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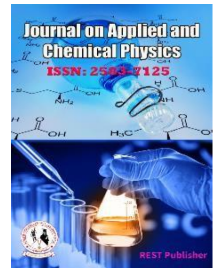

Ranking of Aluminum-Coconut Shell Ash (CSA) Composites using the WASPAS Method

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Abstract: *To select the optimum option for the structure or component under consideration, a careful and effective material selection technique is required. The intricacy of the evaluation of material assortment is perfectly suited to the multi-criteria decision making (MCDM) methodologies. Coconut shell ash is a byproduct obtained during the burning of coconut shells. It has gained significant attention due to its potential applications in various industries. Some of the research studies have shown that coconut shell ash can be used as a low-cost adsorbent material for the removal of heavy metals and organic pollutants from wastewater. Overall, the research on coconut shell ash has shown its potential as a valuable resource that can be utilized in various industries, contributing to sustainable development. Depending on the desired qualities and uses, multiple production techniques can be used to create coconut shell ash composites. The methodology used to produce coconut shell ash composites will depend on the desired properties and applications of the final product. The choice of method will also affect the mechanical, thermal, and other properties of the composite. The WASPAS method is for optimizing the Alluminium-Coconut Shell Ash (CSA) Composites. Alternate Parameter: AI-1100, AI-5%CSA, AI-10%CSA, AI-15% CSA, AI-20%CSA. Evaluation parameter: Ultimate tensile strength (N/mm2), Toughness (J/mm3), Density (g/cc) and Wear rate (10-3 mm3 /m) .Al-1100 has a preference score of 0.674158, placing it in the 5th rank. Al-5% CSA has a preference score of 0.746743, ranking it 4th. Al-10% CSA has a preference score of 0.8728, earning it the 3rd rank. Al-15% CSA has the highest preference score of 0.992877, making it the top-ranked composite. Al-20% CSA has a preference score of 0.888162, securing the 2nd rank. Ranking aluminum-coconut shell ash composites is a methodical assessment and comparison of their characteristics and functionality utilising a range of resources and techniques. Researchers and engineers can determine whether these composites are appropriate for a given application by taking into account elements like mechanical strength, thermal stability, corrosion resistance, and cost-effectiveness. They can also optimise the composition of these composites to achieve the needed attributes.*

Keywords: *thermal, coconut shell, matrix, composites.*

1. INTRODUCTION

Aluminum-coconut shell ash composites are a relatively new class of materials that have attracted a great deal of attention recently because of their distinctive characteristics and prospective uses. Aluminium and coconut shell ash, a byproduct of burning coconut shells, are combined to create these composite materials. When these components are combined, composites that are superior than conventional aluminium materials in terms of mechanical, thermal, and electrical properties can be produced. As a result, these composites have been investigated in a number of sectors, including construction, automotive, and aerospace. These composites' mechanical strength, thermal stability, and electrical conductivity are just a few of the variables that can be used to rank them. Aluminium and coconut shell ash composites have gained significant attention in the field of materials science and engineering due to their unique combination of properties and potential applications. These composites, formed by incorporating coconut shell ash particles into an aluminium matrix, exhibit enhanced mechanical, thermal, and environmental characteristics compared to pure aluminium. As a result, they have found diverse applications in industries such as aerospace, automotive, construction, and packaging. Ranking the performance of aluminium-coconut shell ash composites plays a crucial role in understanding their suitability for specific applications and optimizing their composition for desired properties. This ranking involves evaluating and comparing various parameters, including mechanical strength, thermal stability, corrosion resistance, and cost-effectiveness. Such an analysis aids researchers, engineers, and manufacturers in making informed decisions regarding material selection and process optimization. Mechanical strength is one of the key factors in ranking these composites. Coconut shell ash particles, being a natural reinforcement, can significantly enhance the strength of the aluminium matrix by forming a reinforcing network within it. Tensile strength, flexural strength, and impact resistance are important parameters considered in evaluating the performance of these composites. Higher values of these properties indicate superior mechanical performance and therefore a higher rank in the composite ranking. Thermal stability is another crucial aspect to consider when ranking aluminium-coconut shell ash composites. The inclusion of coconut shell ash particles can improve the thermal conductivity and resistance of the composites, making them suitable for applications requiring excellent heat dissipation and resistance to high temperatures. Thermal stability can be assessed through thermal conductivity, coefficient of thermal expansion, and thermal shock resistance measurements. Composites with superior thermal stability rank higher in terms of their potential application in heat-intensive environments. Corrosion resistance is a vital consideration, particularly for applications in corrosive environments or those exposed to moisture. The presence of coconut shell ash particles can provide a protective barrier against corrosion, shielding the aluminium matrix from degradation. Evaluating the corrosion resistance of the composites through techniques like electrochemical measurements and salt spray tests helps determine their rank in terms of their durability and longevity. Cost-effectiveness is also an essential factor in ranking aluminium-coconut shell ash composites. The availability and cost of raw materials, ease of manufacturing, and overall economic viability of the composites influence their commercial success. A composite that demonstrates an optimal balance between performance and cost would be ranked higher, as it provides an attractive solution for industrial applications. In conclusion, ranking aluminium-coconut shell ash composites involves a comprehensive evaluation of their mechanical strength, thermal stability, corrosion resistance, and cost-effectiveness. By considering these factors, researchers and engineers can identify and prioritize composites with the most desirable properties for specific applications. This ranking process is crucial for advancing the development and utilization of these composites in various industries, leading to innovative and sustainable material solutions.

