Selection of Additive Manufacturing Processes

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Abstract:
Purpose – Additive manufacturing (AM) has experienced a rapid development in recent years. New technologies, machines and service bureaus are being brought into the market at an exciting rate. While user’s choices are in abundance, finding the right choice can be a nontrivial task. This study reviews the existing methods for AM process selection and evaluates their suitability for Design for Additive Manufacturing (DfAM).

Design/methodology/approach – the AM process selection methods are reviewed based on Decision Theory. We also examine how the user’s preferences and AM process performances are considered and approximated into mathematical models. The pros and cons, and the limitations of these methods are discussed and a new approach has been proposed to support the iterating process of DfAM.

Findings – all current studies follow a sequential decision process and focus on an ‘a priori’ articulation of preferences approach. This kind of method has limitations for the user in the early design stage to implement DfAM process. An ‘a posteriori’ articulation of preferences approach is proposed to support DfAM and an iterative design process.

Originality/value – this paper reviews AM process selection methods in a new perspective. The users need to be aware of the underlying assumptions in these methods. The limitations of these methods for DfAM are discussed and a new approach for AM process selection is proposed.

Keywords: Additive manufacturing, Decision theory, Decision support systems, Design for additive manufacturing, Multi-criteria decision making

Article Classification: Literature review

1. Introduction

Additive manufacturing, also known as 3D printing, creates physical objects from a geometrical representation by successive addition of material (ISO/PRF 17296-1, 2015). This fabrication process, firstly developed in the 1980s, has experienced a phenomenal expansion in recent years. The expansion is driven by the unique capabilities of this process such as complex geometry production,
integrated assemblies and elimination of many conventional manufacturing constraints (Gibson et al., 2010). AM has been found in various applications in engineering industry as well as other domains such as medicine, education, architecture, cartography, toys and entertainment.

A variety of AM technologies have been developed. According to ASTM Standard F2792 (ASTM F2792-12a, 2012), these technologies can be catalogued into seven groups: binder jetting, directed energy deposition, material extrusion, material jetting, powder bed fusion, sheet lamination and vat photo-polymerization. More than 350 industrial AM machines and 450 materials have been identified in the market (Senvol LLC, 2015). The debate about which machine or technology fares better than others has little value as each of them has its targeted applications. AM technologies are no longer limited to prototyping usage, but are increasingly also being used for making end products (Rosen, 2007). Therefore, ‘Design for Additive Manufacture’ (DfAM) becomes increasingly significant for avoiding potential manufacturing pitfalls and maximizing utilization of AM capability (Rosen, 2007; Adam and Zimmer, 2014). To achieve that, the designer needs to be able to select a proper AM process in the early design stage. Therefore, a comprehensive and robust selection system becomes paramount for users to select a machine/technology that is fit for purpose (Moylan et al., 2012).

Unlike conventional manufacturing process selection, AM process selection is still a nontrivial task. For each of the various conventional manufacturing processes, a wealth of knowledge has been accumulated over the years. Much of it has become engineering “common sense”, and different systems have evolved over the years to suit their preferred and perceived applications. The same however cannot be said about AM processes. AM processes are free from many conventional manufacturing constraints in that they can produce nearly any geometric feature with little auxiliary tools. While the different AM processes show considerable overlap in terms of possible applications, there are also significant differences between the various AM technologies and processes in terms of suitable materials and quality of printed parts. Because it is a relatively new technology, most users do not have enough knowledge and experience to make good judgments. Various knowledge based decision support systems (kb-DSS) to help users make sensible decisions have been published. This paper reviews a number of these kb-DSS solutions for AM process selection and examines their ability to guide the user in a DfAM approach which aims at maximising the benefits derived from AM. We propose a framework that uses concepts from decision theory and the notion of performance and preference functions.

Decision support systems can generally be described by the normative decision theory, which addresses the problem of how decisions should be made in order to maximise the value of outcomes for the user. In order to do that, the theory assumes a fully informed and rational user who is able to compute exactly. Obviously, a kb-DSS is particularly suited to improve the level of information available to the user (stored in the knowledge base) and the ability to compute exactly. The commonly
used decision process can be described by a six stage sequential decision making model as proposed by Brim (1962):

- Identification of the problem
- Obtaining necessary information
- Production of possible solutions
- Evaluation of such solutions
- Selection of a strategy for performance
- Implementation and subsequent learning and reformulation

Inclusion of a kb-DSS alters this process considerably, in particular stages 2 and 3. Without a kb-DSS, in stage 2 the user would obtain information about potential solutions and then assemble that information into possible solutions (stage 3). In contrast, the kb-DSS holds this information about possible solutions within its knowledge base and requests the user’s problem description as ‘necessary information’ in stage 2. A common characteristic for both alternatives is the need of a complete understanding of the problem by the user as a starting point. The ‘problem’ in this case can be described as a set of user preferences, through which all relevant attributes (such as dimensional accuracy and surface finish) as well as their desired/preferred target values are identified and ranked against each other.

