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ORIGINAL ARTICLE

Selection of suitable additive manufacturing machine and materials through best–worst method (BWM)

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Abstract

In this competitive world, industries are looking for smart technologies to compete; these technologies help R&D people to explicit the ideas and bring the product to the market at shorter lead times and with affordable cost. Each AM machine has its own unique capabilities in manufacturing a product, utilising materials, material intake and wastages. Machine and material costs are the significant parameters, which play a major role in cost estimation of the prototypes. Costs of both machine and materials are prime factors in AM and it can be helpful for cost reduction due to their uniqueness. However, an alternate strategy is being concentrated on process optimization and consumption of material to reduce the overall cost of the prototype. In this paper, multi criterion decision making (MCDM) technique, namely, best-worst method (BWM), was adopted to select the suitable material for the product. This is along with the end user expectations in AM. In the initial phase, the suitable machine to be selected from the available machines is based on the parameters like cost, accuracy, variety of materials and material wastage. From the variety of materials, the suitable material was selected based on the respondent requirement. The criteria that influenced more in the overall cost of the product manufacture through AM is identified and used. According to BWM, the criteria to be selected by the decision maker based on the respondent expectations are identified. In BWM method, pairwise comparisons are carried out between the best and worst criterion suggested by the decision makers, as that it leads to the selection of the suitable material. Here, a demonstration of such a selection is detailed; this is certainly based on the respondent requirements. The result attained through the proposed methodology can be varied based upon the respondent requirements and further machine availabilities. In conclusion, the end result helps to identify the suitable machine and build materials for the prototype to be produced based on the respondent requirements.

Keywords Additive manufacturing · Rapid prototyping · MCDM · Best worst method · Material selection · Machine selection

1 Introduction

Additive manufacturing (AM) transforms 3D model to physical objects by the process of adding materials layer by layer [38]. Along with that, the speed in which the product is built helps to reduce the lead time of the product cycle and help designers to work on complex shapes effectively. Most of the researchers stated that choosing appropriate AM technology plays a major role in either planning to accelerate the production cycle or to enhance the design of the product, which is not a simple task.

Here, the raw material is in the form of solid, semi-solid or in liquid form that is forced in to desired shape and solidified. AM process is initiated from 3D CAD model with various inputs like MRI and CT scan to manufacture the prototype. The source of the inputs may be in any form, but finally it is reformatted into STL file format, which is read by all AM machines [15]. Every AM process has its uniqueness like materials, process parameters, etc. Before initiating an AM process, the type of product to be manufactured and the necessary parameters are to be understood thoroughly based on the end user requirements. Further, this can be achieved by knowledge sharing at the time of decision making, thereby

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resulting in high-quality product, improved product efficiency and reduced lead time to market in new product development [13].

In the competitive environment, the efficiency improvement in any sector is not only dependent on quantitative data; sometimes qualitative data plays a vital role. At this juncture, the need for the researchers is that they require a complex decision-making tool, which considers quantitative and qualitative data for decision making. Several MCDM techniques and approaches have been suggested by various researchers, which help to identify the appropriate criteria as per their requirements [42]. In recent decades, researchers used various techniques like graph theory, matrix, FAHP, FTOPSIS, DEMATEL, rule-based expert system, etc. for comparing the machine parameters and they select the appropriate process [7]. Here, the efficiency of the product is not only dependent on the machine selection, build materials also play a major role in it. In this paper, both the machine-based and material-based approaches of selection are undergone for the AM process by considering the respondent requirements.

The remaining part of the paper is organised as follows: a detailed literature review is conducted in order to review various research approaches and techniques adopted towards machine and material selection in AM process. This is followed by the problem identification and adopted a research methodology to be carried out towards achieving the research objective. It can be achieved by brief comparative study to select the machines, and initial screening of materials is carried out by project engineer. Applying BWM techniques, criteria are sorted based on respondent requirements and ranking of the material is as per the normalised score and material performance. Finally, the proposed methodology is validated through a case study.

2 Literature survey

2.1 Additive manufacturing process

AM involves generation of less waste during manufacturing, it has the capability to optimise geometries and create light weight components that reduce material consumption. Further, AM also provides an option of optimising the process parameters. In recent years, AM has experienced phenomenal expansion and is used widely. It has been driven by unique characteristics alike, dealing with complex geometry, integrated assemblies and provides solution for the problems faced in conventional method. It has some drawbacks like material cost, the availability of the material, high prototype cost and in some cases, real-time functional testing are difficult [46]. The prototypes are produced closer to the acceptable levels at short lead times and at an affordable cost while compared to conventional manufacturing techniques [49]. In the frame work, design iterations are reduced through linear design flow and the design aspects, design dependence and their considerations are defined accurately [4]. Ramola et al. [30] conducted a study in selection of AM process to manufacture customised products for healthcare. Frandsen et al. [12] developed a methodology for selecting the suitable AM process to produce the spare parts and new products. Better selection of AM was done by systematic review; this was with certain identified criteria and methodologies for reducing the failures and increasing the productivity.

Petrovic et al. and Gibson et al. reported a study on AM, which stated that AM has an advantage of saving materials and gives an excellent explanation of basic concepts through to the state-of-the-art making this a great starting point for in-depth research, whilst the process selection tools and business opportunities are found to be a lack [16, 26]. Drizo and Pegna investigated third industrial revolution and claimed that AM would revolutionise as it can produce products to a wider range of market segments like prototypes to functional parts, shoes to hearing aids to jewelry etc. [10].

Pham et al. compared various types of rapid prototyping technologies and reported that the main advantage of AM technologies is that it can reduce the manufacturing lead time and time to market [27]. Bak focusing from different perspective stated that the non-involvement of tools in fabrication process is the main advantage of RP and it leads to mass production of customised product [3].

Rao and Padmanabhan adopted graph theory and matrix approach for selection of rapid prototyping process from various alternatives for prototyping a given product. Considering the selection parameters in qualitative and quantitative data, their interrelations are ranked as per the evaluated selected index [31]. Following which, Xu and Wong stated that selection of suitable process is a difficult task and proposed a generic model for comparing four rapid prototyping processes with a benchmark part and the parameters were build time, surface roughness and build cost [48]. Masood and Soo mentioned that the rapid prototyping processes are increasing rapidly in recent days and it leads to creating problem in process selection for industry as well as educational sector. Adopting rule-based expert system to overcome the above said problem is by considering the user requirement was found to be important [25]. Mentioning of selection method, TOPSIS method was adopted in the selection of suitable RP process to fabricate prototype by considering parameters like accuracy, strength of the build material, elongation, prototype cost, build time etc. [6].

Kim et al. conducted research on quantitative comparisons of mechanical properties, accuracy, roughness, speed and material cost. They also indicated that AM provides minimal material wastage during manufacturing stages [21]. Groth et al. and Ramalingam carried out a study on application of three-dimensional printing in orthodontistry application and multi-modal 3D face recognition, respectively. It results in more accuracy and the material wastage is reduced by the adoption of 3D printing technology [18, 29].

