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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 alternatives, considering four criteria. The four criteria are castability, machinability, durability and weight, while the four 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 (MCDA)

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 (Grandi *et al.*, 2025; İsmayil *et al.*, 2025; Lin *et al.*, 2025). 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 (Egwuonwu and Nwanna, 2025; Ponomarenko *et al.*, 2025). 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 (Ugoji *et al.*, 2022; Wofuru-Nyenke, 2021a, 2023c). 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 (Pagone *et al.*, 2020; Saxena *et al.*, 2021).

Traditionally, material selection for gear manufacturing has been based on engineering experience, empirical knowledge, and standard design guidelines (Wofuru-Nyenke, 2024f). 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, 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 (Wofuru-Nyenke, 2022, 2024e, 2025). This complexity necessitates the adoption of systematic and scientific decision-making approaches that can evaluate multiple criteria in a structured and objective manner (Wofuru-Nyenke, 2024c; Wofuru-Nyenke and Briggs, 2022; Wofuru-Nyenke, 2026).

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 (Wofuru-Nyenke, 2024a). 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 (Ferla *et al.*, 2024).

Among the many MCDA techniques developed for engineering applications (Wofuru-Nyenke, 2024d; Wofuru-Nyenke, 2023b), 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 (Jha *et al.*, 2022; Singh *et al.*, 2023; Yu *et al.*, 2022). 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 (Cinelli *et al.*, 2022).

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 (Wofuru-Nyenke *et al.*, 2023). 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 (Wofuru-Nyenke, 2024b; Wofuru-Nyenke, 2020). 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 (Wofuru-Nyenke, 2023a; Wofuru-Nyenke, 2021b; Wofuru-Nyenke *et al.*, 2019).

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 to accomplish the aim and objectives.

METHODOLOGY

This study evaluates four (4) materials for manufacturing metal gears, in order to find the best material considering various properties 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 $X = (x_{ia})$, where $i = 1, \dots, m$ and $a = 1, \dots, n$.

The five computation steps of the TOPSIS method are (Ishizaka and Nemery, 2013):

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:

$$r_{ia} = \frac{x_{ia}}{\sqrt{\sum_{a=1}^n x_{ia}^2}} \text{ for } a = 1, \dots, n \text{ and } i = 1, \dots, m \quad (1)$$

- b) Ideal normalization is given by:

For maximizing criterion,

$$r_{ia} = \frac{x_{ai}}{u_a^+} \text{ for } a = 1, \dots, n \text{ and } i = 1, \dots, m \quad (2)$$

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

For minimizing criterion,

$$r_{ai} = \frac{x_{ai}}{u_a^-} \text{ for } a = 1, \dots, n \text{ and } i = 1, \dots, m \quad (3)$$

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

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 .

$$v_{ai} = w_i \cdot r_{ai} \quad (4)$$

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 performances for each criterion in the normalised decision matrix. For the ideal action, this is given by,

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

For the anti-ideal action, this is given by,

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

- b) Assume an absolute ideal, $A^+ = (1, \dots, 1)$ and anti-ideal point $A^- = (0, \dots, 0)$, 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 the anti-ideal action.

For the ideal action distance,

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

For the anti-ideal action distance,

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

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 the closeness coefficient closest to 1 is the best alternative, considering the various criteria.

RESULTS 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.

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,

Table 1: Weights of selection criteria and rating of the alternatives.

	Cast-ability	Machin-ability	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

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.

	Cast-ability	Machin-ability	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 Eq. (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.

	Cast-ability	Machin-ability	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 criterion 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 are 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.

	Cast-ability	Machin-ability	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

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

Table 4: Distance between normalized weighted ratings and the negative ideal solution.

	Cast-ability	Machin-ability	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 Eq. (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.

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. As 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, 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 behaviour, 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 sub-optimal 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. Further research can also analyse the suitability of various metals for casting based on factors such as strength, hardness, density, corrosion resistance, and cost. 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 (Godwin and Okpala, 2026; Ogbodo *et al.*, 2026; Okpala, 2026).

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy, have been completely observed by the authors.

