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A multi-criteria decision making approach for 3D printer nozzle material selection

Saikat Chatterjee[1], Shankar Chakraborty[2]
[1] Department of Mechanical Engineering, Sikkim Manipal Institute of Technology, Sikkim Manipal University, Sikkim, India
[2] Department of Production Engineering, Jadavpur University, Kolkata, India

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ABSTRACT

Rapid advancements in 3D printing technology have compelled the manufacturers to search for better nozzle material in the extruder of 3D printers. Materials ranging from brass to tungsten carbide and ruby are primarily used as the nozzle material. In 3D printing technology, no one nozzle material provides all the required qualities for a real-world application due to significant limits imposed by the filament material and other critical considerations. For improved 3D printing performance, it is now essential to choose the most suitable nozzle material with the needed qualities. The performance of eight candidate nozzle materials is evaluated using nine selection criteria in this paper. To calculate weights and determine the best 3D printer nozzle material, the entropy and evaluation based on distance from average solution (EDAS) methods are used, respectively. The best outcome is tungsten carbide, followed by titanium alloy (TiAl6V4). This paper also proposes a sensitivity analysis to determine the robustness of the adopted methodology.

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Corresponding Author:

Saikat Chatterjee,
Department of Mechanical Engineering, Sikkim Manipal Institute of Technology, Sikkim Manipal University, Sikkim, India
Email: saikatchatterjee007@gmail.com

1. Introduction

In the manufacturing sector, increasing competition and survival have compelled organizations to develop high-quality, low-cost, and better-performing products. In recent times, development of many new materials has resulted in substitution of the earlier available ones. Selection of the apt material for a specific application due to multiple conflicting characteristics, like machinability, formability and heat treatability, electrical, magnetic and chemical properties, cost, product shape and size, impact on environment, market trends and availability of the material, culture and aesthetics, recyclability, intended target customers, safety etc. makes it an exigent task for the decision makers. An efficient and robust approach is thus necessary for proper material selection to reach the desired goals (Shokr., I; Torabi, 2015). For any material selection problem, there are several non-beneficial properties which are required to be minimized, while the beneficial properties need to be maximized. As a result, in order to achieve the desired final product performance, decision makers must use suitable multi-criteria decision making (MCDM) approaches to identify the most effective possible material with the required properties. Additionally, performing sensitivity analysis guides in deciding the robustness of the adopted MCDM methods and reliability of the derived solutions. However, MCDM methods can produce diverse, not compulsorily coinciding ranking results.

The 3D printing technology has propelled the growth of additive manufacturing with an ever expanding variety of products based on various available processes (Lu et al., 2015). Designing and fabrication of 3D printer's components significantly influence development of the end product. In fused deposition modelling, a prevalent rapid prototyping procedure, inside the extruder, there is a motor which feeds the filament to the hot end where the filament melts and the nozzle helps to deposit the molten filament to form layers of the desired product in a controlled way, as shown in Figure 1. Continuous lifting of the nozzle or lowering of the platform after each layer results in building of the product layer upon layer (Xia et al., 2017).

The nozzle, as exhibited in Figure 2 is the last component that the filament material contacts before it gets extruded. It needs to be exchangeable according to the requirements. Proper designing and fabrication of the nozzle in a 3D printer considerably impact development of the final product. The nozzle thus plays one of the most important roles in 3D printing technology. Size, shape and material of the nozzle are observed to be the influencing factors to be considered while selecting a nozzle. Dimension of the nozzle diameter directly affects horizontal resolution and thickness of the 3D printed product. The most commonly available and preferable nozzle bore diameter is 0.4 mm which is in agreement with both resolution and speed (*Nozzle Sizes, Materials, and Shapes for 3D Printers*, 2017). As the nozzle diameter increases, layer thickness also increases with decrement in resolution, but increment in the printing speed. On the other hand, as the nozzle diameter decreases, layer thickness decreases, causing resolution to increase and printing speed to decrease. Smaller diameter nozzles help in achieving more detailed, smoother and accurate products. Bigger diameter nozzles mostly provide more reliability as compared to smaller diameter nozzles, as blocking of the molten filament flow due to over-extrusion is a major detriment for effective functioning of 3D printers. Under-extrusion of the molten filament leads to weaker bonding between the layers of the developed product. Shape styles include nozzle nose length and width. Short nose designs mandate the molten filament to travel less distance with insufficient cooling time. Conversely, the molten filament travels a greater distance in a long-nosed nozzle, allowing for adequate cooling time. On the other hand, broad nose results in loss of the detailed product design and narrow nose are responsible for bulging of the extruded filament. Moreover, pointed nozzles provide better quality and flat head nozzles are used for more sturdiness. Thickness of the conduits limits the interior design of a nozzle. Another major determinant of the performance of the nozzle is its constituent material. Brass is a soft material, relatively cheap, good conductor of heat and easy to machine, but it wears out easily if abrasive filaments are used. Hardened steel and stainless steel are better for abrasive filaments, but they are not good conductors of heat (Carolo, 2022). Ruby, plated copper and aluminium alloys are also employed to make harder nozzles that can withstand constant abrasion. Brass and aluminum start to become extremely weak at higher temperatures. Nickel layer plated over copper is preferred for higher corrosion resistance and thermal conductivity. It has already been acknowledged that while designing a mechanical component, the properties of the constituent materials play significant roles. Due to huge availability of the candidate materials, and considering the constraints and criteria requirements imposed by the designers, it has now become extremely challenging for the manufacturers. Conflicting criteria requirements along with the presence of several candidate alternatives lead to the deployment of an MCDM method. As a result, for the first time in the field of material selection, this study proposes using the evaluation based on distance from average solution (EDAS) approach to identify the best material for a 3D printer nozzle. A thorough sensitivity analysis research is used to assess the method's soundness and solution correctness.

