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Additive Manufacturing Service Provider Selection Using a Neutrosophic Best Worst Method

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Abstract

Additive manufacturing (AM) is poised to disrupt the manufacturing industry due to its distinctive (layer-by-layer) approach to part production, as AM comprises a range of fabrication techniques that facilitate the production of customized and highly complex parts. For a particular part selecting the most suitable AM machine and material is an indispensable decision due to several AM machines, their process and material constraints like size, accuracy, mechanical properties etc. This paper demonstrates the multi-criteria framework using Delphi and neutrosophic best-worst method to determine the best suitable AM machine and feasible material from the spool of databases. The Delphi method is employed to determine and validate essential criteria for a selected part, which results in shortlisting the 9 most relevant criteria. Further, the neutrosophic best-worst method is utilized to compute the criteria weights. A rating and normalization approach is deployed to calculate each AM machine and compatible material aggregate score to determine the optimal AM machine, material and ultimately, the AM service provider.

Keywords: Additive Manufacturing, 3D printing, AM service providers, Neutrosophic best worst, Best worst, Delphi

1. Introduction

Additive Manufacturing (AM), one of the distinctive manufacturing technology of Industry 4.0 (I4), has been widely espoused in various industries due to its capabilities of state-of-the-art and complex shape with customization of part manufacturing with no need for tooling [1,2]. AM has been uncovered in numerous applications in the

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engineering industries like automotive, aviation etc., as well as in more areas, for instance, education, architecture, toys, medicine, entertainment and cartography [2,3]. According to [4], more than 1750 AM machines and 3750 types of materials are available in the global market. Considering the several AM machine options, choosing the most appropriate ones corresponding to a particular part is still evolving. There are some case examples of AM process selections which used selective laser sintering (SLS), fused deposition modelling (FDM), and stereolithography (SLA) technologies. Although there are enough literature articles available for suitable AM process selection for a specified part, this literature is limited to criteria like accuracy, tensile strength, elongation, build time and cost [3,5–7]. These studies exclusively discuss AM process selection; thus, the suitable AM machine and material selection are overlooked as each machine has some constrain like build volume, size, tensile strength etc.

Further, The AM service provider cost and lead time might vary for the same product, and different types of machines increase the intricacy more. Thus, the first step in identifying the most feasible machine, material and service provider for specified parts is to identify the relevant criteria. The second step is to an assessment of each AM machine and material based on the shortlisting criteria for selecting the most compatible AM service provider. The work is shallow in this area of research. Thus the present research work is established to bridge this gap in the existing knowledge and introduce a Delphi methodology to identify the most relevant criteria. Further, a neutrosophic best worst methodology (NBWM) is deployed to determine each criterion's relative weights, which are used to calculate the aggregated score of each AM machine according to AM service provider to select the best one.

2. Methodology

The present study uses a two-stage methodological approach to determine the most suitable AM process (combination of machine and material) and AM service provider for a specified part. The intent of this research is accomplished by contemplating the subsequent research objectives:

RO 1. Shortlisting the most relevant criteria used for the specified part.

RO 2. Computation of relative criteria weight for each criterion.

RO 3. Calculate the aggregate score for each AM process to determine the best suitable AM machine, material and service provider.

