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Research Article

A Decision-Making Model for Selection of the Suitable FDM Machine Using Fuzzy TOPSIS

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Additive manufacturing (AM) or 3D printing has been playing a very important role in the manufacturing sector in recent decades. The AM basic process is meant to produce an object layer by layer and has many advantages that include the occurrence of only minimal production waste during production and easy manufacture of even the most geometrically complex materials. However, there are many challenging decision-making situations in the production of AM for its users, for example, the build chamber, material specification, technology types, and application requirements. This includes the choice of the best AM machine (AMM) from many AMM with slightly different features that are identical on the market, especially on a real-time basis. This research explored ways that AMM is to be selected using multi-criteria decision-making (MCDM) on a real-time basis. This includes the use of the MCDM fussy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to help select the most suitable fusion deposition modeling (FDM) for an Indian nongovernment organization (NGO) from nine different machines based on contemporary. Practice in this research paper, an Indian NGO is considered as a decision-maker in the choice of the best FDM machine based on nine common criteria because an NGO has prescribed nine different FDM machines and the NGO needs the help for the purchase of the suitable FDM to produce different fields of prototypes. The outcome of this research is to recommend a suitable FDM machine from the nine similar to slightly different features of FDM machines by the suggestion of the field experts (AM machine users). The contribution of this research is not only to enable the purchase of the suitable AM machine but also to reveal the various contemporary FDM machines and the general criteria to be considered in choosing them.

1. Introduction

Conventional manufacturing (CM) or subtractive manufacturing methods have been used in the manufacturing industry for the past several years. Alternatively, for the past 3.5 decades, AM has been one of the leading technologies in the manufacturing sector, wherever the product is converted from digital format to standard triangle language (STL) file and can be easily produced a product directly layer by layer [1–3]. According to a previous research report, AM is found in the manufacturing industry under many names. This AM production method has been divided into seven types based on the report of the American Society for Testing and Materials (ASTM), and the previous literature on each method has its own unique features. These seven methods are stereolithography, material jetting, material extrusion, binder jetting, powder bed fusion, sheet lamination, and direct energy deposition [4]. What researchers consider to be the hallmark of AM is such simplicity that helps the production of products with accuracy, freedom in design, low inventory, low lead time, and very rigorous production design [5–8]. Many of the challenges in AM are related to product quality, mechanical property, supply chain-related requirements, shrinkage, printing underutilization, etc. [9–12]. Choice of the suitable AM machine, in particular, is also a challenge. This is due to the continuous increase in the number of machinery suppliers and in the number of machinery with slightly different features, which makes the selection of suitable machine challenging. AM executes its shares in a number of key sectors. The Wohlers 2021 report also reveals that 3D printing sales increased by 7.5% compared with previous years [13–16].

The aim of this research paper was to present a method that aid the selection of a suitable FDM 3D printers machine in many real-time markets for the production of prototypes of various fields required for a nongovernment organization (NGO), taking into account nine 3D printing-based criteria for the selection of a suitable FDM machine for a particular NGO from the nine FDM machines in the current market. The main purpose of this research paper was to calculate the criteria weight of the nine FDM machines using the MCDA technique called fuzzy TOPSIS and ultimately give ranking based on priority value and help the decision-maker in easy selection of the most suitable machine. Experts in the field were given questions online for the calculation of criteria weight using the fuzzy TOPSIS method. The first part of this research paper describes the AM and MCDM or MCDA using a literature survey, and TOPSIS technique can be used especially in complex decision-making challenges, a component that has traditionally been used in operation research to assist decision-makers. The other parts of this research paper include detailed problem identification, research methodology, result and discussion, and conclusion.

2. Literature Survey

2.1. 3D Printing or Additive Manufacturing. 3D printing technology is capable of creating an object with very little waste during production reducing the quantity of raw materials needed for production. The use of 3D printing has been on the rise in various fields in recent decades, according to a research report [6]. The most important reason for this is the ability of 3D printing to produce very complex objects very easily and with options also provided for selecting modes of action in 3D printing. However, some of the problems that researchers consider in 3D printing are high prototype costs, high material cost, unavailability of material, and some real-time experiments that make it difficult [17–19]. At the same time, 3D printing results in shorter prototype production time and lower production costs compared with CM [20]. The 3D printing technology industry has less design flow, design dependence, and design aspects compared with CM [21]. Ramola et al. [22] have conducted research on 3D printing process selection in the field of health care. It includes instructions for creating customized healthcare products with the help of 3D printing. Following this, Kokotsaki et al. [23] found a methodology for selecting AM processes in the spare parts and a new manufacturing industry. The authors have discovered a methodology to reduce production failures and increase productivity by a systematic review of the best AM criteria. Rashid [24] and Petrovic et al. [25] have provided a study on 3D printing, in that authors have explored the basic explanations of 3D printing in the best way. The authors have also narrated the demerits relating to business opportunity and process selection tool in AM. Drizo and Pegna have the market dominance of 3D printing technology in many fields, from shown manufacturing to medicine, cosmetics, defense, etc., in the third industrial revolution [26].

Pham and Gault have explained the main advantages of 3D printing by comparing it with several techniques. 3D printing reduces the time in manufacturing an item and taking it to market [27]. Bak [28] has recorded rapid prototype (RP) that leads to mass customized production without tools. Rao and Padmanaban [29] used a matrix approach and graph theory for the selection of 3D printing processes. It is possible to estimate the selected index by assigning ranks using quantitative and qualitative data as selection parameters. Following this, Xu and Wong explored a model 3D printing process selection. They made a comparison between process parameters such as build time, build cost, surface roughness, and benchmark parts [30]. Masood and Soo used the rule-based expectation system for solving 3D printing education process selections [31]. Previous researchers have similarly used the TOPSIS method for the selection of 3D printing processes. The criteria including elongation prototype cost, build material, and build time were considered [32].

In 3D printing, Kim and Oh [33] recorded low material wastage compared with accuracy, material properties, speed, material cost, and roughness in the quantitative comparison method. Groth et al. and Ramalingam who are known for their investigation of orthodontistry application have published a report that reports the abilities of 3D printing to improve accuracy and reduce material wastage [34, 35]. Touelf et al. Gay et al. and Vlasea et al. found that significant property orientation can be identified by manufacturing mechanical properties in 3D printing [36–38]. In recent years, multi-criteria decision analysis (MCDA) methods have played an important role in solving any problem in decision-making. MCDA also plays an important role in the most complex selection situations [17]. The following section describes the MCDA objective, need, and technique with the help of a research paper by previous researchers on multiple disciplines and MCDA applications.

2.2. Multi-Criteria Decision Analysis (MCDA). The method of selecting the right and suitable homogeneous alternative from more than one based on the decision-maker's wishes is called MCDA [39]. The basis of the MCDA system helps rank all the alternatives using any one of the MCDA methods, taking into account some common criteria from the alternatives and selecting the appropriate alternative for the decision-maker [40, 41]. The basic steps of MCDA include the choice of the best alternative using criteria and alternatives according to the decision-maker's opinion [42].

This MCDA has been used in many fields in recent decades and plays an important role in operational research. According to previous researchers, MCDA has several techniques, namely analytical hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization Method for Enrichment of Evaluations (PROMTHEE), and Decision Making Trial and Evaluation Laboratory (DEMATEL) [43]. Previous researchers have used many

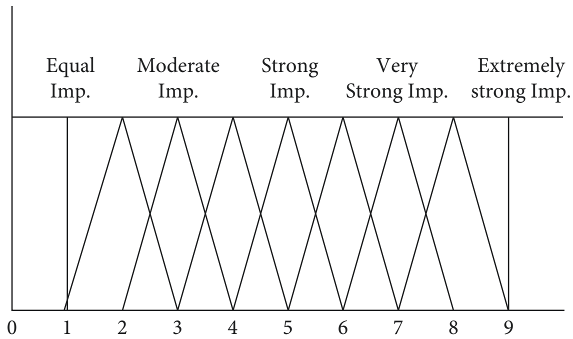

Figure 1: Triangular membership function.

MCDA methods in many fields. For example, the lot process selection has been done by the AHP-MCDA method [44]. Researchers in the agile manufacturing sector generally use fuzzy techniques with TOPSIS, AHP, and DEMATEL for selection [45].