The following are the sections of the paper: Section 2 provides a brief review of the literature on the use of MCDM tools in mechanical component material selection. Section 3 outlines the step-by-step procedures for implementing the Entropy and EDAS methods. Section 4 presents a real-world 3D printer nozzle selection. In Section 5, the EDAS method's ranking performance comparison. Section 6 conducts a sensitivity analysis to test the EDAS method's robustness. Finally, Section 7 concludes the paper by summarizing the key findings and implications of the study.

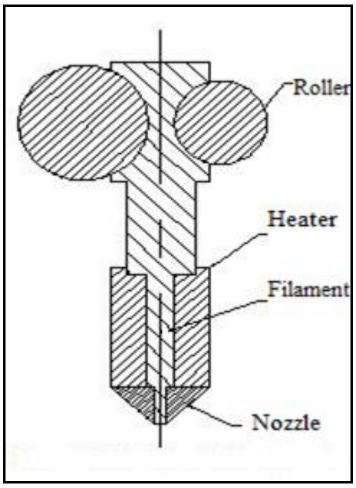

Figure 1. Schematic diagram of a 3D printer extruder

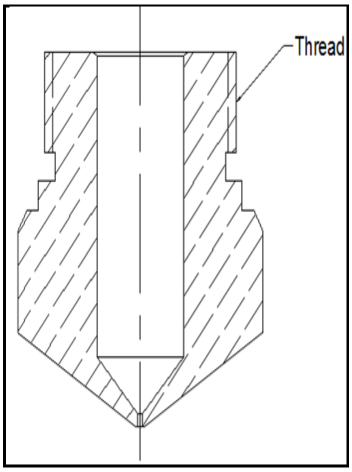

Figure 2. Sectional view of a 3D printer nozzle

2. Literature review

Previously, researchers investigated the applicability of MCDM methods in a variety of engineering fields, particularly material selection. Various MCDM methods, like technique for order of preference by similarity to ideal solution (TOPSIS) (Chede et al., 2020; Hasanzadeh et al., 2017; Kumar & Singal, 2015; Rastogi et al., 2015; Sen et al., 2016; Yang et al., 2017), complex proportional assessment (COPRAS) (Sen et al., 2016), additive ratio assessment (ARAS) (Goswami & Behera, 2020; Sen et al., 2016), multi-objective optimization on the basis of ratio analysis (MOORA) (Hasanzadeh et al., 2017; Sen et al., 2016), Vlse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Dev et al., 2020; Giorgetti et al., 2017; Ishak et al., 2016; Sen et al., 2016), preference ranking organization method for enrichment of evaluations (PROMETHEE) (Anojkumar et al., 2016; Gul et al., 2018; Maity & Chakraborty, 2015), preference selection index (PSI) (Singh et al., 2015), analytic hierarchy process (AHP) (AL-Oqla et al., 2016), fuzzy axiomatic design (FAD) principles (Khandekar & Chakraborty, 2015), Q-analysis (Bhattacharyya & Chakraborty, 2015), fuzzy multi-attributive border approximation area comparison (F-MABAC) (Xue et al., 2016), grey relational analysis (GRA) (Jayakrishna & Vinodh, 2017), TODIM (an acronym in Portuguese for interactive and multi criteria decision making) (Zindani et al., 2017), hybrid TOPSIS-PSI (Yadav et al., 2019), multi-attributive ideal real comparative analysis (MAIRCA) (Chatterjee et al., 2020; Chatterjee & Chakraborty, 2022), weighted sum method (WSM) (Saputra et al., 2023), etc. have been extensively applied to solve diverse material selection problems.

Review reveals that AHP, MOORA, PSI, TOPSIS, VIKOR, and PROMETHEE MCDM methods are commonly used for material selection in various mechanical components. However, no prior research related to selection process of 3D printer nozzle material, has been conducted. To address this issue, a newly developed EDAS method is used in this study. Although EDAS has not yet been used in mechanical components material selection, it has numerous application in other domains such as social responsibility project prioritization (Karaşan et al., 2019), steam boiler selection (Kundakcı, 2019), site selection (Schitea et al., 2019), supplier selection (Stević et al., 2019), and so on. The restricted use of the EDAS method in previous studies has inspired an exploration of its potential in addressing the material selection problem for 3D printer nozzles. A comparison of its ranking performance with other widely used MCDM methods has been conducted, and a sensitivity analysis has been carried out to determine its suitability for solving material selection problems.

3. Methodologies adopted

The entropy method for computing weights and the EDAS method for ranking candidates are used to reduce subjectivity and increase objectivity in the decision-making process. The procedural steps to solve the considered 3D printer nozzle material problem are presented in Figure 3.

3.1. Entropy method

It is based on the permanent existing information of various criteria to determine their weights, leading to better objectified results. In a decision matrix, assume that there are m material alternatives and n criteria, and x_{ij} is an element of that matrix representing the value of j^{th} criterion corresponding to i^{th} alternative, now to eradicate the influences of different dimensions in criteria values, the decision matrix must first be normalized using the equations:

$$P_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \text{, for beneficial criteria} \tag{1}$$

$$P_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \text{, for non-beneficial criteria} \tag{2}$$

According to the definition, entropy of j^{th} criterion is determined using Eq. (3) (Zou et al., 2006).

$$e_j = -\frac{\sum_{i=1}^{m} f_{ij} \ln(f_{ij})}{\ln m} \quad (i=1,2,\ldots,m; j=1,2,\ldots,n) \tag{3}$$

where $f_{ij} = \frac{P_{ij}}{\sum_{i=1}^{m} P_{ij}}$

The entropy weight (w_j) of j^{th} criterion is determined as follows:

$$w_j = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j} \tag{4}$$

where $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j = 1$.

