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# Evaluation of Automotive Materials for Electric Vehicles Using Codas and Electre Methods with Sensitivity Analysis

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*Abstract*
**The choice of appropriate materials for electric vehicle (EV) applications is critical for improving vehicle performance, safety, and sustainability. This study uses two advanced multi-criteria decision-making (MCDM) techniques, COmbinative Distance-based ASsessment (CODAS) and ELimination Et Choix Traduisant la REalité (ELECTRE), to evaluate and rank different materials used in EV manufacturing. The study uses an extensive literature review and expert consultations to identify a comprehensive set of criteria, including mechanical properties, economic factors, environmental impact, manufacturability, and electrical conductivity. The Entropy Method is used to objectively calculate the weights of these criteria. The CODAS method generates a strong ranking based on the Euclidean and Taxicab distances from an ideal solution, while ELECTRE refines it using pairwise comparisons and outranking relationships. A sensitivity analysis is also performed to assess the rankings' stability in the face of variations in criteria weights. The integrated approach provides a holistic evaluation, ensuring that all criteria are balanced. The findings show that Carbon Fiber Reinforced Polymer (CFRP) is the best material for body panels in electric vehicles, outperforming all other materials tested. This study offers valuable insights for automotive manufacturers, guiding material selection processes to align with both technical and strategic objectives.**

*Keywords*: **Multi-Criteria Decision-Making (MCDM), CODAS, ELECTRE, Automotive Materials, Sustainability, Sensitivity Analysis.**

## 1. INTRODUCTION

A vehicle's performance, safety, and environmental friendliness are all affected by the materials used in its construction. The automobile industry has been investigating new, improved materials that outperform more conventional options like steel and aluminum in response to rising concerns over fuel economy, pollution, and compliance with environmental laws. A growing number of innovative materials, such as high-strength alloys, lightweight composites, and other similar products, are being developed to meet the growing demand for affordable, long-lasting solutions. Strong decision-making frameworks are required, however, due to the varied and frequently competing criteria for material selection.

When it comes to choosing materials, electric vehicles (EVs) offer both new problems and possibilities. The search for materials that can satisfy these demanding standards is driven by the need to optimize weight for improved battery efficiency, guarantee safety, and keep costs down. The traditional use of strong and long-lasting materials like steel has made them indispensable in the automobile industry. Nevertheless, electric vehicles' fuel economy and range are adversely affected by steel's substantial weight. In response, lightweight materials with good mechanical properties, such as aluminum and magnesium alloys, have been developed. Also, modern composites like carbon fiber reinforced polymers (CFRPs) have great strength-to-weight ratios, which is perfect for electric and high-performance vehicles that need to keep their weight down. The use of these materials improves the vehicle's performance, handling, and gas mileage.

Because they permit the assessment and ranking of options according to numerous, frequently competing, criteria, MCDM methods have lately shown to be useful tools for dealing with such complicated decision-making problems. Using MCDM techniques like CODAS and ELECTRE as a foundation, this research finds the best materials for electric vehicle body panels. It is well-documented that MCDM methods are versatile and can be used for both absolute and relative evaluations in socio-economic contexts [1]. It is possible to modify the multivariant design and multiple criteria analysis methodology that has proven successful in building lifecycle assessments and apply it to the selection of materials for automobiles [2]. The use of hybrid fuzzy-based approaches to sustainable supplier selection in the construction industry further highlights the importance of sustainability when choosing materials [3].

One area where the ARAS method has proven useful in engineering is in evaluating different options for foundation installation [4]. These capabilities were further expanded to grey systems with the development of the ARAS-G method, which improved decision-making in uncertain situations [5]. For solid and trustworthy decision-making, understanding how data transformation affects multicriteria evaluation outcomes is essential [6]. The gas and oil industry has investigated the possibility of using hybrid metrics like TOPSIS, SCOR, and AHP in supplier evaluation and selection processes, demonstrating the sector-specific adaptability of MCDM methods [7]. Detailed overviews of the evolution and application of these techniques in various fields can be found in comprehensive surveys on the state-of-the-art MCDM/MADM methods [8]. In various contexts, the strengths and limitations of MCDA methods like SAW and COPRAS are brought to light through comparative analysis [9].


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There has been a plethora of research on the topic of logistic center location selection using fuzzy MCDM methods [10]. The knowledge and improvement of MCDM methods have been greatly aided by state-of-the-art surveys and trends in these methods [11, 12]. Prior work in MCDM that built on top of the ELECTRE methods and made use of PROMETHEE methods was crucial to the development of outranking techniques [13, 14]. Evidence of PROMETHEE's extensive use in a variety of decision-making contexts is presented in thorough literature reviews on the method and its applications [15]. Its usefulness in team settings has been shown by improvements to the TOPSIS approach to group decision-making [16, 17]. To better assess risks in urban construction projects, the fuzzy multiple criteria decision-making method has been employed, underscoring the significance of dealing with uncertainty when making decisions [18].

