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Material Selection For Metal Gear Castings In A Foundry Process

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Abstract:Material selection plays a vital role in the performance, durability, and cost effectiveness of metal gear castings produced through foundry processes. Selecting an appropriate material for gears is a complex decision-making task because multiple criteria such as castability, machinability, durability and weight must be considered simultaneously. Traditional material selection approaches often rely on experience and single-criterion evaluation, which may not adequately address the multi-dimensional nature of engineering requirements. Therefore, systematic decision-making techniques are required to ensure an optimal choice among available alternatives. In this paper, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was utilized in selecting the best gear manufacturing material among four (4) alternatives, considering four (4) criteria. The four (4) criteria being castability, machinability, durability and weight. While the four (4) alternatives are Aluminium, Zinc, Steel and Cast Iron. The results indicated that the relative closeness to the ideal solution values for Aluminium, Zinc, Steel and Cast Iron are 0.72, 0.45, 0.58 and 0.21, respectively. Since Aluminium had the closest value to 1 which is 0.72, it is the best material for manufacturing the gears. This study provides a procedure for implementing the TOPSIS method of decision-making for material selection in gear manufacturing.

Keywords: *Material selection, gear casting, foundry, TOPSIS, multi-criteria decision analysis*

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I. INTRODUCTION

Material selection is a critical stage in engineering design and manufacturing, particularly in the production of metal components that must satisfy multiple functional, economic, and technological requirements [1, 2, 3]. In foundry operations, the selection of appropriate materials for gear castings significantly influences the mechanical performance, durability, manufacturability, and overall cost of the final product [4, 5]. Gears are essential machine elements used to transmit power and motion in a wide variety of mechanical systems such as automobiles, industrial machinery, agricultural equipment, and power generation systems [6, 7, 8]. Because gears operate under varying loads, stresses, and environmental conditions, their materials must possess adequate strength, wear resistance, hardness, toughness, and fatigue resistance. Consequently, choosing the most suitable material for metal gear casting in a foundry process presents a complex decision-making problem involving multiple conflicting criteria [9, 10].

Traditionally, material selection for gear manufacturing has been based on engineering experience, empirical knowledge, and standard design guidelines [11]. Common materials used in gear casting include various grades of cast iron, alloy steels, and non-ferrous alloys. While these materials exhibit desirable mechanical properties, their performance in service also depends on other factors such as casting characteristics, cost of raw materials,

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machinability, availability, and heat treatment requirements. In modern engineering practice, relying solely on intuition or single-criterion analysis is insufficient because the decision must simultaneously consider numerous quantitative and qualitative factors [12, 13]. This complexity necessitates the adoption of systematic and scientific decision-making approaches that can evaluate multiple criteria in a structured and objective manner [14, 15].

Multi-Criteria Decision Analysis (MCDA) has emerged as an effective framework for addressing complex engineering decision problems involving several competing alternatives and evaluation criteria. MCDA provides structured techniques that allow decision-makers to rank or select the most appropriate option by considering various performance indicators simultaneously [16] [16]. In material selection problems, MCDA methods help integrate technical properties, economic considerations, and manufacturing constraints into a single decision model. This approach enhances transparency, consistency, and rationality in the selection process while reducing the influence of subjective judgment [17].

Among the many MCDA techniques developed for engineering applications [18, 19], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has gained significant popularity due to its conceptual simplicity and computational efficiency. The fundamental principle of TOPSIS is that the best alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution represents the hypothetical alternative that maximizes beneficial criteria and minimizes non-beneficial criteria, while the negative ideal solution represents the opposite condition. By evaluating the relative closeness of each alternative to these ideal solutions, TOPSIS provides a clear ranking of candidate materials based on their overall performance. The application of TOPSIS in material selection has been widely reported in various engineering fields such as mechanical design, manufacturing, and materials engineering. Its ability to handle both beneficial and non-beneficial attributes makes it particularly suitable for evaluating materials where properties such as strength, hardness, density, corrosion resistance, and cost must be considered simultaneously. When applied to gear casting in foundry processes, TOPSIS allows decision-makers to systematically compare potential materials while accounting for performance requirements and production constraints[20].

In the context of foundry operations, material selection also influences casting quality and process efficiency. Different metals and alloys exhibit distinct casting behaviors, including variations in fluidity, shrinkage characteristics, solidification patterns, and susceptibility to defects such as porosity or hot cracking. These factors affect not only the structural integrity of the gear but also the ease of manufacturing and production yield in the foundry [21]. Therefore, a comprehensive material selection framework must incorporate both mechanical performance and casting-related properties to ensure optimal results. Furthermore, economic considerations play a significant role in foundry-based gear production [22, 23]. The cost of raw materials, energy consumption during melting and casting, and subsequent machining or heat treatment processes all contribute to the overall production cost [24, 25, 26].