MCDA also plays a key role in supply chain management (SCM) [46], management science system engineering sustainability [47, 48], product development evaluation, strategic management, and planning [49]. MCDA is also used in fuzzy TOPSIS and failure mode effect analysis (FMEA) in risk evaluation processes [50]. Fuzzy TOPSIS plays an important role in facility layout planning [51], and each of these MCDA methods has its own uniqueness [52]. The FTOPSIS method used in recent years has been used in this research paper. The fuzzy TOPSIS method is unique in finding the FNIS and FPIS for selected decision-making problems, which differ from other MCDA methods [53]. This method helps solve innovative problems in comparison with the other methods using the case study technique. Further detailed descriptions of the FTOPSIS method can be found below with the help of the researchers' research paper.

2.3. Fuzzy TOPSIS. The basis of fuzzy TOPSIS has in finding the best alternative to the longest geometric distance from the negative ideal solution and the shortest geometric distance from the positive ideal solution [54]. Fuzzy TOPSIS also helps in the selection of the best alternative by finding out how close the selected alternative is to the desired solution [55]. The fuzzy TOPSIS method is used in this research paper as follows.

Step 1. Fundamental concept

The linguistic term is used in this study, which is the first step in the measurement of alternatives and criteria. The linguistic terms are then converted to the fuzzification mode as a triangular membership function. The fuzzification method is one of the parts of a fuzzy term. Membership functions can be of many types, for example, in terms of shape trapezoidal, which is detailed under bell-shaped. The triangle membership function has been used in this research paper. Fuzzy value is usually denoted by the symbol (μÅ). The further triangle membership function is shown in Figure 1.

$$\mu Å\ (X) = Å. \tag{1}$$

The lower, middle, and upper fuzzy numbers in the triangle membership functions have been obtained from formula (1).

The Saaty scale used in the AHP system is referred to as the relative of alternative. This Saaty scale is generally used only as a crisp value. Hence, the decimal value is incalculable. For example, a decimal value like 3.5 cannot be calculated when a decision-maker has to make a choice between moderate and intermediate values and strong values on the Saaty scale given below [19, 56]. A fuzzy number is calculated for solving this problem based on the triangular membership function as shown in Table 1.

The five linguistic terms shown in Table 2 have been used in this research paper. The fuzzy numbers described above the same triangular membership function-based are also used here.

More than one integrated decision-making systematic group decision-making has been used in this research paper. Then, the common decision matrix for alternatives and criteria is created through the use of linguistic term and then the equivalent fuzzy value is modified as shown in Table 2.

Step 2. Combined decision matrix

The group decision matrix queues conversion into a decision matrix using the formula given below for the achievement of the purpose of this research paper.

$$\begin{aligned} X_{ij} &= \left(a_{ij} \cdot b_{ij} \cdot c_{ij}\right), \\ a_{ij} &= \frac{\min}{k}\left\{a_{ij} \cdot k\right\}, \\ b_{ij} &= \frac{1}{K}\sum_{k=1}^{k} b_{ij}, \\ c_{ij} &= \frac{\max}{k}\left\{c_{ij} \cdot k\right\}. \end{aligned} \tag{2}$$

The terms of the formula are detailed in Section 4.3 (refer step 2).

Step 3. Weightage with single decision matrix

Here, the criteria weightage is meant to change the weightage value from a single decision matrix to fuzzy numbers from the linguistic term (refer Table 2).

Step 4. Compute normalized decision matrix

The following two steps are required in this step.

(i) Identify the beneficial criteria
(ii) Identify the nonbeneficial criteria or cost criteria

Step 5. Find the beneficial criteria and cost criteria

The beneficial and cost criteria are found by the use of formula given below and a detailed explanation of the formula terms that follow in Section 4.3 (refer step 5).

Table 1: Triangular membership function values for AHP Saaty scale [56].

Saaty parameters	Saaty scale	Fuzzy values based on triangular membership function
Equal importance	1	1, 1, 1
Moderate importance	3	2, 3, 4
Strong importance	5	4, 5, 6
Very strong importance	7	6, 7, 8
Extremely strong importance	9	9, 9, 9
Intermediate importance	2	1, 2, 3
	4	3, 4, 5
	6	5, 6, 7
	8	7, 8, 9

Table 2: Linguistic terms and fuzzy number.

Linguistic terms	Linguistic scales	Fuzzy values based on triangular membership function
Very low (VL)	1	1, 1, 3
Low (L)	2	1, 3, 5
Average (A)	3	3, 5, 7
High (H)	4	5, 7, 9
Very high (VH)	5	7, 9, 9

$$r_{ij} = \left[\frac{a_{ij}}{c*}, \frac{b_{ij}}{c*}, \frac{c_{ij}}{c*}\right]. \tag{3}$$

$C^* = \max\{c_{ij}\}$ beneficial criteria

$$r_{ij} = \left[\frac{a_j}{c_{ij}}, \frac{a_j}{b_{ij}}, \frac{a_j}{a_{ij}}\right]. \tag{4}$$

$a_j = \min\{a_{ij}\}$ cost criteria

Step 6. Compute the weighted normalized fuzzy decision matrix

The weighted normalized fuzzy decision matrix has been obtained by the use of formula (1) and a detail of the below-mentioned formula in Section 4.3.

$$\begin{aligned} V_{ij} &= r_{ij} \times_{Wj} \\ A_1 \times A_2 &= (a_1, b_1, c_1) \times (a_2, b_2, c_2) \times (a_3, b_3, c_3) \\ &= (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2). \end{aligned} \tag{5}$$

Step 7. Compute the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)

The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) have been obtained by the use of the formula given below and a detail of the below-mentioned formula in a later section.

$$\begin{aligned} A^* &= (V_1, V_2, \ldots, V_n^*), \quad V = \max\{V_{ij}\} \\ A=^* &= (V_1, V_2 \ldots V_n^*), \quad V = \min\{V_{ij}\}. \end{aligned} \tag{6}$$

Step 8. Compute the distance from each alternative to the FPIS and to the FNIS

The distances from each alternative to the FPIS and to the FNIS have been obtained by the use of the formula given below and a detail of the below-mentioned formula in the section that follows.

$$d(\dot{x}, \dot{y}) = \mathrm{sq}\sqrt{\left(\frac{1}{3}\left[(a_1 - a_2)\wedge 2 + (b_1 - b_2)\wedge 2 + (c_1 - c_2)\wedge 2\right]\right)}. \tag{7}$$

Step 9. Find d_i^* and d_i^-

The total distances from each alternative to the FPIS and to the FNIS have been obtained by the use of the formula given below and a detail of the below-mentioned formula in a later section.

$$\begin{aligned} d_i^* &= \sum_{j=1}^{n} d(V_{ij}, V_j), \\ d_i &= \sum_{j=1}^{n} d(V_{ij}, V_j). \end{aligned} \tag{8}$$

Step 10. Compute the closeness coefficient (CC_i) for each alternative and give the ranking based on CC_i

The final step of fuzzy TOPSIS method, closeness coefficient (CC_i), for each alternative has been obtained by the use of the below formula and the ranking based on higher CC_i for getting the first rank, while other alternatives help obtain simultaneous ranks into details of the below-mentioned formula in a later section.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*}. \tag{9}$$

3. Problem Description

Earlier researchers have provided a detailed description of the use of AM in many fields and the many optimizations used in the production method. One of these research studies deals with help to a customer in the choice of selection of the right and most suitable FDM machine from a contemporary basis using the technique of choice.