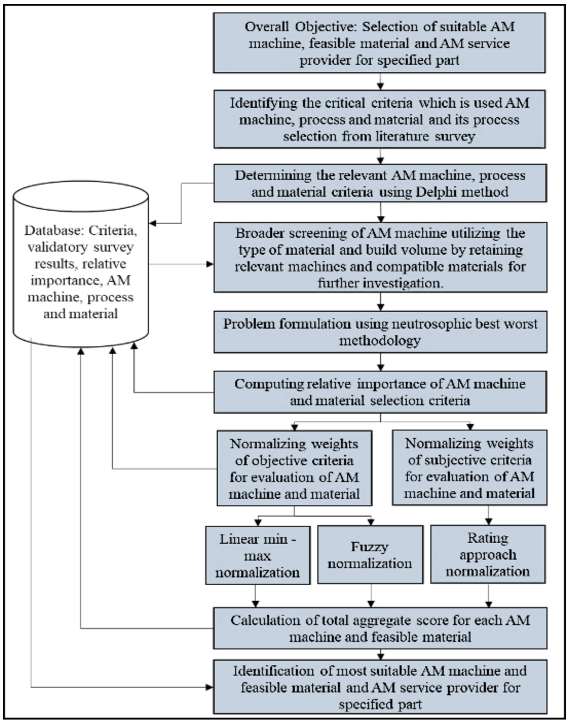

Fig. 1. Methodology

Initially, an extensive literature review is carried out to determine the available criteria that are used in AM machine, process and material selection. Further, the Delphi methodology is employed to shortlist the relevant criteria that can use to identify the compatible AM machine and material for a specified part (see Fig. 1). NBWM methodology is employed to determine the relevant criteria weights. To assess each criterion value according to each AM machine, material and AM service bureau, three normalization approaches are utilized (linear min-max, rating and fuzzy normalization). Lastly, the aggregate score is computed according to each AM machine, material and service provider to select the best one.

3. Case Example

A real-life industrial case example is demonstrated to showcase the methodology's efficacy for practitioners in decision-making on the best suitable AM machine and material selection from available databases for the specified part. Initially, the authors performed the workshop to identify the suitable parts produced through AM for case company experts working in production, maintenance, and procurement departments with the expertise of over 7 years. This workshop, at the outset, exemplifies AM's benefits, limitations, and applications. Further, an outline of the most compatible parts for AM has been discussed by showcasing some examples and carrying out some exercises to shortlist the compatible parts that can be manufactured through AM, which leads to shortlisting the specified part (see Fig.2).

3.1. Determining relevant criteria – Delphi

At first, the author extensively surveyed the available criteria used in AM machine, process and material selection, which is incorporated and resulted in summarizing the 25 criteria used for AM machine and process selection[2,3]. The authors employed the Delphi approach to ascertain the relevant criteria for the specified part. It is an iterative method to calculate well-versed judgements of experts by eliminating the shortcomings due to disagreements of thoughts [2]. The consensus among the experts has reached after three rounds. Thus, the content validity ratio (CVR) is employed to gauge the consensus. The CVR is demonstrated by:

$$CVR = \frac{N_{PE} - (^{N}/_{2})}{(^{N}/_{2})} \tag{1}$$

Where,

"CVR= Content validity ratio", "N= Total no. of experts", "N_{PE}= No. of experts indicating the criteria is critical for part".

CVR threshold limit to retain or choose the criteria is 0.29 [2], which means that the criteria with CVR $\geqslant$ 0.29 is retained, and the rest of the others are excluded. 7 AM experts have participated in the study who have extensive expertise in part design, development, manufacturing, quality and testing with a minimum of 5 years of experience. These experts assist in retaining the most significant AM machines, process and material selection criteria for further study. As demonstrated in Table 1, Delphi determined the 9 most relevant criteria for the specified part: build volume, type of material, traditional manufacturing (TM) part material, accuracy, surface finish, unit cost, lead time, tensile strength and flexural strength. The build volume and type of material are used to screen out the non-relevant AM machine from the spool of the database.

Table 1. Criteria shortlisted for AM machine and its process selection by Delphi approach

Screening criteria	Evaluation criteria	Information criteria
Build volume	Cost (C1)	Actual part material
Type of Material	Surface Finish (C2)	
	Accuracy (C3)	
	Tensile Strength (C4)	
	Flexural Strength (C5)	
	Lead Time (C6)	

Initially, the authors contacted 9 AM service providers, of which 2 AM service providers shared their interest in contributing to this study. These 2 AM service providers share the available machine, its process and suitable material information, which is gathered to develop the database according to the criteria specified. Further, as exemplified in Table 4, the authors have removed the incompatible machine by utilizing the screening criteria of the type of material used by the machine and build volume. For example, direct metal laser sintering (DMLS), electron beam melting (EBM) and directed energy deposition (DED) machines are exclusively used for the fabrication of metal parts; consequently, polymers and ceramic parts are not viable for production by these machines. Likewise, every AM machine has the limitation of build volume; thus, the machines with a build volume less than the size of the specified part are removed from this study.

