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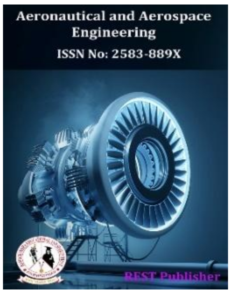

A Decision-Support System for Cryogenic Storage Tank Material Selection Based on WASPAS

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Abstract: *Material selection problem of cryogenic storage tank the material selection for cryogenic storage tanks is a critical and complex problem due to the extreme operating conditions and specific requirements of cryogenic applications. Cryogenic storage tanks are designed to store liquefied gases at very low temperatures, typically below -150°C (-238°F) Common materials used for cryogenic storage tanks include stainless steels, aluminum alloys, and certain low-temperature carbon steels. Additionally, specialized materials such as nickel alloys or composite materials may be utilized for specific applications where enhanced properties are required. The material selection process for cryogenic storage tanks involves a comprehensive evaluation of the aforementioned factors, often utilizing material databases, testing, and simulation tools. It is essential to consult with experts in cryogenic engineering and consider the specific requirements of the intended application to ensure the optimal material choice for cryogenic storage tanks. he Weighted Aggregated Sum Product Assessment (WASPAS) methodology is a multi-criteria decision-making (MCDM) technique used to solve problems where multiple criteria need to be considered for decision-making. The WASPAS methodology allows decision-makers to systematically evaluate alternatives based on multiple criteria and their relative importance. It provides a structured approach for decision-making that takes into account the preferences and priorities of the decision-maker. The weights assigned to the criteria play a crucial role in determining the final ranking of the alternatives. 2024 aluminium in the T6 temper, 2024 aluminium in the O temper, 301 Full Hard Tempered Stainless Steel, Stainless Steel 310, TC4, Ti64, or ASTM Grade 5, nickel-chromium-molybdenum super alloy, Brass. Yield Strength, Elastic Modulus, Toughness Index, Density, Specific Heat, Thermal Expansion. From the result we can see that ss301-FH got 1st rank and AL5052-0 got last rank. by using waspas method we obtained that ss301-FH got 1st rank and AL5052-0 got last rank .*

Key words: *Yield Strength, Elastic Modulus, Toughness Index, Density, Specific Heat, Thermal Expansion.*

1. INTRODUCTION

Material selection plays a crucial role in determining the performance, durability, and cost-effectiveness of a component or product. It requires a clear understanding of the functional requirements and a detailed knowledge of the criteria that are relevant to the specific design. The improper selection of materials can have serious consequences, including increased costs and premature failure of components or products. Therefore, designers need to carefully consider the characteristics, advantages, and limitations of different materials to make informed decisions. The process of material selection is a challenging task due to the vast number of available alternatives, each with its own unique properties. It is essential to identify and evaluate materials that possess the specific functionalities required for the desired output. This involves considering factors such as mechanical properties, thermal properties, chemical compatibility, manufacturability, and environmental considerations .Since material selection often involves multiple, conflicting criteria, it can be approached as a multi-criteria decision-making (MCDM) problem. Designers need to weigh and prioritize different criteria based on their relative importance to the application. This requires a systematic and efficient approach to ensure the best material alternative is chosen .Various methods and tools can assist in the material selection process, such as material property databases, decision matrices, and computer-aided design software. These resources help designers evaluate and compare different materials based on their performance against specific criteria.