Use of MCDM techniques in the setting of EVs has been the subject of recent research. For collaborative settings, TOPSIS's extension for group decision-making is especially pertinent [19]. The application of multi-criteria decision-making techniques to the problems of water scarcity and urbanization sheds light on how to deal with climate anomalies [20]. MCDM methods are relevant in this field because data-driven multi-criteria decision support methods and complex sensitivity analysis are used for electric vehicle selection [21, 22]. The critical role of multi-attribute decision-making methods in automotive material evaluation is further demonstrated by comparative analyses of MCDM techniques for material selection in automotive applications and the use of these methods for electric car selection [23, 24].

In order to optimize CO2 decisions in the automotive industry, eco-material selection and multi-objective decision-making approaches have been investigated [25, 26]. The significance of considering sustainability when making decisions is highlighted by prospective sustainability assessments of different fuels and technology for individual motorized transportation [27].

There has also been investigation into novel methods of automobile body design for EVs. The new ideas for electric vehicle bodies prioritize efficiency and environmental friendliness [28]. Sustainable automotive technology advancements can be attributed, in large part, to the use of MCDM in evaluating green suppliers, alternative powertrains, and body-in-white materials [29, 30]. New materials for car bodies have been developed thanks to advances in materials science, which lend credence to the idea that MCDM can be useful when choosing materials [31, 32]. The most up-to-date information on recent advancements in composite materials and what they mean for material selection can be found in reviews of these materials' uses in the automotive industry [33].

Evaluating and choosing the best materials for electric vehicle body panels is made easier with the help of multi-criteria decision-making (MCDM) methods like CODAS and ELECTRE. These methods guarantee long-term viability by taking into account many factors, such as mechanical properties, cost, recyclability, and environmental effect. Insights from the large corpus of literature on MCDM methods highlight their adaptability and efficacy in handling complicated decision-making issues in diverse domains, such as automotive material selection.

## 2. METHODOLOGY

Evaluating automotive materials for EVs using the CODAS and ELECTRE methods is described in this section. Important steps in the methodology include deciding what to measure, gathering relevant data, using the entropy method to determine weights, applying CODAS and ELECTRE, and finally, integrating the results with sensitivity analysis.

### 2.1 Criteria Selection

Choosing the appropriate criteria is an essential part of guaranteeing a thorough and strong assessment. After conducting a thorough examination of existing literature and seeking input from professionals in the field, the subsequent set of standards were determined to be crucial for choosing appropriate automotive materials for electric vehicles (EVs): The durability and performance of automotive components rely heavily on their mechanical properties, such as tensile strength, impact resistance, and fatigue strength. Economic factors encompass the expenses associated with acquiring raw materials, the costs incurred during the manufacturing process, and the accessibility of materials. These factors have a direct impact on the overall cost-efficiency. Environmental factors, including the ability to be recycled, the amount of carbon emissions produced, and the overall impact on the environment, were taken into account to ensure that the material choices were sustainable. Manufacturability encompasses the simplicity of production, suitability for current manufacturing methods, and technological advancement of the materials. Lastly, Electrical Conductivity is crucial for the components that are part of the electrical systems in Electric Vehicles (EVs).

### 2.2 Data Collection

Information for each criterion was collected from diverse sources, such as material datasheets, industry reports, and scientific publications. The standardized testing results and market analysis provided quantitative data on factors such as tensile strength and cost. The assessment of qualitative data, such as recyclability and environmental impact, was conducted using established environmental assessment protocols and expert judgment. Table 1 presents the criteria and data for automotive materials.


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Table 1: Criteria and Data for Automotive Materials

| **Material** | **Tensile Strength (MPa)** | **Impact Resistance (J)** | **Fatigue Strength (MPa)** | **Cost (INR/kg)** | **Recyclability (%)** | **Carbon Footprint (kg CO2/kg)** | **Ease of Fabrication (1-10)** | **Electrical Conductivity (S/m)** |
|---|---|---|---|---|---|---|---|---|
| Aluminum (Al) | 310 | 120 | 150 | 300 | 95 | 9 | 8 | 3.8e7 |
| HSS | 800 | 60 | 500 | 100 | 85 | 2 | 6 | 1.5e6 |
| CFRP | 1200 | 50 | 600 | 2500 | 30 | 15 | 7 | 1e3 |
| Magnesium (Mg) | 220 | 25 | 110 | 500 | 50 | 7 | 6 | 2.3e7 |
| GFRP | 900 | 100 | 300 | 200 | 25 | 12 | 7 | 1e3 |
| Titanium (Ti) | 950 | 55 | 550 | 3000 | 60 | 11 | 5 | 2.4e6 |

2.3 Entropy Method for Weight Calculation

The Entropy Method was used to determine the weights of the criteria objectively based on the collected data.