2. MATERIALS AND METHOD

Materials and Methods for Ranking Aluminium-Coconut Shell Ash Composites:
To rank aluminium-coconut shell ash composites based on their properties and performance, various materials and methods can be employed. Here, we outline a general approach that encompasses the key aspects of evaluation and comparison:

1. Raw Materials:

a. Aluminium Matrix: High-quality aluminium alloys or pure aluminium can be used as the matrix material for the composites.

b. Coconut Shell Ash: Obtained from coconut shells through a controlled combustion process, the ash should be finely ground to achieve desired particle size and distribution.

2. Composite Preparation:

a. Mixing: The coconut shell ash particles are blended with the molten aluminium matrix using techniques like stir casting, mechanical alloying, or powder metallurgy.

b. Composite Composition: Varying compositions of coconut shell ash particles (typically in weight percentages) can be incorporated into the aluminium matrix to create different composites for evaluation.

3. Mechanical Strength Evaluation:

a. Tensile Testing: ASTM standard tests can be performed to measure the tensile strength, yield strength, and elongation of the composites using a universal testing machine.

b. Flexural Testing: ASTM standard tests such as the three-point bending test can assess the flexural strength and modulus of elasticity of the composites.

c. Impact Testing: ASTM standard tests like the Izod or Charpy impact tests can determine the impact resistance and toughness of the composites.

4. Thermal Stability Evaluation:

a. Thermal Conductivity: The thermal conductivity of the composites can be measured using standardized techniques, such as the transient hot wire or laser flash methods.

b. Coefficient of Thermal Expansion (CTE): The CTE can be determined through methods like dilatometry or thermo mechanical analysis to assess the dimensional stability of the composites under temperature variations.

c. Thermal Shock Resistance: Thermal shock tests involving rapid heating and cooling cycles can be performed to evaluate the resistance of composites to thermal stresses.

5. Corrosion Resistance Evaluation:

a. Electrochemical Measurements: Techniques like electrochemical impedance spectroscopy (EIS) and potentiodynamic polarization can be used to assess the corrosion behavior of composites in different environments.

b. Salt Spray Testing: ASTM B117 standard test can be conducted to simulate corrosive conditions and evaluate the corrosion resistance of the composites.

6. Cost-Effectiveness Evaluation:

a. Cost Analysis: A comprehensive analysis of the raw material costs, manufacturing process costs, and overall economic feasibility is essential for evaluating the cost-effectiveness of the composites.

WASPAS Method: The WASPAS method is a decision-making technique that assesses and ranks alternatives by considering multiple criteria. It is a variant of the MCDA approach and is commonly used in fields like operations research, engineering, and management. To apply the WASPAS method, several steps are followed. Firstly, a set of criteria is defined, representing different factors relevant to the decision at hand. Each criterion is assigned a weight, indicating its relative importance. Next, the alternatives being considered are evaluated against each criterion using a rating scale or numerical values. These evaluations are then combined by multiplying each criterion's weight by its corresponding evaluation score. The resulting products are then added up for each alternative, generating an aggregated score. Subsequently, the alternatives are ranked based on their aggregated scores. The alternative with the highest score is considered the most favorable or preferred choice. This ranking reflects the best alternative while considering the relative importance of the criteria. The WASPAS method provides a systematic and structured approach to decision-making by incorporating multiple criteria and their respective weights. It assists decision-makers in considering various factors and their relative significance, enabling them to make well-informed choices through a comprehensive evaluation process.