Additionally, knowledge of industry standards, regulations, and past experiences with similar applications can also contribute to effective material selection. In conclusion, the selection of the most appropriate material for engineering applications is a critical task that requires careful consideration of functional requirements, knowledge of criteria, and a systematic approach. By employing appropriate methods and tools, designers can make informed decisions that optimize performance, minimize costs, and ensure the desired functionality of components and products. The selection of materials for a product is indeed a challenging task, as it directly influences the quality and cost of the end product. Material selection is an ongoing process that aims to identify the most suitable material to meet specific requirements. This decision is typically made during the initial design stage or during redesigns of a component. Choosing the wrong material can result in premature component failure and unnecessary costs. However, the development of new materials and production methods in recent decades has provided designers with a wider range of options. This allows for innovation and the potential to achieve enhanced performance at a lower cost. The emergence of substitute materials and the availability of numerous engineering materials further complicate the material selection process. Designers must navigate through a vast set of alternatives while considering various selection criteria, including technological, economical, and environmental factors. To make informed decisions, designers need a comprehensive understanding of the properties and behaviour of different materials under varying working conditions. Properties such as strength, durability, flexibility, weight, heat and corrosion resistance, cast ability, weld ability, mach inability, and electrical conductivity are among the important considerations. The material selection process aims to identify the dominant selection criteria and find the most appropriate combination of conflicting criteria based on the requirements. Designers must evaluate both qualitative and quantitative criteria when selecting the best material for a specific application. In summary, the material selection process is crucial for achieving desired product outcomes. Designers must possess knowledge about material properties, consider a wide range of criteria, and navigate through numerous alternatives to identify the most suitable material for a given application. The selection of material for a specific engineering component is indeed a critical factor that greatly influences its design and proper functioning. The material chosen for a component can have a substantial impact on its performance, durability, reliability, and overall functionality. Here are some key considerations regarding the selection of materials: Functional Requirements: The material must fulfill the functional requirements of the component. This includes factors such as mechanical strength, dimensional stability, thermal properties, electrical conductivity, corrosion resistance, and compatibility with other materials or fluids in the system. Load and Stress Considerations: The material should be capable of withstanding the anticipated loads, stresses, and environmental conditions that the component will experience during its operational life. The selection should account for factors like tensile strength, yield strength, fatigue resistance, and toughness. Manufacturing and Fabrication: The material should be suitable for the manufacturing and fabrication processes involved in producing the component. Considerations include the ease of casting, forging, machining, welding, and forming the material. Cost and Availability: The cost of the material, including its sourcing, processing, and any additional treatments, should be considered. Availability and sourcing constraints should also be taken into account, especially for large-scale production. Environmental and Sustainability Factors: The environmental impact of the material, such as its recyclability, energy consumption during production, and potential for pollution, should be considered from a sustainability perspective. Longevity and Maintenance: The material should be chosen to ensure the desired lifespan and minimize the need for frequent maintenance or replacement. Factors such as resistance to wear, corrosion, and degradation over time should be evaluated. Regulatory and Standards Compliance: Compliance with relevant industry standards, regulations, and safety requirements is crucial. The material should meet the necessary certifications and specifications for the intended application.To select the most suitable material, designers must carefully evaluate these factors, often using material databases, testing, simulations, and expertise in the field. Collaboration with material scientists, engineers, and suppliers can also provide valuable insights and support in the decision-making process. Indeed, materials have had a profound impact on society throughout history, and their significance is unlikely to change in the future. The development of engineering materials such as concrete, steel, and plastics has played a pivotal role in the growth of modern civilization. Advanced materials with unique and superior properties will continue to be essential in finding solutions to the grand challenges faced by humanity. Selecting the appropriate material is a crucial aspect of engineering design and product development. Designers must determine the required material properties for a specific product and evaluate candidate materials based on those properties. However, material selection can be challenging due to incomplete or unavailable material data. Traditionally, material selection has been done manually using handbooks, thumb-rules, and heuristics. Ashby's material selection charts have been a valuable graphical tool for initial screening of materials, providing insight into property trade-offs. Additionally, tools like the Cambridge Engineering Selector (CES) have been developed to aid in material selection. CES is a sophisticated web-enabled tool that provides access to materials and design information, assisting designers in making informed decisions, checking for potential issues, and reducing turnaround time.The availability of comprehensive material databases would significantly simplify the material selection process. Storing knowledge related to the properties of a large number of materials in a database would eliminate the need for tedious handbook searches. Advances in computing, communications, and data acquisition technologies have made it possible to gather and store vast volumes of material property data. With the continuous development of new material alternatives, these databases can be regularly updated to meet the demands of modern manufacturing.In summary, materials play a critical role in shaping society, and their selection is an important aspect of engineering design. The availability of comprehensive material databases and sophisticated selection tools can greatly aid designers in making informed decisions, improving efficiency, and promoting innovation in material selection and product development.