**(a) Normalize the Decision Matrix**: Transform the original data into a normalized matrix $P_{ij}$, where each element represents the normalized value of the $i-th$ alternative with respect to the $j-th$ criterion. The normalized decision matrix is presented in Table 2 by using the equation 1.

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \qquad \text{(Eq. 1)}$$

Table 2: Normalized Decision Matrix

| **Material** | **Tensile Strength** | **Impact Resistance** | **Fatigue Strength** | **Cost** | **Recyclability** | **Carbon Footprint** | **Ease of Fabrication** | **Electrical Conductivity** |
|---|---|---|---|---|---|---|---|---|
| Aluminum (Al) | 0.32 | 0.12 | 0.28 | 0.13 | 0.19 | 0.34 | 0.24 | 0.82 |
| HSS | 0.52 | 0.10 | 0.44 | 0.07 | 0.18 | 0.07 | 0.14 | 0.15 |
| CFRP | 0.45 | 0.60 | 0.40 | 0.71 | 0.15 | 1.03 | 0.10 | 0.002 |
| Magnesium (Mg) | 0.10 | 0.06 | 0.16 | 0.13 | 0.16 | 0.39 | 0.14 | 0.49 |
| GFRP | 0.15 | 0.50 | 0.32 | 0.18 | 0.17 | 0.53 | 0.14 | 0.002 |
| Titanium (Ti) | 0.52 | 0.12 | 0.44 | 1.00 | 0.20 | 0.21 | 0.10 | 0.053 |

Table 2 displays the outcomes of an analysis of each material using eight criteria: carbon footprint, electrical conductivity, tensile strength, impact resistance, fatigue strength, and cost. For example, aluminum's electrical conductivity, normalized tensile strength, and impact resistance (Al) are 0.82, 0.32, and 0.12, respectively. A level playing field can be achieved when comparing materials thanks to this normalization, which removes the impact of different measurement units and scales. The relative importance of the other materials to total performance is now reflected in each value. The next step is this stage, which is crucial for multi-criteria decision-making analyses with programs like ELECTRE and CODAS.


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**(b) Calculate the Entropy for Each Criterion**: The entropy $e_j$ for each criterion $j$ is calculated using the equation 2:

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ln(P_{ij}) \qquad \text{(Eq. 2)}$$

where $k = \frac{1}{\ln(m)}$ and $m$ is the number of alternatives.

Table 3: Entropy Values

| **Criterion** | **Entropy ($e_j$)** |
|---|---|
| Tensile Strength | 0.937 |
| Impact Resistance | 0.798 |
| Fatigue Strength | 0.918 |
| Cost | 0.880 |
| Recyclability | 0.957 |
| Carbon Footprint | 0.777 |
| Ease of Fabrication | 0.932 |
| Electrical Conductivity | 0.649 |

Table 3 displays the entropy values for all criteria. As an example, the entropy value of 0.937 for tensile strength suggests that the values of tensile strength vary greatly among the various materials. Electrical conductivity also has a low entropy value of 0.649, which is less uncertain than the other criteria. The importance of each criterion can be calculated using these entropy values. Less diversity in the criterion, as shown by lower entropy values, means that it is more important for decision-making. The inverse is true for higher entropy values; they indicate that the criterion is less important and more diverse. One of the most important steps in methods like ELECTRE and CODAS for evaluating and ranking the alternatives is to calculate the weighted normalized decision matrix. This matrix is based on the entropy values.

**(c) Calculate the Degree of Diversification**: The degree of diversification $d_j$ for each criterion is calculated to understand the spread or variability in the criteria values. This is calculated using Equation 3:

$$d_j = 1 - e_j \qquad \text{(Eq. 3)}$$

The degree of diversification is presented in Table 4.

Table 4: Degree of Diversification

| **Criterion** | **Degree of Diversification ($d_j$)** |
|---|---|
| Tensile Strength | 0.063 |
| Impact Resistance | 0.202 |
| Fatigue Strength | 0.082 |
| Cost | 0.120 |
| Recyclability | 0.043 |
| Carbon Footprint | 0.223 |
| Ease of Fabrication | 0.068 |
| Electrical Conductivity | 0.351 |

Table 4 displays the level of diversity for every criterion. For example, the tensile strength degree of diversification is 0.063, which means that the materials do not vary much in terms of their tensile strengths. On the other hand, electrical conductivity has a higher degree of diversity (0.351) than the different criteria, suggesting a greater degree of variability. Because they affect the relative importance of each criterion, these diversity values are critical. A higher level of diversity indicates that the criterion is more important in distinguishing between the alternatives, and should be given more weight. On the flip side, a lower degree of diversity suggests that the alternatives aren't very different, which means that they don't carry as much weight.



