Hybrid GRA-EDAS-Based Evaluation of Electrode Materials for Automotive Spot Welding Applications

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ABSTRACT

The performance of Resistance Spot Welding (RSW) in the automotive industry is heavily influenced by the selection of appropriate electrode materials, which must balance multiple and often conflicting criteria such as conductivity, hardness, cost, and wear resistance. This study presents a hybrid Multi-Criteria Decision-Making (MCDM) method, integrating Grey Relational Analysis (GRA) and Evaluation based on Distance from Average Solution (EDAS) to systematically evaluate and rank eight alternative electrode materials. EDAS evaluates alternatives against average performance benchmarks, while GRA determines the weights of the objective criteria. The study considers seven key criteria: electrical conductivity, thermal conductivity, Rockwell hardness, yield strength, density, cost, and wear resistance. The hybrid GRA-EDAS approach involves an eight-step procedure, with results indicating that C18150 consistently outperformed other materials at every evaluation stage, followed by C17510 and C16200. The robustness and reliability of the proposed method were validated by comparison with established techniques such as WASPAS and MAUT, showing strong agreement using Spearman's correlation (ρ=0.929 with WASPAS and ρ=0.833 with MAUT). The findings highlight the effectiveness and consistency of the hybrid GRA-EDAS framework in delivering comprehensive and reliable evaluations for material selection decisions in industrial settings.

Keywords-hybrid MCDM; GRA-EDAS; electrode material selection

I. INTRODUCTION

Resistance Spot Welding (RSW) is the main method used in the automotive industry to join sheet metals, and the quality and durability of the weld depend heavily on the electrode material selection. Improper electrode materials can result in rapid wear, weak welds, and frequent electrode replacement downtime. The electrodes carry the welding current and are subjected to repeated mechanical and thermal cycles. High electrical and thermal conductivity for effective current transfer, enough hardness and wear resistance to preserve tip geometry, and sufficient strength at high temperatures are all requirements for ideal electrode materials. In [1], it was found that wear resistance, hardness, thermal conductivity, and electrical conductivity are important characteristics that affect electrode performance.

A Multi-Criteria Decision-Making (MCDM) problem, such as choosing a material that satisfies all these requirements, necessitates a methodical assessment of the trade-offs between competing criteria [2]. Many MCDM techniques have been used over time to help engineers choose materials [3]. Such problems are frequently structured using the Analytic Hierarchy Process (AHP) [4], which assigns weights by pairwise comparisons of criteria importance and hierarchically decomposing criteria. Although subjective preferences can be captured by AHP, as the number of criteria increases, it can become unreliable or complicated. Researchers often use distance-based MCDM or outranking techniques to directly rank alternatives. For instance, the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) [5] favors materials that are closest to the ideal by calculating the Euclidean distance of each candidate material from the ideal (best values for all criteria) and the anti-ideal (worst values) solutions. VIKOR is another popular technique that focuses on finding a compromise solution that is more similar to the "ideal" in a maximal sense [6], which is particularly helpful when decision-makers try to strike a balance between criteria. Grey system theory-based techniques, such as Grey Relational Analysis (GRA) [7], have also been used to solve material selection problems. To measure the relative performance of each material, GRA calculates a relational grade for each alternative by comparing it with an idealized reference sequence across all criteria. This method is useful when information is scarce or unclear because it only needs the relative ordering of the performance data.

In recent years, new MCDM approaches have been proposed to address decision problems from various angles. In [8], the Evaluation Based on Distance from Average Solution (EDAS) was introduced, which calculates the positive and negative distance of each option from the average (mean) solution for each criterion to assess the desirability of alternatives. Stated differently, the evaluation of a material is determined by how well or poorly it performs in relation to the average performance of all candidates for each criterion. Compared to methods that rely on ideal or worst-case references, this approach tends to be less sensitive to extreme values and provides a stable reference point (the average). Each has complementary strengths, and both EDAS and GRA have demonstrated promise in material evaluation applications [2, 7]. While GRA is excellent at identifying performance patterns even with sparse data, EDAS offers a strong baseline-driven evaluation. Although there are many different MCDM techniques available, no method is always the best for every selection scenario. Since each approach employs a different computation principle (e.g., distance to ideal, pairwise comparison, average deviation) and may emphasize criteria differently, different approaches may produce different ranking results for the same problem [3, 6]. Researchers are increasingly supporting hybrid MCDM approaches, combining two or more methods to increase confidence in decision results. By combining several approaches, hybrid models can leverage each approach's advantages and reduce its drawbacks, producing more robust and reliable alternative rankings [9-12].

