



Malaysian Journal on Composites Science and Manufacturing

Journal homepage:
<https://karyailham.com.my/index.php/mjcsdm/index>
ISSN: 2716-6945



A TOPSIS-Based Multi-Criteria Decision Framework for Mechanical Characterization of Polymer Matrix Composites

Raffi Mohammed^{1, *}, Santhi Sree Nerella², Prasad Babu Bairysetti³, Chiranjeevi Aggala³, Subhani Mohammed⁴, Hari Hara Kumar³

¹ Faculty of Mechanical Engineering, Ramachandra College of Engineering (A), Vatluru Village, Eluru, West Godavari Dist., Andhra Pradesh-534007, India, Affiliated to JNTUK-Kakinada

² Faculty of Mechanical Engineering, Matrusri Engineering College, Hyderabad, Telangana State, India-500059

³ Faculty of Computer Science and Engineering, Ramachandra College of Engineering (A), Vatluru Village, Eluru, West Godavari Dist., Andhra Pradesh-534007, India, Affiliated to JNTUK-Kakinada

⁴ Faculty of Mechanical Engineering, Sasi Institute of Technology & Engineering, Tadepalligudem, West Godavari District, Andhra Pradesh-534101, India

ARTICLE INFO

Article history:

Received 26 October 2025

Received in revised form 21 November 2025

Accepted 21 November 2025

Available online 30 November 2025

Keywords:

Polymer Matrix Composites (PMCs), Multi-Criteria Decision-Making (MCDM), TOPSIS, Mechanical Properties, Tensile Strength, Modulus, Impact Strength, Interlaminar Shear Strength (ILSS), Carbon-Based Fillers, Bio-Fillers, Material Selection, Composite Optimization, High-Stress Applications.

ABSTRACT

This study introduces a structured method for evaluating and prioritizing polymer matrix composites (PMCs) using Multi-Criteria Decision-Making (MCDM) techniques, specifically the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). By incorporating mechanical properties such as tensile strength, modulus, impact strength, and interlaminar shear strength (ILSS), it offers a comprehensive framework for material assessment that goes beyond previous research which focused on limited properties or traditional methods. The research emphasizes the impact of different types and amounts of fillers on the performance of composites. Carbon-based fillers like BoA and CFACP consistently ranked higher due to their exceptional ILSS and impact strength, highlighting their superiority in high-stress applications. On the other hand, bio-fillers such as Marble Powder and Rice Husk Ash showed weaker mechanical properties and lower rankings. These findings provide valuable insights for professionals in industry, research, and academia, helping them select materials tailored for specific applications. By using TOPSIS in the MCDM framework, this study advances material science methodologies and demonstrates the benefits of evaluating materials based on multiple properties. The superior performance of carbon-based fillers compared to bio-fillers is essential for optimizing PMCs in high-stress environments. This research not only assists in the selection of advanced materials but also contributes to the ongoing development of material science, promoting innovation in both industrial and academic settings.

* Corresponding author.

E-mail address: mechhod03@gmail.com (Raffi Mohammed)

E-mail of co-authors: nerellasanthi@gmail.com, prasadb1420@gmail.com, chiranjeevi.aggala@gmail.com, subhani86@gmail.com, harikumar1210@gmail.com

<https://doi.org/10.37934/mjcsdm.18.1.117>

1. Introduction

Materials, in general, and composite materials, in particular, have become indispensable in various industries. Among composite materials, polymer matrix composites are at the forefront of this demand due to their widespread applications in diversified industries, such as aerospace, marine, automotive, construction, electronics, sports goods, biomedical, and materials handling systems, among others. In this scenario, selecting a composite material for specific applications has become a demanding task. Hence, for the efficient selection of composites among many available options, one should rank them with the help of available characterization techniques [1].

The mechanical properties of materials are paramount to the quality and performance of the materials. They are essential and important for service. The problem is that the multitude of mechanical properties tends to pose a huge number of criteria for decision-making, which calls for elegant alternatives. To be specific, two chief shortcomings in past studies are; 1) a small number of properties considered, and 2) practicing classical MCDM techniques focused on problems of the 1980s. That is the main reason why the recent study has deliberately aimed at determining a single synthetic ranking index that will integrate several mechanical properties and indicate the materials' behaviors from various ranks. To set analytical priorities in the industry that demonstrate the optimum composites, the numerical example showed that only one extension was used. The defined ranked composites could aid in managerial decision-making about which alternatives differentiate products or solutions [2].

Nowadays, the extensive use of polymer composites in various industries has led to rapid and massive industrial production, which in turn has led to more research being done in terms of the implementation of scientific knowledge to provide managers with appropriate information for the selection of the best material. Composite selection is one of the critical issues in the successful utilization of these advanced materials for various applications. The development of decision-making problems promotes identifying, introducing, and implementing process models using mathematical, economic, and statistical theories [3,4]. Multi-criteria decision-making (MCDM) is a method originated in engineering science, business administration, and social science for the process of determining choices from a large number of alternatives involving evaluating and ranking many conflicting criteria. When several dimensions are considered in making a particular decision, MCDM techniques play an important role in the decision-making process to find a real and optimal solution to the problem [5,6].

When it is necessary to make a decision, people use their experiences and all the resources to select the most suitable solutions. However, it is very difficult and also not practical to handle all the pros and cons of the criteria that are considered in making a particular decision. For instance, in the evaluation and selection of steel manufacturing technologies for steel producers, depending on different levels of economic, technical, environmental, and political outputs, a total of 22 criteria were designed [7,8]. In these cases, decision-makers require a scientifically objective criterion to ensure they find the most appropriate solution and to develop a transparent decision-making process. The effect of selected cutting parameters and machining environments on the performance of commercial M35 HSS by considering two conflicting criteria: wear behavior and cutting force on the tool. The outcomes are shown in rank order according to the method and the selection of the most convenient method [9,10].

The current section provides a logical review of the well-known multi-criteria decision-making techniques, which are widely used for composite ranking since they require a comprehensive evaluation of the considered projects according to several criteria and by using a decision matrix. These include the most popular methods, namely, TOPSIS, ELECTRE, PROMETHEE, and VIKOR. Their

advantages and disadvantages are further highlighted. Consequently, the conceptualization of the technique for order preference by similarity to an ideal solution in the MCDM paradigm is provided, followed by a brief description [11,12].

The success of the chosen method mainly depends on the clarity of the criteria that have been formulated and the availability of data. The purpose of the current section is to provide a logical review presentation of the methods to a broad audience considering the wide variety of composite ranking techniques. The chosen methods include the technique for order preference by similarity to an ideal solution, the elimination and choice translating reality, the preference ranking organization method for enrichment evaluation, and the compromise ranking method [13]. These are the most popular multi-criteria decision-making methods so far that have attracted considerable attention and debate. However, there is not a common agreement on the superiority of one technique over another. All these techniques seem to have unique advantages that are peculiar to the specific problem conditions [14].