REFERENCES

- Cinelli, M., Burgherr, P., Kadziński, M., *et al.* (2022) 'Proper and improper uses of MCDA methods in energy systems analysis', *Decision Support Systems*, 163, 113848.
- Ferla, G., Mura, B., Falasco, S., *et al.* (2024) '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*, 946, 174235.
- Godwin, H.C. and Okpala, C.C. (2026) 'Data-driven ergonomic optimization in manufacturing systems: Productivity, safety, and sustainability impacts', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 695-704. <https://ijths.com/wp-content/uploads/IJTHS-0202041.pdf>
- Grandi, D., Jain, Y.P., Groom, A., *et al.* (2025) 'Evaluating large language models for material selection', *Journal of Computing and Information Science in Engineering*, 25(2), 021004.
- Ishizaka, A. and Nemery, P. (2013) *Multi-criteria decision analysis: methods and software*. John Wiley & Sons.
- İsmayil, İ., Garayev, M., Akhundov, R., *et al.* (2025) 'Optimization of composite material selection in the design of military UAV wings', *Collection of Scientific Papers (SCIENTIA)*, Berlin, Germany, pp. 107-115.
- Jha, M.K., Gupta, S., Chaudhary, V., *et al.* (2022) 'Material selection for biomedical application in additive manufacturing using TOPSIS approach', *Materials Today: Proceedings*, 62, pp. 1452-1457.
- Lin, X., Zhang, X., Chen, J., *et al.* (2025) 'Material selection and device design of scalable flexible brain-computer interfaces: A balance between electrical and mechanical performance', *Advanced Materials*, 37(26), pp. 2413938.
- Ogbodo, I.F., Okpala, C.C. and Egwuagu, O.M. (2026) 'From lean waste to measurable sustainability: Data-driven optimization in smart manufacturing', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 523-532. <https://ijths.com/wp-content/uploads/IJTHS-0202020.pdf>
- Okpala, C.C. (2026) 'Human-centered design of jigs and fixtures: A data-driven approach to productivity, safety, and manufacturing sustainability', *International Journal of Technology, Health and Sustainability*, 2(1), pp. 291-299. <https://ijths.com/wp-content/uploads/IJTHS-020185.pdf>
- Pagone, E., Salonitis, K. and Jolly, M. (2020) 'Automatically weighted high-resolution mapping of multi-criteria decision analysis for sustainable manufacturing systems', *Journal of Cleaner Production*, 257, 120272.
- Ponomarenko, O., Yevtushenko, N., Saithareiev, L., *et al.* (2025) 'Modern methods for synchronizing the operation of subsystems of the foundry workshop'. In: *Advances in Design, Simulation, Manufacturing VIII*; Ivanov *et al.*, pp. 85-97. Springer. https://doi.org/10.1007/978-3-031-95211-1_8
- Saxena, P., Pagone, E., Salonitis, K., *et al.* (2021) 'Sustainability metrics for rapid manufacturing of the sand casting moulds: A multi-criteria decision-making algorithm-based approach', *Journal of Cleaner Production*, 311, 127506.
- Singh, S., Agrawal, V., Saxena, K.K., *et al.* (2023) 'Optimization on manufacturing processes at Indian industries using TOPSIS', *Indian Journal of Engineering & Materials Sciences*, 30(1), 32.
- Ugoji, K.U., Isaac, O.E., Nkoi, B., *et al.* (2022) 'Improving the operational output of marine vessel main engine system through cost reduction using reliability', *International Journal of Engineering and Modern Technology (IJEMT)*, 8(2), pp. 36-52.
- Wofuru-Nyenke, O. (2023a) 'Carbon emissions modeling for smarter carbon footprint decisions: a systematic review', *BOHR International Journal of Civil Engineering and Environmental Science (BIJCEES)*, 1(2), pp. 75-87.
- Wofuru-Nyenke, O. (2024a) 'Biodegradable cutting fluids evaluation for sustainable machining processes', *Universal Journal of Green Chemistry*, 2(1), pp. 117-124.
- Wofuru-Nyenke, O. (2024b) 'Reliability assessment and accelerated life testing in a metalworking plant', *Future Technology*, 3(3), pp. 1-7.
- Wofuru-Nyenke, O. (2024c) 'Routing and facility location optimization in a dairy products supply chain', *Future Technology*, 3(2), pp. 44-49.
- Wofuru-Nyenke, O. (2024d) 'Sustainable lathe machine selection using PROMETHEE', *Future Sustainability*, 2(4), pp. 15-21.
- Wofuru-Nyenke, O. and Briggs, T. (2022) 'Predicting demand in a bottled water supply chain using classical time series forecasting models', *Journal of Future Sustainability*, 2(2), pp. 65-80.
- Wofuru-Nyenke, O.K. (2020) 'Design analysis of a portable manual tyre changer', *European Journal of Engineering and Technology Research*, 5(11), pp. 1307-1318.
- Wofuru-Nyenke, O.K. (2021a) 'Leading-edge production engineering technologies', *Journal of Newviews in Engineering and Technology (JNET)*, 3(4), pp. 9-17.
- Wofuru-Nyenke, O.K. (2021b) 'Value stream mapping: A tool for waste reduction', *International Journal of Innovative Research and Development*, 10(6), pp. 13-20.
- Wofuru-Nyenke, O.K. (2022) 'Forecasting model accuracy assessment in a bottled water supply chain', *International Journal of Engineering and Modern Technology*, 8(5), pp. 101-108.
- Wofuru-Nyenke, O.K. (2023b) 'Analytic hierarchy process modelling for supplier selection in a manufacturing supply chain', *International Journal of Applied and Physical Sciences*, 9, pp. 27-35.
- Wofuru-Nyenke, O.K. (2023c) 'Mechanized cover crop farming: Modern methods, equipment and technologies', *Circular Agricultural Systems*, 3(1), 6.
- Wofuru-Nyenke, O.K. (2024e) 'Critical path method utilization for optimal scheduling of production activities', *Future Sustainability*, 2(3), pp. 1-5.
- Wofuru-Nyenke, O.K. (2024f) 'Multi-attribute utility theory modelling for product design evaluation', *International Journal of Technology & Engineering Studies*, 10(1), pp. 26-33.
- Wofuru-Nyenke, O.K. (2025) 'The optimising known warehouses framework for supply chain optimisation', *Nigerian Journal of Oil and Gas Technology*, 5(2), pp. 143-171.
- Wofuru-Nyenke, O.K. (2026) 'Multi-criteria decision analysis for optimal production schedule choice', *International Journal of Technology, Health and Sustainability*, 2(02), pp. 533-539.
- Wofuru-Nyenke, O.K., Briggs, T.A. and Aikhuele, D.O. (2023) 'Advancements in sustainable manufacturing supply chain modelling: a review', *Process Integration and Optimization for Sustainability*, 7(1), pp. 3-27.
- Wofuru-Nyenke, O.K., Nkoi, B. and Oparadike, F.E. (2019) 'Waste and cost reduction for a water bottling process using lean six sigma', *European Journal of Engineering and Technology Research*, 4(12), pp. 71-77.
- Yu, Z., Zhao, W., Guo, X., *et al.* (2022) 'Multi-indicators decision for product design solutions: A TOPSIS-MOGA integrated model', *Processes*, 10(2), pp. 303.