Taufik et al., Gay et al. and Vlasea et al. reported that maintaining mechanical properties are imperative and build orientation has a significant factor in AM process, which can influence mechanical properties [14, 20, 44]. In recent years, the MCDM techniques play a major role in decision making and for selection purpose by considering various alternatives and criteria which influenced more in selecting the feasible one [42]. The following section discusses in detail about the objectives, necessity, benefits of MCDM techniques and its applications in various sectors with the help of literature review.

2.2 Multi-criteria decision-making techniques

The decision-making process deals with the selection of appropriate alternatives from a set of alternatives [37]. The main objective of MCDM is to select the appropriate alternative by ranking all the alternatives and by employing convinced approach [5, 28]. Considering the information from existing decision and influence of various criteria stated, decision makers adopted various methods to take decisions based on their preferences and various alternatives are generally called by the term MCDM [19].

MCDM plays a vital role in operation research; it supports the subjective assessment of decision makers towards criteria through computational and mathematical tools [22]. In recent decades, researchers proposed various MCDM methods like analytical heuristic process (AHP) with internet of things (IoT) for process selection [11]. The technique for order of preference by similarity to ideal solution (TOPSIS), VIKOR, ELECTRE, MEEM, (analytic network process) ANP and interval multiplicative reciprocal matrix (IMRM) [47] are some of the alternative MCDM techniques that were considered. Many researchers incorporated fuzzy techniques with AHP, TOPSIS and DEMATEL in selection of agile concept in manufacturing sector [43]. MCDM plays a vital role in modern decision science like supply chain management [23], management science system engineering, sustainability [1, 24], planning and product development evaluation and strategic management [35]. This is along with FMEA and FTOPSIS to improve risk evaluation process [41], FTOPSIS in facility layout planning [36].

Every method has its unique characteristics and inconsistency while comparing each other. The recent approach of MCDM techniques namely BWM proposed by Jafar Rezeai in 2015 effectively provided remedy for the inconsistency in the area of pairwise comparisons. In BWM, pairwise comparison is carried out in 1–9 scale, which differs from other techniques [34].

2.3 Best worst method

BWM initiated in the identification of best (e.g. most important, most desirable) and worst (e.g. least important, least desirable) criteria by decision makers based on the weight of the criteria that was determined through pairwise comparison [33]. In BWM, the identified best and worst criteria is compared with other criteria through pairwise comparison. This is along with using the non-linear matrix model to identify the criteria weight and the results are attained either in the form of multi-optimal or unique solution as per the decision maker's requirements.

BWM has more salient features and was considered as a robust method among other MCDM techniques. The significant feature like vector-based method requires less data to provide more reliable results and it requires only fewer comparisons to attain reliable results. The fewer comparisons instead of full pairwise comparison reduce the complexity and provide a time consistency for decision makers to take decisions. It is more convenient for the researchers due to less accessible respondents. Next, the inconsistencies in the comparisons are minimised by adopting the approach of structured data collection [45]. BWM is quite easier in execution and more accurate due to elimination of secondary comparisons [2].

BWM was adopted to identify the potential suppliers by incorporating qualitative, quantitative, traditional business and environmental criteria. This is further particularly because, it is stated that BWM requires fewer data to attain reliable results when compared to other MCDM techniques. Rezaei et al. and Goodman et al. used BWM for examining the market segments and identified that there are various parameters that influenced more in the consumer choice [17, 32]. BWM helps decision makers, managers and managements to attain sustainable development and improve the sustainability in their organizational supply chain at the earliest stage of implementation [2]. BWM was used for evaluating the uncertain external forces which affected the sustainability in the supply chain of gas and oil company [45] and few other applications are in freight bundling configuration [32], assessment of the technologies, water resource management [8] and risk assessment [40].

Rezaei proposed BWM method to perform decision making in selection process and it comprises five steps [33], namely,

Step 1: Determine a set of decision criteria.

This implies the identification of criteria (C_1, C_2,..., C_n) that are to be used to arrive at a decision. The performance of the alternatives is determined with respect to these criteria.

Step 2: Determine the best and the worst criteria through respondents and it is to be used for the decision environment.

The best criterion can be the most desirable, the most preferred or the most important while the worst would be the opposite, the least desirable, the least preferred or the least important criteria, which are to be segregated. Here, only the criteria are considered and not the values of the criteria.

Step 3: Determine the preference of the best criterion selected by the respondents over all the other criteria.

A number between 1 and 9 is used to indicate this value. The resulting best-to-others vector would be

$$A_B = (a_{B1}; a_{B2}; \ldots, a_{Bn}),$$

where a_{Bj} indicates the preference of the best criterion B over criterion j.

Step 4: Determine the preference of each of the other criteria over the worst criterion.

A number between 1 and 9 is assigned in this case as well. The others-to-worst vector would be

$$A_W = (a_{1W}; a_{2W}; \ldots, a_{nW})^T,$$

where a_{jW} indicates the preference of the criterion j over the worst criterion W.

Step 5: Find the optimal weights (W^*_1; W^*_2;…, W^*_n).

To determine the optimal weights of the criteria, the maximum absolute differences $\left\{\left|\frac{W_B}{W_j}-a_{Bj}\right|, \left|\frac{W_j}{W_w}-a_{jW}\right|\right\}$ for all j should be minimised. This can be formulated as follows

$$\begin{gathered} \min \max \mathrm{j}\left|\frac{W_B}{W_J}-a_{BJ}\right|, \left|\frac{W_j}{W_w}-a_{jW}\right| \\ \text{s.t.} \\ \sum_j W_j = 1 \\ W_j \geq 0, \text{for all j} \end{gathered} \tag{1}$$

This can be solved by transferring it to the following linear programming formulation:

min ξ^L

$$\begin{gathered} \text{s.t.} \\ \left|\frac{W_B}{W_J}-a_{BJ}\right| \leq \xi^L, \text{for all j} \\ \left|\frac{W_J}{W_W}-a_{jw}\right| \leq \xi^L; \text{for all j} \\ \sum_j W_j = 1 \\ W_j \geq 0, \text{for all j} \end{gathered} \tag{2}$$

Problem (2) is linear and has a unique solution. By solving this problem, the optimal weights (W^*_1, W^*_2, …, W^*_n) and the optimal value of ξ^L, called ξ^{L*}, are obtained. ξ^{L*} is defined as the consistency ratio of the comparison system. Where the consistency ratio is that the closer ξ^{L*} is to a zero value, the more consistent the comparison system provided by the decision maker(s).