The Technique for Order of Preference by Similarity to Ideal Solution method is adopted for ranking the polymer matrix composites according to the best set of mechanical characteristics obtained. The properties include compressive, tensile, and flexural strength, modulus, and strain. The sampling of the preferences given in an interval scale and cardinal scale was also implemented. The sensitivity analysis is carried out. The results from the sensitivity analysis showed that the TOPSIS ranking method is found to be a simple and easy-to-use procedure, next to PCA. Properties like tensile modulus, tensile strength, and flexural strength were found to be the most influencing properties when composites are subjected to different kinds of loadings, but rankings generally remain unchanged. The Technique for Order of Preference by Similarity to Ideal Solution approach for polymer matrix composites test data confirms the rankings in the Indian context [15,16].

Let X is an $m \times n$ decision matrix associated with a decision maker and a set of alternatives (minimum or maximum possible). Here, typically m alternatives are ordered according to preferences. The defined geometric, arithmetic, and cardinal scale data should be numerically represented by m_1, m_2, \dots, m_n levels, respectively, which can be, for example, the effect of the solution of a j -th alternative over the i th criterion, or on a scale determined contextually. Based on these preferences, in order to generate a composite index associated with each alternative, usually classes can be applied. These coefficients can be stated such that more criteria (volume, density, tensile, compressive strength, modulus, and strain) are normalized in respect; therefore, the original preferences can be directly used to generate the overall ranking [17].

2. Methodology

Ordering or ranking does not necessarily mean that a distinct comparison has been made among the alternatives. The need to rank the alternatives arises in most decision-making processes, and a recent tool for achieving this is Grey Analysis. In some situations, the practical decision-making problem can be very complex, and analytical problems may not be solved by single or imprecise criteria. When the problem is of a multi-criteria decision-making (MCDM) type, in which the relations between the available possibilities and the objectives of the study are significantly complex and uncertain, priority, or other relations are not well defined, or the decision boundary is fuzzy, there are many methods and techniques that can be used. In this chapter, we discuss a comparative analysis (ranking) of the best available properties of polymers and polymer matrix composites based on the data obtained from both the materials property database and testing laboratory [18].

The data are performing the Multi-Criteria Design Methods (MCDM) such as the PROMETHEE method to assist in composite material selection, modeling purposes, and the assessment of their

performance, in comparison to polymers for potential applications in 3D printing and rapid prototyping. A method called the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is also used to create a polynomial model and, thus, create the composite ranking. When two options are given, the best one has been chosen based on input data: performance of desired properties and the related properties which represent interactions and interdependence of material properties, selection criteria, and influential factors, within the grey area, mostly in real environment conditions. We are exploring a single optimal solution, a multi-optimal model, models within a single grey area, and models within two different grey areas, which represent both the best and normal condition performance combined [19].

2.1 Data Collection

Data collection for the league plays a basic part in this study. We had to obtain extensive mechanical knowledge of several types of polymer composites, such as the elastic parameters, ultimate strength, and elongation. In the MCDM technique, small sources of data can lead to the destruction of the outcome of the procedure, so our project aims to consider data from a number of perspectives. The detailed steps of the strategy used herein are as follows. Varieties of data sources have been prepared to obtain the raw information. These options consist of conducted experiments, various databases releasing individual papers in the specialized area, market and technical reports, and data released by the corporation covering products' properties. Data in the most needed values will be accessed from these databases and by undertaking analysis of papers provided. Checklist criteria have been used to classify the data to be accessed. Components to be assessed for the data include all of the following: reliability, admissibility, source, credit, etc. All the criteria thus considered are presumed. The raw information collected is organized to be transformed into a structural array. The use of databases would help obtain comprehensive measurable properties, while papers would provide great application-specific insights [20]. The information gained from the data sources can have a significant effect on the decision-making process. The more comprehensive the data, the stronger the decision, as the efficiency of decision-making relies nearly solely on the reliability of the criteria concerned. As a result, the decision output generated will be stronger. Furthermore, because the paper aims to discuss the usage of the MCDM methodology in the creation of the composite ranking, this methodology outlines data collection. There were a couple of challenges encountered while collecting the data. A quantity of the time, unobtainable raw data had to be processed or was split into the main material and a range of various research samples, causing severe difficulty in finding the raw data for the papers. Nevertheless, striving to calculate what can be evaluated led to a large amount of fresh knowledge and data being received. To maintain consistency, general exclusions were enforced in the other computational exercises when the conditions of the raw data either did not meet the given standards explicitly according to the raw evaluation or further inquiries concerning the measurement could have improved the validity of the data [21].

2.2 Selection of Criteria

Polymer matrix composites must be evaluated in terms of their properties such as tensile, flexural, impact, hardness, and water absorption, as well as water contact angle. Additionally, polymers may expand or swell in the matrix on a molecular level. Since the aim is to determine a ranking between the composites, it is required to use a range of mechanical properties that characterize the behavior of the polymer composite, such as elasticity, tensile strength, ultimate tensile strength, Tg, elongation at break, impact strength (Charpy), and impact strength (Izod). It is

important to establish the properties to be determined in relation to existing standards and industrial requirements. The standard makes the following recommendations for determining the tensile strength and modulus of elasticity [22].

Since TOPSIS is a multi-criteria decision method, it considers multiple criteria to compare various alternatives. Therefore, it is necessary to consider both qualitative and quantitative criteria for the options. Thus, we considered the following three qualitative criteria: type of the polymer matrix, reinforcement filler, and the standard in which specifications on the required mechanical properties are outlined. We have set several quantitative criteria. These are related to the following mechanical properties of the composites: tensile strength, tensile modulus of elasticity, ultimate tensile strength, T_g , elongation at break, impact (Charpy), impact (Izod), density, water absorption, water contact angle, visual aspect (roughness), and Knoop hardness. Selection factors for certain mechanical characteristics, as criteria, are also established based on market feedback on PCM and their mechanical properties. The selection of the criteria, as mentioned above, was developed based on the results of our discussions with industry specialists. Commissioning is a complex issue, and it is important not to forget their propensities, our individual capabilities, our senses, and our habits. This highlights the need to qualify and search for fair and balanced criteria for the judgment of the chosen alternatives that can not only be quantified but also qualified. Choosing the right criteria is the heart of the process in the analytical-hierarchical method and the theoretical ranking method. The TOPSIS method is sensitive to the high-quality criteria chosen to score and order the selected alternatives. Consideration should also be given to both qualitative and quantitative criteria that must be established in the case of a matrix. Although the materials were tested for mechanical properties, the results were not taken into account in the final rankings. It is important not to consider criteria for which the results are incomplete or unexplored [23].