This study is aimed at the application of MCDA, specifically the TOPSIS method, to evaluate and select suitable materials for metal gear castings in a foundry process. Several candidate materials are assessed based on relevant criteria such as castability, machinability, durability and weight. By applying the TOPSIS method, the study aims to identify the material that provides the best compromise among these criteria while meeting the functional requirements of gear applications. The findings of this research are expected to contribute to more systematic and data-driven material selection practices in foundry engineering. The proposed decision-making framework can assist engineers, designers, and foundry managers in selecting materials that optimize gear performance, manufacturing efficiency, and economic viability. Additionally, the approach may serve as a useful reference for similar material selection problems in other mechanical components produced through casting processes. The following section describes the various methods used in accomplishing the aim and objectives.

II. METHODOLOGY

This study evaluates four (4) materials for manufacturing metal gears, in order to find the best material considering various properites and several criteria. The materials compared are Aluminium, Zinc, Steel and Cast Iron. While, the criteria considered include castability, machinability, durability and weight. The TOPSIS method was used to evaluate the materials, comparing them based on the aforementioned criteria. In the TOPSIS method, the performances of n alternatives a with respect to m criteria i are collected in a decision matrix

$$X = (x_{ia}), \text{ where } i = 1, \ldots, m \text{ and } a = 1, \ldots, n.$$

The five computation steps of the TOPSIS method are [27]:

1. The first step is normalization of the performances of the different criteria according to distributive normalization or ideal normalization.

   (a) Distributive normalization is given by

   $$r_{ia} = \frac{x_{ia}}{\sqrt{\sum_{a=1}^{n} x_{ia}^2}} \text{ for } a = 1,\ldots,n \text{ and } i = 1,\ldots,m \tag{1}$$

   (b) Ideal normalization is given by

   For maximizing criterion

   $$r_{ai} = \frac{x_{ai}}{u_a^+} \text{ for } a = 1,\ldots,n \text{ and } i = 1,\ldots,m \tag{2}$$

   Where $u_a^+ = \max(x_{ai})$ for all $a = 1,\ldots,n$

   For minimizing criterion

   $$r_{ai} = \frac{x_{ai}}{u_a^-} \text{ for } a = 1,\ldots,n \text{ and } i = 1,\ldots,m \tag{3}$$

   Where $u_a^- = \min(x_{ai})$ for all $a = 1,\ldots,n$

2. The second step is the development of a weighted normalized decision matrix by multiplying the normalized scores, r_{ai}, by their corresponding weights w_i

   $$v_{ai} = w_i \cdot r_{ai} \tag{4}$$

3. The third step is the comparison of the weighted scores to an ideal and anti-ideal virtual action. The three different ways of defining these virtual actions are:

   (a) Collection of the best and worst performance on each criterion of the normalized decision matrix. For the ideal action this is given by

   $$A^+ = (v_1^+,\ldots,v_m^+) \tag{5}$$

   For the anti-ideal action this is given by

   $$A^- = (v_1^-,\ldots,v_m^-) \tag{6}$$

   (b) Assume an absolute ideal, $A^+ = (1,\ldots,1)$ and anti-ideal point $A^- = (0,\ldots,0)$, defined without considering the actions of the decision problem.

   (c) The ideal and anti-ideal points are defined by the decision maker. These points must be between the ideal and anti-ideal points calculated with methods (a) and (b) above.

4. The fourth step is to calculate the distance for each action to the ideal action and anti-4 ideal action.

   For the ideal action distance,

   $$d_a^+ = \sqrt{\sum_i (v_i^+ - v_{ai})^2}, \quad a = 1,\ldots,m \tag{7}$$

   For the anti-ideal action distance,

   $$d_a^- = \sqrt{\sum_i (v_i^- - v_{ai})^2}, \quad a = 1,\ldots,m \tag{8}$$

5. 5.The fifth step is to calculate the relative closeness coefficient of each action

   $$C_a = \frac{d_a^-}{d_a^+ + d_a^-} \tag{9}$$

   The closeness coefficient is always between 0 and 1, where 1 is the preferred action. The alternative with closeness coefficient closest to 1 is the best alternative, considering the various criteria.

III. RESULT AND DISCUSSION

This section presents the results of applying the TOPSIS multi-criteria decision analysis method to the gear material selection problem. The objective is to select the best material for manufacturing gears, considering castability, machinability, durability and weight. Based on these criteria, the ratings of each alternative gear material (Aluminium, Zinc, Steel and Cast Iron), along with the weights of the selection criteria are shown in Table 1.