3. RESULT AND DISCUSSION

TABLE 1. Aluminum-coconut shell ash (CSA) composites properties

Composites	UTS (N/mm^2)	Toughness (J/mm^3)	Density(g/cc)	Wear rate (10^{-3} mm^3 /m)
Al-1100	104.00	17.10	2.72	4.07
Al-5% CSA	128.00	19.13	2.66	3.76
Al-10% CSA	157.00	23.91	2.60	3.12
Al-15% CSA	174.00	26.92	2.47	2.44
Al-20% CSA	151.00	21.12	2.40	2.69

Table 1 presents the properties of aluminum-coconut shell ash (CSA) composites, including ultimate tensile strength (UTS), toughness, density, and wear rate. The results indicate that as the percentage of CSA increases in the composites, the UTS and toughness generally improve, suggesting enhanced strength and resistance to fracture. Additionally, the density decreases with higher CSA content, indicating a reduction in overall weight. The wear rate also decreases as the CSA percentage increases, indicating improved wear resistance and potential for a longer lifespan. Overall, incorporating CSA in aluminum composites offers the benefits of increased strength, toughness, and wear resistance while reducing density, making it advantageous for applications requiring lightweight materials with enhanced mechanical properties.

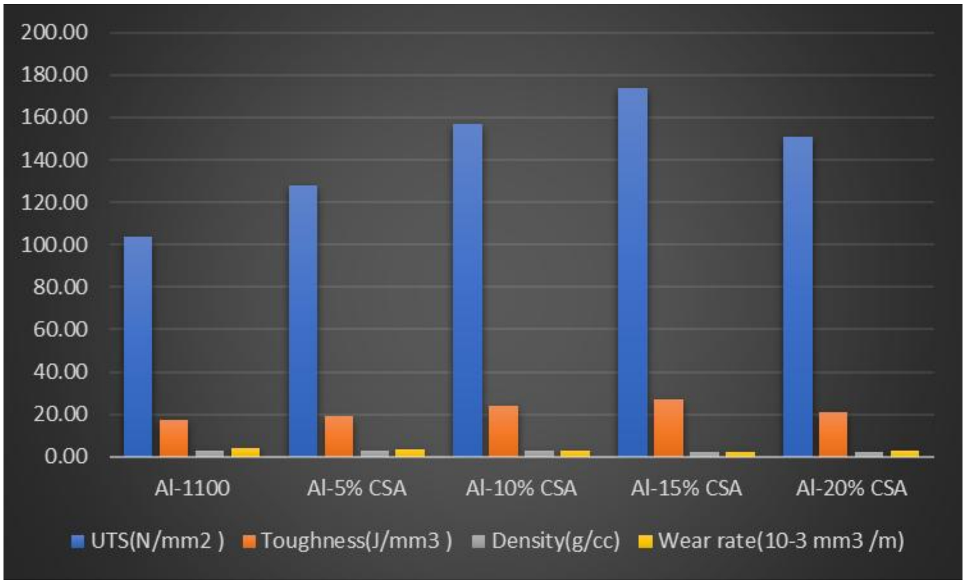

FIGURE 1. Alluminium-coconut shell ash (CSA) composites properties

Figure 1 displays the characteristics of composites made from aluminum and coconut shell ash (CSA), encompassing ultimate tensile strength (UTS), toughness, density, and wear rate. The findings reveal that higher CSA percentages in the composites generally lead to improved UTS and toughness, indicating enhanced strength and fracture resistance. Moreover, an increase in CSA content results in decreased density, implying a reduction in overall weight. The wear rate also decreases with higher CSA percentages, indicating superior wear resistance and the potential for extended durability. In conclusion, the inclusion of CSA in aluminum composites offers the advantages of heightened strength, toughness, and wear resistance, along with reduced density, making it beneficial for applications where lightweight materials with improved mechanical properties are desirable