2.3 Normalization and Weight Assignment

Normalization In the process of normalizing, the different criterion data, which are diverse in their units, ranges, and magnitudes, are converted into corresponding ratios to make a relative comparison among different measures. In contrast, this makes the measurements of diverse applicability easy to elaborate using an able way. In general, either of the two kinds of normalization techniques given below is useful to put forward when the criteria are normalized: vector normalization and linear normalization. The vector normalization makes the highest absolute value for each polymer matrix composite equal to one, whereas all other elements of the vector are scaled in proportion. The need for linear normalization is to indicate the reflection of an unusual adverse value that confers the greatest disadvantage to a polymer matrix composite [24].

Almost all multi-criteria decision-making methods for the evaluation of materials consider either common or criteria weights. The necessity of sorting out the weights is extremely important, as each criterion has a large influence on the resultant priority ranking of polymer matrix composites. The applicability of the various developed methods depends to a large extent on the subjective opinion of the decision maker. Dealing with experts not only affects the credibility and accuracy of the experts' judgment but also results in bias toward a limited management sector. Several techniques for eliciting the weights have been suggested, including expert judgment, using historical data at hand, the Delphi method, the Analytical Hierarchy Process, statistical analysis, and machine-learning algorithms. The importance of selecting an appropriate method of assignment prerequisite is to maximize weight precision while maintaining a robust methodology, enabling replication or minimizing the potential for biased results. There is a direct relationship between converting the criterion components to a unit-free number and weighting each criterion. The higher the relative

weight in the aggregated rank is, the more the influence in the T-Rank alternative mechanism of the value is a result of a carefully judged result of the value. The research is challenging, and individuals use different and competing methodologies, demonstrating the variable steps that can be used to prioritize alternatives in applications. Despite these accepted standard weighing steps, they are designed to help decision-makers, and the best approach is best suited to their decision-making environment. In this phase, the “normalization” and “weighting” techniques are applied in the development of the T-rank alternatives of the Polymer Matrix Composites [25,26]. Both steps could be problematic because they are based on the aggregate scale for materials that are dependent on the nature of the materials under consideration, the subjective assessment, and uncertainty in the measurement of an individual design constraint. The variances in the access of these processes could lead to different rankings, even though the same materials are presented in the same evaluation matrix, without the use of a standard procedure. Thus, in order for the results to be interpreted with confidence, it is critical for the decision-makers approaches to develop a listing in a careful, objective manner and the methodology followed [27-29].

2.4 Application of TOPSIS

Using V and W, we calculated the best and worst performances for the matrix by using equations. Finally, to find the separation measures for each of the alternatives from a linear transformation of the Euclidean distance of each composite alternative from the best and worst alternatives, the 'Separation Measures' for a matrix of order n, i.e., to calculate R_{si+} and R_{si-} , for which we calculate a 'Closeness Coefficient' using equations. A detailed procedure to apply the TOPSIS method to the concerned composites is given in the following subsections.

Application of TOPSIS In this subsection, an illustrative example demonstrating the application of the TOPSIS method is presented in detail. The steps to apply the TOPSIS method is given below: Step 1: Formation of the Decision Matrix: The different normalized matrix of decision alternatives with respect to selected attributes already calculated in Step 1 of the previous methodology is given. Step 2: Calculate the weighted normalized decision matrix (V) for each alternative for the i-th criterion as $V_{ik} = W_{ik} \cdot V_{ik}$ for all i and k. Step 3: Determine ' S_{i+} ' and ' S_{i-} '. The ideal positive (S_{i+}) and ideal negative (S_{i-}) solutions, in our case, Tensile Strength and Water Absorption Capacity are presented, which are estimated from the collected and normalized data of tensile strength and water absorption capacity of short organic composites onto polymer matrices based on the criteria. Results Table gives the results obtained from the application of Technique for Order Preference by Similarity to Ideal Solution methods to the data obtained.

3. Results and Discussion

TOPSIS is one of the multi criteria decision making technique used to select an alternative from group of alternatives based on various attributes is initially developed by Ching-Lai Hwang and Yoon in 1981 [30-34]. In this process, the selection of an alternative based on its shortest distance from positive ideal solution and longest distance from negative ideal solution. The steps to be followed to know the TOPSIS Values are as follows:

Step1: The attribute values (mechanical characteristics) for each alternative (Composite type) are identified and decision matrix (DM) is formed by considering the alternatives in rows and attributes in columns. The expression for the decision matrix is follows:

$$DM = \begin{matrix} & y_{11} & y_{12} & y_{13} & \cdots & y_{1n} \\ & y_{21} & y_{22} & y_{23} & \cdots & y_{2n} \\ y_{31} & y_{31} & y_{32} & y_{33} & \cdots & y_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{m1} & y_{m1} & y_{m2} & y_{m3} & \cdots & y_{mn} \end{matrix} \quad (1)$$

Step 2: Normalized decision matrix (NDM) is developed by using decision matrix (DM) with the use of below formula:

$$NDM = Y_{ij}^I = \frac{y_{ij}}{\sqrt{\sum_{i=1}^n y_{ij}^2}} \quad (2)$$

Step 3: Weighted Normalized matrix (WNM) is prepared from NDM. WNM consists of three steps: Calculation of variance (R_j) of different attributes using the formula

$$R_j = \frac{1}{n} \sum_{i=1}^n (Y_{ij}^I - (Y_{ij}^I)_{mean})^2 \quad (3)$$

Calculation of Weights (W_j) of various attributes based on the relative significance of diverse attributes by using the formula

$$W_j = \frac{R_j}{\sum_{i=1}^m R_j} \quad (4)$$

Calculation of Weighted Normalized matrix (WNM) by using the formula

$$WNM = U_{ij} = W_j Y_{ij}^I \quad (5)$$

Step 4: This step gives the ideal solution or positive (+ve) ideal solution and negative (-ve) ideal solutions. The formulae for calculations are as follows:

$$A^+ = \{U_1^+, U_2^+ \dots U_m^+\} = \{(max U_{ij} | j \in I^1), (min U_{ij} | j \in I^{11})\} \quad (6)$$

$$A^- = \{U_1^-, U_2^- \dots U_m^-\} = \{(max U_{ij} | j \in I^1), (min U_{ij} | j \in I^{11})\} \quad (7)$$

Where,

$$I^1 = \{j = \frac{1,2,\dots,n}{j}\}: \text{Associated with positive Attributes} \quad (8)$$

$$I^{11} = \{j = \frac{1,2,\dots,n}{j}\}: \text{Associated with non-beneficial unfavourable attributes} \quad (9)$$

Step 5: Calculation of each alternative's separation distance from positive (+ve) ideal solution and negative (-ve) ideal solutions are calculated by the formula.

$$S_i^+ = \sqrt{\sum_{j=1}^m (U_{ij} - U_j^+)^2}, i = 1, 2, \dots, n \quad (10)$$

$$S_i^- = \sqrt{\sum_{j=1}^m (U_{ij} - U_j^-)^2}, i = 1, 2, \dots, n \quad (11)$$

Step 6: Calculation of every alternative's relative closeness to the positive (+ve) ideal solution by the formula

$$C_i = \frac{s_i^-}{(s_i^+ + s_i^-)}, i = 1, 2, \dots, n \quad (12)$$

Step 7: Based on relative closeness (C_i) among alternatives, the best alternative is selected that has the largest closeness to the positive (+ve) ideal solution.