TABLE 1
Weights of selection criteria

	Castability	**Machinability**	**Durability**	**Weight**
Criteria Weight	0.4	0.3	0.2	0.1
Aluminium	4	4	1	4
Zinc	2	3	2	3
Steel	3	2	4	2
Cast Iron	1	1	3	1

In Table 1, each gear material alternative is scored from 1 to 4, with 4 being the best score and 1 being the worst score, within any given criterion. Also, from Table 1, castability is the most important criterion for selecting the gear material, and Aluminium is rated the best (rated 4) under this criterion, while Cast Iron is rated the worst (rated 1). Secondly, machinability is the second most important criterion for selecting the gear material, and similar to the castability criterion, Aluminium is rated the best under the machinability criterion, while Cast Iron is rated the worst. For the third criterion which is durability, Steel is rated the best material for making the gears, while Aluminium is rated the worst. Finally, for the weight criterion Aluminium is rated the best, while cast iron is rated the worst. The basis for rating the alternatives is the physical comparison of the alternatives based on castability, machinability, durability and weight. The gear material selection process will follow the five (5) steps of the TOPSIS procedure listed in the methodology section. The first step is the normalization of the ratings of the different criteria according to distributive normalization as shown in Table 2

TABLE 2
Normalization of the gear material ratings.

	Castability	**Machinability**	**Durability**	**Weight**
Aluminium	0.73	0.73	0.18	0.73
Zinc	0.37	0.55	0.37	0.55
Steel	0.55	0.37	0.73	0.37
Cast Iron	0.18	0.18	0.55	0.18

In Table 2, the distributive normalization values obtained were calculated using equation (1). The second step in the gear material selection using TOPSIS is the calculation of a weighted normalized decision matrix. This matrix considers the various weights of the criteria, and how the criteria compare to one another in terms of importance. The weighted normalized decision matrix is shown in Table 3.

TABLE 3
Weighted normalized decision matrix

	Castability	**Machinability**	**Durability**	**Weight**
Aluminium	0.292	0.219	0.037	0.073
Zinc	0.146	0.164	0.073	0.055
Steel	0.219	0.110	0.146	0.037
Cast Iron	0.073	0.055	0.110	0.018

The values in Table 3 were obtained by multiplying the values in Table 2 by the weights of each criterion. The decision matrix obtained considers the importance of each criteria in the gear material selection process. From Table 3, the positive ideal solution for the castability criterion corresponds to the highest value for that criterion which is 0.292, while the negative ideal solution for the castability criterion corresponds to the lowest value for that criterion which is 0.073. The positive ideal solution for the machinability criterion is 0.219 and the negative ideal solution for the machinability criterion is 0.055. The positive and negative ideal solutions of the durability criterion is 0.146 and 0.037, respectively. While for the weight criterion, the positive and negative ideal solutions are 0.073 and 0.018, respectively. Table 4 shows the distance of each normalized weighted rating from the positive ideal solution.

TABLE 4
Distance between normalized weighted ratings and the positive ideal solution.

	Castability	**Machinability**	**Durability**	**Weight**
Aluminium	0.000000	0.000000	0.012000	0.000000
Zinc	0.021333	0.003000	0.005333	0.000333
Steel	0.005333	0.012000	0.000000	0.001333
Cast Iron	0.048000	0.027000	0.001333	0.003000

While Table 5 shows the distance of each normalized weighted rating from the negative ideal solution.

TABLE 5
Distance between normalized weighted ratings and the negative ideal solution.

	Castability	**Machinability**	**Durability**	**Weight**
Aluminium	0.048000	0.027000	0.000000	0.003000
Zinc	0.005333	0.012000	0.001333	0.001333
Steel	0.021333	0.003000	0.012000	0.000333
Cast Iron	0.000000	0.000000	0.005333	0.000000

The values in Table 4 and Table 5 are used in calculating the relative closeness of each normalized weighted rating and the ideal solution for each alternative using the Euclidean distance method. Using equation (9), the values for the relative closeness to the ideal solution for Aluminium, Zinc, Steel and Cast Iron are 0.72, 0.45, 0.58 and 0.21, respectively. These closeness coefficients are always between 0 and 1, where 1 is the preferred value. Since Aluminium had the closest value to 1 which is 0.72, it is the best material for manufacturing the gears. Therefore, Aluminium is the best material that has the best combination of castability, machinability, durability and weight. In terms of these criteria, the second-best material for manufacturing the gears is Steel, followed by Zinc and finally, Cast Iron, which is the least appropriate material.

