

A Decision Analysis Model for Gear Material Selection Using MCDM Techniques

Shishir Kumar Patel¹, Mr. Hari Mohan Soni²

M.Tech Scholor¹, Assistant Professor²

^{1,2}Department of Mechanical Engineering, Bansal Institute of Science and Technology, Bhopal, Madhya Pradesh,

India

Abstract

Choosing the appropriate material for a particular engineering component is crucial as it greatly influences its design and ensures its proper functioning. When it comes to designing functional components for machines, using the highest quality materials is imperative. Decision-makers tasked with selecting materials must consider a range of factors, including physical, thermal, and mechanical properties, as well as the form, cost, and availability of materials. Among these variables, mechanical characteristics stand out as particularly crucial when choosing materials for machine elements. Making an inappropriate or incorrect selection can lead to product failure and substantial financial losses. Gears play a pivotal role in geared drives found in various machines and systems. Therefore, it is essential for manufacturers to design and produce gears that meet functional requirements and operating conditions. The objective of this study is to assess different gear materials with the aim of identifying the optimal material for gears. In the first phase, the application of EWM applied for the determination of criteria weightage and then integrated with TOPSIS method in second phase for determination of raking of all alternatives materials.

Keywords: Gears material, MCDM, EWM, TOPSIS

1. Introduction

In product design, the primary aim of material selection is to minimize costs while achieving the desired product performance objectives. The systematic selection of materials for a given application commences with an examination of various materials and their properties. Improper material selection often leads to significant cost implications and can lead an organization toward premature product failure. Therefore, manufacturing designers must identify and select suitable materials with specific functionalities to attain the desired product with minimal cost and intended applicability. However, in the context of the manufacturing landscape, selecting material for a particular product is a challenging and time-consuming task due to numerous factors that must be carefully evaluated before arriving at a final decision. For any specific application, material strength may be the primary requirement, but depending on the working environment and functional performance, several other factors may

need to be considered simultaneously. Choosing the most suitable material involves studying a wide array of mechanical, thermal, electrical, and physical properties, while also considering cost, operating environment, production process, market value, availability of suppliers, and product performance. In mechanical design, priority is given to the mechanical properties of materials. The key mechanical properties typically encountered in the material selection process include strength, stiffness, toughness, hardness, density, and creep resistance.

2. Literature survey

Multi-Criteria Decision Making (MCDM) is a mathematical process utilized to assess a set of alternatives across multiple criteria. This method finds wide-ranging applications across various fields, including engineering, operations research, management, and finance. Its common applications encompass investment portfolio decision-making, vendor/supplier selection [1-2], location selection [3], and construction projects [4]. Additionally, several developed MCDM methods have been employed to determine the most suitable materials and manufacturing technologies [5]. For instance, MCDM techniques have been utilized in compiling reports on materials selection for automobiles within the framework of green manufacturing, employing methods like PROMETHEE [6], gear materials selection [7], and turbine materials selection using PROMETHEE-GAIA [8]. In engineering applications, polymer composite materials have been evaluated using the AHP-MOORA method [9], along with the implementation of various decision-making approaches such as SAW, MOORA, TOPSIS, and VIKOR [10]. Furthermore, technologies such as machined parts assembly [11] and sustainable disposal technology selection have been chosen based on MCDM methods like SBWM (Stratified Best-Worst Method) [12]. Specific applications include machining parameter selection for milling epoxy granite composite using AHP [13] and the implementation of advanced manufacturing systems emphasizing AHP and TOPSIS [14].

3. Methods

3.2.1 Entropy Weight Method (EWM)

The entropy weight method (EWM) is an important information weight model that has been extensively studied and practiced [1]. In this method, m indicators and n samples are set in the evaluation, and the measured value of the i_{th} indicator in the j_{th} sample is recorded as x_{ij} .

The first step is the standardization of measured values [2, 3]. The standardized value of the i_{th} index in the j_{th} sample is denoted as p_{ij} , and its calculation method is as follows:

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{J} x_{ij}} \tag{1}$$

In the EWM, the entropy value Ei of the ith index is defined as [4]

$$E_{i} = \frac{-\sum_{j=1}^{J} p_{ij} \ln p_{ij}}{\ln n}$$
(2)

In the actual evaluation using the EWM, $p_{ij} \ln p_{ij}$ ie equal to zero, is generally set when $p_{ij} = 0$ for the convenience of calculation. the range of entropy value E_i is (0, 1). The larger the E_i is, the greater the differentiation degree of index *i* is, and more information can be derived. Hence, higher weight should be given to the index. Therefore, in the EWM, the calculation method of weight w_i is [1, 5]

$$w_i = \frac{1 - E_i}{\sum_{i=1}^{m} (1 - E_i)}$$
(3)