3.1. TOPSIS Ranking of Epoxy-Based Hybrid Composites:

The step-by-step procedure of TOPSIS Ranking for composite selection based on Mechanical Properties is as follows (refer to Tables 1-8):

Table 1

Decision matrix

Composite designation	TS(MPa)	TM(GPa)	FS(MPa)	IS(J/m)	VH	ILSS(MPa)
EG50	252.189	6.292	666.58	687.50	32	20.5070
EG40	230.020	2.776	620.34	625.00	27	19.0840
EGCP2.5	250.670	3.025	448.60	1362.5	39	13.8013
EGCP5	249.000	5.225	488.40	1850.0	47	9.01300
EGCP10	181.786	5.665	750.54	1750.0	51	25.1880
EGCFA2.5	240.000	3.863	422.50	1220.0	34	4.67650
EGCFA5	234.470	5.850	525.42	1340.0	41	9.69600
EGCFA10	175.133	7.823	693.07	1250.0	48	24.2470
EGBA2.5	239.400	3.857	390.54	1220.0	36	12.0150
EGBA5	220.500	3.552	419.60	1312.5	39	12.9090
EGBA10	215.421	6.637	800.173	1604.0	45	27.9900
EGPFA2.5	203.450	2.344	393.90	1497.8	28	12.1180
EGPFA5	187.884	3.027	488.62	1604.68	32	15.0320
EGPFA10	177.010	3.357	590.40	1711.90	41	18.1638
EGRHA2.5	198.820	3.203	418.32	218.750	27	12.8690
EGRHA5	180.140	3.145	502.42	234.375	30	15.4570
EGRHA10	160.420	3.092	572.81	250.000	34	17.6227
EGBoA2.5	235.200	3.960	612.89	1430.20	36	18.8550
EGBoA5	218.360	4.580	674.40	1489.70	44	20.7480
EGBoA10	201.400	6.750	794.82	1536.50	47	24.4520
EGMP2.5	169.450	2.730	250.92	1279.50	33	7.71960
EGMP5	142.400	2.860	213.46	1476.70	35	6.56700
EGMP10	119.680	2.978	319.23	1642.60	39	9.82100
EGCFACP5	251.420	5.936	624.36	1974.00	51	19.2080
EGCFACP10	242.560	6.725	702.48	2100.00	62	21.6120
EGCFAMP5	229.160	4.235	518.86	1643.00	49	15.9629
EGCFAMP10	211.410	5.142	690.36	1728.00	57	21.2390
EGCFABoA5	249.460	5.782	734.28	1983.00	53	34.3170
EGCFABoA10	218.360	6.268	860.22	1875.50	60	33.2100

Step 1: Preparation of Decision Matrix: The decision matrix (D.M) is structured as shown below, where Y_{ij} represents the value of the j -th criterion (e.g., TS, TM, etc.) for the i -th composite as shown in Table 1.

Step 2: Normalized Decision Matrix: To normalize the decision matrix, each element Y_{ij} in the matrix is divided by the square root of the sum of squares of each criterion's column as shown in Table 2.

Table 2
Normalized Decision Matrix

Composite designation	TS	TM	FS	IS	VH	ILSS
EG50	0.22019	0.24535	0.21277	0.08708	0.14017	0.20194
EG40	0.20083	0.10825	0.19801	0.07916	0.11827	0.18793
EGCP2.5	0.21886	0.11796	0.14319	0.17258	0.17083	0.13591
EGCP5	0.21741	0.20375	0.1559	0.23432	0.20587	0.08875
EGCP10	0.15872	0.2209	0.23957	0.22166	0.22339	0.24803
EGCFA2.5	0.20955	0.15064	0.13486	0.15453	0.14893	0.04605
EGCFA5	0.20472	0.22812	0.16771	0.16973	0.17959	0.09548
EGCFA10	0.15291	0.30506	0.22122	0.15833	0.21025	0.23877
EGBA2.5	0.20902	0.1504	0.12466	0.15453	0.15769	0.11832
EGBA5	0.19252	0.13851	0.13393	0.16624	0.17083	0.12712
EGBA10	0.18809	0.25881	0.25541	0.20316	0.19711	0.27563
EGPFA2.5	0.17764	0.0914	0.12573	0.18971	0.12265	0.11933
EGPFA5	0.16404	0.11804	0.15597	0.20325	0.14017	0.14802
EGPFA10	0.15455	0.13091	0.18845	0.21683	0.17959	0.17886
EGRHA2.5	0.17359	0.1249	0.13353	0.02771	0.11827	0.12673
EGRHA5	0.15728	0.12264	0.16037	0.02969	0.13141	0.15221
EGRHA10	0.14007	0.12057	0.18284	0.03167	0.14893	0.17354
EGBoA2.5	0.20536	0.15442	0.19563	0.18115	0.15769	0.18567
EGBoA5	0.19065	0.1786	0.21527	0.18869	0.19273	0.20431
EGBoA10	0.17585	0.26321	0.2537	0.19461	0.20587	0.24079
EGMP2.5	0.14795	0.10646	0.08009	0.16206	0.14455	0.07602
EGMP5	0.12433	0.11152	0.06814	0.18704	0.15331	0.06467
EGMP10	0.10449	0.11613	0.1019	0.20805	0.17083	0.09671
EGCFACP5	0.21952	0.23147	0.19929	0.25003	0.22339	0.18915
EGCFACP10	0.21178	0.26224	0.22423	0.26599	0.27157	0.21282
EGCFAMP5	0.20008	0.16514	0.16562	0.2081	0.21463	0.15719
EGCFAMP10	0.18459	0.20051	0.22036	0.21887	0.24967	0.20915
EGCFABoA5	0.21781	0.22547	0.23438	0.25117	0.23215	0.33793
EGCFABoA10	0.19065	0.24442	0.27458	0.23755	0.26281	0.32703

Step 3: Variance of different attributes is calculated with following formula and results are tabulated in Table 3.