To ensure that both subjective preferences and objective distances are taken into account, it has become common practice to combine a weighting method such as AHP with a ranking method such as TOPSIS or VIKOR. Similarly, decision consistency can be increased and bias can be decreased by using techniques such as GRA or EDAS in conjunction with entropy or another objective weight derivation. In this regard, this study suggests a hybrid GRA-EDAS method for assessing and choosing electrode materials for spot welding in automobiles. Combining GRA and EDAS is motivated by the desire to take advantage of their complementary assessment methods; while EDAS provides an aggregate appraisal based on deviations from the average competitor, which improves the evaluation's stability and fairness, GRA can manage the relative performance assessment of each material across multiple criteria (even if the decision maker's information is ambiguous or incomplete). The hybrid model seeks to rank electrode material alternatives more thoroughly and robustly than either approach alone by combining these techniques.

In a nutshell, the suggested GRA-EDAS method functions as follows. First, a set of performance criteria (such as electrical conductivity, thermal conductivity, hardness, wear resistance, and cost) is used to assess potential electrode materials (such as different copper alloys that are frequently used in industry). The overall similarity of each material to an ideal reference material across all criteria is indicated by its Grey Relational Grade (GRC), which is determined using GRA. The positive and negative distances of each material from the average solution are determined simultaneously using EDAS, producing an appraisal score that represents its overall performance compared to the peer group. The final ranking is then determined by combining or comparing the results of the two approaches. The electrode material that provides the best balance of the desired properties for RSW applications can be determined using this hybrid evaluation [13-23].

The contribution of this study is fourfold. First, a novel integration of GRA and EDAS is introduced in the domain of material selection, which, to the best of our knowledge, has not been explored in the prior literature. Second, the hybrid model is applied to a real-world decision problem in automotive manufacturing, the selection of spot-welding electrode material, demonstrating the practical viability of the approach. Third, the study provides a literature-based rationale for the hybrid method, showing how it addresses the limitations of single-method MCDM in this context. Finally, the results provide useful information for industry professionals on the selection of electrode materials, as the GRA-EDAS evaluation points out the best material based on various service needs.

II. PROPOSED METHOD

To evaluate and rank spot welding electrode materials, this study suggests a hybrid MCDM approach that combines GRA and EDAS. Figure 1 describes the proposed framework.

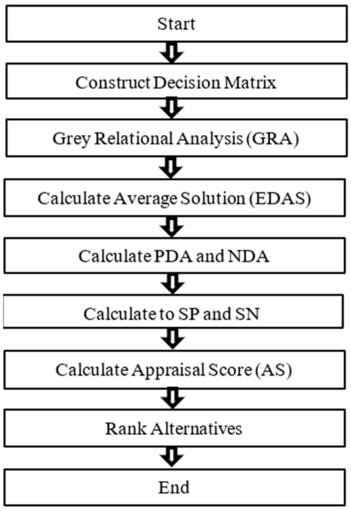

Fig. 1. The framework outlined in this study.

A. Step 1: Construction of the Decision Matrix

A decision matrix $X = (x_{ij})$ is formed, where i represents the alternatives (electrode materials) and j represents the evaluation criteria. The considered criteria include Electric Conductivity (EC), Thermal Conductivity (THC), Rockwell Hardness (RH), Yield Strength (YS), density (D), cost (C) and Wear Resistance (WR). The weights for all criteria were assigned equally by a panel comprising five experts: three specialists in industrial management and two manufacturing engineers [1, 29].