TABLE 2. Normalized matrix

Composites	UTS (N/mm^2)	Toughness (J/mm^3)	Density(g/cc)	Wear rate (10^{-3} mm^3 /m)
Al-1100	0.59770	0.63522	0.88235	0.59985
Al-5% CSA	0.73563	0.71062	0.90226	0.64953
Al-10% CSA	0.90230	0.88819	0.92308	0.78123
Al-15% CSA	1.00000	1.00000	0.97166	1.00000
Al-20% CSA	0.86782	0.78455	1.00000	0.90703

Table 2. displays a normalized matrix created through the WASPAS method. The values, ranging from 0 to 1, signify the relative significance or performance of various criteria or alternatives. Higher values indicate greater importance or better performance, whereas lower values indicate lower importance or poorer performance. The specific interpretation of the table relies on the context and the criteria and alternatives being assessed using the WASPAS method. Without further details regarding the criteria and alternatives, it is challenging to provide a more precise explanation.

TABLE 3. Weight Distribution

Composites	UTS (N/mm^2)	Toughness (J/mm^3)	Density(g/cc)	Wear rate (10^{-3} mm^3 /m)
Al-1100	0.25	0.25	0.25	0.25
Al-5% CSA	0.25	0.25	0.25	0.25
Al-10% CSA	0.25	0.25	0.25	0.25
Al-15% CSA	0.25	0.25	0.25	0.25
Al-20% CSA	0.25	0.25	0.25	0.25

Table 3 illustrates the allocation of weights for a set of criteria or attributes. The values in the table indicate the relative weights assigned to each criterion. In this instance, the weights are evenly distributed, with each criterion having a weight of 0.25. This equal distribution implies that all criteria are regarded as equally significant and carry an equal influence on the overall assessment or decision-making process. The decision-maker has opted for a balanced consideration of all factors by assigning equal weight to each criterion. It is worth noting that this interpretation assumes an even distribution of weights among the criteria.

TABLE 4. Weighted normalized decision matrix (WSM)

Composites	UTS (N/mm^2)	Toughness (J/mm^3)	Density(g/cc)	Wear rate (10^{-3} mm^3 /m)
Al-1100	0.14943	0.15880	0.22059	0.14996
Al-5% CSA	0.18391	0.17766	0.22556	0.16238
Al-10% CSA	0.22557	0.22205	0.23077	0.19531
Al-15% CSA	0.25000	0.25000	0.24291	0.25000
Al-20% CSA	0.21695	0.19614	0.25000	0.22676

Table 4 displays a weighted normalized decision matrix (WSM) that combines the normalized values from the previous table with their corresponding weights for each criterion. In the table, each row represents a specific alternative, while each column represents a criterion. The values presented in the table indicate the weighted normalized scores obtained from multiplying the weights assigned to each criterion with their respective normalized values. These scores reflect the weighted performance of each alternative across the criteria. By incorporating both the weights and the normalized values, the weighted normalized decision matrix provides a comprehensive evaluation of the alternatives based on their importance and performance across the criteria.

TABLE 5. Weighted normalized decision matrix (WPM)

Composites	UTS (N/mm^2)	Toughness (J/mm^3)	Density(g/cc)	Wear rate (10^{-3} mm^3 /m)
Al-1100	0.87927	0.89275	0.96919	0.88006
Al-5% CSA	0.92612	0.91814	0.97461	0.89774
Al-10% CSA	0.97463	0.97079	0.98019	0.94014
Al-15% CSA	1.00000	1.00000	0.99284	1.00000
Al-20% CSA	0.96518	0.94114	1.00000	0.97590

Table 5 displays a weighted normalized decision matrix (WPM) that combines the normalized values from the previous table with their corresponding weights for each criterion. In the table, each row represents a specific alternative, while each column represents a criterion. The values presented in the table indicate the weighted normalized scores obtained from multiplying the weights assigned to each criterion with their respective normalized values. These scores reflect the weighted performance of each alternative across the criteria. By incorporating both the weights and the normalized values, the weighted normalized decision matrix provides a comprehensive evaluation of the alternatives based on their importance and performance across the criteria.