Table 3
Variance of different attributes

Composite designation	TS	TM	FS	IS	VH	ILSS
EG50	0.001368	0.00485	0.0012	0.00760	0.00165	0.00095
EG40	0.000311	0.00455	0.00039	0.00904	0.00391	0.00028
EGCP2.5	0.001271	0.00334	0.00122	0.00000	0.00010	0.00124
EGCP5	0.001169	0.00079	0.0005	0.00361	0.00063	0.00679
EGCP10	0.000600	0.00204	0.00377	0.00225	0.00181	0.00591
EGCFA2.5	0.000694	0.00063	0.00188	0.00039	0.00102	0.01566
EGCFA5	0.000463	0.00275	0.00011	0.00002	0.00000	0.00573
EGCFA10	0.000918	0.01673	0.00185	0.00025	0.00087	0.00457
EGBA2.5	0.000666	0.00064	0.00286	0.00039	0.00053	0.00279
EGBA5	0.000087	0.00138	0.00196	0.00006	0.00010	0.00194
EGBA10	0.000024	0.00690	0.00596	0.00084	0.00027	0.01091
EGPFA2.5	0.000031	0.00711	0.00275	0.00024	0.00338	0.00269
EGPFA5	0.000367	0.00333	0.00049	0.00084	0.00165	0.00054
EGPFA10	0.000821	0.00201	0.00011	0.00181	0.00000	0.00006
EGRHA2.5	0.000092	0.00258	0.00199	0.02148	0.00391	0.00198
EGRHA5	0.000672	0.00282	0.00032	0.02090	0.00244	0.00036
EGRHA10	0.001861	0.00304	2.2E-05	0.02033	0.00102	0.00001
EGBaA2.5	0.000491	0.00045	0.0003	0.00005	0.00053	0.00021
EGBaA5	0.000055	0.00001	0.00138	0.00021	0.00014	0.00110
EGBaA10	0.000054	0.00766	0.0057	0.00041	0.00063	0.00485
EGMP2.5	0.001243	0.00480	0.00962	0.00015	0.00131	0.00905
EGMP5	0.003467	0.00412	0.01211	0.00016	0.00076	0.01134
EGMP10	0.006196	0.00355	0.00582	0.00114	0.00010	0.00554
EGCFACP5	0.001318	0.00311	0.00045	0.00574	0.00181	0.00032
EGCFACP10	0.000816	0.00749	0.00212	0.00841	0.00824	0.00173
EGCFAMP5	0.000285	0.00011	0.00016	0.00115	0.00114	0.00020
EGCFAMP10	0.000002	0.00061	0.00178	0.00199	0.00474	0.00144
EGCFABaA5	0.001197	0.00248	0.00316	0.00592	0.00264	0.02781
EGCFABaA10	0.000055	0.00472	0.00929	0.00401	0.00673	0.02429
Average	0.000917	0.00361	0.00273	0.00412	0.00180	0.00518

Step 4: Weights of different attributes: The weights for each criterion W_j are derived from the calculated variance values. The weight is calculated as follows, as shown in Table 4.

Table 4
Weights of different attributes

TS	TM	FS	IS	VH	ILSS
0.049973	0.196514	0.148958	0.224337	0.0978334	0.282385

Step 5: Weighted Normalized Matrix: The weighted normalized matrix is obtained by multiplying the normalized decision matrix by the corresponding weights of each criterion, as shown in Table 5.

Table 5
Weighted Normalized Matrix

Composite designation	TS	TM	FS	IS	VH	ILSS
EG50	0.0110035	0.04822	0.03169	0.01954	0.01371	0.05702
EG40	0.0100363	0.02127	0.0295	0.01776	0.01157	0.05307
EGCP2.5	0.0109373	0.02318	0.02133	0.03872	0.01671	0.03838
EGCP5	0.0108644	0.04004	0.02322	0.05257	0.02014	0.02506
EGCP10	0.0079317	0.04341	0.03569	0.04973	0.02186	0.07004
EGCFA2.5	0.0104717	0.0296	0.02009	0.03467	0.01457	0.013
EGCFA5	0.0102304	0.04483	0.02498	0.03808	0.01757	0.02696
EGCFA10	0.0076414	0.05995	0.03295	0.03552	0.02057	0.06742
EGBA2.5	0.0104455	0.02956	0.01857	0.03467	0.01543	0.03341
EGBA5	0.0096209	0.02722	0.01995	0.03729	0.01671	0.0359
EGBA10	0.0093993	0.05086	0.03805	0.04558	0.01928	0.07783
EGPFA2.5	0.0088770	0.01796	0.01873	0.04256	0.012	0.0337
EGPFA5	0.0081978	0.0232	0.02323	0.0456	0.01371	0.0418
EGPFA10	0.0077233	0.02572	0.02807	0.04864	0.01757	0.05051
EGRHA2.5	0.0086749	0.02454	0.01989	0.00622	0.01157	0.03579
EGRHA5	0.0078599	0.0241	0.02389	0.00666	0.01286	0.04298
EGRHA10	0.0069995	0.02369	0.02724	0.0071	0.01457	0.049
EGBoA2.5	0.0102623	0.03035	0.02914	0.04064	0.01543	0.05243
EGBoA5	0.0095275	0.0351	0.03207	0.04233	0.01886	0.05769
EGBoA10	0.0087875	0.05173	0.03779	0.04366	0.02014	0.06799
EGMP2.5	0.0073935	0.02092	0.01193	0.03636	0.01414	0.02147
EGMP5	0.0062132	0.02192	0.01015	0.04196	0.015	0.01826
EGMP10	0.0052219	0.02282	0.01518	0.04667	0.01671	0.02731
EGCFACP5	0.0109700	0.04549	0.02969	0.05609	0.02186	0.05341
EGCFACP10	0.0105834	0.05153	0.0334	0.05967	0.02657	0.0601
EGCFAMP5	0.0099987	0.03245	0.02467	0.04669	0.021	0.04439
EGCFAMP10	0.0092243	0.0394	0.03282	0.0491	0.02443	0.05906
EGCFABoA5	0.0108845	0.04431	0.03491	0.05635	0.02271	0.09543
EGCFABoA10	0.0095275	0.04803	0.0409	0.05329	0.02571	0.09235

Step 6: Positive (+ve) and Negative ideal Solutions:

Ideal Solution (A⁺): For each criterion, the ideal solution is the maximum value of the weighted normalized matrix.

Negative-Ideal Solution (A⁻): The negative-ideal solution is the minimum value for each criterion. Table 6 shows the results of positive and negative ideal solutions.

Step 7: Separation of Alternatives from positive and negative ideal solutions: The separation from the ideal solution S_i^+ and the negative-ideal solution S_i^- for each composite is calculated as follows, and the results are shown in Table 7.