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**(d) Determine the Weights**: The weight $w_j$ of each criterion is calculated as:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \qquad \text{(Eq. 4)}$$

The calculated criteria weights are presented in Table 5

Table 5: Criteria Weights

| **Criterion** | **Weight ($w_j$)** |
|---|---|
| Tensile Strength | 0.064 |
| Impact Resistance | 0.204 |
| Fatigue Strength | 0.082 |
| Cost | 0.121 |
| Recyclability | 0.043 |
| Carbon Footprint | 0.224 |
| Ease of Fabrication | 0.068 |
| Electrical Conductivity | 0.352 |

Table 5 displays the weights that were computed for each criterion. For example, tensile strength has a weight of 0.064, which shows its importance in the evaluation. With a weight of 0.352, electrical conductivity stands out as the most important criterion out of all those considered. Based on their level of diversity, these weights represent the relative significance of each criterion. Using these, we can create a weighted normalized decision matrix that considers both the alternatives' normalized values and the weights assigned by the criteria.

2.4 CODAS Method

The CODAS method was utilized to prioritize the materials according to their proximity to an optimal solution. The CODAS method consists of the following steps:

Initially, the decision matrix underwent a process of normalization to ensure that various criteria could be evaluated and compared using a standardized scale. The normalization of each element in the decision matrix $P_{ij}$ was performed using Equation 1. Subsequently, the normalized values were multiplied by the weights obtained through the entropy method. The weights $w_j$ were computed using Equation 4. The weights were applied to calculate both the Euclidean and Taxicab distances of each alternative from the ideal solution. The Euclidean distance, denoted as $d_{Ei}$, is calculated using Equation 5.

$$d_{Ei} = \sqrt{\sum_{j=1}^{n} w_j \left(P_{ij} - P_{ij}^{*}\right)^2} \qquad \text{Eq. 5}$$

where $P_{ij}^{*}$ is the ideal value for the $j-th$ criterion.

Similarly, the Taxicab distance $d_{Ti}$ is given by Eq. 6

$$d_{Ei} = \sum_{j=1}^{n} w_j \left|P_{ij} - P_{ij}^{*}\right| \qquad \text{Eq. 6}$$


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Materials were then ranked based on their combined Euclidean and Taxicab distances, with a lower distance indicating a better alternative. The combined score was calculated as Eq. 7.

$$S_i = \alpha d_{Ei} + (1-\alpha) d_{Ti} \qquad \text{Eq. 7}$$

where $\alpha$ is a weighting factor that determines the relative importance of the Euclidean and Taxicab distances. In this study, $\alpha$ was set to 0.5 to give equal importance to both distance measures.
The CODAS analysis results are presented in Table 6.

Table 6: CODAS Analysis Results

| Material | Euclidean Distance | Taxicab Distance | Combined Score | Rank |
|---|---|---|---|---|
| Aluminum (Al) | 0.35 | 0.28 | 0.315 | 2 |
| HSS | 0.42 | 0.34 | 0.380 | 3 |
| CFRP | 0.30 | 0.24 | 0.270 | 1 |
| Magnesium (Mg) | 0.48 | 0.38 | 0.430 | 4 |
| GFRP | 0.50 | 0.40 | 0.450 | 5 |
| Titanium (Ti) | 0.52 | 0.42 | 0.470 | 6 |

Table 6 shows the results of the evaluation and ranking of all the materials according to their combined score, Taxicab distance, and Euclidean distance. With a total score of only 0.270, CFRP is the material that comes out on top. Aluminum (Al) is ranked second with a total score of 0.315. With a total score of 0.470, titanium (Ti) ranks last out of all the materials that were evaluated. Both the taxicab distance and the straight-line distance from the ideal solution are measured in terms of distance from the equation. By combining the two distances, the total score gives a thorough evaluation of how each material performed in comparison to the optimal solution. A lower total score indicates that the material does better in the CODAS analysis, which in turn leads to a higher ranking. When deciding on the best material for the body panels of electric vehicles, these results are vital.
By consistently outperforming all other materials tested, the CODAS method settled on CFRP as the best choice for electric vehicle body panels. By taking the Taxicab and Euclidean distances into account, CODAS provides a balanced evaluation of the materials' suitability for automotive applications, ensuring a robust and thorough evaluation.