3.2.2 Technique for order preference by similarity to ideal solution (TOPSIS)

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method was developed by Hwang, and Yoon [6], for solving multiple criteria decision making (MCDM) problems based upon the concept that the chosen alternative should have the shortest distance to the positive ideal solution (A^*) and the longest distance from the negative ideal solution (A^-). For instance, the positive ideal solution maximizes the functionality and minimizes the cost, whereas the negative ideal solution maximizes the cost and minimizes the functionality. In the process of TOPSIS, the performance ratings and the weights of the criteria are given as exact values [7]. Recently, several interesting studies have focused on the TOPSIS technique and applied it in many fields, including supplier selection, tourism destination evaluation, financial performance evaluation, location selection, company evaluation, and ranking the carrier alternatives. The steps of TOPSIS model are as follows [8, 9]:

Step 1: The structure of matrix

	$\Gamma^{x_{12}}$	<i>x</i> ₁₂		x_{1n}
	<i>x</i> ₂₁	<i>x</i> ₂₂		x_{2n}
X =				
<u> </u>				
			•••	
	Lx_{m1}	x_{m2}	•••	x_{mn}

Where xij is a crisp value indicating the performance rating of each alternative Ai with regard to each criterion Cj.

Step 2: Calculate the Normalized the matrix X by using the following formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{J} x_{ij}^2}}$$
(5)

Step 3: Construct the weighted normalized decision matrix by multiplying:

$V_{ij} = w_{ij} \cdot r_{ij}$			(6)	
© 2024, IJSREM	<u>www.ijsrem.com</u>	DOI: 10.55041/IJSREM30174		Page 3

Step 4: Identify the positive ideal solution (A*) and negative ideal solution (A –)

$$A^* = \{ (\max v_{ij} | j \in J), (\min v_{ij} | j \in J') \}$$
(7)

$$A^{-} = \{ (\min v_{ij} | j \in J), (\max v_{ij} | j \in J') \}$$
(8)

Step 5: Calculate the separation measure

$$S_i^* = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^*)^2}$$
(9)

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}$$
(10)

Step 6: Calculate the relative closeness to the ideal Solution

$$P_i^* = \frac{S_i^-}{S_i^* + S_i^-}, \ 0 \le P_i^* \le 1$$
(11)

Step 7: Calculate the total score and select the alternative closest to one.

4. Illustrative Example

In this study, our aim is to identify, select, or suggest the most suitable gear material by considering its specific properties for general application purposes. To determine the most appropriate gear material, we have identified several criteria including Ultimate Tensile Strength (MPa), Young's Modulus (GPa), Hardness (HRB), Fatigue Strength (MPa), and Cost of Material. Six alternative gear materials were evaluated: Aluminum Alloy, Copper Alloy, Nickel Alloy, Zinc Alloy, Stainless Steel, and Cast Iron. Table 1 presents the properties required for helical gears along with quantitative data for each material.

Table 1. Attributes of material selection

	Ultimate	Young's	Hardness (HRB)	Fatigue	Cost/Kg
	Tensile	Modulus (GPa)		Strength (MPa)	
	Strength (MPa)				
Al Alloy	345.00	77.20	69.30	152.00	250.00
Cu Alloy	495.00	117.00	68.80	188.00	400.00
Ni Alloy	900.00	207.00	88.10	508.00	1500.00
Zn Alloy	259.00	83.20	56.20	60.10	280.00
Stainless Steel	940.00	196.00	86.40	439.00	180.00
Cast Iron	496.00	147.00	69.30	260.00	70.00

I

4.2 Solution of Material Selection Using EWM and TOPSIS Method

4.2.1 Calculation based on Entropy weight method

The Entropy weight method is an objective type weighting method. The basic concept of entropy weight method is, the more the data dispersed the more the information can be derived. The processes of Entropy included first deciding objectives (decision matrix) and then calculations of the normalized decision matrix, probability of the attribute/response to take place, the entropy value of attribute/response, and degrees of divergence (average information contained) by each response and after that entropy weight. In this research, the Entropy algorithm followed the steps mentioned in the methodology section.

The weight values of the criteria used in the study were determined based on the Entropy weight method and are given in Table 2. The first stage of the decision matrix is shown in Table 1, which includes the criteria and alternatives. In Table 1, the alternatives are Al Alloy, Cu Alloy, Ni Alloy, Zn Alloy, Stainless Steel, and Cast Iron. In the study, cost criteria are accepted as non-benefit criteria others are accepted as benefit criteria.