3.2. EDAS method

It is a new distance-based measurement method that compares favourably to other recently developed methods (Chatterjee et al., 2018; Ghorabaee et al., 2015). According to the literature, TOPSIS, another distance-based MCDM technique, has been extensively employed in material selection problems. The TOPSIS approach chooses the best solution based on its proximity to the positive-ideal solution while being the furthest away from the negative-ideal solution. The TOPSIS approach has a major shortcoming in that it doesnot estimate the relevance between the two measured target points. It implies that the favoured alternative may not be the most suitable solution (Chakraborty & Chatterjee, 2013). The EDAS method's mathematical modelling differs slightly. The EDAS method's mathematical modelling differs slightly from TOPSIS in that it is based on distances from the average solution. The average solution is calculated by taking the arithmetic mean of the candidate alternatives' performance values. When there is a rank reversal, the EDAS technique outperforms TOPSIS (Keshavarz-Ghorabaee et al., 2018). It is straightforward, efficient, and employs fewer computations, resulting in faster solutions. The optimal solution in this method is chosen primarily by calculating both the positive (*PD*) and negative (*ND*) distances for each alternative and criterion from the average solution. These distances represent the disparities, where higher *PD* values indicate superior solutions, but higher *ND* values indicate inferior solutions. The EDAS method consist the following steps:

Step 1: Establish the decision matrix (X), which has m alternatives and n criteria:

$$X = [X_{ij}]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{5}$$

Step 2: Calculate the average solution (AVR) based on all criteria.

$$AVR = [AVR_j]_{1\times n} \tag{6}$$

Where $AVR_j = \frac{\sum_{i=1}^{m} x_{ij}}{m}$ (j =1,2,..,n)

Step 3: Determine *PD* and *ND* matrixes based on beneficial or non-beneficial criteria.

$$PD = [PD_{ij}]_{m\times n}, \tag{7}$$

$$ND = [ND_{ij}]_{m\times n}, \tag{8}$$

If j^{th} criterion is beneficial in nature, then

$$PD_{ij} = \frac{\max(0, (x_{ij} - AVR_j))}{AVR_j}, \tag{9}$$

$$ND_{ij} = \frac{\max(0, (AVR_j - x_{ij}))}{AVR_j} \tag{10}$$

If j^{th} criterion is non-beneficial, then

$$PD_{ij} = \frac{\max(0, (AVR_j - x_{ij}))}{AVR_j}, \tag{11}$$

$$ND_{ij} = \frac{\max(0,\ (x_{ij}\ \text{-}\ AVR_j))}{AVR_j} \tag{12}$$

Step 4: Calculate the weighted sums of *PD* (*WSPD*) and *ND* (*WSND*) for each alternatives.

$$WSPD_i = \sum_{j=1}^{n} w_j PD_{ij} \tag{13}$$

$$WSND_i = \sum_{j=1}^{n} w_j ND_{ij} \tag{14}$$

where w_j is the weight of j^{th} criterion.

Step 5: Normalize the values of *WSPD* (*NWSPD*) and *WSND* (*NWSND*).

$$NWSPD_i = \frac{WSPD_i}{\max_i(WSPD_i)} \tag{15}$$

$$NWSND_i = 1 - \frac{WSND_i}{\max_i(WSND_i)} \tag{16}$$

Step 6: Determine the appraisal score (*APS*) for each alternative.

$$APS_i = \frac{1}{2}(NWSPD_i + NWSND_i) \tag{17}$$

where $0 \le APS_i \le 1$.

Step 7: Rank the candidate alternatives by decreasing *APS* scores. If an alternative's *PD* value > 0, the corresponding *ND* value = 0, and if the *ND* value > 0, the *PD* value = 0.

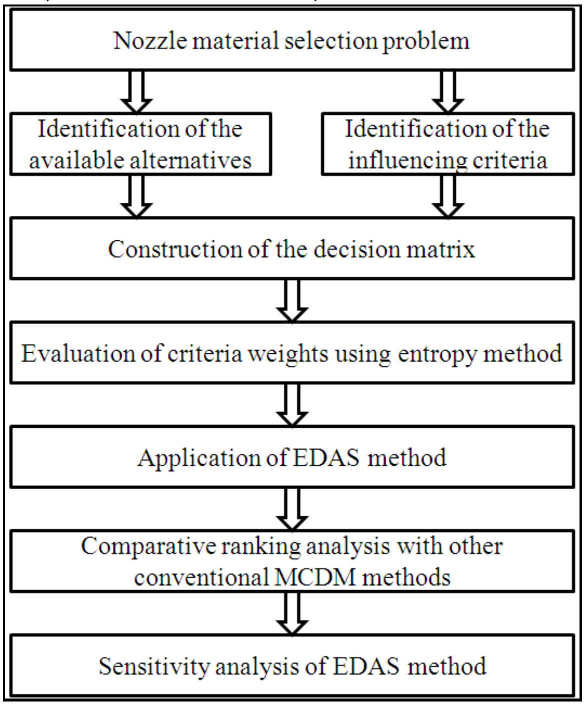

Figure 3. Steps of EDAS method for 3D printer nozzle material selection problem

4. Illustrative example

It has already been mentioned that nozzle is the end most part of the extruder of a 3D printer through which the molten filament material flows. Geometry and quality of the developed products greatly depend on the nozzle material properties. Hence, to have improved additive manufacturing experience with better finished products, it has become crucial to choose the most apposite nozzle material under the given conditions, resulting in minimum wear along with easy flow of the molten filament at minimum cost. Table 1 shows the developed decision matrix, comprising of criteria and nozzle material alternatives, where criteria values are collected from the websites (*MatWeb - Online Materials Information Resource. Automation Creations*, 2023). Table 2 provides the details of those criteria and the corresponding entropy weights.

