

RESEARCH ARTICLE

Multicriteria decision analysis framework for part orientation analysis in additive manufacturing

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Abstract

Additive manufacturing (AM) or three-dimensional printing (3DP) refers to producing objects from digital information layer by layer. Despite recent advancements in AM, process planning in AM has not received much attention compared to subtractive manufacturing. One of the critical process planning issues in AM is deciding part orientation. In this research, the integrative framework of multicriteria decision making for part orientation analysis in AM is investigated. Initially, quantitative data are assessed using the data envelopment analysis (DEA) technique without preferences from a decision maker. In contrast, a decision maker's preferences are qualitatively analysed using the analytic hierarchy process (AHP) technique. Then, the proposed framework combining explicit data as in DEA, implicit preference as in AHP, and linear normalization (LN) technique is used, which reflects both preference and objective data in supporting decision making for 3DP part orientation. Two particular AM technologies, namely Fused Deposition Modelling and Selective Laser Sintering, are used as a case study to illustrate the proposed algorithm, which is further verified with experts to improve process planning for AM.

Keywords: multicriteria decision making; data envelopment analysis (DEA); analytic hierarchy process; linear normalization; orientation selection; additive manufacturing

List of Symbols

I :	A set of input criteria for DEA	A :	Decision matrix of pairwise comparison for AHP
J :	A set of output criteria for DEA	$a_{i,j}$:	Comparison between two consecutive objects for AHP
K :	A set of alternatives called DMUs for DEA	p :	The priority vector for AHP
$x_{i,k}$:	Input parameter for a particular DMU for DEA	λ_{max} :	The maximal Eigenvalue for AHP
$y_{i,k}$:	Output parameter for a particular DMU for DEA	CI :	The consistency index for AHP
X_i :	Decision variables relative to the weight of input for DEA	RI :	The random index for AHP
Y_j :	Decision variables relative to the weight of output for DEA	CR :	The consistency ratio for AHP
		g_i :	The global priority for alternative i for AHP
		$l_{i,j}$:	The local priority of alternative i for criterion j for AHP
		w_j :	The weight of the criterion j for AHP

Received: 11 January 2021; Revised: 2 June 2021; Accepted: 4 June 2021

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- U : The ideal/utopia solution for LN
 p : The anti-ideal/nadir solution for LN
 $n_{i,j}$: The normalized value of alternative i for criterion j for LN

1. Introduction

Additive manufacturing (AM) or three-dimensional printing (3DP) has gained popularity worldwide from using digital technology in various applications, thanks to its critical advantages in design freedom and consolidating part (Sossou et al., 2018; Jiang et al., 2020, 2021). It is estimated that worldwide revenues from AM products grow about 17%, accounting for more than \$3 billion in 2017. In contrast, revenues from AM services also grow approximately 24%, accounting for more than \$4 billion in 2017 (Wohlers, 2018). Regardless, production and process planning for AM is challenged by different materials, technologies, and printer sizes, which impact efficient and effective use of AM (Han, 2013; Ha et al., 2016, 2018, 2020; Thompson et al., 2016; Yao et al., 2017; Jiang et al., 2019a; Ransikarbum et al., 2019a, b, 2020; Ma, 2020; Ransikarbum & Khamhong, 2021; Zhang & Moon, 2021). Among many issues, part orientation is one of the critical factors that affect production and process planning for AM.

Orientation selection of a part refers to the building direction for the part being fabricated by the AM printer. The optimal part orientation is considered a critical issue of AM processes as it can impact key characteristics in part production (Nelson et al., 2014; Zhang et al., 2016a; Jiang et al., 2019b; Jiang & Ma, 2020). As a selection of the part orientation affects multiple factors, the part orientation can be viewed as the multicriteria decision making (MCDM) problem. Standard MCDM methods include analytic hierarchy process (AHP), analytic network process (ANP), data envelopment analysis (DEA), multi-objective programming, and goal programming (e.g. Ransikarbum & Mason, 2016a, b; Ransikarbum et al., 2017; Wattanasang & Ransikarbum, 2019, 2021; Puchongkawan & Ransikarbum, 2020). In this research, a framework that combines explicit data as in DEA and implicit preference as in AHP in the form of linear normalization (LN) is developed to utilize preference and objective data to tackle the drawbacks of using a particular method alone for the orientation-selection problem. Then, the algorithm's validity is verified with technical experts to improve process planning in two particular AM technologies, fused deposition modelling (FDM) and selective laser sintering (SLS).

The remaining sections of this paper are organized as follows. We overview the pertinent literature in Section 2. Then, our proposed framework of the MCDM for the orientation-selection problem in AM is presented in Section 3. Next, an experimental design using our proposed framework and managerial insights are elaborated in Sections 4 and 5, respectively. Finally, Section 6 presents our research conclusions and outlines future research directions.

2. Literature Review

AM refers to a set of technologies used to produce end-use parts directly from 3D computer-aided design (CAD) models by additively building them in layers (Jiang et al., 2018; Jiang, 2020). According to the American Society for Testing and Materials (ASTM, 2012), AM technologies can be categorized into seven main categories: (1) photopolymer vat, (2) material extrusion, (3) powder bed fusion, (4) directed energy deposition, (5) sheet lamination, (6) material jetting, and (7) binder jetting. The survey from Wohlers (2018) suggested that FDM – material

extrusion category; stereolithography (SLA) – photopolymer vat category; and SLS – powder bed fusion category are the top three AM technologies based on the number of installed industrial systems. Thus far, other terms commonly used for AM literature include direct digital manufacturing, solid freeform fabrication, rapid prototyping, rapid manufacturing, and 3DP. Regardless, several studies have been conducted to tackle various process and production issues of AM (e.g. Gibson et al., 2014; Gardan, 2015). Wohlers (2018) also suggested that successful AM builds depend on an effective support structure strategy, the orientation and location of the parts on the building platform, and the number of parts that are produced at one time.

The decision for an orientation selection is an essential factor of process planning in AM. Besides, this process is typically followed by various critical steps, including slicing, support generation, toolpath definition, additive fabrication, and part cleaning. A number of researchers have proposed diverse methodologies to tackle the orientation problem for varied AM types (e.g. Byun & Lee, 2006; Giannatsis & Dedoussis, 2007; Canellidis et al., 2009; Zhang et al., 2016a, b, 2017, 2019; Ransikarbum & Kim, 2017a, b; Di Angelo et al., 2020; Leirimo & Martinsen, 2020). Some prominent studies highlighting existing orientation problems are reviewed next. Byun and Lee (2006) proposed the simple additive weighting method to assess the orientation problem using varied models with a hole feature. The authors evaluate surface quality, build time, and part cost for FDM, SLS, SLA, and laminated object manufacturing (LOM), respectively. Giannatsis and Dedoussis (2007) proposed a software for build parameters selection in SLA using specific test parts of alarm clock and electrical appliance in their study. Canellidis et al. (2009) proposed a decision support system automating the orientation selection task based on three other criteria. Taufik and Jain (2013) reviewed the role of build orientation in AM and find that the best part orientation concerning different AM machine capabilities is not a trivial task as satisfying one objective may adversely affect some other objectives of interest.

Moreover, Lambert (2014) discussed tensile strength and strain at break for both SLS and FDM. According to the author, while FDM parts highly exhibit anisotropic mechanical properties, there is much less directional dependence in SLS parts. Nelson et al. (2014) studied the effect of scan direction and orientation on mechanical properties of SLS and find that the specimen oriented perpendicularly to the x-axis has more excellent elongation with trade-offs in tensile strength. Zhang and colleagues (2016a, 2016b, and 2017) presented a method to obtain an optimal part for build orientation using AM features with associated AM production knowledge and MCDM. Ransikarbum and Kim (2017a, b) proposed the orientation model for a specific part produced from a particular AM technology. The authors suggest that the MCDM tool applying to AM study should integrate different methods. Zhang et al. (2019) developed the non-supervised machine learning to analyse the orientation problem of complex medical models. The authors evaluate surface roughness, support volume, and facet clusters for electron beam melting (EBM) in their study. Di Angelo et al. (2020) proposed the multi-objective optimization model to investigate the orientation problem for FDM using varied case studies. In addition, Leirimo and Martinsen (2020) proposed the feature recognition method to assess the impact of staircase effect to orientation problem from varied parts for SLS. Regardless, the above studies typically use a single and simple method to investigate a single or a few criteria of orientation problem in AM without investigating the problem with varied MCDM methods. Moreover, both quantitative and qualitative evaluation should be further explored to take decision makers' perspectives into account.

Table 1: Summary of literature review in part orientation in AM.

Study	Method	AM type	Criteria	Case study
Byun and Lee (2006)	Simple additive weighting	FDM, SLS, SLA, LOM	Surface quality, build time, part cost	Varied models with a hole feature
Giannatsis and Dedoussis (2007)	MCDM-based decision support tool	SLA	Build time, surface roughness, layering error	Specific models (alarm clock, electrical appliance)
Canellidis et al. (2009)	Genetic algorithm	SLA	Build time, surface roughness, post-processing time	Specific models (pipe, ship, aircraft)
Ingole et al. (2011)	Cost analysis	FDM	Build cost	Complex-shaped parts
Nelson et al. (2014)	Design of experiment (DOE)	SLS	Mechanical properties (physical density, tensile strength, elongation)	General part (dogbone test part)
Moroni et al. (2015)	Mathematical analysis	N/A	Cylindrical feature of the assembly part	Universal joint part
Zhang et al. (2016a)	Surface shape feature concept	FDM	Sharp corners, cutting numbers of fibers, Z-size-error, support volume	Thin wall part model
Zhang et al. (2016b)	Feature concept and production knowledge	SLS, SLA	Surface roughness, accuracy, support volume, build height, tensile strength, time, cost, and favorableness	Varied models with a hole feature
Zhang et al. (2017)	Genetic algorithm and feature concept	SLA	Build time, build cost	Multipart production
Ransikarbum and Kim (2017a)	AHP	FDM	Build time, cost, Surface quality, part accuracy, support volume, mechanical property	The specific model with a hole feature
Ransikarbum and Kim (2017b)	DEA	FDM	Build time, cost, Surface quality, part accuracy, support volume, mechanical property	The specific model with a hole feature
Ga et al. (2019)	Computer-aided analysis	N/A	Support volume, surface quality, time, cost	Industrial cases
Qin et al. (2019)	Fuzzy MCDM	SLA, SLS	Surface roughness, time, cost, support volume, favorableness	Specific model, complex part
Zhang et al. (2019)	Nonsupervised machine learning	EBM	Surface roughness, support volume, facet clusters	Complex medical models
Di Angelo et al. (2020)	Multi-objective optimization	FDM	Cost, surface quality	Varied test cases
Leirimo and Martinsen (2020)	Feature recognition	SLS	Staircase effect	Varied test cases
This study	Integrative MCDM (DEA, AHP, LN)	FDM, SLS	Part cost, time, surface quality, part accuracy, support volume, mechanical property	The specific model with a hole feature

Specifically, MCDM methods have evolved to accommodate various types of applications in the literature (e.g. Dong & Cooper, 2016; Dweiri et al., 2016; Thanki et al., 2016; Chaiyaphan & Ransikarbum, 2020; Ransikarbum & Leksomboon, 2021). Researchers suggest that the trend for MCDM method use is to combine two or more methods to make up for shortcomings in any particular method (e.g. Vaidya & Kumar, 2006; Kokangül et al., 2017). Liu et al. (2013) surveyed the DEA literature using a citation-based approach. According to the authors, the DEA literature's size will grow at least double the size of the existing literature. Vaidya and Kumar (2006) reviewed the applications using the AHP technique in different fields. The authors point out that future applications of AHP include being widely used for decision making and addressing more complex issues based on an integrated application of AHP and other techniques. Although applications in MCDM have been increasingly used, the orientation selection in AM considering a framework incorporating different MCDM approaches is scarce. We highlight existing literature in Table 1 and discuss our proposed study as follows:

1. Whereas MCDM tools are found in a wide range of applications in the literature, studies focusing on advanced manufacturing such as the AM are still scarce.
2. With regard to AM, a few studies use a particular AM technology in their applications. Thus, a framework encompassing standard AM technologies, such as FDM and SLS, is used in this study to enhance rationality and compatibility.
3. Existing studies typically use either AHP or DEA methods alone, with some limitations. Whereas AHP reflects decision maker's preferences without explicit data usage, DEA uses only objective data without considering its preferences. Thus, a framework that combines explicit data as in DEA and implicit preference as in AHP in the form of the LN technique to utilize both preference and objective data is proposed in this work.
4. Our study clearly emphasizes the particular problem of orientation selection for emerging AM. Despite some existing studies, we illustrate a comparative analysis of the orientation problem.