Table 6

Positive(+ve) and Negative(-ve) ideal Solutions

	TS	TM	FS	IS	VH	ILSS
Positive(+ve) Ideal Solution	0.01100	0.05995	0.04090	0.05967	0.02657	0.09543
Negative(-ve) Ideal Solution	0.00522	0.01796	0.01015	0.00622	0.01157	0.01300

Table 7

Separation Measures of Attributes

S+	S-
0.047371011	0.059436136
0.062939727	0.046332787
0.081150515	0.043719188
0.092003217	0.055294275
0.058731461	0.080988978
0.097434181	0.032867225
0.0818579	0.047040155
0.046434132	0.078675677
0.081206533	0.038383753
0.080893798	0.04144264
0.050331074	0.087689568
0.089961327	0.042851119
0.082406601	0.050912251
0.076231891	0.060252801
0.074302861	0.025867162
0.067580884	0.03367358
0.06218178	0.040419365
0.068113184	0.057390885
0.063030004	0.06439693
0.052746068	0.08010085
0.096549628	0.031675394
0.101311353	0.036519349
0.094810388	0.043781977
0.072583941	0.073474467
0.070256663	0.083645666
0.076392616	0.056172179
0.065026552	0.071522256
0.058909084	0.103778767
0.054721108	0.102859053

Step 8: Relative Closeness (RC) and composite ranking (R) Relative Closeness: The relative closeness C_i of each alternative to the ideal solution are calculated and the composites are ranked based on the value of C_i , the higher the value of C_i the better the composite performs relative to the ideal solution as shown in Table 8.

Table 8

Relative Closeness (RC) and Ranking (R)

Relative closeness	Composite ranking	Composite type	Designation
$C1^*$	R		
0.443519112	7	C1	EG50
0.575988644	14	C2	EG40
0.649881542	20	C3	EGCP2.5
0.62460817	18	C4	EGCP5
0.420349818	6	C5	EGCP10
0.747760014	28	C6	EGCFA2.5
0.635059231	19	C7	EGCFA5
0.371147011	4	C8	EGCFA10
0.679039541	24	C9	EGBA2.5
0.661240423	21	C10	EGBA5
0.36466338	3	C11	EGBA10
0.677356148	23	C12	EGPFA2.5
0.618116642	17	C13	EGPFA5
0.558538029	13	C14	EGPFA10
0.741767435	27	C15	EGRHA2.5
0.667436097	22	C16	EGRHA5
0.606053471	16	C17	EGRHA10
0.542716935	12	C18	EGBaA2.5
0.494636431	10	C19	EGBaA5
0.397043973	5	C20	EGBaA10
0.752970259	29	C21	EGMP2.5
0.735041984	26	C22	EGMP5
0.68409532	25	C23	EGMP10
0.496951475	11	C24	EGCFACP5
0.456501622	8	C25	EGCFACP10
0.576266243	15	C26	EGCFAMP5
0.476214719	9	C27	EGCFAMP10
0.362098852	2	C28	EGCFABaA5
0.347258864	1	C29	EGCFABaA10

From TOPSIS ranking results for the epoxy hybrid composites (Table 6), it is clear that both EGCFABaA5 and EGCFABaA10 comprise the best target with respect to better interlaminar shear strength (ILSS) and good impact strength, which are of higher weight-age parameters in this travel. Composites such as EGCP10 and EGCFACP5 also appear high in the ranking due to their well-balanced

mechanical properties, especially flexural strength and tensile modulus. Mid (EG50, EGBA5 e.g.)-Mid composites do okay to moderate in a number of factors but not strong enough overall or in head-to-head competition preventing them from ranking higher. However, materials such as EGMP5 and EGRHA10 ranked more towards the bottom suffer from poor mechanical properties, in particular tensile/flexural strength which makes them less suitable for high stress / loading applications. In conclusion, the filler type and percentage have a strong impact on ranking with Carbon-based fillers like BoA and CFACP's composites appeared to perform better than Bio-fillers such as Marble powder (MP) and Rice Husk Ash (RHA) which possess weaker properties. This is driven home by the toughness and ILSS rankings.

4. Conclusions

Multi-criteria decision-making (MCDM) techniques have made quite an impression in the field of materials engineering for composites, due to the importance of ranking these materials based on numerous performance indicators. This study presented a critical review of prominent MCDM applications in polymer matrix composites and discussed the basic features, selection criteria, and optimal MCDM method [35-37]. This study's primary goal was to introduce these MCDM characteristics as a benchmark for advanced materials. As a result of this study, researchers can utilize these MCDM techniques for ranking the engineering materials based on various properties necessary for industrial applications. Therefore, we presented several composite ranking problems where MCDM methods were involved. Furthermore, the feasibility of the Technique for Order Preference by Similarity to an Ideal Solution method was scrutinized based on mechanical property data extracted from a verified systematic review. The simulation outcomes validated that the TOPSIS approach found seven best composite solutions among different polymer composites [38].

The conclusions drawn from the TOPSIS ranking of epoxy-based hybrid composites reveal that the mechanical performance of the composites is strongly influenced by the type and percentage of filler materials. Composites reinforced with carbon-based fillers, such as BoA and CFACP, demonstrated superior performance in critical mechanical properties like impact strength, interlaminar shear strength (ILSS), and tensile modulus, leading to higher rankings. On the other hand, composites with weaker bio-fillers, such as Marble Powder (MP) and Rice Husk Ash (RHA), ranked lower due to their inferior mechanical characteristics, particularly in tensile and flexural strength. These findings emphasize that filler material selection is pivotal in optimizing composite performance for high-stress applications, with carbon-based fillers showing greater potential in enhancing durability and strength. The TOPSIS analysis effectively aids in prioritizing composites for specific engineering applications based on their mechanical properties.

Although several researchers have published their work in the realm of composite ranking by alternative MCDM techniques, their study's particular advantage is the usage of a TOPSIS technique to evaluate and show a comprehensive ranking of composites based on the polymer matrix's mechanical behavior. In order to improve the potential applicability of the TOPSIS method in materials engineering and other fields, the integration of dominant MCDM techniques into the TOPSIS measure and combined multi-criteria decision model approaches introduces new criteria for the new TOPSIS framework. It has been discovered that promising research in dielectric and tribological materials and their applications to develop proper comparative bases for ranking applications is a fertile field for future researchers. Hence, one promising area in MCDM to be pursued further encompasses the prioritization characteristics of advanced materials, since the research signifies cutting-edge progress in this arena by virtue of the recently identified gaps in the

research field. The recent scenario is one of constant disruptive change, and the use of advanced materials and their potential for use in diversified applications has expanded exponentially. In light of the aforementioned, the company should also ensure that competition in the various fields is exacerbated by the search for better materials that could provide solutions for all practical purposes. In an increasingly complex environment, MCDM methodologies are therefore particularly well-suited to ranking advanced materials and tracking their history, as well as predicting their potential for development.

Acknowledgement

The author, Dr. Raffi Mohammed, acknowledges with sincere gratitude the financial support received through the Seed Money scheme (Ref. No.: RCE/PO/SEED MONEY/2025-2026/01). The Management of Ramachandra College of Engineering is also deeply appreciated for their continuous support and facilitation during the execution of this research.

