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Synopsis Of

A DECISION SUPPORT SYSTEM TO EVALUATE PARTS FOR ADDITIVE MANUFACTURING

A Thesis

To be submitted by

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For the award of the degree

Of

DOCTOR OF PHILOSOPHY

1 Introduction

Traditional Design for Manufacturing (DFM) helps designers to eliminate manufacturing difficulties. Similarly, in Additive Manufacturing (AM), a set of methods and tools are developed under Design for Additive Manufacturing (DfAM). AM has unique capabilities compared to conventional manufacturing methods, like mass customization, high material efficiency, function integration, and part consolidation. So, the decision-making in design and development of parts using AM is crucial in many industries.

A detailed study of all design potentials in AM and its benefits are discussed by Kumke et al. [1], through a semantic network. So, a decision support system (DSS) considering these design potentials and its value additions are required to optimize the industry's needs. Then we performed a centrality analysis on the network to identify the important potential in AM and found that Part Consolidation (PC) has the highest number of connections with the nodes in the network.

Because of the layer-by-layer nature, AM needs a shape complexity metric that can measure the part's internal and external shape complexity. There are few quantitative metrics in the literature based on geometrical parameters like the volume of the part, the surface area of the part, the volume of the bounding box, the thickness of the part, the number of holes, number of sharp corners [2–4]. In our work, we propose a combined shape complexity metric based on view similarity [5] for additional benefits.

2 Research Gap

Among the unique process capabilities of AM, PC eases the assembly of parts in conventional manufacturing by the way of reduction in number of parts. All components in the product need not be manufactured separately and assembled, instead few components can be consolidated into a single part. The existing PC strategies adopted rule-based methods for identifying the candidate parts. So, we propose a network-based approach that uses a centrality score for identifying the potential candidate for PC.

The existing shape complexity metrics used in AM are adopted from the metrics in the conventional manufacturing process and are only capable of measuring the external shape complexity of parts. For example, Conner et al. [3] modified the complexity factor that Ravi et al. [4] developed and used it to select the suitable design for AM. Similarly, Joshi et al. [2] have developed a complexity score to automate the selection of additive, subtractive, and hybrid manufacturing processes. These metrics use geometry-related parameters to calculate the shape complexity and are developed exclusively for conventional manufacturing processes. These metrics are not suitable for evaluating the shape complexity if the design has occlusions and internal lattice structures. So, we have developed a view similarity-based metric that deducts the internal structure and external shape complexity.

3 Objectives

1. Develop quantitative system-level and part-level complexity metrics for the decision-making in the selection of parts.
2. Develop measures to assess the economic viability in the selection of parts for AM.
3. Define a Composite Complexity metric by aggregating the economic factors with the shape complexity metric to assess the suitability of a design variant in additive manufacturing.
4. Develop a Decision Support System by aggregating all the developed metrics to automate the decision-making process.

4 Overall Methodology

The whole methodology of this work involves product/system level identification of parts, followed by part-level evaluation, and then a multicriteria evaluation to narrow down design variants. The overall methodology followed is shown in figure 1 and details of the methodology are discussed in the following sections.