3. Definition of DEA, AHP, and LN

3.1. DEA methodology

DEA is a multifactor productivity analysis model that compares each variable with the best-performing one. Variables in DEA analysis are often referred to as decision-maker units (DMUs), in which the main aim is to provide benchmarking guidelines for inefficient DMUs. Advantages of DEA include the capability to handle multiple inputs and outputs, where the sources of inefficiency can be analysed and quantified for every evaluated unit. Also, DEA allows intercriteria comparison with actual units of criteria (Liu et al., 2013). Following the mathematical notation of the output-oriented, primal CCR model suggested by Charnes et al. (1981), the relative efficiency of a particular DMU can be obtained by solving the model M1 (equations 1–4), where the objective function is to maximize the ratio of the weighted sum of the outputs to the weighted sum of the inputs. Next, given the non-linear form, the M1 model can be converted into the linear programming problem as shown in M2 (equations 5–9).

DEA model (M1):

$$\text{Maximize Efficiency } \frac{\sum_{j \in J} y_{j,k_0} V_j}{\sum_{i \in I} x_{i,k_0} U_i} \quad (1)$$

$$\text{Subject to: } \frac{\sum_{j \in J} y_{j,k} V_j}{\sum_{i \in I} x_{i,k} U_i} \leq 1; \quad \forall k \in K \quad (2)$$

$$U_i \geq 0; \quad \forall i \in I \quad (3)$$

$$V_j \geq 0; \quad \forall j \in I \quad (4)$$

DEA linear programming model (M2):

$$\text{Maximize Efficiency } \sum_{j \in J} y_{j,k_0} V_j \quad (5)$$

$$\text{Subject to: } \sum_{i \in I} x_{i,k_0} U_i = 1 \quad (6)$$

$$\sum_{j \in J} y_{j,k} V_j - \sum_{i \in I} x_{i,k} U_i \leq 0; \quad \forall k \in K \quad (7)$$

$$U_i \geq 0; \quad \forall i \in I \quad (8)$$

$$V_j \geq 0; \quad \forall j \in I \quad (9)$$

A particular DMU will be considered efficient if it obtains a score of one, whereas scores that are lesser than one imply relative inefficiency. Moreover, more than one alternative may be found to be efficient, which can be served as benchmarking guidelines for inefficient DMUs to improve decisions.

3.2. AHP methodology

AHP is essentially based on three critical operations: hierarchy construction, priority analysis, and consistency verification. The logical hierarchy is constructed such that a decision maker or a group of decision makers can systematically assess alternatives' priority by making pairwise comparisons among criteria and their respective alternatives concerning each criterion leading to synchronization of global weight. AHP allows the assessment of judgment consistency, which is the main distinctive contribution of the AHP when contrasted to other techniques.

Initially, after the goal is identified, the hierarchy structure can be constructed for the top (i.e. goal or objective), intermediate (i.e. criteria and sub-criteria), and bottom (i.e. alternatives) levels. All of the pairwise comparison matrices are then constructed and normalized where n is the number of evaluated cri-

teria. The comparison between two elements using AHP can be made in different ways, where the relative importance scale (1–9 scales) between two alternatives is widely used (Saaty & Sagir, 2009). In this study, the 1–9 fundamental scale is used, which can be translated as an equal preference or 1, moderately preferred or 3, strongly preferred or 5, very strongly preferred or 7, and extreme preference or 9, respectively, with 2, 4, 6, and 8 as intermediate values. These comparisons can be recorded in a positive reciprocal matrix as shown in equation (10), such that if the judgment value is on the left-hand side of diagonal elements of 1, we put the actual judgment value; otherwise, we put the reciprocal value if the judgment value is on the right-hand side of 1. In making judgments, the DM can incorporate experience and knowledge (Bayazit & Karpak, 2007). In particular, there are $[n \times (n - 1)]/2$ judgments required to develop the matrix. Then, the comparison matrix can be normalized by dividing each value by the total value in each column.

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \dots & a_{ji} = 1/a_{ij} & 1 & \dots \\ a_{n1} & \dots & \dots & 1 \end{bmatrix} \quad (10)$$

Next, the priority vector (normalized principal Eigenvector) is calculated, and the maximum Eigenvalue (λ_{max}) is obtained. The Eigenvector shows the relative weights between each criterion obtained by computing the arithmetic average of all criteria, where the sum of all values in the vector is one. The meaning of each value determines the weight of that criterion relative to the total result of the goal. Mathematically, equation (11) follows.

$$A \cdot p = \lambda_{max} \cdot p \quad (11)$$

Then, it is important to capture whether a DM is consistent in the choices that are provided. Thus, the consistency check is next performed by calculating the consistency index (CI), the random index (RI), and the consistency ratio (CR) for each matrix (equations 12 and 13). The RI is based on the average CI of 500 randomly filled matrices with the following (n , RI) pairs: (1, 0.00), (2, 0.00), (3, 0.58), (4, 0.90), (5, 1.12), (6, 1.24), (7, 1.32), (8, 1.41), (9, 1.45), and (10, 1.49). Typically, the CR value will be considered to have an acceptable consistency if the resulting ratio of CR is less than 10%. Finally, a global ranking of decision alternatives can be analysed. The traditional approach called distributive mode is used in this study (equation 14), which adopts an additive aggregation with normalization of the sum of the local priorities to unity.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (12)$$

$$CR = \frac{CI}{RI} \quad (13)$$

$$p_i = \sum_j w_j l_{ij} \quad (14)$$

3.3. LN methodology

In a particular decision-making environment, there may be some limited n alternatives of interest under different, conflicting p criteria, in which a decision maker is interested in finding the best alternative among all. This particular problem falls under the so-called category of multicriteria selection problem, in which the decision matrix can be formulated as shown in equation (15). The matrix typically contains a number of alternative (A_i) rows and criterion (C_j) columns. Besides, each cell of the matrix represents data of each alternative for each criterion. All the

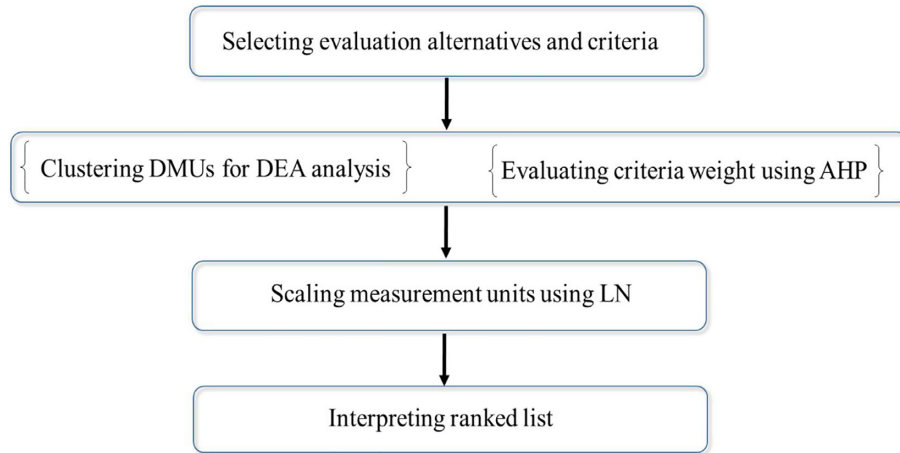


Figure 1: The proposed three-phase MCDA framework.

criteria of interest may certainly have different units with varied magnitude. Thus, it becomes a common problem in decision making as a relative rating of alternatives may change merely because the units of measurement differ. Thus, criteria normalization is typically needed for the MCSP problem to allow inter-criterion comparison.

$$\text{Decision Matrix} = \begin{matrix} & C_1 & C_2 & C_3 & C_p \\ \begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_n \end{matrix} & \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{1p} \\ a_{21} & a_{22} & a_{23} & a_{2p} \\ a_{31} & a_{31} & a_{33} & a_{3p} \\ a_{n1} & a_{n2} & a_{n3} & a_{np} \end{bmatrix} \end{matrix} \quad (15)$$

We illustrate one normalization technique called LN as shown in equations (16) and (17) for a benefit criterion (i.e. a decision maker prefers more of it or more is better) and cost criterion (i.e. a decision maker prefers less of it or less is better), respectively. This technique can convert data for all alternatives concerning each criterion to be in a range between 0 and 1. This normalization technique employs the ideal/utopia (I) and anti-ideal/nadir (AI) solutions, where the I and AI solutions are the best and worst possible alternatives from considering each criterion j , respectively. Whereas I_j represents the ideal alternative based on max value for benefit criterion and min value for cost criterion, AI_j implies the anti-ideal solution based on min value for benefit criterion and max value for cost criterion. We note that all the normalized values (n_{ij}) after performing the LN technique will be transformed to benefit criteria.

$$n_{ij} = \frac{a_{ij} - AI_j}{I_j - AI_j}; \quad \text{Benefit Criterion} \quad (16)$$

$$n_{ij} = \frac{AI_j - a_{ij}}{AI_j - I_j}; \quad \text{Cost Criterion} \quad (17)$$

4. MCDM Framework for Orientation-Selection Problem

To enhance the reliability of the decision-making process, we develop a framework incorporating multiple multicriteria decision-making methods. As shown in Fig. 1, the proposed procedure is divided into three main phases as follows.

Phase 1: Selecting evaluation alternatives and criteria. A problem of interest from diverse decision makers may cover different variables in terms of alternatives and criterion list. Thus,

numerous groups of data can create various kinds of rankings. We note that a ranking is a ranked list resulting from comparing objects using specific evaluation methods with one particular criterion or with multiple criteria. From the DEA perspective, the criteria may be viewed as the input and output criteria, whereas the overall efficiency score can be treated as the outcome of the measurement. Regardless, there may be the case that more than one alternative is efficient among the peers. Besides, DEA does not incorporate the viewpoint or experience of decision makers for the preferred criteria in the ranking.

