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Material selection for sintered pulley in automobile: An integrated CRITIC-MARCOS model

Rajeev Ranjan [1], Sonu Rajak [2], Prasenjit Chatterjee [3]
[1] National Institute of Technology, Patna, India
[1] ICFAI Business School, ICFAI University, Dehradun, India
[2] Department of Mechanical Engineering, National Institute of Technology, Patna, India
[3] Department of Mechanical Engineering, MCKV Institute of Engineering, Howrah, West Bengal, India

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ABSTRACT

Material selection plays a pivotal role in engineering and design, profoundly influencing product performance, cost, and sustainability. Traditional approaches to material selection typically involve an intricate interplay of multiple criteria, encompassing mechanical properties, environmental impact, cost, and availability. To grapple with this complexity, multi-criteria decision-making (MCDM) methods have risen to prominence as systematic frameworks for facilitating well-informed material selection decisions. MCDM methods offer a structured approach to evaluating and ranking materials based on a set of criteria, thereby empowering engineers and designers to make informed choices. In this paper, Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) method has been employed to determine the most suitable material for sintered pulleys used in automobiles. CRiteria Importance Through Intercriteria Correlation (CRITIC) method is applied to assign criteria weights. The analysis reveals that sintered hardened steel emerges as the best choice for sintered pulleys in automotive applications. To validate the outcomes obtained from the proposed method, a performance analysis has been conducted, comparing the results with those generated by other well-established MCDM methods. Additionally, a sensitivity analysis has been carried out using Spearman rank correlation coefficient.

Corresponding Author:

Prasenjit Chatterjee,
Departtment of Mechanical Engineering, MCKV Institute of Engineering, Howrah, West Bengal, India
Email: dr.prasenjitchatterjee6@gmail.com

1. Introduction

Sintered pulley in an automobile primarily serves as a component for power transmission, vibration damping, noise reduction, weight reduction, durability enhancement, and potential cost savings. Its application is most common in engine accessory drive systems, where it contributes to the efficient operation and overall performance of the vehicle. For the better performance of engine of an automobile, a suitable material will enhance the performance. As we know that material selection is a decisive process in various industries and fields, ranging from engineering and manufacturing to design. It involves the careful evaluation and choice of the most suitable materials for a specific application or project based on their properties, characteristics, and performance attributes. The chosen material can significantly impact the overall functionality, durability, aesthetics, and cost-effectiveness of the final product (Çalıskan et al. 2013). The process of material selection typically involves a systematic approach that takes into account various factors, such as mechanical properties (strength, hardness, elasticity), thermal properties (conductivity, expansion), chemical compatibility, corrosion resistance, electrical conductivity, environmental impact, availability, and cost. Additionally, considerations about the manufacturing process, ease of fabrication, maintenance requirements, and the desired lifespan of the product also play a significant role in the decision-making process. There are, however, a number of materials for a sintered pulley used in the engine of an automobile. The selection of suitable sintered pulley material is critical to maintaining the efficiency of an automobile. Design and manufacturing of sintered pulley with suitable material are very critical to ensure the long life of an engine of an automobile. The research reports in this direction have been presented in the literature review section. Different materials, such as metals, polymers, ceramics, composites, and even natural substances, offer a wide range of characteristics that make them suitable for specific applications. For example, metals might be chosen for their high strength in structural components, while polymers could be preferred for their lightweight and corrosion-resistant properties in consumer goods. Ceramics might be selected for their exceptional heat resistance in high-temperature applications, and composites can combine properties of multiple materials to meet specialized requirements. Advances in material science and technology have led to the development of new materials with enhanced properties and functionalities. Engineers, designers, and researchers must stay informed about these innovations to make informed choices that align with the goals of their projects. The ultimate aim of material selection is to create products that not only perform well but also meet safety standards, regulations, and aesthetic preferences. material selection is a vital aspect of product development and design, influencing the success, quality, and sustainability of various products and systems across industries. It requires a comprehensive understanding of materials, their properties, and the specific requirements of the project at hand to make informed decisions that result in effective and efficient solutions. In complex decision-making scenarios where materials with varying properties and charecteristics are available, multi criteria decision making (MCDM) methods provide a systematic approach to evaluating and selecting the most suitable material. It aims to assist decision makers in evaluating alternatives based on a set of criteria that reflect different aspects of the problem. In the context of material selection, MCDM methods help balance factors such as mechanical properties, cost, environment impact, manufacturability and more.