3.2. Part specification and CAD model

The case company has shared the part specification and CAD model with AM service providers for further evaluation. The part shown in Fig. 2 is used in the forging machine; in addition, it incurs the essential parameters, which are illustrated in Table 2.

Table 2. Parts specifications

Build volume in mm (X x Y x Z)	80 x 80 x 90
Type of material	Polymer
Material	ABS (Substitute material can be considered, but the material meets the functional specifications)
Surface finish	Moderate
Accuracy	0.20 mm
Tensile strength (Min)	35 Mpa
Flexural strength (Min)	25 Mpa

As specified in Table 2, the type of material is a polymer, and the build volume is 80 x 80 x 90. Thus, the AM machines are compatible with producing the specified build volume and using polymer materials. Further, the non-relevant machines and materials are eliminated for further studies.

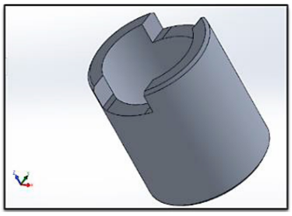

Fig. 2 Part CAD Model

3.3. Computation of criteria weights using the neutrosophic best worst

The best-worst methodology (BWM) invented by Prof. Jafar Rezaei [8] has triumphed over the issues like complexity in dealing with criteria, high computational requirements and inconsistency by devising linear and non-linear equations to solve the problems. This clearly reveals that even if an MCDM method BWM has been popular for use across various industries [9–11]. Even if the BWM is efficient and simple to use, the key drawback is that BWM does not take into account vague information and impreciseness, which typically exist in real-world problems [9–11]. To conquer the traditional BWM drawbacks, there are two methods have been utilized by the researchers to overcome these issues, namely fuzzy and neutrosophic [9,10]. The most significant difference is that fuzzy sets focus on one membership function. In contrast, the neutrosophic focuses on three membership functions: indeterminacy membership, truth membership, and falsity membership. The benefits of neutrosophic contrasted to fuzzy sets: it proposes an indeterminacy degree which facilitates decision-makers to rationalize their subjective judgments more precisely, and it expands decision-makers' disagreements [10,12]. This clearly describes that neutrosophic outperforms fuzzy and delivers the most reliable results [9].

To do so, the authors have considered the 1 - 9 scale of Prof. Saaty, which is further modified using neutrosophic numbers that need to be employed with a best-worst method, which is given in Table 3.

Table 3. Linguistic and corresponding triangular neutrosophic value [11]

Saaty Scale	Corresponding linguistic term	Neutrosophic Triangular Scale	Reciprocal neutrosophic triangular scale
1	Equally Important (EI)	$\{(1,1,1); 0.5, 0.5, 0.5\}$	$\{(1,1,1); 0.5, 0.5, 0.5\}$
2	Intermittent values between (EI) and (MI)	$\{(1,2,3); 0.4, 0.0.65, 0.6\}$	$\{(0.33,0.50,1); 0.4, 0.65, 0.6\}$
3	Moderate Important (MI)	$\{(2,3,4); 0.3, 0.75, 0.7\}$	$\{(0.25,0.33,0.5); 0.3, 0.75, 0.7\}$
4	Intermittent values between (MI) and (SI)	$\{(3,4,5); 0.6, 0.35, 0.4\}$	$\{(0.2,0.25,0.33); 0.6, 0.35, 0.4\}$
5	Strongly Important (SI)	$\{(4,5,6); 0.8, 0.15, 0.2\}$	$\{(0.17,0.2,0.25); 0.8, 0.15, 0.2\}$
6	Intermittent values between (SI) and (VSI)	$\{(5,6,7); 0.7, 0.25, 0.3\}$	$\{(0.14,0.17,0.2); 0.7, 0.25, 0.3\}$
7	Very Strong Important (VSI)	$\{(6,7,8); 0.9, 0.1, 0.1\}$	$\{(0.13,0.14,0.17); 0.9, 0.1, 0.1\}$
8	Intermittent values between (VSI) and (AI)	$\{(7,8,9); 0.85, 0.1, 0.15\}$	$\{(0.11,0.13,0.14); 0.85, 0.1, 0.15\}$
9	Absolute Important (AI)	$\{(9,9,9); 1,0,0\}$	$\{(0.11,0.11,0.11); 1,0,0\}$