Using BWM, the optimal weights of the criteria, W^*_j, are obtained. With these weights and the normalised scores of the alternatives for different criteria for different materials are denoted as x_{ijk}^{norm}. The final score per alternative for material k, where V_{ik}can be calculated using expression (3).

$$V_{ik} = \sum_{j=1}^{n} w_j \, x_{ijk}^{\text{norm}} \tag{3}$$

where

$$x_{ijk}^{\text{norm}} = \begin{cases} \frac{x_{ijk}}{\max\{x_{ijk}\}}, \text{if } x \text{ is positive (such as Mixing number)} \\ 1-\frac{x_{ijk}}{\max\{x_{ijk}\}}, \text{If negative (such as Cost)} \end{cases} \tag{4}$$

3 Problem description

Literature survey revealed that many researchers reported applications of AM technology in various applications and factors which influenced more in attaining the product at affordable cost. Researches also concentrated and compared on optimising a process parameter to improve accuracy of AM parts. The main objective of this research is to identify a suitable AM machine by comparative study and strategy for selecting appropriate material for the selected machine to get the prototype based on requirements.

3.1 Problem identification

Based on the literature review, it is identified that every AM machine has a unique property, technology and it is applied to many fields that fulfill the needs and requirements. Even though AM has many benefits, it lacks behind because of the high production cost when compared to traditional methods. In this regard, AM has its own stand-alone cost which is the main reason for not using AM in most of the cases.

Machine and material cost are the prime factors in AM, which cannot be changed or modified since every AM machine has its own material properties and cost. As the material cost cannot be changed, however, optimization in process and reduction in material wastage (both model and support) can be used as the alternate strategy to minimise the final cost of component or product to be built. On the other hand, another method is to find a cheap or alternate material with same or improved property without sacrificing the quality of the part. In this context, finding an alternate material is beyond the scope of this work. Thereby, focus is towards considering a possible AM machine and material that needs to be chosen, as per the respondent’s requirements.

3.2 Research methodology

This paper is aimed to identify a suitable AM machine to conduct experiment based on the respondent requirements of model materials. The research work considers four machines, which are readily available in the premises and the future researcher adopt the proposed methodology of machine selection for an entire range of available machines. Many parameters are to be considered and compared as per the respondent requirements to attain the objective of this research. Such comparison is to be carried out with the help of MCDM techniques. As per the researchers review, many methods are suggested in various applications. In this work, the recently identified method of BWM is utilised. The main objectives are the selection of suitable AM machine from the available machines and the materials chosen for conducting experiments are according to the respondent requirements. Next is to identify the technical challenges raised during processing and future opportunities of AM.

Figure 1 illustrates the entire research flow. The work initiates with literature survey to identify the recent trends adopted by AM process for selection of machine and material. The scope of the research work is finalised and work is to accomplish the research objective. Initially, the selection of suitable AM machine is done by brief comparative study on the available AM machines. Then, material selection is carried out for the selected AM machine by utilising the BWM technique. Ranking is by the materials based on the material performance and normalised score by considering the respondent requirements. The proposed methodology is finally validated through case study.

4 Selection and screening process

4.1 Selection of suitable AM machine

Many AM machines and materials are available in the market. Initially planned to proceed the experiments only in the available AM machines. This includes Fortus 900mc (FDM), Viper Si2 (SLA), and Sinter station 2500+ (SLS) and Objet260 Connex (PolyJet) [4, 9, 39]. Comparison of selected AM machines will be discussed in subsequent sections, which also include the process parameters, raw materials, specifications and specialised software for individual AM machine. Comparison of selected AM machines are populated in Table 1. However, the age and cost of these machines are quite different and are not included in this study.

Based on comparisons of four available machines, all the machines have their individual characteristics. But here, layer thickness plays a major role in part accuracy, Objet260 Connex holds 0.016 mm (high quality), 0.030 mm (high speed and digital material) and it is very less compared to other three machines. In Objet260, nearly 105 combinations of materials are to be obtained from 15 base materials and it influences more in the selection of Objet260. During the material replacement, Objet260 machine flushes more material than others, referred as wastage of material. Objet260 Connex machine has better resolution and repeatability while comparing to other three machines. In this regard, prototyping cost is expensive in PolyJet technology. Likewise, based on the parameters of respondent requirements and the availability of machine, Objet260 Connex was selected for this work.