2. Litrature Review

Abishini & Karthikeyan (2023) examined applications of MCDM methods like Analytic hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Evaluation based on Distance from Average Solution (EDAS), of VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and Taguchi-based super ranking concepts for the selection of optimal aluminum alloy material for the sheet metal forming process. An integrated Design of Experiment **(**DoE**)** and process simulation were carried out for the best-ranked AA2024 aluminum material. The results showed that the MCDM and Taguchi-based super ranking concept provides an intelligent and methodical assessment for solving material selection from a finite set of alternatives for the sheet metal forming process. Anand & Mitra (2021) proposed Grey Relational Analysis (GRA) and Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method, both methods used for tool holder material selection working under hard milling conditions. The weight of all the six attributes was taken with the help of Entropy method. The ranking of all the available nine materials had done by arranging grey relational grade and priority in descending order in GRA and MOORA method respectively. The results obtained from two different MCDM methods were compared to conclude the effects of different MCDM methods on ranking of materials. Amongst all the nine alternatives, Fe-5Cr-Mo-V was found as the best material in both the MCDM methods. Thus, Fe-5Cr-Mo-V was selected as the best material for tool holder working under hard milling conditions. Anojkumar et al. (2015) described the application of four MCDM methods for solving pipes material selection problem in sugar industry. FAHP-TOPSIS, FAHP-VIKOR, FAHP- ÉLimination Et Choix Traduisant la REalité (ELECTRE), FAHP-Preference Ranking Organization Method for Enrichment Evaluation (PROMTHEE) were the four methods used to choose the best alternative among the various materials. The ranking performance of various MCDM methods were also compared with each other and explored the effectiveness and flexibility VIKOR method. Five stainless steel grades such as J4, JSLAUS, J204Cu, 409 M, 304 and seven evaluation criteria such as yield strength, ultimate tensile strength, percentage of elongation, hardness, cost, corrosion rate and wear rate were focussed in this study to choose the suitable material. Anand et al. (2014) proposed MCDM technique involves fuzzy analytical hierarchy process (FAHP) integrated with TOPSIS and VIKOR techniques. Fuzzy analytical hierarchy process (FAHP) is used to determine the criteria weights, whereas TOPSIS and VIKOR used to find the performance ranking of the alternative materials. Boyacı & Tüzemen (2021) used MCDM tools for assisting material selection for aircraft parts. In this direction, decision models including AHP, COPRAS, TOPSIS, and Borda count methods were used to select the best materials for aircraft wings and nose. AHP was used to determine the criteria weights. According to the criteria weights, the rankings were obtained using AHP, Complex Proportional Assessment (COPRAS), and TOPSIS methods. Then, the final integrated rankings were obtained by Borda count method. Finally, the rankings obtained by AHP, COPRAS, and TOPSIS methods were compared to the final integrated rankings using Spearman's rank correlation coefficient. Çalıskan et al. (2013) proposed a decision model including extended PROMETHEE II, TOPSIS and VIKOR methods were used for the selection of the best material for the tool holder used in hard milling. The criteria weighting was performed by compromised weighting method composed of AHP and Entropy methods. The candidate materials were ranked by using these methods and the results obtained by each method were compared. It was confirmed that MCDM methods can be used for the solution of real time material selection problems. Tungsten carbide-cobalt and Fe-5Cr-Mo-V aircraft steel were found as the best materials for the tool holder production. The proposed approach involves identification of potential composite materials, selection of evaluation criteria, use of fuzzy theory to quantify criteria values under uncertainty and application of fuzzy TOPSIS to evaluate and select the best material for replacing conventional steel material used in making automobile torsion bar by chandrashekar & Raja (2016). There proposed work was the ability to deal with uncertainty arising due to a lack of real data in material selection for replacing the conventional material used in torsion bar. A numerical application was provided to illustrate the approach. Chatterjee & Chakraborty (2022) ranked the performance of eight candidate piston materials was evaluated based on eight selection criteria. Entropy method was applied to estimate the criteria weights and multi-attributive ideal-real comparative analysis technique was adopted to identify the most suitable piston material. AISI 4140 steel emerged as the top ranked piston material followed by AISI 8660 steel. A sensitivity analysis study was also performed to verify the consistency and robustness of the derived ranking results. Chatterjee & Chakraborty (2021) applied the decision-making trial and evaluation laboratory (DEMATEL) to establish and understand the criteria relationship and a comparatively new MCDM method to rank the material. The evaluated result was then compared with the past work and finally Spearman's rank correlation coefficient was also determined indicating the validity and effectiveness of the adopted method. The seven spring material alternatives was considered by Das & Kumar (2015) whose performance was evaluated based on eight selection criteria. A PROMETHEE II and graphical analysis for interactive assistance (GAIA) technique was applied to solve the spring material selection problem, and a full ranking of the spring material alternatives with suitable graphical displays was presented. Chrome silicon alloy steel (ASTM A 401) was the best spring material, followed by high carbon steel (ASTM A 228) and Inconel 600. Monel K500 was the worst chosen spring material. Dušan et. al. (2015) described the use of recently developed MCDM methods, i.e., COPRAS and Weighted Aggregated Sum Product Assessment (WASPAS) for selecting the most suitable hard coating material. Emovon & Oghenenyerovwho (2020) presented a methodical review of application of MCDM method in material selection. The results of the analysis shown the following: the hybrid method which was the combination of two or more MCDM methods was the most applied technique for material selection in all application areas identified; the most frequently applied decision criteria for selecting ideal alternative was the cost; the highest number of articles on material selection was published in 2013; the most significant journal was materials and design and finally, the country with the highest application of MCDM method was India. Farid & Riaz (2022) proposed MCDM approach for material selection of cryogenic storage containers was developed. Additionally, the authenticity analysis and comparison analysis were designed to discuss the validity and rationality of the optimal decision. Garmode et al. (2022) proposed a comprehensive work that included identification of ten possible better materials, finding ten all-encompassing material selection criteria and the use of four suitable mathematical techniques to get the appropriate results. The three different criteria weights were calculated from the AHP, entropy weight method and the average of these two methods. These weights were used in simple additive weighting method, weighted product method, TOPSIS and R-method to get the rankings of the materials. Goswami & Behera (2021) adopted Entropy method for the criteria weightages calculation and Additive Ratio Assessment (ARAS) method was used to select the best option and proposed the preference ranking order of the alternatives. From, the analysis, they have found that cast alloy steel was the best option followed by cast iron and carburized steels, whereas hardened alloy steel was the worst choice among the group. Gupta et al. (2021) presented decision models like MOORA (ranking method based on ration analysis) and TOPSIS (a compromise ranking method) techniques were made as a source of aid to evince the fibre that can be opted in mixing with the base resin for roto moulded product. A comparative study was evaluated in this research and considered these two methods with distinguished natural fibres using various attribute. Hosouli et al. (2023) presented a MCDM methodology based on Graph Theory and Matrix approach for high temperature thermochemical storage (TCS) material selection. Furthermore, the presented approach was used to select the suitable candidate material for recovering the high temperature waste heat (over 500˚C) in Port Talbot Steelworks. Ilangkumaran et al. (2013) used MCDM techniques to evaluate best material to be employed for manufacturing of automobile bumper. They have proposed hybrid MCDM technique involves FAHP integrated with PROMETHEE. FAHP