Density (C_1) of the nozzle material is an important criterion as less material in nozzle shape greatly decreases the weight of the print head. Thermal conductivity (C_2) is the ability to conduct heat and it is important to keep a steady extrusion temperature throughout the flow of the molten filament as heat is able to travel up to the tip of the nozzle keeping the molten filament at appropriate temperature. Corrosion resistance (C_3) is the ability to withstand the damage caused by oxidization or other chemical reactions, ensuring lengthening of the life span of the nozzle head. Hardness (C_4) is a measure of resistance to local plastic deformation induced by either mechanical indentation or abrasion. Presence of abrasive particles in filaments makes hardness a crucial criterion while selecting a nozzle material. Wear resistance (C_5) is the ability to minimize the damage of the nozzle caused by the abrasive particles present in the filament material. Few molten filament particles sometimes stick out and scoop out the nozzle from inside. Presence of hard and sharp particles in the filament and higher loading of filament material would also increase the wear rate. Therefore, for abrasive filament, more wear resistant nozzle material needs to be selected. Cost of the nozzle material (C_6) is a major decisive criterion as it ultimately affects the product cost. Yield strength (C_7) is the tension during which the material begins deforming plastically. Hence, yield strength of a nozzle material must be as high as possible, otherwise, the nozzle shape would be distorted due to plastic deformation. Ultimate tensile strength (C_8) is the ability to withstand tensile loading due to the forced flow of high temperature molten filament through the nozzle and must be high for the selected 3D printer nozzle material. Machinability (C_9) of a nozzle material represents the easiness with which it can be machined. Machinability ratings are relative in nature and are compared against the standard rating of 100% assigned to 160 Brinell hardness B1112 cold drawn steel. In Table 1, absolute values are expressed for all criteria except corrosion resistance, machinability and wear resistance. To indicate the values of the three qualitative material attributes, a 9-point relative scale with 1 indicating extremely low, 3 indicating low, 5 indicating medium, 7 indicating moderate, and 9 indicating very high is used.

Table 1. Decision matrix for the 3D printer nozzle material selection problem

Alternative	Criteria								
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	8.49	124	1	65.1	1	5.44	255	430	7
A_2	7.5	46.9	3	262	3	4.35	810	1010	7
A_3	7.81	16.7	9	252	3	3.12	666	939	3
A_4	15.7	110	7	1006	9	46.17	415	344	1
A_5	4.43	6.7	9	334	5	30.47	880	950	5
A_6	2.71	179	7	88.3	1	1.52	257	301	7
A_7	2.81	153	7	135	1	5.80	370	444	9
A_8	8.64	190	9	145	1	6.53	383	511	5

Table 2. Nozzle material selection criteria

Symbol	Properties of nozzle material	Weight
C_1	Density (g/cc)	0.0218
C_2	Thermal conductivity (W/m-K)	0.1735
C_3	Corrosion resistance	0.0777
C_4	Hardness (BHN)	0.2479
C_5	Wear resistance	0.2203
C_6	Cost (USD/kg)	0.0514
C_7	Yield strength (MPa)	0.0667
C_8	Ultimate tensile strength (MPa)	0.0659
C_9	Machinability	0.0750

Table 3 shows the material alternative for 3D printer nozzle. Brass is mainly an alloy of copper and zinc (Cu 69%, Zn 30%), and is mostly used as a nozzle material for non-abrasive filaments. It is a comparatively good conductor of heat and relatively cheap than most of the other considered materials. Hardened steel is often considered as high carbon steel (Fe 93.6%, C 0.85%, W 4.68%, V 2.53%), and is better with respect to hardness, wear resistance, yield strength and ultimate tensile strength properties in comparison to other material alternatives. Stainless steel (Fe 68.3%, Cr 18.3%, Ni 10.8%, Co 4.37%), though poor in conducting heat, is an excellent corrosion resistant material mainly used for nozzles adopted for manufacturing of medical devices and utensils. Tungsten carbide is an extremely hard material possessing excellent wear resistance property, making it a strong candidate for nozzle material to reduce wearing of nozzles during 3D printing. TiAl6V4 (Ti 89%, Al 5.5%,V 4%), a titanium alloy, though a very poor conductor of heat, is also an excellent corrosion resistant material, comparatively having higher yield strength and ultimate tensile strength than most of the other materials (Shugurov et al., 2022). Titanium nozzles are usually preferred for working over 400^{o}C to print exotic filaments. Aluminium 6065 (Al 95%, Mg 1%, Si 0.6%) is a very good conductor of heat and has very low density. Thus, it would be an appropriate material when low extruder weight is required. Aluminium 7075-T6 (Al 90%, Cu 1.6%, Zn 5.5%, Mg 2.5%) possesses low density, better conductivity of heat and high strength-to-density ratio, which also makes it a suitable choice for nozzle material. Nickel is often plated on copper to enhance the corresponding corrosion resistance along with improved thermal conductivity. At high temperatures, brass and aluminium become very weak which constrains their applicability as 3D printer nozzle materials.

Table 3. Nozzle material alternatives

Symbol	Nozzle material
A_1	Brass
A_2	Hardened steel
A_3	Stainless steel
A_4	Tungsten carbide
A_5	Titanium alloy (TiAl6V4)
A_6	Aluminium 6065
A_7	Aluminium 7075-T6
A_8	Nickel plated copper (cold drawn)

The 3D printer nozzle material selection problem is now solved using EDAS method. In Table 1, Eq. (6) is first applied to obtain the corresponding average solution. Table 4 and 5 shows the positive and negative distances calculated with equations (9)-(12). The weighted sums are subsequently computed, with Eqs. (13) and (14). Table 6 provides appraisal scores for all the alternatives, obtained by employing Eqs. (15)-(17). Based on descending values of appraisal score, the materials are ranked. It can be revealed that tungsten carbide is the best nozzle material. Hardened steel and titanium alloy may also be used as the nozzle material for 3D printer, as they secure the second and third positions respectively.