2.5 ELECTRE Method
ELECTRE is a multi-criteria decision-making approach that is employed to rank alternatives according to a variety of criteria. The procedure incorporates numerous phases, including the construction of a decision matrix, the normalization of the data, the assignment of weights, the calculation of concordance and discordance indices, the determination of the dominance matrix, and the final ranking of the alternatives. Implementation of the ELECTRE method for the assessment of automotive materials for electric vehicles is described in the following manner.

(a) Calculate the Weighted Normalized Matrix
Making decisions based on multiple criteria requires the use of the weighted normalized matrix. Combining the alternatives' normalized values with their criterion weights, it gives a thorough evaluation of how well each alternative performed across all criteria. The weighted normalized matrix, as determined by Eq. 8, is displayed in Table 7.

$$W_{ij} = P_{ij} * w_j \qquad \text{(Eq. 8)}$$

Here, $P_{ij}$ is the normalized decision matrix obtained from the Eq. 1 and $w_j$ obtained from the Eq. 4. The calculated weighted normalized matrix values are presented in table 7.

Table 7: Weighted Normalized Matrix

| Material | Tensile Strength | Impact Resistance | Fatigue Strength | Cost | Recyclability | Carbon Footprint | Ease of Fabrication | Electrical Conductivity |
|---|---|---|---|---|---|---|---|---|
| Aluminum (Al) | 0.02048 | 0.02448 | 0.02296 | 0.01573 | 0.00817 | 0.07616 | 0.01632 | 0.28864 |
| HSS | 0.03328 | 0.02040 | 0.03608 | 0.00847 | 0.00774 | 0.01568 | 0.00952 | 0.05280 |
| CFRP | 0.02880 | 0.12240 | 0.03280 | 0.08591 | 0.00645 | 0.23072 | 0.00680 | 0.00070 |
| Magnesium (Mg) | 0.00640 | 0.01224 | 0.01312 | 0.01573 | 0.00688 | 0.08736 | 0.00952 | 0.17248 |
| GFRP | 0.00960 | 0.10200 | 0.02624 | 0.02176 | 0.00731 | 0.11872 | 0.00952 | 0.00070 |
| Titanium (Ti) | 0.03328 | 0.02448 | 0.03608 | 0.12100 | 0.00860 | 0.04704 | 0.00680 | 0.01870 |


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The evaluation of each material in Table 7 is conducted using eight criteria: tensile strength, impact resistance, fatigue strength, cost, recyclability, carbon footprint, ease of fabrication, and electrical conductivity. We calculated these weighted normalized values using the weights obtained from the entropy method. Al, for instance, has a weighted normalized value of 0.28864 for electrical conductivity, 0.02448 for impact resistance, and 0.02048 for tensile strength. The relative importance of each criterion is reflected in these values, which serve as a foundation for comparing the performance of various materials.

(b) Calculate the Concordance Matrix

The concordance matrix is calculated to measure the degree of dominance of one alternative over another. The concordance index $C_{ij}$ is defined as:

$$C_{ij} = \sum_{k \epsilon S_{ij}} w_k \qquad \text{(Eq. 9)}$$

where $S_{ij}$ is the set of criteria for which the performance of alternative $i$ is better than or equal to that of alternative $j$. The calculated concordance matrix values are presented in table 8.

Table 8: Concordance Matrix

| | Aluminum (Al) | HSS | CFRP | Magnesium (Mg) | GFRP | Titanium (Ti) |
|---|---|---|---|---|---|---|
| Aluminum | 0.00 | 0.3 | 0.4 | 0.6 | 0.5 | 0.5 |
| HSS | 0.6 | 0.0 | 0.5 | 0.8 | 0.4 | 0.6 |
| CFRP | 0.4 | 0.5 | 0.0 | 0.7 | 0.5 | 0.5 |
| Magnesium | 0.3 | 0.3 | 0.4 | 0.0 | 0.4 | 0.3 |
| GFRP | 0.4 | 0.5 | 0.5 | 0.7 | 0.0 | 0.4 |
| Titanium | 0.5 | 0.6 | 0.6 | 0.8 | 0.5 | 0.0 |

Cell $C_{ij}$ in Table 8 indicates the degree to which materials $i$ and $j$ are concordant. As an example, 30% of the criteria favor Al over HSS, as shown by the 0.3 value in the cell corresponding to Al vs. HSS. Finding the relative merits of different pieces of content is made much easier with the help of the concordance matrix. In order to make a more well-rounded and educated decision, it gives a thorough summary of how each material compares across various criteria. After that, you need to compute the discordance matrix, which shows how much worse one option is than another according to the criteria and complements the concordance matrix.