The remainder of this paper is arranged as follows. In the next section, we will briefly explain how we understand and analyse the decision making process using a kb-DSS. Section three looks at how the various kb-DSSs deal with constructing the individual and overall preference functions. Section four reviews the methods of performance evaluation. Section five discusses how preference function and performance function are combined. Discussions about the research gap on this topic are given in Section five. A newly conceived method is explained in the sixth section. Section seven concludes the paper.

2. The basics

Figure 1 summarizes the typical procedure of selecting an AM process according to our framework. There are two predominant issues – preference evaluation and performance evaluation. The outcomes of two modules can be combined and generate the ratings for different alternatives.

Firstly, the user’s problem description can be captured by using the notion of a preference function. A rational user’s preferences can be translated into preference function \( Pr_i(x) \) for the \( i \)th attribute and can be combined into an overall preference function \( Pr^{overall}(x) \), where \( i \) indicates the \( i \)th attribute \((0 < i \leq n)\) and \( x \) indicates the value of an attribute. For example, the preference for a certain build
envelope could be described by a preference function as shown in Figure 2: a build envelope smaller than the size of the object the user wants to print has zero preference to the user. At the same time, the user does not gain further benefit from larger build envelopes, suggesting the preference function in this case would take a step-function shape (Figure 2). Based on the preference function for multiple attributes, trade-offs between these individual attributes can be made.

**Figure 1** Typical procedure of AM process selection

![Preference evaluation and Rating system]

**Figure 2** Overlap of Preference function and Performance function

Similarly, performance functions $P_{i,j}(x)$ can be built, where $j$ indicates the $j$th alternative ($0 < j \leq m$), describing a 3D printer’s performance with respect to the $i$th attribute. As shown in Figure 2, the build envelope could be expressed by a Dirac delta function. For the decision support system, the main tasks as described by our framework then can be formulated as: extracting the user’s preference function from user inputs (stage 2 of the sequential decision making model), extracting performance functions for each available option from the knowledge base (stage 3), evaluating the
performance functions against the user’s preference function by finding the overlap between the two functions (stage 4) and presenting the result of the evaluation (stage 5). In this paper we assume $0 \leq P_i(x) \leq 1$ for demonstration purposes and expect the user to prefer higher values for all attributes.

3. Preference evaluation

As described in the previous section, the merit of a kb-DSS largely depends on the question whether the users are rational with respect to their preferences. A rational user’s preferences have to fulfil two essential requirements: completeness and transitivity (Hansson, 2005). In practical terms, completeness means the user has to be able to articulate a preference for every possible attribute value compared to all other attribute values. Formally, this means: for any elements $A$ and $B$ of its domain, either $A \geq B$ or $B \geq A$ has to hold. While the user in most cases will be able to articulate these preferences, the main challenge will be for the kb-DSS to capture all of that information so that the completeness still holds. The transitivity requirement means that for all elements $A$, $B$ and $C$ of its domain, if $A > B$ and $B > C$, then $A > C$. While this sounds completely logical in theory, practical examples often show that preferences articulated by the user do in fact not satisfy the criteria (Tversky, 1969).

