Research Article

A New Material Selection Method Based on Weighted Mean Values of Overall Performance Scores from Different Multicriteria Decision-Making Methods

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There are many multicriteria decision-making (MCDM) methods applicable to material selection. It may produce considerable differences between the material selection results. However, it is unknown which MCDM method has more rational result and there is no rational method to determine final overall performance scores of alternative materials. We propose a new method to determine final overall performance scores and final ranks of alternative materials combined with results from different MCDM methods in material selection. The outline is as follows. First, calculate the overall performance scores and ranks of the alternative materials using some different MCDM methods. Second, calculate mean values of the rank correlation coefficients between the rankings obtained from different MCDM methods and assign the mean values as the priority weights of each MCDM method. Finally, calculate the weighted mean values of the overall performance scores obtained from different MCDM methods and determine them as final overall performance scores of the alternative materials. To illustrate the effectiveness, we apply the proposed method to select best tool holder materials. The method may help material designers and engineers to apply different MCDM methods to material selection and multi-objective optimization of material composition and process, much more effectively and actively.

1. Introduction

Material selection is a multicriteria decision-making (MCDM) problem that material designers and engineers have to select the optimal material to achieve good properties among two or more alternative materials based on two or more criteria. Many MCDM methods are applicable to the material selection [1–7]. There are simple additive weighting (SAW) method, weighted product method (WPM), analytic hierarchy process (AHP) method, analytic network process (ANP) method, technique for order preference by similarity to ideal solution (TOPSIS) method, gray relational analysis (GRA), Vise Kriterijumska Optimizacija Kompromiso Resenje (VIKOR) method, preference ranking organization method for enrichment evaluations (PROMETHEE), extended PROMETHEE (EXPROM) method, elimination and et choice translating reality (ELECTRE) method, complex proportional assessment (COPRAS) method, preference selection index (PSI) method, range of value method (ROVM), rank sum ratio (RSR) method, graph theory and matrix approach (GTMA), multi-objective optimization on the basis of ratio analysis (MOORA), quadrant constellation graph-based method, etc. [1–8].

Commonly, material designers and engineers have applied one or some MCDM methods to solve the material selection problem. Although many different MCDM methods are applicable to material selection and the methods have their own distinguishing features, it may produce considerable differences and incompatible results in the same material selection problem. It is very important issue to determine which method is the most rational and
appropriate for a given material selection problem among available MCDM methods. One reasonable methodology is to apply more than one MCDM method to the same problem.

Some researchers applied different MCDM methods to solve a material selection problem and conducted comparative studies of different MCDM methods. The results demonstrated that the rankings of the alternative materials obtained using different MCDM methods might differ. Moreover, because there is no method to verify the correctness of MCDM techniques, the only way to evaluate the performance of these MCDM methods is comparisons. Almost, studies considered the superiority of each MCDM method from the viewpoint of rank correlation between the ranking from one MCDM method and the rankings from the other MCDM methods [1–6].

The literature review for applications of different MCDM methods in material selection is shown in Table 1.

The material selection result obtained by combining with different MCDM methods may be more reasonable and more accurate than the result from an individual MCDM method.

For this purpose, some studies have been conducted. The aggregation of individual rankings obtained from different MCDM methods was usually done by an averaging function as a basic aggregation strategy [24]. However, this method has no guarantee to obtain the optimal result for circumstances in which there are large differences between the rankings of alternatives [25]. Borda and Copeland methods have been used for aggregation of the MCDM results as the most common voting aggregation techniques in group decision-making [26, 27]. The Borda rule assigns more points to higher rankings and then adds up those points over all individual voters for the alternatives. The option that has the highest points in the voters’ rankings is then chosen. Copeland’s method is a single-winner strategy in which the winner is identified by finding the candidate with the most pairwise victories. Jahan et al. [25] proposed an aggregation technique for optimal decision-making in material selection. They suggested a linear programming (LP) model for the aggregation of the rankings obtained from various MCDM methods. In this method, the ranking orders obtained from different MCDM methods were used as the inputs of the suggested procedure and the outputs were the aggregation rankings. Yang et al. [4] proposed membership degree-based material selection method combined with different MCDM methods. It is based on the membership degrees and final ranks of the alternative materials, where the final ranks are determined based on the ranks of the alternative materials obtained from different MCDM methods. Yang et al. [6] decided a final result of boron-based tribological coating material selection combined with individual results obtained from TOPSIS with some popular normalization methods. The method is based on the rank frequency rates of the alternative materials obtained from TOPSIS with different normalization methods.