Table 4. Positive distance from the average solution

Alternative	PD_{i1}	PD_{i2}	PD_{i3}	PD_{i4}	PD_{i5}	PD_{i6}	PD_{i7}	PD_{i8}	PD_{i9}
A1	0.00	0.20	0.00	0.00	0.00	0.58	0.00	0.00	0.27
A2	0.00	0.00	0.00	0.00	0.00	0.66	0.61	0.64	0.27
A3	0.00	0.00	0.38	0.00	0.00	0.76	0.32	0.52	0.00
A4	0.00	0.06	0.08	2.52	2.00	0.00	0.00	0.00	0.00
A5	0.39	0.00	0.38	0.17	0.67	0.00	0.74	0.54	0.00
A6	0.63	0.73	0.08	0.00	0.00	0.88	0.00	0.00	0.27
A7	0.61	0.48	0.08	0.00	0.00	0.55	0.00	0.00	0.64
A8	0.00	0.84	0.38	0.00	0.00	0.49	0.00	0.00	0.00

Table 5. Negative distance from the average solution

Alternative	ND_{i1}	ND_{i2}	ND_{i3}	ND_{i4}	ND_{i5}	ND_{i6}	ND_{i7}	ND_{i8}	ND_{i9}
A_1	0.17	0.00	0.85	0.77	0.67	0.00	0.49	0.30	0.00
A_2	0.03	0.55	0.54	0.08	0.00	0.00	0.00	0.00	0.00
A_3	0.08	0.84	0.00	0.12	0.00	0.00	0.00	0.00	0.45
A_4	1.16	0.00	0.00	0.00	0.00	2.57	0.18	0.44	0.82
A_5	0.00	0.94	0.00	0.00	0.00	1.36	0.00	0.00	0.09
A_6	0.00	0.00	0.00	0.69	0.67	0.00	0.49	0.51	0.00
A_7	0.00	0.00	0.00	0.53	0.67	0.00	0.27	0.28	0.00
A_8	0.19	0.00	0.00	0.49	0.67	0.00	0.24	0.17	0.09

Table 6. Final ranking of the 3D printer nozzle materials

Alternative	$WSPD_i$	$NWSPD_i$	$WSND_i$	$NWSPD_i$	APS_i	Rank
A_1	0.09	0.08	0.46	0.00	0.04	8
A_2	0.14	0.13	0.16	0.66	0.39	2
A_3	0.12	0.12	0.21	0.54	0.33	4
A_4	1.08	1.00	0.26	0.44	0.72	1
A_5	0.31	0.29	0.24	0.48	0.39	3
A_6	0.21	0.20	0.38	0.17	0.18	7
A_7	0.18	0.17	0.31	0.32	0.24	6
A_8	0.20	0.19	0.31	0.33	0.26	5

5. Comparative analysis

This section compares the EDAS method to other widely used methods in order to show the ranking similarity of 3D printer nozzle material alternatives and to identify the best suitable method in present problem. To compare the ranking performance of the EDAS approach to other common MCDM methodologies, the rank performance analysis, number of decision points, number of mathematical operations required, and Spearman's rank correlation coefficient are used.

5.1. Rank performance analysis

Figure 4 compares the results of the EDAS method to those derived by other MCDM techniques such as TOPSIS, ELECTRE-II (elimination and choice expressing reality), and AHP, while making the final decision. It can be observed that tungsten carbide (A_4) is still the most favoured material for all of the MCDM approaches studied, whereas brass (A_1) is the least preferred. As a result, when the best and worst choices are taken into account, the EDAS technique performs satisfactorily.

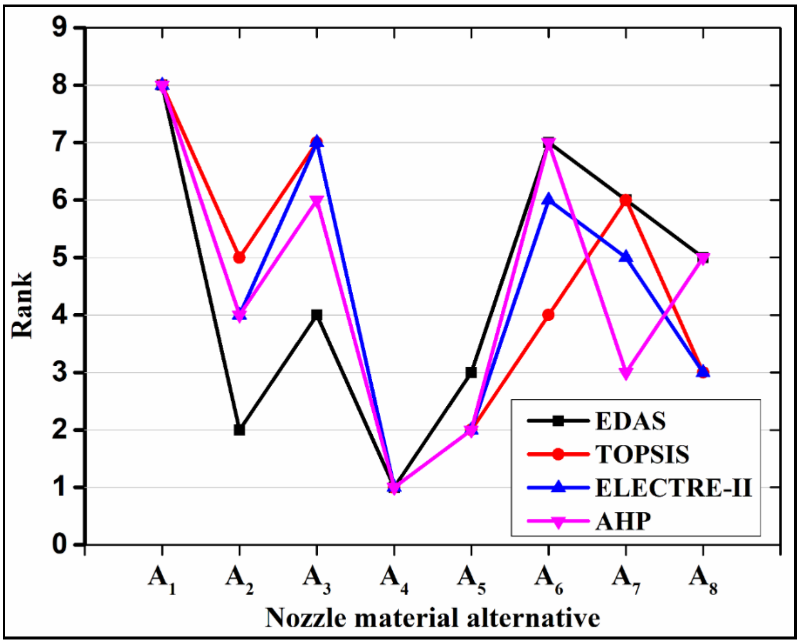

Figure 4. Rankings obtained by different MCDM methods

5.2. Number of decision making points

A specific number of decision-making points are critical from the decision-perspective maker's when solving MCDM problems. Let C represent the number of decision-making points (criteria) for each of the P alternatives. Furthermore, C decision points are required to calculate the corresponding criterion weights. As a result, the total number of decision-making points required to solve the 3D printer nozzle material selection problem in EDAS, TOPSIS, and ELECTRE-II methods can be calculated using the following expression (Yazdani et al., 2020):

$$D^{\text{EDAS, TOPSIS, ELECTRE-II}} = (P \times C) + C = 9 \times 8 + 9 = 81$$

The AHP technique involves the use of C matrices, each of size P×P, for evaluating different criteria, in addition to the decision matrix of size C×C used for determining criteria weights. Therefore, the total number of decision points in the AHP approach can be calculated as

$$D^{\text{AHP}} = C\left(\frac{C-1}{2}\right) + C\left(\frac{P(P-1)}{2}\right) = 9\left(\frac{9-1}{2}\right) + 9\left(\frac{8(8-1)}{2}\right) = 288$$

Figure 5 clearly indicates that EDAS, TOPSIS and ELECTRE-II methods perform better than AHP technique in this analysis.