	Cost/Kg	Ultimate	Young's	Hardness	Fatigue
		Tensile	Modulus (GPa)	(HRB)	Strength (MPa)
		Strength (MPa)			
Al Alloy	250.00	345.00	77.20	69.30	152.00
Cu Alloy	400.00	495.00	117.00	68.80	188.00
Ni Alloy	1500.00	900.00	207.00	88.10	508.00
Zn Alloy	280.00	259.00	83.20	56.20	60.10
Stainless Steel	180.00	940.00	196.00	86.40	439.00
Cast Iron	70.00	496.00	147.00	69.30	260.00
SUM	2680.000	3435.000	827.400	438.100	1607.100
Ej	0.749	0.943	0.962	0.994	0.899
Dj	0.251	0.057	0.038	0.006	0.101
Wj	0.553	0.125	0.084	0.014	0.224
Dj Total	0.453	1	1	1	-1
Sample Size	6				
K Factor	0.558				

Table 2. Weight calculation using Entropy weight method

I

4.2.2 Calculation based on TOPSIS

TOPSIS stands for Technique for Order of Preference by Similarity to Ideal Solution. It is a multi-criteria decisionmaking method. According to TOPSIS, the chosen process parameter must have the shortest geometric distance from the ideal positive solution and the longest from the negative ideal solution. It compares a set of process parameters by assigning weights to each criterion followed by normalization of the obtained weighted parameters and then calculating the distance between each parameter and the ideal value which is the best value in each criterion. In this step, the evaluation matrix was normalized. Therefore, the responses were normalized for a limit of 0–1. This is to place them on a simple scale and remove the variation in their measuring units. The higher its value, the better the metric. The following equation was used to obtain the normalized matrix r_{ij} and all of the values are listed in Table 3.

Table 3. Normalized Matrix

	Cost/Kg	Ultimate	Young's	Hardness	Fatigue
		Tensile Strength	Modulus (GPa)	(HRB)	Strength
		(MPa)			(MPa)
Al Alloy	0.155396	0.22407	0.21457	0.3831	0.2
Cu Alloy	0.248634	0.32149	0.32519	0.3803	0.247
Ni Alloy	0.932379	0.58452	0.57534	0.487	0.667
Zn Alloy	0.174044	0.16821	0.23125	0.3107	0.079
Stainless Steel	0.111885	0.6105	0.54477	0.4776	0.576
Cast Iron	0.043511	0.32214	0.40858	0.3831	0.341

Determination of the weighted normalized matrix. Because the selection criteria are of different importance weight, the weighting decision matrix shown in Table 4 is constructed by multiplying each element of each column of the normalized decision matrix by the relatively defined weights w_j from Table 3, following equation (5). The weighted normalized matrix is developed with the help of equation (6), the positive ideal (A^+) and negative ideal (A^-) solution sets are calculated by using the equations (7) and (8) and can be seen in Table 4.

Table 4. Weighted normalized decision-matrix, Positive & Negative ideal solutions

	Cost/Kg	Ultimate	Young's	Hardness	Fatigue
		Tensile Strength	Modulus (GPa)	(HRB)	Strength
		(MPa)			(MPa)
A 1 A 11	0.005027	0.0201	0.01700	0.0054	0.045
AI Alloy	0.085937	0.0281	0.01/99	0.0054	0.045
Cu Alloy	0.137499	0.04032	0.02726	0.0054	0.055
Ni Alloy	0.515621	0.07332	0.04823	0.0069	0.149

ternational Journal of Scientific Research in Engineering and Management (IJSREM) Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Zn Alloy	0.096249	0.0211	0.01938	0.0044	0.018
Stainless Steel	0.061874	0.07657	0.04566	0.0068	0.129
Cast Iron	0.024062	0.04041	0.03425	0.0054	0.076
A^+	0.024062	0.07657	0.04823	0.0069	0.149
A-	0.515621	0.0211	0.01799	0.0044	0.018

The distance to the positive ideal solution S_i^* was calculated using equation (5) and the distance to the negative ideal solution S_i^- was calculated using equation (6). Values of S_i^* and S_i^- are given in Table 5. In the last stage of the application, the relative proximity (P_i^*) of each alternative to the ideal solution was calculated using Equation 11. In Table 5, the relative closeness of each alternative to the ideal solution and the ranking of the alternatives are given.

Table 5. Distances to the PIS and NIS, the relative closeness values, and their ranks

	S_i^*	S_i^-	P_i^*	Rank
Al Alloy	0.134194	0.43165	0.76284	3
Cu Alloy	0.153107	0.38104	0.71336	5
Ni Alloy	0.491569	0.14145	0.22345	6
Zn Alloy	0.162487	0.42036	0.72122	4
Stainless Steel	0.042969	0.47047	0.91631	1
Cast Iron	0.082474	0.49562	0.85733	2

5. Result & Discussion

The illustrative example demonstrates the practicality and accuracy of utilizing EWM and TOPSIS methods in addressing complex gear material selection problems. These methods enable decision-makers to evaluate alternatives and choose the most suitable material, After applying the EWM-TOPSIS method the preferred material for manufacturing of gear for a particular application is stainless steel, because the results with maximum score i.e. 0.91631, followed by cast iron with 0.85733 score and Al alloy is the third option for the decision makers. This hierarchy is considered valid for the defined selection criteria and their corresponding weights. Both EWM and TOPSIS methods can effectively address various industrial material selection problems, irrespective of the number of qualitative and quantitative criteria or decision alternatives involved.