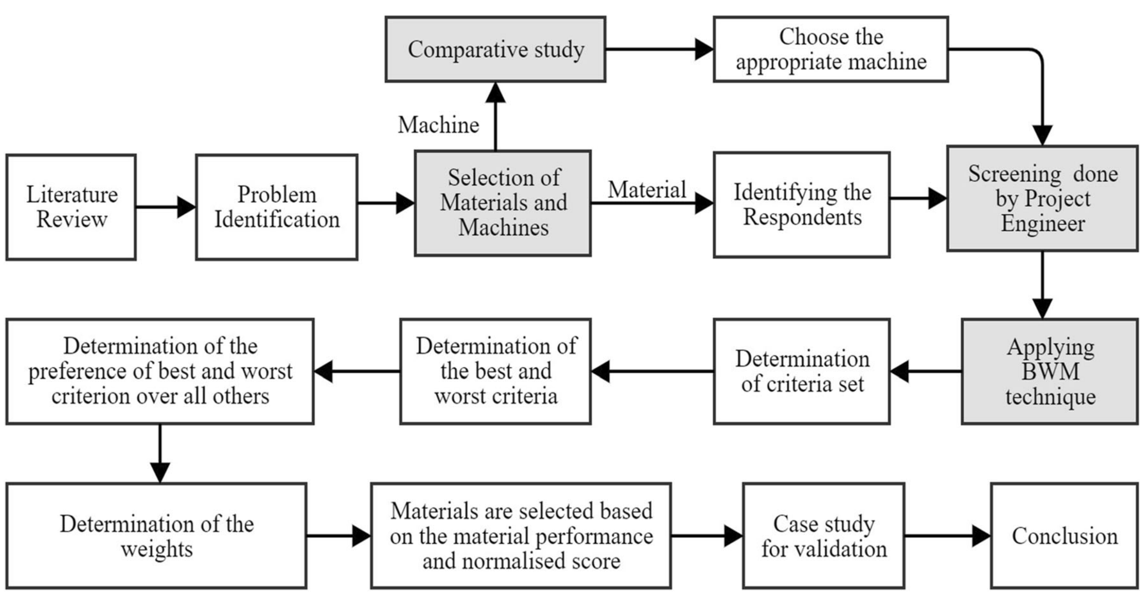

Fig. 1 Research flow pattern

Table 1 Comparison of selected AM machines

S. no	Alternates/parameters	Fortus 900mc	Viper Si2	Sinterstation 2500+	Objet260 Connex
1	Build volume (mm)	914 × 610 × 914	250 × 250 × 250	381 × 350 × 457	254 × 251 × 200
2	Layer thickness (mm)	0.330, 0.254 and 0.178	0.02 to 0.05	0.1016 to 0.508	0.016 and 0.030
3	Material type	Wire/filament	Photo polymer resin	Powder	Photo polymer resin
4	Model material	1. Polycarbonate (white) 2. PC-ABS (black) 3.Polyphenylsulfone (PPSF) 4. ULTEM (high-performance thermoplastic) 5. ABS-M30i (various colour) 6. Production quality ABS (various colour)	1. Accura 55 2. Accura 60 3. Amethist	1. Duraform (PA nylon) 2. Laser form (stainless steel)	1. Vero family 2. Tango family 3. Simulated polypropylene total 105 materials
5	Support material	SR 30, SR 20	Build material	No need	FullCure 705
6	Feed stock	Continuous spool of plastic (later metal)	Liquid plastic	Plastic or metal powder	Liquid plastic
7	Tool path tracing	X,Y movement of Head	X,Y movement of laser	X,Y movement of laser	Selective area jetting
8	Machine size (mm)	2772 × 1683 × 2027	770 × 535 × 1600	2220 × 1683 × 1900	870 × 735 × 1200
9	Advantages	Simple, cheap, is the most popular	Rapid manufacturing large tool	Strong structure	High precision and multi material applications
10	Technology	Material extrusion	Stereolithography	Powder bed fusion	PloyJet matrix
11	Model material supplier	Stratasys	3D System	DTM	Stratasys
12	Material max size	90 in. cube	10 l	10 kg	3600 g
13	Material replacement mode	Cutting and insertion	Replace the loaded one	Clean and fill the new powder	Flushing
14	Post-processing	Breakaway support structure (BASS)/water soluble supports (WSS)	Cleaning and post-curing	De-powdering	Water jet
15	Post-curing	No	Yes	No	No
16	Digital material option	Yes	No	No	Yes
17	Material wastage (change)	Low	High	Medium	Very high
18	Resume option	Yes	No	No	Yes
19	Bottom support layers	Medium	Low	Low	Very high
20	RP software	Insight	3D light layer	Build platform	Objet studio
21	Availability of machine	High	Medium	Low	Very high
22	Accuracy	Low	High	Medium	Very high
23	Thin walls	Difficult	Moderate	Easy	Moderate
24	Resolution	Low	High	Medium	Very high
25	Repeatability	Low	Medium	High	Very high
26	Printing cost	Low	High	Medium	Very high

Table 1 (continued)

S. no	Alternates/parameters	Fortus 900mc	Viper Si2	Sinterstation 2500+	Objet260 Connex
27	Chemical/solvent	1. Propylene glycol mono methyl ether	1. Propylene carbonate 2. Urethane resins 3. Tripropylene glycol 4. Isopropanol	1. Polyamide resin 2. Acrylonitrile butadiene styrene	1. Propylene carbonate 2. Urethane resins 3. Tripropylene glycol 4. Isopropanol
28	Biodegradability	1. No hazardous decomposition products	1. Readily biodegradable (more than 80% degraded in 10 days) 2. Not found to be dangerous to the environment 3. Can be biodegraded by 50% in just 8.7 days, and by 81.9% over a 28-day test period.	1. Form inflammable mixture with some chemicals or long exposure to air 2. Since it is insoluble in water, its eco-toxicity is low	1. Readily biodegradable (more than 80% degraded in 10 days) 2. Not found to be dangerous to the environment 3. Can be biodegraded by 50% in just 8.7 days, and by 81.9% over a 28-day t est period.

Table 2 Possible combination of digital materials in Objet260 Connex

S.no	Material	Vero White	Vero Grey	Vero Clear	Vero Blue	Vero Black	Tango Grey	Tango Black	Tango Black Plus	Tango Plus	RGD 535	RGD 525	RGD 515	MED 610	FullCure 720	Durus White	Mixing numbers and (rank)	Total number of digital materials and (rank)
1	Vero White					A1		A2	A3	A4						A5	5-(2)	3 + 6 + 12 + 8 + 1 = 30 (2)
2	Vero Grey																0-(14)	0 (14)
3	Vero Clear								B1	B2							2-(9)	12 + 8 = 20 (4)
4	Vero Blue					F1		C1								G1	3-(7)	1 + 3 + 1 = 5 (9)
5	Vero Black	A1			F1		F2	C2							F3	F4	6-(1)	3 + 1 + 1 + 3 + 2 + 1 = 11 (7)
6	Tango Grey					F2		C3									2-(10)	1 + 1 = 2 (11)
7	Tango Black	A2			C1	C2	C3								C4		5-(3)	6 + 3 + 3 + 1 + 6 = 19 (5)
8	Tango Black Plus	A3		B1								D1					3-(6)	12 + 12 + 12 = 36 (1)
9	Tango Plus	A4		B2								E1					3-(5)	8 + 8 + 7 = 23 (3)
10	RGD 535												H1				1-(12)	1 (12)
11	RGD 525								D1	E1							2-(11)	12 + 7 = 19 (6)
12	RGD 515										H1						1-(13)	1 (13)
13	MED 610																0-(15)	0 (15)
14	FullCure 720					F3		C4								G2	3-(8)	2 + 6 + 1 = 9 (8)
15	Durus White	A5			G1	F4									G2		4-(4)	1 + 1 + 1 + 1 = 4 (10)

If the suggested strategy is realised in Objet260 means, then it is applied for other machines without difficulty.

4.2 Selection of material using BWM

Literature indicates that different methods or approaches such as graph theory and matrix approach modified TOPSIS method, IRIS intelligent RP system selector, generic models for comparative evaluation and analytic hierarchic process are used for selecting suitable AM technology. However, material selection for a particular AM machine is not addressed by researchers in spite of the availability of various materials. As no proven method is available for selecting suitable material for the part adopting AM, a simple technique known as BWM is selected.

BWM is a comparison-based MCDM method that compares the best criterion (alternative) to the other criteria (alternatives), and all the other criteria (alternatives) to the worst criterion (alternative). This process makes a comparison system composed of two comparison vectors. The goal is to find the optimal weights and consistency ratio through a simple optimization model constructed using the comparison system.

Table 2 details the available material combination to form digital materials in Objet260 Connex machine. For instance, VeroWhite can only be combined with VeroBlack, TangoBlack, TangoBlack Plus, TangoPlus and DurusWhite. A1 indicates the mixture of VeroWhite and VeroBlack. Similarly, A4 forms VeroWhite with TangoPlus and so on. By combining the available materials, it is possible to get 90 digital materials as displayed in Fig. 2. For instance, combination of VeroWhite and VeroBlack produces three digital materials, namely, DM-8310, DM-8320 and DM-8330 as shown in Fig. 2. A total of 105 materials are available with Objet260 Connex machine, which are 15 pure single materials tabulated in first row and column of Table 2. Digital materials are derived from mixing of two pure single materials. The total number of possible combinations with two pure single materials and