2. MATERIALS AND METHOD

***2024 aluminum in the T6 temper*:** 2024 aluminum is a high-strength aluminum alloy that is commonly used in aerospace applications. When in the T6 temper, 2024 aluminum undergoes a specific heat treatment process to enhance its mechanical properties. specific properties of 2024 aluminum in the T6 temper may vary depending on the exact processing, heat treatment, and manufacturing methods. 2024 aluminum in the O temper: 2024 aluminum in the O temper refers to the annealed condition of the alloy. When in the O temper, 2024 aluminum has not undergone any specific heat treatment to enhance its mechanical properties. It's important to note that the O temper of 2024 aluminum is primarily used when the alloy needs to be formed, shaped, or machined. If higher strength is required, the material can be heat treated to achieve the desired mechanical properties in other tempers such as T3, T4, or T6. The specific properties and applications of 2024 aluminum in the O temper may vary depending on the exact composition and manufacturing processes used.301 Full Hard Tempered Stainless Steel: 301 Full Hard Tempered Stainless Steel is a type of austenitic stainless steel that has been cold rolled and then fully hardened through a process known as tempering. the full hard temper of 301 stainless steel is achieved through a specific cold rolling and annealing process. The resulting material is characterized by its high strength and hardness. The specific properties and applications of 301 Full Hard Tempered Stainless Steel may vary depending on the exact composition, processing, and intended use. Stainless Steel 310: Stainless Steel 310 is a high-temperature austenitic stainless steel that offers excellent resistance to oxidation and high-temperature corrosion. It's important to note that the specific properties and performance of Stainless Steel 310 may vary depending on the manufacturing process, heat treatment, and environmental conditions.

TC4, Ti64, or ASTM Grade 5: C4, Ti64, and ASTM Grade 5 are different designations for the same titanium alloy. Here's some information about this alloy: TC4, Ti64, or ASTM Grade 5 refers to a titanium alloy composed of approximately 90% titanium, 6% aluminum, and 4% vanadium (hence the name Ti64). It is a widely used titanium alloy known for its excellent strength, low density, and corrosion resistance. the specific mechanical properties and performance of TC4/Ti64/ASTM Grade 5 can be further tailored through heat treatment and alloy modifications.

nickel-chromium-molybdenum superalloy*:* A nickel-chromium-molybdenum superalloy is a type of alloy that contains nickel as the primary element, along with significant amounts of chromium and molybdenum. These alloys are known for their exceptional strength, heat resistance, and corrosion resistance, making them suitable for high-temperature applications. there are different grades and variations of nickel-chromium-molybdenum superalloys, each with its specific composition and properties. These alloys are often tailored for specific applications, and their performance can be further enhanced through specialized heat treatments and alloy modifications.One well-known example of a nickel-chromium-molybdenum superalloy is Inconel, which encompasses a range of alloys (e.g., Inconel 600, Inconel 625, Inconel 718) with slightly different compositions and characteristics. Brass: Brass is an alloy composed primarily of copper and zinc, with varying proportions of each metal depending on the desired properties and applications. Due to its versatility and desirable properties, brass finds applications in a wide range of industries, including plumbing, electrical, automotive, marine, construction, and decorative arts. It is important to note that there are different types and grades of brass available, each with its specific composition and properties.

TOPSIS Method: The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is one of the numerical methods used in multi-criteria decision making. It is a method with a broad range of applications and a simple mathematical foundation. It is also a very practical method that makes use of computers. Using the TOPSIS supplier rating method.The TOPSIS approach has the following primary benefits: 1. It is easy to operate. 2. It considers both subjective and objective factors of every kind. 3. It makes sense and is rational. 4. The computation techniques are simple. 5. The idea allows for the pursuit of the optimal choices as determined by a straightforward mathematical calculation. Yoon and Hwang originally presented the TOPSIS approach, which was evaluated by surveyors and various operators. A method for making decisions is TOPSIS.