Phase 2: Clustering DMUs for DEA analysis. DEA is a nonparametric method that can be used not only to measure the relative efficiency but also to designate a reference target for an inefficient DMU. Thus, DEA is a type of clustering technique that separates DMUs into two categories of being efficient and inefficient. Also, as the DEA technique shows relative efficiency (not absolute efficiency) among peers of evaluation, data in an experiment of interest may be organized into subgroups, such that DEA analysis is done for each subgroup rather than the entire group for meaningful discussion. Next, an evaluation of the criterion weight can be done using AHP. Although the DEA technique can be used to assess the efficiency of a particular DMU, this method alone does not incorporate the viewpoint or experience of decision makers for the preferred criteria in the ranking. Thus, the AHP technique can be used to secure criterion weight based on preference and experience of the decision maker in making criterion judgment. However, unlike using judgment for criterion evaluation, using AHP to rank all alternatives will transform quantitative data for all alternatives concerning each criterion into a judgment scale during pairwise comparisons and may not reflect actual data collected.

Phase 3: Scaling measurement units using LN. The last phase is to normalize actual data collected from an experiment to ensure that the relative rating of alternatives will not be changed merely because of different measurement units. We use LN in this study and note that there are some other normalization techniques as well. This LN is used to combine explicit data as in DEA and implicit preference as in AHP to utilize both preference and objective data in supporting decision making under various AM environments. Thus, by combining the criterion weight obtained from the AHP in the previous phase with the normalized data in this phase, the list of alternatives can be ranked and interpreted. Also, the ranked list reflects the viewpoint and judgment of a decision maker through the criterion weight that likely

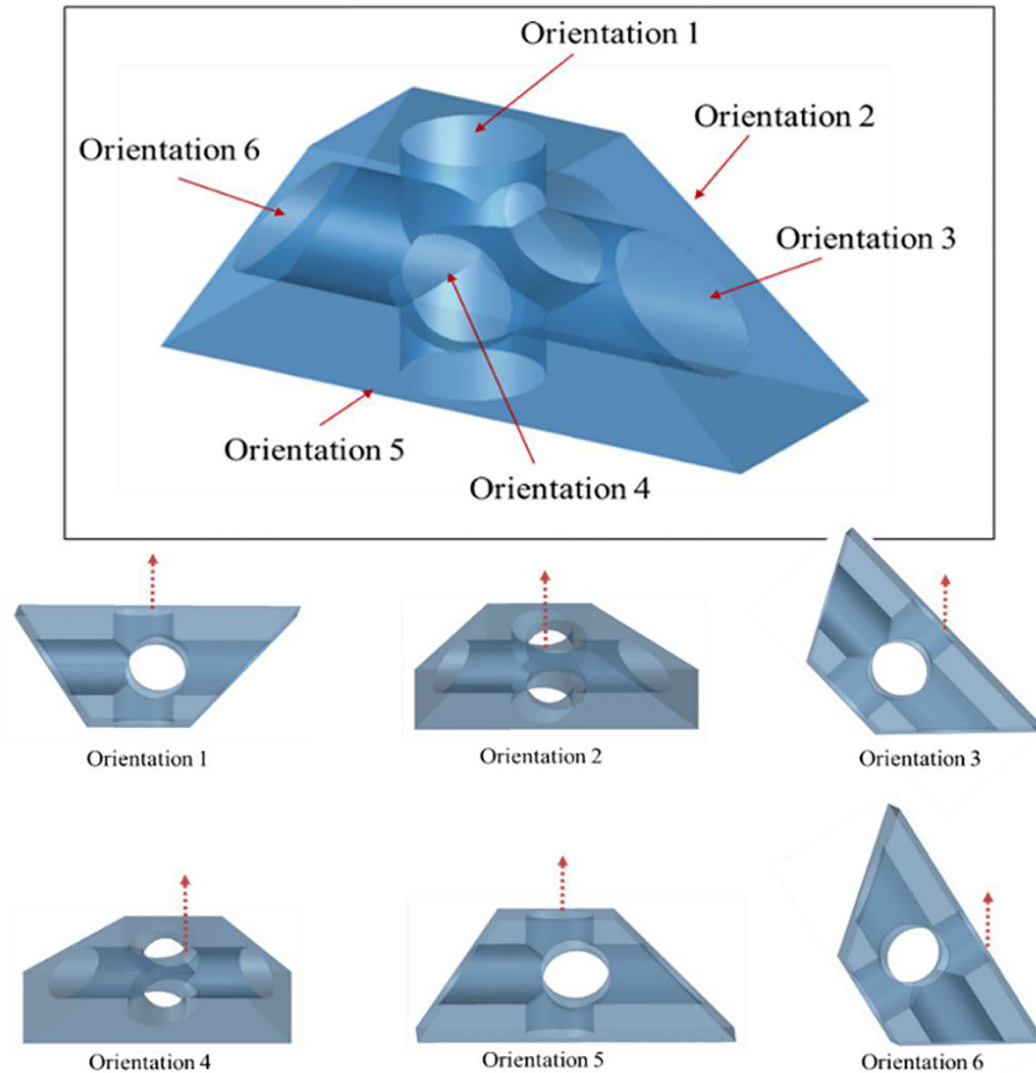


Figure 2: Orientation alternatives for the case study.

differs among decision makers involved in a decision-making process.

4.1. Experimental setup

In this section, we initially conduct an experimental design to illustrate the use of a particular DEA and AHP technique individually using a test part with a hole feature adapted from Cheng *et al.* (1995); that is, the test part model with the size of $70 \times 25 \times 30 \text{ mm}^3$ is evaluated based on the concept of convex envelope comprising of six alternatives for build directions (Fig. 2). We note that orientation alternatives 2 and 4 are further differentiated in this study, such that alternative 2 is oriented with sharp angle between the printing platform and part, whereas alternative 4 is perpendicularly oriented between the printing platform and part. Given a list of related criteria affecting the part orientation (e.g. Ga *et al.*, 2019; Di Angelo *et al.*, 2020), six evaluation criteria are chosen to illustrate the proposed method, which is build time (BT), build cost (BC), surface quality (SQ), part accuracy (PA), mechanical properties (MP), and support volume (SV) for two different AM technologies (i.e. FDM and SLS). Concern-

ing the material and printer specification, PLA material and Form-er's Farm are used for the FDM. In contrast, Duraform PA material and sPro 60 from 3D Systems are used for the SLS. Figure 3a and b illustrate the part component fabricated from both FDM and SLS printers, respectively.

We briefly discuss the criteria in this experiment next. Build-time criterion refers to the time spent on layer scanning dependent on the number of slices. As orientation of the part will affect a part's height, it follows that different orientations greatly impact the build time. Build cost refers to the resources consumed during the manufacturing of a part, which usually contains direct and indirect costs. As the indirect cost can be estimated based on the build time, orientation of a part will have a substantial effect on the part cost. Concerning the surface-quality criterion, parts being typically parallel or perpendicular to the build orientation will tend to have a better surface roughness or finish than those whose face has an angle to the build direction. In contrast, declining faces resulting from an orientation will be affected by the stair-step effect. Next, the part-accuracy criterion refers to the difference between the produced part and the designed model. Part orientation can affect both shrinkage

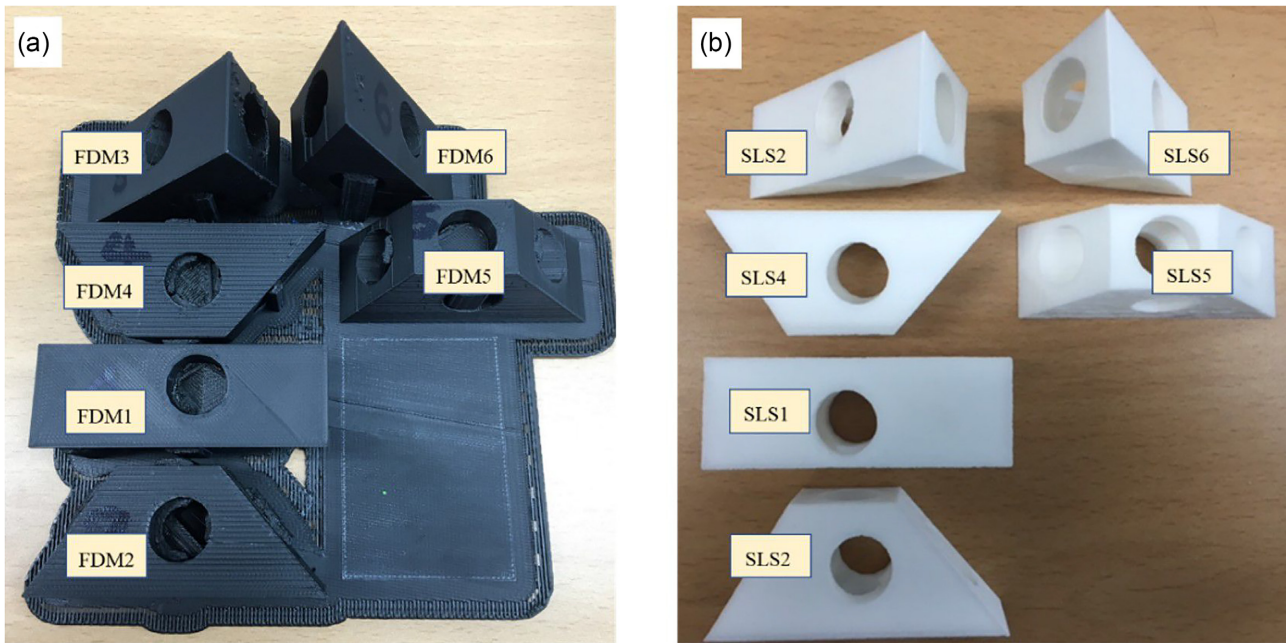


Figure 3: Printed components from (a) FDM and (b) SLS printer.

and distortion, which are the main factors in AM resulting in this difference. Besides, it is well known that the properties of a part produced by AM are anisotropic. Thus, orientation direction affects various mechanical properties. Last but not least, the support-volume criterion depends on the support structure dependent on AM technology. For example, whereas support structure is needed in FDM for overhanging, it is not required in SLS, as un-sintered materials act as a support.

To evaluate each criterion for printed part orientations, a questionnaire filled out by technical experts, part testing, and MagicsTM software developed by Materialise (2016) are used to obtain the necessary information to aid a decision maker to evaluate each orientation alternative. Data related to the build time, build cost, and support volume are estimated from MagicsTM. In contrast, surface quality, part accuracy, and mechanical properties are combined qualitative and quantitative data obtained from part test and expert opinions. Given varied support structures from each orientation, data related to the build cost and build time are computed to account for this aspect. Also, part accuracy in terms of the root mean square (RMS) error is obtained from the 3D scanner using Solutionix REXCAN 4 with an accuracy of 10 micrometers (± 0.01 millimeter). In addition, surface quality in terms of the surface roughness data (R_a) is obtained from measuring the largest surface area of each part on the Mitutoyo FORMTRACER machine with an accuracy of 1.5 micrometers (± 0.0015 millimeter). Figure 4 illustrates the test during the designed experiment to obtain data for surface quality (Fig. 4a and b) and part accuracy (Fig. 4c and d), respectively. In particular, we illustrate the analysed data for part accuracy using a 3D scanner for FDM and SLS as shown in Fig. 5a and b, in which the shrinkage is found for SLS affecting the final dimensional accuracy.