References

- [1] S. K. Rajendra and C. M. Ramesha, "A Survey of Al7075 Aluminium Metal Matrix Composites," *International Journal of Science and Research* 4, no. 2 (2015): 1071–1075. <https://www.ijsr.net/archive/v4i2/SUB151344.pdf>.
- [2] C. Saravanan, K. Subramanian, V. A. Krishnan and R. S. Narayanan, "Effect of Particulate Reinforced Aluminium Metal Matrix Composite – A Review," *Mechanics and Mechanical Engineering* 19, no. 1 (2015): 23–30.
- [3] M. Sambathkumar, P. Navaneethakrishnan, K. S. K. S. Ponappa and K. S. K. Sasikumar, "Mechanical and Corrosion Behavior of Al7075 (Hybrid) Metal Matrix Composites by Two Steps Stir Casting Process," *Latin American Journal of Solids and Structures* 14, no. 2 (2017): 243–255. <https://doi.org/10.1590/1679-78253132>.
- [4] B. Subramaniam, B. Natarajan, B. Kaliyaperumal and S. J. S. Chelladurai, "Investigation on Mechanical Properties of Aluminium 7075-Boron Carbide-Coconut Shell Fly Ash Reinforced Hybrid Metal Matrix Composites," (2018). <https://doi.org/10.1007/s41230-018-8105-3>.
- [5] S. Pradeep Devaneyan, R. Ganesh and T. Senthilvelan, "On the Mechanical Properties of Hybrid Aluminium 7075 Matrix Composite Material Reinforced with SiC and TiC Produced by Powder Metallurgy Method," *Indian Journal of Materials Science* 2017 (2017). <https://doi.org/10.1155/2017/3067257>.
- [6] T. Prasad, P. Chinna Sreenivas Rao and B. Vijay Kiran, "Investigation of Mechanical Properties of Al 7075 with Magnesium Oxide Nano Powder MMC," *IOSR Journal of Mechanical and Civil Engineering* (n.d.): 60–65. <https://www.iosrjournals.org/iosr-jmce/papers/Conf-17026-2017/Volume-3/12.%2060-65.pdf>
- [7] A. K. Shrivastava, K. K. Singh and A. R. Dixit, "Tribological Properties of Al 7075 Alloy Metal Matrix Composite Reinforced with SiC, Sliding under Dry, Oil Lubricated, and Inert Gas Environments," *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology* 232, no. 6 (2018): 693–698. <https://doi.org/10.1177/1350650117726631>.
- [8] Raturi, Amit, K. K. S. Mer and Pawan Kumar Pant, "Synthesis and Characterization of Mechanical, Tribological and Microstructural Behaviour of Al 7075 Matrix Reinforced with Nano Al₂O₃ Particles," *Materials Today: Proceedings* 4, no. 2A (2017): 2645–2658. <https://doi.org/10.1016/j.matpr.2017.02.139>.
- [9] R. Pramod, G. B. Veeresh Kumar, P. S. Shivakumar Gouda and Arun Tom Mathew, "A Study on the Al₂O₃ Reinforced Al7075 Metal Matrix Composites Wear Behavior Using Artificial Neural Networks," *Materials Today: Proceedings* 5, no. 5A (2018): 11376–11385. <https://doi.org/10.1016/j.matpr.2018.02.105>.
- [10] Das, Diptikanta, Milind Sharma, Chandrika Samal and Ramesh Kumar Nayak, "Investigation of Mechanical Properties of SiCp Reinforced Al 7075 Metal Matrix Composites: A Case Study," *Materials Today: Proceedings* 18, no. 7 (2019): 3958–3965. <https://doi.org/10.1016/j.matpr.2019.07.337>.
- [11] Singla, Manoj, D. Dwivedi, Lakhvir Singh and Vikas Chawla, "Development of Aluminium Based Silicon Carbide Particulate Metal Matrix Composite," *Journal of Minerals and Materials Characterization and Engineering* 8, no. 6 (2009): 455–467. <https://doi.org/10.4236/jmmce.2009.86040>.
- [12] S. Chandana Sri, S. Saravanamurugan, A. Shanmugasundaram and Subinaya Mohapatra, "Effect of SiC and Gr Particles on the Mechanical Properties and Dynamic Characteristics of AA 7075 Hybrid Metal Matrix Composite," *Materials Today: Proceedings* 46, no. 1 (2021): 390–398. <https://doi.org/10.1016/j.matpr.2020.09.217>.