Many researchers have used different artificial intelligence (AI), machine learning (ML), and optimization technologies for the various practical problems. Adefris Legesse et al. [28] evaluated the physical-mechanical properties of three-layer particleboard made from sorghum stalk and sugarcane bagasse hybrid reinforced bonded with urea-formaldehyde resin. The particleboards were produced with their proportions through the Taguchi design of the experiment (L9) approach. The experimental results were analyzed using Taguchi design and ANOVA with a general linear model. Chadha et al. [29] reviewed AI models implemented in metal melting processes or the metal melting aspect, alongside explaining additive manufacturing as a competitor to the current melting processes and its advances in metal melting and AI implementations. Chadha et al. [30] reviewed the machine learning techniques such as the adaptive neurofuzzy interference system, regression model, support vector machine, and artificial neural networks to optimize manufacturing techniques and examined machine learning applications in FSW by utilizing an artificial neural network (ANN) to control fracture failure and a convolutional neural network (CNN) to detect faults. Selvaraj et al. [31] classified different neural networks used for different metals with a description of their benefits and inconveniences and an overview and use of the different types of wear.

However, abovementioned methods have non-negligible drawbacks. The computation process is not simple, it is complicated, and it is impossible to determine the final overall performance scores of the alternative materials, while it is possible to determine the final ranks. On the other hand, it is impossible to reflect the influences (priority weights) of each MCDM method in the final results by using the previous methods, while each MCDM method has equal influences (equal contributions) to the final result.

In order to overcome these drawbacks, we propose a new method to determine final overall performance scores of materials combined with different MCDM methods in material selection.

The remaining part of this paper is organized as follows. In the following section, we propose a new method to determine final overall performance scores of alternative materials combined with different MCDM methods. In the next section, we apply the proposed method to select optimal tool holder materials and illustrate its effectiveness.

2. Methods

2.1. A New Material Selection Method Based on Weighted Mean Values of Overall Performance Scores from Different MCDM Methods. In this subsection, we propose a new material selection method based on weighted mean values of overall performance scores obtained from different MCDM methods.

The outline is as follows:

(i) First, calculate the overall performance scores and ranks of the alternative materials using some different MCDM methods.

(ii) Second, calculate mean values of the rank correlation coefficients between the rankings obtained
from different MCDM methods and assign the mean values as the priority weights of each MCDM method.

(iii) Third, calculate the weighted mean values of the overall performance scores obtained from different MCDM methods and determine them as final overall performance scores of the alternative materials.

(iv) Finally, select the alternative material with maximum final overall performance score as an optimal material.

Let $A_1, A_2, \ldots, A_n$ ($n \geq 2$) be $n$ alternative materials, and $u_1, u_2, \ldots, u_p$ be $p$ criteria. Suppose each alternative material is evaluated with respect to $p$ criteria, whose values constitute a decision matrix $X = (x_{ik})_{n \times p}$, where $x_{ik}$ is the performance value of $k$th criterion for $i$th alternative material ($i = 1, 2, \ldots, n$, $k = 1, 2, \ldots, p$).

The main steps for material selection method based on weighted mean values of overall performance scores obtained from different MCDM methods are as follows:

Step 1. Choose some MCDM methods for material selection.

Step 2. Construct a normalized decision matrix $Z = (z_{ik})_{n \times p}$ from the decision matrix $X = (x_{ik})_{n \times p}$.

We use the linear max-min normalization method. The normalization formula is as follows [32]:
Step 4. Calculate the overall performance scores \( z_{ik} \) as
\[
z_{ik} = \begin{cases} \frac{(x_{ij} - L_k)}{(U_k - L_k)}, & k \in K^+, \\ \frac{(U_k - x_{ij})}{(U_k - L_k)}, & k \in K^- \end{cases}
\] (1)
where \( U_k \) and \( L_k \) are the maximum and minimum values of \( k \)-th material criterion, respectively (\( i = j \)), \( J' \) is the index set of the benefit criteria (where larger values are desirable), and \( J' \) is the index set of the cost criteria (where smaller value is desirable).