Implicitly or explicitly, all the methods for selecting AM processes formulate various preference functions to describe users’ preferences. Usually more than one attributes need to be considered. To exactly describe users’ preferences, a plurality of information is needed from users, e.g. the thresholds (lowest and/or highest levels) they accept for each attribute, the shape (monotonicity and curvature) of the preference curve for each attribute, the interdependency of the attributes and the trade-offs between all attributes. The monotonicity of preference indicates whether the preference is consistently increasing/decreasing (monotonic) or increasing/decreasing towards a goal (non-monotonic). Simple examples are displayed in Figure 3(b) and (c), respectively. The curvature of the preference function indicates the trend of preference changing such as linear, concave and convex as shown in Figure 3(b), (d) and (e), respectively. In principle, with all this information available, the decision support system can formulate comprehensive preference functions and generate results precisely matching users’ intention. However, getting all this information from a user needs a lot of learning and input efforts. Fernandez et al. (2005) tried to build a precise mathematical model to describe users’ preferences using the u-sDSP method but the system is very complex and users are required to answer a long list of questions. Some users may be unable to answer all these questions correctly. Focusing on easy usability, other systems require less input from users but in return ignore some aspects of the users’ preferences. Table 1 displays the required level of input in different systems. Currently, no kb-DSS is able to fully capture the user’s preferences.
Depending on the level of the detail to which the user’s preferences have been captured, we divide AM process selection methods into two groups: *Judgement of Feasibility* (JoF) and *Judgement of Suitability* (JoS). The JoF approach only considers the lowest acceptable level for each attribute and uses that to decide whether a given solution can fulfil users’ requirements. In contrast, the JoS approach mainly considers the trade-offs between different attributes and recommends the best marked solution for users while the threshold is usually not taken into account. Some systems integrate two approaches together, using either one for each attribute (Lan *et al.*, 2005; Munguia *et al.*, 2010). The u-sDSP method, as mentioned before, considers all kinds of users’ preferences except for interdependency. The PROMETHEE method also considers the thresholds for each attribute as well as the shape of the preference function and trade-offs. It is worth noting that in this case the users are asked to articulate their preferences in form of pairwise comparison between solutions on each
attribute, rather than the absolute value of each attribute (Rao and Patel, 2010). The classification is displayed in Table 2. In this section, we assume that the performance vector is,

$$\mathbf{x} = [x_1, x_2, \ldots, x_n]$$  \hspace{1cm} (1)

### 3.1 JoF approach

The Judgement of Feasibility approach is utilized to rule out unfeasible solutions, i.e. solutions with a performance below the threshold. This approach defines two indifference levels. Any performance above the threshold is equally preferable for users, i.e. the preference function for each attribute takes the form of a step function as shown in Figure 3(a). The function can be expressed as:

$$P_{r_i}(x) = \begin{cases} 0 & x < \theta \\ 1 & x \geq \theta \end{cases}$$  \hspace{1cm} (2)

where $\theta$ is the threshold value, characterizing the user’s requirement and $x$ is the performance value for the corresponding attribute.

The overall preference function can then simply be expressed as the sum of individual attribute preference functions:

$$P_{r_{\text{overall}}}(x) = \sum_{i=1}^{n} P_{r_i}(x_i)$$  \hspace{1cm} (3)

This is an efficient approach to narrow down the option space. Some attributes are particularly suitable for this kind of function, e.g. build envelope and minimum feature size. However, when all of the user’s preferences are simplified into step functions, the approach becomes too rigid and does not allow for trade-offs between attributes. In terms of a DfAM approach that intends to help the user modify the design towards benefiting from the use of AM, the JoF approach therefore has limited value.

### 3.2 JoS approach

For the Judgement of Suitability approach, the preference function can have an arbitrary shape. It is important to note that preference functions are not unique. Instead, different preference functions can be extracted from the same preference structure. $P_{r_{\text{overall}}}(x)$ and $P_{r_{\text{overall}}}(x)$ are strategically equivalent if $P_{r_{\text{overall}}}(x)$ and $P_{r_{\text{overall}}}(x)$ have the same indifference curves and induced preferential ordering (Keeney and Raiffa, 1976). If there is just one attribute, then the curvature of $P_{r_{\text{overall}}}(x) = P_{r_j}(x)$ is not important because the indifference curve will not change as long as
$Pr_{overall}^i(x)$ shows a certain monotony. When considering multiple attributes, however, the curvature of $Pr^i(x)$ does matter since it may influence the monotony of $Pr_{overall}^i(x) = f(Pr^1_i(x), Pr^2_i(x), ..., Pr^n_i(x))$, which causes the different indifference curves.

### 3.2.1 Preference function for a single attribute

For a single attribute, except for u-sDSP (Fernandez et al., 2005) and PROMETHEE (Rao and Patel, 2010) the user is not able to define their preference curve in detail. Most systems apply a simplified monotonic function, while Knowledge Value Measuring (KVM) (Zhang et al., 2014), fuzzy inference (Munguia et al., 2010) and fuzzy logic (Mahesh et al., 2005) are using non-monotonic (target-matching) functions, as shown in Figure 3(c). In some cases, the target-matching approach may inadvertently be too selective, though. For instance, when a user chooses a low level for the accuracy attribute, the alternatives with low performance on accuracy will be given a high score while the alternatives with high accuracy performance will be marked down. In practice, higher accuracy performance probably does not bother the user as long as the values of other attributes are similar.

