composites are due to its very important properties such as light weight, high strength, corrosion resistance, improved hardness, wear resistance etc. [6]. One can get desired performance or properties by combining two or more materials in desired proportions by specific methods. Now-a- days, ceramics has wide applications and used in reinforcement materials in fabrication of composites. Alumina, zirconia, silicon carbide etc. are included in composite fabrication. The matrix phase of composite materials such as titanium, aluminium, zinc etc. are generally continuous in nature but the reinforcement materials such as fibers, flakes, particulates etc. are the dispersed phase [7]. In comparison of conventional monolithic alloys with metal alloys, metal alloy composites exhibits improved as well as superior properties such as high strength to weight ratio, low thermal expansion at cheap cost, high wear resistance, etc. [8].

While using metal alloy composites in marine applications, the main problems are chemical and environmental effects on the composites. For marine applications, only corrosion resistant materials are selected in order to avoid attack of metal surface from oxidation. Metal alloy composites converts the metal surface into the oxides and these oxides become the reason of reduction of material, reduction of properties and reduction of the performance. Due to oxidation, properties like chemical, mechanical, electrical, thermal etc. of metal alloy composites are disturbed. To overcome the problem of enhancing the service life and surface coating of metal alloy composites, many efforts have been taken [9]. In case of aluminium alloy and aluminium composites, corrosion plays an important role because the oxide film which forms naturally prevent them from corroding. The ceramic particulate added in aluminium based alloys and composites may be the reason of localized or specified breakdown of protective films and this may also be the reason for corrosion [10]. A design engineer considers various attributes for material selection so that functions and properties of manufactured products can be enhanced. Some important attributes that are generally considered for material selection are material cost, mechanical characteristics, physical characteristics, safety and corrosive characteristics [11], [12], [13], [14], [15]. Based on the different attributes, the performance of materials are different and sometimes, it is conflicting in nature [16]. Materials who meet all the desired criteria is very rare. So, MCDM is very useful in selecting the best material when contrasting and conflicting attributes are considered. To select the best material, proper systematic and logical methodology is required. Various mathematical approaches have been applied for material selection based on the different attributes in the past years.

Manya and Bhatt applied a novel method for selection of material to meet the requirement of the engineer known or called as PSI [17] and PSI stands for preference selection index. Shanian and Savadogo applied a MCDM method for material selection i.e., ELECTRE [18]. In ELECTRE method, there were no demand of normalization of score. This was the main advantage of proposing this method. For material selection, Zhou et al [19] applied genetic algorithm as well as artificial neural network for material selection. Chan and Tong [20] proposed grey relational analysis for selection of material and analysis of life cycle i.e., one of the multi-criteria decision problem. Complex assessment method were applied by some researchers for checking performance in different design application and selection of the best material for cutting tool [21], [22]. In this research work, Material selection for tool holder working under hard milling conditions has done with the help of GRA and MOORA method.

2. MATERIALS AND METHODS FOR MATERIAL SELECTION FOR TOOL HOLDER

Caliskan et al [23] proposed different MCDM methods for material selection for tool holder when working under the hard milling conditions. They applied MCDM methods such as TOPSIS, PROMETHEE II and VIKOR. In case of milling, material for tool holder should definitely have high energy dissipation rate and high stiffness. Other than this, the tool holder cost should be economical or cheap as possible. There cannot be any tool holder which sustain all the desired properties along with minimal cost. So, one need to compromise with the some of the properties of materials or cost so that among the available alternatives, best alternatives or best material can be selected for tool holder for hard milling. For material selection for tool holder working under hard milling conditions, nine alternatives are considered. For these nine alternatives, six different attributes (sufficient hardness (H), compressive strength (CS), mechanical loss coefficient (MLC), Young Modulus (YM), cost (C) and fracture toughness (FT)) have been considered for selection of material for tool holder working under hard milling conditions as shown in Table 1 [24]. Among all the attributes, sufficient hardness (H), compressive strength (CS), mechanical loss coefficient (MLC), Young Modulus (YM) and fracture toughness (FT) are beneficial attributes. It means these attributes require high values for material selection. The only attribute i.e., cost is non-beneficial which requires less or low value for selection of material for tool holder working under hard milling conditions.

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	210	330	54.5	0.00111	150	0.673
AISI 1040	212	632.5	46	0.00117	355	0.7045
AISI 4140	212	655	87.5	0.000515	305	0.864
AISI 6150	206.5	1575	38	0.00026	483	1.175
AISI 8620	206.5	360	111.5	0.00089	190	0.8665
Maraging Steel	187.5	1825	80	0.00071	532.5	6.97
AISI S5	210	1930	21	0.0000205	771	7.99
Tungsten carbide-cobalt	593	4405	14.05	0.00135	1250	79.6
Fe-5Cr-Mo-V	212.5	1655	120	0.00113	448.5	1.73

Table 1. Quantitative Data of Materials and Attributes for Tool Holder Working Under Hard Milling Conditions

Material selection for tool holder working under hard milling conditions, the weight of each attribute has been found out by entropy method as shown in Table 2 [24] . The weight of each attribute obtained from entropy method has been used for material selection for tool holder working under hard milling conditions using two popular MCDM methods such as Grey Relational Analysis and MOORA method. Finally, the results obtained from GRA and MOORA method have been compared to validate the solution.

