PROCEEDINGS OF
2017 4TH INTERNATIONAL CONFERENCE ON INDUSTRIAL ENGINEERING AND APPLICATIONS

ICIEA 2017

April 21-23, 2017
Nagoya, Japan

IEEE

✧ Industrial Production and Planning

Data Envelopment Analysis-based Multi-Criteria Decision Making for Part Orientation Selection in Fused Deposition Modeling

Kasin Ransikarbum
Department of Industrial Engineering
Ubonratchathani University
Thailand
kasinphd@gmail.com

Namhun Kim
System Design and Control Engineering
Ulsan National Institute of Science and Technology
South Korea
nhkim@unist.ac.kr

Abstract—**Additive manufacturing (AM) has become popular in various fields, not only for industrial use, but also for personal use due to its key advantages in almost unlimited design freedom and material efficiency. Manufacturers in the industry recognize AM as a promising method in direct digital manufacturing for their design, research and development, and production processes. However, the applicability of AM technology is limited due to its process instability from several factors including the orientation selection of the part. Orientation of a part refers to the building direction with respect to the part being fabricated by the AM machine. In addition, available quantitative methods to determine the part orientation are limited. In this paper, we examine the part orientation alternatives' efficiency using data envelopment analysis (DEA). We illustrate a case study for one AM process; fused deposition modeling (FDM). The orientation alternatives' efficiency is identified and presented through trade-offs among conflicting criteria and machines. By using the DEA analysis, it provides insights regarding efficiency of each alternative, which can be used for the benchmarking leading to a best-practice frontier. The proposed method can be applied to other AM technologies in the industrial AM-based production environments for effective management.**

Keywords-multi-criteria decision-making; data envelopment analysis; part orientation; additive manufacturing; fused deposition modeling

I. INTRODUCTION AND MOTIVATION

Additive manufacturing (AM) has become popular in various industries, not only for high-quality industrial use of three-dimensional printing (3DP), but also for personal 3DP use. These three-dimensional (3D) printers and technologies are categorized by materials and operations, each of which has their own advantages and disadvantages [1-3]. Manufacturers in the industry recognize AM as a promising method and have attempted to operate various types of 3D printers in their design, research and development, and production processes. In contrast to the traditional method, AM can provide almost a perfect design freedom for part fabrication. Although companies recognize the significance of AM technologies, the applicability of 3DP technology is considered limited due to its low cost-efficiency and quality variation from machine control parameters and part layout issues [4]. Among many issues, the part orientation is one of the critical factors that can affect processing time, part cost, surface quality, and anisotropic properties of a part.

Orientation of a part refers to the building direction with respect to the part being fabricated by the AM machine. The optimal part orientation is considered to be a critical issue of AM processes as it can impact many key characteristics in part production, including processing cost and time, mechanical properties, and support volume. Researchers have studied the impacts of the part orientation in AM and proposed models to aid a process planning for the part building (e.g., [5-7]). However, existing models that show orientation efficiency and account for process planner's preference are lacking. Two key tasks to solve the part orientation concern are to determine the alternative orientation and to select the most suitable orientation among these alternatives [8]. Although no deterministic way of part orientation can be theoretically arranged, only a certain number of them are practical in the actual process planning [9]. As a selection of the part orientation can affect multiple and conflicting factors, such as processing cost and time, mechanical properties, etc.; the part orientation, thus, can be viewed as the multi-criteria decision-making (MCDM) problem.

MCDM is a sub-discipline of operations research and management science (OR/MS) that explicitly considers multiple criteria in a decision-making environment. It is mainly used to support decision-makers (DMs) facing decision and planning problems that a unique optimal solution does not exist and decision-maker's preferences are involved. Common MCDM methods have been proposed in a variety of applications including analytic hierarchy process (AHP), data envelopment analysis (DEA), multi-attribute utility theory (MAUT), multi-objective mathematical programming (MOMP), and goal programming (GP) (e.g., [10-11]). Among MCDM methods, DEA is a linear programming methodology to measure efficiency of multiple decision-making units (DMUs) when the problem is presented with multiple inputs and outputs. Solution methods for these problems are inclusive of exact, heuristic, and combined simulation methodologies (e.g., [12-14]).

