Sādhanā (2020) 45:101
https://doi.org/10.1007/s12046-020-01338-w

A decision support system for the selection of an additive manufacturing process using a new hybrid MCDM technique

JAIRAM RAIGAR[1], VISHAL S SHARMA[2], SHEKHAR SRIVASTAVA[1,*], RAMESH CHAND[1] and JAIVIR SINGH[1]

[1]Department of Industrial and Production Engineering, Dr. B R Ambedkar National Institute of Technology, Jalandhar 144011, India
[2]School of Mechanical, Industrial and Aeronautical Engineering, University of Witwatersrand, Johannesburg, South Africa
e-mail: jrmkhajotiya@gmail.com; vishal.sharma@wits.ac.za; shekhars.ip.17@nitj.ac.in; rameshchandjanjua@gmail.com; er.jaivirsingh@gmail.com

MS received 25 November 2019; revised 18 March 2020; accepted 31 March 2020

Abstract. Recently, Additive Manufacturing (AM) has been widely used in many applications. For a particular AM component, the choice of available AM processes is critical to the component's quality, mechanical properties, and other important factors. In that context, this article presents an efficient decision support system for the selection of an appropriate AM process. A novel hybrid Multi-Criteria Decision Making (MCDM) technique has been proposed to select an appropriate AM process from available AM processes. The Best Worst Method (BWM) is used to determine optimal weights of criteria and the Proximity Indexed Value (PIV) method is employed to rank the available AM processes. For benchmarking the abilities of an AM process, a conceptual model of spur gear was fabricated by four available AM processes viz., Vat Photopolymerization (VatPP), Material Extrusion (ME), Powder Bed Fusion (PBF), and Material Jetting (MJ). Additionally, Dimensional accuracy (A), surface roughness (R), tensile strength (S), percentage elongation (%E), heat deflection temperature (HDT), process cost (PC) and build time (BT) has been considered as most significant criteria. Further, sensitivity analysis has been performed to validate the reliability of the results. The results suggested that the Material Jetting (MJ) process produces dimensionally accurate and quality parts among available alternatives AM processes. The ranking obtained using the PIV method is consistent and reliable.

Keywords. Additive manufacturing (AM); best worst method; proximity indexed value method; hybrid MCDM technique; decision support system; AM process selection.

1. Introduction

Additive manufacturing (3D printing) is defined as the process of layer by layer manufacturing of a 3D object directly from its 3D CAD model [1]. Additive manufacturing (AM) was developed in the early 1980s and gained popularity in recent years. The capability of producing complex geometry parts with integrated assemblies and reduced production time has been contributing to the recent popularity of AM processes. AM processes have gained popularity in various industries, i.e., aerospace, automotive, construction, ornaments, food processing, pharmaceuticals, and biomedical industries [2]. According to ASTM/ISO 52900:2015, AM processes are categorized into eight groups, i.e., Vat photopolymerization (VatPP), material extrusion (ME), material jetting (MJ), binder jetting (BJ), sheet lamination, directed energy deposition (DED), powder bed fusion (PBF), and direct-write (DW) [3, 4]. Since its introduction, more than 1000 industrial AM machines and 850 compatible materials have been recognized in the global market [5]. Various online outlets are providing AM services to the industries and individuals by using available machines and materials. Accordingly, the availability of the options putting pressure on the researchers to develop a decision support system for AM processes. The expected framework should provide a suitable choice of AM machine and material as per the demand of end-user. Since, every AM process has its advantages, applications, and limitations. It requires a comprehensive understanding of the interaction of the process parameters such as accuracy, surface finish, time, cost, material properties [6]. Therefore, the selection of the most appropriate AM process to achieve the specific part's requirements is significantly important.

*For correspondence
Published online: 04 May 2020

A substantial research contribution has been done in the selection of the AM process as per desirability over the period of time. Earlier, a few decision support systems using a mathematical model and multi-criteria decision making (MCDM) techniques have been developed for AM process selection. Consequently, Pham and Gault [7] presented an overview of the AM technologies with its strength and weakness by using a logical flowchart technique. It was suggested for the selection of AM process based on the part's requirement. Braglia and Petroni [8] proposed an Analytical Hierarchy Process (AHP) based management support technique for the selection of the AM process considered with the subjective and objective criteria. Masood and Soo [9] developed a rule-based expert system considering 39 rapid prototyping systems commercially available from 21 manufacturers. The developed method for AM process selection was named as *Intelligent RP System Selector* based on the interactive question-answer session with the user. Byun and Lee [6] performed a benchmark study to develop a system for the selection of an appropriate AM process. The modified TOPSIS method and fuzzy approach had been used for ranking and assigning values for cost and build time, respectively. Rao and Padmanabhan [10] developed a methodology for the selection of the AM process using Graph Theory and Matrix Approach (GTMA). The relative importance of criteria had modelled in digraph and matrix-style and evaluated with permanent function. Munguia *et al* [11] proposed an artificial intelligence-based information system integrating fuzzy logic, neural network and a relational database to execute decision-making. In this study, the process variables (part cost estimation, material selection and ranking of chosen AM systems) had been selected by the screening method and rule-based reasoning. Kumar and Jain [12] developed a systematic AHP approach with the help of potential industrial and academic users. Six different technologies had been selected in the study (SLS, SLA, FDM, 3DP, SGC, and LOM), by considering the various product, process, social and environmental issues. Mahapatra and Panda [13] proposed a combined Grey Relational Analysis (GRA) and fuzzy TOPSIS approach for the selection of the AM process. Ghazy [14] developed an AM decision support system (AMDSS) to select appropriate AM process chains, materials, finishing methods, and machines. A Simple Multi-Attribute Rating Technique (SMART) had been utilized for ranking the processes and compatible materials based on the desirability. Shende and Kulkarni [15] introduced an experimentation-based methodology for AM process selection using the GTMA technique. Additionally, a comparison had been made with the TOPSIS method considering part quality, cost and time. Also, the important criteria, such as surface finish, accuracy, tensile strength, elongation, heat deflection temperature, part cost, process time had been considered for ranking of four AM processes. Kek *et al* [16] developed a decision support system using the fuzzy ANP-TOPSIS methodology to select an environment-friendly AM process with required mechanical properties for SLA, SLS, 3DP, and LENS process. Vinodh and Nagraj [17] applied the fuzzy VIKOR method for AM process selection in an agile environment by considering 20 criteria for selection of best AM process among SLA, SLS and FDM processes.