Finding the alternative that comes the closest to the optimal answer is done using a goal-based approach. This approach grades solutions according to how closely they resemble the ideal solution. An option receives a better score if it is more comparable to the ideal course of action. A solution that is ideal from any perspective but does not actually exist is one we attempt to approximate. In order to determine how closely a design (or alternative) resembles ideal and non-ideal levels, we primarily take into account the design's distance from ideal and non-ideal solutions. The best option from a list of possibilities is chosen using a multi-criteria decision-making (MCDM) approach termed TOPSIS (tactic for Order of Preference by Similarity to Ideal Solution). It comprises comparing alternatives to the best and worst possibilities and evaluating alternatives in relation to a set of standards. The TOPSIS method functions as follows: Criteria Identification Establish the relevant criteria that will be used to evaluate the alternatives. These standards ought to reflect the preferences of the decision-maker and be quantifiable and independent. For instance, while comparing several car models, factors may include cost, fuel economy, safety score, and interior room.To bring the criteria values to a single scale, normalise them. This phase makes sure that each criterion receives the same amount of weight when making a decision. Standardisation or min-max normalisation procedures are frequently used to convert the raw data into a unitless scale, such as a range between 0 and 1.The criteria should be given weights in order to indicate their respective relevance. The weights, which represent the decision-maker's preferences or priorities, are arbitrary. For instance, the safety rating criterion would be given more weight if it were thought to be more significant than price. The decision matrix should be built with the normalised values for each choice and criterion. The dimensions of the decision matrix will be m x n, where m represents the number of possibilities and n represents the number of criteria. the Best and Worst Solutions are Determined: Add up the normalised numbers for each criterion to determine the best solution and worst solution. For each criterion, the best performance is represented by the ideal solution, whilst the poorest performance is represented by the worst solution. This is accomplished by choosing, for each criterion, the maximum and minimum values.Using the performance of each alternative in comparison to the best and worst solutions, get the similarity scores for each one. A distance metric, such as the Manhattan distance or the Euclidean distance, is used to get the similarity score. Alternatives that are closer to the best option and farther from the worst option are deemed to be preferable.Prioritise the alternatives: Based on the similarity scores of the alternatives, order them. The option with the highest similarity rating is regarded as the best option.The TOPSIS method offers a methodical approach to decision-making by taking into account several variables at once. It aids decision-makers in objectively assessing alternatives and selecting the best choice in light of their preferences and the established criteria.Identifying the criteria that will be used to evaluate the alternatives is the first stage in the TOPSIS technique. These standards ought to be pertinent, quantifiable, and consistent with the choice issue. For instance, when choosing a supplier, factors may include cost, level of quality, timeliness of delivery, and level of customer service.The data must be normalised after the criteria have been developed in order to place all of the criteria on a common scale. This is carried out to guarantee that evaluation criteria with different measurement scales or units are appraised equally. Two examples of normalisation methods are min-max normalisation and linear normalisation.Weighting: Based on each criterion's relative importance or priority, decision-makers must assign weights to each one. The weights represent how significant each criterion was in the decision-making process. The weights can be determined using a variety of techniques, such as expert judgement, the analytical hierarchy process (AHP), or the preferences of other stakeholders. Putting together the Decision Matrix By arranging the normalised values of each criterion for each choice, the decision matrix is produced. Each column denotes a need, while each row denotes an option. The performance of the options in comparison to the criteria is numerically represented in the decision matrix.Making the Perfect Solution: The positive ideal solution (PIS) and the negative ideal solution (NIS) are two categories of ideal solutions that are taken into account by the TOPSIS approach.The PIS and NIS represent the best and worst possible results for each criterion, respectively. On the basis of either maximising or minimising each criterion, these ideal solutions are built.Making an estimate of the closeness coefficient The distance between each alternative and the ideal solutions is calculated using the closeness coefficient. The distances between each alternative and the PIS and NIS are compared to determine it. Different distance metrics, such as the Manhattan distance or the Euclidean distance, can be used to determine the distances.Putting the Alternatives in Order The final step is to rank the options according to their closeness coefficients. The option that is closest to the ideal solution, as measured by the closeness coefficient, is deemed to be the best option.When faced with several criteria and options, the TOPSIS approach is a helpful decision-making tool. It offers a methodical and organised methodology for assessing alternatives and ranking them according to how well they perform in comparison to the optimal solutions. Identification of Criteria: List the standards by which the alternatives will be judged. These standards ought to be pertinent, quantifiable, and directly tied to the decision-making issue.Give each criterion a weight to represent their relative relevance or order of importance. The decision-maker's subjective preferences are reflected in the weights, which can be established using a variety of techniques, including surveys, expert judgement, and analytical procedures.Normalisation: To counteract the impact of various measurement scales, normalise the assessment matrix. This is accomplished by standardising the raw data through transformation, usually When faced with several criteria and options, the TOPSIS approach is a helpful decision-making tool. It offers a methodical and organised Give each criterion a weight to represent their relative relevance or order of importance. The decision-maker's subjective preferences are reflected in the weights, which can be established using a variety of techniques, including surveys, expert judgement, and analytical procedures. Normalisation: To counteract the impact of various measurement scales, normalise the assessment matrix. This is accomplished by standardising the raw data through transformation, usually Determine Ideal and Negative Ideal Solutions: Using the normalised values for each criterion, determine the ideal solution (maximum for benefit criteria and minimum for cost criteria) and the negative ideal solution (minimum for benefit criteria and maximum for cost criteria). Calculate the Euclidean Distances: Determine how far apart the ideal and the negative ideal are from each choice. Each alternative's resemblance or proximity to the ideal and contra-ideal solutions is quantified by the Euclidean distance. Calculate the Relative Closeness: To determine how close each alternative is to the ideal and negative ideal solutions, divide the distance to the negative ideal solution by the sum of those distances. The choices should be ranked according to how near they are to each other. The best option is regarded as having the most relative proximity.The TOPSIS method enables decision-makers to evaluate choices in a methodical manner that takes both the advantages and disadvantages of each option into account. It can be used to enhance informed decision-making in a variety of areas, including project selection, supplier selection, investment decisions, and strategy planning.