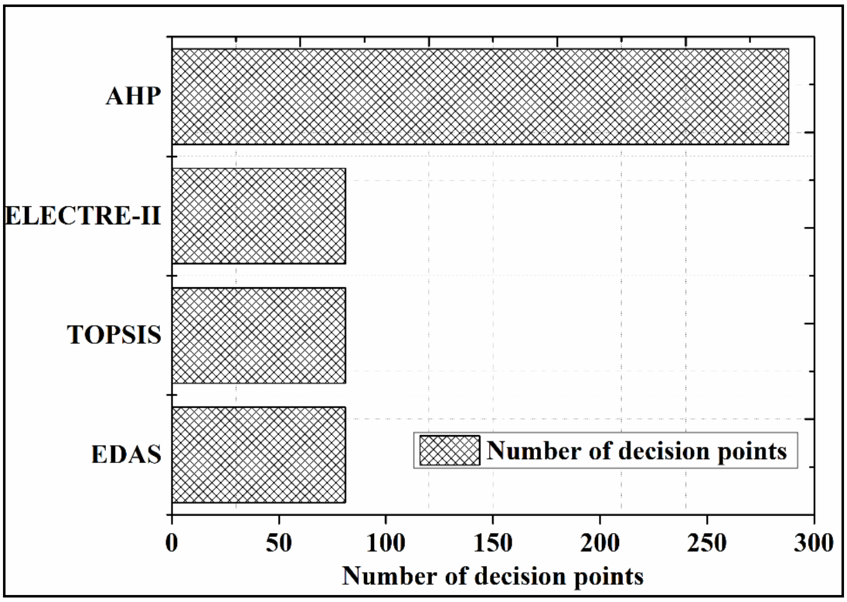

Figure 5. Number of decision making points

5.3. Number of mathematical operations

In order to assess the complexity of various MCDM methods, the number of mathematical operations implicated in their computations is identified, which can be likened to measuring time complexity based on the number of calculations performed (Chang, 1996; Chatterjee & Chakraborty, 2022; Ghaleb et al., 2020; Lima Junior et al., 2014; Yazdani et al., 2020). Given that there are *P* alternatives for nozzle materials and *C* criteria for evaluation, the EDAS method requires *PC* operations to calculate the positive distance from the average solution, *PC* operations to estimate the negative distance from the average solution, *P* operations to calculate the sum of positive distances, *P* operations to calculate the sum of negative distances, *2P* operations to normalize the sums of the distances, and *P* operations to determine the appraisal score. Therefore, the total number of operations needed to apply the EDAS method is *2PC + 5P*. On the other hand, the TOPSIS approach requires *PC* operations to compute the normalized decision matrix, *PC* operations to calculate the weighted normalized decision matrix, *P(C+1)* operations to calculate the positive distances, *P(C+1)* operations to calculate the negative distances, and *P* operations to estimate the relative closeness to the ideal solution. Thus, the total number of operations for the TOPSIS approach is *4PC + 3P*. The ELECTRE-II method needs two *PC* operations to develop the normalized and weighted normalized decision matrix, $P \times P$ operations to calculate the concordance matrix (matrix composed of collection of attributes where one alternative is better than or equal to other alternative for all criteria) and $P \times P$ operations to calculate the discordance matrix (matrix indicating the disagreement among the alternatives), *P* operations to compute pure concordance index, *P* operations to calculate pure discordance index, and finally *P* operations to determine the average ranking based on the pure concordance and discordance indexes. Thus, ELECTRE-II method requires $2P^2 + 2PC + 3P$ operations. On the other hand, AHP method requires $(C \times C)$ operations to perform the criteria pair-wise comparison and derive the criteria weights, $C(P \times P)$ number of operations for alternative pair-wise comparison, and finally *PC* operations to calculate the performance scores. Thus, AHP approach requires $C^2 + P^2C + PC$ operations.

Figure 6 shows a comparative analysis between the considered MCDM methods with reference to the total number of mathematical operations required. From this figure, it can be unveiled that in order to solve this 3D printer nozzle material selection problem, EDAS method needs 184 operations, TOPSIS requires 312 operations, ELECTRE-II method needs 296 operations and 729 operations are required for AHP method. Thus, in terms of time complexity and the number of augmentations inside the calculations, the EDAS technique outperforms all of the evaluated MCDM methods.

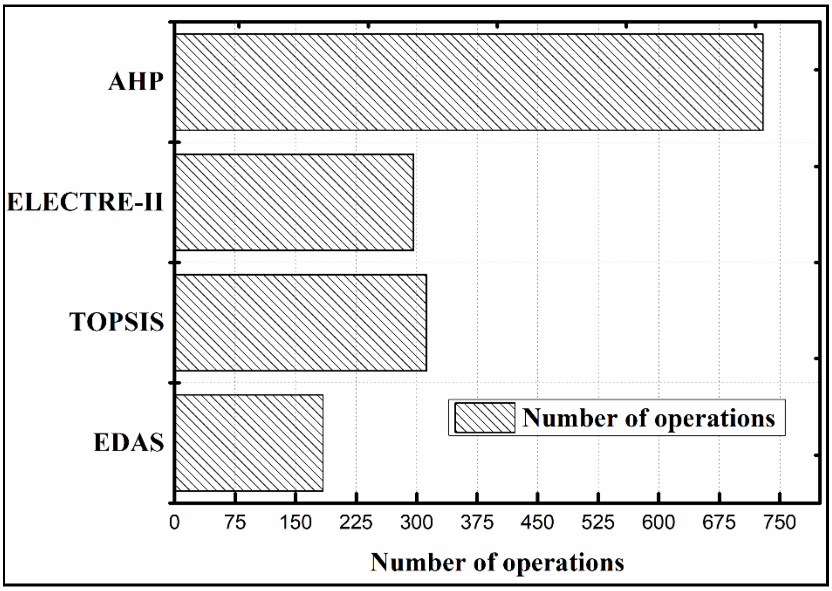

Figure 6. Number of mathematical operations required for different MCDM methods

5.4. Calculation of Spearman's rank correlation coefficients

Figure 7 shows the values of Spearman's correlation coefficients among the ranking patterns that were obtained using various MCDM methods. Clearly, EDAS method shows a close relationship with AHP and ELECTRE-II, followed by TOPSIS method.