MCDM methods (AHP, TOPSIS, fuzzy AHP-TOPSIS) have been used widely to solve the problem of selection of AM processes [18–21]. These MCDM methods have also been used in the selection of other manufacturing processes, i.e., CNC machine tool selection [22], resilient supplier selection [23], maintenance strategy selection for ship machinery [24]. The AHP and TOPSIS methods have some drawbacks related to a large number of pair-wise comparison for calculating weights. This drawback leads to inconsistency in results and rank reversal problems. Recently developed MCDM methods (Best-Worst Method (BWM) and Proximity Index Value (PIV) method) have been proposed by the researchers in manufacturing with simple calculation steps and minimum rank reversal problem [25, 26]. Since BWM and PIV methods have certain advantages over previously used MCDM techniques and its application has not been explored in this field. Therefore, this article explored an application of a hybrid BWM-PIV MCDM technique to select the most appropriate AM process as per part requirements. In that context, BWM employed to enumerate the user's preferences in defining the criteria weights and subsequently PIV method employed to rank the AM processes. Further, sensitivity analysis has been done to validate the reliability of the results.

2. Methodology

A flowchart of the work performed can be seen and understood in figure 1.

2.1 *Description of the selected decision criteria*

According to literature survey and ISO 17296-3 [27], the most commonly used criteria in the selection of AM process with specific part requirement related to quality, cost, and time can be considered as dimensional accuracy (A), surface roughness (R), mechanical properties such as tensile strength (S), percentage elongation (%E), heat deflection temperature (HDT), part cost (PC), and build time (BT). In that context, dimensional accuracy (A) is defined as the ability of the final product to fall within the tolerance bands for each specified dimension, whereas, surface roughness (R) is defined as the surface texture deviation of a real surface from its ideal surface in the normal direction. The dimensional accuracy (A) and surface roughness (R) is critical to a component produced through any manufacturing process. However, mechanical properties such as tensile strength (S) and percentage elongation (%E) is also critical for the component in service. It is defined as the ability to resist deformation and shape without cracking due to external loads. Heat deflection temperature (HDT) is defined as the temperature at which polymer/plastic starts deforming under a specified load. HDT describes the thermal resistant property of the material used in the fabrication through the AM process. The standard values in degree centigrade (*°C) obtained from a service provider's material datasheet [5]. Additionally, overall process cost (PC) and build time (BT) associated with the additively manufactured component is the economic consideration in the study. The process cost (PC) includes material, machine, labour, tax and other costs. In contrast, build time (BT) is the actual processing time of the component, which includes pre-processing, processing and post-processing.

3. Description of the AM processes

The description of alternative AM processes considered in the present study are as follows.

3.1 *Material Jetting (MJ): Projet MJP 2500*

Projet MJP 2500 plus (figure 2) is the latest professional 3D printer by 3D Systems (USA). It uses piezo printhead technology to deposit either photocurable plastic resin or casting wax material. A high-quality part and speed are the qualities of these 3D Printer series.

Technical Specifications:

Model :	Projet MJP 2500
Technology :	MultiJet Printing (MJP)
Build Volume :	294×211×144 mm
Resolution (XYZ) :	800×900×790 DPI, 32 µ layers
Accuracy :	±0.025 – 0.05 mm per 25.4 mm
Input data files :	STL, OBJ, PLY, 3DS, FBX, IGES, IGS, STEP, STP
Operating Temperature :	18–28 °C, print speed reduced at 25 °C
Post-processing :	MJP EasyClean System for easy removal of wax supports

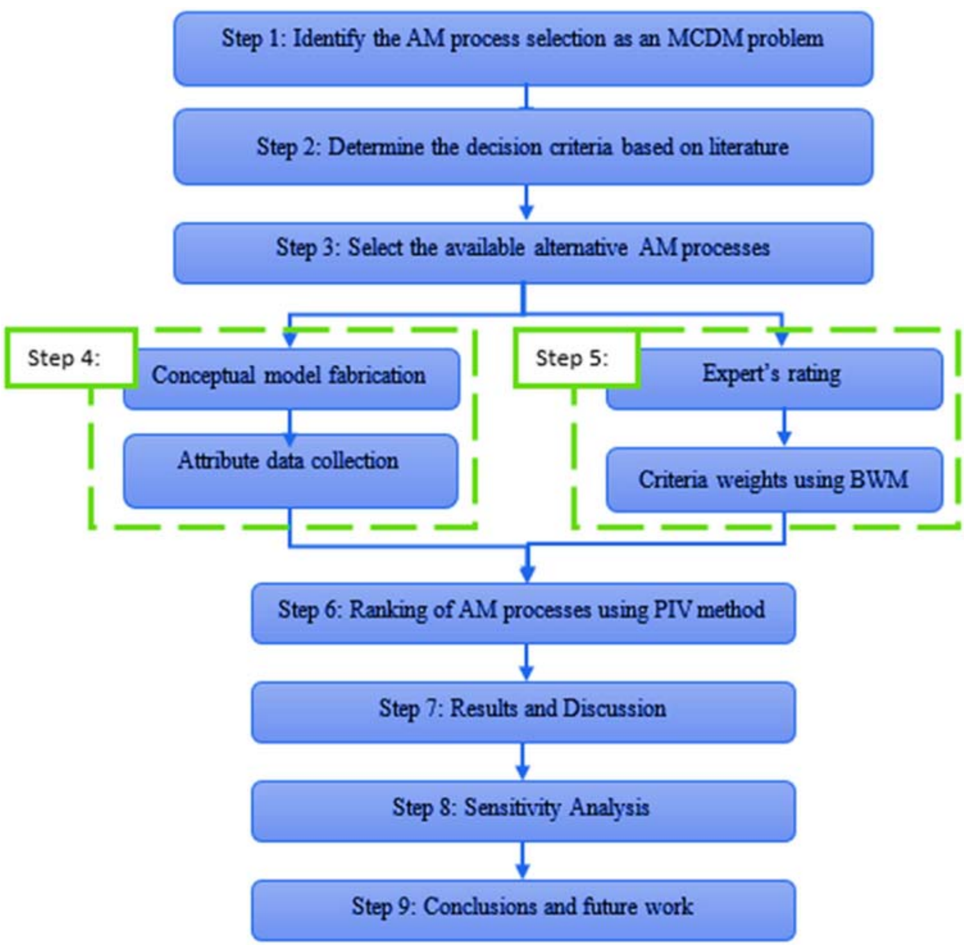

Figure 1. Methodology framework.