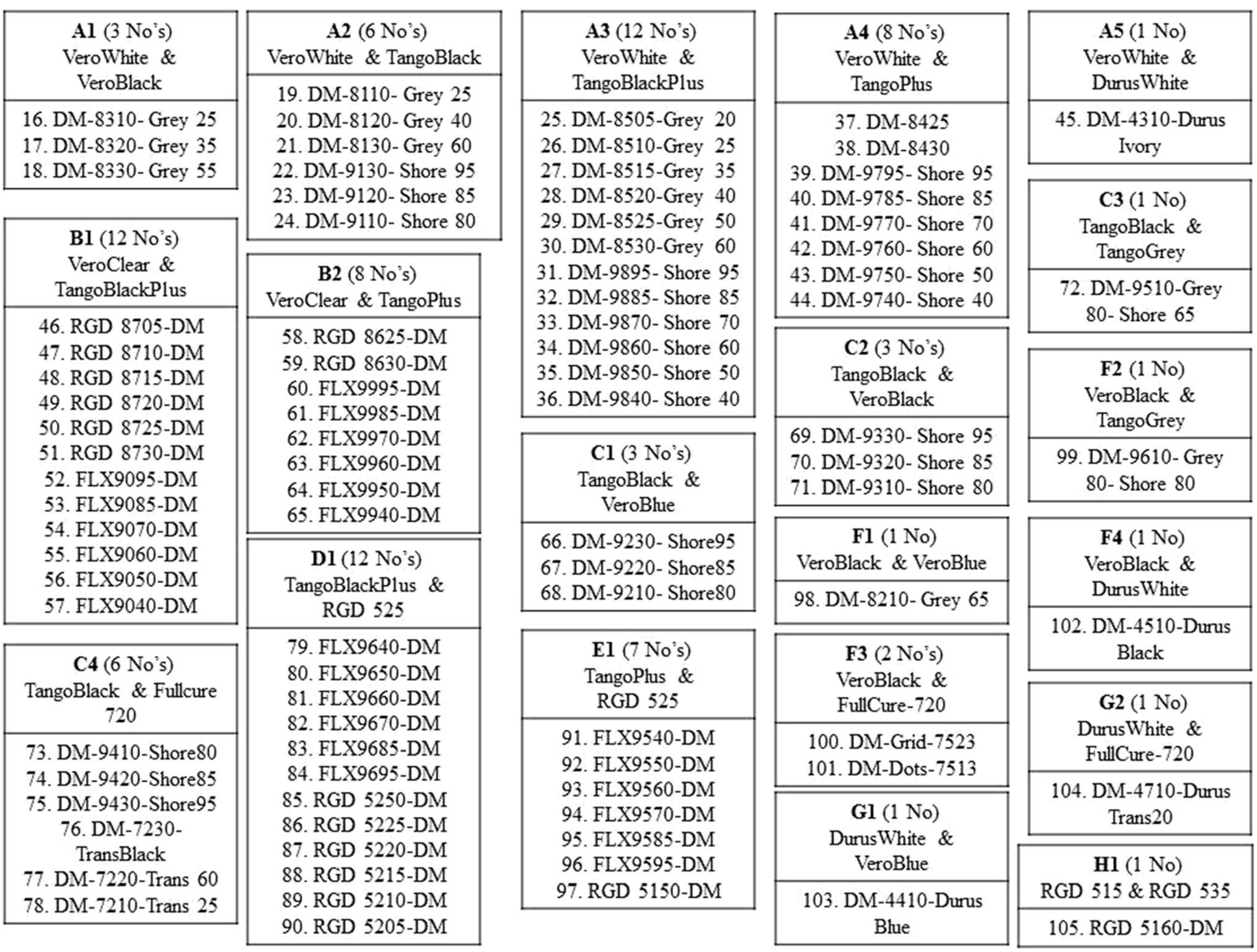

Fig. 2 Composite digital materials available with Objet260 Connex machine

their total number of digital materials are listed in the last two columns of Table 2. Based on a maximum number of mixing and their number of digital materials derived from particular combination, all the materials are ranked. The ranks are indicated in closed bracket as populated in the last two columns of Table 2.

4.2.1 Screening

The screening process helps to select the suitable material from the available material list which meets the respondent expectation and it requires specific criteria to evaluate it. These are obtained from the questionnaire distributed to the respondents. Here, 33 customers, 19 post-graduates, 15 research scholars, 48 number of under graduate students, 12 project engineers and 4 proprietors are selected as respondents. These respondents are requested to choose the best and worst criteria from the suggested eight criteria like cost, elongation at break, tensile strength, shore hardness, frequent order, mixing number and number of digital materials with the help of questionnaire.

Initially, the materials are screened with the help of project engineer based on criteria and requirements of each respondent. Six different screening criteria are selected, which relate to material acceptance by Objet260 Connex machine, mixed with other materials, toughness, form and fit testing, tooling/patterns and finishing-coatings and coloring. The identified materials are screened based on six criteria as shown in Table 3.

As these are minimum requirements, a material can either have an acceptable score indicated by ‘A’ or an unacceptable score which is indicated by ‘U’ and not eligible/does not apply for the material is indicated by ‘NE’. Under the conjunctive filtering approach, a material is considered qualified if the material receives an A for each of the screening criteria. A material that receives U for any criterion is considered unqualified. Due to lack of certain material property, the Tango family materials are eliminated as they are not suitable for tooling and pattern making. As a result, selected are 15 materials from the pool of 21 materials on the basis of holding all the properties. Next to the screening process, from these 15 materials, 7 materials obtain first five ranks based on the respondent requirements. Table 3 indicates the conjunctive screening of initial pool of 21 materials. In the rest of this research work, those materials that have secured top 7 ranks are only considered.

Table 3 Conjunctive screening of initial pool of 21 materials

S. No	Material	Acceptance by machine	Mixed with other material	Toughness	Form and fit testing	Tooling/ patterns	Finishing-coating and colouring
1	Durus White	A	A	A	A	A	A
2	Digital ABS-Green	U	A	A	A	A	A
3	Digital ABS-Ivory	U	A	A	A	A	A
4	Fullcure 720	A	A	A	A	A	A
5	MED 610	A	U	A	A	A	A
6	RGD 515	A	A	A	A	A	A
7	RGD 525	A	A	A	NE	A	A
8	RGD 535	A	A	A	A	A	A
9	Rigur	U	A	A	A	A	A
10	Tango Plus	A	A	NE	A	NE	A
11	Tango Black Plus	A	A	NE	A	NE	A
12	Tango Black	A	A	NE	A	NE	A
13	Tango Grey	A	A	NE	A	NE	A
14	Vero Black	A	A	A	A	A	A
15	Vero Blue	A	A	A	A	A	A
16	Vero Clear	A	A	A	A	A	A
17	VeroCyan	U	A	A	A	A	A
18	Vero Grey	A	U	A	A	A	A
19	VeroMagenta	U	U	A	A	A	A
20	VeroYellow	U	U	A	A	A	A
21	Vero White	A	A	A	A	A	A

A acceptable, *U* unacceptable, *NE* not eligible/does not apply for the material

The material selection process is carried out using a five-step method, which is called as BWM. These steps are executed in order to complete the second phase.