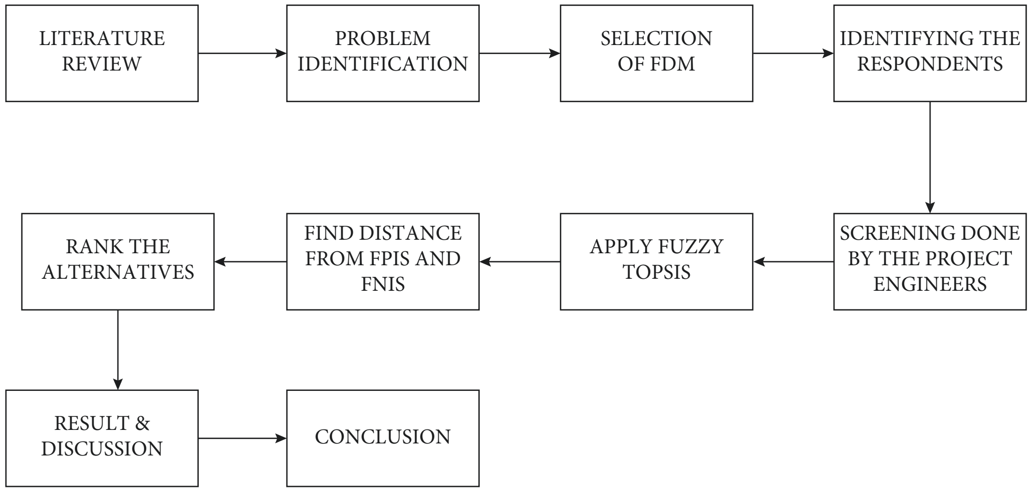

Figure 2: Research flow of the paper.

According to previous researchers, 3D printing technology is used in many fields, but AM has seven types with their own unique characteristics. Although there are many advantages to 3D printing technology, manufacturers often avoid this method due to its production cost being slightly higher than that of the conventional manufacturing method. The price of a commodity includes the costs of those relating to the machine used in production and items used in manufacturing and profits. The choice of the right production machine by optimization enables a slight reduction in the cost of production. The purpose of this research paper was therefore to enable the NGO (respondent) to select the best production FDM with the help of an optimization tools with nine criteria such as price, build, and volume.

4. Research Methodology

The purpose of this research paper was to enable the selection of a specific NGO (respondent) of the most suitable FDM with the help of the multi-criteria decision-making (MCDM) technique. The 9 criteria in this research study and the nine alternatives suggested by the NGO (respondent) help selection of the best and most suitable alternative using the fuzzy TOPSIS MCDA method. The basic objective is to select an optimal and suitable FDM, and the criteria including price (C1), build volume (C2), extruder type (C3), printing speed (C4), operating temperature (C5), filament material (C6), tolerance (C7), environmental factor (C8), and safety of the machine (C9) are considered. Also, recommended FDM alternatives by NGO (respondent) include Make 3D Pratham 6.0 (A1), Cube Pro Duo (A2), Make 3D Pratham 5.0 (A3), Global Pramaan 310 HT (A4), Belity 3 Max (A5), Botzlab Drona (A6), Make 3D Pratham 3.0 (A7), 3Idea Max 300 (A8), and 3Idea Creality (A9) in the choice of the best and the most suitable machine from the present. Figure 2 illustrates the overall research flow of this study.

Moreover, the objective of this research was determined and work began. The first step was to identify common and important criteria from NGO (respondent) recommended FDMs through the papers of previous literary researchers. Then, FPIS and FNIS were calculated using the Fuzzy TOPSIS MCDA method and ranked for alternatives.

4.1. Selection Process. Despite the presence of various additive manufacturing machines (AMMs) in the market, it is very important for the manufacturers to choose the optimal manufacturing machine. This research paper assists the NGO (respondent) in the selection of suitable FDM needed to produce the prototype from nine different FDMs based on the present. The reasons for selecting the 9 machines specified by the NGO (respondent) have been confirmed by the literature. This is due to the reduction in the cost of manufactured product as the most important goal to be done through the selection of the high and most suitable FDM machine for NGO (respondent). In the Indian automobile market, Maruti Suzuki has retained its number one position in the area of sales service through service centers setup in all cities. Considering the most problematic among the customers is the repairs to the goods purchased after the sale and the required raw material with focus by Maruti Suzuki [57].

In the opinion of previous literary researchers also, the most important factors in the selection of a machine include the spare part production, the raw material, and the after-sales service of the machine [2, 3]. Therefore, nine FDM machines recommended by NGO (respondent) are used as alternatives in this research paper due to the presence of all these factors in NGO (respondent) recommended machines.

4.2. Screening Process. The screening process has been further enhanced by the field experts (AM machine users) dealing in to the objective of this research question about criteria and alternatives asked and resolved through a Google Form. Here with 46 project managers, 70 research scholars, 22 professors, 3 college students, and 31 other AM industry experts participated in this research as respondents, experts in the field were asked questions about alternatives and criteria, such as the very low (VL), low (L), average (A), high (H), and very high (VH) linguistic term, from one to five points. This screening process was carried out with the help of available data and the project engineer of the NGO (respondent). The nine alternatives and their overall specific features are shown in Figure 3. Table 3 shows some more criteria and alternatives. The group decision matrix was designed with three maximum points for each alternative. The selection of the respondents (AM machine users) of the maximum value of the criteria was used as the criteria weights in this research paper. Based on this, the following fuzzy TOPSIS method has been designed, and their ranking from the decision matrix helps to achieve the objective of this research paper. Table 3 represents a comparison of alternatives A and B and NGO (respondent) prescribed alternatives. Tables 4 and 5 represent the field expert (AM machine users) weightage for the criteria and alternatives. In this research, a total of 172 respondents (AM machine users) were involved in different locations and working positions. Figure 3 shows the working area of the respondent (AM machine users) as shown as follows.

Figure 3 shows the different geolocation of the respondents (AM machine users) that include 71.5% of respondents (AM machine users) from India, 7% of respondents (AM machine users) from the USA, and the remaining respondents (AM machine users) chosen from China and other countries.

Figure 4 shows the working areas of respondents (AM machine users), and it represents 51.7% from research institute and 26.7% from industry, 12.2% from entrepreneurs, and the remaining were from AM-based work.

Figure 5 shows the designation of respondent (AM machine users) and the data already detailed above.

This research expresses the data of respondents (AM machine users) who experienced the particular brands and FDM process in their institutional or industries. Figure 6 shows all the respondents (AM machine users) holding the AMM with a proper background in the field of additive manufacture. Figure 6 shows 100 percent of respondent (AM machine users) institutes or industries holding additive manufacturing machines. Figure 7 expresses the raw material used by the respondents (AM machine users) in their working institution or industry.

Figure 7 shows the raw material used mostly by the respondents (AM machine users) that include plastic/polymer (PA, ABS, PLA, PEEK, etc.) and metals (Ti, SS, bronze, brass, gold, etc.).

Tables 4 and 5 data are taken from Figures 8 and 9 as shown as follows.

Criteria weight in Figure 8 shows the questions to the respondents (AM machine users) for calculating the criteria weight. The maximum values of respondent (AM machine users) answers were taken as criteria weights as shown in Table 4. Figure 9 represents the question to the respondents (AM machine users) for forming the decision matrix by the answers of respondent (AM machine users) about the alternatives. Figure 8(a) shows the most respondents (AM machine users) according to 4 points for criteria 1 as mentioned in Table 4 as criteria 1 (C1) equals 4 as criteria weight by the respondent (AM machine users) points. Figures 8(b)–8(i) show the most respondents (AM machine users) according to 5, 2, 3, 3, 4, 1, 4, and 5 points for C2 to C9 criteria weight. Similarly, all the criteria weight values have been taken from Figure 8 and it is mentioned in Table 4.

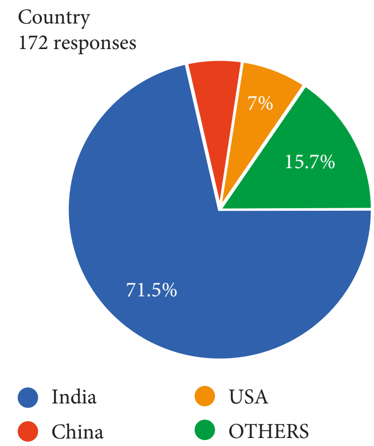

Figure 3: Location of respondents (AM machine users).

Table 5 indicates the alternatives and alternative weight used by the respondent (AM machine users) point. For example, Figure 9(a) shows the question and answers relating to the alternative one (A1). Here, in A1, most of the respondents (AM machines users) were seen according to four points and secondly gave 5 points and thirdly gave 3 points. For group decision matrix purpose, the top 3 points are taken into account to solve the novel problem. Then, it is mentioned in Table 5 and the rest of the alternative values are taken in the same manner.