Support Material :	VisiJet M2 SUP
Build Materials :	VisiJet ProFlex M2G-DUR Tough, clear polypropylene-like VisiJet M2R-WT– Rigid white VisiJet M2R-BK– Rigid black, etc.

3.2 *Vat Photopolymerization (VP): EKA DLP 3D Printer*

EKA DLP 3D Printer (figure 3) is the high-speed and precise DLP 3D printer with a printing speed of 100 mm/hr by Make3D (Surat, India). This machine comes with a Full HD UV LED Projector Engine, which gives 30000 hours of working life to make prototypes/components mainly for jewellery/ornaments.

Technical Specifications:

Model :	EKA
Technology :	DLP, Full HD UV LED Projector Engine
Platform Size :	65×110×120 mm
Resolution XY :	53 µm
Resolution Z :	10 to 50 µm
Printing Speed :	Up to 2500 layers/hour
Input files :	*.STL
Resins :	Castable and Non castable (Plastic epoxy resins)

3.3 *Material Extrusion (ME): Pratham*

Pratham desktop 3D printer (figure 4) is an accurate and reliable liquefied fused filament fabrication (FFF) technology-based 3D printer manufactured by Make3D (Surat, India). Aluminium heat bed, filament finish sensor, advanced smart cooling, and multi-material support (ABS/PLA/metal fill/wood fill) are the key feature of this 3D printer.

Technical specifications

Model :	Pratham
Technology :	Liquefied filament fabrication/Fused deposition modeling
Platform Size :	200×200×250 mm
Resolution XYZ :	11 µm
Dimensional Tolerance :	± 0.1 mm
Extruder Temperature :	280 °C (max)
Printing Speed :	40–120 mm/sec
Nozzle size :	0.4 mm (E3D standard)
Filament Diameter :	1.75 mm
Input files :	*.STL/GCODE
Filament compatible :	ABS/PLA/HIPS/Composites

3.4 *Powder Bed Fusion (PBF): EOS P396*

EOS P 396 (figure 5) is a medium-sized industrial SLS 3D printer produced by EOS-GmbH, Germany. A CO_2 laser is used to transform powder layer into finished objects. The EOS P 396 3D printing machine can produce high-quality functional prototypes and components using various powder materials.

Technical specifications:

Model :	EOS P 396
Technology :	Selective Laser Sintering (SLS)
Building volume :	340×340×600 mm
Laser type :	CO_2 Laser
Building rate :	Up to 3.0 l/h
Layer thickness :	0.06–0.10–0.12–0.15–0.18 mm (depending on material)
Precision optics :	F-theta lens, high-speed scanner
Scan speed :	up to 6 m/s

Figure 2. Projet MJP 2500 Machine [28].

Figure 3. EKA DLP 3D Printer [29].

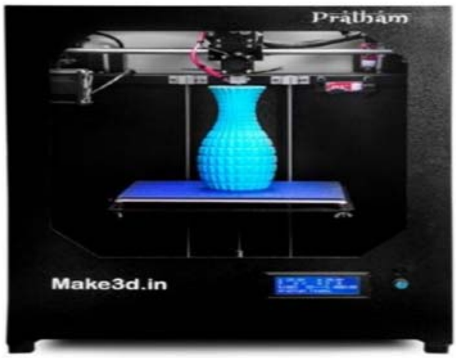

Figure 4. Pratham 3D Printer [30].

Software :	EOS Parameter Editor, EOSAME, EOSYSTEM
Materials compatible :	Polyamide-Nylon 11, Nylon 12 (PA 2200) and Polystyrene

4. Conceptual model fabrication

A conceptual model (spur gear) has been fabricated using four alternative AM processes to benchmark respective attribute abilities. A flowchart for the development of the 3D part is shown in figure 6. The 3D model of spur gear was developed in CAD software PTC Creo 4.0.

4.1 *AM process attribute data collection*

Material Jetting (MJ), Vat Photopolymerization (VatPP), Material Extrusion (ME), and Powder Bed Fusion (PBF) processes have been used to fabricate benchmark spur gear (figure 7). The numerical values of dimensional accuracy have been recorded by measuring the bore diameter with the *Mitutoyo Dial Vernier Caliper* for each manufactured part. While the surface roughness was measured on the face part of the gear teeth (z-direction) by *Roughness Tester Taylor Hobson Surtronic S128* device. The measured attribute data (three iterations) is given in table 1.

Figure 5. EOS P 396 Machine [31].

The values of mechanical properties (tensile strength and percentage elongation) and the thermal property (heat deflection temperature - HDT) has been obtained from the manufacturer's standard material datasheet. The economic criteria (build time) has been recorded from the AM machine console. Additionally, the process cost (material cost, machine cost, and labour cost) has been estimated for each AM process. The numerical values of the considered attributes for each process are shown in table 2.

5. Decision making methods

In this study, a hybrid MCDM technique has been used to develop a decision support system for the selection of an AM process combining Best-Worst Method (BWM) and Proximity Indexed Value (PIV) method.

5.1 *Best worst method (BWM)*

Rezaei has developed Best Worst Method (BWM) in 2015 [25, 32], being a new MCDM method used to calculate an optimal weight of the criteria. The better ordinal consistency, consistent comparisons, minimum total deviation that ensures a closer weight ratio and a lesser number of comparisons are the key advantages of this method over AHP [32–34]. The selection of the best factor (most important) and the worst factor (least important) is the critical step of this method [35]. Subsequently, in this study, a pair-wise comparison of best and worst factors with other considered criteria has been performed on a 9-point scale. A linear optimization model has been used to determine optimal weights and consistency, which is later used to check the reliability and optimality of criteria weights. The necessary steps of BWM involved in this study include:

Step 1: Identification of a set of decision criteria $\{c_1, c_2, \ldots, c_n\}$ for the selection of the AM process. In this study, dimensional accuracy (A), surface roughness (R), tensile strength (T), elongation (E), heat deflection temperature (HDT), process cost (PC) and build time (BT) has been chosen as a set of decision criteria.