Attributes	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
Entropy Weight	0.194	0.067	0.141	0.128	0.131	0.340

Table 2. Weight of all the Attributes for Material Selection for Tool Holder Working Under Hard Milling Conditions by Entropy Method

3. METHODOLOGY FRAMEWORK FOR SELECTION OF THE BEST MATERIAL FOR TOOL HOLDER

Methodology framework for material selection for tool holder working under hard milling conditions using GRA method and MOORA method have been shown in Figure 1 and 2.

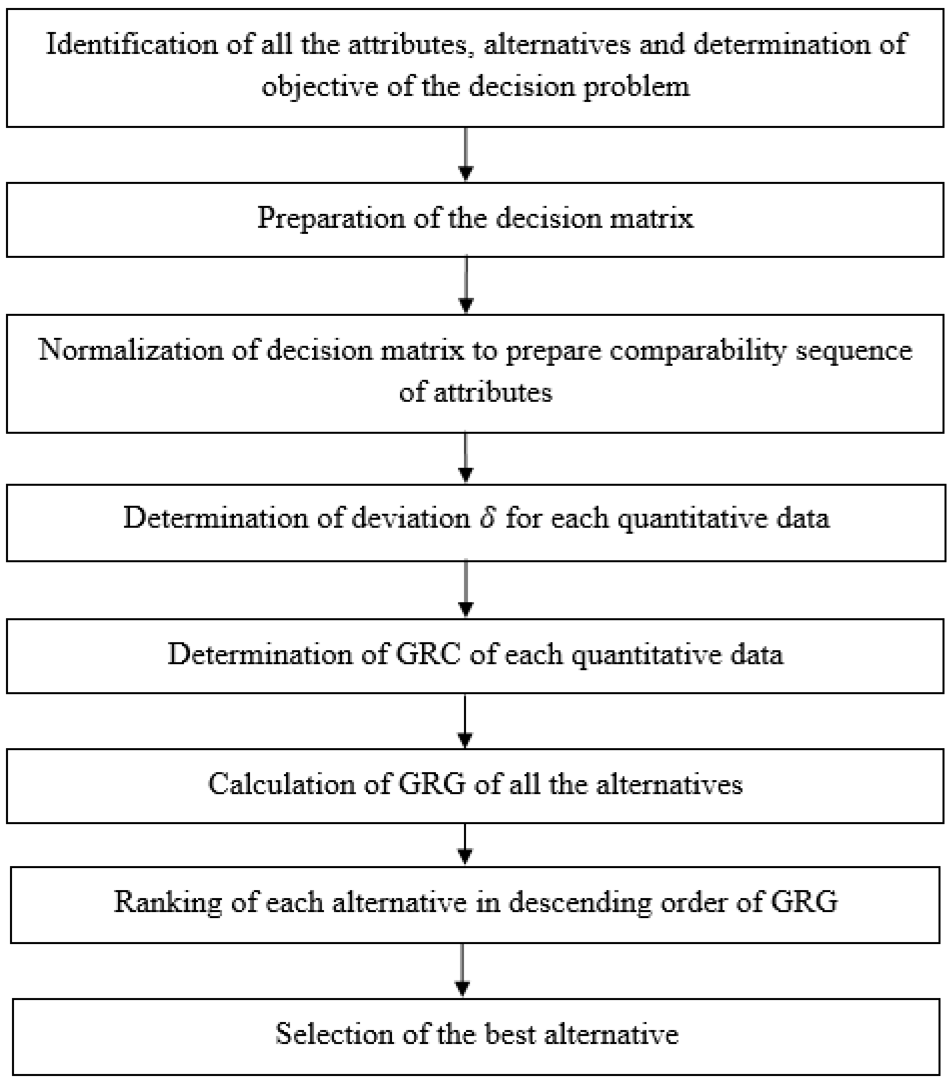

Figure 1. Methodology Framework for Material Selection for Tool Holder Working Under Hard Milling Conditions Using GRA Method