Step 3. Constitute a weighted normalized decision matrix \( Y = (y_{ik})_{n \times p} \).

The element \( y_{ik} \) of \( Y = (y_{ik})_{n \times p} \) is calculated as follows:
\[
y_{ik} = w_k \times z_{ik}, \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, p,
\] (2)
where \( w_k \) represents the weight of \( k \)-th criterion \((w_1 + w_2 + \ldots + w_p = 1, w_p > 0, j = 1, 2, \ldots, p)\).

The weights are commonly determined using analytic hierarchy process (AHP) method or entropy weighting method [5, 7, 32].

Step 4. Calculate the overall performance scores \( \{V_{m1}, \ldots, V_{mM} \} \) of the alternative materials using each MCDM method \((m = 1, 2, \ldots, M)\).

\( V_{mi} \) is the overall performance score of \( i \)-th alternative material using \( m \)-th MCDM method \((m = 1, 2, \ldots, M, i = 1, 2, \ldots, n)\), where \( M \) is the number of MCDM methods and \( n \) is the number of the alternative materials.

In some popular MCDM methods, the overall performance score of the alternatives is as follows:

(i) SAW: simple weighted sum
(ii) TOPSIS: relative closeness value
(iii) GRA: gray relational degrees
(iv) VIKOR: VIKOR index
(v) PROMETHEE: net outranking flow
(vi) RSR: rank sum ratio.

In the almost MCDM methods, the overall performance scores of the alternatives belong to \([0, 1]\), and the higher the overall performance score is, the better (more superior) the alternative is. However, some MCDM methods such as VIKOR and PROMETHEE do not satisfy this condition. When the overall performance scores from a certain MCDM method do not belong to \([0, 1]\), it needs to transform original overall performance scores so that the best alternative should have a high score (close to 1) and the worst alternative should have a lower score (close to 0).

In the traditional VIKOR method, the overall performance scores (VIKOR indices) for each alternative are calculated as
\[
Q_i = v \frac{S_i S^-}{S^+ - S^-} + (1 - v) \frac{R_i R^-}{R^+ - R^-}, \quad i = 1, 2, \ldots, n
\] (3)
and the values belong to \([0, 1]\), where \( S_i \) and \( R_i \) are, respectively, the utility measure and the regret measure for \( i \)-th alternative, and \( S^+ = \max S_i \), \( S^- = \min S_i \), \( R^+ = \max R_i \), and \( R^- = \min R_i \). The smaller the value is, the better the alternative is. In this case, it needs to modify so that the higher the value is, the better the alternative is.

To do this, we propose a modified VIKOR index as follows:
\[
Q_i = 1 - \left[ \frac{S_i S^-}{S^+ - S^-} + (1 - v) \frac{R_i R^-}{R^+ - R^-} \right].
\] (4)
This modified VIKOR index belongs to \([0, 1]\), and the larger the value is, the better the alternative is. We call this method modified VIKOR method.

In the traditional PROMETHEE method, the overall performance scores (net outranking flows) for each alternative are calculated as
\[
F(i) = F^+(i) - F^-(i), \quad i = 1, 2, \ldots, n
\] (5)
and the values belong to \([-1, 1]\), where \( F^+(i) \) and \( F^-(i) \) are, respectively, leaving (positive) and entering (negative) flows for \( i \)-th alternative. In this case, it needs to modify so that the net outranking flow belongs to \([0, 1]\).

To do this, we propose a modified net outranking flow as follows:
\[
F(i) = \frac{[F^+(i) - F^-(i) + 1]}{2}.
\] (6)
This modified net outranking flow belongs to \([0, 1]\), and the larger the value is, the better the alternative is. We call this method modified PROMETHEE method.

Step 5. Constitute the overall performance score matrix \( V = (V_{mi})_{M \times n} \) using \( M \) different MCDM methods.

Step 6. Constitute the overall performance rank matrix \( R = (r_{mi})_{M \times n} \) from the overall performance score matrix \( V = (V_{mi})_{M \times n} \), where \( r_{mi} \) is the rank of overall performance score of \( i \)-th alternative material using \( m \)-th MCDM method \((m = 1, 2, \ldots, M, i = 1, 2, \ldots, n)\).