Step 2: To select the best and worst criteria. In this study, the best and worst criteria chosen according to the expert's opinion.

Step 3: Determination of the preference of best criterion over other criteria through pair-wise comparisons (see figure 8 to understand comparison) using a 9-point scale (or a scale of relative importance) is shown in table 3.

This step would form the best to others (BO) vector as:

$$X_B = [x_{B1}, x_{B2}, x_{B3} \ldots, x_{Bn}]$$

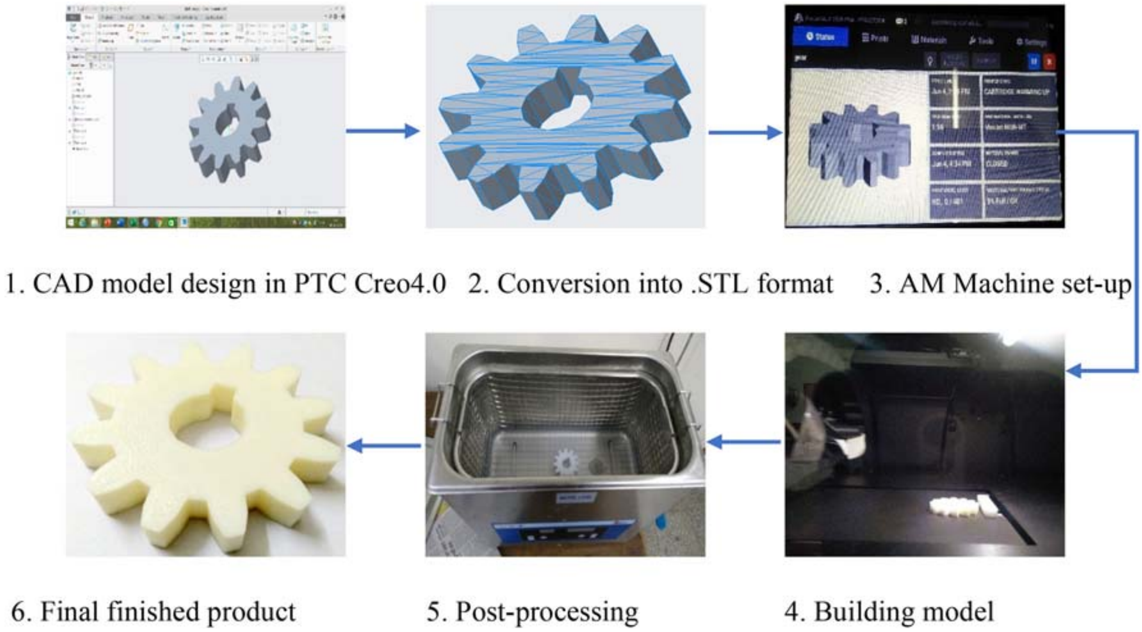

Figure 6. Steps involved in model fabrication by the AM process.

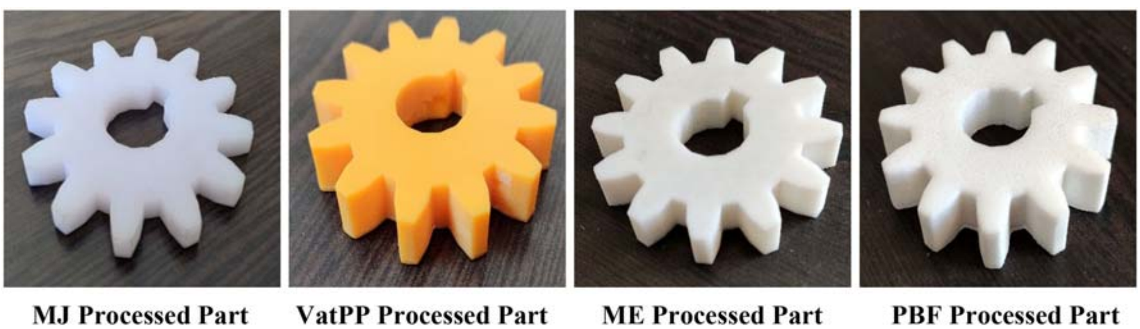

Figure 7. Models fabricated by four alternative AM processes.

Table 1. Measured attribute data values.

AM process Iterations	Material	Dimensional accuracy (± mm)				Surface roughness-Ra (µm)			
		1	2	3	Average	1	2	3	Average
MJ	Visijet M2R-WT	0.11	0.13	0.08	0.106	6.37	5.94	6.03	6.11
VP	ABS TRU Resin	0.81	0.88	0.54	0.743	3.87	2.80	2.50	3.06
ME	PLA Plus	0.28	0.19	0.50	0.323	21.0	21.0	17.9	19.96
PBF	Nylon 12 PA2200	0.15	0.20	0.06	0.136	15.7	10.6	9.07	11.79

Where x_{Bj} is the importance of best criterion over the jth criterion and hence $x_{BB} = 1$.

Step 4: This step is similar to step 3. As the comparison (see figure 8 to understand comparison) of all the criteria with the worst criterion has been performed. It leads to the formation of others-to-worst (OW) vector as:

$$Y_w = [y_{1w}, y_{2w}, y_{3w} \ldots, y_{nw}]$$

Table 2. AM Process attributes/criteria data collection.

AM process	Machine	Material	Dimensional accuracy* (A)	Surface roughness (R)	Tensile strength (S)	Elongation (%E)	Heat deflection Temp. (HDT)	Process cost (PC)	Build time (BT)
Units			mm	µm	MPa	%	°C	Rs	Min
Goal			(−)	(−)	(+)	(+)	(+)	(−)	(−)
Material jetting (MJ)	Projet MJP 2500	Visijet M2R-WT	0.106	6.11	45	30	51	1000	140
Vat Photopolymerization (VatPP)	EKA DLP 3D Printer	ABS TRU resin	0.743	3.06	49	10.2	50	700	30
Material extrusion (ME)	Pratham LFF 3D Printer	PLA Plus	0.323	19.96	60	29	52	300	72
Powder bed fusion (PBF)	EOS P 396	Nylon12 PA2200	0.136	11.79	48	18	163	1180	160

*Deviation of bore diameter from the nominal value (in mm)

Where y_{jw} is the importance of the j^{th} criterion for the worst criterion and hence $y_{ww} = 1$.