The summary of data is shown in Table 2. Data from different AM technologies and altered orientation alternatives are conflicting with each other. For example, while the build time and the build cost for different alternatives in FDM are found to be in a similar range, SLS shows to have varied build time and build

cost. This is due to the difference between the energy source and material between them. Besides, although the support material is not required in SLS, it is typically needed in FDM.

The mechanical properties are also clearly rated differently between SLS and FDM. The total height of the oriented part technically affects the anisotropic property of a part; that is, there exists a higher probability of inhomogeneous density affected by gravity in a taller part. The part produced in the Z-direction on FDM typically has the lowest tensile strength when comparing to X- and Y-directions. Thus, orientation 4 containing the least height on the Z-direction is rated with a higher score. In contrast, orientation 1 has the least bottom area for SLS, which helps minimize thermal contraction by layers during the printing process and is rated with a higher score. Besides, the surface roughness data of orientations 3 and 6 obtained from the experiment for both SLS and FDM are higher (worst) than the others. However, while the value of orientation 4 in FDM is found to be the lowest (i.e. the best surface quality), orientation 5 in SLS is found to be the best one. On the other hand, while the RMS values representing the part accuracy of orientations 4 and 5 for FDM are lower than the others (i.e. good part accuracy), orientations 1 and 4 for SLS exhibit good part accuracy with low RMS values. Also, all part orientation alternatives from SLS are found to have shrinkage.

4.2. DEA analysis and discussion

We now illustrate the DEA analysis to obtain relative efficiency of each part orientation alternative, given multiple input and output. Given six conflicting criteria, build time and build cost are chosen in this study as input criteria that reflect limited resources of the process planner in AM. In contrast, other criteria of interest are selected as output criteria to reveal desired performance measures. To illustrate how DMUs are clustered, we create two subgroups based on AM technology. The relative efficiency scores for all alternatives are reported in Table 3. The orientation alternative 4 of FDM is found to be efficient, whereas

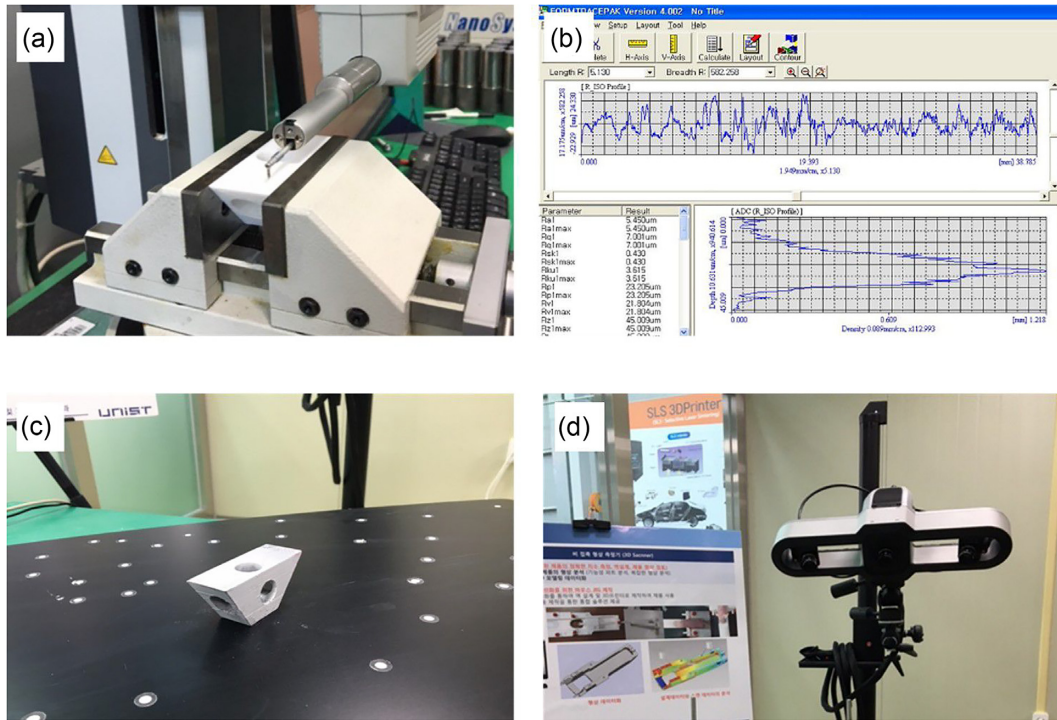


Figure 4: Test procedure to obtain surface roughness and part accuracy.

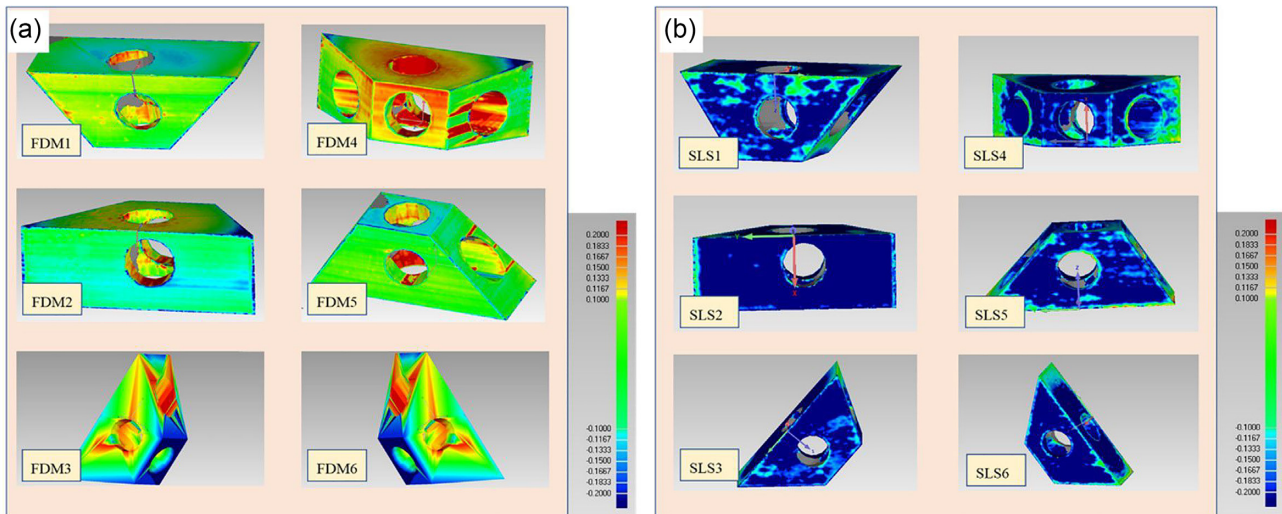


Figure 5: Test for data accuracy for (a) FDM and (b) SLS printer.

alternatives 1 and 4 for SLS are found to be efficient. It is cautionary noted that efficiency obtained from DEA is relative among peers rather than absolute. Thus, how data are set up for clustering, as well as how criteria are chosen for input/output set, will also impact relative efficiency.

4.3. AHP analysis and discussion

We next illustrate the AHP approach to obtain a ranking list for orientation alternatives. Rather than using the nonparametric DEA method without decision maker's involvement, the pairwise comparison-based AHP approach is introduced to incorporate the decision maker's preference and prior knowledge into a

ranking list. In particular, AHP's criterion weight is initially obtained to reflect requirements for two decision maker's types (i.e. a decision maker prioritizing BC first called economic decision maker and a decision maker prioritizing MP first called performance-first decision maker). The economical type illustrates a user who desires to pay less for a printed part regardless of other factors. On the other hand, the performance type is willing to pay more as long as the printed part has a high performance and good mechanical properties. Given that there are two decision-maker types, two comparison matrices, each with the size of 6×6 based on six criteria, are needed for the criterion level. Following equations (10)–(13), the pairwise comparison matrix for the criteria filled by the economic decision maker

Table 2: Summary of data in an experimental design.

FDM	Alt. 1	Alt. 2	Alt. 3	Alt. 4	Alt. 5	Alt. 6
BT (hrs.)	4.5–5.0	5.0–5.5	4.5–5.0	4.0–4.5	4.5–5.0	4.5–5.0
BC (\$)	\$12	\$15	\$13	\$12	\$13	\$13
SQ (R_a)	R_a 5.58	R_a 5.45	R_a 13.06	R_a 2.75	R_a 9.98	R_a 11.22
PA (RMS in mm.)	0.128	0.127	0.146	0.109	0.103	0.141
MP (good 5 bad 1)	Score 2	Score 3	Score 1	Score 5	Score 4	Score 1
SV (g)	3	1	5	1	3	4
SLS	Alt. 1	Alt. 2	Alt. 3	Alt. 4	Alt. 5	Alt. 6
BT (hrs.)	4.0–4.5	5.0–5.5	6.0–6.5	3.5–4.0	4.0–4.5	7.5–8.0
BC (\$)	\$70–80	\$75–85	\$80–90	\$50–60	\$70–80	\$90–100
SQ (R_a)	R_a 17.54	R_a 25.67	R_a 36.68	R_a 31.49	R_a 11.72	R_a 35.63
PA (RMS in mm.)	0.211	0.283	0.271	0.232	0.244	0.249
MP (good 5 bad 1)	Score 5	Score 3	Score 1	Score 4	Score 2	Score 1
SV (g)	No need	No need	No need	No need	No need	No need

Note: R_a denotes the profile roughness parameter; RMS denotes error between CAD file and part.

Table 3: Relative efficiency score from DEA analysis.

AM	Orientation	Relative efficiency	AM	Orientation	Relative efficiency
FDM	Alternative 1 (DMU 1)	0.5	SLS	Alternative 1 (DMU 1)	1.0
	Alternative 2 (DMU 2)	0.4		Alternative 2 (DMU 2)	0.5
	Alternative 3 (DMU 3)	0.2		Alternative 3 (DMU 3)	0.2
	Alternative 4 (DMU 4)	1.0		Alternative 4 (DMU 4)	1.0
	Alternative 5 (DMU 5)	0.7		Alternative 5 (DMU 5)	0.4
	Alternative 6 (DMU 6)	0.2		Alternative 6 (DMU 6)	0.2

is illustrated in Table 4. The pairwise-comparison matrix is then normalized, the Eigenvector is calculated, and the CI and CR are calculated. Next, $\lambda_{\max} = 6.44$ is computed, and the CI can be calculated, such that $CI = (6.44 - 6) / (6 - 1) = 0.09$. After the $RI = 1.24$ is chosen, the CR can be calculated as $CR = 0.09 / 1.24 = 0.07$. Since the CR's value is less than 10% (i.e. 0.1), the judgments are found to be acceptably consistent. We note that a similar pairwise-comparison matrix for the performance-first decision maker can be similarly computed.

