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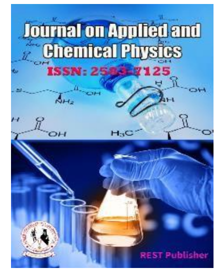

A GRA Approach For Selecting The Best Materials With The Use Of Decision Theory

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Abstract: *The process of selecting the best material for a certain application or product is known as optimal material selection in engineering and design. Mechanical qualities, cost, availability, environmental effect, and manufacturing requirements are all important considerations. The purpose for optimal material selection was to determine the material that best fits the application's performance inherent functional requirements while taking into account the limits or trade-offs associated with other materials. Engineers and designers may make informed judgments that maximize the performance, durability, as well as cost-effectiveness of the finished item by carefully assessing the features and attributes of various materials. Analyzing and comparing materials based on mechanical strength, stiffness, thermal characteristics, corrosion resistance, and electrical conductivity is part of optimal material selection. Identifying the precise needs and restrictions for each application, performing a materials search finally evaluation, material testing and evaluation, and finally selecting the material which most closely matches the necessary criteria are all part of the process. To summaries, optimal material selection involves a systematic process that takes into account a variety of parameters in order to select the best material for a certain application. It helps engineers and designers to develop high-performance, low-cost products that meet the specified functional requirements and standards. The research significance of optimal material selection lies in its ability to inform and guide engineers and designers in making informed decisions about material choices for various applications. the research on optimal material selection is significant as it empowers engineers, designers, and businesses to make informed decisions that enhance product performance, reduce costs, promote sustainability, drive innovation, and improve industry competitiveness.[1] The GRA approach is commonly used to choose the best optimal material selection. Take as Alternative parameters for "Low strength steels, High strength steels, Advanced high strength steels, Ultra-high strength steels, Stainless steels, Aluminumalloy7×××series, Aluminumalloy6×××series, Aluminumalloy5×××series, Aluminum extrusion profiles, cast aluminum, Magnesium alloy, Ti alloy, Thermo plastic sting plastics (PP), Thermo setting plastics (UP), Carbon fiber/epoxy Composites, S-glass fiber /epoxy Composites". Taken as Evaluation parameters for Density, Modulus of elasticity, Yield, Strength tensile strength, and Corrosion resistance. From the result it is seen that Carbon fiber/epoxy Composites got highest rank whereas Magnesium alloy got lowest rank According to the results, Carbon fiber/epoxy Composites was ranked first.*

Keywords: *Density, Modulus of elasticity, Yield, Strength tensile strength, Corrosion resistance.*

1. INTRODUCTION

One of the greatest fundamental difficulties in engineering design is material selection. It is critical and difficult to select from over 200,000 materials that are able to suit various design demands and have the attributes required by the designer. Many experts have been looking for the best material for varied uses for over twenty years. The choice of the best materials in the design of engineering is regarded as a critical stage in the design process. The utilization of each item necessitates a methodology for selection, which can be viewed as a problem-solving exercise. This activity necessitates a decision-making process based on extensive knowledge and engineering methods. The importance and difficulty of tackling the challenge can be better appreciated by using examples from everyday life. A tractor, for example, has 15-20 thousand pieces, a car has 25-30 thousand, an armoured vehicle has 40 thousand, an underwater vessel has 120 thousand, and a plane has 2-6 million parts composed of various materials. Ashby &

Granta's CES selector 2014 computer-aided material selection software was used to determine the material alternatives for the hip prosthesis in terms of boundary restrictions including biocompatibility, biomechanical performance, and cost. The material choices identified by the CES software have been uploaded to ANSYS software, when the mechanical behaviour of a hip prosthesis was studied using FEA for each model. The optimum material candidate for THA was found based on osseointegration micromotions at the implant-bone cement contact.