Step 5: Calculation of the optimal weights (w_1*, w_2*, w_3* …, w_n*). To determine the optimal weights, the absolute maximum differences {$|w_B^- x_{Bj}w_j|$, $|w_j^- y_{jw}w_w|$} for all j should be minimum, which can be written as:

$$\begin{aligned} &\mathrm{Min} - \max\left\{ |w_B - x_{Bj}w_j|, |w_j - y_{jw}w_w| \right\} \\ &\text{Subject to :} \\ &\qquad \Sigma_j w_j = 1 \\ &w_j \geq 0, \text{ for all j} \end{aligned} \tag{1}$$

Eq. (1), can be converted in terms of the linear programming model:

$$\begin{aligned} &\mathrm{Min}\ \xi^L \\ &\text{Subject to:} \\ &\qquad |w_B - x_{Bj}w_j| \leq \xi^L \text{ for all j} \\ &\qquad |w_j - y_{jw}w_w| \leq \xi^L \text{ for all j} \\ &\qquad \Sigma_j w_j = 1 \\ &\qquad w_j \geq 0, \text{ for all j} \end{aligned} \tag{2}$$

On solving Equation (2), a unique solution for the optimal weights (w_1*, w_2*, w_3* …, w_n*) and the optimal value of the consistency ratio ξ^{L*} has been obtained. The value of ξ^{L*} close to zero indicates a high degree of consistency and vice-versa.

5.2 *Proximity Indexed Value (PIV) method*

Mufazzal and Muzakkir developed the PIV method in 2018 [26]. The ranking of the alternative AM processes has been obtained by this new method to minimize the rank reversal problem compared to other MCDM methods. The steps involved in this method are (workflow is shown in figure 9):

Step 1: Identify the available alternatives Ai (i = 1, 2, …, m) and decision criteria Cj (j = 1, 2,.., n) involved in the decision making problem.

Step 2: Construct a decision matrix *R* by arranging alternatives in rows and criteria in columns, as shown in Eq. (3)

$$R = [r_{ij}] = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1j} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & \cdots & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ r_{i1} & \cdots & \cdots & r_{ij} & \cdots & r_{in} \\ \cdots & \cdots & \cdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \tag{3}$$

Where r_{ij} represents the i^{th} alternative actual value of j^{th} criteria, n is the number of criteria, and m is the number of alternatives.

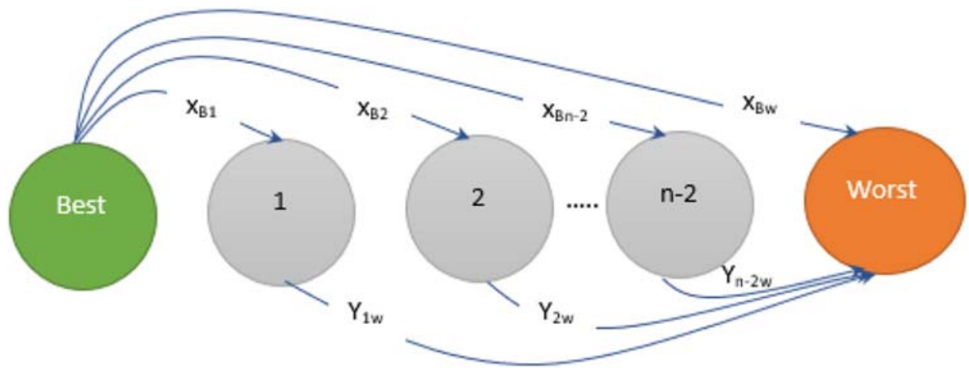

Figure 8. Preference comparison in BWM [32].

Table 3. The scale of the relative importance.

Relative important scale	Description
1	**Equal** Importance
2	Somewhat between equal & moderate
3	**Moderately** more Important
4	Somewhat between moderate & strong
5	**Strongly** more Important
6	Somewhat between strong & very strong
7	**Very Strongly** Important
8	Somewhat between very strong & extreme
9	**Extremely** Important

Step 3: Normalize the decision matrix using vector normalization formulae given as:

$$r^*_{ij} = \frac{r_{ij}}{\sqrt{\sum_1^m r^2_{ij}}} \tag{4}$$

Where, r^*_{ij} = Normalized value of ith alternative of jth criteria.

Step 4: Calculation of the weighted normalized decision matrix using weights calculated by the BWM method.

$$V_{ij} = r^*_{ij} \times w_j \tag{5}$$

Where V_{ij} = is the weighted normalized value, w_j = weight of criterion

Step 5: To determine the Weighted Proximity Index (WPI) (u_i) through Equation (6)

$$u_i = \begin{cases} v_{max} - v_i; & \textit{for beneficial criteria} \\ v_i - v_{\min} & \textit{for cost criteria} \end{cases} \tag{6}$$

Step 6: Determine the overall proximity value (d_i) which indicates the closeness of alternative for the best alternative, which can be calculated through Equation (7)

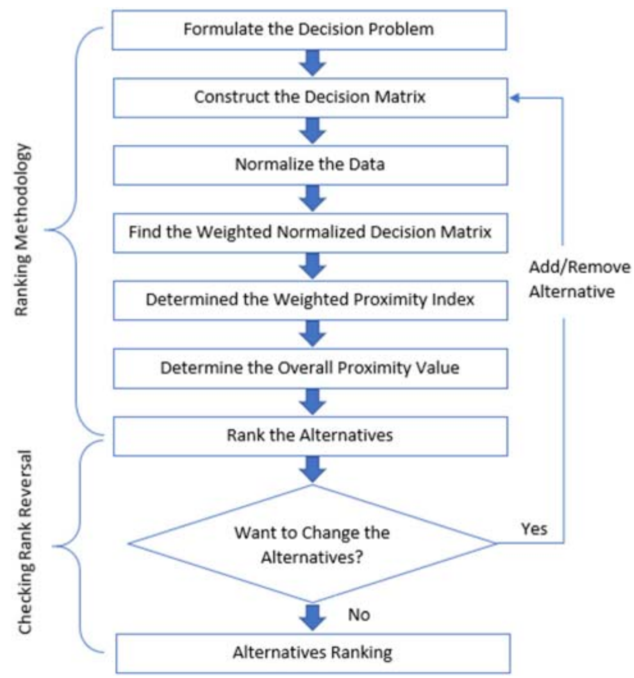

Figure 9. Flowchart depicting the PIV method [26].

$$d_i = \sum_{j=1}^{m} u_i \tag{7}$$

Step 7: Rank the alternative AM processes based on increasing d_i values. The least value of $d_i$has been ranked first as it has a minimum deviation from the best.