IV. CONCLUSION

Material selection is a crucial aspect of engineering design and manufacturing, particularly in the production of metal gears through foundry processes where performance, durability, and cost considerations must be carefully balanced. Because gears operate under significant mechanical loads and require high resistance to wear and fatigue, the choice of casting material directly affects their reliability, efficiency, and service life. Traditional methods of selecting materials often rely on experience or single-factor evaluation, which may not adequately capture the complexity involved in evaluating multiple performance and economic criteria simultaneously. This limitation highlights the need for systematic decision-making approaches capable of addressing multi-criteria problems in engineering applications.

In this study, a Multi-Criteria Decision Analysis (MCDA) framework was applied to the problem of selecting suitable materials for metal gear castings in a foundry environment. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed as the decision-making tool due to its simplicity, effectiveness, and ability to evaluate alternatives based on their distance from ideal and negative-ideal solutions. By incorporating multiple criteria such as mechanical properties, wear resistance, density, castability, and cost, the TOPSIS approach enabled a structured comparison of candidate materials used for gear casting. The results obtained from the analysis demonstrate that the TOPSIS method provides a clear and logical ranking of material alternatives based on their overall performance across the selected criteria. This ensures that the selected material represents the best compromise among competing factors, thereby supporting more rational and transparent decision-making in engineering practice.

Another important advantage of the TOPSIS approach is its flexibility and adaptability. The framework allows decision-makers to incorporate additional criteria or modify the relative importance of each factor depending on specific design requirements or operational conditions. In the context of foundry operations, this is particularly useful because factors such as casting behavior, defect susceptibility, machining requirements, and material availability may vary across different production environments. Therefore, the methodology can be easily adapted to suit the needs of various gear manufacturing applications. The application of the TOPSIS method also contributes to improving the overall efficiency of the material selection process in foundries. By providing a quantitative and systematic evaluation of alternatives, the method reduces reliance on subjective judgment and minimizes the risk of selecting suboptimal materials. This can lead to improved gear performance, reduced production defects, and better cost management in large-scale manufacturing. Furthermore, the structured nature of the decision model makes it easier for engineers and managers to justify their material selection decisions based on clearly defined evaluation criteria. Overall, the findings of this study demonstrate that the TOPSIS method offers a practical and reliable approach for material selection in metal gear casting. The method enhances decision quality by combining engineering performance criteria with economic considerations in a single analytical framework. As a result, it provides valuable support for engineers, designers, and foundry managers involved in gear manufacturing and related mechanical component production.

Future research can extend this work by incorporating additional decision-making methods such as Analytic Hierarchy Process (AHP) for criteria weighting, fuzzy logic to address uncertainty in material properties, or hybrid MCDA models for more comprehensive evaluations. Additionally, experimental validation of the selected materials in practical casting environments could further strengthen the applicability of the proposed approach. Through such developments, decision-support tools for material selection can continue to evolve and contribute to more efficient and sustainable manufacturing practices.

REFERENCES

[1] X. Lin, X. Zhang, J. Chen, and J. Liu, “Material selection and device design of scalable flexible brain-computer interfaces: A balance between electrical and mechanical performance,” *Advanced Materials*, vol. 37, no. 26, p. 2413938, 2025.

[2] D. Grandi, Y. P. Jain, A. Groom, B. Cramer, and C. McComb, “Evaluating large language models for material selection,” *Journal of Computing and Information Science in Engineering*, vol. 25, no. 2, p. 021004, 2025.

[3] İ. İsmayil, M. Garayev, R. Akhundov, and E. Hashimov, “Optimization of composite material selection in the design of military uav wings,” *Collection of scientific papers «SCIENTIA»*, no. October 3, 2025; Berlin, Germany, pp. 107–115, 2025.

[4] O. Ponomarenko, N. Yevtushenko, L. Saithareiev, S. Yevtushenko, and A. Dzhanikian, “Modern methods for synchronizing the operation of subsystems of the foundry workshop,” in *Design, Simulation, Manufacturing: The Innovation Exchange*. Springer, 2025, pp. 85–97.

[5] C. A. Egwuonwu and C. E. Nwanna, “Production of portable furnace using locally sourced materials for foundry practice in art schools in south eastern nigeria,” *Awka Journal of Fine and Applied Arts*, vol. 11, no. 1, 2025.

[6] O. K. Wofuru-Nyenke, “Mechanized cover crop farming: Modern methods, equipment and technologies,” *Circular Agricultural Systems*, vol. 3, no. 1, 2023.