Then, for a particular AM process, six comparison matrices, each with the size of 6×6 based on six alternatives required for each criterion, are needed for the level of the alternative. Table 5 shows the pairwise comparison for all the alternatives concerning each criterion in the SLS process. The pairwise comparison matrices for the FDM process can be similarly performed. Finally, after obtaining the Eigenvectors of criteria and all alternatives for each criterion, we can develop an overall priority ranking as shown in Fig. 6. In particular, the decision maker with economic type ranks orientation alternatives 4, 5, 1, 2, 3, and 6 for SLS, indicating that orientation 4 is the best orientation for him or her. When the FDM is ranked, the ranked list is orientation 4, 1, 5, 3, 2, and 6, showing that alternative 4 is the most suitable. Next, when the performance-first decision maker ranks SLS, the ranked list for all orientation alternatives is 1, 4, 5, 2, 3, and 6, whereas the ranked list for FDM is 4, 5, 1, 2, 3, and 6.

Although the results are found to be consistent for both SLS and FDM, some insights are next discussed. The DEA approach shows that DMU 4 from FDM is the only efficient one, whereas DMUs 1 and 4 from SLS are efficient. DEA analysis does not take any preferences or knowledge of a decision maker into account. On the other hand, even though the AHP-based ranking also

consistently shows that alternative 4 is found to be the best one for FDM regardless of decision-maker types, the best ranking for SLS is affected by decision-maker types, such that the economical type will prefer alternative 4 and the performance-first type will choose alternative 1. Next, considering the worst relative efficiency, DMUs 3 and 6's efficiency scores are found to be equally the lowest for both SLS and FDM. However, the AHP-based analysis shows that although alternatives 3 and 6 are the worst in SLS ranking, alternative 3 is preferred to alternative 6, given a decision maker's judgment. Finally, the AHP-based ranking for FDM shows that alternative 6 is the worst one regardless of decision-maker types. However, the economical type ranks alternative 2 as the second worst, but the performance-first type ranks alternative 3 as the second worst.

It is clear that DEA does not involve decision makers during a decision-making process and ultimately convert collected input and output data into justified efficient and inefficient clusters. In contrast, even if the AHP takes knowledge from a decision maker, there may be some inconsistencies in making judgment, especially for comparing alternatives for each criterion. This is the case as AHP uses the complete decision maker's judgments and opinions based on the collected data. Thus, we next emphasize the use of a normalization technique called LN combined with the AHP-based criterion weight, which utilizes both actual collected data as in DEA and decision maker's judgments on criteria as in AHP.

4.4. LN analysis and discussion

We next illustrate the LN technique to scale different unit measurements to a range between 0 and 1 to allow intercriteria comparison. Following equations (15)–(17), the ideal and anti-ideal

Table 4: Pairwise comparison and normalized matrix (economic decision maker).

Criteria	BT	BC	SQ	PA	MP	SV	
BT	1	1/3	3	3	4	2	
BC	3	1	5	6	6	5	
SQ	1/3	1/5	1	2	3	2	
PA	1/3	1/6	1/2	1	3	2	
MP	1/4	1/6	1/3	1/3	1	1/3	
SV	1/2	1/5	1/2	1/2	3	1	
(sum)	5.42	2.07	10.33	12.83	20.00	12.33	
							Eigenvector
BT	0.19	0.16	0.29	0.23	0.20	0.16	0.21
BC	0.55	0.48	0.48	0.47	0.30	0.41	0.45
SQ	0.06	0.10	0.10	0.16	0.15	0.16	0.12
PA	0.06	0.08	0.05	0.08	0.15	0.16	0.10
MP	0.05	0.08	0.03	0.03	0.05	0.03	0.04
SV	0.09	0.10	0.05	0.04	0.15	0.08	0.09
(sum)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 5: Pairwise comparison matrices of all alternatives for SLS (economical DM).

BT	O1	O2	O3	O4	O5	O6		PA	O1	O2	O3	O4	O5	O6	
O1	1	2	4	1/3	1	8	0.19	O1	1	7	6	3	4	4	0.42
O2	1/2	1	3	1/5	1/5	6	0.10	O2	1/7	1	1/3	1/6	1/4	1/4	0.04
O3	1/4	1/3	1	1/7	1/6	4	0.06	O3	1/6	3	1	1/5	1/4	1/2	0.06
O4	3	5	7	1	2	7	0.37	O4	1/3	6	5	1	2	3	0.23
O5	1	5	6	1/2	1	7	0.25	O5	1/4	4	4	1/2	1	3	0.16
O6	1/8	1/6	1/4	1/7	1/7	1	0.03	O6	1/4	4	2	1/3	1/3	1	0.09
BC	O1	O2	O3	O4	O5	O6		MP	O1	O2	O3	O4	O5	O6	
O1	1	2	4	1/4	1	7	0.17	O1	1	5	8	2	6	8	0.45
O2	1/2	1	5	1/5	1/3	5	0.12	O2	1/5	1	5	1/2	3	3	0.15
O3	1/4	1/5	1	1/7	1/5	2	0.05	O3	1/8	1/5	1	1/6	1/2	1	0.04
O4	4	5	7	1	4	8	0.45	O4	1/2	2	6	1	3	6	0.24
O5	1	3	5	1/4	1	5	0.18	O5	1/6	1/3	2	1/3	1	2	0.07
O6	1/7	1/5	1/2	1/8	1/5	1	0.03	O6	1/8	1/3	1	1/6	1/2	1	0.04
SQ	O1	O2	O3	O4	O5	O6		SV	O1	O2	O3	O4	O5	O6	
O1	1	2	7	3	1/3	6	0.22	O1	1	1	1	1	1	2	0.19
O2	1/2	1	4	4	1/5	4	0.15	O2	1	1	1	1	1	1	0.17
O3	1/7	1/4	1	1/4	1/8	1/2	0.03	O3	1	1	1	1	1	1	0.17
O4	1/3	1/4	4	1	1/5	4	0.09	O4	1	1	1	1	1	1	0.17
O5	3	5	8	5	1	8	0.45	O5	1	1	1	1	1	2	0.19
O6	1/6	1/4	2	1/4	1/8	1	0.04	O6	1/2	1	1	1	1/2	1	0.13

values are initially obtained. We note that MP is classified as a benefit criterion (i.e. the max value is better), whereas other criteria are classified as cost criterion (i.e. min value is better) in this study. Next, the normalized values for all alternatives concerning each criterion are computed as shown in Table 6. Considering FDM, for instance, the ideal value (the minimum value) of all alternatives concerning the SQ criterion is 2.75, whereas the anti-ideal value (the maximum value) is 13.06. Thus, equation (17) is applied such that the normalized value for alternative 1 concerning the SQ criterion is $(13.06 - 5.58) / (13.06 - 2.75) = 0.73$. On the other hand, the ideal value (the maximum value) of all alternatives for the MP criterion is 5, whereas the anti-ideal value

(the minimum value) is 1. Thus, equation (16) is used and the normalized value for alternative 1 is $(2 - 1) / (5 - 1) = 0.25$.

Then, the ranked list of all alternatives is obtained using AHP analysis for criterion weight to incorporate decision maker's preferences and judgments as shown in Table 7. Initially, we illustrate equal weight for all criteria and compute the overall score for both FDM and SLS. For example, the score 0.57 for alternative 1 of FDM can be computed as the sum of the product between the normalized values of alternative 1 for all the criteria and the criterion weight; that is, $0.57 = (0.50 * 1/6) + (1.00 * 1/6) + (0.73 * 1/6) + (0.42 * 1/6) + (0.25 * 1/6) + (0.5 * 1/6)$. Thus, based on the score of all alternatives, the ranked list considering equal weight

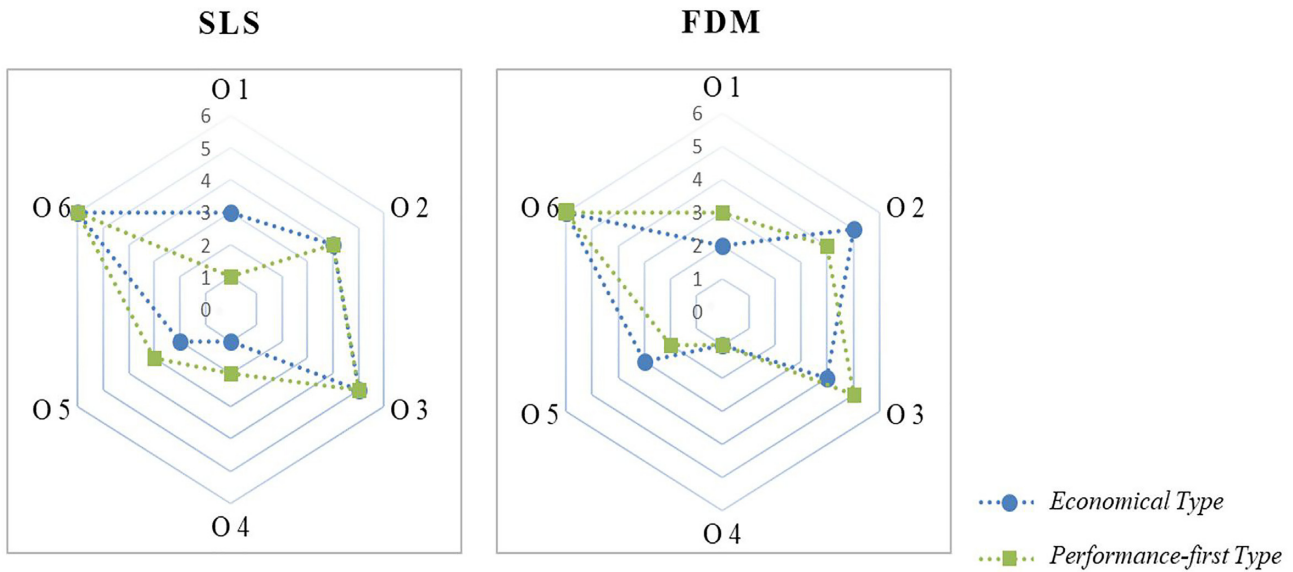


Figure 6: AHP-based ranking representation for FDM and SLS technology.

Table 6: LN matrix using ideal and anti-ideal values.