6. Results and discussion

Vat Photo-polymerization (VatPP), Material Extrusion (ME), Powder Bed Fusion (PBF), and Material Jetting (MJ) has been included as an available AM process in this study. Also, the seven evaluation criteria have been selected as dimensional accuracy (A), surface roughness (R), tensile strength (S), percentage elongation (%E), heat deflection temperature (HDT), process cost (PC), and build time (BT). In table 2, the beneficial criteria with higher values have been preferred and indicated by (+) and cost criteria with lower values have been preferred and indicated by (−). For the validation of the study, a conceptual model of spur gear has been fabricated using available AM processes. It was set to achieve high dimensional accuracy and surface quality for design verification purposes. The experimentally measured average values of dimensional accuracy and surface roughness have been listed in table 1. The other criteria values (tensile strength, percentage elongation, heat deflection temperature, build time, and process cost) have been presented in table 2, i.e., a decision matrix used as a database in a decision support framework for the selection of an appropriate AM process.

The data collected, for the calculation of criteria weights using the BWM, based on the interview conducted of five users (first 3 was chosen as academic experts in AM processes, one as industry expert engineer, and one as manufacturer service bureau expert). The purpose has been explained to the experts during interaction for identification of the best and the worst criteria. The experts and users have been asked to provide their preferences of the best criterion over other criteria on a scale of 1 to 9, which forms the Best to Others (BO) vector as given in table 4. Similarly, they have also been asked to give importance to other criteria over the worst criterion on the same scale, which form others to Worst (OW) vector as given in table 5.

Consequently, the data collected in tables 4 and 5 have been used to calculate optimal weights for each criterion considering the expert's opinion with the help of Equation (2). The values of the criteria weight and consistency ratio are listed in table 6. The final optimal weight of each criterion is obtained by averaging the weights of all experts (shown in the last row of table 6 and the graphical representation of the obtained criteria weights in figure 10).

It can be observed from table 6, that the average consistency ratio (ξ^{L*} = 0.0876) is minimal compared to 1. Hence, the weights of criteria are optimal and reliable.

The normalized decision matrix has been obtained by using Equation (4) and presented in table 7.

The last row of table 6 shows the weights of the criteria calculated by the BWM. Further, it has been used in Equation (5) to determine the weighted normalized decision matrix (table 8).

The Weighted proximity index (u_i) values have been obtained using Equation (6) given in table 9.

Lastly, the ranking of alternative AM processes has been done based on the increasing overall proximity values (d_i) calculated by using Equation (7). The overall proximity values and ranking of the alternative processes are presented in table 10.

Table 4. Best criterion and best to others (BO) vector.

Expert no.	Best criterion	A	R	S	%E	HDT	PC	BT
1	A	1	1	3	5	7	6	6
2	R	1	1	4	6	6	7	8
3	A	1	2	1	7	8	9	7
4	S	1	3	1	2	5	7	7
5	R	1	1	2	5	6	9	8

Table 5. Worst criterion and others to worst (OW) vector.

Expert no.	1	2	3	4	5
Worst criterion	HDT	BT	PC	BT	PC
A	7	8	9	7	9
R	7	8	8	6	9
S	5	6	7	7	8
%E	4	5	5	4	7
HDT	1	7	6	5	5
PC	3	3	1	3	1
BT	3	1	2	1	3

Table 10 and figure 11 have revealed the ranking of the alternative AM processes. The minimum value of $\mathbf{d_i}$ corresponds to Material Jetting (MJ) process (ranked 1), is the most suitable AM process in this study. The ranking order has been obtained as MJ > PBF > ME > VP.

The ranking of the alternative AM processes obtained through PIV method in table 10 clearly shows that the Material Jetting (MJ) process is the best choice among four available AM processes. For the fabrication of models for design verification purpose and end-use applications, Material Jetting (MJ) process has been found suitable as it has a least dimensional variation (i.e., 0.106 mm) and high percentage elongation. Vat photopolymerization (VP) is the worst choice as it gives high dimensional variation (i.e., 0.743 mm) due to liquid material contraction changing phase from liquid to solid. Although it has a better surface finish, still, considering other all criteria it is ranked 4. Material Extrusion has the highest tensile strength though it is ranked 3. Depending upon the application, the ranking may be varied on providing different weights to the criteria.

7. Sensitivity analysis

Sensitivity analysis has been performed to ensure the integrity of the obtained results and also absolve the effect of the highest weight criteria on the other criteria considered in this study. The methodology available in the references [36–38] has been used to perform sensitivity analysis to test the ranking obtained by varying the weights of all criteria with respect to the highest weighted criterion.

Table 6. Optimal weights of criteria.

Expert no.	A	R	S	%E	HDT	PC	BT	Consistency-ratio (ξ^{L*})
1	0.3163	0.3163	0.1275	0.0765	0.0357	0.0637	0.0637	0.0663
2	0.3268	0.3268	0.1100	0.0733	0.0733	0.0628	0.0266	0.1133
3	0.3216	0.2094	0.2718	0.0598	0.0523	0.0249	0.0598	0.0972
4	0.2780	0.1175	0.2780	0.1763	0.0705	0.0503	0.0290	0.0746
5	0.2976	0.2976	0.1922	0.0769	0.0640	0.0234	0.0480	0.0869
Average	0.3080	0.2535	0.1959	0.0925	0.0591	0.0450	0.0454	0.0876

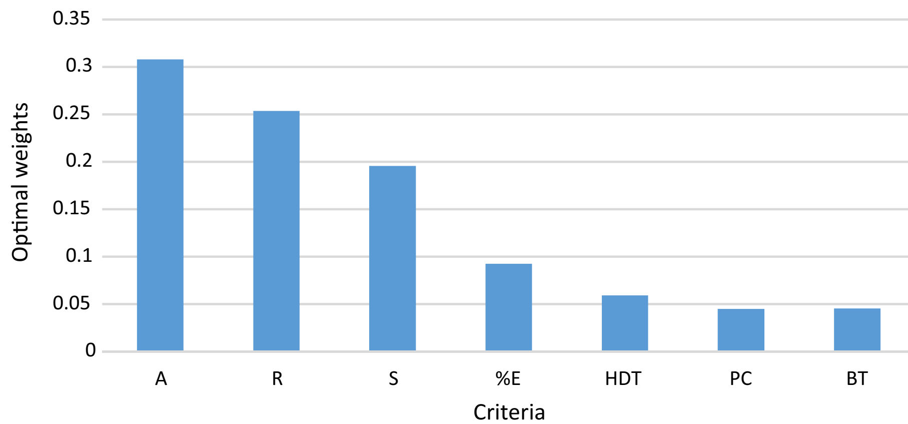

Figure 10. Optimal weights of criteria.