Looking at the curvature, there are three main types: linear, concave and convex as shown in Figure 3(b), (d) and (e). While the normalization algorithms may vary between the different systems, the majority of systems simplify the preference curve by using linear preference functions. As an exception, KVM adopted concave functions (Zhang et al., 2014).

More importantly, no matter what kind of function is used, most methods just have one type of function and users cannot change it. A single type of function is unable to precisely describe users’ preferences in all situations. A user may prefer a monotonic function on one attribute and a non-monotonic function on another attribute or even concave or convex functions on yet another attribute. Accordingly, the u-sDSP method is the only system to give users a great level of freedom to define the characteristics of the preference functions (Fernandez et al., 2005).

### 3.2.2 Overall preference function

When calculating $Pr_{overall}^i(x) = f(Pr^1_i(x), Pr^2_i(x), ..., Pr^n_i(x))$, generally the independency assumption is used to simplify the problem. It assumes that the attributes are preferentially independent from each other, i.e. changing the value of one attribute will not influence the user’s preferences to all other attributes (Keeney and Raiffa, 1976). However, such independency rarely exists. The DNP method deals with the problem of dependent attributes but this leads to a high calculation burden (Liao et al., 2014). Utility theory is also able to deal with dependency issues but, again, a huge commitment from the user is required (Fernandez et al., 2005).
For the JoS approach, two essential elements need to be defined in order to get to the overall preference function: the relative importance of each attribute and the operation of the combination.

### 3.2.2.1 Relative importance

The relative importance (or weighting) of attributes, is usually defined by users articulating their preferred trade-offs between the attributes (subjective method). An objective method has also been adopted to weigh attributes automatically (Lan et al., 2005). With subjective methods, users can define the relative importance mainly through two ways: direct assignment or pairwise comparison.

For the direct assignment, a user can directly evaluate the relative importance of one attribute over others on a certain scale. For example, in the works of Jones and Campbell (1997), Munguia et al. (2010), Vinodh et al. (2014), Wang et al. (2013), Ghazy (2012), 3-, 4-, 7-, 9-, 10-point scales are used, respectively. This technique is simple and straightforward. Users who can precisely describe their preferences in this way will benefit from its simple input. Otherwise, they may face difficulties to choose correct values especially in early design stages.

The second technique asks users to compare a pair of attributes each time. It is based on the assumption that a decision maker can more easily come up with a comparative rather than an absolute value (Braglia and Petroni, 1999). A typical method is Saaty’s 1–9 scale in an AHP approach, which represents the comparison results as a pairwise comparison matrix and calculates the eigenvectors (Saaty, 1977). It has been widely used in many selection systems (Armillotta, 2008; Braglia and Petroni, 1999; Byun and Lee 2005; Lan et al., 2005; Lokesh and Jain, 2010; Wilson and Rosen, 2005; Zhou and Chen, 2010; Rao and Patel, 2010). However, the relative importance matrix may show inconsistency in judgments (Rao and Padmanabhan, 2007). Besides, this approach is based on the hypothesis that the attributes are independent. Any dependency present implies a heavier weight of these joint attributes (Ishizaka and Nemery, 2013). To avoid this problem, Liao introduced the DNP method combining DEMAEL and ANP to calculate the weights of attributes for selecting 3DP service bureaus (Liao et al., 2014). In the GT&MA method, users are also required to input pairwise comparisons of relative importance, but eigenvectors of the comparison matrix are not calculated (Rao and Padmanabhan, 2007).

Overall, the ranking scores are very sensitive to the changes in the attribute weightings (Yurdakul and Ic, 2009). Therefore, decision makers need to be very careful to set the weightings. Otherwise, the methods may not be able to return meaningful advice. The stability of an MCDM methods should always be analysed. Most of the methods are sensitive to user input, especially the methods relying on relative importance.
3.2.2.2 Combination of all preference functions for single attribute

The most common practice for combining the preference function for each attribute is calculating a weighted sum. The process can be expressed as follows,

\[ Pr(x)^{overall} = \sum_{i=1}^{n} w_i Pr_i(x_i) \]  

(4)

where \( w_i \) is the relative importance of the \( i^{th} \) attribute.