Step 7. Calculate Spearman’s rank correlation coefficient \( \rho_{mk} \) between the overall performance rank vector \( r_m = (r_{m1}, \ldots, r_{mM}) \) using \( m \)-th MCDM method and the overall performance rank vector \( r_k = (r_{k1}, \ldots, r_{kn}) \) using \( k \)-th MCDM method as follows \((m, k = 1, 2, \ldots, M)\):
\[
\rho_{mk} = 1 - 6 \frac{\sum_{i=1}^{n} (r_{mi} - r_{ki})^2}{n(n^2 - 1)}.
\] (7)
When \( r_m = (r_{m1}, \ldots, r_{mM}) \) and \( r_k = (r_{k1}, \ldots, r_{kn}) \) are the same, it is sure \( \rho_{mk} = 1. \)
Step 8. Calculate the mean values of the rank correlation coefficients \( \rho_m \) between the overall performance rank vector \( r_m = (r_{m1}, \ldots, r_{mn}) \) using \( m \)-th MCDM method and other MCDM methods as follows (\( m = 1, 2, \ldots, M \)):

\[
\rho_m = \frac{1}{M-1} \sum_{k=1, k \neq m}^{M} \rho_{mk}.
\]  (8)

The larger the mean value of the rank correlation coefficients is, the more the ranks from the corresponding MCDM method are similar to the ranks from the other MCDM methods.

Step 9. Determine the priority weights \( \beta_m \) by normalizing the mean values of the rank correlation coefficients \( \rho_m \); \( m = 1, 2, \ldots, M \) as follows:

\[
\beta_m = \frac{\rho_m}{\sum_{k=1}^{M} \rho_k}.
\]  (9)

Step 10. Calculate the final overall performance scores of the alternative materials using the weighted mean values of the overall performance scores as follows:

\[
V_{0i} = \sum_{M=1}^{M} \beta_m \cdot V_{mi}, i = 1, 2, \ldots, n.
\]  (10)

Step 11. Determine the final ranks \( FR_1, FR_2, \ldots, FR_n \) of the alternative materials in the descending order based on the values of the final overall performance scores \( V_{01}, V_{02}, \ldots, V_{0n} \).

Step 12. Select the alternative material with maximum final overall performance score as an optimal material.

2.2. Evaluating Method for Effectiveness of the MCDM Method. To evaluate the effectiveness of the proposed method, the following metrics are used.

Mean values of the correlation coefficients between the overall performance scores using \( m \)-th MCDM method and other MCDM methods (\( m = 0, 1, 2, \ldots, M \)) are

\[
R_m = \frac{1}{M} \sum_{k=0, k \neq m}^{M} R_{mk},
\]  (11)

where

\[
R_{mk} = \frac{\sum_{i=1}^{n} (V_{mi} - \bar{V}_m) \cdot (V_{ki} - \bar{V}_k)}{\sqrt{\sum_{i=1}^{n} (V_{mi} - \bar{V}_m)^2 \cdot \sum_{k=1}^{n} (V_{ki} - \bar{V}_k)^2}}.
\]  (12)

\( R_{mk} \) is the correlation coefficient between the overall performance scores using \( m \)-th MCDM method and \( k \)-th MCDM method (\( m, k = 0, 1, 2, \ldots, M \)).

\( \bar{R}_m = 1/M \sum_{k=1}^{M} R_{mk} \) is the mean value of the correlation coefficients between the final overall performance scores and the overall performance scores using \( M \) MCDM methods.

\( \bar{R}_m = 1/M \sum_{k=0, k \neq m}^{M} R_{mk} \) is the mean value of the correlation coefficients between the overall performance scores using \( m \)-th MCDM method and the overall performance scores using other MCDM methods containing the final overall performance scores.

The larger the value \( \bar{R}_m \) is, the better the result is coincided with the results using the other MCDM methods and the more rational the result using the MCDM method is.