4.2.2 Determination of criteria set

The criteria set are determined on the basis of the input obtained from the respondents. Their input is gathered through a number of interviews. A total of 131 respondents of various levels from customers, post graduates, research scholars, under graduate students, project engineers and proprietors are requested to fill the questionnaire. In this work, totally, 131 respondents took part and stated the preferences based on their requirements. The respondents are decision makers who are directly involved in selecting the materials. During these interviews, the respondents were asked for their preference and view on the most important criteria.

Over 30 criteria were identified by the respondents, ranging from very generic to extremely specific. A ranking was constructed in order to determine how often a criteria was identified by the respondents, then aggregating the number of times a particular criterion had been identified as important by respondents, selection of criteria is made. Based on this ranking and considering the complexity and applicability of the criteria in a new market situation, eight criteria are selected and presented in Table 4.

4.2.3 Determination of the best and worst criteria

The second step in the formation of the BWM is the determination of the best and the worst criteria. The best criterion is the one identified by each respondent as the most important criterion in material selection, while the worst criterion is the one which is the least important one in material selection based on the opinion of each decision maker. This information is obtained from respondents through a short questionnaire. A total of 131 respondents from various levels indicated best and worst criteria and it can be seen in Table 5. In the Table 5, the respondents are denoted in numerals as 1-customers, 2-post graduates, 3-research scholars, 4-under graduate students, 5-project engineers, 6-proprietors. The requirements differ for each respondent and respondent of same category also differ. Here, a consolidated feedback from the respondent preference was considered. This is by averaging the response collected through questionnaire and it is detailed.

Table 4 Criteria used for the final choice phase

Criteria	Symbol
Mixing number	C1
Number of digital materials	C2
Cost (INR/gram)	C3
Elongation at break	C4
Tensile strength	C5
Shore hardness	C6
Frequent order	C7
Visual and aesthetic modelling	C8

Table 5 Best and worst criteria identified by respondents

Criterion	Identified as 'best' by respondents	Identified as 'worst' by respondents
Mixing number		1
Number of digital materials	5	6
Cost	1, 4	
Elongation at break		
Tensile strength	3	
Shore hardness	2	
Frequent order	6	2, 3, 4
Visual and aesthetic modelling		5

4.2.4 Determination of the preference of best criterion

The third step consists of identifying the preferences of the best criterion from amongst all the criteria. This information is also obtained with the help of the questionnaire. The respondents are asked to compare their selected best criterion to each of the other criteria and state their preference by using a value between 1 and 9. A score of 1 implies an equal importance over the other criterion. A score of 9 implies that the most important criterion is extremely more preferred to the other criterion. This results in the best-to-other (BO) vectors which can be seen in Table 6.

4.2.5 Determination of the preference of all criteria over the worst criterion

The fourth step of the BWM is similar to the third step; at this point, respondents are asked to state their preferences of all other criteria over the least important criterion. Again, a value between 1 and 9 is used; results in the others-to-worst (OW) vectors can be seen in Table 7.

4.2.6 Determination of weights

The weights are determined with a linear model of BWM for the response of various respondents. The criterion average weight can be calculated for various respondent responses, which results in a single weight vector and it is tabulated in Table 8.

Table 6 BO vectors for 6 respondents

Response No.	Best	Mixing number	Number of digital materials	Cost	Elongation at break	Tensile strength	Shore hardness	Frequent order	Visual and aesthetic modelling
1	Cost	9	8	1	5	3	4	6	2
2	Shore Hardness	7	6	4	2	3	1	9	5
3	Tensile Strength	8	6	5	3	1	2	9	4
4	Cost	6	8	1	3	5	4	9	2
5	Number of digital materials	2	1	4	6	8	7	3	9
6	Frequent order	7	9	2	4	6	5	1	3

Table 7 OW vectors for 6 respondents

Response No. Worst	1 Mixing number	2 Frequent order	3 Frequent order	4 Frequent order	5 Visual and aesthetic modelling	6 Number of digital materials
Mixing number	1	3	2	4	8	3
Number of digital materials	2	4	4	2	9	1
Cost	9	6	5	9	6	8
Elongation at break	5	8	7	7	4	6
Tensile strength	7	7	9	5	2	4
Shore hardness	6	9	8	6	3	5
Frequent order	4	1	1	1	7	9
Visual and aesthetic modelling	8	5	6	8	1	7

As it can be seen from the results, for the case respondents, ‘cost’ and ‘shore hardness’ are the most important criteria for material selection, followed by tensile strength, visual and aesthetic modelling. This is well-aligned with the previous findings in the literature.

4.2.7 Material selection using BWM

The final material scores are obtained in three steps. First, the supplier performance on different criteria is determined both by using archival and secondary data sources. Different dimensions are used per criterion. For some of the qualitative criteria such as frequent order, a nine-point Likert scale (1: very low to 9: very high) is used. For each other measure, corresponding measuring units are used in order to indicate number of digital materials, elongation at break and tensile strength. Table 9 indicates the material performance scores.

The second step consists of normalization of the scores using expression 4. The normalised scores are summarised in Table 10. The third step consists of using expression (4) to find the overall scores of materials, which are shown in the last column of Table 10.

As can be seen from the results, for the selected criteria, VeroWhite is the most important material, followed by VeroBlack and VeroClear. From Table 10, VeroWhite scores high value of 0.836 and TangoBlackPlus scores low value of 0.362. As per the normalised score, ranks of the materials are as follows: VeroWhite secures first rank and subsequently VeroBlack, VeroClear, TangoBlack, DurusWhite, TangoPlus and TangoBlackPlus. This approach is utilised by the researchers in the place of material selection and decision making for criteria selection based on the respondent requirements.

Table 8 Overall weights of the criterion preferred by decision makers

Criteria	Weight
Mixing number	0.078
Number of digital materials	0.101
Cost	0.192
Elongation at break	0.12
Tensile strength	0.134
Shore hardness	0.146
Frequent order	0.104
Visual and aesthetic modelling	0.125

Table 9 Material performance

Criterion	C1	C2	C3	C4	C5	C6	C7	C8
VeroBlack	6	11	4	25	65	86	6	8
VeroWhite	5	30	5	25	65	86	9	8
TangoBlack	5	19	6	55	2.4	62	7	5
DurusWhite	4	4	7	50	30	78	2	2
TangoPlus	3	23	8	220	1.5	28	9	6
TangoBlackPlus	3	36	8	220	1.5	28	7	5
VeroClear	2	20	9	25	65	76	9	9
Unit	Numbers	Numbers	Likert	%	MPa	Scale	Likert	Likert

5 Application and case study

In this case study, customer is considered as a key player, while the need is to identify a suitable material based on the requirements. Customer from automotive industry needs to print a template for cutting neoprene rubber gasket. The customer expectations are "better physical properties like tolerance to a wide temperature range, moderate resistance to oils and grease". Before going for mass production, customer need was to test few samples of gasket and the samples are made by hand cutting technique. Based on the customer response, it was observed that they are expecting the same for different gaskets with complex profiles. The technique is widely used in more applications since the required shape can be attained without any special tooling, involving faster to produce and at an affordable cost.