was used to compute the criteria weights. PROMETHEE I was used to find out the leaving and entering flows, whereas PROMETHEE II was used to find the total ranking of the material. Jahan et al. (2021) addressed the issue of material selection using a combined compromise solution (CoCoSo). This method combined a compromise decision algorithm with an aggregation strategy to obtain a compromise solution. Two illustrative examples related to material selection, i.e., for a cryogenic storage tank and wagon wall material selection, were considered in this paper, and CoCoSo method was applied to rank the available substitute materials to select the best one. Jajimoggala & Karri (2013) developbed user friendly two-stage decision support hybrid MCDM model. The first stage was to prioritise the different criteria using and the second stage was to select the material using TOPSIS. An example was solved to illustrate the effectiveness and feasibility of the suggested model to the material selection for an impellor and AISI 4340 was found to be the best material alternative based on the given priorities of the criteria. Kumar et al. (2022) used MCDM techniques to select the optimum thermochemical material from the alternatives to be used for low temperature energy storage. The best thermochemical material was selected using different MCDM techniques like simple additive method (SAM), weighted product model, TOPSIS, Evaluation based on Distance from Average Solution, Multi-Objective Optimization on The Basis of Ratio Analysis, PROMETHEE, and VIKOR. The criteria weights for optimization were evaluated by different methods such as mean weight method, standard deviation method, AHP, Entropy method, criteria importance through inter-criteria correlation and Compromised weight method. In all MCDM-Weighting method combinations MgCl26H2O ranked first (optimum material) and Na2S9H2O ranked last. The ranking obtained from various MCDM-weighting method combination were compared with each other using average Spearman rank correlation coefficient and found that Evaluation based on EDAS, MOORA, PROMETHEE II and VIKOR with AHP weighting method had the highest correlation coefficient ($r_s = 0.9857$) and CRITIC-VIKOR method ($r_s = 0.5143$) had the lowest correlation coefficient. Mousavi-Nasab & Sotoudeh-Anvai (2017) provided a simple and comprehensive MCDM-based framework for solving material selection problem. Under the scrutiny of over 100 scientific articles, COPRAS and TOPSIS were chosen for tackling material selection problem in general. They observed that the suggested approach by integrating these MCDM techniques was simple and effective. Also, they examine the use of data envelop analaysis (DEA) as an MCDM tool in material selection problem. MOORA, TOPSIS and VIKOR methods were used by Moradian et al. (2018) for selecting the best material for braking booster valve body. The alternative materials were ranked using these methods and the results of the analysis were compared using Spearman's rank correlation. PET-gf35 (PET reinforced with 35 wt% glass fiber) was found to be the best material for the valve body. AHP-TOPSIS method was used to select good wear resistance material along with the structural applications point of view by Patnaik et al. (2019). The ranking was carried out according to the physico-mechanical and wear properties of the composite materials viz, density, hardness, tensile, flexural and impact strength with specific wear rate. Lohakare et al. (2022) developed a methodology to select the material of piston for a new design of engine by using MCDM method to solve the piston material selection problem. The AHP was designed to select material of the piston for a particular application. Open-source data related to critical parameters of Caterpillar engine (viz. temperature and peak cylinder pressure) were considered, which directly affect the strength of piston material. To accurately predict the values of these parameters Ansys forte FEA simulation tool was used for combustion analysis. Simulation results were used as input to design material selection benchmark using AHP methodology. From the results obtained from Ansys forte simulation used as input to AHP based MCDM design methodology turned out to be fruitful for selecting Piston material for rapid decision making at the designer level. Okokpujie et al. (2020) used a quantitative research approach using AHP and TOPSIS multi-criteria decision method. They have extracted the data used for the selection process from the 130-research questionnaire distributed to materials engineers and renewable energy professionals. For this research they have considered four alternatives that is, aluminum alloy, stainless steel, glass fiber, and mild steel to determine the best material for the wind turbine blade. The result shows that a consistency index of 0.056 and a consistency ratio of 0.062 gotten via the AHP method was workable for material selection practice. 78%, 43%, 67%, and 25% were the performance scores for the four alternatives via the TOPSIS techniques. In conclusion, aluminum alloy is the best material, followed by glass fibre. Patnaik et al. (2020) applied a hybrid AHP-MOORA methodology which helped in selecting the best alternative polymer composite material for engineering applications. Raju et al. (2020) integrated MCDM approaches like AHP-TOPSIS and AHP–MOORA methods were used to rank aluminum-coconut shell ash (CSA) composites. The weightage for each criterion was calculated by AHP method and utilized in the TOPSIS and MOORA approaches to rank the materials. A detailed study on the MCDM approaches revealed that Al-15% CSA composite emerged as the best material followed by Al-10% CSA composite among all, whereas the base matrix is found as the poor performed material in this study. Rahim et al. (2020) done a comprehensive systematic literature review (SLR) guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement on methods or approaches reported for supporting material selection processes. This review covers various published literature, spanning from 2000 to 2018. The review also found that there is an increasing trend of research in recent years in the area of OR-based method application specifically on the multi-criteria decision-making supporting material selection processes. Rahim et al. (2021) developed a fuzzy-TOPSIS MCDM model for material selection with integrated safety, health, and environment risk assessment. The proposed method facilitates the designer to select, evaluate, and rank material alternatives based on given attributes from design requirements and weighting given by the decision-makers. Additionally, the other benefits of the proposed methodology were the elimination of a complex structure and a black-box algorithm. A numerical example of selected material for automotive body panels used the proposed method was discussed. Sen et al. (2016) explored the applicability and effectiveness of some well-known MCDM techniques for the connecting rod material selection. Singh et al. (2020) selected a fibrous raw material which was treated as an MCDM problem where chemical, morphological and physical properties of the fibers were considered as different criteria and study was done in context of Indian Pulp and Paper Mills. TOPSIS, its fuzzy variant (FTOPSIS) and its modified variant (MTOPSIS) were employed to identify the suitable selection of fibers. Zakeri et al. (2023) proposed a new decision-making method called the simple ranking process (SRP) to solve complex material selection problems. The frst scenario of vital-immaterial mediocre method (VIMM) was used as a tool to derive criteria weights based on expert assessment. The result of SRP was compared with a number of MCDM methods. In order to evaluate the findings of analytical comparison, a novel statistical measure known as compromise decision index (CDI) was proposed in this paper. Zhang et al. (2020) developed a novel MCDM method based on group generalized Pythagorean fuzzy weighted average (GGPFWA) operator. In the novel method, decision makers are divided into advisers and deciders. The advisers used Pythagorean fuzzy set (PFS) to represent the criteria information of alternative materials. PFS was a new extension of fuzzy set, which can effectively represent fuzzy and uncertain information. The deciders use group generalized parameters (GGPs) to judge the accuracy of criteria information provided by each adviser. The GGPs are expressed by Pythagorean fuzzy numbers. Then, the criteria information and the GGPs are aggregated by GGPFWA operator, and the aggregate value of each material was obtained. By processing the aggregate value, the ranking of alternative materials was determined and the optimal material was selected. Zindani et al. (2020) proposed a novel aggregation multiplicative rule, taking into account the compromising attitude to rank the material alternatives for automobile leaf spring. Epoxy composite reinforced with E-glass fiber was revealed to be the most suitable material for the automobile leaf spring.