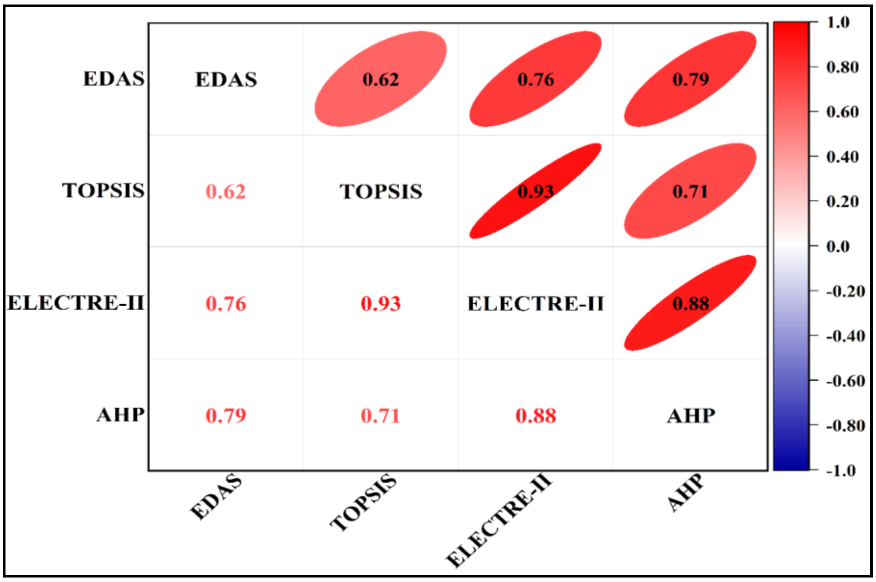

Figure 7. Correlation coefficient of considered MCDM method

Based on the results of various performance metrics, it can be propounded that EDAS supersedes the other MCDM methods while solving this 3D printer nozzle material selection problem.

6. Sensitivity analysis

Sensitivity analysis studies are conducted in this part to demonstrate the reliability and ranking stability of the EDAS method results. This study examines the impacts of changing the weights of the criteria and removing the less significant criteria from the subsequent evaluation of the alternatives on the EDAS method's ranking performance. Additionally, a preference order is developed based on the percentage of times the ranks appeared during the analysis phases.

6.1. Effect on ranking while removing the least important criterion

Figure 8 displays the sensitivity analysis ranking results of the alternatives for various cases, where each case consists of an entirely new set of criterion weights derived by removing the least significant criterion one at a time. Case 1 essentially represents the initial ranking order obtained while taking into consideration all of the evaluation criteria. In Case 2, the ranking of the alternatives is obtained by excluding the least significant criterion (with the lowest weight), namely density (C_1), from further consideration. Following that, new criteria weights are computed, and all alternatives are reranked. In case 3, the ranking of the alternatives is determined after removing two of the least essential criteria from the assessment process, namely density and material cost. This evaluation procedure continues until case 8, when only the two most relevant criteria must be considered. The appropriate ranking patterns for the eight potential nozzle material alternatives are thus generated for all scenarios with a reduced number of criteria, as shown in figure 8.

Table 7, which is an extension of the result displayed in figure 8, exhibits the preference order on the basis of percentage of their appearances in the ranking lists for different cases in figure 8. Tungsten carbide (A_4) remains as the top ranked alternative in all the cases with its 100% appearance. On the other hand, brass (A_1) is the least preferred 3D printer nozzle material with its 100% appearance in all the cases. Alternatives A_3, A_6, A_7 and A_8 are firmly placed at fourth, seventh, sixth and fifth positions respectively in the ranking order with their 100% appearances in the considered cases. Similarly, alternatives A_2 and A_5 secures the third and second positions respectively with 75% appearance in all the cases.

It can thus be observed that removal of the least important criterion from the evaluation process would not change the final rankings of the alternative nozzle materials. But when the other less important criteria are subsequently removed one by one, the positions of hardened steel (A_2) and titanium alloy (A_5) would just reverse. For all the cases, the ranks of the remaining alternative materials would remain unaltered. Table 7 thus suggests an improved ranking order based on this analysis. It proves the robustness of EDAS method in solving this 3D printer nozzle material selection problem.

Table 7. Preference order based on percentage appearance of the alternatives

Alternative	Percentage of appearance	Preference order
A_1	8 (100%)	8
A_2	2 (25%), 3 (75%)	3
A_3	4 (100%)	4
A_4	1 (100%)	1
A_5	3 (25%), 2 (75%)	2
A_6	7 (100%)	7
A_7	6 (100%)	6
A_8	5 (100%)	5

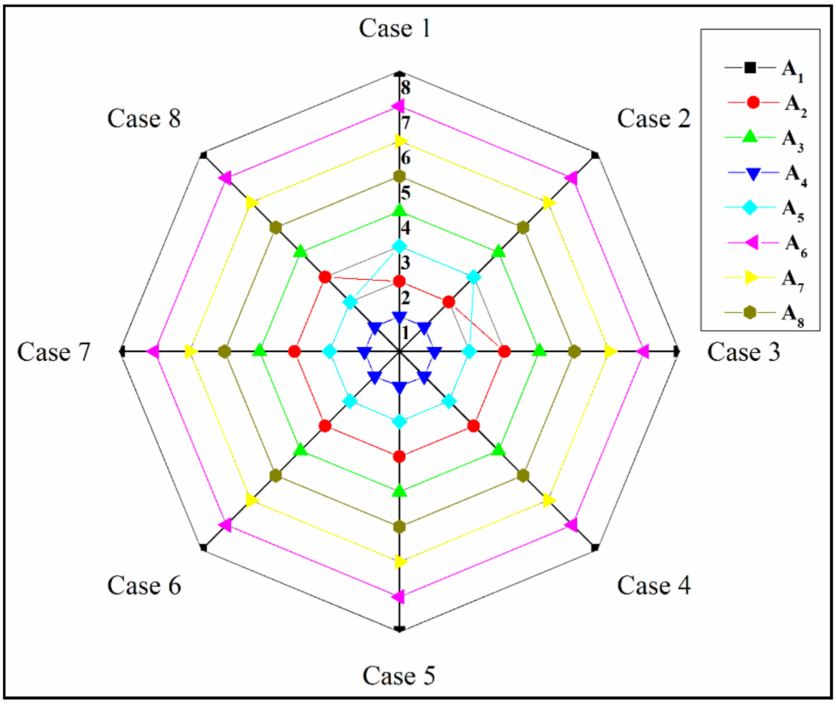

Figure 8. Results of sensitivity analysis by gradual removal of least important criterion