TABLE 6. Preference Score (WSM & WPM)

Composites	Preference Score (WSM)	Preference Score (WPM)
Al-1100	0.67878	0.66953
Al-5% CSA	0.7495115	0.743974
Al-10% CSA	0.8736982	0.871903
Al-15% CSA	0.992915	0.992838
Al-20% CSA	0.8898479	0.886476

Table 6 presents preference scores for different composites, calculated using the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) in accordance with the WASPAS method. These scores indicate the relative rankings or preferences of the composites based on the evaluation criteria and their corresponding weights. The table includes the composite names, preference scores obtained from WSM, and preference scores obtained from WPM. The preference scores range between 0 and 1, with higher values representing higher preferences or rankings. For instance, Al-1100 has a WSM preference score of 0.67878 and a WPM preference score of 0.66953, while Al-5% CSA has a WSM preference score of 0.7495115 and a WPM preference score of 0.743974. These preference scores assist in assessing the relative performance and desirability of the composites based on the evaluation criteria and their assigned weights. However, further information regarding the specific criteria, weights, and context of the evaluation is necessary to provide a more precise interpretation of the preference scores.

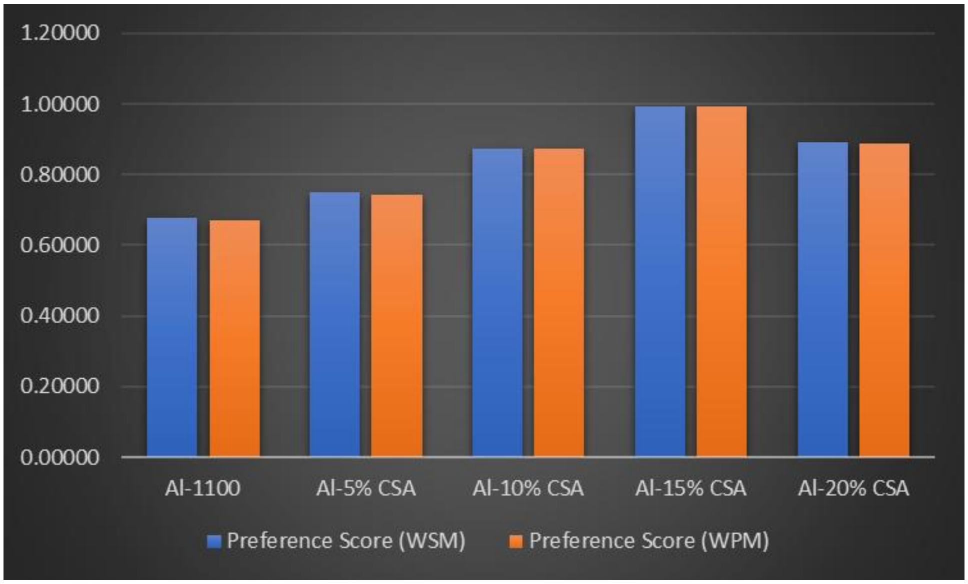

FIGURE 2. Preference Score (WSM & WPM)

Figure 2 displays preference scores for different composites calculated using the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) in the context of the WASPAS method. These scores indicate the relative rankings or preferences of the composites based on evaluation criteria and weights. Higher scores reflect higher preferences or rankings. For example, Al-1100 has a WSM preference score of 0.67878 and a WPM preference score of 0.66953, while Al-5% CSA has a WSM preference score of 0.7495115 and a WPM preference score of 0.743974. These scores assist in assessing the relative performance and desirability of the composites. However, additional information about the specific criteria, weights, and evaluation context is needed for a more precise interpretation.

TABLE 7. Preference score and Rank (WASPAS method [lambda 0.5])

Composites	Preference Score (WASPAS)	Rank
Al-1100	0.674158	5
Al-5% CSA	0.746743	4
Al-10% CSA	0.8728	3
Al-15% CSA	0.992877	1
Al-20% CSA	0.888162	2

Table 7 displays preference scores and ranks for different composites calculated using the WASPAS method with a lambda value of 0.5. The preference scores reflect the relative desirability or preference of each composite, considering the evaluation criteria and their corresponding weights. The ranks indicate the relative positions of the composites in terms of preference, with rank 1 being the most preferred. For instance, Al-1100 has a preference score of 0.674158, placing it in the 5th rank. Al-5% CSA has a preference score of 0.746743, ranking it 4th. Al-10% CSA has a preference score of 0.8728, earning it the 3rd rank. Al-15% CSA has the highest preference score of 0.992877, making it the top-ranked composite. Al-20% CSA has a preference score of 0.888162, securing the 2nd rank. These preference scores and ranks offer insights into the relative performance and desirability of the composites based on the evaluation criteria and their assigned weights.