Thus, the authors consider the newly demonstrated neutrosophic Best worst method to determine the most suitable AM machine to produce the specified part. The detailed steps are given below:

Step 1: Determine the expert with prior experience in AM part development and testing and shortlist the AM machine, process and material selection criteria (C_1, C_2, C_3, ……, C_n).

Step 2: The second step contains the finalization of the best (C_B) and worst criteria (C_W) as suggested by the expert.

Step 3: Develop the pairwise comparison for best criteria and worst criteria.

The outcome would be:

For the best criteria,

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots \dots, \tilde{a}_{Bn}) \tag{2}$$

For the best criteria,

$$\tilde{A}_W = (\tilde{a}_{w1}, \tilde{a}_{w2}, \dots \dots, \tilde{a}_{wn}) \tag{3}$$

Where,

$\tilde{a}_{Bj}$= Prefernce of best criteria B over criteria j and $\tilde{a}_{BB}$value is 1.

$\tilde{a}_{jw}$ = Prefernce of best criteria B over criteria j and $\tilde{a}_{ww}$ value is 1.

Step 4: Transformation of experts' preference into triangular neutrosophic sets (deterministic value) using equations 4 and 5 [13,14]. Considering $\tilde{n} = \langle (n_1, n_2, n_3);\ \alpha_{\tilde{n}}, \beta_{\tilde{n}}, \theta_{\tilde{n}} \rangle$ as a single value triangular neutrsophic number, then

$$S(\tilde{n}_{ij}) = {}^1\!/_8\,[n_1 + n_2 + n_3] \times (2 + \alpha_{\tilde{n}} - \beta_{\tilde{n}} - \theta_{\tilde{n}}) \tag{4}$$

$$A(\tilde{n}_{ij}) = {}^1\!/_8\,[n_1 + n_2 + n_3] \times (2 + \alpha_{\tilde{n}} - \beta_{\tilde{n}} - \theta_{\tilde{n}}) \tag{5}$$

These equations 4 and 5 are the scores and accuracy degree of $\tilde{n}_{ij}$, respectively. The transformation converts the AM machine, process and material selection preference into a deterministic decision value which is employed to compute the AM machine and process selection criteria weights and consistency.

Step 5: calculate the optimal weights $(W^*_{c1}, W^*_{c2}, \dots \dots, W^*_{cn})$,
which is given by,

For best criteria,

$$\frac{W_B}{W_j} = \tilde{a}_{Bj} \tag{6}$$

For worst criteria,

$$\frac{W_j}{W_W} = \tilde{a}_{jw} \tag{7}$$

To satisfy equations 6 and 7 for all j, a solution needs to be found where the maximum absolute difference of $\left|\frac{W_B}{W_j} - a_{Bj}\right|$ and $\left|\frac{W_j}{W_w} - a_{jw}\right|$ or all j will be minimized. Considering the non-negativity and sum condition for the weights, the subsequent problem is developed,

$$\min \max_j \left\{ \left|\frac{W_B}{W_j} - a_{Bj}\right|, \left|\frac{W_j}{W_w} - a_{jw}\right| \right\},$$

s.t

$\Sigma W_j = 1$

$$W_j \geq 0 \text{ for all j}$$

Thus, the model is transformed as follows,

$$\min \xi,$$

$$\left|\frac{W_B}{W_j} - a_{Bj}\right| \le \xi \text{ for all j,}$$
$$\left|\frac{W_j}{W_w} - a_{jw}\right| \le \xi \text{ for all j}$$
$$\Sigma W_j = 1$$
$$W_j \ge 0 \text{ for all j}$$

By solving the problems, the optimal AM machine and process selection weights$(W_{c1}^*, W_{c2}^*, \dots \dots, W_{cn}^*)$ and ξ^* are obtained. Utilizing the ξ^*value consistency ratio will be calculated [9].