3. Methods for ranking of materials

In order to rank the materials on the basis of their properties the following methods are applied

3.1. CRITIC – MARCOS Method

The ranking process starts with the CRITIC method in the first stage which determines the weightage for the selected criteria. In the second stage, MARCOS method is used for the materials ranking. The weightages found-out from CRITIC stage is used latter in the ranking stage of the materials used in this study. The steps for the CRITIC-MARCOS method are mentioned below:

Figure 1. A typical sintered pulley

Stage I: CRITIC Method (for criteria weightage calculations)

Criteria play a very important role in decision-making and are a source of information, carrying a weight that reflects the amount of information contained in them all. In fact, this weight is called objective weight. Diakoulaki et al. (1995) established CRITIC method as a tool for determining the weight of the criteria in the MCDM problem. This method determines the weight of the criteria by using the intensity of the modification of each criterion, which is considered the standard deviation, and the difference between the terms, which is considered the coefficient of correlation between the criteria (Jahan et al. (2012); Keshavarz Ghorabaee et al. (2017). There are following steps in CRITIC method. Supposed that there is a set of m feasible alternatives A_i (i = 1, 2…, m) and n evaluation criteria C_j (j = 1, 2,…,n).

Step- 1: Development of the decision matrix (X), expressed as follows.

$$x_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad where\ (i = 1,2, \dots\dots..m\ and\ j = 1,2, \dots \dots, n) \qquad (1)$$

The elements (x_{ij}) of the decision matrix (X) represent the performance value of i^{th} alternative on j^{th} criterion.

Step- 2. Normalization of original decision matrix using the following equations

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad \text{for benefit criterion} \qquad (2)$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad \text{for cost criterion} \qquad (3)$$

Step- 3: Calculation of symmetric linear correlation matrix (m_{ij}): The linear coefficient between each pair of crietria is measured using the following calculation to calculate the resulting conflict between the different criteria. It can be seen that when option points are significantly separated from the two terms i and j, the m_{ij} value decreases.

Step- 4: Objective weight determination using the CRITIC method and requires measurement of both standard deviation and its correlation to determining criteria. In this regard, the weight of the j^{th} criterion (w_j) is obtained using Equation (4).

$$W_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \qquad (4)$$

where, C_j is the amount of information contained in the criterion j and is determined as follows:

$$C_j = \sigma \sum_{j=1}^{n} 1 - m_{ij} \qquad (5)$$

where σ is the standard deviation of j^{th} criterion and is the coefficient of correlation between the two criteria. CRITIC method provides maximum weight to the criterion with higher value of σ and low correlation with the other criteria. A higher value of C_j indicates the greater amount of information contained in a particular criterion, which is why it is given a higher weight value.

Sintered pulleys find applications in automotive systems where power transmission is critical, such as in engines, alternators, water pumps, and various accessory drives. The sintering process allows manufacturers to create pulleys with the necessary strength, durability, and dimensional accuracy required for these demanding applications. Sintered pulleys offer a cost effective and versatile solution for various industries, including the automotive sector, where efficient power transmission is crucial for optimal vehicle performance. The materials for the sintered pulley playing an important role for this performance. Select a right material for this auto part is very important. For selecting the right materials for sintered pulley required a various criterion like yield strength, tensile strength, cost, thermal conductivity etc. For material selection of sintered pulley 10 criteria are considered, shown in Table 1.

Table 1. Criteria for material selection of sintered pulley for automobile application

Sl. No.	Criteria	Symbol
1	Yield Strength (MPa)	C_1
2	Tensile Strength (MPa)	C_2
3	Modulus of elasticity in Tension (GPa)	C_3
4	Hardness (HB)	C_4
5	Density (Kg/m3)	C_5
6	Compressive Strength (MPa)	C_6
7	Coefficient of thermal expansions ((µm/m°C)	C_7
8	Thermal conductivity (W/m·°C)	C_8
9	Poisson's Ratio	C_9
10	Cost (Rs/Kg)	C_{10}