2. MATERIALS AND METHODS

Density: Density is a physical property that describes how much mass is contained in a given volume of a substance. It is defined as the mass of an object divided by its volume. In simpler terms, density tells us how tightly packed the particles are in a material. The formula for density is: Density = Mass / Volume

Modulus of elasticity: The modulus of elasticity, also known as Young's modulus, is a measure of the stiffness or rigidity of a material. It quantifies how a material deforms when subjected to an applied force or stress. In simpler terms, it describes a material's ability to stretch or compress under load. The modulus of elasticity is defined as the ratio of stress to strain within the elastic limit of a material. Stress is the force applied to a material per unit area, while strain is the resulting deformation or change in shape of the material.

The formula for modulus of elasticity is: Modulus of Elasticity = Stress / Strain

Yield: In the context of materials and engineering, yield refers to the point at which a material undergoes significant plastic deformation or permanent deformation when subjected to an applied stress or load. In simpler terms, it is the stress level at which a material starts to change shape permanently instead of returning to its original shape when the stress is removed.

yield refers to the point at which a material undergoes permanent deformation under applied stress. The yield strength indicates the stress level at which this deformation occurs and is crucial for engineering design and ensuring the structural integrity of materials.

Strength tensile strength: Tensile strength is an important property for evaluating the mechanical strength and performance of materials. It provides information on the material's ability to withstand stretching or elongation without breaking. High tensile strength indicates a material that can withstand greater pulling forces before failure, while low tensile strength suggests a material that is more prone to breaking under tension.

Corrosion resistance: Corrosion resistance is a critical consideration in various industries, including construction, transportation, manufacturing, and marine applications. It ensures the durability and reliability of structures, equipment, and components exposed to corrosive environments, ultimately reducing maintenance costs and improving safety.

corrosion resistance refers to a material's ability to withstand degradation caused by chemical reactions with its environment. It plays a crucial role in determining the lifespan and performance of materials in corrosive conditions and is an essential factor in material selection and design.

3. GRA METHOD

The Grey Relational Analysis (GRA) approach is a quantitative analysis tool that is used to assess the relationship between several variables or components. It is especially effective when working with systems or circumstances with limited knowledge or data. Preparation of Data: The initial stage in GRA is to gather and normalize data for every variable or component. Normalization is required to guarantee all of the variables are on the same scale with an equal weight in the study. Calculating the Grey Relational Coefficient: The Grey Relational Coefficient (GRC) is calculated by the GRA technique to measure the resemblance or proximity of each variable to a reference variable. The GRC denotes the degree of connection between variables and their relevance in regard to the reference variable. Calculating the Grey Relational Grade (GRG): The Grey Relational Grade (GRG) is calculated by averaging the GRC values for each variable over all reference variables. The GRG provides a rating or rating system that measures each variable's similarity or proximity to the original variables. Rank Ordering: The variables are placed according to the degree of their proximity or resemblance to the standard variables based on their GRG values. This ranking assists in identifying the variables in the evaluation that are the most impactful or relevant. Decision-Making: The GRA analysis results can be utilised to aid decision-making by highlighting the factors with the greatest grey relational grade with the closest relationship to the references variables. These variables are worthy of further examination. In summary, the GRA method is a quantitative analysis tool that uses the Grey Relational Coefficient and Grey Relational Grade to quantify the relationship and relevance of variables. It aids in the ranking of variables according to their similarity or closeness with other variables, providing useful information for decision-making processes.

4. RESULT AND DESCUSSION

TABLE 1. data set

Material alternatives	density	modulus of elasticity	yield strength	tensile strength	corrosion resistance
Low strength steels	7.85	205	200	260	5
High strength steels	7.85	205	470	535	5
Advanced high strength steels	7.85	200	860	1150	6
Ultra-high strength steels	7.85	205	970	1250	5
Stainless steels	7.85	205	310	620	5
Aluminumalloy7×××series	2.8	72	385	460	7
Aluminumalloy6×××series	2.8	70	260	310	7
Aluminumalloy5×××series	2.8	69.5	170	220	7
Aluminum extrusion profiles	2.7	70	160	215	7
Cast aluminum	2.7	73	210	290	7
Magnesium alloy	1.79	45	130	237	3
Ti alloy	4.5	108	1100	1200	9
Thermo plastic sting plastics(PP)	0.9	1.6	35	35	9
Thermo setting plastics(UP)	1.2	3.16	51.3	65	9
Carbon fiber/epoxy Composites	1.61	115	1100	1400	9
S-glass fiber/epoxy Composites	1.83	23.8	354.5	448.8	9