Using the pairwise comparison, a mathematical formulation for each AM machine and suitable material using NBWM is performed as follows:

$$\left|\frac{W_{c1}}{W_{c1}} - \tilde{1}\right| \le \xi \,, \left|\frac{W_{c1}}{W_{c2}} - \tilde{9}\right| \le \xi \,, \left|\frac{W_{c1}}{W_{c3}} - \tilde{3}\right| \le \xi \,, \left|\frac{W_{c1}}{W_{c4}} - \tilde{2}\right| \le \xi \,, \left|\frac{W_{c1}}{W_{c5}} - \tilde{2}\right| \le \xi \,, \left|\frac{W_{c1}}{W_{c6}} - \tilde{3}\right| \le \xi \,,$$
$$\left|\frac{W_{c2}}{W_{c2}} - \tilde{1}\right| \le \xi \,, \left|\frac{W_{c3}}{W_{c2}} - \tilde{4}\right| \le \xi \,, \left|\frac{W_{c4}}{W_{c2}} - \tilde{5}\right| \le \xi \,, \left|\frac{W_{c5}}{W_{c2}} - \tilde{6}\right| \le \xi \,, \left|\frac{W_{c6}}{W_{c2}} - \tilde{7}\right| \le \xi \,,$$
$$W_{c1} + W_{c2} + W_{c3} + \; + W_{c4} + W_{c5} + W_{c6} = 1$$
$$W_{c1}, W_{c2}, W_{c3}, W_{c4}, W_{c5}, W_{c6} \ge 0$$

Where,

$W_{c1}, W_{c2}, W_{c3}, W_{c4}, W_{c5}, W_{c6}$are the AM machine and compatible material selection criteria weights.

Now the above equations prepared by expert opinion are transformed from neutrosophic value into deterministic value using equations 3 and 4. Thus the equation converted the problem into traditional BWM, as demonstrated by [9].

Authors have employed the Lingo© to compute the above non-linear programming problem. The outcome shows surface finish (W_{c2}) received the lowest relative wights (0.036), accuracy (W_{C3}) (0.143), tensile strength (W_{c4}) (0. 149) and flexural strength (W_{c5}) (0. 149), lead time (W_{c6}) (0.207) and cost (W_{c1}) (0. 351).

Further, the consistency index (CI) is brought from the consistency index table [9]. The consistency index value is the highest value of $a_{bw} = 9$ (maximum score given by an expert within best and worst pairwise comparison). Thus, the consistency ratio (CR) is calculated by $\frac{Objective\ function\ (\xi)}{Consistancy\ index\ (CI)} = \frac{1.249287}{15.135} = 0.0824$, which is extrapolated as very good consistency.

3.4. Criteria evaluation using a normalization approach

The normalization approach measures a criterion over a single value scale (0 to 1) [2]. The nature of the evaluation criteria is either subjective or objective. There are a total of 6 criteria considered for assessment; the surface finish is the only criterion which is subjective (qualitative), and the rest of the other five criteria are objective (quantitative). The objective criteria are further clustered into two groups[2]. First, cost (C_1) and lead time (C_6) are evaluated using linear min-max. The second cluster includes three criteria, namely accuracy (C_3), tensile strength (C_4), and flexural strength (C_5), which are gauged using one side fuzzy normalization approach. The subjective criteria, surface finish (C_2), is assessed using a five-point Likert scale [2]. For criteria evaluation, all the specified part information has been shared by AM service providers to gather each machine and compatible material information that will be employed to calculate the normalization score (subjective and objective).

3.4.1 Subjective Criteria normalization

In the subjective criteria, the experts have to measure the influence of each AM machine against the selected criteria considering five points Likert scale (very high, high, medium, low, very low), as demonstrated by [15–17] and summaries by [2] in his article Table 5. To obtain the rating of each process, the authors have contacted AM experts with at least 7 years of experience in part and process development to gauge each AM machine's surface finish value. For instance, the surface finish of Formlabs Form 3 (SLS technology) of service provider A received a rating of H from AM experts, with a corresponding value of 0.51 (Table 4). A similar process is carried out for the rest of the AM machines.