Mean values of absolute deviations between the overall performance scores using \( m \)-th MCDM method and other MCDM methods (\( m = 0, 1, \ldots, M \)) are

\[
\bar{\Delta}_m = \frac{1}{M} \sum_{k=0, k \neq m}^{M} \Delta_{mk},
\]  (13)
\( \Delta_{mk} \) is the absolute deviation between the overall performance scores \( V_{m1}, \ldots, V_{mn} \) using \( m \)th MCDM method and the overall performance scores \( V_{k1}, \ldots, V_{kn} \) using \( k \)-th MCDM method \((m, k = 0, 1, 2, \ldots, M)\).

\[ \Delta_{mk} = \frac{1}{n} \sum_{i=1}^{n} |V_{mi} - V_{ki}|, \quad (14) \]

\( \overline{\Delta}_{m} = \frac{1}{M} \sum_{k=1}^{M} \Delta_{mk} \) is the mean value of the absolute deviations between the final overall performance scores and the overall performance scores using \( M \) MCDM methods.

\( \overline{\Delta}_{m} = \frac{1}{M} \sum_{k=0, k \neq m}^{M} \Delta_{mk} \) is the mean value of the absolute deviations between the overall performance scores using \( m \)th MCDM method and the overall performance scores using other MCDM methods containing the final overall performance scores. The smaller the value \( \Delta_{mk} \) is, the better the result is coincided with the results using the other MCDM methods and the more rational the result using the MCDM method is.

We developed the MATLAB program for the above-mentioned methods.

### 3. Results and Discussion

This section deals with the tool holder material selection using some well-known MCDM methods such as SAW, TOPSIS, GRA, VIKOR, PROMETHEE, and RSR methods.
Tool holders are widely used in machining operations such as turning and milling [9]. Tool holders are very important in connection of spindle and the inserts, providing the necessary rake, flank, radial, and axial angles to the inserts. Table 2 shows the alternative tool holder materials and their properties [9].

The criteria weights were calculated by combining the AHP and the entropy methods. The calculated criteria weights are, respectively, 0.291, 0.079, 0.206, 0.188, 0.098, and 0.139 [9].

Table 3 shows the normalized decision matrix. Table 4 and Figure 1 show the overall performance scores of the alternative materials obtained from different MCDM methods.

The ranks of the overall performance scores of the alternative materials obtained from different MCDM methods are shown in Table 5.

Tables 4, 5 and Figure 1 demonstrate that the overall performance scores and ranks of the alternative materials differ according to the MCDM methods. Therefore, it is necessary to determine the final overall performance scores and final ranks of the alternative magnesium alloys in consideration of the results from individual MCDM methods.

Table 6 shows the rank correlation coefficients between the overall performance scores from six MCDM methods and their mean values.

The priority weights of each MCDM method obtained by normalizing the mean values of the rank correlation coefficients are, respectively, 0.165, 0.173, 0.173, 0.174, 0.165, and 0.150.

Table 7 and Figure 2 show the final overall performance scores and final ranks of the alternative materials.

To evaluate the effectiveness of the proposed method, we calculate the mean values of the correlation coefficients and absolute deviations between the overall performance scores obtained from different MCDM methods using equations (11) and (13). The results are shown in Table 8.

Table 8 shows that the final overall performance scores using the proposed method have the maximum mean value of correlation coefficients and minimum mean value of the
absolute deviations compared with the results obtained from other MCDM methods. This demonstrates that the proposed method is a rational method to determine the final overall performance scores and ranks of the alternative materials by combining different MCDM methods.

### 4. Conclusions

In this paper, we proposed a new materials selection method based on weighted mean values of overall performance scores from different MCDM methods. We apply the proposed method to select optimal tool holder materials.

Conclusively, the following conclusions were drawn:

(i) The proposed method can determine not only the final ranks but also the final overall performance scores of the alternative materials combined with the results obtained from individual MCDM methods, while the previous methods determine only the final ranks, not the final overall performance scores.

(ii) The proposed method enables to reflect the priority weights of individual MCDM methods to the final overall performance scores and ranks of the alternative materials.

(iii) The proposed method may be more reasonable, clear, and simpler than the previous methods.

(iv) The proposed method could be widely used to get more reasonable, appropriate, and robust material selection result by combining with different available MCDM methods.

In the almost MCDM methods, the overall performance scores of the alternatives belong to [0, 1], and the higher the overall performance score is, the better (more superior) the alternative is. However, some MCDM methods such as VIKOR and PROMETHEE do not satisfy this condition. One drawback of the proposed method is that it needs to transform the original overall performance scores so that the best alternative should have a higher score (close to 1) and the worst alternative should have a lower score (close to 0) when the overall performance scores from a certain MCDM method do not belong to [0, 1]. Therefore, future work needs to study a rational transformation method applicable to deal with this problem.