Table 1 showing the data set of "optimal material selection for Low strength steels, High strength steels, Advanced high strength steels, Ultra-high strength steels, Stainless steels, Aluminumalloy7×××series, Aluminumalloy6×××series, Aluminumalloy5×××series, Aluminum extrusion profiles, Cast aluminum, Magnesium alloy, Ti alloy, Thermo plastic sting plastics(PP), Thermo setting plastics(UP), Carbon fiber/epoxy Composites, S-glass fiber /epoxy Composites".

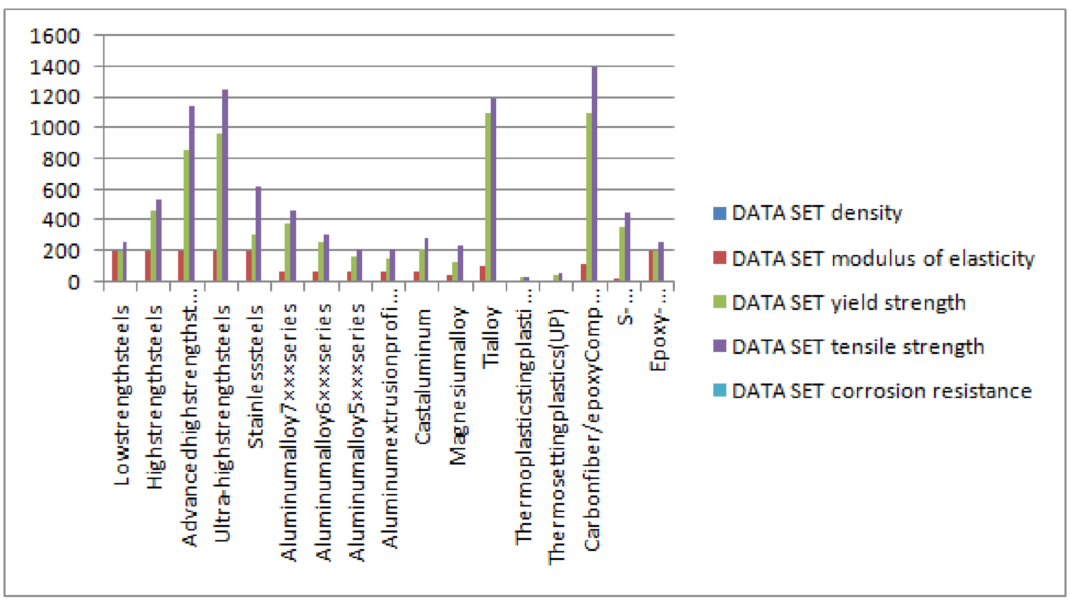


FIGURE 1. Data Set

Figure 1 showing the data set of "optimal material selection for Low strength steels, High strength steels, Advanced high strength steels, Ultra-high strength steels, Stainless steels, Aluminumalloy7×××series, Aluminumalloy6×××series, Aluminumalloy5×××series, Aluminum extrusion profiles, Cast aluminum, Magnesium alloy, Ti alloy, Thermo plastic sting plastics(PP), Thermo setting plastics(UP), Carbon fiber/epoxy Composites, S-glass fiber /epoxy Composites".