In this research, we examine the part orientation decision making using DEA methodology. Initially, the orientation alternatives are generated based on the concept of the convex envelope of a part visualized as the smallest convex set that contains a part. Next, six conflicting criteria are determined including build time, build cost, surface quality, part accuracy, mechanical properties, and support volume. Then, these orientation alternatives are fabricated from fused deposition modeling (FDM) printer so that data related to

different criteria can be collected with both qualitative and quantitative measures and used to aid a DM to evaluate orientation alternatives. These criteria may be more-or-less measureable and intangible [15]. Given multiple input and output data, we examine the efficiency of each orientation alternative. Next, the best orientation of the part is identified and presented through trade-offs among these conflicting criteria. The validity of the algorithm is verified with technical staffs to improve optimal, effective process planning in the AM.

The remaining sections of this research paper are organized as follows. We overview the MCDM-based part orientation framework using DEA in Section 2. Next, an experimental design and a case study are discussed in Sections 3 and 4, respectively. Finally, Section 5 presents our research conclusions and outlines directions for future research.

II. DATA ENVELOPMENT ANALYSIS METHOD

DEA is used for both the production theory in economics and for benchmarking in operations management, where a set of measures is selected to benchmark the performance of manufacturing and service operations [20]. It is a multi-factor productivity analysis model that compares each variable with the best performing one. Variables in a DEA analysis are often referred to as DMUs, in which the main aim is to provide benchmarking guidelines for inefficient DMUs. It can be useful in handling models with multiple inputs and outputs. Advantages of DEA include the capability to handle multiple inputs and outputs, where the sources of inefficiency can be analyzed and quantified for every evaluated unit. Mathematically, the relative efficiency of a particular DMU can be obtained by solving the following model (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.

Sets

I : Set of inputs, indexed by i

J : Set of outputs, indexed by j

K : Set of criteria (DMUs), indexed by k

Parameters

$x_{i,k}$: Amount of input data for input i of DMU k

$y_{j,k}$: Amount of output data for output j of DMU k

Decision variables

U_i : The weight assigned to input i

V_j : The weight assigned to output j

DEA mathematical model

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

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

$$U_i \ge 0 \quad ;\forall i \in I \tag{3}$$

$$V_j \ge 0 \quad ;\forall j \in J \tag{4}$$

Next, given the non-linear form of the above mathematical model, it can be converted into the linear programming problem by enforcing $\sum_{i\in I} x_{i,k_0} U_i = 1$ in the constraint set. That is, we will obtain the following model (Equations (5)-(9)).

DEA linear programming model

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

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

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

$$U_i \ge 0 \quad ;\forall i \in I \tag{8}$$

$$V_j \ge 0 \quad ;\forall j \in J \tag{9}$$

After the DEA linear programming model is solved, a particular DMU will be considered efficient if it obtains a score of one, whereas scores that are lesser than one imply relative inefficiency.

III. DESIGNED EXPERIMENT

We discuss the experimental design of the proposed DEA-based MCDM framework in this section. An experimental design is conducted based on the six criteria (i.e., build time, build cost, surface quality, part accuracy, mechanical properties, and support volume) and one particular AM technology (i.e., FDM) to demonstrate an applicability and scalability of the proposed framework.

A. Orientation Alternatives

Theoretically, an infinite number of orientation alternatives may be arranged; however, only a certain number of them are practical in the process planning. The test model in Figure 1, with the size of 70×25×30 mm3, is used in this study to demonstrate the determination of orientation alternatives. We note that the test part similar to the one studied by [16] is used to aid a comparative study. Figures 1a) and 1b) show orientation alternatives based on the concept of convex envelope and build direction of the model, respectively. Mathematically, the convex envelope or convex hull of a set of points is the smallest convex set that contains all the points. Thus, six orientation alternatives can be identified from this illustrative part. We note that

orientation alternatives 2 and 4 are differentiated, 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.

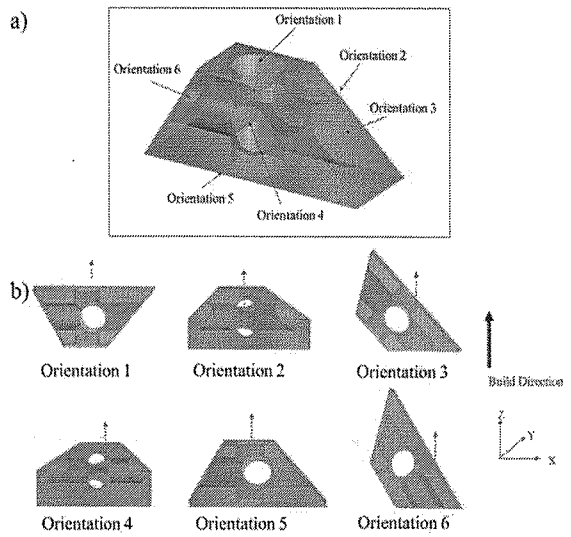

Figure 1. Orientation alternatives a) based on the convex envelope; b) based on the build direction.