AM	Alt.	BT (Min)	BC (Min)	SQ (Min)	PA (Min)	MP (Max)	SV (Min)
	Ideal	4	12	2.75	0.103	5	1
	Anti-Ideal	5	15	13.06	0.146	1	5
FDM	Alt. 1	0.50	1.00	0.73	0.42	0.25	0.50
	Alt. 2	0.00	0.00	0.74	0.44	0.50	1.00
	Alt. 3	0.50	0.67	0.00	0.00	0.00	0.00
	Alt. 4	1.00	1.00	1.00	0.86	1.00	1.00
	Alt. 5	0.50	0.67	0.30	1.00	0.75	0.50
	Alt. 6	0.50	0.67	0.18	0.12	0.00	0.25
	Ideal	3.5	60	11.72	0.211	5	0
	Anti-Ideal	7.5	100	36.68	0.283	1	0
SLS	Alt. 1	0.88	0.50	0.77	1.00	1.00	1.00
	Alt. 2	0.63	0.38	0.44	0.00	0.50	1.00
	Alt. 3	0.38	0.25	0.00	0.17	0.00	1.00
	Alt. 4	1.00	1.00	0.21	0.71	0.75	1.00
	Alt. 5	0.88	0.50	1.00	0.54	0.25	1.00
	Alt. 6	0.00	0.00	0.04	0.47	0.00	1.00

for FDM is alternatives 4, 5, 1, 2, 6, and 3, whereas the ranked list for SLS is alternatives 1, 4, 5, 2, 3, and 6. It is worth observing that the ranked lists for FDM and SLS considering equal weight are consistent with the relative efficiency scores found from using DEA analysis. Recall that DEA analysis does not take any preferences among criteria from a decision maker. For example, when rearranging DEA’s relative efficiency scores of DMUs 1–6 for FDM from the highest to the lowest, it follows that DMU 4 (efficiency 1.0) > DMU 5 (efficiency 0.7) > DMU 2 (efficiency 0.5) > DMU 1 (efficiency 0.4) > DMUs 3 and 6 (efficiency 0.2). In addition, rearranging DEA’s relative efficiency scores for SLS shows that DMUs 1 and 4 (efficiency 1.0) > DMU 2 (efficiency 0.5) > DMU 5 (efficiency 0.4) > DMUs 3 and 6 (efficiency 0.2).

Besides, the AHP-based criterion weights from a decision maker with economical and performance-first types show that

the ranked lists can also be computed when preferences among criteria are involved. Based on the criterion weight of the economical decision maker, the ranked list for FDM is alternatives 4, 1, 5, 6, 3, and 2. In contrast, the ranked list for SLS is alternatives 4, 1, 5, 2, 3, and 6. Besides, based on the criterion weight of performance-first decision maker, the ranked list for FDM is alternatives 4, 5, 1, 2, 6, and 3. In contrast, the ranked list for SLS is alternatives 1, 4, 5, 2, 3, and 6.

4.5. Analysis of the proposed MCDM framework

We further analyse the ranked list for the proposed MCDM framework and a particular method from implementing either DEA or AHP alone as illustrated in Table 8. In particular, only implementing the DEA technique lacks a perspective of judg-

Table 7: Ranking list for combined LN and AHP-based criterion weight.

AHP weight	Equal weight	1/6	1/6	1/6	1/6	1/6	1/6
	Economical type	0.21	0.45	0.12	0.10	0.04	0.09
	Performance-first type	0.20	0.11	0.06	0.15	0.44	0.04
		Alt. 1	Alt. 2	Alt. 3	Alt. 4	Alt. 5	Alt. 6
FDM	Score (equal)	0.57	0.45	0.19	0.98	0.62	0.29
	Ranking (equal)	3	4	6	1	2	5
	Score (economical)	0.74	0.24	0.41	1.00	0.62	0.46
	Ranking (economical)	2	6	5	1	3	4
	Score (performance-first)	0.45	0.37	0.17	0.98	0.69	0.21
	Ranking (performance-first)	3	4	6	1	2	5
SLS	Score (equal)	0.86	0.49	0.30	0.78	0.69	0.25
	Ranking (equal)	1	4	5	2	3	6
	Score (economical)	0.73	0.46	0.30	0.88	0.68	0.14
	Ranking (economical)	2	4	5	1	3	6
	Score (performance-first)	0.91	0.45	0.17	0.80	0.52	0.11
	Ranking (performance-first)	1	4	5	2	3	6

Table 8: Comparison of the analysed ranking list for orientation alternatives.

Ranked list	DEA technique	AHP technique			LN technique	
		Economical type	Performance-first type	Equal weight	Economical type	Performance-first type
FDM	Alt. 1	3	2	3	2	3
	Alt. 2	4	5	4	6	4
	Alt. 3	5	4	5	5	6
	Alt. 4	1	1	1	1	1
	Alt. 5	2	3	2	3	2
	Alt. 6	5	6	6	4	5
SLS	Alt. 1	1	3	1	2	1
	Alt. 2	3	4	4	4	4
	Alt. 3	5	5	5	5	5
	Alt. 4	1	1	2	1	2
	Alt. 5	4	2	3	3	3
	Alt. 6	5	6	6	6	6

Remark: The bold values indicate the best alternative under each category.

ments from any decision makers and may include a number of efficient orientation alternatives that are difficult for reaching a final decision (i.e. Alternative 4 for FDM and Alternatives 1 and 4 for SLS). In contrast, the AHP technique employed in this analysis incorporates preferences from economical decision maker and performance-requiring decision maker to analyse the best ranking list (i.e. Alternative 4 for FDM's economical type and performance-first type, Alternative 4 for SLS's economical type, and Alternative 1 for SLS's performance-first type). However, the caution should be noted as the AHP technique alone requires subjective judgment at both the level of criterion evaluation and the level of alternatives with respect to criteria. Thus, uncertainty and inconsistency in making judgments from AHP should be carefully treated (Khamhong et al., 2019; Munier & Hontoria, 2021). On the other hand, the LN technique employs AHP-based subjective weights for criteria and explicit data for the level of alternatives with respect to criteria, which allows the ranking list to be analysed (i.e. Alternative 4 for FDM's economical type, performance-first type, and equal-weight type, Alternative 4 for

SLS's economical type, Alternative 1 for SLS's performance-first type, and Alternative 1 for SLS's equal-weight type). We note that although the ranking lists between AHP and LN techniques are found to be similar, it may not always be the case since subjective judgments concerning alternative judgments from AHP are avoided.

The analysed ranking lists obtained from the proposed framework are further confirmed with the technical experts to understand the validity of the proposed algorithm. Across the FDM process, alternative 4 with perpendicular orientation for the printing platform is found to be the best orientation. Given the least build cost, build time, and little support volume, while providing the best mechanical properties and surface quality combining with moderate part accuracy, the combination of orientation 4 under simultaneous criteria consideration is shown to be the best one. Concerning the SLS process, both alternatives 4 and 1 are shown to be efficient. Whereas alternative 4 performs well when the economic preference is driven, alternative 1 comparatively performs well when the performance-first preference

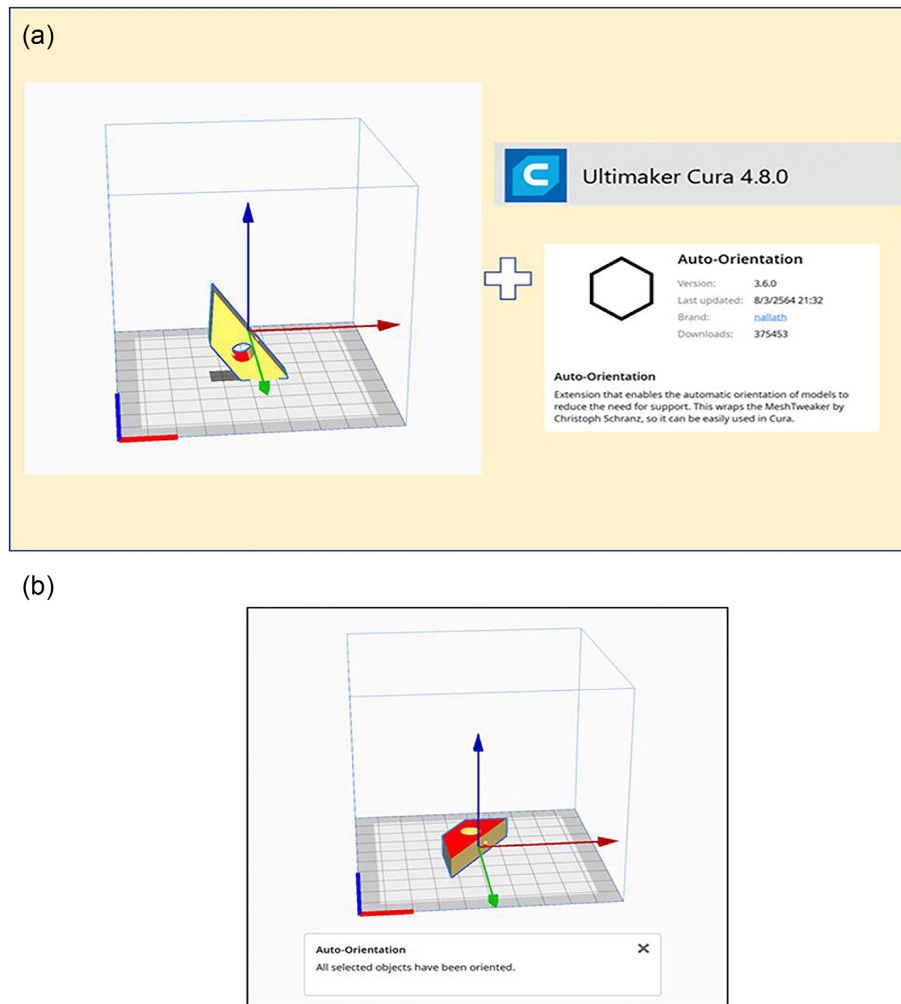


Figure 7: Verification with the open-source, auto-orientation module Tweaker.

is motivated. This is due to that orientation 4 uses the least time and the least cost in printing. On the other hand, alternative 1 is found to have the best combination of part accuracy and mechanical properties.

4.6. Verification and comparison of the proposed MCDM framework

We further verify the proposed analysis with the open-source Python application called Tweaker, which is embedded with Ultimaker Cura (Tweaker-3, 2020), to illustrate the efficacy of the proposed method as shown in Fig. 7. Various algorithms have been integrated in the Tweaker module to analyse the object's mesh representation concerning bottom area, overhang, contour length, and unprintable characteristics (Schrantz, 2016). According to Schrantz (2016), Tweaker is the first open-source, auto-orientation module to search for optimal orientation on the printing platform to improve the efficiency of AM printing. That is, Fig. 7a shows the initial random placement, while Fig. 7b presents the result obtained from the Tweaker's auto-orientation suggestion. The result obtained from Tweaker shows that the orientation 4 is the best orientation. Thus, similar result between the proposed MCDM framework and the Tweaker module is found, which illustrates the validity of our proposed algo-

rithm. Regardless, in contrast to our proposed methodology, we note that the Tweaker module cannot justify the effectiveness of other orientation alternatives. Additionally, decision makers' subjective preferences are not incorporated in the Tweaker module.

Next, the result obtained from the proposed MCDM framework is compared with other studies that use a similar part with a hole feature for a case study. We note that other objects with hole features have also been used as a case study by various studies for comparative study of orientation alternatives (e.g. Xu et al., 1999; Giannatsis & Dedoussis, 2007; Zhang et al., 2019). Table 9 presents the top-three ranking list obtained from the proposed MCDM framework in this study by comparing with the results from Cheng et al. (1995), Byun and Lee (2006), and Zhang et al. (2016b). We illustrate the AHP with economical decision maker and LN with equal weight for the comparative study. In addition, possible discrepancy concerning the case study between this study and other studies should be noted; that is, orientation alternatives 2 and 4 are differentiated in this study, such that while alternative 2 is oriented with sharp angle between the printing platform and part, alternative 4 is perpendicularly oriented between the printing platform and part. Besides, criterion list and AM type analysed in this study and other comparative studies may not necessarily be the same. For example,

Table 9: Comparison of this study with other studies for the similar case study.