All the above criteria are so carefully chosen that they are totally uncorrelated. The appropriate data for these criteria are gathered from the various books and journals. Among these criteria first six are beneficial (Higher the better), and remaining four are non-beneficial (lower the better). The cost is a crucial criterion and also a non-beneficial criterion during this evaluation process because the impact of material selection is directly associated with this criterion. The Poisson's ratio is an important mechanical property that relates to how a material deforms under an applied load. It's defined as the ratio of the lateral strain to the axial strain within the elastic range of deformation. This ratio can influence the material selection process for various engineering applications. The coefficient of thermal expansion (CTE) is a crucial factor in material selection, especially when considering applications that involve temperature variations. Selecting materials with appropriate CTE values can help prevent dimensional changes, thermal stress-related failures, and compatibility issues in various manufacturing applications. Thermal conductivity is a critical factor in the design, performance and safety of automotive parts. It affects heat dissipation, component longevity, efficiency and overall vehicle performance. Selecting materials with appropriate thermal conductivity properties is essential to ensure that automotive components can effectively manage the heat generated during operation and maintain optimal functionality. Yield strength is a key consideration in material selection, influencing the load-bearing capacity, safety, durability, formability and overall performance of engineered components. Decision makers carefully assess yield strength along with other mechanical properties to choose materials that will meet the specific requirements of the application while ensuring the reliability and longevity of the design. Tensile strength playing an important role in material selection, as it directly influences a materials ability to withstand applied loads and maintain structural integrity. Engineers assess tensile strength along with other mechanical properties to choose materials that will provide the required performance and reliability for the intended application. The modulus of elasticity, also known as young's modulus, is a fundamental mechanical property that quantifies a material's stiffness or ability to deform elastically under an applied load. When considering material selection for automobile parts subjected to tension, the modulus of elasticity is of great importance. Hardness is directly affecting wear resistance, durability, manufacturing processes, load bearing capacity, and overall performance. It is considered to choose materials that will provide the required level of protection, longevity, and functionality for the proposed application. Next important beneficial criterion is density, which is a fundamental material property that has a significant role in the selection of materials for various automobile parts. It represents the mass of a material per unit volume and affects several important aspects of components design, performance and efficiency. Compressive strength measures a materials ability to withstand compressive loads without undergoing deformation or failure. When considering material options for automotive components, compressive strength of the chosen material is of great importance. Table 3 shows the choice matrix as developed for material selection for Sintered pulley in automobile, where the relevant information for the materials with relation to different criteria are collected from various websites and published reports (www.wikipedia.com) the standards weights are estimated using CRITIC method (Diakoulaki, 1995), as shown in Table 5 and the decision matrix as shown in Table 2.

Table 2. Decision Matrix for material selection of sintered pulley for automotive application

Material	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Carbon Steel (A_1)	550	700	210	357	7850	600	12.5	50	0.27	61
Copper Clad Steel (A_2)	261	359	210	220	8400	400	15	385	0.30	350
Nickel Steel (AISI 4340) (A_3)	760	689	200	240	8050	1000	15	50	0.30	1999
Low Alloy Steel (A_4)	590	1100	210	600	8050	1500	14	45	0.28	90
Sinter Hardened Steel (A_5)	500	1000	220	700	7800	1200	15	48	0.30	55
Stainless Steel (A_6)	1000	2000	210	300	8050	2000	17	45	0.30	180
Red Brass (A_7)	220	450	105	120	8600	300	20	120	0.33	600
Yellow Brass (A_8)	350	500	115	100	8600	350	20	120	0.34	480
Nickel Silver (A_9)	300	550	120	150	8600	380	18	25	0.34	1500
Aluminium 7075 (A_{10})	500	600	79	70	2700	280	24	250	0.35	210

Stage II: MARCOS Method (for ranking of alternatives)

The MARCOS method is provided in this section. There is an obligation among other things and reference prices (ideal and anti-ideal alternatives) in MARCOS method. This bond determines the activities for alternative uses and creates a level of compromise in relation to ideal and anti-ideal solutions (Stević et al., 2020). Decision options are drawn on the basis of utility functions. The functions of the service represent the position of the alternative in relation to a good and contradictory solution (Stević et al., 2020). One of the most effective alternatives is the one that is closest to the ideal location and at the same time is very far from the reference point as opposed to ideal. The MARCOS method is developed in the following steps (Puška et al., 2020):

Step 1: Expansion of the first decision-making matrix. Multi-condition models correspond to criteria n and alternatives m. In the case of group decision-making, a group of r experts should be set up to evaluate alternatives according to the criteria. In the case of group decision-making, professional assessment matrices are grouped into the first decision-making matrix.

Step 2: Enlargement of an *extended* initial matrix. In this step, the extension of the initial matrix is executed by defining the ideal (*AI*) and anti-ideal (*AAI*) solution.

$$X = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \dots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{aa1} & x_{aa2} & \dots & x_{aan} \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{22} & \dots & x_{mn} \\ x_{ai1} & x_{ai2} & \dots & x_{ain} \end{bmatrix} \end{array} \tag{6}$$

The anti-ideal solution (AAI) is the foulest alternative while the ideal solution (AI) is an alternative with the best characteristic. Depending on the nature of the criteria, AAI and AI are defined by applying Equations (7) and (8):

$$AAI = \min_i x_{ij} \quad if \ \ j \in B \quad and \quad \max_i x_{ij} \quad if \ \ j \in C \tag{7}$$

$$AI = \max_i x_{ij} \quad if \ \ j \in B \quad and \quad \min_i x_{ij} \quad if \ \ j \in C \tag{8}$$

where *B* represents a benefit group of criteria, while *C* represents a group of cost criteria.
Step 3: Normalization of the extended initial matrix (*X*). The elements of the normalized matrix $N = \left[n_{ij}\right]_{m\times n}$ are obtained by applying Equations (9) and (10):

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \quad if \ \ j \in C \tag{9}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \quad if \ \ j \in B \tag{10}$$

where elements x_{ij} and x_{ai} represent the elements of the matrix *X*.

Step 4: Calculation of the weighted matrix $V = \left[v_{ij}\right]_{m\times n}$. The weighted matrix *V* is obtained by multiplying the normalized matrix *N* with the weight coefficients of the criterion w_j, Equation (11).

$$v_{ij} = n_{ij} \times w_j \tag{11}$$

Step 5: Evaluation of the utility degree of alternatives *Ki*. By applying Equations (12) and (13), the utility degrees of an alternative in relation to the anti-ideal and ideal solution are calculated.

$$K_i^- = \frac{S_i}{S_{aai}} \tag{12}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{13}$$

where S_i (*i*=1,2,..,*m*) represents the sum of the elements of the weighted matrix *V*.