B. *Criteria for AM Orientation*

The part orientation problem is a typical MCDM problem, in which trade-offs among conflicting criteria should be compromised. In this study, we consider six key criteria discussed in the literature as follows.

1) Build time (BT) criterion: Build time is related to the time spent on layer scanning, which is dependent on the number of slices. The number of slices is also determined by mainly two parameters (i.e., layer thickness and the height of the part from the z building direction). As an orientation of the part will directly affect a part's z height, it follows that different orientations impact greatly the build time.

2) Build cost (BC) criterion: Build cost refers to the resources consumed during the manufacturing of a part in AM, which usually contains direct (e.g., material) and indirect cost (e.g., machine, energy, labor, etc.). While the direct cost can be calculated from the materials, the indirect cost can be typically estimated based on the build time. Thus, it follows that an orientation of a part will have an important effect on the part cost.

3) Surface quality (SQ) criterion: Parts which are typically parallel or perpendicular to the build orientation tend to have a better surface roughness or finish than those whose face normal has an angle to the build direction. Additionally, declining faces will be affected more severely by the staircase deformation. Thus, the build direction of the part will affect the surface quality of a part.

4) Part accuracy (PA) criterion: Parts accuracy refers to the difference between the produced part and the design model. Part orientation can affect both shrinkage and distortion, which are the main factors in AM resulting in this difference. For example, a part with a tall and thin structure oriented in parallel to the build direction can suffer a more serious distortion than the part being perpendicular to the build direction.

5) Mechanical properties (MP) criterion: It is well known that the properties of a part produced by AM are anisotropic (i.e., the property of being directionally dependent). For example, tensile strength and yield strength are found to be higher in the horizontal direction than in the vertical direction based on the build direction. Other properties, such as thermal and electric conductivity are also affected by the build orientation.

6) Support volume (SV) criterion: Support structure is needed in some particular AM processes, such as FDM for over-hangings; while it is typically not needed in selective laser sintering (SLS), as un-sintered materials acts as a support. Support volume also affects the building time, building cost, and post-processing of a part. As the building orientation affects the quantity of over-hangings of a part, it follows that the building direction also impacts support volume.

IV. Case Study and Analysis

A. *Part Fabrication for FDM*

We fabricate parts for all orientation alternatives from FDM printer at the center for 3D advanced additive manufacturing at Ulsan National Institute of Science and Technology (UNIST) (Figure 2). In particular, PLA material and Sprout from Former's Farm are used for the FDM. Next, in order to evaluate each criterion for printed part orientations, a questionnaire filled out by technical experts, part testing, and MagicsTM software developed by Materialise [17] are used to obtain necessary information to aid a DM to evaluate each orientation alternative. MagicsTM is a versatile data preparation and file editor software for 3DP that equips with build time and cost estimators. In particular, data related to the build time, build cost, and support volume are quantitative and are estimated from MagicsTM; whereas surface quality, part accuracy, and mechanical properties are combined qualitative and quantitative data obtained from part test and expert opinions. That is, part accuracy in terms of root mean square (RMS) error is obtained from using the 3D scanner; surface quality in terms of surface roughness data (R_a) is obtained from measuring the largest surface area of each part on the Formtracer machine; and mechanical properties are implied qualitative data evaluated by technical experts based on existing literature that study dog-bone specimens for different orientations (e.g., [18-20]).

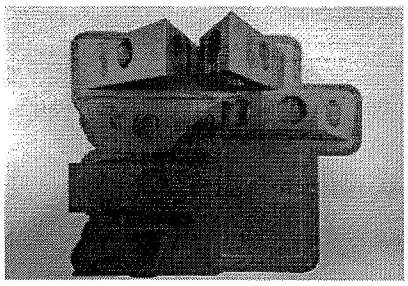

Figure 2. Part fabrication for orientation alternatives from FDM

Figures 3a) illustrates part accuracy test between CAD file and printed part for FDM, whereas Figures 3b) and 3c) show 3D scanner to obtain printed part's geometry and surface roughness test on the Formtracer, respectively.