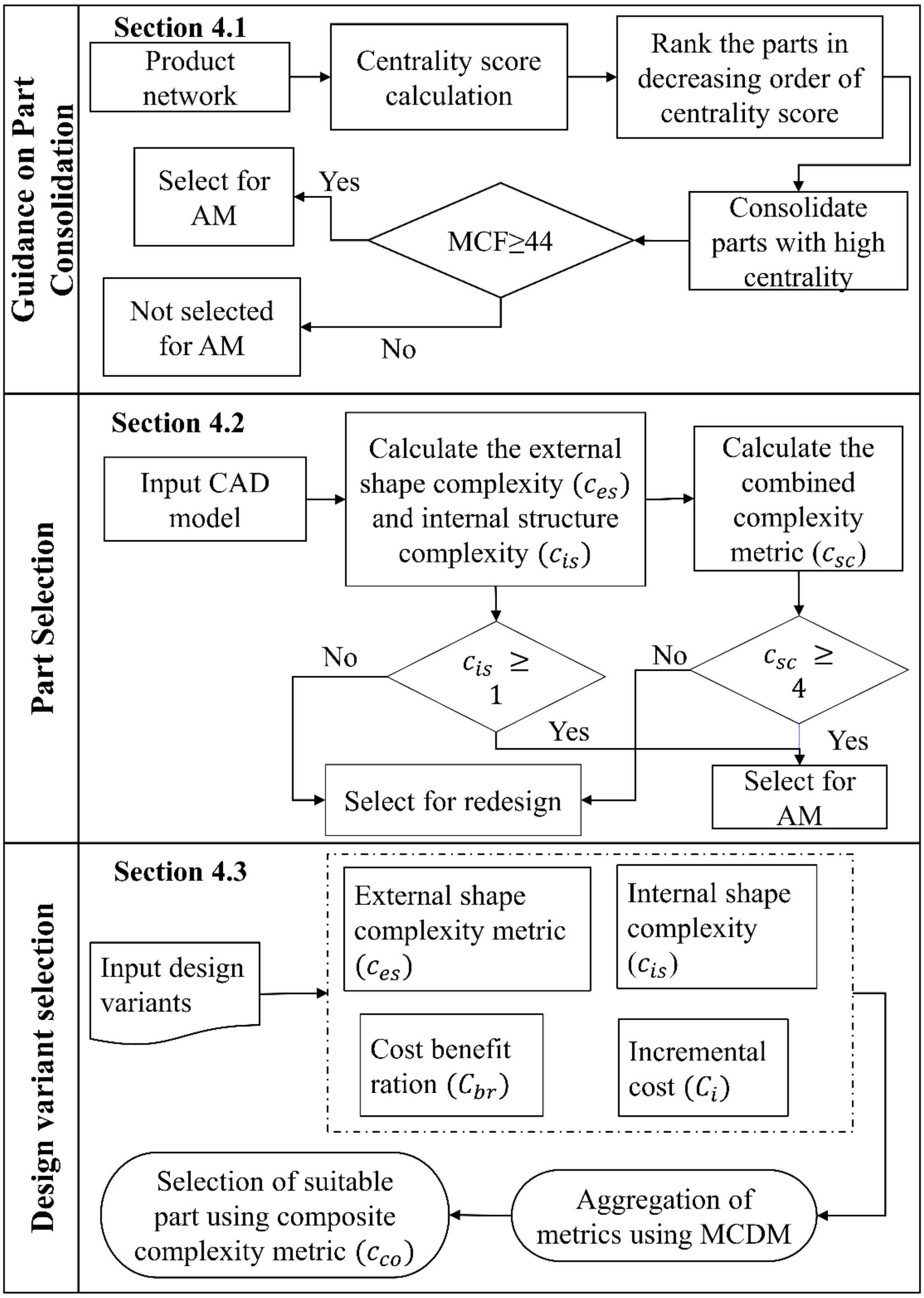


Fig. 1 Overview of the methodology followed in the presented study

4.1 PC in DfAM: A two-level approach using complexity metrics

The suitable candidate for part consolidation is identified by performing complex network analysis on the product architecture or Design Structure Matrix (DSM). The product network is constructed from a part interaction matrix created from the assembly/bill of materials. Then the centrality of each component in the product network is calculated and the component with high centrality score is selected as the candidate for PC. The centrality score is defined by the number of connections incident on each node and it is used as an estimate of parts importance in the network. The part with the highest centrality score will be selected as a candidate for PC. After consolidation the manufacturability of the consolidated design is decided based on the Modified Complexity Factor (MCF).

4.1.1 Case study: Motorcycle steering assembly

Initially, there were seven components in the design, figure 2 shows the initial design and components in the design. The total number of parts in the assembly is reduced to four by using the network measure. The network from the relationship matrix is drawn as shown in figure 3(a) and the centrality score is calculated for each node. Based on the centrality score the candidate for part consolidation is identified and the part count is reduced to four from seven. The product network after the consolidation is shown in figure 3(b) and the centrality score of each part is graphically represented in figure 4.