In this case study, initially, the parameters influencing the required template are obtained through the questionnaire. The dimensions of required template are as shown in Fig. 3a. The obtained parameters involve the mixing of available materials, number of digital materials, printing cost, elongation at break, tensile strength, shore hardness, frequent order and aesthetic modelling. Using BWM, the best and worst criteria are identified based on the rank provided by the decision makers. Based on the rank, the criteria like cost (C3), visual and aesthetic modelling (C8), tensile strength (C5) and shore hardness (C6) are placed top in the criteria list. Similarly, the top worst criteria list is mixing number (C1), number of digital materials (C2), frequent order (C7) and elongation at break (C4). The normalised material score of BWM shows that VeroWhite is the appropriate one for the customer requirements. Due to high accuracy, durability, rigidity, detailing of fine features and economic conditions VeroWhite is identified to be a perfect fit for the specified customer criterion. Figure 3 b illustrates the 3D printed hand cutting template made up of VeroWhite material.

The success of this proposed method is noted as the customer not only selected the appropriate machine and materials but it also helps to identify the most appropriate one based on their requirements which is not in the customer list. For example, the material identified through this approach is cheaper and met the requirements better than the material suggested by the customer. In proprietor point of view, this avoids the process of overstocking and stocking of least feasible material and also helps to suggest the equivalent material in the time of unavailability. This method indirectly helps to improve the inventory management of the materials that are held.

6 Results and discussion

The main objective of this research is to increase the usability of AM processes for manufacturing components or parts for various applications. The novelty of this paper provides the

Table 10 Normalised material score

Criterion Weight	C1 0.078	C2 0.101	C3 0.192	C4 0.120	C5 0.134	C6 0.146	C7 0.104	C8 0.125	Overall material score
VeroBlack	0.078	0.031	0.107	0.106	0.134	0.146	0.069	0.111	0.782
VeroWhite	0.065	0.084	0.085	0.106	0.134	0.146	0.104	0.111	0.836
TangoBlack	0.065	0.053	0.064	0.090	0.005	0.105	0.081	0.069	0.533
DurusWhite	0.052	0.011	0.043	0.093	0.062	0.132	0.023	0.028	0.444
TangoPlus	0.039	0.065	0.021	0.000	0.003	0.048	0.104	0.083	0.363
TangoBlackPlus	0.039	0.101	0.021	0.000	0.003	0.048	0.081	0.069	0.362
VeroClear	0.026	0.056	0.000	0.106	0.134	0.129	0.104	0.125	0.680

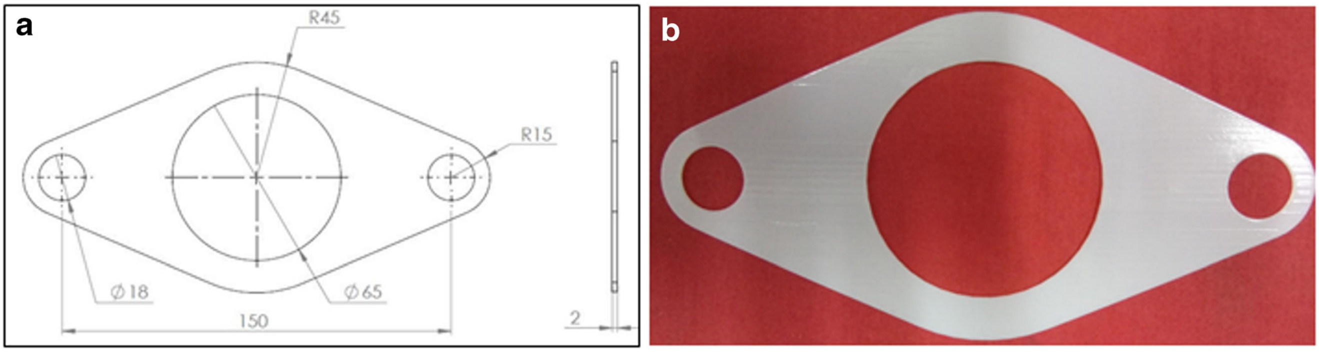

Fig. 3 **a** 2D drawing and **b** 3D printed hand cutting template for industrial gasket

proof concept of BWM technique in AM machine and material selection. Recommendation of AM machine for a particular job should be based on advantages and disadvantages of material savings, machine time saving, quality achievement and environmental effects. Selection of AM machine for this research was completed by a brief comparison study of four different available AM machines. The comparison is made based on the parameters like accuracy, variety of materials, material wastage and availability of machine.

Through comparative study, Objet260 Connex was selected for this research work with the help of specification sheets of machine and materials, provided by the manufacturer and discussion made with the field experts. At this stage, consideration of qualitative data during comparative study is limited. This is based on requirements expected by the respondents. Next to compare the study, initial screening of available materials for the selected AM machine is performed by project engineer. This is followed by material selection, which is a strategic decision that was performed by using BWM. In BWM, the preliminary step is to determine through criteria set; then, best and worst criterion are identified and given are the preferences of the criterion over others. Subsequently, the criteria weights are calculated based on the respondent requirements and finally the materials are selected based on the material performance and normalised score.

From this proposed method, it is identified that Objet260 Connex material of VeroWhite scores high value of 0.836 and TangoBlackPlus scores a low value of 0.362. Based on the BWM results, top ranked materials are loaded in machine to fulfill the respondent's requirements. When the need is of an alternative material, still the option "Economy mode" of flushing can be adopted rather than going for "High performance" or "Efficiency" flushing mode. This is certainly because it will provide the minimal wastage of material during the flushing operation and as well holds minimum machine running time. Due to structured data collection approach of BWM, the inconsistencies in the comparisons are minimised and it was found to be quite easier for execution. The results are also accurate in decision-making process due to elimination of secondary comparisons. The consideration of numerous factors that span disciplines and organizational functions is added to support in the approach of machine and material selection. This proposed strategy is found to be valuable, as it helps the future researcher to carry out similar strategy on various machines.

7 Conclusion

Additive manufacturing gives the potential to bring new designs into market as quickly as possible and helps to sustain in the market for longer period of time. Selection of the most suitable machine of Objet260 Connex was identified by comparing large number of alternatives between the available machines. Next, BWM of MCDM technique is adopted in this work, which helps in selection of a suitable material from large number of available materials for the selected Objet260 Connex machine. This work provides a novel and optimum way of manufacturing process and decision-making strategy in AM, in spite of the design complications. It gives best ranking of the build materials based upon the respondent requirements and it helps to provide service based on the requirements of the customer. This is certainly with minimal wastage of materials during changing of materials based on the product type and helps the customer to know broadly about the available feasible material for the requirements which is not considered early. In future, this research can be extended in terms of incorporating fuzzy techniques to be considered for qualitative data along with quantitative data for both machine and build material selection process. Additionally, the same input data will be executed in other MCDM techniques and the developed model can be validated.