Instead of simply adding single preference functions together, some more complicated calculation are also used. For example, the GT&MA approach, uses the permanent\(^1\) of the process selection attributes matrix of each alternative as the overall preference (Rao and Padmanabhan, 2007). Rao (2007) proved its reliability by comparing its result with the results of some other MCDM methods. TOPSIS and VIKOR utilize the distances of an alternative to the ideal and non-ideal solution to measure the overall preference (Byun and Lee 2005; Vinodh et al., 2014). Both methods are derived from the same formula but adopt different orders (Opricovic and Tzeng, 2004). Opricovic and Tzeng (2004) pointed out that some problems may occur when using TOPSIS. In this paper we take the weighted sum as an example to illustrate how the selection process works.

3.3 Discussions

A number of methods have been presented for evaluating the preference of AM processes. For JoF methods, assorted rule repositories and capability databases have been built to host the capability information. The information is of importance for users to make decisions, in particular for those users who already have a completed design and specific requirements. However, the type of preference function utilized in this approach, i.e. step function, is too rigid and prone to exclude some potential choices due to the lack of tolerance over users’ misjudgement of their requirements (Zhang et al., 2014). Furthermore, the conditional expressions such as IF, THEN, ELSE statements or CASE statements being used in these cases are difficult to help users make trade-offs and predict the best option (Lan et al., 2005; Munguia et al., 2010).

For JoS, a series of multi-criteria decision making (MCDM) and other methods have been proposed. According to how the decision maker articulates their preferences or requirements, all the methods reported here can be regarded as methods with an \textit{a priori} articulation of preferences, which means the user needs to indicate their preferences before running the algorithm (Marler and Arora, 2004). However, user preferences could be difficult to obtain without the subjective and bias effect (Zhang and Bernard, 2014). Another issue is that the independency of attributes needs to be checked before

\(^1\) The permanent function is similar to the determinant of a matrix but considering all the determinant terms as positive terms
using these methods in order to select the ones that can be utilized in a given situation. Otherwise, it may lead to over-weighting of some attributes.

More complex systems have also been published. Some studies combine a Design of Experiment (DoE) method with TOPSIS (Ic, 2012) and GRA (Wang et al., 2013). They use a regression model to decrease the calculation and response time of their methods. This can have an impact on the accuracy of the results, too. A slight difference has shown between the result of the regression model and the TOPSIS method (Ic, 2012). Another limitation is that the attribute values of alternatives need to be within their allowed value ranges. Other examples for the combination are integrating expert system and fuzzy inference (Munguia et al., 2010) or FSE (Lan et al., 2005), or the later work of Munguia et al. (2011), where an ANNs module is integrated in their system to evaluate build time and cost.

In general, the amount of user inputs decides how accurate the systems model the users’ preferences. The simple preference functions and weighting processes require low input effort but are relatively inaccurate. In contrast, the u-sDSP and PROMETHEE methods can reflect users’ intentions more precisely but much more learning and input efforts are required. It will discourage users to use this system if it becomes too complicated (Borille et al., 2010). Different users may have different requirements on the level of accuracy and input effort for process selection. Current methods are developed to only serve a specific group of users. There is a need to develop a method to fulfil the requirements of diverse customers. Furthermore, customers’ requirements are vague and non-parametric sometimes. A better way of dealing with this situation needs to be found. Therefore, a new approach will be proposed in Section six to tackle this problem.

4 Performance evaluation

Another important issue in AM process selection is related to performance evaluation of AM processes. Selection systems are only as good as the information that is utilized to make suggestions (Rosen and Gibson, 2002). Thus, collecting and collating capability information about AM processes is a primary task. If the performance of AM processes can be properly described, the user can make a more informed decision on process selection and gain more confidence on using AM technologies. Besides, designers can adjust the design effectively to better utilize AM processes. However, precisely describing the performance of AM processes is a challenge. The performance is influenced by assorted factors including materials, process parameters, post-processing, the condition of the machine, the ambience of the machine, etc. By varying these factors, a different performance can be achieved. Thus, a single machine can achieve different levels of performance. For example, the same machine can, through adjusting the parameters, achieve a high resolution at a low speed or a low resolution with high speed. Understanding all these combinations and their corresponding performance needs a big effort. Furthermore, the performance cannot be well controlled even under
the same combination. Some unpredictable factors, such as ambient temperature, nozzle jam in material extrusion processes and particle size of powder materials, have impacts on the performance as well. The heterogeneous properties of printed parts make it more difficult to precisely predict the performance. Therefore, it is reasonable to simplify the situation appropriately, as current research has done.

