Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 12 Issue 5, May - 2025

Integration Of Mcdm Methods For Cutting Tool Material Selection

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***Abstract*—Cutting tool materials hold a paramount role in machining processes. Nevertheless, selecting a specific type from a multitude of available options presents a complex undertaking due to the diverse criteria characterizing these materials, which can often exhibit conflicting attributes across the available choices. To navigate this challenge, the selection of cutting tool materials necessitates the application of Multi-Criteria Decision Making (MCDM) methodologies. This research was conducted to identify the optimal material from a set of twelve candidates. The Entropy method was employed to determine the weights of the criteria. To rank the cutting tool material alternatives, four distinct MCDM techniques were concurrently utilized: the TOPSIS method, the MOORA method, the PIV method, and the RAM method. Notably, all applied methods consistently identified the same superior material among the twelve options. This convergence of results provides users with robust confidence in the selected material. Finally, future research directions are also discussed in the concluding section of this paper.**

Keywords—cutting tool material, MCDM, TOPSIS method, MOORA method, PIV method, RAM method.

1. INTRODUCTION

Material selection constitutes a pivotal aspect in the fabrication of cutting tools specifically, and across a myriad of broader engineering applications. In the context of cutting tools, the material directly dictates the productivity, precision, and lifespan of the machining process [1]. A cutting edge fashioned from an appropriate material will maintain its sharpness, resist wear, endure high temperatures and substantial cutting forces generated during operation, thereby yielding quality products and minimizing production costs [2]. Similarly, in diverse applications such as construction, aerospace, or medicine, the choice of materials with optimal mechanical, physical, and chemical properties ensures the safety, efficiency, and durability of the product or structure [3-5].

However, the selection of materials for cutting tools presents a complex problem demanding meticulous consideration of numerous factors. It transcends mere hardness or strength, requiring a harmonious balance between parameters such as wear resistance, toughness, thermal conductivity, coefficient of friction, oxidation resistance, and a host of other attributes [6]. For instance, an excessively hard material might exhibit excellent wear resistance but be prone to brittleness, while an overly ductile material may experience rapid wear. Consequently, to arrive at an optimal decision, engineers frequently resort to Multi-Criteria Decision Making (MCDM) methodologies [7, 8]. These methods facilitate the evaluation and comparison of potential materials based on various criteria, assigning weights to each criterion according to the specific demands of the application, and ultimately yielding the most suitable material selection [9-13].

A substantial body of published literature has applied diverse MCDM methods in the selection of cutting tool materials in particular, and material selection in other applications more generally. Some studies have employed a singular MCDM method to rank materials for a specific application, such as the TOPSIS method for ranking gear manufacturing materials [14], the MARCOS method for selecting sintered pulleys in automobiles [15], the MACONT method for choosing thermal insulation materials for buildings [16], and the GRA method for selecting composite materials [17], among others. However, certain reports have indicated that to ensure the accuracy of material ranking, the simultaneous utilization of several different methods for a given problem is advisable [18, 19].

Following this trend, numerous studies have concurrently applied multiple MCDM methods to rank materials for specific applications. Examples include the use of SAW and MOORA methods for material selection in agricultural production [20], the application of MARA, PIV, and RAM methods for selecting lubricants for two-stroke engines and materials for screw production [21], the utilization of MOORA, COPRAS, and VIKOR methods for material selection in the cane sugar manufacturing industry [22], the ranking of construction materials using CRADIS and AHP methods [23, 24], the ranking of brake disc materials by employing COPRAS, VIKOR, ELECTRE, ARAS, and MOORA methods [25], and the application of DEMATEL, ANP, and TOPSIS methods for selecting green materials for sustainability [26], etc.

To contribute novel insights to this evolving trend, this research simultaneously employs four methods – TOPSIS, MOORA, PIV, and RAM – for the selection of cutting tool materials. The rationale behind selecting these four methods lies in the established prominence of TOPSIS and MOORA, evidenced by their extensive use in numerous studies, including recently published research [27, 28]; the PIV method's recognized advantage in mitigating rank reversal phenomena [29]; and the utilization of RAM due to its recent emergence as a novel methodology [30].

The subsequent sections of this paper are structured as follows: Section 2 compiles data on commonly used cutting tool materials and presents the theoretical underpinnings of the Entropy method for criteria weighting, as well as the theoretical frameworks of the TOPSIS, MOORA, PIV, and RAM methods. The results of applying these methods to rank the cutting tool materials are detailed in Section 3. Finally, the conclusions drawn from this research and potential avenues for future work are summarized in the concluding section of this paper.

2. MATERIALS AND METHODS

2.1. Cutting Tool Materials

Table 1 compiles information regarding twelve material types commonly employed in the fabrication of cutting tools, denoted correspondingly by the letters M1 through M12 (the alternatives). Seven parameters were utilized to characterize each material, encompassing hardness, Young's modulus, elastic recovery, coefficient of friction, load-bearing capacity, an index of coating deformation resistance, and an index of coating wear resistance. These parameters are denoted as C1 through C7, respectively. Notably, criterion C4 (coefficient of friction) is a parameter for which lower values are preferred (a non-beneficial criterion, NB), while the remaining criteria are those for which higher values are desirable (beneficial criteria, B) [31].