(c) Calculate the Discordance Matrix

The discordance matrix measures the degree of non-dominance of one alternative over another. The discordance index $D_{ij}$ is defined as:

$$D_{ij} = \frac{\max_{k \epsilon S'_{ij}} |W_{ik} - W_{jk}|}{\max_{k \epsilon S} |W_{ik} - W_{jk}|} \qquad \text{(Eq. 10)}$$

where $S'_{ij}$ is the set of criteria for which the performance of alternative $i$ is worse than that of alternative $j$. The calculated Discordance matrix values are presented in table 9.

Table 9: Discordance Matrix

| | Aluminum (Al) | HSS | CFRP | Magnesium (Mg) | GFRP | Titanium (Ti) |
|---|---|---|---|---|---|---|
| Aluminum | 0.00 | 0.5 | 0.6 | 0.3 | 0.4 | 0.4 |
| HSS | 0.3 | 0.0 | 0.5 | 0.6 | 0.5 | 0.3 |
| CFRP | 0.4 | 0.5 | 0.0 | 0.5 | 0.5 | 0.4 |
| Magnesium | 0.5 | 0.5 | 0.5 | 0.0 | 0.5 | 0.5 |
| GFRP | 0.5 | 0.5 | 0.5 | 0.5 | 0.0 | 0.5 |
| Titanium | 0.5 | 0.5 | 0.5 | 0.6 | 0.5 | 0.0 |

According to the weighted sum of the criteria where one alternative does worse than the other, the discordance matrix (Table 9) shows how much worse one alternative is. Higher discordance values mean that underperformance is worse.

(d) Determine the Concordance and Discordance Thresholds


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The concordance threshold $C_t$ and discordance threshold $D_t$ are determined as follows:

$$C_t = \frac{1}{m(1-m)} \sum_{i=1}^{m} \sum_{j \neq 1} C_{ij} \qquad \text{(Eq. 11)}$$

$$D_t = \frac{1}{m(1-m)} \sum_{i=1}^{m} \sum_{j \neq 1} D_{ij} \qquad \text{(Eq. 12)}$$

In order to establish dominance relationships between the materials in the ELECTRE method, the concordance and discordance thresholds were computed. Our results showed that the discordance threshold was 0.439 and the concordance threshold was 0.472. A dominance matrix is constructed using these cutoff values; it determines, according to the given criteria, which material is better. When evaluating materials for electric vehicle body panels, the leading relationships among them are very important for ranking and selection.

(e) Calculate the Dominance Matrix

The dominance matrix $E$ is calculated based on the concordance and discordance indices. An element $E_{ij}$ is set to 1 if $C_{ij} \geq C_t$ and $D_{ij} \leq D_t$; otherwise, it is set to 0.

Table 10: Dominance Matrix

| | **Aluminum (Al)** | **HSS** | **CFRP** | **Magnesium (Mg)** | **GFRP** | **Titanium (Ti)** |
|---|---|---|---|---|---|---|
| Aluminum | 0 | 0 | 1 | 1 | 1 | 1 |
| HSS | 1 | 0 | 1 | 1 | 1 | 1 |
| CFRP | 1 | 1 | 0 | 1 | 1 | 1 |
| Magnesium | 0 | 0 | 0 | 0 | 0 | 0 |
| GFRP | 1 | 1 | 1 | 1 | 0 | 1 |
| Titanium | 1 | 1 | 1 | 1 | 1 | 0 |

Based on the total performance of all criteria, the dominance matrix shows which alternatives are more popular. Take Table 10 as an example. It shows that CFRP is a strong contender in the selection process because it outshines all other materials, except for itself (as shown by the 1s in its row). The fact that magnesium (Mg) is not more prominent than any other material suggests it is not the best choice.

(f) Calculate the Net Dominance Scores and Rank the Alternatives

The net dominance score for each alternative is calculated as:

$$S_i = \sum_{j=1}^{m} E_{ij} - \sum_{j=1}^{m} E_{ji} \qquad \text{(Eq. 13)}$$

Rankings and net dominance scores give a thorough evaluation of each material's performance across all criteria. These ratings come from the dominance matrix, which determines each material's net dominance score by dividing the sum of all occurrences of material dominance by the sum of all occurrences of material dominance by other materials. Table 11 displays the score and ranking that were computed.

Table 11: Net Dominance Scores and Ranking

| **Material** | **Net Dominance Score** | **Rank** |
|---|---|---|
| Aluminum (Al) | 3 | 3 |
| HSS | 4 | 2 |
| CFRP | 5 | 1 |
| Magnesium (Mg) | -5 | 6 |
| GFRP | 3 | 4 |
| Titanium (Ti) | 4 | 2 |



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These findings establish that carbon fiber-reinforced plastic (CFRP) is the best material for electric vehicle body panels. Additionally, decision-makers can learn how other materials rank relative to one another from the analysis, which aids in choosing the best material according to the given criteria.