3.4.2 Objective Criteria Normalization

3.4.2.1 Linear Min-Max normalization

The authors utilize the linear min-max approach due to the benefits of simplicity, robustness, less computation time,

and removing criteria units [18–21] in this case study.
Linear min-max is given by,

$$N\_L_n = \frac{L_n - L_{n\,min}}{L_{n\,max} - L_{n\,min}} \tag{8}$$

Where,
N_L_n= Normalized value of specified AM process (n)
$L_{n\,max}$, $L_{n\,min}$ = maximum and minimum values amongst all the AM processes
L_n= actual value of specified AM process
For instance, According to Table 10, the Union Tech RSPro 600 (SLS technology) with a clear material unit cost of the specified part is 13750 INR, and the lead time is 7 days. For cost and lead time, a minimum value is prefered; thus, a reciprocal of 13750 and 7 is taken, which is 0.0000727 and 0.143. The unit cost maximum and the minimum value are 0.0000687 and 0.0003484, respectively. The normalization value is calculated using equation 1. Then the normalized unit cost of the Union Tech RSPro 600 (SLS technology) is $N\_L_{c1} = \frac{0.0000727-0.0000687}{0.0003484-0.0000687} = 0.014$. Similarly, for a lead time, the normalized value is $N\_L_{c6} = \frac{0.143-0.143}{0.333-0.143} = 0$.

3.4.2.2 Fuzzy normalization Approach

The fuzzy approach is employed to identify the level of compatibility between specified parts' technical requirements and the AM process compatibility range. The approach gauges the AM process values on the normalized scale (0 - 1) to assess satisfaction levels compared to the specified parts criteria requirements [2,22,23]. On one side, the specified part's features are closer to the limit; thus, these features will be more tricky to fabricate; on the other side, within the limit feature's chances to succeed are more [2,22,23]. AM machine and suitable material selection values are normalized (between 0 and 1), and the value closer to 1 signifies more compatibility with the particular AM process. The AM process compatibility declines from the minimum normal specification range until the maximum limit is reached. The process becomes incompetent to produce the specified criteria features (see Fig. 3 and Fig. 4).

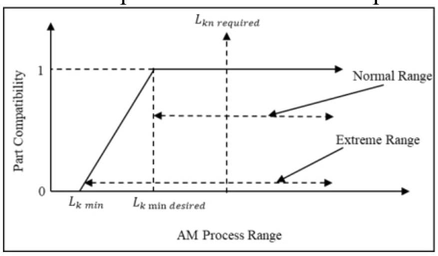

Fig. 3. Fuzzy illustration used for AM processes meant for each AM machine and feasible material (tensile and flexural strength)

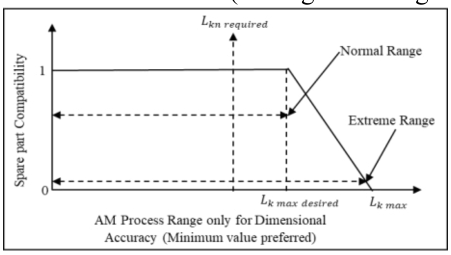

Fig. 4. Fuzzy illustration used for AM processes meant for each AM machine and feasible material (Dimensional accuracy)

$$Norm\_L_k = \begin{cases} 1 & , \quad if\ L_{k\,\min desired} < L_k \\ \dfrac{L_k - L_{k\,min}}{L_{k\,\min desired} - L_{nk\,min}}, & \quad if\ L_{k\,min} < L_k < L_{k\,\min desired} \\ 0 & , \quad Otherwise \end{cases} \tag{9}$$

$$Norm\_L_k = \begin{cases} 1 & , \quad if\ L_{k\,\max desired} < L_k \\ \dfrac{L_{k\,max} - L_{kn}}{L_{k\,max} - L_{k\,\max desired}}, & \quad if\ L_{k\,\max desired} < L_k < L_{k\,max} \\ 0 & , \quad Otherwise \end{cases} \tag{10}$$