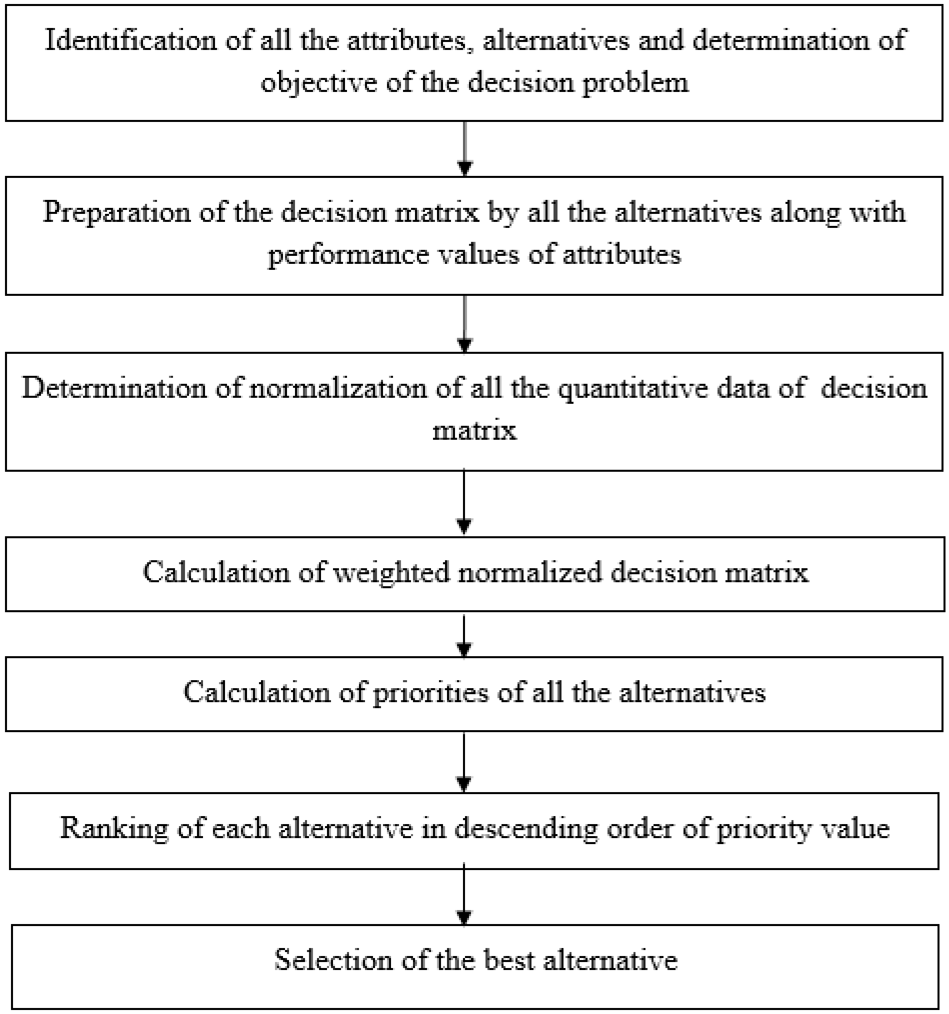

Figure 2. Methodology Framework for Material Selection for Tool Holder Working Under Hard Milling Conditions Using MOORA Method

4. GREY RELATIONAL ANALYSIS (GRA)

This is very clear that Fuzzy AHP is very useful for taking the best decision based on the qualitative attribute but for selecting the best decision on the basis of the quantitative criteria, GRA is very useful and one of the most important method or technique which is widely used in the field of engineering and management. This method or technique was introduced in 1982 by Julong Deng. The grey Relational Analysis method was initially applied for study air pollution [25] and thereafter, this method was used for investigating impact on city by air pollution due to socio-economic activities [26]. Further, this method was used for studying the research output as well as growth of countries [27]. GRA has been used in combination or integration with the some other MCDM methods for problem like selection of supplier [28]. Various problems related to optimization of the process, financial problems and logistic problems have been solved with the help of GRA [29]. GRA theory applies on various complex problem and have incomplete information. [30] inferred that Grey Relational Analysis are suitable and applicable for multi criteria decision problems when the information or data are available in the form of numerical values but this method or technique will fail for MCDM problems when the information or data are available in the form of Triangular Fuzzy Numbers (interval valued). This is very interesting that the system with known information is known as white while system with unknown information is known as black. The system in between black and white is known as grey. In GRA method, data is normalized by smaller the better or larger the better responses [31]. Normalization is obtained after finding out deviation, grey relation coefficient and grade and the final score or ranking is obtained.

The basic steps involved in Grey Relational Analysis are as shown below :

Step 1 : Generation of Grey Relational Sequence (GRS)

For MCDM problems, a decision matrix is prepared or formulated with the help of all the alternatives along with attributes' performance values. For generating GRS, decision matrix is normalized to prepare comparability sequence of all the attributes.

If number of alternatives and number of attributes available are m and n respectively in the decision matrix, then performance value can be calculated as :

$P_i = (p_{i1}, p_{i2}, \dots, p_{ij}, \dots, p_{in})$ …… (1)

Where, p_{ij} = Performance values of attribute j of alternative i.