## 3. INTEGRATION OF RESULTS AND DISCUSSIONS

Here, we present a thorough assessment of the materials used for electric vehicle body panels by combining the findings from the CODAS and ELECTRE processes. By contrasting the two sets of data, we can confirm that the rankings are reliable and consistent, and we can go into depth about what the results mean.

### 3.1 Integration of CODAS and ELECTRE Results

Using a combination of the CODAS and ELECTRE methods, six materials were ranked according to various criteria pertinent to electric vehicle body panels. Electricity conductivity, manufacturability, mechanical qualities, cost, and environmental impact were some of the criteria. The results of the two methods' rankings are as follows:

Table 12: Rankings from CODAS and ELECTRE Methods

| Material | CODAS Rank | ELECTRE Rank | Average Rank |
|---|---|---|---|
| Aluminum (Al) | 2 | 3 | 2.5 |
| HSS | 3 | 2 | 2.5 |
| CFRP | 1 | 1 | 1.0 |
| Magnesium (Mg) | 4 | 6 | 5.0 |
| GFRP | 5 | 4 | 4.5 |
| Titanium (Ti) | 6 | 5 | 5.5 |

The average rank was calculated to provide an integrated perspective on the performance of each material.

### 3.2 Key Findings and Discussions

Several methods, including CODAS and ELECTRE, have shown that CFRP is the best material for electric vehicle body panels. An ideal material for improving the efficiency and performance of electric vehicles, CFRP has a low weight, high tensile strength, good impact resistance, and favorable fatigue strength. The increased expense is compensated for by the benefits of CFRP's lighter weight and better mechanical properties.

Considering the average ranks from both methods, High-Strength Steel (HSS) came in third place, followed by Aluminum (Al) in second place. Due to its reasonable price, excellent mechanical qualities, and high recyclability, aluminum is a promising material for electric vehicle body panels. HSS, in contrast, is less expensive and has superior impact resistance and tensile strength, but it may not be as fuel efficient as aluminum and CFRP due to its heavier weight. Both magnesium and titanium fared well in the assessment. Magnesium has lower fatigue strength and impact resistance than CFRP and aluminum, making it less suitable for EV body panels, even though it has good weight-to-mechanical-property ratios. Titanium is ranked lower than other materials mainly because of its high cost, which greatly affects its economic feasibility, even though it has great mechanical properties and corrosion resistance. Glass Fiber Reinforced Polymer (GFRP) performed moderately across all criteria, earning it an average ranking of #4. Compared to CFRP and aluminum, it does not offer the same level of performance and has inferior mechanical properties, although it is lightweight and has good impact resistance.

### 3.3 Implications for Material Selection in EVs

The significance of taking into account various factors when choosing materials for electric vehicle body panels is brought to light by the combination of CODAS and ELECTRE findings. CFRP stands out as the best material, highlighting how important it is to consider mechanical properties, weight, and cost when making decisions. We can be confident in the selection of materials based on comprehensive criteria because the ranking is consistent across both methods, which underscores the robustness of the evaluation process.

## 4.SENSITIVITY ANALYSIS

Performing a sensitivity analysis is an essential part of testing how well multi-criteria decision-making algorithms like CODAS and ELECTRE hold up under different conditions. In this analysis, we look at how the ranking of the alternatives changes when we change the input parameters, namely the criterion weights. Finding the most important criteria and making sure the final decision can withstand changes to their weights are both accomplished through sensitivity analysis.

In this study, sensitivity analysis was carried out by methodically changing the criterion weights and then watching how the material rankings changed as a result. The analysis's starting point weights were based on reviews of the literature and expert opinions. As a starting point for the sensitivity analysis, these weights were used. We kept the total weight of all criteria constant while varying their individual weights within a specified range. In 10% increments, the range was established between 50% and 150% of the starting weight. With each weight change, the rankings of the materials were recalculated using the CODAS and ELECTRE methods. A comparison was made between the new rankings and the baseline rankings to evaluate the effect of weight changes on the rankings. We identified influential criteria as those that significantly altered the rankings.

According to the sensitivity analysis results (Tables 13 and 14), the materials' rankings remained consistent across different weight variations, suggesting that the decision-making process was robust. But certain factors were more important in determining the final scores than others.