B. Step 2: Normalization of the Decision Matrix

Min-max normalization is applied to standardize data and remove dimensional inconsistency. For benefit criteria (the higher, the better, EC, THC, RH, YS, WR):

$$x'_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \tag{1}$$

For cost criteria (the lower, the better, D, C):

$$x'_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \tag{2}$$

C. Step 3: Grey Relational Analysis (GRA)

1) Step 3.1: Computation of Absolute Differences

Each normalized value x'_{ij} is compared with the ideal value x_j^* (which is 1 for benefit and 0 for cost):

$$\Delta_{ij} = \left| x_j^* - x'_{ij} \right| \tag{3}$$

2) Step 3.2: Grey Relational Coefficient (GRC)

$$\xi_{ij} = \frac{\Delta_{min} + \zeta . \Delta_{max}}{\Delta_{ij} + \zeta . \Delta_{max}} \tag{4}$$

where $\Delta_{min} = \min_{i,j}(\Delta_{ij})$, $\Delta_{max} = \max_{i,j}(\Delta_{ij})$, and ζ is the distinguishing coefficient, generally set to 0.5.

3) Step 3.3: Grey Relational Grade (GRG)

The GRG for each criterion is the average of its corresponding GRC values:

$$GRG = \frac{1}{m} \sum_{i=1}^{m} \xi_{ij} \tag{5}$$

4) Step 3.4: GRA Weight Derivation

$$w_j = \frac{GRG_j}{\sum_{j=1}^{n} GRG_j} \tag{6}$$

D. Step 4: Calculation of the Average Solution (EDAS)

For each criterion j, the average value is calculated:

$$\bar{x}_j = \frac{1}{m} \sum_{i=1}^{m} x_{ij} \tag{7}$$

E. Step 5: Computation of Positive and Negative Distances

For benefit criteria:

$$PDA_{ij} = max\left(0, \frac{x_{ij} - \bar{x}_j}{\bar{x}_j}\right),$$

$$NDA_{ij} = max\left(0, \frac{\bar{x}_j - x_{ij}}{\bar{x}_j}\right) \tag{8}$$

For cost criteria:

$$PDA_{ij} = max\left(0, \frac{\bar{x}_j - x_{ij}}{\bar{x}_j}\right),$$

$$NDA_{ij} = max\left(0, \frac{x_{ij} - \bar{x}_j}{\bar{x}_j}\right) \tag{9}$$

F. Step 6: Aggregation of Weighted Distances

The weighted sums of PDA and NDA are calculated:

$$SP_i = \sum_{j=1}^{n} w_j \cdot PDA_{ij},$$

$$SN_i = \sum_{j=1}^{n} w_j \cdot NDA_{ij} \tag{10}$$

G. Step 7: Calculation of the Appraisal Score (AS)

The final score for each alternative is calculated as:

$$AS_i = \frac{SP_i + (1 - SN_i)}{2} \tag{11}$$

H. Step 8: Ranking of the Alternatives

All alternatives are ranked in descending order based on their AS values. The alternative with the highest AS is deemed the most suitable electrode material.

III. RESULTS

A. Results of Hybrid GRA–EDAS

1) Step 1: Construction of the Decision Matrix

Eight electrode materials (C18150, C17510, C16200, C17500, C17540, 75W-25Cu, C1990, and C17200) were selected for evaluation based on seven performance criteria. Table I shows details on the attributes of the selected materials [1].

2) Step 2: Normalization of the Decision Matrix

The data were normalized using min-max normalization to ensure comparability across criteria. Beneficial criteria and cost criteria were treated accordingly and were calculated based on (1) and (2). Table II provides comprehensive details of the additional normalization of decision matrix results.

TABLE I. ATTRIBUTE DETAILS FOR THE SELECTED MATERIALS

Material	EC (S/m)	THC (W/m.K)	RH (B Scale)	YS (N/m^2)	D (kg/m^3)	C (THB)	WR
C17500	40.000	120.000	90.000	450.000	8.750	1565.200	0.860
C16200	90.000	200.000	70.000	475.000	8.890	469.560	0.500
C18150	74.000	190.000	85.000	425.000	8.890	273.910	0.680
C17510	50.000	140.000	95.000	495.000	8.890	293.480	1.000
C17200	22.000	75.000	85.000	650.000	8.250	1565.200	0.130
C17540	40.000	135.000	90.000	390.000	8.810	1956.500	0.860
75W-25Cu	40.000	100.000	95.000	670.000	14.300	2739.100	1.000
C1990	50.000	45.000	98.000	800.000	8.700	3913.000	1.000