3. RESULT AND DISCUSSION

TABLE 1 Material selection problem of cryogenic storage tank

BIM for Smart Hospital Management	Yield Strength	Elastic Modulus	Toughness Index	Density	Specific Heat
Al2024-T6	420	74.2	75.5	2.8	0.16
Al5052-O	91	70	95	2.68	0.16
SS301-FH	1365	189	770	7.9	0.08
SS310-3AH	1120	210	187	7.9	0.08

Table 1 showing WSM alternative parameters Al2024-T6, Al5052-O, SS301-FH ,SS310-3AH evaluation parameters yield strength, elastic modules, toughness index, density, specific heat, under topsis method.

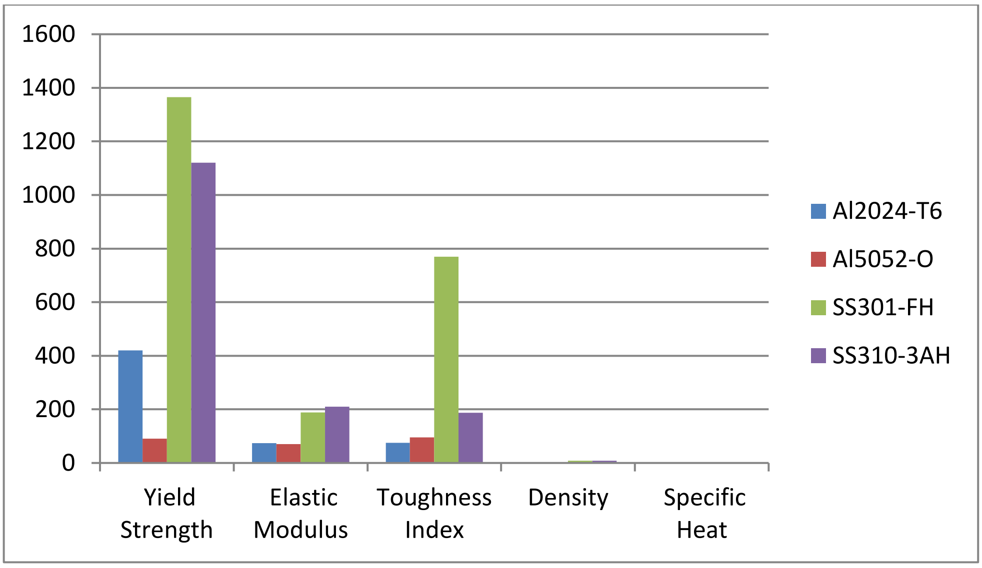

FIGURE 1. Material selection problem of cryogenic storage tank

Figure 1 showing WSM alternative parameters Al2024-T6, Al5052-O, SS301-FH ,SS310-3AH Ti6Al4V, and evaluation parameters yield strength, elastic modules, toughness index, density, specific heat.

TABLE 2 Normalized Data

	Yield Strength	Elastic Modulus	Toughness Index	Density	Specific Heat
Al2024-T6	0.1846814	0.602883	0.567403	0.74009	0.719864
Al5052-O	0.0361404	0.558376	0.148322	0.02512	0.238226
SS301-FH	0.052801	0.067625	0.429019	0.78474	0.509397
SS310-3AH	0.0164696	0.62619	0.690878	0.159273	0.689889

Table 2 showing Normalized Data Al2024-T6, Al5052-O, SS301-FH ,SS310-3AH evaluation parameters yield strength, elastic modules, toughness index, density, specific heat, under topsis method.