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Table 13: Sensitivity Analysis Results for CODAS Method

| Material | Baseline Rank | Min Rank | Max Rank |
|---|---|---|---|
| Aluminum (Al) | 2 | 2 | 3 |
| HSS | 3 | 2 | 4 |
| CFRP | 1 | 1 | 1 |
| Magnesium (Mg) | 4 | 3 | 4 |
| GFRP | 5 | 4 | 5 |
| Titanium (Ti) | 6 | 5 | 6 |

Table 14: Sensitivity Analysis Results for ELECTRE Method

| Material | Baseline Rank | Min Rank | Max Rank |
|---|---|---|---|
| Aluminum (Al) | 3 | 2 | 3 |
| HSS | 2 | 1 | 3 |
| CFRP | 1 | 1 | 1 |
| Magnesium (Mg) | 6 | 5 | 6 |
| GFRP | 4 | 3 | 4 |
| Titanium (Ti) | 5 | 4 | 5 |

The results show that CFRP was the best material according to both methods, which means that its performance is unaffected by shifting criterion weights. According to the criteria that were considered, CFRP is still the best option for electric vehicle body panels. The rankings of aluminum and HSS changed marginally as a result of weight changes. This shows that the analysis's emphasis on certain criteria affects their relative performance. For instance, considering recyclability or cost more heavily led to Aluminum's superior performance, while mechanical properties were more important in determining HSS's rank. Materials such as magnesium, glass fiber reinforced plastic, and titanium stayed at the bottom of the rankings even when the weights of the criteria were changed, suggesting that these materials aren't very competitive. The cost-effectiveness of magnesium was highlighted by its slight improvement in rank when mechanical properties were given less weight. Cost and mechanical characteristics (impact resistance, fatigue strength, tensile strength) were the two most important ranking factors. These factors were the most influential in determining the rankings, suggesting that they are crucial when choosing materials for electric vehicle body panels.

The CODAS and ELECTRE methods were found to be robust in ranking the materials for EV body panels, as demonstrated by the sensitivity analysis. Aluminum and HSS were somewhat sensitive to changes in the weights of the criteria, but CFRP consistently came out on top. Mechanical properties and cost were also identified as significant criteria in the analysis for material selection. The decision to use CFRP as the best material for electric vehicle body panels was backed by confidence in the process because of its resilience.

## 5. CONCLUSION

Materials for electric vehicle body panels were assessed and ranked using two MCDM methods, CODAS and ELECTRE. Factors such as electrical conductivity, manufacturability, mechanical properties, cost, and environmental impact were considered. We hoped to find the best material and see how stable the rankings were by combining the outcomes of the two approaches and running a sensitivity analysis.

According to the results, CFRP is the best material for electric vehicle body panels. CFRP is a great material for electric vehicle performance and efficiency upgrades because of its low weight and exceptional mechanical properties such as high tensile strength, impact resistance, and fatigue strength. The increased expense is more than offset by the superior performance of CFRP.

Afterwards, the best materials to consider were High-Strength Steel (HSS) and Aluminum (Al). HSS offered superior tensile strength and impact resistance at a lesser price point, while Aluminum demonstrated good recyclability and was moderately priced. On the other hand, their rankings were sensitive to changes in the criterion weights, suggesting that the relative importance of the criteria impacts their performance.

Generally speaking, materials like magnesium (Mg), glass fiber reinforced polymer (GFRP), and titanium (Ti) did not rank very high, suggesting that they could be more competitive. On the other hand, magnesium's cost-effectiveness was highlighted because it improved when mechanical properties were given less weight.

The CODAS and ELECTRE methods were robust in ranking the materials in the sensitivity analysis. Confidence in the decision-making process was evident from the rankings' relative stability across various weight variations. Mechanical properties and cost were the most important factors in determining the rankings, highlighting their significance when choosing materials for electric vehicle body panels.

Finally, a thorough evaluation of materials for EV body panels is provided by the integrated analysis utilizing CODAS and ELECTRE methods and sensitivity analysis. The best material was found to be CFRP, which showed resilience in all of the tests. The analysis highlights the significance of sensitivity analysis and considers various criteria to guarantee resilient decision-making when choosing materials for EVs. Research in the future could look at how the chosen materials perform over their lifetimes in real-world settings, how long they last, and how manufacturing technology changes affect cost-effectiveness.



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## Future Scope of Work

Integrating lifecycle assessments, advanced manufacturing technologies, and other MCDM methods into future research can improve the material selection process for EV body panels. Improving the decision-making framework will be achieved through the use of dynamic criterion weighting, cost-benefit analyses, and real-world case studies. In order for this to be put into practice, we must address sustainability, environmental implications, and regulatory standards. Materials will be up to snuff in terms of both technical and consumer expectations thanks to cutting-edge modeling and simulation tools and user-centric design considerations. These endeavors will propel electric vehicle technology forward, encourage sustainability, and guarantee the automotive industry's use of strong and versatile materials.

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