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{14}$$

Step 6: Determination of the utility function of alternatives *f(Ki)*. The utility function is the compromise of the observed alternative in relation to the ideal and anti-ideal solution. The utility function of alternatives is defined by Equation (15).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}}; \tag{15}$$

where $f\left(K_i^-\right)$ represents the utility function in relation to the anti-ideal solution, while $f\left(K_i^+\right)$ represents the utility function in relation to the ideal solution.
Utility functions in relation to the ideal and anti-ideal solution are determined by applying Equations (16) and (17).

$$f\left(K_i^-\right) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{16}$$

$$f\left(K_i^+\right) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{17}$$

Step 7: Ranking of the alternatives. Ranking of the alternatives is determined on the basis of the final values of utility functions. It is required that an alternative has the highest possible value of the utility function.

4. Result and Discussion

4.1. CRITIC - MARCOS Method

Stage I: CRITIC Method (for weighting criteria)

In this stage, CRITIC method is applied for calculating weights of the criteria. Firstly, decision matrix is normalized by using equations (2) and (3). The normalized decision matrix shown in Table 3. The last row of Table 3 shows the values of standard deviations for all criteria. The values of correlation coefficient are then calculated and shown in Table 4. Finally, the criteria weights of Table 5 are determined using equations (4) and (5). According to Table 5, C_{10} and C_7 are the most and least important criteria respectively.

Table 3. Normalized Matrix for the sintered pulley material selection case study

Material	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.423	0.208	0.929	0.456	0.873	0.186	1.000	0.931	1.000	0.997
A_2	0.053	0	0.929	0.238	0.966	0.070	0.783	0.000	0.625	0.848
A_3	0.692	0.201	0.858	0.270	0.907	0.419	0.783	0.931	0.625	0
A_4	0.474	0.452	0.929	0.841	0.907	0.709	0.870	0.944	0.875	0.982
A_5	0.359	0.391	1.000	1.000	0.864	0.535	0.783	0.936	0.625	1.000
A_6	1.000	1.000	0.929	0.365	0.907	1.000	0.609	0.944	0.625	0.936
A_7	0	0.055	0.184	0.079	1.000	0.012	0.348	0.736	0.250	0.720
A_8	0.167	0.086	0.255	0.048	1.000	0.041	0.348	0.736	0.125	0.781
A_9	0.103	0.116	0.291	0.127	1.000	0.058	0.522	1.000	0.125	0.257
A_{10}	0.359	0.147	0	0	0	0	0	0.375	0	0.920
σ_j	0.310	0.294	0.394	0.338	0.301	0.348	0.303	0.323	0.341	0.343

Table 4. Correlation coefficient values

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
C_1	1.0000	0.8480	0.4992	0.3109	-0.1110	0.8378	0.2676	0.4345	0.4389	0.0137
C_2	0.8480	1.0000	0.4753	0.4444	0.0481	0.9302	0.2207	0.4573	0.3789	0.3003
C_3	0.4992	0.4753	1.0000	0.7514	0.4272	0.6797	0.9104	0.1908	0.9145	0.1738
C_4	0.3109	0.4444	0.7514	1.0000	0.2190	0.6451	0.6837	0.3976	0.7081	0.3861
C_5	-0.1110	0.0481	0.4272	0.2190	1.0000	0.1916	0.5882	0.3479	0.3658	-0.2342
C_6	0.8378	0.9302	0.6797	0.6451	0.1916	1.0000	0.4532	0.4857	0.5709	0.1982
C_7	0.2676	0.2207	0.9104	0.6837	0.5882	0.4532	1.0000	0.3047	0.9236	0.0278
C_8	0.4345	0.4573	0.1908	0.3976	0.3479	0.4857	0.3047	1.0000	0.2444	-0.2243
C_9	0.4389	0.3789	0.9145	0.7081	0.3658	0.5709	0.9236	0.2444	1.0000	0.2647
C_{10}	0.0137	0.3003	0.1738	0.3861	-0.2342	0.1982	0.0278	-0.2243	0.2647	1.0000

Table 5. Weights of the sintered pulley materials selection criteria

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
weight	0.097	0.083	0.090	0.087	0.124	0.080	0.080	0.118	0.082	0.159

Stage II: MARCOS Method (for ranking of alternatives)

After determining the weight values of the criteria by using CRITIC method (from Table 5), the application of MARCOS method for obtaining the ranks of alternatives is initiated. The formation of a multi-criteria model consists of 10 criteria and 10 alternatives. Using equations (10) and (11), an extended initial decision –making matrix is obtained, as shown in Table 6. The anti-ideal solution (AAI) represents the worst characteristics, i.e., the highest values of criteria C_7, C_8, C_9 and C_{10}, while for all other criteria of benefit type, minimum values are part of the AAI solution. The ideal solution (AI) is opposite to the anti-ideal.

Table 6: An extended initial decision-making matrix

Material	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
AAI	220	359	79	70	2700	280	24	385	0.35	1999
A_1	550	700	210	357	7850	600	12.5	50	0.27	61
A_2	261	359	210	220	8400	400	15	385	0.30	350
A_3	760	689	200	240	8050	1000	15	50	0.30	1999
A_4	590	1100	210	600	8050	1500	14	45	0.28	90
A_5	500	1000	220	700	7800	1200	15	48	0.30	55
A_6	1000	2000	210	300	8050	2000	17	45	0.30	180
A_7	220	450	105	120	8600	300	20	120	0.33	600
A_8	350	500	115	100	8600	350	20	120	0.34	480
A_9	300	550	120	150	8600	380	18	25	0.34	1500
A_{10}	500	600	79	70	2700	280	24	250	0.35	210
AI	1000	2000	220	700	8600	2000	12.50	25	0.27	55

Applying equation (12) and equation (13), the normalized values for the non-beneficial and beneficial criteria are obtained, and a complete normalized matrix, shown in table 7.