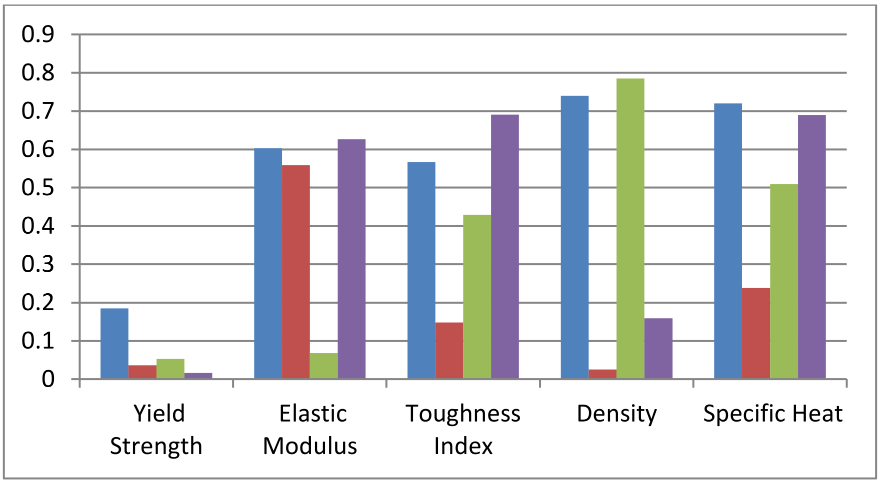

FIGURE 2 Normalized Data

Figure 2 showing alternative parameters Al2024-T6, Al5052-O, SS301-FH ,SS310-3AH Ti6Al4V, and evaluation parameters yield strength, elastic modules, toughness index, density, specific heat

TABLE 3. weight

	Yield Strength	Elastic Modulus	Toughness Index	Density	Specific Heat
Al2024-T6	0.2	0.2	0.2	0.2	0.2
Al5052-O	0.2	0.2	0.2	0.2	0.2
SS301-FH	0.2	0.2	0.2	0.2	0.2
SS310-3AH	0.2	0.2	0.2	0.2	0.2

Table 3 shows weights and alternative parameters Al2024-T6, Al5052-O, SS301-FH ,SS310-3AH Ti6Al4V, and evaluation parameters yield strength, elastic modules, toughness index, density, specific heat

TABLE 4. Weighted Normalized Decision Matrix

	Yield Strength	Elastic Modulus	Toughness Index	Density	Specific Heat
Al2024-T6	155.9592	10.89565	11.14514	0.42834	0.021786
Al5052-O	33.79117	10.27892	14.02368	0.409983	0.021786
SS301-FH	506.8675	27.75308	113.6656	1.208531	0.010893
SS310-3AH	415.8913	30.83676	27.60451	1.208531	0.010893

Table 4 shows weighted normalized decision matrix and alternative parameters Al2024-T6, Al5052-O, SS301-FH, SS310-3AH Ti6Al4V, and evaluation parameters yield strength, elastic modules, toughness index, density, specific heat.

TABLE 5. Positive Matrix

	Yield Strength	Elastic Modulus	Toughness Index	Density	Specific Heat
Al2024-T6	506.8675	30.83676	113.6656	1.208531	0.021786
Al5052-O	506.8675	30.83676	113.6656	1.208531	0.021786
SS301-FH	506.8675	30.83676	113.6656	1.208531	0.021786
SS310-3AH	506.8675	30.83676	113.6656	1.208531	0.021786

Table 5 presents the positive (normalized) matrix for five key material properties: Yield Strength, Elastic Modulus, Toughness Index, Density, and Specific Heat. The materials considered—Al2024-T6, Al5052-O, SS301-FH, and SS310-3AH—exhibit identical normalized values across all criteria. This indicates that, after applying the normalization procedure, each material attains the same positive reference value for every property. Such a result suggests that all alternatives perform equally with respect to the selected criteria in the positive ideal matrix. Consequently, no single material shows dominance over the others at this stage of analysis, and further evaluation using weighting or distance-based MCDM methods is required to differentiate and rank the materials effectively.

TABLE 6 Negative Matrix

	Yield Strength	Elastic Modulus	Toughness Index	Density	Specific Heat
Al2024-T6	33.79117	10.27892	11.14514	0.409983	0.010893
Al5052-O	33.79117	10.27892	11.14514	0.409983	0.010893
SS301-FH	33.79117	10.27892	11.14514	0.409983	0.010893
SS310-3AH	33.79117	10.27892	11.14514	0.409983	0.010893

Table 6 illustrates the negative matrix values corresponding to Yield Strength, Elastic Modulus, Toughness Index, Density, and Specific Heat for the selected materials: Al2024-T6, Al5052-O, SS301-FH, and SS310-3AH. All materials show identical values across each criterion, indicating that they are equally distant from the negative ideal solution after normalization. The negative matrix represents the least desirable performance levels for each criterion, serving as a reference for comparison in distance-based MCDM methods. Since no variation is observed among the alternatives in this matrix, the materials exhibit the same relative deviation from the worst-case scenario, implying that further analysis using separation measures or weighted aggregation is necessary to achieve meaningful ranking.