Table 7. Normalized decision matrix.

AM process Goal	A (−)	R (−)	S (+)	%E (+)	HDT (+)	PC (−)	BT (−)
MJ	0.1279	0.2528	0.4427	0.6441	0.2725	0.5800	0.6182
VP	0.8970	0.1266	0.4821	0.2190	0.2993	0.4060	0.1324
ME	0.3899	0.8258	0.5903	0.6226	0.2779	0.1740	0.3179
PBF	0.1642	0.4878	0.4722	0.3865	0.8711	0.6844	0.7065

Table 8. Weighted normalized decision matrix (V_{ij}).

AM process Goal	A (−)	R (−)	S (+)	%E (+)	HDT (+)	PC (−)	BT (−)
MJ	0.0394	0.0641	0.0867	0.0595	0.0161	0.0261	0.0280
VP	0.2763	0.0321	0.0944	0.0202	0.0176	0.0182	0.0060
ME	0.1201	0.2093	0.1156	0.0576	0.0164	0.0078	0.0144
PBF	0.0505	0.1236	0.0925	0.0357	0.0514	0.0307	0.0320

Table 9. Weighted proximity index (u_i values).

AM process Goal	A (−)	R (−)	T (+)	%E (+)	HDT (+)	PC (−)	BT (−)
MJ	0	0.0319	0.0289	0	0.0353	0.0182	0.0220
VP	0.2368	0	0.0212	0.0393	0.0338	0.0104	0
ME	0.0807	0.1772	0	0.0019	0.0350	0	0.0084
PBF	0.0111	0.0915	0.0231	0.0238	0	0.0229	0.0260

Table 10. Overall proximity (di) value and ranking.

AM process	Overall proximity value (d_i)	Rank
MJ	0.1366	1
VP	0.3416	4
ME	0.3034	3
PBF	0.1987	2

In this work, the highest weighted criterion is dimensional accuracy (A), and therefore its weight has been varied from 0.1 to 0.9. Further weights of all other criteria have been calculated using the following equations [36].

- If the weight of the *Pth* attribute changes by Δp, then the weight of other attributes changes by Δj, where:

$$\Delta j = \frac{\Delta p * w_j}{w_p - 1}; \quad \mathrm{j} = 1, 2, ..\mathrm{k}\ ;\ \mathrm{j} \neq p \tag{8}$$

- The new weight of P_{th} attribute (Maximum weighted) changes as:

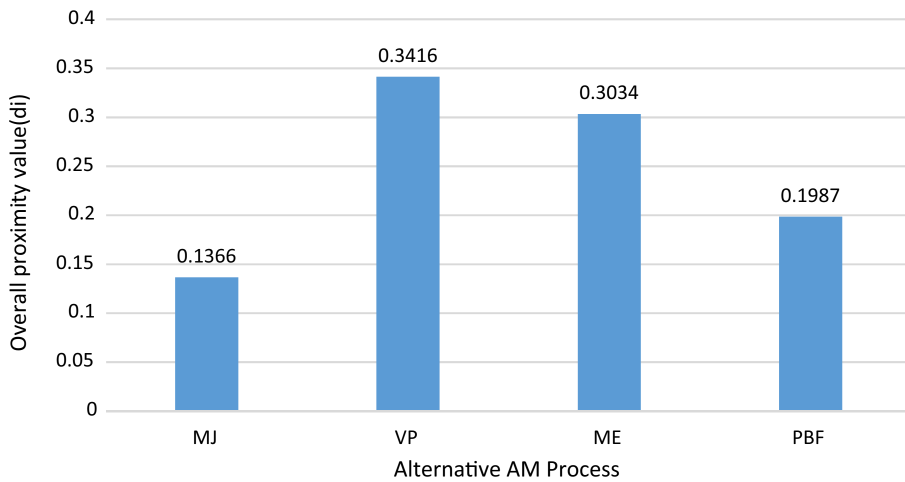

Figure 11. Ranking of alternative AM processes.

Table 11. Weights of the criteria during sensitivity analysis.

Criteria	Normal	Modified weights of all criteria when the weight of A is varied from 0.1 to 0.9								
A	0.3081	0.1000	0.2000	0.3000	0.4000	0.5000	0.6000	0.7000	0.8000	0.9000
R	0.2535	0.3298	0.2931	0.2565	0.2198	0.1832	0.1466	0.1099	0.0733	0.0366
S	0.1959	0.2548	0.2265	0.1982	0.1699	0.1416	0.1132	0.0849	0.0566	0.0283
%E	0.0926	0.1204	0.1070	0.0936	0.0803	0.0669	0.0535	0.0401	0.0268	0.0134
HDT	0.0592	0.0769	0.0684	0.0598	0.0513	0.0427	0.0342	0.0256	0.0171	0.0085
PC	0.0450	0.0586	0.0521	0.0455	0.0390	0.0325	0.0260	0.0195	0.0130	0.0065
BT	0.0454	0.0591	0.0525	0.0459	0.0394	0.0328	0.0263	0.0197	0.0131	0.0066
Sum	1	1	1	1	1	1	1	1	1	1

Table 12. Ranking of AM Processes during sensitivity analysis.

Alternative AM Process	Normal (0.3080)	Run0.1	Run0.2	Run0.3	Run0.4	Run0.5	Run0.6	Run0.7	Run0.8	Run0.9
MJ	1	1	1	1	1	1	1	1	1	1
VP	4	2	4	4	4	4	4	4	4	4
ME	3	4	2	3	3	3	3	3	3	3
PBF	2	3	3	2	2	2	2	2	2	2

$$w'_p = w_p + \Delta p \tag{9}$$

- Weight of other attributes changes as:

$$w'_j = w_j + \Delta j \tag{10}$$

Table 11 shows the new weights during sensitivity analysis of all criteria calculated by varying weight of dimensional accuracy from 0.1 to 0.9.