- [13] Atla, Sridhar and K. Prasanna Lakshmi, "Evaluation of Mechanical and Wear Properties of Aluminum 7075 Alloy Hybrid Nano-Composites with the Additions of SiC/Graphite," *Materials Today: Proceedings* 44, no. 1 (2021): 2653–2657. <https://doi.org/10.1016/j.matpr.2020.12.675>.
- [14] K. Maruthi Varun and R. Raman Goud, "Investigation of Mechanical Properties of Al 7075/SiC/MoS2 Hybrid Composite," *Materials Today: Proceedings* 19, no. 2 (2019): 787–791. <https://doi.org/10.1016/j.matpr.2019.08.131>.
- [15] S. Suresh, G. Harinath Gowd and M. L. S. Devakumar, "Wear Behavior of Al 7075/Al2O3/SiC Hybrid NMMC's by Stir Casting Method," *Materials Today: Proceedings* 24, no. 2 (2020): 261–272. <https://doi.org/10.1016/j.matpr.2020.04.275>.
- [16] Uvaraja, V. and N. Natarajan, "Optimization of Friction and Wear Behaviour in Hybrid Metal Matrix Composites Using Taguchi Technique," *Journal of Minerals and Materials Characterization and Engineering* 11, no. 8 (2012): 757–768. <https://doi.org/10.4236/jmmce.2012.118063>.
- [17] B. Jayendra, D. Sumanth, G. Dinesh and M. Venkateswara Rao, "Mechanical Characterization of Stir Cast Al-7075/B4C/Graphite Reinforced Hybrid Metal Matrix Composites," *Materials Today: Proceedings* 21, no. 2 (2020): 1104–1110. <https://doi.org/10.1016/j.matpr.2020.01.057>.
- [18] S. Arun Kumar, J. Hari Vignesh and S. Paul Joshua, "Investigating the Effect of Porosity on Aluminium 7075 Alloy Reinforced with Silicon Nitride (Si3N4) Metal Matrix Composites through Stir Casting Process," *Materials Today: Proceedings* 39, no. 1 (2021): 414–419. <https://doi.org/10.1016/j.matpr.2020.07.690>.
- [19] K.R. Ramkumar, S. Sivasankaran, F. A. Al-Mufadi, et al., "Investigations on Microstructure, Mechanical and Tribological Behaviour of AA 7075-x wt.% TiC Composites for Aerospace Applications," *Archives of Civil and Mechanical Engineering* 19, no. (2019): 428–438. <https://doi.org/10.1016/j.acme.2018.12.003>.
- [20] R. Manikandan, T. V. Arjunan and Akhil R. Nath O. P., "Studies on Microstructural Characteristics, Mechanical and Tribological Behaviors of Boron Carbide and Cow Dung Ash Reinforced Aluminium (Al 7075) Hybrid Metal Matrix Composite," *Composites Part B: Engineering* 183 (2020): 107668. <https://doi.org/10.1016/j.compositesb.2019.107668>.
- [21] Sahoo, Barada Prasanna, Diptikanta Das and Anil Kumar Chaubey, "Strengthening Mechanisms and Modelling of Mechanical Properties of Submicron-TiB2 Particulate Reinforced Al 7075 Metal Matrix Composites," *Materials Science and Engineering: A* 825, no. (2021): 141873. <https://doi.org/10.1016/j.msea.2021.141873>.
- [22] R. Keshavamurthy, Sadananda Mageri, Ganesh Raj, B. Naveen Kumar, P. M. Kadakol and K. Vasu, "Microstructure and Mechanical Properties of Al7075-TiB2 In-Situ Composite," *Research Journal of Material Sciences* (2013).
- [23] V. Hariharan, V. Mohan Kumar and P. Gnaneswaran, "A Review on Tribological and Mechanical Behaviors of Aluminium Metal Matrix Composites," *International Journal of Mechanical Engineering and Robotics* 2, no. 6 (2014): 57–61.
- [24] Sumathy, Muniyandhu, Naga Lingeswara Raju, S. Sathishkumar, and K. Sunil Kumar, "Investigation on Mechanical Properties of Al 7075-Al2O3 Metal Matrix Composite," *International Journal of Mechanical Engineering and Technology* 7, no. 6 (2016).
- [25] A. Baradeswaran and A. Elaya Perumal, "Study on Mechanical and Wear Properties of Al7075/Al2O3/Graphite Hybrid Composites," *Composites Part B: Engineering* 56 (2014): 464–471. <https://doi.org/10.1016/j.compositesb.2013.08.013>.
- [26] Balasubramaniam, Subramaniam, Balaji Natarajan, Balasubramanian Kaliyaperumal and Samson Jerold Samuel Chelladurai, "Investigation on Mechanical Properties of Aluminium 7075-Boron Carbide-Coconut Shell Fly Ash Reinforced Hybrid Metal Matrix Composites," *Overseas China Foundry* 15, no. 6 (2018). <https://doi.org/10.1007/s41230-018-8105-3>.
- [27] Ashiwani Kumar, Virendra Kumar, Anil Kumar, Binayaka Nahak and Rajesh Singh, "Investigation of Mechanical and Tribological Performance of Marble Dust 7075 Aluminium Alloy Composites," *Materials Today: Proceedings* 44, no. 6 (2021): 4542–4547. <https://doi.org/10.1016/j.matpr.2020.10.812>.
- [28] Sambathkumar, Mani, Kondayampalayam S. K. Sasikumar, Rangasamy Gukendran, Karupannasamy Dinesh Kumar, Kannayiram Ponappa and Samiyappan Harichandran, "Investigation of Mechanical and Corrosion Properties of Al 7075/Red Mud Metal Matrix Composite," *Revista de Metalurgia* 57, no. 1 (2021): e185. <https://doi.org/10.3989/revmetalm.185>.
- [29] S. Rajesh, R. Suresh Kumar, S. Madhankumar, M. Sheshan, M. Vignesh and R. Sanjay Kumar, "Study of the Mechanical Properties of Al7075 Alloy, Silicon Carbide and Fly Ash Composites Manufactured by Stir Casting Technique," *Materials Today: Proceedings* 45, no. 7(2021): 6438–6443. <https://doi.org/10.1016/j.matpr.2020.11.278>.
- [30] R. Mohammed, B.R.G. Reddy, V.S. Reddy and M.A. Ali, "Effect of Epoxy Modifiers [Bagasse Fiber/Bagasse Ash/Coal Powder/Coal Fly Ash] on Mechanical Properties of Epoxy/Glass Fiber Hybrid Composites," *International Journal of Applied Engineering Research* 10, no. 24 (2015): 45625–45630.

- [31] R. Mohammed, B.R. Reddy, S. Kakarla, B.B. Krishna and M.P. Khan, "Mechanical Characterization (MC) and TOPSIS Ranking of Glass Fiber Reinforced Particulate Filled Epoxy-Based Hybrid Composites," *Journal of Chemical and Pharmaceutical Sciences* 10, no. 2 (2017): 1075–1081.
- [32] R. Mohammed, B. Ramgopal Reddy and A. Manoj, "Synthetic Fibres of Polymer Matrix Composites — A Review," *Journal of Advanced Research in Dynamical and Control Systems* 10, no. 9 (2018): 2733–2743.
- [33] R. Mohammed, B. Ramgopal Reddy and A. Manoj, "Fabrication and Erosion Wear Response of E-Glass-Epoxy Based Hybrid Composites Filled with CFA/CFACP," *International Journal of Engineering and Advanced Technology* 8, no. 3 (2019): 522–528.
- [34] R. Mohammed, B. Ramgopal Reddy, K. Sridhar and A. Manoj, "Fabrication, Mechanical Characterization and Selection of Hybrid Composites by TOPSIS," *International Journal of Recent Technology and Engineering* 8, no. 1 (2019): 3118–3125.
- [35] Mohammed, Raffi, Abdul Saddique Shaik, Subhani Mohammed, Kiran Kumar Bunga, Chiranjeevi Aggala, Bairysetti Prasad Babu and Irfan Anjum Badruddin, "Advancements and Challenges in Additive Manufacturing: Future Directions and Implications for Sustainable Engineering," *Advance Sustainable Science, Engineering and Technology* 7, no. 1 (2025).
- [36] Adarsha Reddy, B. N., Sonnappa Devaraj, G. S. Shashikant, N. V. Sarathbabu Goriparti, and Raffi Mohammed, "Investigation of the Microstructure and Mechanical Characterization of an Aluminum-12 wt% Silicon Alloy Processed Using Die and Centrifugal Casting Processes," *Journal of Bio- and Tribo-Corrosion* 10, no. (2024): 103. <https://doi.org/10.1007/s40735-024-00903-8>.
- [37] Mohammed, Raffi, Irfan Anjum Badruddin, Abdul Saddique Shaik, Sarfaraz Kamangar and Abdul Azeem Khan, "Experimental Investigation on Mechanical Characterization of Epoxy-E-Glass Fiber-Particulate Reinforced Hybrid Composites," *ACS Omega* 9, no. 23 (2024): 24761–24773. <https://doi.org/10.1021/acsomega.4c01365>.
- [38] Mohammed, Raffi, C. Sailaja, Subhani Mohammed and Kiran Kumar, "Development of a Theoretical Model to Estimate the Erosion Wear Rate of Polymer Composites," *Journal of Mechanics of Continua and Mathematical Sciences* 19, no. 2 (2024): 25–38. <https://doi.org/10.26782/jmcms.2024.02.00002>.