Appendix

1. Additive manufacturing survey on material selection

Name:			
Organization / College:			
Address:			
City:		**Postal Code:**	
Email:		**Phone:**	

1.	Please choose the industry / project category that best describes your primary function		
	a) Aerospace & Defense	e) Education	i) Industrial & Packing Machinery
	b) Automotive & Transportation	f) Electronics	j) Jewelry
	c) Consumer Products	g) Energy, Plant and Process	k) Medical
	d) Design & Engineering Services	h) Engineering and Construction	l) Mold Design
	m) Others, please specify: ______________________________		
2.	Job Title		
	a) Administrator	d) Engineer	g) Proprietor
	b) Designer	e) Executive	h) Research Scholar
	c) Educator	f) Manager	i) Student
	j) Others, please specify: ______________________________		
3.	Are you aware of Additive Manufacturing (AM) and /or 3D printing?	a) Yes	b) No
	If Yes, Kindly select the known AM technologies given below		
	a) Direct Metal Laser Sintering	d) Indirect Inkjet Printing	g) PolyJet / Inkjet Printing
	b) Electronic Beam Welding	e) Laser Engineered Net Shaping	h) Selective Laser Sintering
	c) Fused Deposition Modeling	f) Laminated Object Manufacturing	i) Stereolithography

<table>
<tr><td></td><td colspan="10">j) Others, please specify: ____</td></tr>
<tr><td rowspan="8">4.</td><td colspan="10">Please tick and specify preliminary expectations of 3D printing in your consideration</td></tr>
<tr><td colspan="2">a) Not at all</td><td colspan="2">b) Probably no</td><td colspan="2">c) I don't know</td><td colspan="2">d) Possibly yes</td><td colspan="2">e) Definitely</td></tr>
<tr><td colspan="5"></td><td>(a)</td><td>(b)</td><td>(c)</td><td>(d)</td><td>(e)</td></tr>
<tr><td colspan="5">i) 3D printing offer new possibilities to your own work?</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td></tr>
<tr><td colspan="5">ii) It helps to improve the functionality of parts / assemblies?</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td></tr>
<tr><td colspan="5">iii) 3D printing offer help to improve competitiveness?</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td></tr>
<tr><td colspan="5">iv) It can be used as end-use production?</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td></tr>
<tr><td colspan="5">v) It will become common option within normal manufacturing methods?</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td><td>☐</td></tr>
<tr><td rowspan="4">5.</td><td colspan="10">Which type of printer is useful to your industry / project?</td></tr>
<tr><td colspan="5">a) Filament Based Printers</td><td colspan="5">c) Metal Printers</td></tr>
<tr><td colspan="5">b) Resin Based Printers</td><td colspan="5">d) Food Printers</td></tr>
<tr><td colspan="5">e) Others, please specify: ______________________</td><td colspan="5">f) No idea</td></tr>
<tr><td rowspan="8">6.</td><td colspan="6">Do your Organization / College currently have any AM machine(s)?</td><td colspan="2">a) Yes</td><td colspan="2">b) No</td></tr>
<tr><td colspan="10">If Yes, kindly select the technology used and specify the machine name in below</td></tr>
<tr><td colspan="5">Technology</td><td colspan="5">Machine Name</td></tr>
<tr><td colspan="5">a) Fused Deposition Modeling</td><td colspan="5">______________________________ __________</td></tr>
<tr><td colspan="5">b) PolyJet / Inkjet Printing</td><td colspan="5">______________________________ __________</td></tr>
<tr><td colspan="5">c) Selective Laser Sintering</td><td colspan="5">______________________________ __________</td></tr>
<tr><td colspan="5">d) Stereolithography</td><td colspan="5">______________________________ __________</td></tr>
<tr><td colspan="10">e) Others, please specify the technology & Machine name: ____</td></tr>
<tr><td rowspan="3">7.</td><td colspan="10">What type of product is required for your industry / project? (If more than one also selected)</td></tr>
<tr><td colspan="5">a) Concept models</td><td colspan="5">d) Implants</td></tr>
<tr><td colspan="5">b) For design review</td><td colspan="5">e) Reverse engineering</td></tr>
</table>

<table>
<tr><td rowspan="2"></td><td colspan="3">c) Academic / research projects</td><td colspan="3">f) New Product Development</td></tr>
<tr><td colspan="6">g) Others, please specify: ______________________________</td></tr>
<tr><td rowspan="5">8.</td><td colspan="6">What type of material is required for your industry / project? (If more than one also selected)</td></tr>
<tr><td colspan="3">a) Plastics / Polymers (ABS, PA, PLA, PEEK etc.,)</td><td colspan="3">d) Bio Compatible (Bio Ink, bone materials)</td></tr>
<tr><td colspan="3">b) Metals (Titanium, SS, brass, bronze, Gold etc.,)</td><td colspan="3">e) Building materials (Gypsum, Sand stone etc.,)</td></tr>
<tr><td colspan="3">c) Digital Materials (Rubber, multi-color etc.,)</td><td colspan="3">f) Foods (Chocolate, pizza etc.,)</td></tr>
<tr><td colspan="6">g) Others, please specify: ______________________________</td></tr>
<tr><td rowspan="2">9.</td><td colspan="6">Please tick the accuracy level of product as per your requirement</td></tr>
<tr><td>a) Very low</td><td>b) Low</td><td>c) Medium</td><td colspan="2">e)High</td><td>f) Very High</td></tr>
<tr><td rowspan="3">10.</td><td colspan="6">What is your plan to printing the final CAD files? (If more than one also selected)</td></tr>
<tr><td colspan="2">a) Ready to print</td><td colspan="2">c) General Investigation</td><td colspan="2">e) Regular order</td></tr>
<tr><td colspan="2">b) Evaluating concepts</td><td colspan="2">d)Print once in a year</td><td colspan="2">f) No plans</td></tr>
<tr><td rowspan="5">11.</td><td colspan="6">Please rank (1 to 8) the following criteria as per your requirements</td></tr>
<tr><td colspan="3">a) Mixing Number __________</td><td colspan="3">e) Tensile Strength __________</td></tr>
<tr><td colspan="3">b) Number of Digital Materials __________</td><td colspan="3">f) Shore Hardness __________</td></tr>
<tr><td colspan="3">c) Cost (INR/Gram) __________</td><td colspan="3">g) Frequent order __________</td></tr>
<tr><td colspan="3">d) Elongation at Break __________</td><td colspan="3">h) Visual & Aesthetic Modeling __________</td></tr>
<tr><td>12.</td><td colspan="6">Any other relevant information (Please Give your Comments)</td></tr>
<tr><td></td><td colspan="6"></td></tr>
</table>

Signature

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