4.3. Evaluation by Fuzzy TOPSIS

Step 1

The evaluation process started with the group decision matrixes such as decision-maker I, decision-maker II, and decision-maker III. As per Table 4 data, the 3 highest points given by the respondent (AM machine users) to alternatives were taken as decision-maker I, decision-maker II, and decision-maker III. Thus, the group decision matrixes are shown in Tables 6(A)–6(C). This decision-making table was formed by the use of information of response provided by the respondents (AM machine users) as per Tables 4 and 5; it initially takes linguistic terms as per Table 2 followed by the linguistic terms replaced by the fuzzy number as these Tables 6(D)–6(F) represented. The fuzzy numbers are formed by the triangular matrix with the help of analytical hierarchy process Saaty scale. This was explained in Section 2.3.

Step 2

The combined decision matrix for calculating purpose was formed from the group decision matrix. The combined decision matrix is shown in Table 6(G). The combined decision matrix was obtained by the use of the formula given as follows:

$$X_{ij} = \left(a_{ij} \cdot b_{ij} \cdot c_{ij}\right), \tag{10}$$

Table 3: Comparison of alternatives (A and B).

(A)

Properties/brand	Make 3D Pratham 6.0	Cube Pro Duo	Make 3D Pratham 5.0	Global Pramaan 310 HT
Price	500000 INR	162000 INR	380000 INR	380000 INR
Accuracy	±0.1 mm	±0.1 mm	±0.1 mm	±0.1 mm
Extruder type	Dual	Dual	Dual	Dual
Filament size	1.75 mm	1.75 mm	1.75 mm	1.75 mm
Layer capability	Fine	Fine	Fine	Fine
Build volume	$600 * 600 * 600$	$575 * 575 * 580$	$500 * 500 * 500$	$500 * 500 * 500$
Filament capabilities	PLA/TPU/PETG	PLA/TPU/PETG	PLA/TPU/PETG	PLA/TPU/PETG
Software	MAC/Windows XP/7	MAC/Windows XP/7	CURA/Windows XP/7	CURA/Windows XP/7
Warranty	1 year	1 year	1 year	1 year
Frame color	Black	White	Black	Black
Temperature	$280 * C$	$400 * C$	$280 * C$	$280 * C$
Electrical input	220–240 V	220–240 V	220–240 V	220–240 V
Power requirement	320 W	750 W	320 W	320 W
Net weight	100 kg	48 kg	80 kg	80 kg
Chassis	Metal	Metal	Metal	Metal
Body	Metal construction	Metal construction	Metal construction	Metal construction
Build platform	Aluminum	Metal	Glass	Glass
Bearing	Metal	Metal	Aluminum	Aluminum
Motor used	Stepper	Stepper	Stepper	Stepper
Connectivity	USB/online/SD	USB/online	USB/online/SD	USB/online/SD
Printing speed	30–120 mm/s	30–120 mm/s	30–120 mm/s	30–120 mm/s
Operating control	Auto/manual	Auto/manual	Auto/manual	Auto/manual
Tolerance	±0.1 mm	±0.1 mm	±0.1 mm	±0.1 mm
Heated build platform	Yes	Yes	Yes	Yes
Display	Touch screen	LCD	LCD	LCD
Closed print chamber	Yes	Yes	Yes	Yes
Bed leveling	Manual	Auto/manual	Manual	Automatic
Smart sensors	Nil	Yes	Nil	Yes
Language support	STL/OBJ/AMF	STL/OBJ/AMF	STL/OBJ/AMF	STL/OBJ/AMF
Lighting	Blue and white	Blue and white	Blue and white	Blue and white
Environmental factors	Yes	Yes	Yes	Yes
Resolutions	300 microns	300 microns	100 microns	100 microns
Cooling	Yes	Yes	Yes	Yes

(B)

Properties/brand	3Ides Creality	Belity 3Max	Botzlab Drona	Make 3D Pratham 3.0	3Idea Max 300
Price	45000 INR	85699 INR	140000 INR	180000 INR	175000 INR
Accuracy	±0.1 mm	±0.1 mm	±0.1 mm	±0.1 mm	±0.1 mm
Extruder type	Single	Single	Single	Dual	Dual
Filament size	1.75 mm	0.1.75 mm	1.75 mm	1.75 mm	1.75 mm
Layer capability	—	—	—	—	Good
Build volume	$300 * 300 * 400$	$300 * 300 * 340$	$300 * 300 * 300$	$300 * 300 * 300$	$300 * 300 * 300$
Filament/capabilities	PLA/TPU/PETG	PLA/TPU/PETG	PLA/ABS/WOOD	PLA/TPU/PETG	PLA/TPU/PETG
Software	MAC/Windows XP/7	MAC/Windows XP/7	MAC/Windows/7/8	MAC/Windows/71	MAC/Windows XP/7
Warranty	Nil	Nil	1 year	1 year	6 months
Frame color	Black metal	Black metal	Black	Black metal	Black
Temperature	$100 * C$	$220 * C$	$270 * C$	$220 * C$	$265 * C$
Electrical input	220–240 V	220–240 V	220–240 V	220–240 V	220–240 V
Power requirement	Standard	Standard	Standard	Standard	Standard
Net weight	15 kg	13 kg	23 kg	75 kg	50 kg
Chassis	Metal	Metal	Metal	Metal	Metal
Body	Metal construction	Metal construction	Metal construction	Metal construction	Metal construction
Build platform	Glass	Glass	Metal	Aluminum	Glass
Bearing	Standard	Standard	Standard	Standard	Standard
Motor used	Stepper	Stepper	Stepper	Stepper	Stepper
Connectivity	USB/online	USB/online	USB/online	USB/online	USB/online
Printing speed	30–60 mm/s	30–60 mm/s	30–60 mm/s	30–120 mm/s	30–60 mm/s
Operating control	Auto/manual	Auto/manual	Auto/manual	Auto/manual	Auto/manual
Tolerance	±0.2 mm	±0.2 mm	±0.2 mm	±0.2 mm	±0.2 mm
Heated build platform	Yes	Yes	Yes	Yes	Yes
Display	LCD	LCD	LCD	LCD	LCD
Closed print chamber	No	No	No	Yes	Yes
Bed leveling	Manual	Manual	Manual	Manual	Manual
Smart sensors	Nil	Nil	Nil	Nil	Nil
Language support	STL/OBJ/AMF	STL/OBJ/AMF	STL/OBJ	STL/OBJ/AMF	STL/OBJ/AMF
Lighting	LED	Blue and white LED	Blue and white LED	Blue and white LED	LED
Environmental fac.	No	No	No	Yes	Yes
Resolutions	100 microns	50 microns	50 micron	50 microns	300 microns
Cooling	Yes	Yes	Yes	Yes	Yes

Table 4: Criteria and criteria weight by respondent points.

Criteria	Criteria weight by respondent points
C1	4
C2	5
C3	2
C4	3
C5	3
C6	4
C7	1
C8	4
C9	5

Table 5: Alternatives and alternative weight by respondent (AM machine users).

Alternatives	Alternative weight by respondent (AM machine users) points
A1	4, 5, 3
A2	4, 5, 3
A3	3, 4, 2
A4	4, 3, 2
A5	3, 2, 1
A6	5, 4, 3
A7	3, 4, 2
A8	4, 3, 2
A9	2, 3, 1

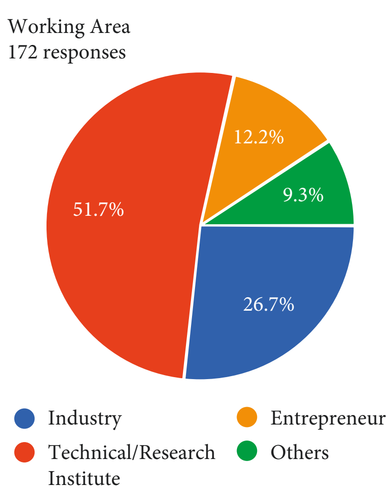

Figure 4: Working area.

where X_{ij} = value in each cell. i = number of row and j = number of column (refer Tables 6(D)–6(F) with 6(G)). (a_{ij}, b_{ij}, c_{ij}) represents each cell fuzzy number as Tables 6(D)–6(F).

An example of the combined decision matrix as shown in Table 6(G) first shells is solved below. Let first shell values of Tables 6(D)–6(F) be 3, 5, and 7 in decision-maker I, 5, 7, and 9 in decision-maker II, and 1, 3, and 5 in decision-maker III.