Table 7: Normalized decision matrix

Material	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
AAI	0.220	0.180	0.359	0.100	0.314	0.140	0.521	0.065	0.771	0.028
A_1	0.550	0.350	0.955	0.510	0.913	0.300	1.000	0.500	1.000	0.902
A_2	0.261	0.180	0.955	0.314	0.977	0.200	0.833	0.065	0.900	0.157
A_3	0.760	0.345	0.909	0.343	0.936	0.500	0.833	0.500	0.900	0.028
A_4	0.590	0.550	0.955	0.857	0.936	0.750	0.893	0.556	0.964	0.611
A_5	0.500	0.500	1.000	1.000	0.907	0.600	0.833	0.521	0.900	1.000
A_6	1.000	1.000	0.955	0.429	0.936	1.000	0.735	0.556	0.900	0.306
A_7	0.220	0.225	0.477	0.171	1.000	0.150	0.625	0.208	0.818	0.092
A_8	0.350	0.250	0.523	0.143	1.000	0.175	0.625	0.208	0.794	0.115
A_9	0.300	0.275	0.545	0.214	1.000	0.190	0.694	1.000	0.794	0.037
A_{10}	0.500	0.300	0.359	0.100	0.314	0.140	0.521	0.100	0.771	0.262
AI	1	1	1	1	1	1	1	1	1	1

To find the weighted normalized matrix using equation (11), multiplying all the values of the normalized matrix with the criteria weights. The weighted normalized matrix is shown in Table 8.

Table 8: Weighted normalized matrix

Material	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
AAI	0.021	0.015	0.032	0.009	0.039	0.011	0.042	0.008	0.091	0.004
A_1	0.021	0.029	0.086	0.044	0.113	0.024	0.080	0.059	0.118	0.144
A_2	0.053	0.015	0.086	0.027	0.121	0.016	0.067	0.008	0.106	0.025
A_3	0.025	0.029	0.082	0.030	0.116	0.040	0.067	0.059	0.106	0.004
A_4	0.074	0.046	0.086	0.074	0.116	0.060	0.072	0.066	0.114	0.097
A_5	0.057	0.041	0.090	0.087	0.112	0.048	0.067	0.062	0.106	0.159
A_6	0.049	0.083	0.086	0.037	0.116	0.080	0.059	0.066	0.106	0.049
A_7	0.097	0.019	0.043	0.015	0.124	0.012	0.050	0.025	0.097	0.015
A_8	0.021	0.021	0.047	0.012	0.124	0.014	0.050	0.025	0.094	0.018
A_9	0.034	0.023	0.049	0.019	0.124	0.015	0.056	0.118	0.094	0.006
A_{10}	0.029	0.025	0.032	0.009	0.039	0.011	0.042	0.012	0.091	0.042
AI	0.097	0.083	0.090	0.087	0.124	0.080	0.080	0.118	0.118	0.159

By applying equation (14), all the values (by rows) from the weighted normalized matrix for all alternatives are added up to obtain S_i values, as shown in Table 9.The utility degrees in relation to the anti-ideal solution and for the ideal solution are calculated by equations (12) and (13). While the utility function in terms of anti-ideal and ideal solution is obtained using equations (16) and (17). Finally, the utility function of alternatives A_1 is obtained by applying equation (15). Ranking of the alternatives is based on the final values of utility functions. It is desirable that an alternative has the highest possible value of the utility function. Applying equations (12) - (17), the final results of Table 9 are obtained.

Table 9: Results of MARCOS method

Material	Si	ki-	ki+	FK-	FK+	f(Ki)	Rank
AAI	0.272	1.000					
A_1	0.718	2.639	0.693	0.208	0.792	0.657	4
A_2	0.524	1.925	0.506	0.208	0.792	0.480	7
A_3	0.558	2.049	0.538	0.208	0.792	0.510	5
A_4	0.804	2.953	0.776	0.208	0.792	0.736	2
A_5	0.830	3.047	0.801	0.208	0.792	0.759	1
A_6	0.730	2.681	0.704	0.208	0.792	0.668	3
A_7	0.495	1.819	0.478	0.208	0.792	0.453	8

A_8	0.426	1.565	0.411	0.208	0.792	0.390	9
A_9	0.537	1.972	0.518	0.208	0.792	0.491	6
A_{10}	0.331	1.218	0.320	0.208	0.792	0.303	10
AI	1.036	3.806	1.000				

5. Performance comparision and sensitivity analysis

5.1 Computation of ranking stability based on different MCDM method comparisons

To give the final ranking of the best material for sintered pulley used in automobile, and to elucidate the reliability of MARCOS method, a comparative performance study between this approach and other five vastly applied MCDM methods for the material selection of sintered pulley including EDAS, CODAS, MABAC, TOPSIS, and VIKOR presented here. These methods have been chosen due to their several advantages, wide applications and potentials to efficiently rank alternatives in multi-criteria environment. EDAS method is one of important tool of MCDM. In this method the distances in the both positive and negative direction are calculated from the average solution separately and accordingly to the beneficial or non-beneficial criteria chosen (Ghorabaee et. al., 2015). CODAS method is an efficient and updated decision-making methodology. In this method the desirability of alternatives is determined based on l1-norm and l2-norm indifference spaces for criteria. According to these spaces a combinative form of the Euclidean and Taxicab distances is utilized for calculation of the assessment score of alternatives. On the basis of assessment scores, ranking of alternatives has been done (Ghorabaee et al., 2016). MABAC method has several benefits over many other traditional MCDM methods. Mathematical formulas are remains same irrespective of the number of alternative and criteria. The basic setting of MABAC method consists in defining the distance of the criteria function of every observed alternative from the border approximate area (Pamucar & Cirovic, 2015). This method is applicable for both qualitative and quantitative type of criteria. TOPSIS is one of the important distance-based MCDM approaches which prioritize the alternatives based on the shortest distance from the ideal solution and the farthest distance from the anti-ideal solution (Chang et al., 2010). This tool is realistic and valuable for the evaluation and selection of several reciprocally conflicting alternatives through the determination of the two distance measures. VIKOR, a compromise ranking technique, applied by comparing the proximity measure of each alternative with the ideal alternative and eventually a multi criteria ranking index is estimated based on the L_p metric of a compromise programming method (Ranjan et al., 2016). The compromise solution helps the decision makers to find out the best alternatives. From Figure 2, it compares the degree of similarity in the ranking obtained using MARCOS method and the results of the previously utilized MCDM methods taken from literature after an extensive review on this sintered pulley material selection problem. Comparison of results and its correlation with other methods are analysed to assess the performance and applicability of MARCOS method in material selection problems of mechanical components. Table 10 shows the ranking results of the MARCOS and other MCDM methods adopted in the past. it is observed that the alternative materials sintered hardened steel(A5), stainless steel (A6) and the alloy steel (A4) can be the best material choice for sintered pulley and aluminium 7075 (A10) can be the worst selection for the sintered pulley used in the automobile.