TABLE 2. Grey relation coefficient

Material alternatives	density	modulus of elasticity	yield strength	tensile strength	corrosion resistance
Low strength steels	1.0000	1.0000	0.3717	0.3745	0.4286
High strength steels	1.0000	1.0000	0.4581	0.4410	0.4286
Advanced high strength steels	1.0000	0.9531	0.6893	0.7319	0.5000
Ultra-high strength steels	1.0000	1.0000	0.8038	0.8198	0.4286
Stainless steels	1.0000	1.0000	0.4026	0.4667	0.4286
Aluminumalloy7×××series	0.4076	0.4333	0.4269	0.4206	0.6000
Aluminumalloy6×××series	0.4076	0.4297	0.3880	0.3850	0.6000
Aluminumalloy5×××series	0.4076	0.4288	0.3641	0.3664	0.6000
Aluminum extrusion profiles	0.4029	0.4297	0.3616	0.3655	0.6000
Cast aluminum	0.4029	0.4352	0.3743	0.3808	0.6000
Magnesium alloy	0.3644	0.3886	0.3544	0.3698	0.3333
Ti alloy	0.5092	0.5118	1.0000	0.7734	1.0000
Thermo plastic sting plastics(PP)	0.3333	0.3333	0.3333	0.3333	1.0000
Thermo setting plastics(UP)	0.3432	0.3350	0.3368	0.3383	1.0000
Carbon fiber/epoxy Composites	0.3577	0.5305	1.0000	1.0000	1.0000
S-glass fiber/epoxy Composites	0.3660	0.3595	0.4167	0.4178	1.0000

Table 2 Showing the Grey relation coefficient of optimal material selection. Grey relation coefficient, also known as grey relational analysis, is a method used in decision-making and analysis to determine the relationship between multiple variables or factors. It is commonly used in fields such as engineering, economics, and management. The grey relation coefficient measures the degree of similarity or correlation between different factors or variables. It is used to evaluate the relative importance or influence of these factors in a given system or decision-making process. The grey relation coefficient is calculated by comparing the pattern or trend of each factor with a reference pattern. The closer the pattern of a factor is to the reference pattern, the higher its grey relation coefficient, indicating a stronger relationship or influence. The grey relation coefficient is usually expressed as a value between 0 and 1, where 1 represents a perfect match or strong correlation, and 0 indicates no correlation. The grey relational analysis can help in various applications, such as evaluating the performance of different alternatives, prioritizing factors for optimization, or identifying critical variables in a system. It's important to note that grey relation coefficient is just one of the methods used in grey system theory, which is a mathematical modeling approach for dealing with systems that have insufficient or uncertain information.

TABLE 3. Grey Relation Coefficient

	GRG
Material alternatives	**0.5437**
Low strength steels	**0.5819**
High strength steels	**0.7303**
Advanced high strength steels	**0.7630**
Ultra-high strength steels	**0.5745**
Stainless steels	**0.4638**
Aluminumalloy7×××series	**0.4452**
Aluminumalloy6×××series	**0.4345**
Aluminumalloy5×××series	**0.4325**
Aluminum extrusion profiles	**0.4395**
Cast aluminum	**0.3555**
Magnesium alloy	**0.8206**
Ti alloy	**0.5000**
Thermo plastic sting plastics(PP)	**0.5046**
Thermo setting plastics(UP)	**0.8394**
Carbon fiber/epoxy Composites	**0.5501**
S-glass fiber/epoxy Composites	**0.5437**