Due to change in the weights of the criteria, the ranking of the alternative AM process has also been changed. Hence, the ranking of the alternative AM process is shown in table 12.

It is evident from table 12 that when the weight of the dimensional accuracy (A) is varied from 0.1 to 0.9, then MJ occupies rank 1 (throughout). However, during run 0.1 and 0.2, the rank of the VP and ME process get interchanged from 4 to 2, and vice versa and PBF process occupy rank 3. Table 12 also reveals that for all the weights' variation from 0.2 to 0.9, the VP process always occupies 4th rank. The weights of criteria and ranking of alternative AM

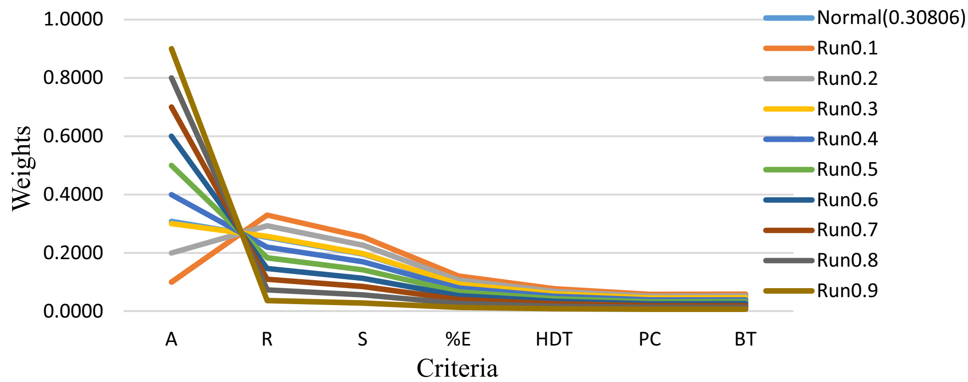

Figure 12. Weights of all the criteria during sensitivity analysis.

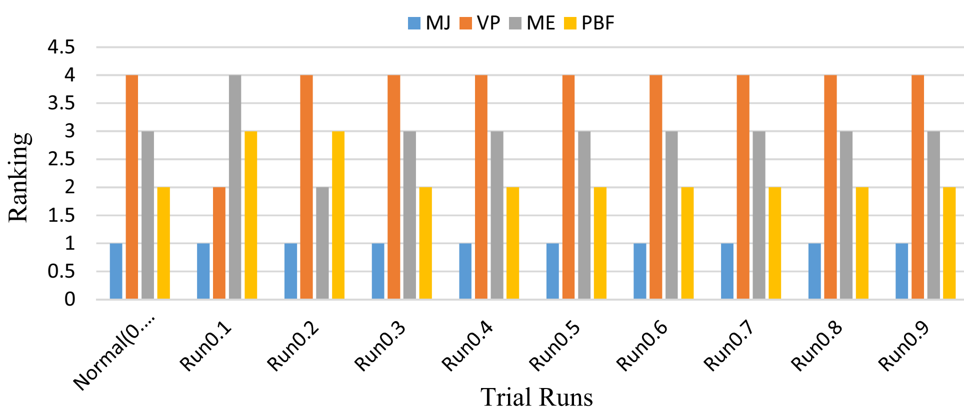

Figure 13. Ranking of alternative AM processes during sensitivity analysis.

processes derived from the sensitivity analysis are also shown in Figures 12 and 13, respectively.

From the sensitivity analysis, it is evident that in 7 evaluation criteria, dimensional accuracy (A) and surface roughness (R) is the most important criteria for the selection of a suitable AM process. Material Jetting (MJ) process takes rank 1 as the most suitable AM process. Hence the results obtained using PIV are highly consistent and reliable.

8. Conclusions and future work

Additive manufacturing is a new manufacturing technology, which can produce complex geometry and intricately shaped parts in a relatively short time and at a low cost. Factually, limited information related to the AM process makes the choice of selection of suitable AM process difficult. Multi-criteria decision-making (MCDM) methods can quickly solve the selection of available AM processes based on various conflicting criteria. This article presents a methodology for a decision support system for the selection of the AM process. A conceptual model (spur gear) was fabricated on four available AM processes to benchmark its ability for practical application. Based on the results obtained, the following conclusions can be drawn from the study.

1. The proposed new hybrid MCDM technique can provide a suitable framework for the selection of AM process according to a particular application and a conceptual model.
2. The ranking obtained to achieve the desired dimensional accuracy, and surface quality is Material Jetting (MJ) > Powder Bed Fusion (PBF) > Material extrusion (ME) > Vat photopolymerization (VP).
3. The Material Jetting (MJ) process appears to the most feasible option among the available four processes to provide the best component as it can provide better dimensional accuracy and lower surface roughness.

4. The data obtained through this benchmarking study can lead to a basis for database creation for the selection of AM processes.
5. The proposed methodology can be used in the selection problem of other application areas of manufacturing, such as material selection, machine tool selection, etc.

Future scope of the work could be the inclusion of more AM processes and compatible materials. Additionally, more experts can be involved to obtain more precise results related to benchmarking of AM processes and materials.

Nomenclature

AM	Additive Manufacturing
3DP	Three-Dimensional Printing
CAD	Computer-Aided Design
ISO	International Standards Organization
ASTM	American Society for Testing and Materials
MCDM	Multi-Criteria Decision Making
LOM	Laminated Object Manufacturing
LENS	Laser-Engineered Net Shaping
SGC	Solid Ground Curing
SLS	Selective Laser Sintering
FDM	Fused Deposition Modeling
SLA	Stereolithography
BWM	Best Worst Method
PIV	Proximity Indexed Value
AHP	Analytical Hierarchy Process
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
HDT	Heat Deflection Temperature
PC	Part Cost
BT	Build Time
MJ	Material Jetting
ME	Material Extrusion
PBF	Powder Bed Fusion
VatPP	Vat Photopolymerization

Symbols

A	Dimensional Accuracy
R	Average Surface Roughness
S	Tensile Strength
E	%age Elongation
w_j	Weight of criteria
di	Overall Proximity Value
ξ^{L*}	Average consistency ratio
*.STL	Stereo-Lithography file

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