Table 1. A selection of cutting tool materials

No.	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*
M1	34	380	60	0.6	30	0.089	0.272
M2	31	380	59	0.49	50	0.082	0.206
M3	20	280	49	0.45	41	0.071	0.102
M4	23	300	46	0.45	46	0.077	0.135
M5	19	270	45	0.45	46	0.7	0.094
M6	30	370	53	0.52	22	0.081	0.197
M7	19	270	43	0.51	47	0.07	0.094
M8	25	340	47	0.45	90	0.074	0.135
M9	17	280	40	0.5	67	0.061	0.063
M10	23	300	48	0.52	54	0.077	0.135
M11	20	260	46	0.43	37	0.077	0.118
M12	19	280	44	0.45	41	0.068	0.087

It is evident that a mere observation of the data presented in Table 1 does not readily reveal the optimal material among the twelve under consideration. Consider a simplified example to further illustrate this point. Criterion C1 attains its maximum value of 34 for material M1, criterion C2 peaks at 380 for materials M1 and M2, criterion C3 reaches its highest value of 60 for material M1, criterion C4 has its minimum value of 0.43 for material M11, and criterion C5 achieves its maximum of 90 for material M8, and so forth. Consequently, it is clear that no single material simultaneously exhibits the highest values for all beneficial criteria (C1, C2, C3, C5, C6, C7) and the lowest value for the non-beneficial criterion (C4). Instead, it is only possible to select a material that achieves a concurrently "best" compromise across these criteria. Naturally, to address this issue, it becomes necessary to determine the weights of the criteria and employ MCDM methods to rank the materials, thereby identifying the most suitable option.

2.2. Method for Determining Criteria Weights

To ascertain the weights of the criteria, this study employs the Entropy method. This approach is utilized due to its recognized accuracy and its recommended application in decision-making processes. The procedural steps for implementing this method are as follows [32]:

- Establish the number of alternatives to be ranked and the number of criteria characterizing each alternative. Let *m* represent the number of alternatives requiring ranking, and *n* denote the number of criteria used to describe each alternative. Let x_{ij} be the value of criterion *j* for alternative *i*, where *j* ranges from 1 to *n*, and *i* ranges from 1 to *m*.

- Determine the normalized values for the criteria using Equation (1).

$$n_{\mathrm{ij}} = \frac{x_{\mathrm{ij}}}{m + \sum_{i=1}^{m} x_{\mathrm{ij}}^{2}} \quad (1)$$

- Calculate the Entropy measure for each criterion using Equation (2).

$$e_j = \sum_{i=1}^{m}\left[n_{ij} \times \ln(n_{ij})\right] - \left(1-\sum_{i=1}^{m} n_{ij}\right) \times \ln\left(1-\sum_{i=1}^{m} n_{ij}\right) \quad (2)$$

- Compute the weight for each criterion using Equation (3)

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)} \quad (3)$$

2.3. Ranking Methods for Alternatives Employed

2.3.1. TOPSIS Method

The procedure for ranking the alternative options using the TOPSIS method is outlined as follows [9]:

- Determine the normalized values according to Equation (4).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \quad (4)$$

- Calculate the weighted normalized values using Equation (5).

$$y_{ij} = w_j . n_{ij} \quad (5)$$

- Identify the positive ideal solution (A^+) and the negative ideal solution (A^-) for the criteria based on Equations (6) and (7). Where y_j^+ and y_j^- represent the optimal and worst values, respectively, of the weighted normalized value for criterion *j*.

$$A^+ = \{y_1^+, y_2^+, \ldots, y_j^+, \ldots, y_n^+\} \quad (6)$$

$$A^- = \{y_1^-, y_2^-, \ldots, y_j^-, \ldots, y_n^-\} \quad (7)$$

- Determine the separation measures S_i^+ and S_i^- using Equations (8) and (9).

$$\boldsymbol{S_i^+} = \sqrt{\sum_{j=1}^{n}(\boldsymbol{y_{ij}} - \boldsymbol{y_j^+})^2} \quad i = 1, 2, \ldots, m \quad (9)$$

$$\boldsymbol{S_i^-} = \sqrt{\sum_{j=1}^{n}(\boldsymbol{y_{ij}} - \boldsymbol{y_j^-})^2} \quad i = 1, 2, \ldots, m \quad (10)$$

- Calculate the relative closeness coefficient (C_i^*) for each alternative using Equation (10).

$$\boldsymbol{C_i^*} = \frac{\boldsymbol{S_i^-}}{\boldsymbol{S_i^+} + \boldsymbol{S_i^-}} \quad i = 1, 2, \ldots, m;\ 0 \le C_i^* \le 1 \quad (10)$$

- Rank the alternatives based on the principle that the alternative with the largest C_i^* value is considered the best option.

2.3.2. MOORA Method

The procedure for ranking the alternative options using the MOORA method is as follows [9]:

- Calculate the normalized values using Equation (4).