6.2. Effect on ranking by changing criteria weights

This analysis is performed to study the effects of changing criteria weights arbitrarily on the final rankings of the alternatives. For this purpose, eight new criteria weight sets are developed. The weight set 1 is evolved while reducing the weights of the three most important criteria (C_2, C_4 and C_5) by 10%, and increasing weights of the remaining six criteria by 5%. Set 2 represents an increase in the weights of three most important criteria (C_2, C_4 and C_5) by 10%, while the remaining criteria weights are decreased by 5%. Set 3 considers increased weights of the three least important criteria (C_1, C_6 and C_8) by 10%, while the weights of the other criteria are reduced by 5%. Set 4 includes equal weights assigned to all the criteria. On the contrary, set 5 assumes equal weights of 0.25 allocated to the four most important criteria (C_2, C_3, C_4 and C_5) while not taking the other criteria into consideration. Set 6 includes the first five important criteria with equal weights of 0.12, and the others with identical weights of 0.1. Set 7 consists of only beneficial criteria with equal weights and set 8 considers only non-beneficial criteria (C_1 and C_6) with identical weights. Based on these eight criteria weight sets, the corresponding appraisal scores for the 3D printer nozzle materials are computed using EDAS method. Based on the appraisal scores rankings are derived, and from figure 9, it becomes evident that tungsten carbide (A_4) is ranked as the most preferred alternative in 5 out of 8 sets. Set 1 has tungsten carbide at the top position where the values of the three most important criteria are reduced. It is also the most favoured material in weight sets 2 and 3. In set 4, it is replaced by hardened steel (A_2) as the most suitable material, while in sets 5 and 7, it again regains its top position. Set 6 has hardened steel at the first position, while in set 8, aluminium (6065) (A_6) emerges out as the best candidate material. It is also interesting to notice that hardened steel secures the top position when all the criteria have equal weights, while aluminium (6065) becomes the best choice when only density and material cost (non-beneficial) criteria are considered in the evaluation process. It thus validates the robustness, consistency and ranking stability of EDAS method while solving this material selection problem.

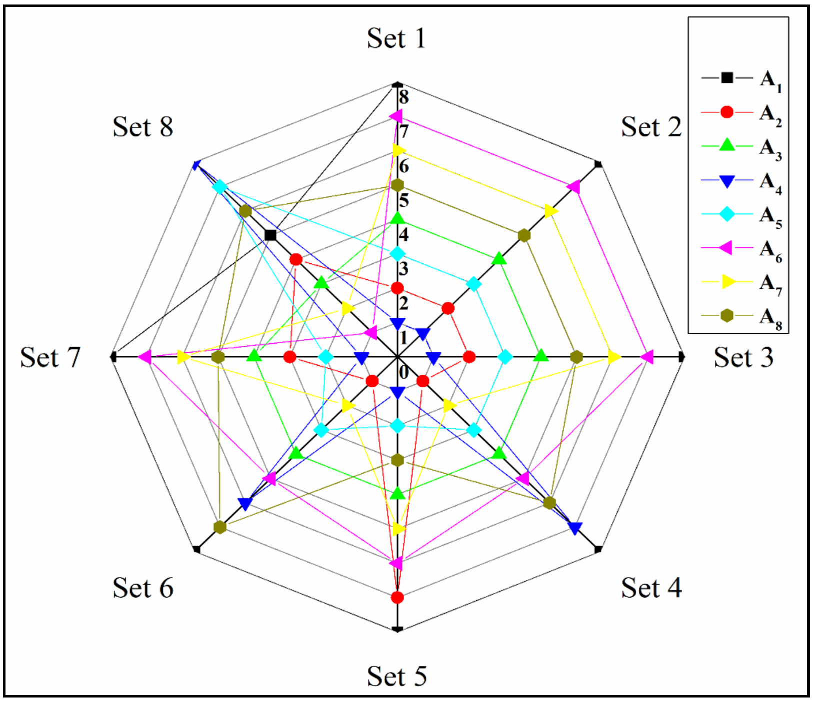

Figure 9. Results of sensitivity analysis by changing criteria weights arbitrarily

7. Conclusions

A 3D printer's nozzle is an essential part because it has a significant impact on the quality of the produced objects. Thus, it becomes crucial to use a sound mathematical strategy in order to choose the most suitable nozzle material from a pool of accessible options. The EDAS method is utilized here to fulfill this requirement. In this technique, the performance of eight different nozzle materials is assessed using both quantitative and qualitative criteria. Tungsten carbide emerges out as the most preferred alternative. It performs extremely well with respect to hardness and wear resistance properties. Moreover, its performance with reference to corrosion resistance and thermal conductivity is also moderately well. Due to its high hardness, it is also difficult to machine. In the ranking list derived using EDAS method, brass evolves as the least preferred material due its several weak properties. This study validates the applicability of the EDAS method in terms of ranking efficiency, decision-making points, operations needed, and Spearman's rank correlation coefficient. This method is also simpler to adopt with less computations and complexities. Its ranking performance is also not significantly affected by the reduction of the less important criteria in the decision matrix and change in the criteria weights. Thus, it can be successfully employed for material selection for other mechanical components, like bearings, brakes and clutches, crankshafts etc. and also in biomaterials selection.

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