In this paper, we applied the proposed method to select optimal tool holder materials by combining some well-known MCDM methods such as SAW, TOPSIS, GRA, VIKOR, PROMETHEE, and RSR methods. The proposed method could be applied to decide more reasonable materials selection result by combining much more different well-known MCDM methods.

On the other hand, the proposed method could be applied to not only material selection problems but also multi-objective optimization problems for materials composition and process parameters. Almost optimization problems for materials composition and process parameters are multi-objective optimization problems with two or more optimizing mechanical properties, environmental factors, and sustainability criteria. Commonly, in order to solve the multiobjective optimization problem, we should transform it to single objective optimization problem. For this purpose, the proposed final overall performance score may become a useful and practical methodology. By setting the final overall performance scores as the values of a single objective function, we can solve single objective optimization problem and determine the optimal materials composition and process parameters.

The proposed method may help material designers and engineers to apply different MCDM methods to not only the material selection and optimization problems but also many practical multi-objective optimization problems in various relevant industries, much more effectively and actively.

### Data Availability

All data used to support the findings of this study are included within the article.

### Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and publication of this article.  

### References

[1] C. L. Hwang and K. Yoon, *Multiple Attribute Decision Making: Methods and Applications*, Springer-Verlag, New York, NY, USA, 1981.

[2] A. Jahan, K. L. Edwards, and M. Bahraminasab, *Multi-criteria Decision Analysis for Supporting the Selection of Engineering Materials in Product Design*, Butterworth-Heinemann, Oxford, England, 2016.

[3] V. M. Athawale and S. Chakraborty, “Material selection using multi-criteria decision-making methods: a comparative study,” in *Proceedings of the Institution of Mechanical Engineers - Part L: Journal of Materials: Design and Applications*, vol. 226, no. 4, pp. 266–285, 2012.

[4] W. C. Yang, S. H. Chon, C. M. Choe, and U. H. Kim, “Materials selection method combined with different MADM methods,” *Journal of Artificial Intelligence*, vol. 1, no. 2, pp. 89–100, 2019.

[5] W. -C. Yang, J.-S. Kim, and J.-Y. Yang, “A quantitative and intuitive materials selection multi-attribute decision-making method based on quadrant circular constellation graph,” in...
Advances in Materials Science and Engineering, vol. 235, no. 7, pp. 1686–1702, 2021.

W. C. Yang, S. H. Chon, C. M. Choe, and J. Y. Yang, “Materials selection method using TOPSIS with some popular normalization methods,” Engineering Research Express, vol. 3, no. 1, pp. 1–10, Article ID 015020, 2021.

W. C. Yang, J. B. Ri, J. Y. Yang, and J. S. Kim, “Materials selection criteria weighting method using analytic hierarchy process (AHP) with simplest questionnaire and modifying method of inconsistent pairwise comparison matrix,” in Proceedings of the Institution of Mechanical Engineers - Part L: Journal of Materials: Design and Applications, vol. 234, no. 7, pp. 1032–1059, 2020.

H. Çalıskan, B. Kursuncu, C. Kurbanoglu, and S. Y. Güven, “Material selection for the tool holder working under hard milling conditions using different multi criteria decision making methods,” Materials & Design, vol. 45, pp. 473–479, 2013.

H. Çalıskan, “Selection of boron based tribological hard coatings using multi-criteria decision making methods,” Materials & Design, vol. 50, pp. 742–749, 2013.

A. Jahan, M. Y. Ismail, F. Mustapha, and S. M. Sapuan, “Material selection based on ordinal data,” Materials & Design, vol. 31, no. 7, pp. 3180–3187, 2010.

A. Jahan, F. Mustapha, M. Y. Ismail, S. Sapuan, and M. Bahraminasab, “A comprehensive VIKOR method for material selection,” Materials & Design, vol. 32, no. 3, pp. 1215–1221, 2011.

K. Maniya and M. G. Bhatt, “A selection of material using a novel type decision-making method: preference selection index method,” Materials & Design, vol. 31, no. 4, pp. 1785–1789, 2010.