In this paper, we call each available option within a kb-DSS a ‘solution’. The solution can be defined at different levels of granularity. A common way to define a solution is an AM machine itself (Byun and Lee, 2005). Lan et al. (2005) defined an AM technology as a solution. Fernandez et al. (2005) regarded an AM machine together with a certain material as a solution. Some considered the printing service providers and treat each service provider as one solution (Liao et al., 2014; Zhou and Chen, 2010).

The performance of solutions can be measured using various attributes. Part 3 of the ISO 17296 standard lists numerous characteristics from the perspective of part requirement and catalogues them into four types – surface requirements, geometric requirements, mechanical requirements and build material requirements (ISO/PRF 17296-3, 2014). These attributes, together with process related aspects are commonly used to evaluate performance of 3D printer systems (Table 3). Various knowledge bases have been built to host the performance information. Some databases or rule repositories host the data of some common attributes, e.g. build envelope and material properties (Lan et al., 2005; Munguia et al., 2010; Ghazy, 2012; Singh and Sewell, 2012). A benchmark database was used in (Mahesh et al., 2005). Campbell and Bernie (1996) built a database carrying not only basic specifications of machines, but also tolerance data with respect to a particular feature. However, freeform or complex features that designers tend to use are not covered. Smith and Rennie (2008) set up a relational database which allows users to enter certain keywords to retrieve suitable solutions. In their later work (Smith et al., 2012), an AM capability database is built containing minimum achievable feature dimensions and volume capacity.

Once the performance information is acquired, the performance function can be constructed. One way to formulate the performance function is the use of probability distributions (Fernandez et al., 2005). This kind of function displays the probability of achieving different performance under a specific condition. In this paper, we adopted this perspective to review these researches.

4.1 Data sources

Various sources of performance data for 3D printers are available, of which four types are discussed in more detail.
Vendor documents
Basic information, such as build envelope, layer thickness, resolution, accuracy, materials and so forth is often given in datasheets by the equipment manufacturers. The information is limited and often unclear as to under what conditions the data have been obtained and how they may be applied to what the user is trying to achieve (Pham and Gault, 1998; Chuk and Thomson, 1998).

Expert and engineer experience
Using questionnaires to collect information from experts and engineers and capture their accumulated process knowledge is a popular approach (Braglia and Petroni, 1999; Lan et al., 2005; Liao et al., 2014; Lokesh and Jain, 2010; Masood and Soo, 2002). However, most of the information derived from experts and engineers is vague and incomputable and therefore there is a need to translate it into numerical values. What is more, people’s opinions are often subjective. To overcome this problem, it is necessary to involve more participants, which leads to heavy workload and an increased difficulty of keeping the information up to date.

Benchmarking
Benchmarking plays an overarching role in AM process evaluation (Moylan et al., 2012). The experimental results from tests are often more persuasive than those from other sources. For AM process selection, Campbell and Bernie (1996) decomposed components into manufacturing features and collated the tolerance of each feature from benchmarking. Byun and Lee (2005) designed a test part and measured the performance of six AM machines. Mahesh et al. (2005) adopted an existing benchmark part and collected quality characteristics data such as geometric accuracy and surface finish. Roberson et al. (2013) used further modified version of the Grimm test structure and tested five desktop printers. Data from benchmarking could be more reliable and persuasive, but this approach may be time-consuming and very expensive (Lan et al., 2005; Masood and Soo, 2002).

Mathematical models
Some attributes (e.g. build time and cost) are influenced by assorted factors and are contingent on specific cases. Measuring them with static values is difficult. Linguistic values can be used to express the comparative performance of each alternative, but they are often vague and less technical for a decision maker. Therefore, mathematic models are used to tackle this issue. Yim and Rosen (2012) proposed a general and simplified model that is applicable to a wide range of AM processes for comparison in terms of build time and cost. Munguia et al. (2011) also integrated a cost estimation module in their RMADS system using ANNs for build time and cost estimation. Xu et al. (2000) proposed generic models for surface finish, building time and building cost. Various empirical modelling approaches for performance prediction have also been proposed (Garg et al., 2014). The models need to be comprehensive and accurate enough to reflect the real situation.
4.2 Performance function construction