TABLE II. NORMALIZATION OF DECISION MATRIX

Material	EC (S/m)	THC (W/m.K)	RH (B Scale)	YS (N/m^2)	D (kg/m^3)	C (THB)	WR
C17500	0.265	0.484	0.714	0.146	0.917	0.645	0.839
C16200	1.000	1.000	0.000	0.207	0.894	0.946	0.425
C18150	0.765	0.935	0.536	0.085	0.894	1.000	0.632
C17510	0.412	0.613	0.893	0.256	0.894	0.995	1.000
C17200	0.000	0.194	0.536	0.634	1.000	0.645	0.000
C17540	0.265	0.581	0.714	0.000	0.907	0.538	0.839
75W-25Cu	0.265	0.355	0.893	0.683	0.000	0.323	1.000
C1990	0.412	0.000	1.000	1.000	0.926	0.000	1.000

3) Step 3: GRA-Based Weight Determination

GRA was employed to determine the objective weights of the evaluation criteria. The analysis involved the computation of GRCs and GRGs, which were subsequently normalized to obtain the final weighting values. The calculations, as presented in Table II, were based on the formulations defined in (3) to (6).

TABLE III. GREY RELATIONAL COEFFICIENTS (GRC)

Material	EC (S/m)	THC (W/m.K)	RH (B Scale)	YS (N/m^2)	D (kg/m^3)	C (THB)	WR
C17500	0.405	0.492	0.636	0.369	0.858	0.585	0.757
C16200	1.000	1.000	0.333	0.387	0.825	0.903	0.465
C18150	0.680	0.886	0.519	0.353	0.825	1.000	0.576
C17510	0.459	0.564	0.824	0.402	0.825	0.989	1.000
C17200	0.333	0.383	0.519	0.577	1.000	0.585	0.333
C17540	0.405	0.544	0.636	0.333	0.844	0.520	0.757
75W-25Cu	0.405	0.437	0.824	0.612	0.333	0.425	1.000
C1990	0.459	0.333	1.000	1.000	0.871	0.333	1.000

TABLE IV. GRG AND GRA WEIGHT

Criteria	GRG	GRA weight
EC (S/m)	0.518	0.116
THC (W/m.K)	0.580	0.130
RH (B Scale)	0.661	0.148
YS (N/m^2)	0.504	0.113
D (kg/m^3)	0.798	0.179
C (THB)	0.667	0.149
WR	0.736	0.165

4) Step 4: Computation of Average Solution (EDAS)

The average value of each criterion across all alternatives was calculated to establish the reference solution in the EDAS method. This benchmark was subsequently used to evaluate the positive and negative distances for each alternative, as determined in (7). Table V summarizes the results of this calculation.

TABLE V. THE AVERAGE SOLUTION

Criteria	Average Value
EC (S/m)	50.750
THC (W/m.K)	125.625
RH (B Scale)	88.500
YS (N/m^2)	544.375
D (kg/m^3)	9.435
C (THB)	1596.994
WR	0.754

5) Step 5: Calculation of PDA and NDA

The Positive Distance from Average (PDA) and Negative Distance from Average (NDA) were calculated for each material to evaluate its deviation from the average solution. Materials with performance exceeding the average exhibited higher PDA values, while those underperforming relative to the average displayed higher NDA values. These calculations were performed based on (8) and (9). Table VI presents the results of the PDA matrix, and Table VII summarises the corresponding NDA matrix.

TABLE VI. POSITIVE DISTANCE FROM AVERAGE (PDA)

Material	EC (S/m)	THC (W/m.K)	RH (B Scale)	YS (N/m^2)	D (kg/m^3)	C (THB)	WR
C17500	0.000	0.000	0.017	0.000	0.073	0.020	0.141
C16200	0.773	0.592	0.000	0.000	0.058	0.706	0.000
C18150	0.458	0.512	0.000	0.000	0.058	0.828	0.000
C17510	0.000	0.114	0.073	0.000	0.058	0.816	0.327
C17200	0.000	0.000	0.000	0.194	0.126	0.020	0.000
C17540	0.000	0.075	0.017	0.000	0.066	0.000	0.141
75W-25Cu	0.000	0.000	0.073	0.231	0.000	0.000	0.327
C1990	0.000	0.000	0.107	0.470	0.078	0.000	0.327

TABLE VII. NEGATIVE DISTANCE FROM AVERAGE (NDA)