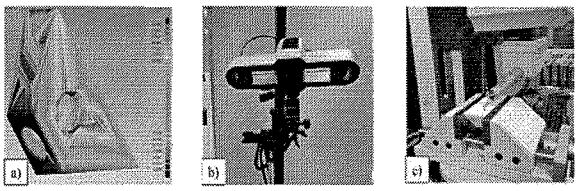

Figure 3. Part test a) part accuracy test between CAD model and printed part for FDM, b) 3D scanner to obtain the printed part's geometry c) surface quality test on the Formtracer

The summary of the data for FDM are illustrated in Table 1. It is clear that data for all criteria from altered orientation alternatives are conflicting with each other. For example, the build time and the build cost for different alternatives in FDM are found to be in a similar range due to the energy source and used material. In addition, the support material is typically required in FDM. The mechanical properties are then rated for FDM. In terms of surface roughness, the values of orientations 3 and 6 for FDM are found to be similarly higher than the others (i.e., the worst). In addition, the value of orientation 4 in FDM is found to be lowest (i.e., the best surface quality). On the other hand, the RMS values representing the part accuracy of orientations 4 and 5 for FDM are found to be lower than the others (i.e., good part accuracy).

B. *DEA Results and Analysis*

We now illustrate the DEA analysis for multiple input and output based on evaluated criteria to obtain efficiency of each part orientation alternative. In this study, we model the linear programming model of DEA in AMPL and analyzed using CPLEX solver on a PC with an Intel (R) Core (TM) i7- 6500 CPU @2.50 GHz and 8.0 GB of RAM. The computational time is found to be practically negligible (i.e., in seconds). Given six conflicting criteria, it is common that the build cost and the build time are available, limited resources of the process planner in AM. Thus, the build time and the build cost are used as input data, whereas all the criteria of interest are chosen as output for FDM. The efficiency scores for all orientation alternatives are reported in Table 2. The orientation alternative 4 of FDM is found to be the most efficient with a score of 1 when comparing to other alternatives.

Table 1. Summary of data to aid DEA analysis for FDM

	Ori. 1	Ori. 2	Ori. 3	Ori. 4	Ori. 5	Ori. 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 5.58	R_a 5.45	R_a 13.06	R_a 2.75	R_a 9.98	R_a 11.22
PA (in RMS)	0.128 mms	0.127 mms	0.146 mms	0.109 mms	0.103 mms	0.141 mms
MP *(5-1)*	Score 2	Score 3	Score 1	Score 5	Score 4	Score 1
SV	3 grams	1 gram	5 grams	1 gram	3 grams	4 grams

Table 2. Efficient score for each orientation alternative in FDM

AM	Orientation	Efficiency score
FDM	Alternative 1	0.4
	Alternative 2	0.5
	Alternative 3	0.2
	Alternative 4	1.0
	Alternative 5	0.7
	Alternative 6	0.2

C. *Discussion*

By using the DEA analysis, it provides insights regarding efficiency of each alternative whether it is efficient when multiple inputs and outputs are considered. We note, however, that it is possible that more than one alternative may be efficient among the others. The efficient DMUs defined by DEA can also be used for the benchmarking leading to a best-practice frontier [20]. The DEA approach shows that orientation 4 from FDM is the most efficient one following with orientations 5, 2, 1, and 3/6. Orientations 3 and 6, in particular, are found to have similar efficient scores of 0.2. This implies that they are equally efficient in terms of the inputs and outputs when comparing to other alternatives. When we compare the results from this study with the study from Byun and Lee [16], the best orientation alternative is found to be consistent with them.

V. Conclusions and Future Research

This research paper presents the MCDM-based part orientation framework using DEA, which considers multiple

criteria to analyze two key tasks for the part orientation in FDM; determining the alternative orientation and selecting the most suitable one among alternatives. This paper provides a 'proof-of-concept' case study to demonstrate how the orientation alternatives can be analyzed for their efficiency. We note that this paper is the first phase of our integrated AM process planning studies by analyzing the part orientation decision making using the MCDM framework. Our future works are to integrate the orientation model with the part-to-printer optimization assignment problem using the multiple-objective optimization approach and the part-location-in-the-printer problem using genetic algorithm. Additionally, part orientation alternatives produced from other AM technologies can be further tested.