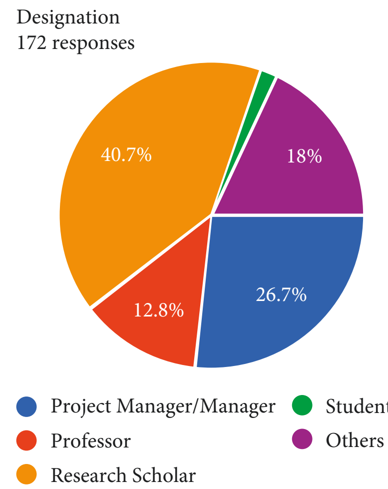

Figure 5: Designation of respondent (AM machine users).

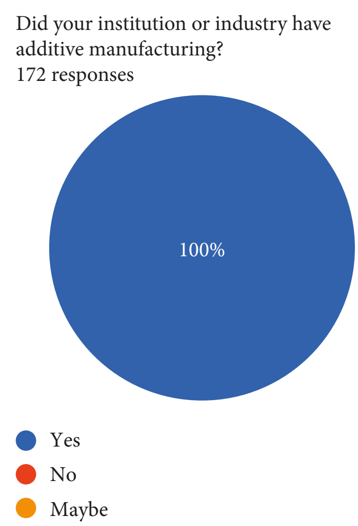

Figure 6: Ensuring the respondents (AM machine users) on field of additive manufacturing.

$$
\begin{aligned}
\text{Here } a_{11} &= 3, 5, 1,\\
b_{11} &= 5, 7, 3,\\
c_{11} &= 7, 9, 5\text{: } k - \text{number of decision maker},\\
a_{ij} &= \frac{\min}{k}\left\{a_{ij}k\right\},\\
a_{ij} &= \min(3, 5, 1) = 1,\\
b_{ij} &= \frac{1}{K}\sum_{k=1}^{k} b_{ij},\\
b_{ij} &= \frac{1}{3}(5, 7, 3) = 5,\\
c_{ij} &= \frac{\max}{k}\left\{c_{ij}k\right\},\\
c_{ij} &= \max(7, 9, 5) = 9.
\end{aligned}
\tag{11}
$$

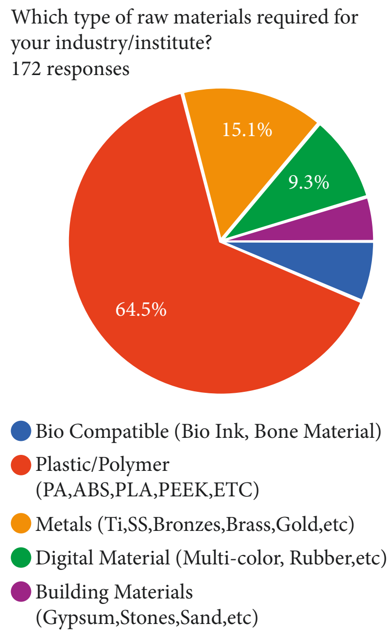

Figure 7: Raw materials used by respondent (AM machine users) industry/institute.

Hence, in the decision matrix Table 6(G) first shells were obtained (1, 5, and 9) and the rest of the terms were obtained in a similar manner.

Step 3

In the third step, Table 6(H) was formed with the help of respondent (AM machine users) response (refer Table 4) for the criteria weight and the term in the linguistic term. Then, Table 6(I) was formed by the replacement of the linguistic terms with fuzzy number as per Table 2.

Step 4

Table 6(J) is a normalized fuzzy decision matrix, and before finding this, the criteria are identified in two categories namely cost criteria or nonbeneficial criteria and beneficial criteria. In this research paper, the beneficial criteria are build volume, extruder type, printing speed, operating temperature, filament material, tolerance, environmental factors, and the safety of machine. The nonbeneficial criteria or cost criteria are only the price of the machine in our novel problem.

Step 5

Table 6(J) normalized fuzzy decision matrix is obtained by the following formula.

$$r_{ij} = \left[\frac{a_{ij}}{c*}, \frac{b_{ij}}{c*}, \frac{c_{ij}}{c*}\right]. \tag{12}$$

$C^* = \max\{c_{ij}\}$ beneficial criteria

$$r_{ij} = \left[\frac{a_j}{c_{ij}}, \frac{a_j}{b_{ij}}, \frac{a_j}{a_{ij}}\right]. \tag{13}$$

$a_j^* = \min\{a_{ij}\}$ cost criteria

Let Table 6(I) cost criteria be only price and the rest be beneficial criteria.

Here, $C^* = \max\{c_{ij}\}$ beneficial criteria, and it is the maximum value of "C" component in all individual alternatives.

Then, $a_j^* = \min\{a_{ij}\}$ cost criteria, and it is the minimum value of "a" component in all individual alternatives.

Note: in the normalized decision matrix, (a_j^*) in cost criteria section, "c" component is taken in the first place in denominator and "a" component is taken in the last row of denominator (refer Table 6(J)).

Finally, each value of beneficial criteria was divided by c^* and with the above note each value of cost criteria was divided by a_j^*.

Step 6

The criteria weight on Table 6(J) was multiplied on each component with each component as below. For example, "a" component was multiplied by "a" component. Similar to Table 6 (J), the rest of the criteria weight and alternatives were determined. Finally, Table 6(K) weighted normalized fuzzy decision matrix was obtained by the use of the formula given as follows.

$$\begin{aligned} V_{ij} &= r_{ij} \times W_j \\ A_1 \times A_2 &= (a_1, b_1, c_1) \times (a_2, b_2, c_2) \times (a_3, b_3, c_3) \\ &= (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2), \end{aligned} \tag{14}$$

where V_{ij} = fuzzy decision matrix, r_{ij} = row and column of each alternative, and w_j = weightage of each column.

Step 7

The next step was to find the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) using the formula given as follows:

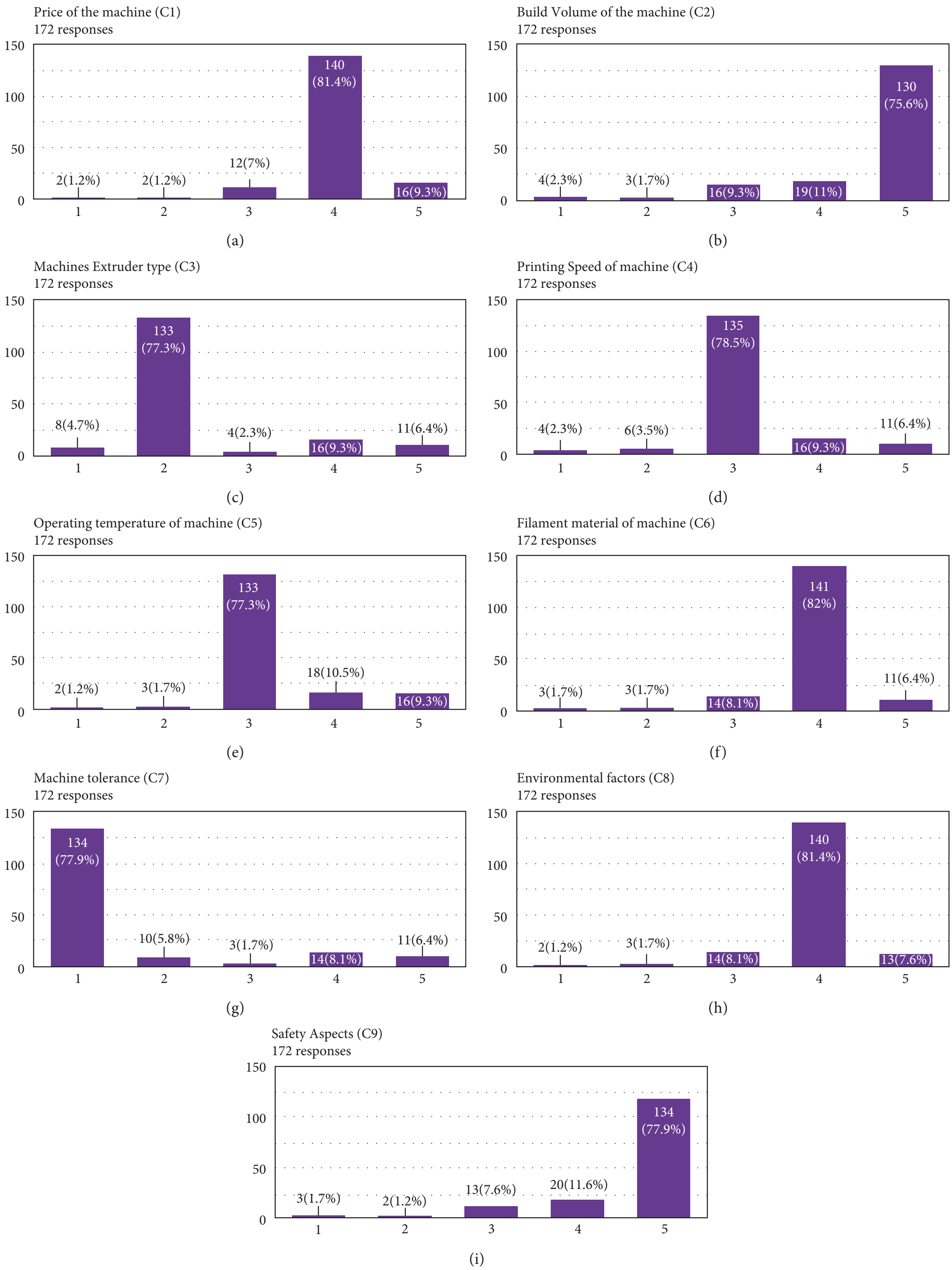

Figure 8: Criteria weights by respondents (AM machine users) (refer Table 4). (Figures 8(a)–8(i) show the response from field experts (AM machine users) about the criteria of selected AM machines, and it is considered as criteria weight).

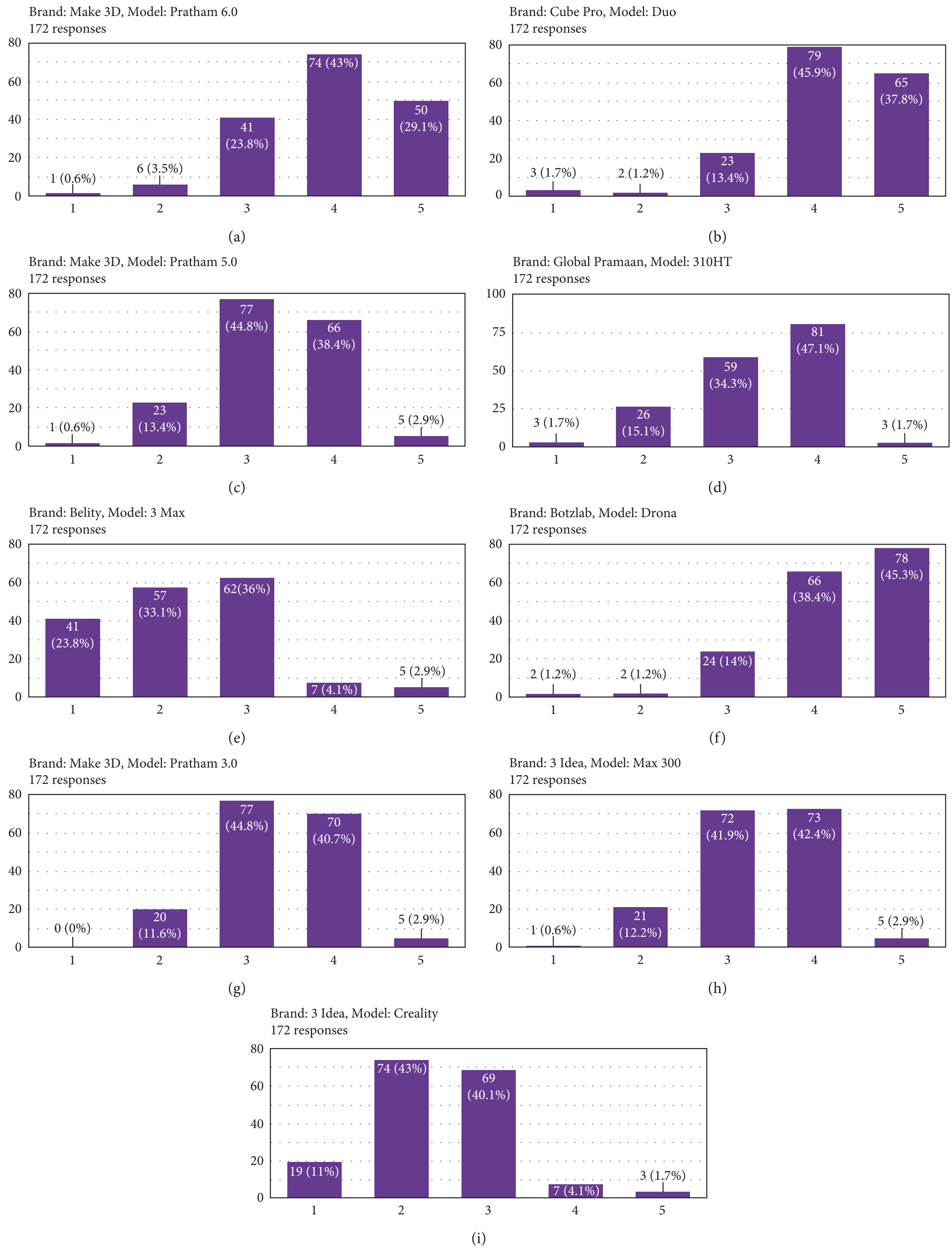

Figure 9: Alternative weights by respondents (AM machine users). (Figures 9(a)–9(i) show the response from field experts (AM machine users) about the alternatives (selected AM machines), and it is considered as alternative weight (refer Table 5)).

$$A^* = (V_1, V_2, \ldots, V_n^*), \quad V = \max\{V_{ij3}\}$$
$$A^{-*} = (V_1, V_2, \ldots, V_n^*), \quad V = \min\{V_{ij}\}. \tag{15}$$

Here, v_{ij3} = fuzzy number of "c" component, A^* = fuzzy positive ideal solution (FPIS), and A^{-*} = fuzzy negative ideal solution (FNIS).

The fuzzy positive ideal solution of A^* was found by the maximum value of "c" components and the fuzzy negative ideal solution of A^- was found by the minimum value of "a" component in the weighted normalized fuzzy decision matrix Table 6(K) in each alternative.

Step 8

The distance from each alternative to the FPIS and to the FNIS was obtained by the use of formula given below from the weighted normalized fuzzy decision matrix Table 6(K).

$$d(\dot{x}, \dot{y}) = \mathrm{sq}\sqrt{\left(\frac{1}{3}\left[(a_1 - a_2)\wedge 2 + (b_1 - b_2)\wedge 2 + (c_1 - c_2)\wedge 2\right]\right)}, \tag{16}$$

where a_1, b_1, and c_1 are solved fuzzy numbers of weighted normalized fuzzy decision matrix, and a_2, b_2, and c_2 are A^* fuzzy numbers solved in the previous steps.

Similarly, the weighted normalized fuzzy decision matrix Table 6(K) is solved with the same above formula, but a_2, b_2, and c_2 are A^- fuzzy numbers solved in the previous steps. Finally, the single values were obtained for each alternative and it is known as distance values.

Step 9

The distance (d^*) for the positive ideal solution was obtained from the A^* term of previous steps, and the distance (d^-) for the negative ideal solution was obtained from A^-.

$$d_i^* = \sum_{j=1}^{n} d\left(V_{ij}, V_j\right),$$
$$d_i = \sum_{j=1}^{n} d\left(V_{ij}, V_j\right). \tag{17}$$

Thus, the values are summed with their each row as final d^* and d^- for each alternative. Then, it is shown in Table 6(L).

Step 10

final step of the coefficient of closeness (CC_i) was found by the below formula and the final ranking is given to the alternatives based on the CC_i values. More value alternatives obtained the first rank, and others obtained higher rank. The ranking is shown in Table 6(L).