P_i can normalized into comparability sequence $Q_i = (q_{i1}, q_{i2}, \dots, q_{ij}, \dots, q_{in})$

q_{ij} can be expressed as :

$q_{ij} = \frac{p_{ij} - \min(p_{ij},\ i=1,2,3,\dots,m)}{max(p_{ij},\ i=1,2,\dots,m) - min(p_{ij},\ i=1,2,3,\dots,m)}$ for i = 1, 2, 3, …, m ; j = 1, 2, 3, …, n …… (2)

$q_{ij} = \frac{\max(p_{ij},\ i=1,2,3,\dots,m) - p_{ij}}{max(p_{ij},\ i=1,2,3,\dots,m) - min(p_{ij},\ i=1,2,3,\dots,m)}$ for i = 1, 2, 3, …, m ; j = 1, 2, 3, …, n …… (3)

For finding value of attributes, equation 2 and 3 are used. For finding larger performance attribute, equation 2 is used and similarly for finding smaller performance attribute, equation 3 is used [32].

Step 2 : Determination of reference sequence

After generating relational sequence, the comparability sequence Q_i values are scaled in 0-1 range. The alternative having greater value of Q_i will definitely have better performance than other available alternatives, but these type of performance do not usually exist. Therefore, when the value of q_{ij}=1 is defined and differentiated with the sequence that is generated. Between the two sequences, the alternative having the largest degree of similarity is taken as better alternative.

The reference sequence can written as :

$Q_0 = (q_{01}, q_{02}, \dots, q_{0j}, \dots, q_{0n}) = (1, 1, \dots, 1, \dots, 1)$ …… (4)

Step 3 : Determination of Grey Relational Coefficient

The Grey Relational Coefficient is very useful in determining the degree of similarity between q_{0j} and q_{ij}.

The GRC between q_{0j} and q_{ij} can be expressed as [32] :

$\gamma(q_{0j}, q_{ij}) = \frac{\Delta_{min} + \delta\Delta_{max}}{\Delta_{ij} + \delta\Delta_{max}}$ …… (5)

where, $\Delta_{ij} = |q_{0j} - q_{ij}|$

$\Delta_{min} = \min(\Delta_{ij}, i = 1, 2, 3, \dots, m; j = 1, 2, 3, \dots, n)$

$\Delta_{max} = \max(\Delta_{ij}, i = 1, 2, 3, \dots, m; j = 1, 2, 3, \dots, n)$

δ = Distinguishing coefficient, $\delta \in [0, 1]$

Generally, the decision maker has to determine the distinguishing coefficient. Variation in the distinguishing coefficient directly affects the results of the GRA. In the case of selection of the best pest petrol car, the distinguished coefficient is assumed as 0.5.

Step 4 : Calculation of Grey Relational Grade (GRG)

Using GRG, the correlation level between the reference and comparability sequences are determined [32] as :

$\Gamma(Q_0, Q_i) = \sum_{j=0}^{n} w_j\, \gamma(q_{0j}, q_{ij})$ …… (6)

Where, w_j = weight assigned to j^{th} attribute

Sum of weight of each attribute must be always unity i.e., 1 and can be expressed as

$\sum_{j=0}^{n} w_j = 1$ …… (7)

The best performance is represented by the reference sequence that can be obtained by any sequence and comparability sequence having the largest Grey Relational Grade and that will be very similar to reference sequence. Then, the corresponding comparability sequence of that alternative will have the best result or performance among the available alternatives.

5. MULTI – OBJECTIVE OPTIMIZATION ON THE BASIS OF RATIO ANALYSIS (MOORA)

MOORA technique was firstly developed in 2004 by Brauers to solve many types of complex MCDM problems. Multi-objective optimization is the technique by which two or more objectives can be optimized simultaneously. Some of the examples of multi-objective optimization problems are maximizing performance together with minimizing fuel consumption of the automobile ; maximizing strength of the engineering materials or components and minimizing weight of that engineering components ; and increasing the profit and decreasing the cost of the materials [33]. Due to different choices, values and interests of a decision maker in any real time MCDM problems, the decision problem becomes complex or tough. In a decision problem, every criteria must be measurable in such a way that outcomes of every individual can also be measured. In all the available conflicting criteria or attributes, some may be beneficial attributes and some may be non-beneficial attributes. Beneficial attributes are those where maximum or higher value of the attribute is desired for the decision problem, whereas non-beneficial attributes are those where minimum or lower value of the attribute is desired for the decision problem. Ranking or selection of the optimum or the best alternative is done by considering beneficial and non-beneficial attributes in MOORA method [34], [35].

The decision matrix, M as shown in equation (8) denotes performance measures of each alternative or i^{th} criteria w.r.t. all attributes or j^{th} attribute.

$$M = \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array} \\ \begin{bmatrix} b_{11} & b_{12} & b_{13} & \dots & b_{1n} \\ b_{21} & b_{22} & b_{23} & \dots & b_{2n} \\ b_{31} & b_{32} & b_{33} & \dots & b_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & b_{m3} & \dots & b_{mn} \end{bmatrix} \end{array} \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ \dots \\ A_m \end{array} \quad \text{...... (8)}$$

Steps involved in MOORA method for determining the rank of all the available alternatives are as shown below [36], [37]:

Step 1 : Calculation of normalized decision matrix (x_{ij})

$$x_{ij} = \frac{b_{ij}}{\sqrt{\sum_{i=1}^{m} {b_{ij}}^2}} \quad \text{…… (9)}$$

where, b_{ij} is the performance value of alternative A_i for attribute C_j.