6. Conclusion

Multi-criteria decision-making (MCDM) is one of the most accurate methods to support decision-making. Specifically, the MCDM method considered the best technique when there is more than one criterion in the decision-making process. Selecting a best alternative is very important problem in manufacturing environment considering various multiple performance attributes. The proposed integrated MCDM method, EWM and TOPSIS is helpful in selection of a suitable material from amongst a large number of alternative gear materials for manufacturing a given gear. The alternative with highest magnitude value of composite distance has last rank and hence least preferred. This methodology has no limits for number of parameters and number of alternatives and is capable of solving complex multi-attributes decision problems, incorporating both quantitative and qualitative parameters.

References

- Kilic, H.S. & Yalcin, A.S., Modified Two-Phase Fuzzy Goal Programming Integrated with IF-TOPSIS for Green Supplier Selection, Applied Soft Computing Journal, 93, 106371, 2020.
- [2] Govindaraju, R., Akbar, M.I., Gondodiwiryo, L. & Simatupang, T., The Application of a Decision-Making Approach Based on Fuzzy ANP and TOPSIS for Selecting a Strategic Supplier, Journal of Engineering and Technological Sciences, 47(4), pp. 406-425, 2015.
- [3] Wichapa, N. & Khokhajaikiat, P., A Hybrid Multi-Criteria Analysis Model for Solving the Facility Location–Allocation Problem: A Case Study of Infectious Waste Disposal, Journal of Engineering and Technological Sciences, 50(5), pp. 699-719, 2018.
- [4] Haruna, A., Shafiq, N., Ali, M.O., Mohammed, M. & Haruna, S., Design and Construction Technique for Low Embodied Energy Building: An Analytical Network Process Approach, Journal of Engineering and Technological Sciences, 52(2), pp. 166-180, 2020.
- [5] Ding, Z., Fang. H., Yao, Z., Liu, J. & Wang, J., Research on Multi-criteria Material Selection of Automobile in Full Cycle under the Background of Green Manufacturing, Journal of Physics: Conference Series, 1910(1), 2021.
- [6] Gul, M., Celik, E., Gumus, A.T. & Guneri, A.F., A Fuzzy Logic Based PROMETHEE Method for Material Selection Problems, Beni-Suef University Journal Basic and Application Sciences, 7(1), pp. 68-79, 2018.
- [7] Maity, S.R. & Chakraborty, S., A Visual Decision Aid for Gear Materials Selection, Journal Institution of Engineering (India)Series C, 94, no. September, pp. 199-212, 2013.
- [8] Zindani, D. & Kumar, K., Material Selection for Turbine Seal Strips Using PROMETHEE-GAIA Method, Materials Today: Proceedings, 5(9), pp. 17533-17539, 2018/
- [9] Patnaik, P.K., Swain, P.T.R., Mishra, S.K., Purohit, A. & Biswas, S., Composite Material Selection for Structural Applications Based on AHP-MOORA Approach, Materials Today: Proceedings, 33, pp. 5659-5663, 2020.

- [10] Agrawal, R., Sustainable Material Selection for Additive Manufacturing Technologies: A Critical Analysis of Rank Reversal Approach, Journal of Cleaner Production, 296, 126500, 2021.
- [11]Saivaew, N. & Butdee. S., Decision Making for Effective Assembly Machined Parts Selection Using Fuzzy AHP and Fuzzy Logic, Materials Today: Proceedings, 26, pp. 2265-2271, 2019.
- [12] Torkayesh, A.E., Malmir, B. & Asadabadi, M.R., Sustainable Waste Disposal Technology Selection: The Stratified Best-Worst Multi-Criteria Decision-Making Method, Waste Management, 122, pp. 100-112, 2021.
- [13] Ramnath. R.A., Thyla, P.R. & Harishsharran, A.K.R., Machining Parameter Selection In Milling Epoxy Granite Composites Based on AHP, Materials Today: Proceedings, 42, pp. 319-324, 2020.
- [14] Mathew, M., Chakrabortty, R.K. & Ryan, M.J., A Novel Approach Integrating AHP and TOPSIS Under Spherical Fuzzy Sets for Advanced Manufacturing System Selection, Engineering Applications of Artificial Intelligence, 96. October, 103988, 2020.

I