- Compute the weighted normalized values of the criteria according to Equation (11).

$$V_{ij} = w_j \times n_{ij} \quad (11)$$

- Determine the values of P_i and R_i using Equations (12) and (13).

$$P_i = \frac{1}{|B|}\sum_{j \in B} W_{ij} \quad (12)$$

$$R_i = \frac{1}{|NB|}\sum_{j \in NB} W_{ij} \quad (13)$$

- Calculate the overall appraisal value (Q_i) for each alternative using Equation (14).

$$Q_i = P_i - R_i \quad (14)$$

- Rank the alternatives based on the principle that the alternative with the highest Q_i value is considered the most preferred option.

2.3.3. PIV Method

The procedure for ranking the alternative options using the PIV method is as follows [29]:

- Calculate the normalized values using Equation (4).

- Compute the weighted normalized values of the criteria according to Equation (15).

$$v_{ij} = w_j \times n_{ij} \quad (15)$$

- Evaluate the weighted proximity indices using Equations (16) and (17).

$$u_i = v_{\max} - v_i \quad if \quad j \in B \quad (16)$$

$$u_i = v_i - v_{\min} \quad if \quad j \in NB \quad (17)$$

- Determine the overall proximity value using Equation (18).

$$d_i = \sum_{j=1}^{n} u_i \quad (18)$$

- Rank the alternatives based on the principle that the alternative with the smallest di value (overall proximity value) is considered the most preferred option.

2.3.4. RAM Method

The procedure for ranking the alternative options using the RAM method is as follows [30]:

- Normalize the data using Equation (19).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (19)$$

- Calculate the weighted normalized values of the criteria according to Equation (20).

$$y_{ij} = w_j \cdot r_{ij} \quad (20)$$

- Compute the aggregate weighted normalized scores for each alternative with respect to positive and negative ideal references using Equations (21) and (22).

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \quad if \quad j \in B \quad (21)$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \quad if \quad j \in NB \quad (22)$$

- Calculate the final score for each alternative using Equation (23).

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \quad (23)$$

- Rank the alternatives in descending order based on their final scores.

3. RESULTS AND DISCUSSION

Implementing the steps of the Entropy method yielded the weights for each criterion, as summarized in Table 2.

Table 2. Weights of the criteria

C1	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*
0.1292	0.1110	0.1204	0.2158	0.1195	0.1480	0.1562

Applying the procedural steps of the TOPSIS method resulted in the calculation of the C_i* score for each alternative, as well as the determination of the ranking of the alternatives. Similarly, implementing the MOORA method yielded the Q_i score and the corresponding ranking. The application of the PIV method produced the d_i score and the associated ranking. Finally, the RAM method provided the RI_i score and the resulting ranking of the alternatives. All these calculated values and rankings are consolidated in Table 3.

Table 3. Ranking of cutting tool materials using different methods

No.	*TOPSIS*		*MOORA*		*PIV*		*RAM*	
	C_i^*	*Rank*	Q_i	*Rank*	d_i	*Rank*	RI_i	*Rank*
M1	0.3557	2	-0.0341	9	0.1843	3	1.4365	2
M2	0.3095	3	-0.0222	3	0.1835	2	1.4361	3
M3	0.1617	10	-0.0295	6	0.2529	9	1.4286	9
M4	0.2064	6	-0.0263	4	0.2336	6	1.4307	7
M5	0.6565	1	-0.0094	1	0.1322	1	1.4490	1
M6	0.2675	5	-0.0309	7	0.2162	5	1.4328	5
M7	0.1389	12	-0.0381	12	0.2660	11	1.4274	11
M8	0.3012	4	-0.0201	2	0.1962	4	1.4345	4
M9	0.1852	8	-0.0371	11	0.2665	12	1.4272	12
M10	0.2046	7	-0.0341	10	0.2357	7	1.4307	6
M11	0.1771	9	-0.0271	5	0.2512	8	1.4288	8
M12	0.1463	11	-0.0313	8	0.2632	10	1.4274	10

The data presented in Table 3 reveals inconsistencies in the ranking of the materials when evaluated using different MCDM methods. This is a common occurrence when multiple MCDM techniques are concurrently employed to address a single problem and has been documented in numerous studies [33]. However, notably, all four methods utilized in this research – TOPSIS, MOORA, PIV, and RAM – consistently identified M5 as the top-ranked alternative. This convergence strongly substantiates that M5 represents the most suitable material for cutting tool fabrication among the twelve materials considered in this study.

4. CONCLUSION

This research marks the inaugural concurrent application of four MCDM methods – TOPSIS, MOORA, PIV, and RAM – for the ranking of cutting tool materials. The integrated use of these four methodologies consistently identified a single cutting tool material as the most preferred among the twelve available options.

The utilization of the Entropy method for determining criteria weights relies solely on the technical specifications of the materials, without incorporating user preferences regarding the relative importance of these criteria. In scenarios where the role of user input on criteria significance is crucial, subjective weighting methods could be employed to ascertain the criteria weights. Furthermore, following the application of MCDM methods to identify the putatively optimal cutting tool material, subsequent experimental validation is warranted. These endeavors should be pursued in future research.

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