5.2 Spearman rank Correlation coefficient

Spearman rank correlation coefficient is calculated to have a comparative analysis of results obtained using different MCDM methods. Value of the spearman correlation coefficient closer to 0.8 and more than it denotes an excellent relationship between the rankings. Table 11 reflects the values of spearman correlation coefficient between the different MCDM techniques used. Table 11 shows that ranking obtained using MARCOS is in an excellent match with the that obtained using the other MCDM techniques. Only CODAS shows an unsuitable correlation because most values are less than 0.8.

Table 10. Computation of ranking stability based on different MCDM method comparisons

Material	MARCOS	EDAS	CODAS	MABAC	TOPSIS	VIKOR
A_1	4	4	3	4	4	4
A_2	7	8	8	6	10	7
A_3	5	7	4	5	5	9
A_4	2	2	2	2	2	2
A_5	1	3	1	3	3	3
A_6	3	1	5	1	1	1
A_7	8	6	6	8	8	6
A_8	9	5	9	7	7	5
A_9	6	10	7	9	6	8
A_{10}	10	9	10	10	9	10

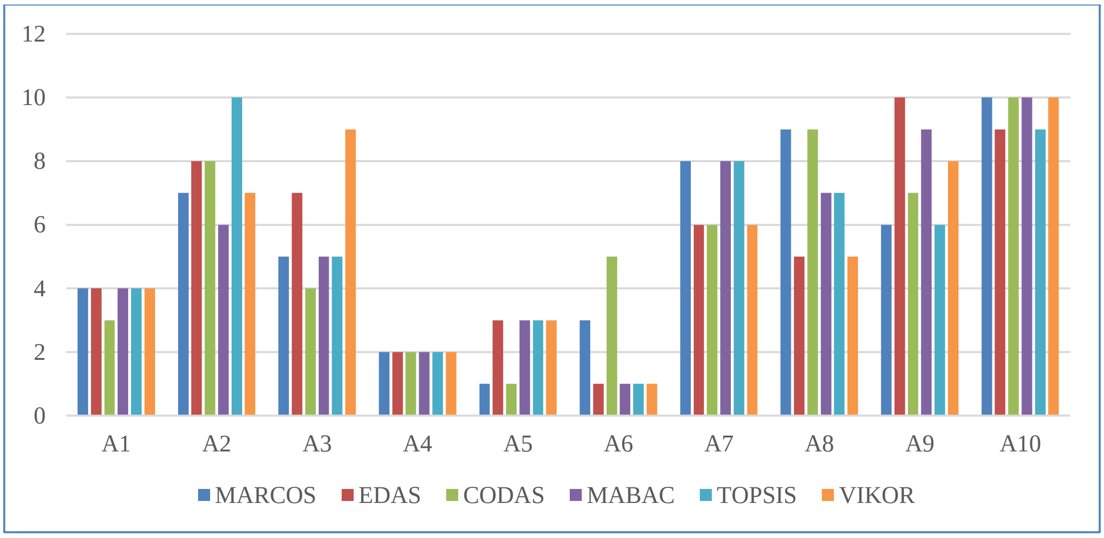

Figure 2: Materials ranking by different MCDM methods

Table 11. Spearman's coefficient of the rankings obtained using different MCDM tools for the Sintered Pulley used in Automobile

MCDM Method	MARCOS	EDAS	CODAS	MABAC	TOPSIS	VIKOR
MARCOS	1	0.70	0.93	0.87	0.87	0.71
EDAS	0.70	1	0.66	0.89	0.81	0.94
CODAS	0.93	0.66	1	0.77	0.78	0.61
MABAC	0.87	0.89	0.77	1	0.84	0.84
TOPSIS	0.87	0.81	0.78	0.84	1	0.77
VIKOR	0.71	0.94	0.61	0.84	0.77	1

6. Conclusions

Selection of a proper material for a definite engineering application's one of the utmost challenging problems due to rise in intricacy and advanced features and facilities that are continuously being incorporated into the components by the designers and manufacturers. This paper provides information on various important attributes required to be considered for the optimum evaluation and selection of materials and also explored methods to facilitate solution for the decision-making problems. CRITIC-MARCOS has been applied in the current problem, and then summarized the ranking orders. The approach started with CRITIC and obtained the weightage by keeping goal as wear resistant and structural applications. Incorporated these weights in MARCOS and obtained the ranking in which sinter hardened steel is emerged as the rank 1 material among all. This method is quite simple to comprehend and easy to apply for the selection of best alternatives. This method can also be applied to the other decision-making scenario with any number of alternatives and criteria. It has been found out with the help of different MCDM approaches like EDAS, CODAS, MABAC, TOPSIS and VIKOR, finally concluded that sintered hardened steel, stainless steel and low alloy steel can be considered as the best material for sintered pulley used for automobile. Results shows that aluminium 7075 can not be use for the said above pupose. Final findings of spearman's ranking coefficient had shown good correlation among all the different MCDM approaches.

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