Step 2 : Calculation of the weighted normalized decision matrix (W_{ij})

$$W_{ij} = w_j . x_{ij} \quad \text{…… (10)}$$

where, w_j represents the weight of the attribute C_j

Step 3 : Determination of priorities (Q_i)

Priorities can be calculated as the difference between the sum of all the beneficial attributes and the sum of all the non-beneficial attributes.

$$Q_i = \sum_{j=1}^{g} W_{ij} - \sum_{j=g+1}^{n} W_{ij} \quad \text{…… (11)}$$

where, g represents the number of criteria to be maximized

(n-g) represents the number of criteria to be minimized.

Step 4 : Ranking of alternatives

The alternative which is having the maximum or highest value of priorities (Q_i) is ranked as rank 1. Similarly, 2nd highest value of Q_i is ranked as rank 2. Similarly, ranking of all the available alternatives are done.

6. MATERIAL SELECTION FOR TOOL HOLDER BY GRA METHOD

All the quantitative data of materials and attributes for selection of the best tool holder have been illustrated in Table 3. The weight of all the attributes have been taken by Entropy method as illustrated in Table 2. Table 3 has been normalized with the help of equation 2 and 3 as shown in Table 4. Since sufficient hardness (H), compressive strength (CS), mechanical loss coefficient (MLC), Young Modulus (YM) and fracture toughness (FT)) are beneficial attributes, so these attributes been normalized as larger the better. Cost is only one non-beneficial attribute, so cost has been normalized as smaller the better response. After normalization, deviation (δ) value of each material for six different attributes have been calculated as illustrated in Table 5. Grey Relational Coefficient of each material for six different attributes have been calculated in Table 6 with the help of equation 5. Finally, grey relational grade has been determined for ranking of each material for nine different alternatives have been calculated in Table 7 with the help of equation 6. The ranking of each alternatives has been done by descending order of the grey relational grade.

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	210	330	54.5	0.00111	150	0.673
AISI 1040	212	632.5	46	0.00117	355	0.7045
AISI 4140	212	655	87.5	0.000515	305	0.864
AISI 6150	206.5	1575	38	0.00026	483	1.175
AISI 8620	206.5	360	111.5	0.00089	190	0.8665
Maraging Steel	187.5	1825	80	0.00071	532.5	6.97
AISI S5	210	1930	21	0.0000205	771	7.99
Tungsten carbide-cobalt	593	4405	14.05	0.00135	1250	79.6
Fe-5Cr-Mo-V	212.5	1655	120	0.00113	448.5	1.73
Entropy Weight	0.194	0.067	0.141	0.128	0.131	0.34

Table 3. Quantitative Data of Materials and Attributes for Material Selection for Tool Holder Working Under Hard Milling Conditions

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	0.055487	0	0.381784	0.819481	0	1
AISI 1040	0.06042	0.074233	0.301557	0.864611	0.186364	0.999601
AISI 4140	0.06042	0.079755	0.693252	0.371944	0.140909	0.99758
AISI 6150	0.046856	0.305522	0.22605	0.180143	0.302727	0.99364
AISI 8620	0.046856	0.007362	0.919773	0.654005	0.036364	0.997548
Maraging Steel	0	0.366871	0.622463	0.518616	0.347727	0.920217
AISI S5	0.055487	0.392638	0.065597	0	0.564546	0.907294
Tungsten carbide-cobalt	1	1	0	1	1	0
Fe-5Cr-Mo-V	0.061652	0.325153	1	0.834524	0.271364	0.986608

Table 4. Normalization of Each Material Based on Six Different Attributes

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	0.944513	1	0.618216	0.180519	1	0
AISI 1040	0.939581	0.925767	0.698443	0.135389	0.813636	0.000399
AISI 4140	0.939581	0.920245	0.306748	0.628056	0.859091	0.00242
AISI 6150	0.953144	0.694478	0.77395	0.819857	0.697273	0.006360
AISI 8620	0.953144	0.992648	0.080227	0.345995	0.963636	0.002452
Maraging Steel	1	0.633129	0.377537	0.481384	0.652273	0.079783
AISI S5	0.944513	0.60736	0.934403	1	0.435454	0.092706
Tungsten carbide-cobalt	0	0	1	0	0	1
Fe-5Cr-Mo-V	0.938348	0.674847	0	0.165476	0.728636	0.013392

Table 5. Determination of Deviation, (δ) Value of Each Material for Six Different Attributes

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	0.346137	0.333333	0.447141	0.734733	0.333333	1
AISI 1040	0.347323	0.350688	0.417208	0.786919	0.380623	0.999202
AISI 4140	0.347323	0.352052	0.619772	0.443241	0.367893	0.995183
AISI 6150	0.344081	0.418593	0.392480	0.378829	0.417616	0.987439
AISI 8620	0.344081	0.334977	0.861732	0.59102	0.341615	0.995121
Maraging Steel	0.333333	0.441256	0.569777	0.509485	0.433925	0.862392
AISI S5	0.346137	0.451524	0.348577	0.333333	0.5345	0.843589
Tungsten carbide-cobalt	1	1	0.333333	1	1	0.333333
Fe-5Cr-Mo-V	0.347621	0.425587	1	0.751342	0.406955	0.973914