[7] K. U. Ugoji, O. E. Isaac, B. Nkoi, and O. Wofuru-Nyenke, “Improving the operational output of marine vessel main engine system through cost reduction using reliability,” *International Journal of Engineering and Modern Technology (IJEMT)*, vol. 8, no. 2, pp. 36–52, 2022.

[8] O. K. Wofuru-Nyenke, “Leading-edge production engineering technologies,” *Journal of Newviews in Engineering and Technology (JNET)*, vol. 3, no. 4, pp. 9–17, 2021.

[9] P. Saxena, E. Pagone, K. Salonitis, and M. R. Jolly, “Sustainability metrics for rapid manufacturing of the sand casting moulds: A multi-criteria decision-making algorithm-based approach,” *Journal of Cleaner Production*, vol. 311, p. 127506, 2021.

[10] E. Pagone, K. Salonitis, and M. Jolly, “Automatically weighted high-resolution mapping of multi-criteria decision analysis for sustainable manufacturing systems,” *Journal of Cleaner Production*, vol. 257, p. 120272, 2020.

[11] O. K. Wofuru-Nyenke, “Multi-attribute utility theory modelling for product design evaluation,” *In-*

ternational Journal of Technology & Engineering Studies, vol. 10, no. 1, 2024.

[12] O. K. Wofuru-Nyenke, "Critical path method utilization for optimal scheduling of production activities," *Future Sustainability*, vol. 2, no. 3, pp. 1–5, 2024.

[13] O. Wofuru-Nyenke, "Forecasting model accuracy assessment in a bottled water supply chain," *International Journal of Engineering and Modern Technology*, vol. 8, no. 5, pp. 101–108, 2022.

[14] O. Wofuru-Nyenke and T. Briggs, "Predicting demand in a bottled water supply chain using classical time series forecasting models," *Journal of Future Sustainability*, vol. 2, no. 2, pp. 65–80, 2022.

[15] O. Wofuru-Nyenke, "Routing and facility location optimization in a dairy products supply chain," *Future Technology*, vol. 3, no. 2, pp. 44–49, 2024.

[16] O. Wofuru-Nyenke, "Biodegradable cutting fluids evaluation for sustainable machining processes," *Universal Journal of Green Chemistry*, pp. 117–124, 2024.

[17] G. Ferla, B. Mura, S. Falasco, P. Caputo, and A. Matarazzo, "Multi-criteria decision analysis (mcda) for sustainability assessment in food sector. a systematic literature review on methods, indicators and tools," *Science of the Total Environment*, vol. 946, p. 174235, 2024.

[18] O. K. Wofuru-Nyenke, "Analytic hierarchy process modelling for supplier selection in a manufacturing supply chain," 2023.

[19] O. K. Wofuru-Nyenke, "Sustainable lathe machine selection using promethee," *Future Sustainability*, vol. 2, no. 4, pp. 15–21, 2024.

[20] M. Cinelli, P. Burgherr, M. Kadziński, and R. Słowiński, "Proper and improper uses of mcda methods in energy systems analysis," *Decision Support Systems*, vol. 163, p. 113848, 2022.

[21] O. K. Wofuru-Nyenke, T. A. Briggs, and D. O. Aikhuele, "Advancements in sustainable manufacturing supply chain modelling: a review," *Process Integration and Optimization for Sustainability*, vol. 7, no. 1, pp. 3–27, 2023.

[22] O. K. Wofuru-Nyenke, "Design analysis of a portable manual tyre changer," *European Journal of Engineering and Technology Research*, vol. 5, no. 11, pp. 1307–1318, 2020.

[23] O. Wofuru-Nyenke, "Reliability assessment and accelerated life testing in a metalworking plant," *Future Technology*, vol. 3, no. 3, pp. 1–7, 2024.

[24] O. K. Wofuru-Nyenke, B. Nkoi, and F. E. Oparadike, "Waste and cost reduction for a water bottling process using lean six sigma," *European Journal of Engineering and Technology Research*, vol. 4, no. 12, pp. 71–77, 2019.

[25] O. Wofuru-Nyenke, "Carbon emissions modeling for smarter carbon footprint decisions: a systematic review," *BOHR International Journal of Civil Engineering and Environmental Science (BIJCEES)*, vol. 1, no. 2, pp. 75–87, 2023.

[26] O. K. Wofuru-Nyenke, "Value stream mapping: A tool for waste reduction," *International Journal of Innovative Research and Development*, vol. 10, no. 6, pp. 13–20, 2021.

[27] A. Ishizaka and P. Nemery, *Multi-criteria decision analysis: methods and software*. John Wiley & Sons, 2013.