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*}. \tag{18}$$

5. Result and Discussion

The most important objective of this research is also to highlight the many modern 3D printing technologies in the manufacturing market and increase the usability of additive manufacturing. The novelty of this research is that the fuzzy TOPSIS system helps the selection of an FDM machine that is necessary and suitable for NGO (respondent) from several slightly different FDM machines seen as identical. For this purpose, FPIS and FNIS were identified through the creation of a decision matrix with the help of 172 additive manufacturing industry experts (AM machine users) for the selection of the right and appropriate FDM machine from the FDM machines currently on the market recommended to the NGO. Further criteria and alternatives based on MCDA were first identified using the research papers. Also highlighted were the 9 criteria and 9 alternatives used in this research. The 9 criteria used are price, build volume, extruder type, printing speed, operating temperature, filament material, tolerance, environmental factor, and safety. Also used as 9 alternatives were Make 3D Pratham 6.0, Cube Pro Duo, Make 3D Pratham 5.0, Global Pramaan 310 HT, Belity 3 Max, Botzlab Drona, Make 3D Pratham 3.0, 3Idea Max 300, and 3Idea Creality. The views of previous literary researchers have been presented in detail in part 2 in three sections. It explains the use of AM, many methods, the advantages, the challenges, etc., the MCDA methods, and the fuzzy TOPSIS method and its steps. Then, the novel problem of this research paper has been mentioned. This research flows through the research methodology, and the details of the experts (AM machine users) involved in the research are outlined. It explains the basic data required for use in the fuzzy TOPSIS method. Finally, Table 6(L) is gradually diagnosed using fuzzy TOPSIS. Wherever alternative 2 (A2) takes the first place, alternatives 1, 3, 4, and 8 take the second place, alternative 9 takes the third place, and alternatives 5 and 7 take the fourth place (refer Table 6(L)). It is therefore recommended that the Cube Pro Duo AM machine is the most optimal. The purpose of this research was to help future researchers in finding the most useful and various features of 3D printing.

6. Conclusion

The 3D printing system incorporates many innovative technologies with many machines on the market every day coming with the same slightly different features. Choice of the right machine from these machines in the market is one of the most challenging choices for the customers. In this research, with the help of experts (AM machine users) in the field, the authors have identified the optimum among the nine machines recommended for the specific NGO (respondent) using the MCDA systemic fuzzy TOPSIS based on the most important criteria. This entire research was carried out with the help of field experts (AM machine users) by the online mode on a qualitative survey via Google Forms. All the machines referred to in this study have been used or explored by industry experts (AM machine users). 172 field expert (AM machine users) responses about the selected criteria and alternatives play a major role to find the most optimum FDM machine for the NGO (respondent). From the final result obtained, alternative 2 Cube Pro Duo FDM machine selected for NGO (respondent) is a better choice compared with other alternatives with 9 criteria. This study was conducted for NGO (respondent) to produce prototypes in the fields of medicine and construction. The prototypes will be made with any materials most of the time, and with FDM technology, the biodegradable polymers are used as raw material (filament). This decision is subject to changes when other machines or criteria or applications are used. Similarly, only machines specific to the NGO (respondent) have been used in this study. Finally, testing this study using other MCDA methods will be a novelty for future researchers.

Data Availability

The data that support the findings of this study are available on request from the corresponding author (John Rajan A). The data are not publicly available due to privacy concerns.

Additional Points

(i) Selection of AM machine in the real-time basis. (ii) Machine selection problem using fuzzy TOPSIS. (iii) Current 3D printing technology.

Conflicts of Interest

The authors declare that there are no financial interests/ personal relationships, which may be considered as potential conflicts of interest.

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Supplementary Materials

Numerical evaluation by fuzzy TOPSIS method. (*Supplementary Materials*)

References

[1] M. Sugavaneswarn, “A multi-criteria decision making method for vapor smoothening fused deposition modelling part,” *Rapid Prototyping Journal*, vol. 28, 2021.

[2] K. Ransikarbum and P. Khamhong, “Integrated fuzzy analytic hierarchy process and technique for order of preference by similarity to ideal solution for additive manufacturing printer selection,” *Journal of Materials Engineering and Performance*, vol. 30, 2021.

[3] M. Palanisamy, A. Pugalendhi, and R. Ranganathan, “Selection of suitable additive manufacturing machine and materials through best–worst method (BWM),” *International Journal of Advanced Manufacturing Technology*, vol. 107, no. 5–6, pp. 2345–2362, 2020.

[4] Astm, *Standard Terminology for Additive Manufacturing Technologies*, ASTM International, West Conshohocken, PA, 2012.

[5] M. Ancău and C. Caizar, “The computation of Pareto-optimal set in multi-criteria optimization of rapid prototyping processes,” *Computers & Industrial Engineering*, vol. 58, pp. 696–708, 2010.

[6] J. Y. Han, “A study on the prototype modeling method using 3D printing,” *J. Packag Culture Design Res.*vol. 34, pp. 97–109, 2013.

[7] M. K. Thompson, G. Moroni, T. Vaneker et al., “Design for Additive Manufacturing: Trends, Opportunities, Considerations, and Constraints,” *CIRP Annals-Manufacturing Technology*, vol. 65, 2016.

[8] S. Ha, K. Ransikarbum, H. Han, D. Kwon, H. Kim, and N. Kim, “A dimensional compensation algorithm for vertical bending deformation of 3D printed parts in selective laser sintering,” *Rapid Prototyping Journal*, vol. 24, no. 6, pp. 955–963, 2018.

[9] K. Ransikarbum, S. Ha, J. Ma, and N. Kim, “Multi-objective optimization analysis for part-to-Printer assignment in a network of 3D fused deposition modeling,” *Journal of Manufacturing Systems*, vol. 43, pp. 35–46, 2017.

[10] K. Ransikabum, C. Yingviwatanapong, R. Leksomboon, T. Wajanavisit, and N. Bijaphala, “Additive manufacturing-based healthcare 3D model for education: literature review and A feasibility study,” in *Proceedings of the 2019 Research, Invention, and Innovation Congress (RI2C)*, pp. 1–6, IEEE, Bangkok, Thailand, December, 2019.

[11] K. Ransikarbum, R. Pitakaso, and N. Kim, “A decision-support model for additive manufacturing scheduling using an integrative analytic hierarchy process and multi-objective optimization,” *Applied Sciences*, vol. 10, no. 15, p. 5159, 2020.

[12] K. Nyembwe, D. de Beer, K. van der Walt, S. Bhero, and K. Katuku, “Comparison of Additive Manufacturing Processes for Rapid Casting for Tooling Application Using the Analytic Hierarchy Process (AHP),” in *Proceedings of the Computers and Industrial Engineering*, p. 42, Cape Town, South Africa, July, 2012.

[13] K. Ransikarbum and S. J. Mason, “Multiple-objective analysis of integrated relief supply and network restoration in humanitarian logistics operations,” *International Journal of Production Research*, vol. 54, no. 1, pp. 49–68, 2016.

[14] K. Ransikarbum and S. J. Mason, “Goal programming-based post-disaster decision making for integrated relief distribution and early-stage network restoration,” *International Journal of Production Economics*, vol. 182, pp. 324–341, 2016.

[15] C. Puchongkawarin and K. Ransikarbum, “An integrative decision support system for improving tourism logistics and public transportation in Thailand,” *Tourism Planning & Development*, vol. 18, pp. 1–16, 2020.

[16] T. Wohlers, “Wohlers Report 2021 Inc,” 2021.

[17] B. Ceballos, M. T. Lamata, and D. A. Pelta, “A comparative analysis of multi-criteria decision-making methods,” *Progress in Artificial Intelligence*, vol. 5, no. 4, pp. 315–322, 2016.

[18] F. T. S. Chan and N. Kumar, “Global supplier development considering risk factors using fuzzy extended AHP-based approach,” *Omega*, vol. 35, no. 4, pp. 417–431, 2007.

[19] Y. Wang, R. Blache, and X. Xu, “Selection of additive manufacturing processes,” *Rapid Prototyping Journal*, vol. 23, no. 2, pp. 434–447, 2017.