Table 6. Determination of Grey Relational Coefficient of Each Material for Six Different Attributes

Material	Grade	Rank
AISI 1020	0.63024	5
AISI 1040	0.64002	4
AISI 4140	0.62165	6
AISI 6150	0.58906	8
AISI 8620	0.66944	3
Maraging Steel	0.58984	7
AISI S5	0.54606	9
Tungsten carbide-cobalt	0.68033	2
Fe-5Cr-Mo-V	0.71757	1

Table 7. Determination of Grey Relational Grade to Find Rank of Each Material Based on Six Different Attributes

7. SELECTION OF THE BEST MATERIAL FOR TOOL HOLDER BY MOORA METHOD

All the quantitative data of materials and attributes for material selection for tool holder have been illustrated in Table 8. The weight of all the attributes have been taken by using Entropy method as shown in Table 2. For calculation of normalization of decision matrix, square root of sum of the square of all the quantitative data were needed, so it has been illustrated in Table 9. Decision matrix has been normalized in Table 10 with the help of equation 9. After finding the normalization of decision matrix, weighted normalized decision matrix has been determined with the help of Entropy weight and equation 10 and this is illustrated in Table 11. Sufficient hardness, compressive strength, mechanical loss coefficient, Young Modulus and fracture toughness are beneficial attributes while cost is one and only one non-beneficial attribute. Finally, priorities of all the alternatives have been determined with the help of equation 11 and ranking of all the materials have been done in descending order of the priorities as illustrated in Table 12.

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	210	330	54.5	0.00111	150	0.673
AISI 1040	212	632.5	46	0.00117	355	0.7045
AISI 4140	212	655	87.5	0.000515	305	0.864
AISI 6150	206.5	1575	38	0.00026	483	1.175
AISI 8620	206.5	360	111.5	0.00089	190	0.8665
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Fe-5Cr-Mo-V	212.5	1655	120	0.00113	448.5	1.73
Entropy Weight	0.194	0.067	0.141	0.128	0.131	0.34

Table 8. Quantitative Data of Materials and Attributes for Material Selection for Tool Holder Working Under Hard Milling Conditions

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	44100	108900	2970.25	1.232E-06	22500	0.452929
AISI 1040	44944	400056.25	2116	1.369E-06	126025	0.49632
AISI 4140	44944	429025	7656.25	2.652E-07	93025	0.746496
AISI 6150	42642.25	2480625	1444	6.76E-08	233289	1.380625
AISI 8620	42642.25	129600	12432.25	7.921E-07	36100	0.750822
Maraging Steel	35156.25	3330625	6400	5.041E-07	283556.25	48.5809
AISI S5	44100	3724900	441	4.203E-10	594441	63.8401
Tungsten carbide-cobalt	351649	19404025	197.4025	1.823E-06	1562500	6336.16
Fe-5Cr-Mo-V	45156.25	2739025	14400	1.277E-06	201152.25	2.9929
Sum	695334	32746781	48057.15	7.33E-06	3152588.5	6455.401
$\sqrt{Sum}$	833.8669	5722.4803	219.2194	0.0027074	1775.553	80.34551

Table 9. Square of all the Quantitative Data Available in Table 8 and the Square Root of Sum of Square of all the Quantitative Data Column Wise

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	0.251839	0.057667	0.248609	0.409992	0.084481	0.008376
AISI 1040	0.254237	0.110529	0.209835	0.432154	0.199938	0.008768
AISI 4140	0.254237	0.114461	0.399143	0.190222	0.171778	0.010754
AISI 6150	0.247641	0.275230	0.173342	0.096034	0.272028	0.014624
AISI 8620	0.247641	0.06291	0.508623	0.328732	0.107009	0.010785
Maraging Steel	0.224856	0.318918	0.364931	0.262247	0.299907	0.086750
AISI S5	0.251839	0.337266	0.095794	0.007572	0.434231	0.099446
Tungsten carbide-cobalt	0.711145	0.769771	0.064091	0.498639	0.704006	0.990721
Fe-5Cr-Mo-V	0.254837	0.28921	0.547397	0.417379	0.252597	0.021532

Table 10. Determination of Normalization of Each Material Based on Six Different Attributes