Material	EC (S/m)	THC (W/m.K)	RH (B Scale)	YS (N/m^2)	D (kg/m^3)	C (THB)	WR
C17500	0.212	0.045	0.000	0.173	0.000	0.000	0.000
C16200	0.000	0.000	0.209	0.127	0.000	0.000	0.337
C18150	0.000	0.000	0.040	0.219	0.000	0.000	0.098
C17510	0.015	0.000	0.000	0.091	0.000	0.000	0.000
C17200	0.567	0.403	0.040	0.000	0.000	0.000	0.828
C17540	0.212	0.000	0.000	0.284	0.000	0.225	0.000
75W-25Cu	0.212	0.204	0.000	0.000	0.516	0.715	0.000
C1990	0.015	0.642	0.000	0.000	0.000	1.450	0.000

6) Step 6: Aggregation to SP and SN

The weighted sums of the Positive Distance from Average (SP) and the Negative Distance from Average (SN) were calculated for each alternative using the criterion weights derived through GRA. These scores reflect the extent to which each alternative demonstrates superiority (SP) or inferiority (SN) relative to the average solution. The calculations were carried out using (10).

7) Step 7: Appraisal Score (AS) Calculation

The Appraisal Score (AS) for each alternative was computed using (11). This score reflects an integrated measure of each alternative's proximity to the ideal and distance from the worst-case scenario. Table VIII presents the results of the aggregation of SP, SN, and AS.

8) Step 8: Final Ranking of Electrode Materials

Table VIII presents the results of the final rankings. C18150 achieved the highest appraisal score (0.604) and was ranked first, followed closely by C17510 and C16200. C17200 had the lowest appraisal score (0.393).

TABLE VIII. THE AGGREGATION TO SP, SN, AND AS

Material	SP	SN	AS	Rank
C17500	0.042	0.050	0.496	4
C16200	0.283	0.101	0.591	3
C18150	0.254	0.047	0.604	1
C17510	0.212	0.012	0.600	2
C17200	0.047	0.260	0.393	8
C17540	0.047	0.090	0.478	5
75W-25Cu	0.091	0.250	0.420	6
C1990	0.137	0.302	0.417	7

B. Comparative Analysis and MCDM Validation

Table IX presents a comparative analysis and validation of the rankings obtained using the WASPAS, MAUT, and the proposed hybrid GRA-EDAS methods. It can be seen that there is a high degree of consistency among these MCDM methods, particularly at the upper and lower ends of the rankings. Specifically, C18150 and C17510 consistently occupy the first and second ranks across all methods, demonstrating their superior performance in terms of balancing the critical properties required for spot welding applications. Similarly, C17200 consistently ranks last, indicating that it is less suitable according to the criteria. However, there are some variations within the midrange rankings. In particular, C17500 is ranked fourth by WASPAS and GRA-EDAS but fifth by MAUT, while C1990 is ranked differently across methods, being fifth in WASPAS, fourth in MAUT, and seventh in GRA-EDAS. These slight differences can be attributed to the different computation principles and sensitivity to specific criterion values inherent in each MCDM method [25-28]. The strong alignment of rankings provided by the GRA-EDAS method with established approaches such as WASPAS and MAUT further reinforces its reliability and practical applicability. These results are also consistent with previous studies that applied other prominent MCDM methods, such as VIKOR and PROMETHEE, where the Cu-Cr-Zr alloy (C18150) was consistently ranked as the most suitable material for spot welding applications due to its optimal balance of critical properties (EC, THC, RH, YS, D, C, and WR) [29]. These findings validate the robustness and effectiveness of the proposed method, making it a suitable and dependable choice for electrode material selection problems in industrial contexts.

These results are further supported by the Spearman correlation matrix in Figure 2, which provides important information on the consistency and reliability of the ranking methods employed. The matrix shows that the WASPAS, MAUT, and the proposed hybrid GRA-EDAS methods are closely related, with the strongest connection between MAUT and the proposed method. These two methods are closely aligned in evaluating the relative performance of electrode materials. Specifically, the great correlation (ρ=0.833) between MAUT and the proposed method suggests that both methods produced identical ranking sequences. This high degree of concordance reinforces the validity of the hybrid GRA-EDAS approach as a robust decision-making tool. The strong relationship between WASPAS and the other methods (with ρ values greater than 0.929) shows that the rankings are consistent and emphasizes that the methods of weighing and scoring criteria are reliable across different MCDM methods. These results are important in proving that the hybrid GRA-EDAS method is strong and that the rankings it produces match well with well-known methods. The Spearman correlation matrix provides clear proof that the proposed method works well in situations where multiple criteria need to be considered, especially for choosing electrode materials in car manufacturing.