With the performance data collected from different sources, performance functions can be derived. Table 4 displays the type of performance function in the existing studies. According to different conditions, decision-making can be partitioned into three types: decision-making under certainty, risk or uncertainty (Luce and Raiffa, 1957). In many studies, researchers simply tackled AM process selection under certainty, which means each solution leads to one specific performance. Its possibility distribution (Figure 4(a)) can be expressed as follows,

\[
P_{i,j}(x) = \begin{cases} 
1 & \text{if } x = x_{i,j} \\
0 & \text{if } x \neq x_{i,j}
\end{cases}
\]

(5)

where \( x_{i,j} \) is the performance value of the \( j \)th alternative on the \( i \)th attribute.

Figure 4 Different probability distributions of AM process performance

This kind of function provides no allowance for the fluctuation of machines’ performances. Fuzzy set theory is introduced to describe vague information, but the settings of fuzzy membership functions are often subjective. Fernandez et al. (2005) considered this problem under risk, and uniform probability distribution was used as an example (Figure 4(b)). Mahapatra and Panda (2013) adopted interval grey number to express the uncertainty of performance. Potentially, this approach also assumes the performance distribution to be uniform. This kind of function can be expressed as,

\[
P_{i,j}(x) = \begin{cases} 
\frac{1}{b-a} & x \in [a,b] \\
0 & x \notin [a,b]
\end{cases}
\]

(6)

where \([a,b]\) is the interval that the performance value of the \( j \)th alternative on the \( i \)th attribute may fall into.
4.3 Discussions
Performance information is important not only for AM process selection but for the whole DfAM process. With a better understanding of the constraints, designers can adjust their design accordingly. It can be collected in different ways, from single or multiple sources. In any case, the data need to be reliable and comparable. The definition or granularity of a solution also plays a crucial role because it decides how precisely the solutions can be described. A general concept of a solution (e.g. treating an AM machine as a solution) cannot tell users the real capability of the machine since most of the AM machines are able to achieve a wide range of performance by carefully adjusting the operation. Current studies pay little attention to this problem. For some unstable attributes such as tensile strength, it is reasonable to describe the performance in a range rather than a value based on historical data or prediction software.

5 Rating process
The rating process combines the performance function with the preference function. The performance vector of the $j$th solution can be denoted as,

$$x_j = \left[ P_{1,j}(x) \quad P_{2,j}(x) \quad \ldots \quad P_{n,j}(x) \right]$$  \hspace{1cm} (7)

For JoF, the rating of the $j$th alternative for the $i$th attribute can be calculated as,

$$Pr_i(x) = \begin{cases} 
0 & \int P_r(x)P_{i,j}(x)dx \leq \omega \\
1 & \int P_r(x)P_{i,j}(x)dx > \omega 
\end{cases}$$ \hspace{1cm} (8)

where $\omega$ is the threshold as specified by the user.

Then, the feasible alternative needs to fulfil,

$$Pr^{\text{overall}}(x_j) = \sum_{i=1}^{n} Pr_i(x) = n$$ \hspace{1cm} (9)

where $n$ is the number of attributes.

The systems return the list of feasible alternatives with further information.

For JoS, the rating for a single attribute can be regarded as,

$$Pr_i(x) = \int P_r(x)P_{i,j}(x)dx$$ \hspace{1cm} (10)

By substituting equation (10) into (4), a ranking can be generated according to the value of $Pr^{\text{overall}}(x_j)$ and usually the alternative displaying the highest value is recommended.
In practice, different methods may engender different rankings. Borille et al. (2010) compares several MCDM methods for AM process selection and not all methods result in exactly the same RP ranking. To some extent, this finding reveals the potential risk of adopting these methods. Different results from different methods will confuse users who do not understand the rationales behind these methods and this may negatively influence their confidence in the results.

The result is usually presented as a list of feasible solutions or various rankings and scores such as in Table 2. There is very limited information in there for users to fully understand the differences in performance between the different solutions. Those scores have different scalars and the analysis takes place in a “black box”, i.e. the user is unable to understand the details and does not know how the systems simplify or approximate the problem.

As mentioned in Section one, all current kb-DSSs adopt a sequential model of the decision process that is linear and straightforward. The calculation and rating processes are done in a black box fashion which is difficult for users to comprehend. The results are just a list of alternatives or rankings with obscure scores. The users have little insights into the possibilities as to how AM processes might be able to improve their design. The only way the user can gain these types of insights would be by repeatedly inserting different values and then inspecting and comparing the updated results. Clearly, this is not an ideal approach.