Material	YM (GPa)	CS (MPa)	FT (MPa m)$^{1/2}$	MLC	H (HV)	C ($/kg)
AISI 1020	0.048857	0.003864	0.035054	0.052479	0.011067	0.002848
AISI 1040	0.049322	0.007405	0.029587	0.055316	0.026192	0.002981
AISI 4140	0.049322	0.007669	0.056279	0.024348	0.022503	0.003656
AISI 6150	0.048042	0.01844	0.024441	0.012292	0.035636	0.004972
AISI 8620	0.048042	0.004215	0.071716	0.042078	0.014018	0.003667
Maraging Steel	0.043622	0.021367	0.051455	0.033568	0.039288	0.029495
AISI S5	0.048857	0.022597	0.013507	0.000969	0.056884	0.033811
Tungsten carbide-cobalt	0.137962	0.051575	0.009037	0.063826	0.092225	0.336845
Fe-5Cr-Mo-V	0.049438	0.019377	0.077183	0.053425	0.03309	0.007321

Table 11. Determination of Weighted Normalization of Each Material Based on Six Different Attributes

Material	Priority	Rank
AISI 1020	0.1484724	6
AISI 1040	0.1648406	3
AISI 4140	0.1564651	5
AISI 6150	0.1338799	7
AISI 8620	0.1764023	2
Maraging Steel	0.1598051	4
AISI S5	0.1090026	8
Tungsten carbide-cobalt	0.017779	9
Fe-5Cr-Mo-V	0.2251923	1

Table 12. Determination of Priorities and Rank of Each Material Based on Six Different Attributes

8. CONCLUSION

The material selection for tool holder working under hard milling conditions from nine alternatives based on six attributes or criteria was very complex or tough MCDM problem. The complexity of material selection for tool holder increases with increase in vague or unclear attribute. GRA and MOORA method have been used for material selection for tool holder working under hard milling conditions in the research work. The result of this research work has been obtained in Table 7 and 12.

Based on grey relational analysis method, Fe-5Cr-Mo-V has been obtained as the most suitable material for tool holder working under hard milling conditions which has 212.5 GPa young modulus, 1655 MPa compressive strength, (120 MPa m)$^{1/2}$ fracture toughness, 0.00113 mechanical loss coefficient, 448.5 sufficient hardness and cost 1.73 \$/kg. Comparison of each material or alternative with the final score and rank as obtained from GRA method has been illustrated in Table 7 and Figure 3.

Based on MOORA method, Fe-5Cr-Mo-V has also been obtained as the most suitable material for tool holder working under hard milling conditions which has 212.5 GPa young modulus, 1655 MPa compressive strength, (120 MPa m)$^{1/2}$ fracture toughness, 0.00113 mechanical loss coefficient, 448.5 sufficient hardness and cost 1.73 \$/kg. Comparison of each material or alternative with the final score and rank as obtained from MOORA method has been illustrated in Table 12 and Figure 4.

Thus, it can be concluded from Table 7 & 12 and Figure 3 & 4, irrespective of different MCDM methods (GRA or MOORA), there is either no change or little change in order or preference of material selection for tool holder working under hard milling conditions from nine alternatives based on six attributes or criteria.

This research can be further extended by changing the method of estimation of weight or alteration in the weight of attributes used for material selection for tool holder. This research can also be extended by increasing or decreasing the number of attributes. Any type of modification or changing will definitely change the rank of each material. Similar type of research can be applied in various science, engineering and management fields. One can rank unlimited alternatives based on GRA and MOORA method.