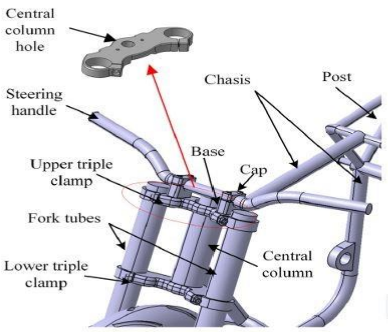


Fig. 2. Motorcycle steering assembly *(with permission from ASME)*

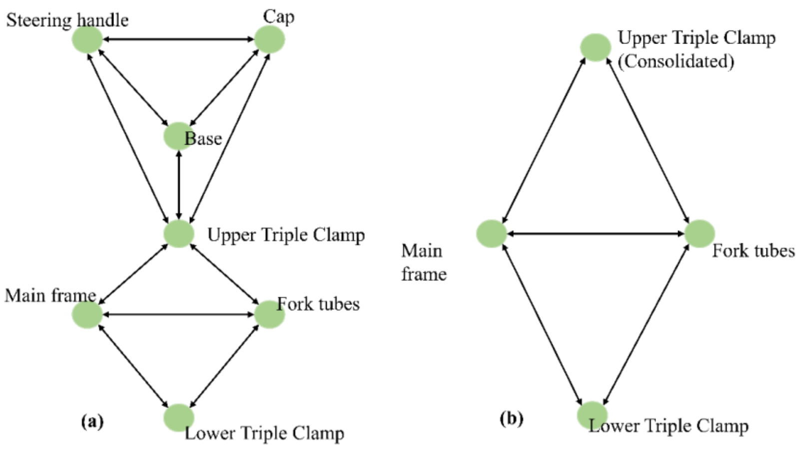


Fig. 3. (a) Product network before consolidation (b) Product network after consolidation

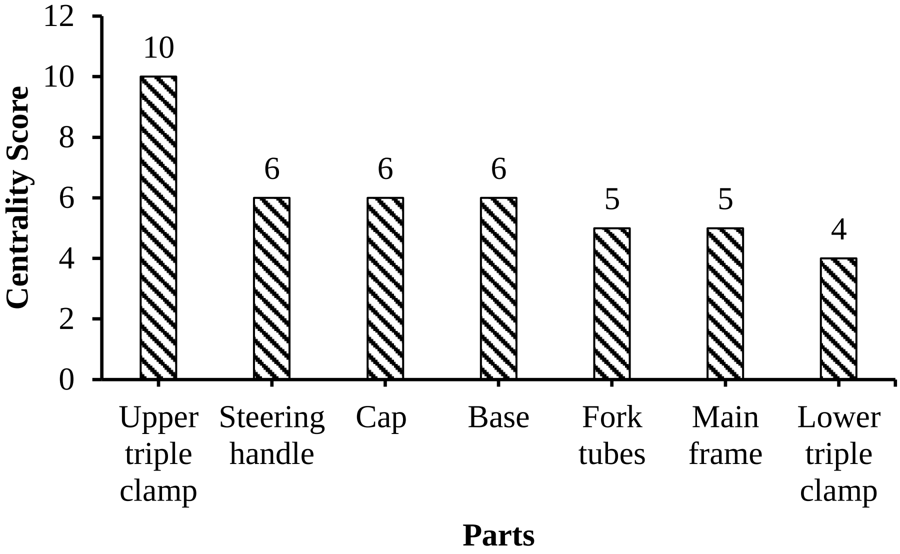


Fig. 4. All degree centrality of the motorcycle steering assembly

From figure 4, it can be seen that the upper triple clamp has the highest centrality score, so the upper triple clamp is the most important node in the product network. The next step is to consolidate the possible parts along with the upper triple clamp without eliminating the functionality of the assembly the parts need to be consolidated. So, out of seven components the lower triple clamp, upper triple clamp, and fork tubes can be considered as standard parts, and without eliminating the functionality steering handle, and cap, the base is combined with the upper triple clamp, and it can be made as a single part. The next step is to check the manufacturability of the consolidated part using equation (1). The consolidated design is shown in figure 5.