Study	Criteria evaluation	AM Type	Method	1st rank	2nd rank	3rd rank
This study	Surface roughness, time, cost, accuracy, support volume, mechanical property	FDM	DEA	Alt. 4	Alt. 5	Alt. 1
			AHP (economical)	Alt. 4	Alt. 1	Alt. 5
		SLS	LN (equal)	Alt. 4	Alt. 5	Alt. 1
			DEA	Alt. 1 and Alt. 4	Alt. 2	
Cheng et al. (1995)	Accuracy, time	SLA	Multi-objective model	Alt. 4	Alt. 1	Alt. 5
Byun and Lee (2006)	Surface roughness Time Cost	SLA	Simple additive weighting	Alt. 4	Alt. 6	Alt. 1
				Alt. 4	Alt. 5	Alt. 1
				Alt. 4	Alt. 5	Alt. 1
Zhang et al. (2016b)	Surface roughness, time, cost, favorableness	SLS	AM feature/production knowledge-based MCDM	Alt. 4	Alt. 5	Alt. 1

while this study assesses both FDM and SLS, Cheng et al. (1995) and Byun and Lee (2006) use SLA for the test part. In addition, the SLS printer is investigated by Zhang et al. (2016b).

In particular, the overall optimal part orientation (i.e. the 1st rank) obtained from this study is found to be the same with other studies except for the case of LN technique with equal weight for SLS; that is, orientation alternative 4 is found to be the best option, in which the perpendicular direction for the printing platform is used. Regardless, when considering the 2nd and 3rd ranks for all the comparative studies, the results show good agreement even though a little difference exists among them. Additionally, orientation alternatives 5 and 1 are found to be acceptable options for most of the results obtained from the evaluated studies. Regardless, orientation alternative 6 is also noted as a 2nd rank for the surface roughness criterion in the Byun and Lee (2006) study.

5. Managerial Insights

MCDM has been proven a successful method that can evaluate multiple conflicting criteria in making decisions and planning. Process planning in AM faces a similar issue, given conflicting criteria with trade-offs among criteria of interest. It is also necessary to understand the context of each particular AM technology, in which the quality of 3D part fabrication highly depends on the processing printer. In this study, the selection problem for part orientation planning of both material extrusion (FDM) and powder bed fusion (SLS) is illustrated. We propose a framework that combines explicit data as in DEA and implicit preference as in AHP in the form of LN technique to utilize both preference and objective data in supporting AM process planning. Several authors suggest that the limitation of using a particular method alone can be minimized (e.g. Hadad & Hanani, 2011; Keren et al., 2014; Rashidi, 2020). Thus, combining AHP and DEA in the framework for a selection problem using LN technique allows a reduction of subjective opinions for alternatives with respect to each criterion and provides the concrete ranking list that suits well requirements from each decision maker. In addition, LN technique also allows considering what-if analysis in various scenarios based on preferences to criteria and allows ranking of efficient decision-making units.

Initially, careful consideration should be taken in selecting alternatives of interest and variables for a criterion list. During this step, an expert opinion from an experienced decision maker for FDM and SLS technology is required. In this study, the crite-

ria are selected to reflect both consumed resources and desired outputs for AM process planning. Next, when DMUs are clustered to evaluate efficiency using DEA analysis, it should be cautious that the DEA's efficiency score is relative to the peers and not absolute value that should be set as an ultimate target. Also, the comparison of DMUs in a clustered group should be reasonably comparable. Thus, we categorize the orientation DMUs into two clusters based on each AM technology for a fair evaluation (i.e. FDM and SLS). The relative efficiency scores found in this study show that the orientation alternative 4 of FDM is efficient and alternatives 1 and 4 for SLS are efficient. Thus, more than one alternative may be found efficient in a clustering group. We note, however, that DEA methodology does not involve decision makers during a decision-making process and ultimately convert collected input and output data into justified efficient and inefficient clusters. Thus, AHP technology may be used to rate judgments from a decision maker.

We next reflect requirements for two decision maker's types by implementing the AHP methodology. The AHP-based ranking is consistent with DEA showing that alternative 4 is the best one for FDM regardless of decision-maker types. In contrast, the best ranking for SLS is affected by decision maker's preferences between economical and performance-first types. Still, it is worth mentioning that by synthesizing the local weight of criterion level and alternative level using AHP, the collected data are not explicitly used in the computation. Rather, the decision maker's judgments use pairwise comparison based on these data. Next, the LN is then used by combining with the AHP-based criterion weight to explicitly use both actual collected data and decision maker's judgments on criteria in the synthesis. The ranked lists for FDM and SLS considering equal weight are found to be consistent with the relative efficiency scores from DEA. This is expected as DEA also does not take any preference from a decision maker, which is analogous to having no preferences among the criterion list. However, the ranked lists from using LN with other criterion-weight settings are affected by how decision maker's preferences are involved.

6. Conclusions and Future Research

AM processes have gained many communities' interests as they can provide several benefits in design flexibility, time-to-market reduction, high speed of the process, product customization, material savings, etc. While an emphasis in the AM has moved toward end-use parts, some issues related to process

inefficiency and instability resulting from certain factors, including the orientation selection of a part, still exist and need to be addressed. In this research, we propose the integrative framework using MCDM methods to tackle the drawbacks of each approach for the part orientation decision in AM. Initially, we propose a framework that combines explicit data as in DEA and implicit preference as in AHP in the form of LN technique to utilize both preference and objective data in supporting decision making under various AM environments. An experimental design was conducted following the selection of alternatives and criteria (build time, build cost, surface quality, part accuracy, mechanical properties, and support volume). Then, the alternatives or DMUs are clustered using DEA analysis for two AM processes (FDM and SLS). Then, to integrate a judgment or preference from two types of decision makers (economic and performance-first types), the criterion weight was analysed using the pairwise comparison-based AHP approach. Finally, the LN technique was proposed to scale and normalize actual collected data for all alternatives concerning each criterion so that the relative rating of alternatives will not be changed merely because of different units of measurement in the study.

This paper provides a case study to demonstrate how the orientation alternatives can be analysed using a framework of integrative multicriteria decision analysis for their efficiency cluster and ranked list based on both quantitative and qualitative measurements. We note, however, that this paper is the first phase of our integrated AM process planning studies by synthesizing three modules of printer selection, part orientation decision, and part-to-printer scheduling. Thus, our future works are to integrate the orientation model with the other two modules of printer selection and part-to-printer optimization. Additionally, part orientation alternatives produced from other AM technologies should be further tested and compared. Besides, while this study provides a single case study to illustrate a proof-of-concept evaluation of the proposed integrative MCDM framework, the technique employed can be further extended for selecting the orientation of a part component with highly complex structures, such as parts with a topologically optimized structure like brackets and cellular solids.

The MCDM framework based on AHP, DEA, and LN proposed in this study also exhibits some limitations. Interdependence among criteria, such as the dependence between build time and support volume, and between part accuracy and surface quality, may exist in reality. Thus, other MCDM techniques that allow a consideration of the interdependence among criteria, such as the ANP, the decision making trial and evaluation laboratory (DEMATEL), and the structural equation modelling (SEM), may be employed. Regardless, it is noted that considering interdependence among criteria may involve complex procedure, bias of associated human judgment, and a larger sample size. Moreover, other criteria, such as scan path and machine parameters, can be further investigated for the dependent effect to the best orientation alternative. Additionally, decision makers' judgments based on varied application areas will also interestingly affect how part orientation is to be selected. Finally, the proposed framework in this study can be extended for other selection problems related to AM, such as 3DP material selection and AM printer selection.

Acknowledgments

This research was supported in part by the Office of the Higher Education Commissions (OHEC) and the Thailand Research

Fund (TRF) under research grant MRG6180181, and the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government (MOTIE; 20193310100030, "Development of highly efficient F-class gas turbine hot component by controlling and applying Design for Additive Manufacturing"). The opinions expressed herein are those of the authors and do not necessarily reflect the views of the funding agencies. The authors are also grateful and would like to thank the anonymous reviewers for their valuable comments and suggestions that helped us to improve our research presentation.

Conflict of interest statement

None declared.

References

- ASTM(2012). *Standard terminology for additive manufacturing technologies*. ASTM International.
- Bayazit, O., & Karpak, B. (2007). An analytical network process-based framework for successful total quality management (TQM): An assessment of Turkish manufacturing industry readiness. *International Journal of Production Economics*, 105, 79–96.
- Byun, H. S., & Lee, K. H. (2006). Determination of the optimal build direction for different rapid prototyping processes using multi-criterion decision making. *Robotics and Computer-Integrated Manufacturing*, 22(1), 69–80.
- Canellidis, V., Giannatsis, J., & Dedoussis, V. (2009). Genetic-algorithm-based multi-objective optimization of the build orientation in Stereolithography. *The International Journal of Advanced Manufacturing Technology*, 45, 714–730.
- Chaiyaphan, C., & Ransikarbum, K. (2020). Criteria analysis of food safety using the analytic hierarchy process (AHP)-A case study of Thailand's fresh markets. In *E3S Web of Conferences*(Vol. 141, p. 02001). EDP Sciences.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. *Management Science*, 27(6), 668–697
- Cheng, W., Fuh, J. Y. H., Nee, A. Y. C., Wong, Y. S., Loh, H. T., & Miyazawa, T. (1995). Multi-objective optimization of part-building orientation in stereolithography. *Rapid Prototyping Journal*, 1(4), 12–23
- Di Angelo, L., Di Stefano, P., Dolatnezhadsomarin, A., Guardiani, E., & Khorram, E. (2020). A reliable build orientation optimization method in additive manufacturing: The application to FDM technology. *The International Journal of Advanced Manufacturing Technology*, 108, 263–276.
- Dong, Q., & Cooper, O. (2016). A peer-to-peer dynamic adaptive consensus reaching model for the group AHP decision making. *European Journal of Operational Research*, 250(2), 521–530.
- Dweiri, F., Kumar, S., Khan, S. A., & Jain, V. (2016). Designing an integrated AHP based decision support system for supplier selection in automotive industry. *Expert Systems with Applications*, 62, 273–283.
- Ga, B., Gardan, N., & Wahu, G. (2019). Methodology for part building orientation in additive manufacturing. *Computer-Aided Design and Applications*, 16(1), 113–128.
- Gardan, J. (2015). Additive manufacturing technologies: State of the art and trends. *International Journal of Production Research*, 54(10), 1–15.