REFERENCES

[1] J. Y. Han. A study on the Prototype Modeling Method using 3D Printing, Journal Packaging Culture Design Research, 34, 97-109, (2013).

[2] C. Beyer. Strategic implications of current trends in additive manufacturing, ASME Journal of Manufacturing Science and Engineering, 136, 064701, (2014).

[3] M. K. Thompson, M. K., Moroni, G., Vaneker, T., Fadel, G., Campbell, R. I., Gibson, I., Bernard, A., Schulz, J., Graf, P., Ahuja, B., and Martina, F. Design for Additive Manufacturing: Trends, opportunities, considerations, and constraints. CIRP Annals-Manufacturing Technology, 65, 737-760, (2016).

[4] S. Ha, K. Ransikarbum., N. Kim. Phenomenological Deformation Patterns of 3D Printed Products in a Selective Laser Sintering Process. In the 18th International Conference on Industrial Engineering, October 10-12, Seoul, Korea, (2016).

[5] K. Ransikarbum, J. Ma, and N. Kim. A Process Planning Perspective Using Multi-Criteria Decision-Making" In the 18th International Conference on Industrial Engineering, October 10-12, Seoul, Korea, (2016).

[6] Y. Zhang, A. Bernard, A., R. K. Gupta, and R. Harik, Feature based building orientation optimization for additive manufacturing. Rapid Prototyping Journal, 22, 358-376, (2016).

[7] D. S. Ingole, T. R. Deshmukh, A. M. Kuthe, and K. M. Ashtankar. Build orientation analysis for minimum cost determination in FDM. Proceedings of the Institute of Mechanical Engineers, Part B: Journal of Engineering Manufacture, DOI: 10.1177/0954405411413694, (2011).

[8] P. Kulkarni., A. Marsan, and D. Dutta. A review of process planning techniques in layered manufacturing. Rapid Prototyping, 6, 18-35, (2000).

[9] Y. Zhang and A. Bernard. Using AM feature and multi-attribute decision making to orientate part in additive manufacturing, In High value manufacturing: Advanced research in virtual and rapid prototyping. Proceedings of the 6th International Conference on Advanced Research in Virtual and Rapid Prototyping, 411-416, (2013).

[10] K. Ransikarbum and S. J. Mason. Multiple-Objective Analysis of Integrated Relief Supply and Network Restoration in Humanitarian Logistics Operations. International Journal of Production Research, 54, 49-68, (2016).

[11] K. Ransikarbum and S. J. Mason. Goal programming-based post-disaster decision making for integrated relief distribution and network restoration. International Journal of Production Economics, 182, 324-341, (2016).

[12] P. Kriengkorakot and N. Kriengkorakot. Web-based Cutting Plan System for One Dimensional Stock Problem. UBU Engineering Journal, 1, 47-60, (2012).

[13] R. Pitakaso. Problem and Methodology to Solve Lot Sizing Problems. UBU Engineering Journal, 2, 47-64, (2009).

[14] J. Kim, K. Ransikarbum, and N. Kim. Agent-based Simulation Modeling of Low Fertility Trap Hypothesis. ACM SIGSIM Conference on Principles of Advanced Discrete Simulation (PADS), May 15-18, Alberta, Canada, (2016).

[15] T. L. Saaty and M. Sagir. Extending the measurement of tangibles to intangibles, International Journal of Information Technology and Decision Making, 8, 7-27, (2009).

[16] H. S. Byun and K. H. Lee. Determination of the optimal build direction for different rapid prototyping processes using multi-criterion decision making. Robotics and Computer-Integrated Manufacturing, 22, 69-80, (2006).

[17] Materialise Magics. [Online]. Available: http://www.materialise.com. (2016).

[18] Z. Chen and Y. Chen. Selection of Build Orientation with Minimum Tensile Strain. Computer-Aided Design and Applications, 7, 639-647, (2010).

[19] P. Lambert. Tensile properties of materials: FDM printer and SLS printer [Online]. Available: http://www.sculpteo.com/en/. [Accessed 05-June-2016], (2014).

[20] W. D. Cook, K. Tone, and J. Zhu. Data envelopment analysis: Prior to choosing a model. Omega, 44, 1-4. (2014)