$$\text{Modified Complexity Factor, MCF} = 5.7 + 10.8C_{pr} + 18C_{ar} + 32.7C_{nh} \quad (1)$$

$$\text{Where, Part volume ratio, } C_{pr} = 1 - \frac{Volume\ of\ part}{Volume\ of\ bounding\ box} = 1 - \frac{V_p}{V_b} \quad (2)$$

$$\text{Area ratio, } C_{ar} = 1 - \frac{Surface\ area\ of\ part}{Surface\ area\ of\ sphere} = 1 - \frac{A_p}{A_s} \quad (3)$$

$$\text{Hole ratio, } C_{nh} = 1 - \frac{1}{\sqrt{1+N_h}}, \quad (4)$$

Where, V_p is the volume of part, V_b is the volume of bounding box, A_p is the surface area of part, A_s is surface area of sphere, and N_h is the number of holes

Fig. 5. Consolidated upper triple clamp.

Table 1. Mass properties and parameters for calculating the MCF.

Volume of the part (cm^3)	Volume of the Bounding box (cm^3)	Surface area of the part (cm^2)	Surface area of the sphere (cm^2)	No of holes (N_h)	Volume ratio (C_{pr})	Area ratio (C_{ar})	Hole ratio (C_{nh})	MCF
582.827	4215.809	1139.952	337.424	2	0.8617	0.7040	0.50	44.03

From table 1, the MCF value of the consolidated design is more than 44, so the design is suitable for manufacturing using AM as discussed by Conner et al. [3].

4.2 A View Similarity-based Shape Complexity Metric to Guide Part Selection for Additive Manufacturing

The methodology involves calculating a part’s shape complexity based on the concept of view similarity, that is, the similarity of different views of the outer shape and internal cross-sectional geometry. The combined shape complexity metric (weighted sum of the external shape (c_{es}) and internal structure complexity (c_{is})) has been used to rank various 3D models. The metric has been tested for its sensitivity to various input parameters and thresholds are suggested for effective results. The proposed metric's applicability for part selection has also been investigated and compared with the existing metric-based part selection. The proposed shape complexity metric can distinguish parts of different shapes, sizes, and parts with minor design variations.

The proposed metric is sensitive to input parameters, such as the number of viewpoints, design orientation, image resolution, and different lattice structures. To address this issue, a sensitivity analysis is performed to suggest thresholds for each input parameter for optimum results. The number of viewpoints for capturing the external views are chosen as 22 based on the sensitivity analysis. The minimum support volume is selected for orientation and a slice height of 3mm is used for capturing the internal structure of the given 3D model. The orientations of the 3D model and viewpoints are presented in figure 6. The equation for calculating the combined shape complexity is given in Eq. (5).

$$\text{Combined Shape Complexity Metric, } c_{sc} = (w_1 c_{es} + w_2 c_{is}) \quad (5)$$

where w_1 and w_2 are the weights.

The effectiveness of the proposed metric was evaluated using a group of 3D models with obvious shapes that were both simple and complex, as shown in figure 7. Among the shapes designed with labelled text, conformal cooling channels, and manifolds are also included. Using Eq. (5), the combined complexity metric can be calculated for this group of parts. Figure 8 shows the calculated c_{es}, c_{is}, and c_{sc} values for these parts.

The fractal 3D model shown in figure 7(j) has a higher shape complexity compared to other models in the group because it has high dissimilarity in the views of the external shape and internal structure. Because of the considerable difference in internal structure views compared to other models in figure 7, fractal and Klien bottles only have c_{is} values. The proposed metric can rank 3D models based on their shape complexity and effectively differentiate simple from complex models. Also, the proposed metric can be able to accommodate the fine features like labels and conformal cooling channels present in the design.