TABLE 8 SI positive values

SI PLUS	SI positive
Al2024-T6	366.122
Al5052-O	483.8936
SS301-FH	308.3695
SS310-3AH	125.2325

Table 8 presents the positive separation index (SI^+) values for the selected materials, namely Al2024-T6, Al5052-O, SS301-FH, and SS310-3AH. The SI^+ value represents the distance of each alternative from the positive ideal solution; hence, a higher SI^+ value indicates a greater deviation from the ideal performance, while a lower value reflects closer proximity to the best possible solution. Among the materials, Al5052-O exhibits the highest SI^+ value (483.8936), indicating that it is farthest from the positive ideal solution. In contrast, SS310-3AH shows the lowest SI^+ value (125.2325), suggesting that it is closest to the positive ideal solution. The intermediate values of Al2024-T6 (366.122) and SS301-FH (308.3695) indicate moderate distances. These results highlight clear differentiation among the materials and play a crucial role in the final ranking process when combined with negative separation and closeness coefficients.

TABLE 9 SI Negative Values

	SI Negative
Al2024-T6	122.1696
Al5052-O	287.8566
SS301-FH	484.3735
SS310-3AH	383.0074

Table 9 shows the negative separation index (SI^-) values for the materials Al2024-T6, Al5052-O, SS301-FH, and SS310-3AH. The SI^- value represents the distance of each alternative from the negative ideal solution, which corresponds to the worst possible performance across all criteria. Higher SI^- values indicate that a material is farther away from the negative ideal solution and therefore more desirable, while lower values suggest closer proximity to the least preferred condition. Among the alternatives, SS301-FH exhibits the highest SI^- value (484.3735), indicating strong performance by being farthest from the worst-case scenario. This is followed by SS310-3AH (383.0074) and Al5052-O (287.8566). In contrast, Al2024-T6 shows the lowest SI^- value (122.1696), implying that it is relatively closer to the negative ideal solution. These SI^- values, when combined with SI^+ values, are essential for computing the closeness coefficient and final material ranking.

TABLE 10 CI values

	CI
Al2024-T6	0.250198
Al5052-O	0.005914
SS301-FH	0.993674
SS310-3AH	0.753596

Table 10 presents the Closeness Index (CI) values for the four materials: Al2024-T6, Al5052-O, SS301-FH, and SS310-3AH. The CI value represents the relative closeness of each alternative to the ideal solution by simultaneously considering its distance from both the positive ideal (SI^+) and the negative ideal (SI^-). A higher CI value indicates better overall performance, as the material is closer to the positive ideal solution and farther from the negative ideal solution. Among the evaluated materials, SS301-FH achieves the highest CI value (0.993674), indicating that it is the most suitable material based on the selected criteria. This is followed by SS310-3AH with a CI of 0.753596, showing strong overall performance. Al2024-T6 attains a moderate CI value (0.250198), suggesting average suitability. In contrast, Al5052-O records the lowest CI value (0.005914), indicating the least preference among the alternatives.

TABLE 11 Rank

	RANK
Al2024-T6	3
Al5052-O	4
SS301-FH	1
SS310-3AH	2

Table 9 presents the final ranking of the selected materials based on their calculated Closeness Index (CI) values. The ranking reflects the overall performance of each material by considering its proximity to the positive ideal solution and its distance from the negative ideal solution. SS301-FH is ranked first, indicating that it demonstrates the most favorable balance of mechanical and thermal properties among all alternatives. SS310-3AH secures the second rank, showing strong overall performance but slightly lower suitability compared to SS301-FH. Al2024-T6 is placed in the third position, suggesting moderate performance across the evaluated criteria. Finally, Al5052-O is ranked fourth, indicating the least suitability under the given decision framework. This ranking provides a clear and systematic basis for material selection, supporting informed and objective decision-making.