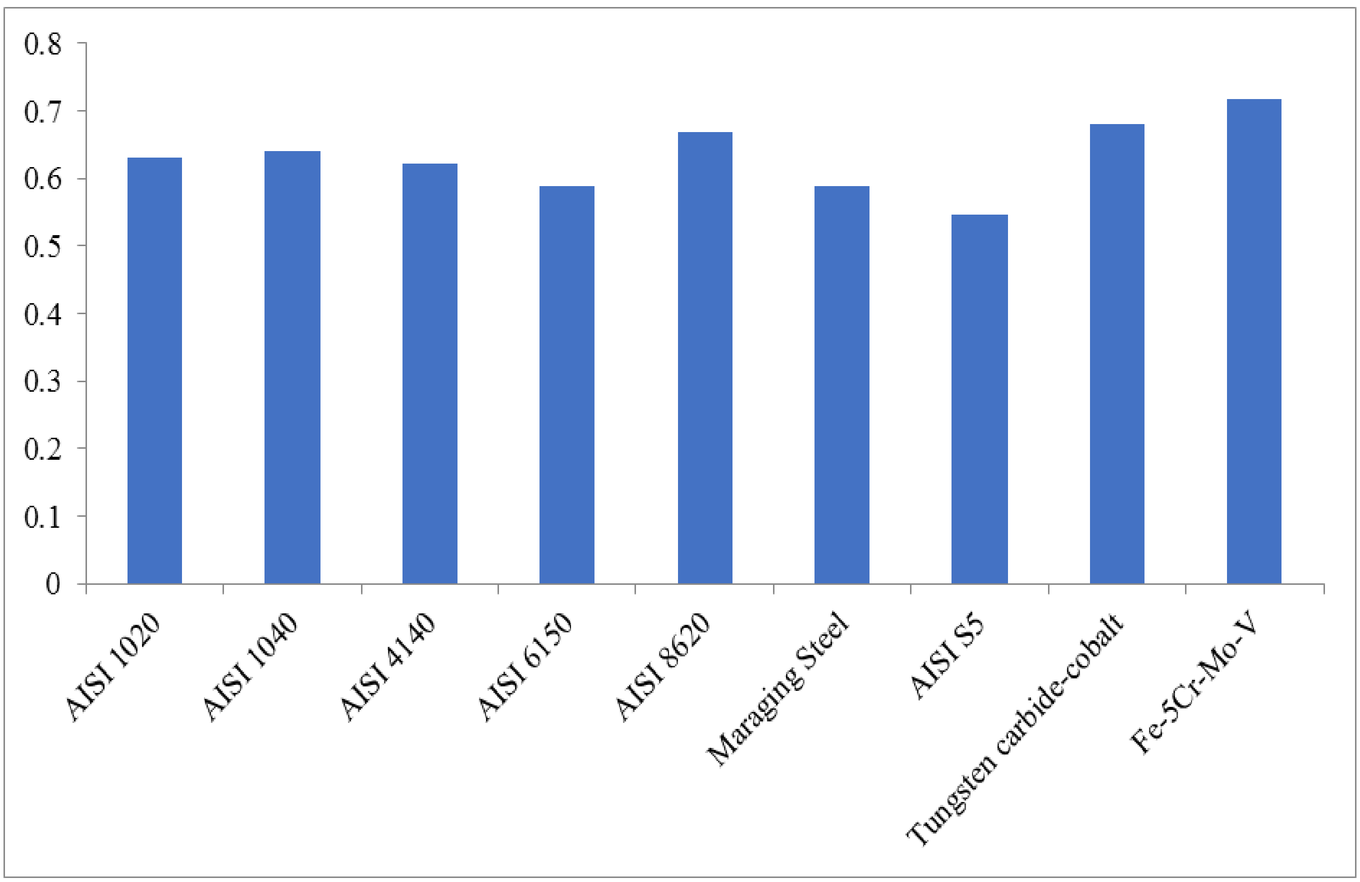

Figure 3. Material for Tool Holder vs Grade of all the Alternatives Obtained by GRA Method

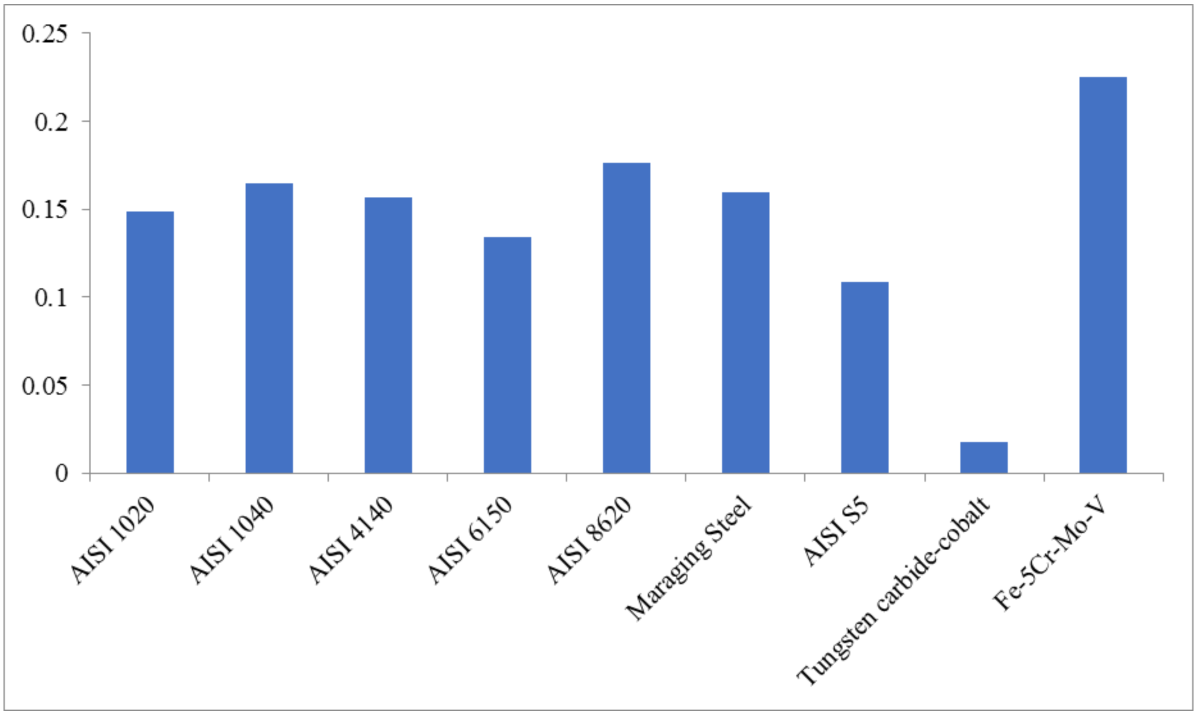

Figure 4. Material for Tool Holder vs Priority of all the Alternatives Obtained by MOORA Method

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