R. Khorshidi and A. Hassani, “Comparative analysis between TOPSIS and PSI methods of materials selection to achieve a desirable combination of strength and workability in Al/SiC composite,” Materials and Design, vol. 52, pp. 999–1010, 2013.

D. S. Kumar and K. N. S. Suman, “Selection of magnesium alloy by MADM methods for automobile wheels,” International Journal of Engineering and Manufacturing, vol. 4, pp. 31–41, 2014.

R. Kumar and S. K. Singal, “Penstock material selection in small hydropower plants using MADM methods,” Renewable and Sustainable Energy Reviews, vol. 52, pp. 240–255, 2015.

S. H. Mousavi-Nasab and A. Sotoudeh-Anvari, “A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems,” Materials and Design, vol. 121, 2017.

S. H. Mousavi-Nasab and A. Sotoudeh-Anvari, “A new multi-criteria decision making approach for sustainable material selection problem: a critical study on rank reversal problem,” Journal of Cleaner Production, vol. 182, pp. 466–484, 2018.

S. R. Maity and S. Chakraborty, “Tool steel material selection using PROMETHEE II method,” International Journal of Advanced Manufacturing Technology, vol. 78, no. 9-12, pp. 1537–1547, 2015.

A. Shanian and O. Savadogo, “A material selection model based on the concept of multiple attribute decision making,” Materials & Design, vol. 27, no. 4, pp. 329–337, 2006.

A. Shanian and O. Savadogo, “A methodological concept for material selection of highly sensitive components based on multiple criteria decision analysis,” Expert Systems with Applications, vol. 36, no. 2, pp. 1362–1370, 2009.

G. D. Tian, H. H. Zhang, Y. X. Feng, D. Wang, Y. Peng, and H. Jia, “Green decoration materials selection under interior environment characteristics: a grey-correlation based hybrid MCDM method,” Renewable and Sustainable Energy Reviews, vol. 81, pp. 682–692, 2018.

M. Yazdani and A. F. Payam, “A Comparative Study on Material Selection of Microelectromechanical Systems Electrostatic Actuators Using Ashby, VIKOR and TOPSIS,” Materials and Design, vol. 65, 2014.

M. Aatasi, Multi-criteria Decision Making, Shahrood University of Technology, Shahrood, Iran, 2010.

A. Jahan, M. Y. Ismail, S. Shuib, D. Norfazidah, and K. L. Edwards, “An aggregation technique for optimal decision-making in materials selection,” Materials & Design, vol. 32, no. 10, pp. 4918–4924, 2011.

J. C. Pomerol and S. Barba-Romero, Multicriteria Decision in Management: Principles and Practice, Springer, Netherlands, Europe, 2000.

C. L. Hwang and M. J. Lin, Group Decision Making under Multiple Criteria: Methods and Applications, Springer, New York, NY, USA, 1987.

A. Adefis Legesse, D. Desalegn, S. K. Selvaraj, V. Paramasivam, and U. Chadha, “Experimental investigation of sorghum stalk and sugarcane bagasse hybrid composite for particleboard,” Advances in Materials Science and Engineering, vol. 2022, Article ID 1844004, 17 pages, 2022.

U. Chadha, S. K. Selvaraj, A. Raj et al., “AI-Driven Techniques for Controlling the Metal Melting Production: A Review, Processes, Enabling Technologies, Solutions, and Research Challenges,” Materials Research Express, vol. 9, 2022.

U. Chadha, S. K. Selvaraj, N. Gunreddy et al., “A survey of machine learning in friction stir welding, including unresolved issues and future research directions,” Material Design: Processing Communications, vol. 2022, Article ID 2568347, 28 pages, 2022.

S. K. Selvaraj, A. Raj, M. Dharamdharka et al., “A cutting-edge survey of tribological behavior evaluation using artificial and computational intelligence models,” Advances in Materials Science and Engineering, vol. 2021, Article ID 9529199, 17 pages, 2021.

W. C. Yang, C. M. Choe, J. S. Kim, M. S. Om, and U. H. Kim, “Materials selection method using improved TOPSIS without rank reversal based on linear max-min normalization with absolute maximum and minimum values,” Materials Research Express, vol. 9, no. 6, Article ID 065503, pp. 1–16, 2022.