Where,
$Norm\_L_{kn}$ = Normalized score of the AM process for particular criteria concerning the specific part value
L_k = Actual value of AM process (k) for the defined value of criteria concerning specified part,
$L_{k\ min}$ = Minimum permissible limit for required criteria concerning specified part
$L_{k\ max}$ = Maximum permissible limit for required criteria concerning specified part
$L_{k\ min\ desired}$ = Minimum preferred limit for required criteria concerning specified part
$L_{k\ max\ desired}$ = Minimum preferred limit for required criteria concerning specified part

The minimum and maximum preferred limit for 6 AM processes according to each criterion are considered 10% of the minimum and maximum range defined for AM process by discussing AM service provider. For instance, in the specified part, the accuracy limit is 0.20 mm (maximum); therefore, the allowable preferred limit is 0.18 mm (10% less than the actual value) (Fig. 5). As the actual value of, which is well within the specified permissible limit thus, the normalized value is devised as 1 (see Fig.5) using equation 9.

For instance, the Union Tech RSPro 600 (SLA) machine accuracy is 0.15 mm (AM service providers have shared their process capabilities of tensile, flexural, accuracy and surface finish according to each AM machine and material, which might vary from one AM service provider to another). Thus the allowable preferred limit is 0.135 (10% of actual value), and the part specification is 0.20 mm, as the minimum value is preferred; this clearly demonstrates that the part is within the range of the process limit (see Fig. 4).

A similar process is carried out for tensile and flexural strength, as discussed in Fig. 3 and values are derived from equation 10. Further, the actual values of each AM machine considering the criteria of build volume, material, cost, surface finish, accuracy, tensile strength, flexural strength and lead time are demonstrated in Table 4. These are then normalized using the relevant normalization method according to the type of criteria (objective or subjective), which are illustrated in Table 4.

3.5. Computation of aggregate scores of each AM machine, material and service provider

The aggregate score is calculated for each AM machine utilizing each criterion weights and normalized values. The aggregate score is determined by the sum of the score, which covers the multiplication of the normalized score and the criterion weights according to each criterion. The comprehensive process is described in a further section. The total aggregate score is computed in this stage for each process using equation 10.

The outcome of this step is given in Table 5, where the sum of each AM machine and material is computed.

$$Aggregate\ Score\_AM\ Process\ N = \sum_{C=1}^{C} W_{cn} \times Norm\_L_k \tag{11}$$

3.6. Results and Discussion

This section explores a multi-criteria-based framework to identify the most suitable AM machine and material for the specified part. The selection of each AM machine and compatible material includes the AM process limitation criteria like accuracy and surface finish as well as material constraints criteria like tensile strength and flexural strength. Further, it utilizes a Delphi and novel neutrosophic best-worst methodology in shortlisting the most compatible AM machine to produce the specified part according to the expert's objectives which are validated by a real-life case example.

Three types of AM machines and AM materials have been considered for evaluation, and the criteria weights (AM machine selection with a suitable material) were computed by taking consciences from the company expert using a neutrosophic best worst methodology and computed the aggregate score of each AM machine as described in section 3. The results inferred that the 3D Systems iPro 9000, an SLA technology (service provider B), is the best machine with the highest aggregate score of 0.952, followed by HP Jet Fusion 3D 4210 with an aggregate score of 0.883.

To demonstrate the robustness of NBWM, the authors have computed the sensitivity analysis (see Fig. 5). The sensitivity analysis is carried out by modifying the weights of the highest contributing criteria (i.e. cost-0.351) by 10% each time on the negative and positive side which results in four different criteria weights and the reduced criteria weights are equally distributed in the rest of the criterion. Further, the impact of these four criteria weights on the output has been studied. The results demonstrate that the output remains unchanged at +20% and -20%, i.e. 3D Systems iPro 9000, an SLA technology (service provider B), is the best machine. This clearly demonstrates that the adopted model is robust enough for this case example (see Fig. 5).