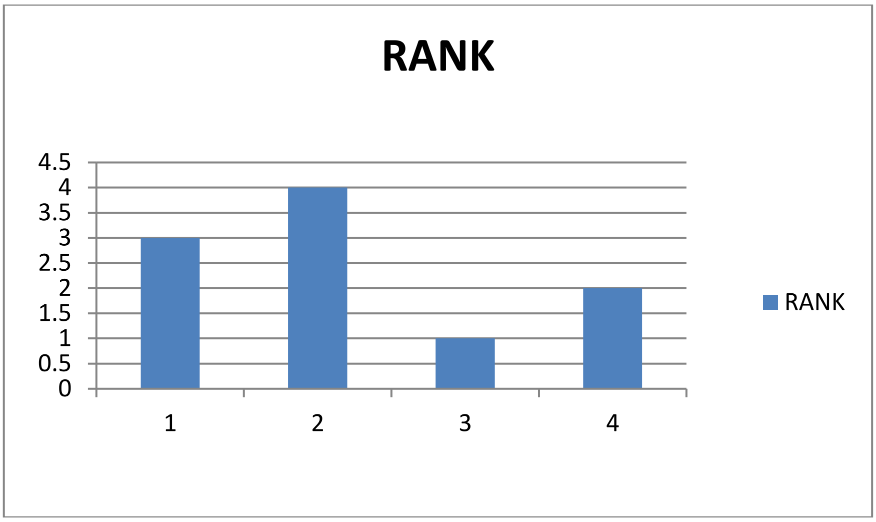

FIGURE 10 Rank

Figure 10 showing the final ranking of the materials based on their evaluated performance using the Closeness Index values. The ranking represents how effectively each material satisfies the selected criteria by being closer to the ideal solution and farther from the least desirable one. SS301-FH achieves the top rank, indicating superior overall performance among the alternatives. SS310-3AH follows in second place, demonstrating strong suitability with slightly lower performance than the top-ranked material. Al2024-T6 is positioned third, reflecting an average level of performance across the criteria. Al5052-O ranks fourth, showing comparatively lower suitability within the adopted decision-making framework. This final ranking clearly supports an objective and systematic approach to material selection.

4. CONCLUSION

Careful consideration of a number of criteria is necessary while solving the material selection problem for cryogenic storage tanks. Performance, safety, and cost-effectiveness of the tank are all impacted by the material selection. Due to their high mechanical strength and resistance to corrosion, stainless steel alloys like 304L and 316L are frequently utilised. Their ductility at very low temperatures, however, may restrict their usage in several cryogenic applications. Aluminium alloys with good cryogenic characteristics, including 5083 and 6061, provide lightweight choices.. They are appropriate for non-pressurized cryogenic storage tanks, such as LNG tanks, however they have less mechanical strength than stainless steel.Although carbon steel, such ASTM A516 Grade 70, offers affordable solutions, it needs more insulation and corrosion protection. At cryogenic temperatures, it provides enough strength and hardness but is more prone to corrosion. At cryogenic temperatures, nickel-based alloys with exceptional corrosion resistance and high strength, such as Inconel 600 and Incoloy 825, are available. Despite being more expensive, they are chosen in specialised applications with harsh cryogenic conditions or corrosive surroundings. Composite materials, such carbon fibre reinforced polymers (CFRP), hold promise due to their ability to reduce weight and withstand corrosion. However, before to deployment, significant consideration is required due to their high cost and long-term durability. In the end, the choice of material for cryogenic storage the material selection problem for cryogenic storage tanks is a complex task that requires careful consideration of multiple factors. The choice of material directly impacts the tank's performance, safety, and cost-effectiveness. Based on the analysis of various materials, the following key points can be summarized: Stainless steel, such as 304L and 316L, is a popular choice due to its good mechanical properties, corrosion resistance, and reasonable cost. It is suitable for moderate cryogenic temperatures and offers a balance between performance and affordability. Aluminum alloys, Lightweight choices that thrive in non-pressurized cryogenic applications like LNG storage tanks include 5083 and 6061. They have reasonable low-temperature embrittlement resistance and cryogenic qualities, although they are less strong mechanically than stainless steel. For cryogenic storage tanks, carbon steel, such as ASTM A516 Grade 70, offers affordable solutions. Although it provides enough strength and toughness at cryogenic temperatures, its sensitivity to corrosion necessitates additional corrosion prevention measures. Extremely cold or corrosive situations favour nickel-based alloys, such as Inconel 600 and Incoloy 825. Although they have strong strength at low temperatures and excellent corrosion resistance, their more expensive price may prevent them from being widely used. For cryogenic storage tanks, composite materials like carbon fibre reinforced polymers (CFRP) show potential.

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