The table 3 provides the grey relation coefficient (GRG) values for each material alternative. The GRG represents the degree of similarity or correlation between the material alternative and the reference pattern, with higher values indicating a stronger relationship or influence. Material alternatives grey relation coefficient values, "Low strength steels grey relation coefficient value is 0.5437, High strength steels grey relation coefficient values 0.5819, Advanced high strength steels grey relation coefficient values 0.7303, Ultra-high strength steels grey relation coefficient values 0.7630, Stainless steels grey relation coefficient values0.5745, Aluminumalloy7×××series grey relation coefficient values 0.4638, Aluminumalloy6×××series grey relation coefficient values 0.4452, Aluminumalloy5×××series grey relation coefficient values 0.4345, Aluminum extrusion profiles grey relation coefficient values 0.4395, Cast aluminum grey relation coefficient values 0.3555, Magnesium alloy grey relation coefficient values 0.8206, Ti alloy grey relation coefficient value s0.5000, Thermo plastic sting plastics(PP) grey relation coefficient values 0.5046, Thermo setting plastics(UP) grey relation coefficient values 0.8394, Carbon fiber/epoxy Composites grey relation coefficient values0.5501, S-glass fiber /epoxy Composites grey relation coefficient values0.5437", as seeing figure 2.

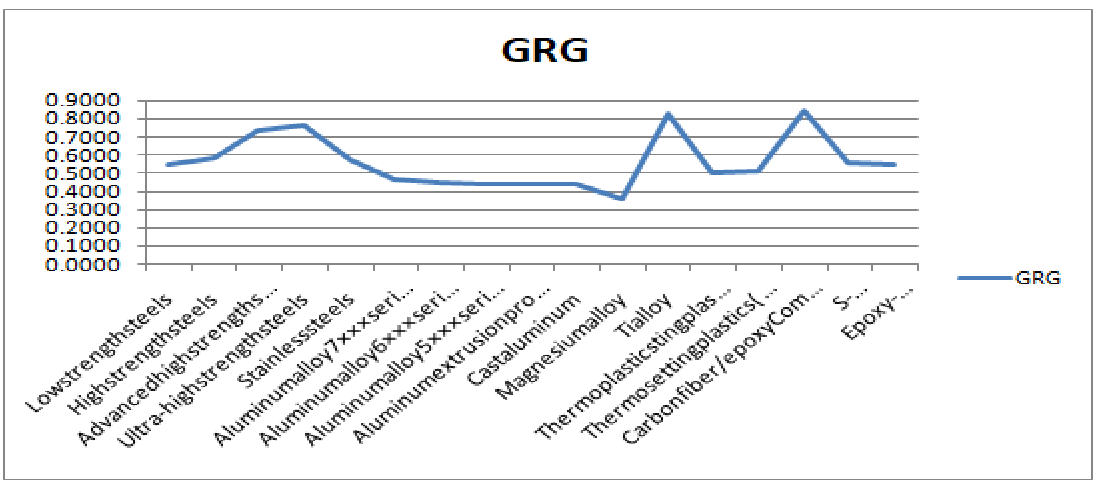


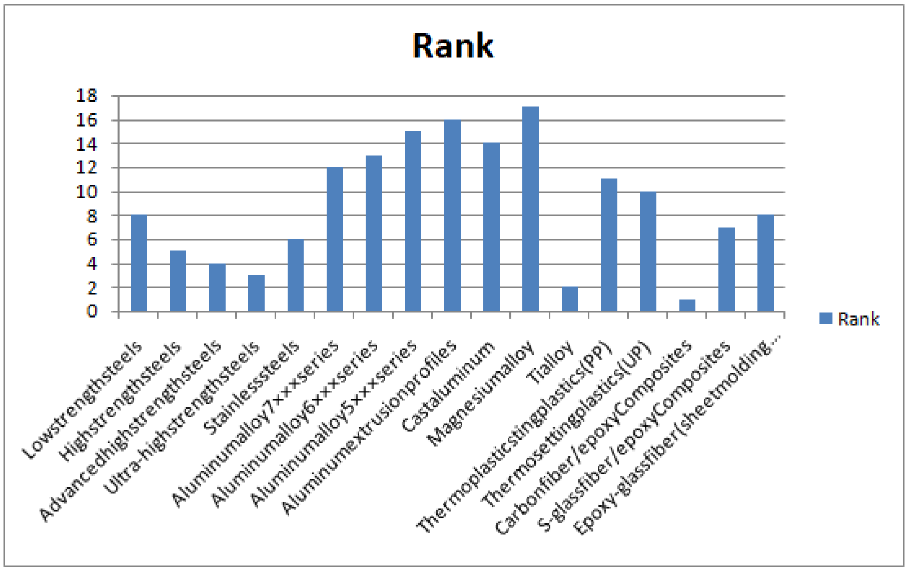
FIGURE 2. GRG

figure 2 showing "Low strength steels grey relation coefficient value is 0.5437, High strength steels grey relation coefficient values 0.5819, Advanced high strength steels grey relation coefficient values 0.7303, Ultra-high strength steels grey relation coefficient values 0.7630, Stainless steels grey relation coefficient values0.5745, Aluminumalloy7×××series grey relation coefficient values 0.4638, Aluminumalloy6×××series grey relation coefficient values 0.4452, Aluminumalloy5×××series grey relation coefficient values 0.4345, Aluminum extrusion profiles grey relation coefficient values 0.4395, Cast aluminum grey relation coefficient values 0.3555, Magnesium alloy grey relation coefficient values 0.8206, Ti alloy grey relation coefficient value s0.5000, Thermo plastic sting plastics(PP) grey relation coefficient values 0.5046, Thermo setting plastics(UP) grey relation coefficient values 0.8394, Carbon fiber/epoxy Composites grey relation coefficient values0.5501, S-glass fiber /epoxy Composites grey relation coefficient values0.5437".

TABLE 4. Ranking

Material alternatives	Rank
Low strength steels	8
High strength steels	5
Advanced high strength steels	4
Ultra-high strength steels	3