3.7. Conclusion and Future Research

This paper demonstrates the multi-criteria-based decision-making framework that seamlessly identifies the best AM machine and compatible material for the selected parts. An extensive literature survey is performed to shortlist the most compatible AM machine, process and material selection criteria, resulting in 21 decision-making criteria. The Delphi approach is employed to determine the most important criteria for the AM machine and material selection which results in retaining 9 criteria which are further grouped into 2 screening, 6 evaluation criteria and 1 to understand the exact material used (see Table 1). The 2 AM service provider’s machines and materials information are used to develop the database, considering the material, build volume, accuracy, surface finish, tensile strength, and flexural strength. Further, the authors share a CAD model of the specified part to gather the lead time and cost data according to each process, which is included in the database. By exploiting this information, the authors have developed a database of 5 types of AM machines and materials (see Table 4). The priority of criteria weights is calculated by deploying the neutrosophic best worst method. According to the nature of the criteria (objective or subjective), the rating and normalization approaches are used to evaluate the score of each AM machine and feasible material. Lastly, the aggregate score is calculated according to each AM machine, compatible material, and AM service provider, which is further discussed with the case company experts.

There are some future research opportunities. First, instead of utilizing the rating values of surface finish, the actual value would give more accurate results. Second, the obtained results need to be compared with other methods. Lastly, more AM processes, materials and machines databases with multiple experts and criteria subgrouping can be thought to enhance the preciseness of the findings.

Table 4. Aggregate score of calculation

			Service Provider A		Service Provider B		
		Machine	Union Tech RSPro 600	Formlabs Form 3	HP Jet Fusion 3D 4210	3D Systems iPro 9000	3D Systems SLS 380
Criteria	Part Specifications	Technology	SLA	SLA	MultiJet Fusion	SLA	SLS
Build volume in mm (X x Y x Z)	80 x 80 x 90		600 x 600 x 500	145 x 145 x 185	600 x 333 x 302	1500 x 750 x 550	381 x 330 x 460
Material	ABS (Flexible with the material, but it meets the functional specifications)	Criteria Weights	Clear	Tough 2000	PA 12	White ABS	Durable polyamide (nylon)
Based on data provided by AM service providers							
Cost in INR	------	0.351	13750	12480	12190	12386	14552
Surface Finish	------	0.036	Moderate	High	Moderate	High	Moderate
Accuracy in mm	0.20	0.143	0.150	0.150	0.160	0.160	0.180
Tensile Strength (Min) in Mpa	35	0.149	48.00	46.00	48.00	52.00	43.00
Flexural Strength (Min) in Mpa	25	0.149	86.00	65.00	65.00	93.00	48.00
Lead Time in Days	------	0.207	7	7	4	3	4
Aggregate score calculation							
Cost in INR	------	0.351	0.095	0.270	0.315	0.285	0.000
Surface Finish	------	0.036	0.009	0.018	0.009	0.018	0.009
Accuracy in mm	0.20	0.143	0.143	0.143	0.143	0.143	0.143
Tensile Strength (Min) in Mpa	35	0.149	0.149	0.149	0.149	0.149	0.149
Flexural Strength (Min) in Mpa	25	0.149	0.149	0.149	0.149	0.149	0.149
Lead Time in Days	------	0.207	0.000	0.000	0.117	0.207	0.117
Aggregate Score			**0.545**	**0.730**	**0.883**	**0.952**	**0.545**

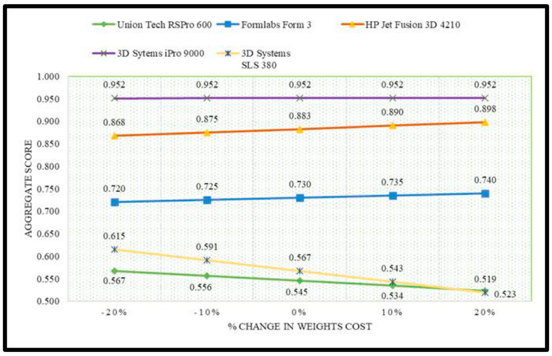

Fig. 5. Sensitivity Analysis

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