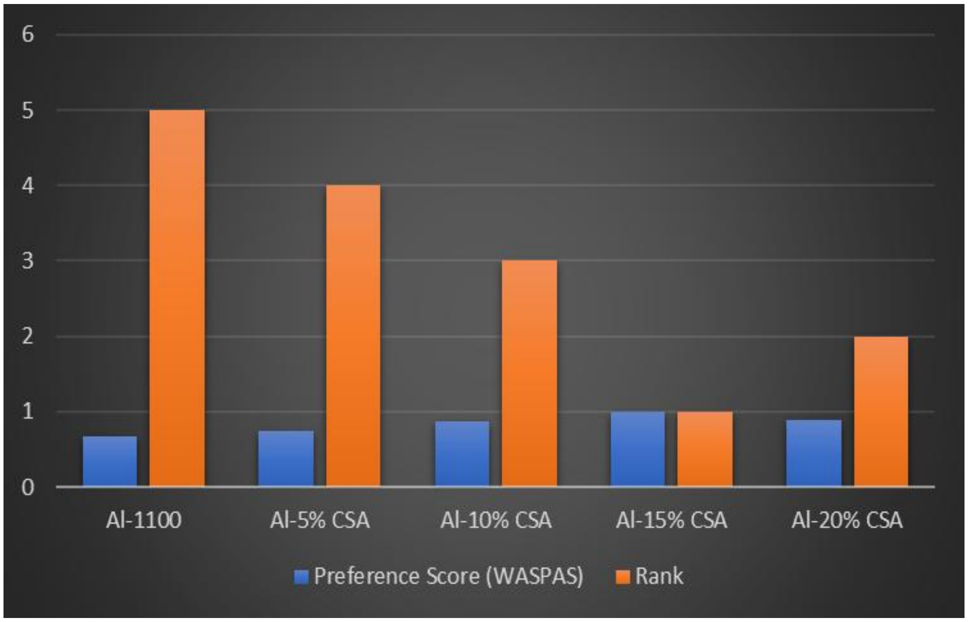

FIGURE 3. Preference score and Rank (WASPAS method [lambda 0.5])

The table presented as Figure 3 provides preference scores and ranks for different composites using the WASPAS method with a lambda value of 0.5. The preference scores indicate the relative desirability or preference of each composite, considering the evaluation criteria and their respective weights. The ranks represent the relative positions of the composites in terms of preference, with rank 1 indicating the highest preference. For example, Al-1100 has a preference score of 0.674158, placing it in the 5th rank. Al-5% CSA has a preference score of 0.746743, ranking it 4th. Al-10% CSA has a preference score of 0.8728, earning it the 3rd rank. Al-15% CSA has the highest preference score of 0.992877, making it the top-ranked composite. Al-20% CSA has a preference score of 0.888162, securing the 2nd rank. These preference scores and ranks offer valuable insights into the relative performance and desirability of the composites based on the evaluation criteria and their assigned weights.

4. CONCLUSION

Ranking aluminum-coconut shell ash composites is a methodical assessment and comparison of their characteristics and functionality utilising a range of resources and techniques. Researchers and engineers can determine whether these composites are appropriate for a given application by taking into account elements like mechanical strength, thermal stability, corrosion resistance, and cost-effectiveness. They can also optimise the composition of these composites to achieve the needed attributes. Testing criteria including tensile strength, flexural strength, and impact resistance are used to assess the mechanical strength of the composite and reveal how well it can handle outside forces. A higher rank in the composite ranking is correlated with higher values for these metrics, which imply superior mechanical performance. In applications requiring high temperatures or heat dissipation, thermal stability is essential. assessing variables including heat conductivity, thermal expansion coefficient, and In applications requiring high temperatures or heat dissipation, thermal stability is essential. The ability of the composite to tolerate thermal loads and preserve dimensional stability may be evaluated by taking into account factors like thermal conductivity, coefficient of thermal expansion, and thermal shock resistance. Composites with greater heat stability have more potential applications in these types of settings

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