6 Research gaps and proposed approach

A large number of methods have been developed and used in kb-DSSs. The major focus of activities has been in the area of MCDM, i.e. how to balance the different requirements. Mostly due to practical limitations, capturing the details of both the user’s requirements and the technology performance was treated rather simplistically. Therefore, we have identified a few outstanding issues:

- The level of detail for evaluating AM machine performance needs to be improved. Most of the printers have multiple modes and are able to achieve different results according to different settings, materials or other factors. To better consider these factors, a better understanding of AM processes is required.
- Stability or repeatability of an AM process needs to be provided to the user in order to give them more confidence.
- A more effective approach is needed to capture user preferences. Translating users’ vague preferences into quantitative values is difficult. Inadequate inputs often lead to incorrect results.
The result should contain more information so that the user can understand the difference between different solutions. This can help them adjust their design and requirements to explore better solutions.

From the DfAM point of view, the methods reported in the literature provide little opportunities for users to modify their designs and learn about the kind of requirements for a given AM process. This is because users are unable to intuitively understand the capability of an AM process. AM is mostly treated as one technology yet, the principles and mechanisms of different AM process vary in great deal. Consequently, the characteristics of printed parts vary, too. There is therefore a need for the user to understand the decisions made for them. It is also necessary to inform and educate users through the process of selecting an AM process.

Design is an iterative process. The sequential model of a decision process therefore is not a good fit for DfAM. It is our belief that users can reap more benefits from a non-sequential model of a decision-making process, which will allow them to develop new designs or modify existing ones to suit an AM process (Mintzberg et al., 1976). To support this process, we propose an approach with *a posteriori* articulation of preferences (Figure 5), whereby decision makers and end users can choose from a palette of solutions without articulating clear preference (Marler and Arora, 2004). Firstly, users can choose the attributes of their concerns – without specifying values or preferences. A group of solutions are then generated from the option space and stored in a Pareto set. Data visualization technology is used to present the performance functions of the options in the Pareto set to the user in such a way that they can easily compare these options and make informed decisions. The user can input constraints to brush out undesired alternatives. In this way, the user can skip the process of preference function construction and directly impose requirements and preferences on the choice they make. Such an approach makes users feel more in control of the selection process and the final solution reflects the decision maker’s preferences more accurately. Furthermore, users can see all the optimal options in the Pareto set and directly compare one with another. In this process, users can access the information about AM process capability and it is conducive to adjusting their design or demands for a better solution. The challenge in this scenario will be to firstly capture sufficient performance information and secondly to visualize it in a way that can be comprehended by the user. While the latter will be specific to this approach, we would argue that the required level of performance information per se is not greater than in an a priori approach, it just becomes more visible to the end user rather than being hidden behind a black box MCDM algorithm. On the other hand, the problem of capturing the user’s preferences is dramatically simplified, as the users make decisions and trade-offs based on the performance data they can see.
7 Conclusions

The problem of AM process selection has been discussed for many years. During the process of reviewing the methods of AM process selection, we analysed the user’s preferences, AM process performance and how these may be matched.

- For performance evaluation, a simplified approach of using constant values is widely applied. Uniform probability distribution has also been adopted. A real life case however tends to be more dynamic and complex.
- For preference evaluation, two different types of preference function for a single attribute have been identified: piecewise constant function for JoF methods and continuous function for JoS methods. Again, this is considered as an over-simplification to the real situation.
- For the calculation of the overall preference value, a simple weighted sum is mainly utilized. Other operations have also been adopted.
- In most methods, the final result is represented as a list of techniques, ranked by a single figure. Therefore, it does not convey much information to the user about how the results may be improved.
- The methods simplified the problem to different extents. Simpler methods do not require high input effort but in return lose some information. More complicated methods can generate more precise results but need a lot of input and coding effort.

In summary, all of these methods follow a sequential model of decision making, which in our opinion is not suitable for a DfAM process that should allow users to learn about the full potentials of AM techniques. To better support this process, an *a posteriori* articulation of preferences approach has
been proposed to help users explore existing solutions and make their designs more suitable to an AM process. In this way, the designer can not only make better decisions by seeing and comparing potential solutions, but can gain more knowledge about which AM process is better under which kind of demands. This approach can serve diverse customers since the user is not required to quantify their preferences.

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