Stainless steels	6
Aluminumalloy7×××series	12
Aluminumalloy6×××series	13
Aluminumalloy5×××series	15
Aluminum extrusion profiles	16
Cast aluminum	14
Magnesium alloy	17
Ti alloy	2
Thermo plastic sting plastics(PP)	11
Thermo setting plastics(UP)	10
Carbon fiber/epoxy Composites	1
S-glass fiber/epoxy Composites	7

Table 4 Showing the rank of optimal material selection. "Low strength steels is eighth ranking, High strength steels is 5th ranking, Advanced high strength steels is 4 th ranking, Ultra-high strength steels is 3rd ranking, Stainless steels is 6 th ranking, Aluminumalloy7×××series is 12 th ranking, Aluminumalloy6×××series is 13 th ranking, Aluminumalloy5×××series is 15th ranking, Aluminum extrusion profiles is 16th ranking, Cast aluminum is 14th ranking, Magnesium alloy is 17th ranking, Ti alloy is 2nd ranking, Thermo plastic sting plastics(PP) is 11th ranking, Thermo setting plastics(UP) is 10th ranking, Carbon fiber/epoxy Composites is 1st ranking, S-glass fiber /epoxy Composites is 7th ranking."



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5. CONCLUSION

Finally, optimal material selection is an important step in engineering and design since it has a substantial impact on product performance, cost efficiency, sustainability, and innovation. Engineers and designers can make informed selections about the best material for a certain application by carefully analyzing criteria such as mechanical qualities, cost, availability, environmental impact, and production needs. The best material selection research is significant because it provides essential insights, techniques, and tools to support decisions for professionals in a variety of industries. It enables them to improve product performance by choosing materials that fulfill the functional needs and specifications. Furthermore, optimal choice of material research aids in cost effectiveness by identifying resources that reduce manufacturing costs without sacrificing quality. Furthermore, optimal material selection research supports product innovation by investigating novel substances, composites, and new technologies. It pushes the limits of material science, allowing for the creation of innovative and high-performance goods. Overall, optimal material selection research is critical for improving product quality, lowering costs, encouraging sustainability, promoting innovation, and increasing industry competitiveness. Businesses may make educated choices that optimise their material selections and achieve better in general efficiency and achievement in their particular industries by harnessing the results and approaches from this research.

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