- Giannatsis, J., & Dedoussis, V. (2007). Decision support tool for selecting fabrication parameters in stereolithography. *The International Journal of Advanced Manufacturing Technology*, 33(7-8), 706-718.
- Gibson, I., Rosen, D., & Stucker, B. (2014). *Additive manufacturing technologies: 3D printing, rapid prototyping, and direct digital manufacturing*. Springer.
- Ha, S., Park, E., & Kim, N. (2020). Analysis of shape deformation from densification of additive manufacturing parts in selective laser sintering. *International Journal of Precision Engineering and Manufacturing*, 21, 1571-1580.
- Ha, S., Ransikarbum, K., & Kim, N. (2016). Phenomenological deformation patterns of 3D printed products in a selective laser sintering process. In *The 18th International Conference on Industrial Engineering*(pp. 10-12).
- Ha, S., Ransikarbum, K., Han, H., Kwon, D., Kim, H., & Kim, N. (2018). A dimensional compensation algorithm for vertical bending deformation of 3D printed parts in selective laser sintering. *Rapid Prototyping Journal*, 24(6), 955-963.
- Hadad, Y., & Hanani, M. Z. (2011). Combining the AHP and DEA methodologies for selecting the best alternative. *International Journal of Logistics Systems and Management*, 9(3), 251-267.
- Han, J. Y. (2013). A study on the prototype modeling method using 3D printing. *Journal Packaging Culture Design Research*, 34, 97-109.
- Ingole, D. S., Deshmukh, T. R., Kuthe, A. M., & Ashtankar, K. M. (2011). Build orientation analysis for minimum cost determination in FDM. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 225(10), 1925-1938.
- Jiang, J. (2020). A novel fabrication strategy for additive manufacturing processes. *Journal of Cleaner Production*, 272, 122916.
- Jiang, J., & Ma, Y. (2020). Path planning strategies to optimize accuracy, quality, build time and material use in additive manufacturing: A review. *Micromachines*, 11(7), 633.
- Jiang, J., Xu, X., & Stringer, J. (2018). Support structures for additive manufacturing: A review. *Journal of Manufacturing and Materials Processing*, 2(4), 64.
- Jiang, J., Xu, X., & Stringer, J. (2019a). Optimisation of multi-part production in additive manufacturing for reducing support waste. *Virtual and Physical Prototyping*, 14(3), 219-228.
- Jiang, J., Xu, X., & Stringer, J. (2019b). Optimization of process planning for reducing material waste in extrusion-based additive manufacturing. *Robotics and Computer-Integrated Manufacturing*, 59, 317-325.
- Jiang, J., Xiong, Y., Zhang, Z., & Rosen, D. W. (2020). Machine learning integrated design for additive manufacturing. *Journal of Intelligent Manufacturing*, 1-14. <https://doi.org/10.1007/s10845-020-01715-6>.
- Jiang, J., Newman, S. T., & Zhong, R. Y. (2021). A review of multiple degrees of freedom for additive manufacturing machines. *International Journal of Computer Integrated Manufacturing*, 34(2), 195-211.
- Keren, B., Hadad, Y., & Laslo, Z. (2014). Combining AHP and DEA methods for selecting a project manager. *Management: Journal of Sustainable Business and Management Solutions in Emerging Economies*, 19(71), 17-28.
- Khamhong, P., Yingviwatanapong, C., & Ransikarbum, K. (2019). Fuzzy analytic hierarchy process (AHP)-based criteria analysis for 3D printer selection in additive manufacturing. In *2019 Research, Invention, and Innovation Congress (RI2C)*(pp. 1-5). IEEE.
- Kokangül, A., Polat, U., & Dağsuyu, C. (2017). A new approximation for risk assessment using the AHP and Fine Kinney methodologies. *Safety Science*, 91, 24-32.
- Lambert, P. (2014). *Tensile properties of materials: FDM printer and SLS printer* [Online]. Available: <http://www.sculpteo.com/en/>. [Accessed 5 June 2016].
- Leirmo, T. S., & Martinsen, K. (2020). Deterministic part orientation in additive manufacturing using feature recognition. *Procedia CIRP*, 88, 405-410.
- Liu, J. S., Lu, L. Y., Lu, W. M., & Lin, B. J. (2013). Data envelopment analysis 1978-2010: A citation-based literature survey. *Omega*, 41, 3-15.
- Ma, J. (2020). Environmentally sustainable management of 3D printing network: Decision support for 3D printing work allocation. *International Journal of Precision Engineering and Manufacturing*, 21(3), 537-544.
- Materialise Magics. (2016). [Online]. Available: <http://www.materialise.com>. [Accessed 5 March 2016].
- Moroni, G., Syam, W. P., & Petrò, S. (2015). Functionality-based part orientation for additive manufacturing. *Procedia Cirp*, 36, 217-222.
- Munier, N., & Hontoria, E. (2021). Shortcomings of the AHP Method. In *Uses and limitations of the AHP method*(pp. 41-90). Springer.
- Nelson, J. A., Galloway, G., Rennie, A. E., Abram, T. N., & Bennett, G. R. (2014). Effects of scan direction and orientation on mechanical properties of laser sintered polyamide-12. *International Journal of Advanced Design and Manufacturing Technology*, 7, 19-25.
- Puchongkawarin, C., & Ransikarbum, K. (2020). An integrative decision support system for improving tourism logistics and public transportation in Thailand. *Tourism Planning & Development*, 1-16. <https://doi.org/10.1080/21568316.2020.1837229>.
- Qin, Y., Qi, Q., Scott, P. J., & Jiang, X. (2019). Determination of optimal build orientation for additive manufacturing using Muirhead mean and prioritised average operators. *Journal of Intelligent Manufacturing*, 30(8), 3015-3034.
- Ransikarbum, K., & Mason, S. J. (2016a). Multiple-objective analysis of integrated relief supply and network restoration in humanitarian logistics operations. *International Journal of Production Research*, 54, 49-68.
- Ransikarbum, K., & Mason, S. J. (2016b). Goal programming-based post-disaster decision making for integrated relief distribution and network restoration. *International Journal of Production Economics*, 182, 324-341.
- Ransikarbum, K., & Kim, N. (2017a). Multi-criteria selection problem of part orientation in 3D fused deposition modeling based on analytic hierarchy process model: A case study. In *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*(pp. 1455-1459). IEEE.
- Ransikarbum, K., & Kim, N. (2017b). Data envelopment analysis-based multi-criteria decision making for part orientation selection in fused deposition modeling. In *Industrial Engineering and Applications (ICIEA), 2017 4th International Conference on IEEM*(pp. 81-85). IEEE.
- Ransikarbum, K., Ha, S., Ma, J., & Kim, N. (2017). Multi-objective optimization analysis for part-to-printer assignment in a network of 3D fused deposition modeling. *Journal of Manufacturing Systems*, 43, 35-46.
- Ransikarbum, K., Yingviwatanapong, C., Leksomboon, R., Wajanavit, T., & Bijaphala, N. (2019a). Additive manufacturing-based healthcare 3D model for education: Literature review and a feasibility study. In *2019 Research, Invention, and Innovation Congress (RI2C)*(pp. 1-6). IEEE.

- Ransikarbum, K., Pitakaso, R., & Kim, N. (2019b). Evaluation of assembly part build orientation in additive manufacturing environment using data envelopment analysis. In *MATEC Web of Conferences*(Vol. 293, p. 02002). EDP Sciences.
- Ransikarbum, K., Pitakaso, R., & Kim, N. (2020). A decision-support model for additive manufacturing scheduling using an integrative analytic hierarchy process and multi-objective optimization. *Applied Sciences*, 10(15), 5159.
- Ransikarbum, K., & Khamhong, P. (2021). Integrated fuzzy analytic hierarchy process and technique for order of preference by similarity to ideal solution for additive manufacturing printer selection. *Journal of Materials Engineering and Performance*, 1–12. <https://doi.org/10.1007/s11665-021-05816-y>.
- Ransikarbum, K., & Leksomboon, R. (2021). Analytic hierarchy process approach for healthcare educational media selection: Additive manufacturing inspired study. In *2021 IEEE 8th International Conference on Industrial Engineering and Applications (ICIEA)*(pp. 154–158). IEEE.
- Rashidi, K. (2020). AHP versus DEA: A comparative analysis for the gradual improvement of unsustainable suppliers. *Benchmarking: An International Journal*, 27(8), 2283–2321.
- Saaty, T. L., & Sagir, M. (2009). Extending the measurement of tangibles to intangibles. *International Journal of Information Technology and Decision Making*, 8, 7–27.
- Schranz, C. (2016). *Tweaker-auto rotation module for FDM 3D printing*.
- Sossou, G., Demoly, F., Montavon, G., & Gomes, S. (2018). An additive manufacturing oriented design approach to mechanical assemblies. *Journal of Computational Design and Engineering*, 5(1), 3–18.
- Taufik, M., & Jain, P. K. (2013). Role of build orientation in layered manufacturing: A review. *International Journal of Manufacturing Technology and Management*, 27, 47–73.
- Thanki, S., Govindan, K., & Thakkar, J. (2016). An investigation on lean-green implementation practices in Indian SMEs using analytical hierarchy process (AHP) approach. *Journal of Cleaner Production*, 135, 284–298.
- Thompson, M. K., Moroni, G., Vaneker, T., Fadel, G., Campbell, R. I., Gibson, I., Bernard, A., Schulz, J., Graf, P., Ahuja, B., & Martina, F. (2016). Design for additive manufacturing: trends, opportunities, considerations, and constraints. *CIRP Annals-Manufacturing Technology*, 65(2), 737–760.
- Tweaker-3. (2020). <https://github.com/ChristophSchranz/Tweaker-3>. [Accessed 15 January 2021].
- Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications, *European Journal of Operational Research*, 169, 1–29.
- Wattanasang, N., & Ransikarbum, K. (2019). Cost optimization model for plant assignment in industrial estate planning. In *2019 Research, Invention, and Innovation Congress (RI2C)*(pp. 1–6). IEEE.
- Wattanasang, N., & Ransikarbum, K. (2021). Model and analysis of economic-and risk-based objective optimization problem for plant location within industrial estates using epsilon-constraint algorithms. *Computation*, 9(4), 46.
- Wohlers, T. (2018). *Wohlers report 2018*. Wohlers Associates, Inc.
- Xu, F., Loh, H. T., & Wong, Y. S. (1999). Considerations and selection of optimal orientation for different rapid prototyping systems. *Rapid Prototyping Journal*, 5(2), 54–60.
- Yao, X., Moon, S. K., & Bi, G. (2017). Multidisciplinary design optimization to identify additive manufacturing resources in customized product development. *Journal of Computational Design and Engineering*, 4(2), 131–142.
- Zhang, Y., De Backer, W., Harik, R., & Bernard, A. (2016a). Build orientation determination for multi-material deposition additive manufacturing with continuous fibers. *Procedia Cirp*, 50, 414–419.
- Zhang, Y., Bernard, A., Gupta, R. K., & Harik, R. (2016b). Feature based building orientation optimization for additive manufacturing. *Rapid Prototyping Journal*, 22(2), 358–376.
- Zhang, Y., Bernard, A., Harik, R., & Karunakaran, K. P. (2017). Build orientation optimization for multi-part production in additive manufacturing. *Journal of Intelligent Manufacturing*, 28(6), 1393–1407.
- Zhang, Y., Harik, R., Fadel, G., & Bernard, A. (2019). A statistical method for build orientation determination in additive manufacturing. *Rapid Prototyping Journal*, 25(1), 187–207.
- Zhang, Y., & Moon, S. K. (2021). Data-driven design strategy in fused filament fabrication: status and opportunities. *Journal of Computational Design and Engineering*, 8(2), 489–509.