TABLE IX. COMPARATIVE ANALYSIS AND MCDM VALIDATION

Material	WASPAS	Rank	MAUT	Rank	Proposed	Rank
C17500	0.607	4	0.573	5	0.496	4
C16200	0.747	3	0.639	3	0.591	3
C18150	0.817	1	0.693	2	0.604	1
C17510	0.805	2	0.723	1	0.600	2
C17200	0.454	8	0.430	8	0.393	8
C17540	0.593	6	0.549	6	0.478	5
75W-25Cu	0.577	7	0.503	7	0.420	6
C1990	0.595	5	0.620	4	0.417	7

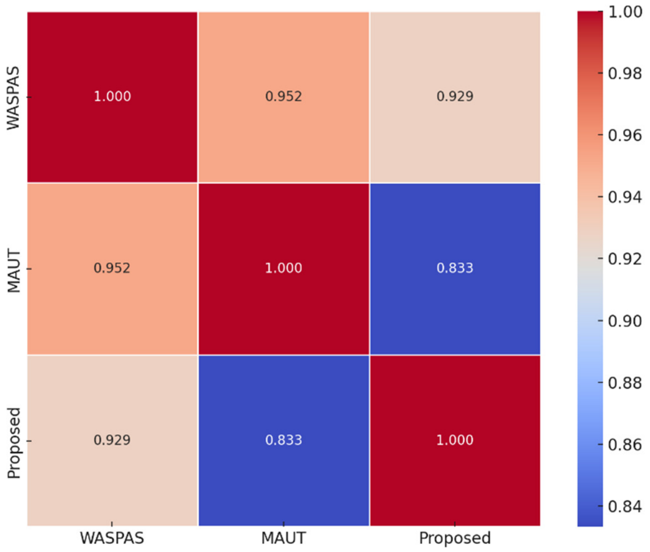

Fig. 2. Spearman correlation matrix for the electrode material rankings.

IV. CONCLUSION

This study presented a new combined method using GRA and EDAS to choose the best electrode materials for RSW in cars. By using the best parts of both methods, the hybrid GRA-EDAS approach allowed a thorough assessment of eight electrode materials based on seven important factors, such as electrical conductivity, thermal conductivity, hardness, yield strength, density, cost, and wear resistance. The results consistently identified C18150 as the most suitable material, closely followed by C17510 and C16200. The strength of the proposed approach was confirmed by comparing it with well-known MCDM methods such as WASPAS and MAUT, showing strong agreement in the results (ρ=0.833 with MAUT and ρ=0.929 with WASPAS). This shows that the hybrid GRA-EDAS method is effective and trustworthy for objectively and systematically evaluating electrode materials, especially in complicated decision-making situations in industry. The proposed framework aligns well with prior research using MCDM methods, such as VIKOR and PROMETHEE, which also highlighted the suitability of Cu-Cr-Zr-based alloys for spot welding applications. In general, this hybrid approach offers a practical, adaptable, and rigorous decision-support tool for manufacturing and engineering fields where balancing multiple performance and cost-related factors is critical.

This study effectively demonstrated the utility of the hybrid GRA-EDAS method in selecting optimal electrode materials for automotive spot welding. However, there are several avenues for future research to further develop and refine these findings. First, the incorporation of additional performance criteria, such as environmental sustainability, material recyclability, and supply chain resilience, could yield a more comprehensive evaluation framework that aligns with the principles of sustainable manufacturing. Second, extending the model to include fuzzy logic, interval-valued, or neutrosophic variants of GRA-EDAS could enhance its capacity to handle data uncertainties and the inherent imprecision of real-world decision contexts. Third, broadening the application of the proposed approach to other material selection challenges across industries such as aerospace, electronics, and biomedical engineering may offer new insights into its versatility and effectiveness. Last, the integration of machine learning or deep learning techniques with other advanced MCDM methods [24, 30-33] could facilitate the development of automated, adaptive, and data-driven decision-making systems capable of dynamically adjusting to evolving manufacturing conditions and requirements. Together, these future research directions promise to advance the state of multi-criteria material selection and contribute to the optimization of complex industrial processes.

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