[20] S. Zanoni, M. Ashourpour, A. Bacchetti, M. Zanardini, and M. Perona, "Supply chain implications of additive manufacturing: a holistic synopsis through a collection of case studies," *International Journal of Advanced Manufacturing Technology*, vol. 102, no. 9–12, pp. 3325–3340, 2019.
[21] H. Bikas, P. Stavropoulos, and G. Chryssolouris, "Additive manufacturing methods and modeling approaches: a critical review," *International Journal of Advanced Manufacturing Technology*, vol. 83, no. 1–4, pp. 389–405, 2016.
[22] M. Ramola, V. Yadav, and R. Jain, "On the adoption of additive manufacturing in healthcare: a literature review," *Journal of Manufacturing Technology Management*, vol. 30, no. 1, pp. 48–69, 2019.
[23] D. Kokotsaki, V. Menzies, and A. Wiggins, "Durham research online woodlands," *Critical Studies on Security*, vol. 2, no. 2, pp. 210–222, 2014.
[24] A. Rashid, "Additive manufacturing technologies," in *CIRP Encyclopedia of Production Engineering*Springer, New York, NY, USA, 2019.
[25] V. Petrovic, J. Vicente Haro Gonzalez, O. Jordá Ferrando, J. Delgado Gordillo, J. Ramón Blasco Puchades, and L. Portolés Griñan, "Additive layered manufacturing: sectors of industrial application shown through case studies," *International Journal of Production Research*, vol. 49, no. 4, pp. 1061–1079, 2011.
[26] A. Drizo and J. Pegna, "Environmental impacts of rapid prototyping: an overview of research to date," *Rapid Prototyping Journal*, vol. 12, no. 2, pp. 64–71, 2006.
[27] D. T. Pham and R. S. Gault, "A comparison of rapid prototyping technologies," *International Journal of Machine Tools and Manufacture*, vol. 38, no. 10–11, pp. 1257–1287, 1998.
[28] D. Bak, "Rapid prototyping or rapid production? 3D printing processes move industry towards the latter," *Assembly Automation*, vol. 23, no. 4, pp. 340–345, 2003.
[29] R. V. Rao and K. K. Padmanabhan, "Rapid prototyping process selection using graph theory and matrix approach," *Journal of Materials Processing Technology*, vol. 194, no. 1–3, pp. 81–88, 2007.
[30] F. Xu, Y. S. Wong, and H. T. Loh, "Toward generic models for comparative evaluation and process selection in rapid prototyping and manufacturing," *Journal of Manufacturing Systems*, vol. 19, no. 5, pp. 283–296, 2001.
[31] S. H. Masood and A. Soo, "A rule based expert system for rapid prototyping system selection," *Robotics and Computer-Integrated Manufacturing*, vol. 18, no. 3–4, pp. 267–274, 2002.
[32] H. S. Byun and K. H. Lee, "A decision support system for the selection of a rapid prototyping process using the modified TOPSIS method," *International Journal of Advanced Manufacturing Technology*, vol. 26, no. 11–12, pp. 1338–1347, 2005.
[33] G. D. Kim and Y. T. Oh, "A benchmark study on rapid prototyping processes and machines: quantitative comparisons of mechanical properties, accuracy, roughness, speed, and material cost," *Proceedings of the Institution of Mechanical Engineers - Part B: Journal of Engineering Manufacture*, vol. 222, no. 2, pp. 201–215, 2008.
[34] P. Jones, *Three-Dimensional Printing Technology*, 2020.
[35] S. Ramalingam, "Fuzzy interval-valued multi criteria based decision making for ranking features in multi-modal 3D face recognition," *Fuzzy Sets and Systems*, vol. 337, pp. 25–51, 2018.
[36] M. Taufik and P. K. Jain, "Role of build orientation in layered manufacturing: a review," *International Journal of Manufacturing Technology and Management*, vol. 27, no. 1–3, pp. 47–73, 2013.
[37] P. Gay, D. Blanco, F. Pelayo, A. Noriega, and P. Fernández, "Analysis of factors influencing the mechanical properties of flat PolyJet manufactured parts," *Procedia Engineering*, vol. 132, pp. 70–77, 2015.
[38] M. Vlasea, R. Pilliar, and E. Toyserkani, "Control of structural and mechanical properties in bioceramic bone substitutes via additive manufacturing layer stacking orientation," *Additive Manufacturing*, vol. 6, pp. 30–38, 2015.
[39] R. K. Gavade, *Multi-Criteria Decision Making: An overview of different selection problems and methods*, vol. 5, no. 4, pp. 5643–5646, 2014.
[40] F. E. Boran, S. Genç, M. Kurt, and D. Akay, "A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method," *Expert Systems with Applications*, vol. 36, no. 8, Article ID 11363, 2009.
[41] S. PrasannaVenkatesan and M. Goh, "Multi-objective supplier selection and order allocation under disruption risk," *Transportation Research Part E: Logistics and Transportation Review*, vol. 95, pp. 124–142, 2016.
[42] W. Ho, "Review on Supplier Selection. Iii," 2018, http://hdl.handle.net/11343/118668.
[43] L. F. C. S. Durão, M. M. Carvalho, S. Takey, P. A. Cauchick-Miguel, and E. Zancul, "Internet of Things process selection: AHP selection method," *International Journal of Advanced Manufacturing Technology*, vol. 99, no. 9–12, pp. 2623–2634, 2018.
[44] A. Kumar, B. Sah, A. R. Singh et al., "A review of multi criteria decision making (MCDM) towards sustainable renewable energy development," *Renewable and Sustainable Energy Reviews*, vol. 69, no. November, pp. 596–609, 2017.
[45] Z.-J. Wang, "A note on "A group decision making model based on a generalized ordered weighted geometric average operator with interval preference matrices"," *Fuzzy Sets and Systems*, vol. 341, pp. 145–153, 2018.
[46] S. Vinodh, T. S. Sai Balagi, and A. Patil, "A hybrid MCDM approach for agile concept selection using fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS," *International Journal of Advanced Manufacturing Technology*, vol. 83, no. 9–12, pp. 1979–1987, 2016.
[47] R. Ranganathan, "Prioritized fsn analysis of inventory management in private and hospital pharmacy followed by questionnaire," *International Research Journal of Pharmacy*, vol. 7, no. 12, pp. 104–113, 2017.
[48] A. Amindoust, S. Ahmed, A. Saghafinia, and A. Bahreininejad, "Sustainable supplier selection: a ranking model based on fuzzy inference system," *Applied Soft Computing*, vol. 12, no. 6, pp. 1668–1677, 2012.
[49] A. Mardani, A. Jusoh, K. Md Nor, Z. Khalifah, N. Zakwan, and A. Valipour, "Multiple criteria decision-making techniques and their applications - a review of the literature from 2000 to 2014," *Economic Research-Ekonomska Istraživanja*, vol. 28, no. 1, pp. 516–571, 2015.
[50] J. Sarkis and S. Talluri, "A model for strategic supplier selection," *Journal of Supply Chain Management*, vol. 38, no. 4, pp. 18–28, 2002.
[51] J. Rezaei, J. Wang, and L. Tavasszy, "Linking supplier development to supplier segmentation using Best Worst Method," *Expert Systems with Applications*, vol. 42, no. 23, pp. 9152–9164, 2015.
[52] R. Muvunzi, K. Mpofu, and I. Daniyan, "An evaluation model for selecting part candidates for additive manufacturing in the transport sector," *Metals*, vol. 11, no. 5, 2021.

[53] B. Vahdani, M. Salimi, and M. Charkhchian, “A new FMEA method by integrating fuzzy belief structure and TOPSIS to improve risk evaluation process,” *International Journal of Advanced Manufacturing Technology*, vol. 77, no. 1–4, pp. 357–368, 2015.

[54] P. Sharma and S. Singhal, “Implementation of fuzzy TOPSIS methodology in selection of procedural approach for facility layout planning,” *International Journal of Advanced Manufacturing Technology*, vol. 88, no. 5–8, pp. 1485–1493, 2017.

[55] M. B. Anand, “Application of Fuzzy AHP – TOPSIS for ranking Additive manufacturing process for micro-fabrication,” *Rapid Prototyping Journal*, vol. 24, 2016.

[56] S. NĂdĂban, S. Dzitac, and I. Dzitac, “Fuzzy TOPSIS: a general view,” *Procedia Computer Science*, vol. 91, no. Itqm, pp. 823–831, 2016.

[57] J. Fitria, D. dan, and E. Sudaryati, “International journal of research in commerce and management studies,” *International Journal of Research in Commerce and Management Studies*, vol. 2, no. 04, pp. 74–89, 2020.