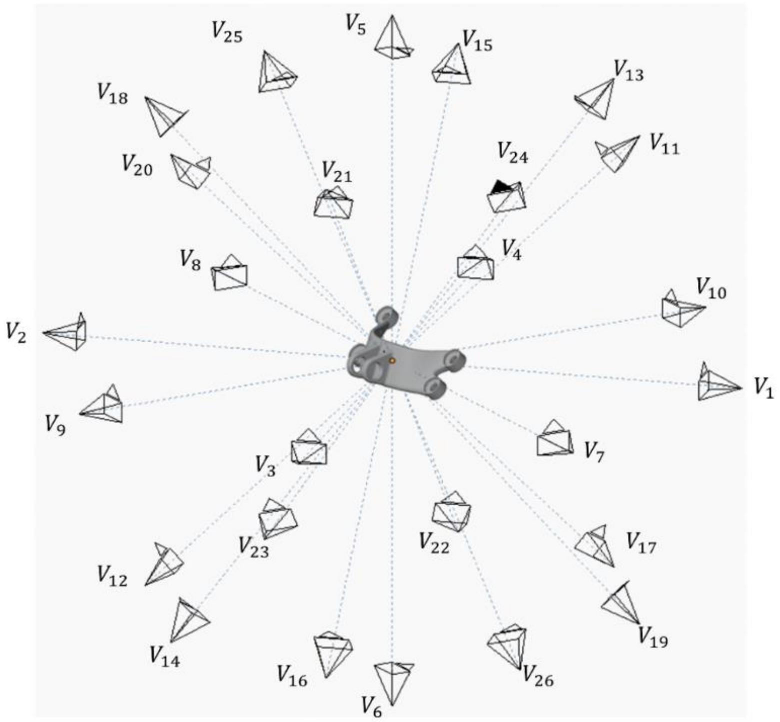


Fig. 6 Arrangements of viewpoints around the 3D model for capturing external images

4.2.1 Part selection for redesign using c_{sc}

Weight reduction is one of the objectives of both topology and lattice optimization, and we propose using c_{sc} to decide whether parts need redesign before selecting them for AM. If $c_{sc} \geq 4$, we can be selected the design for AM without any redesign. If the $c_{sc} < 4$, such models can benefit from computational tools for redesign, such as TO and generative design.

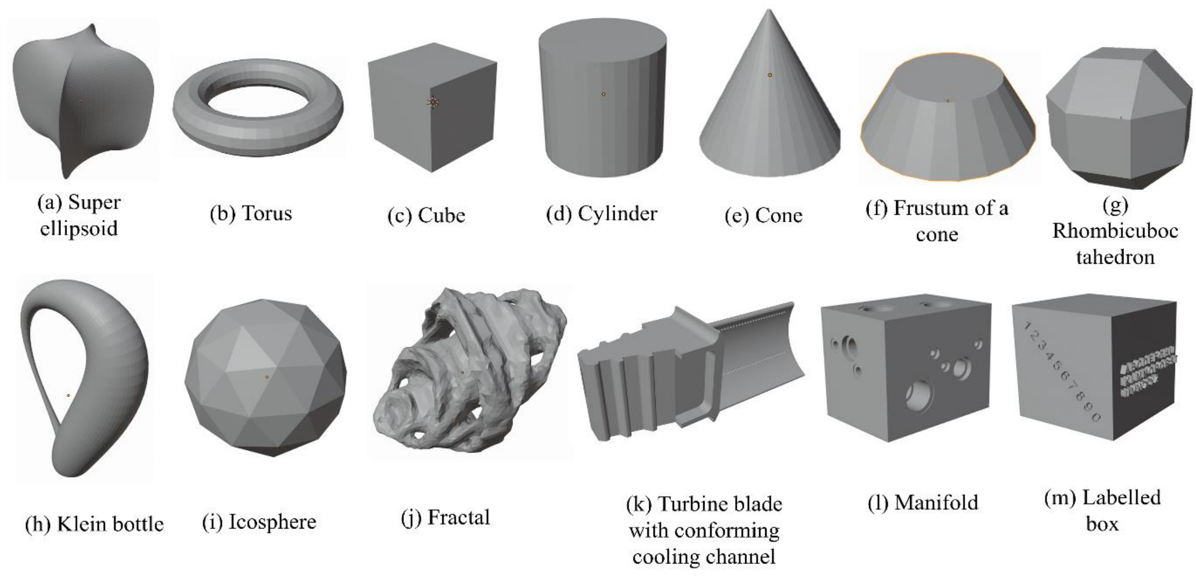


Fig. 7 3D models selected for validation of the proposed metric

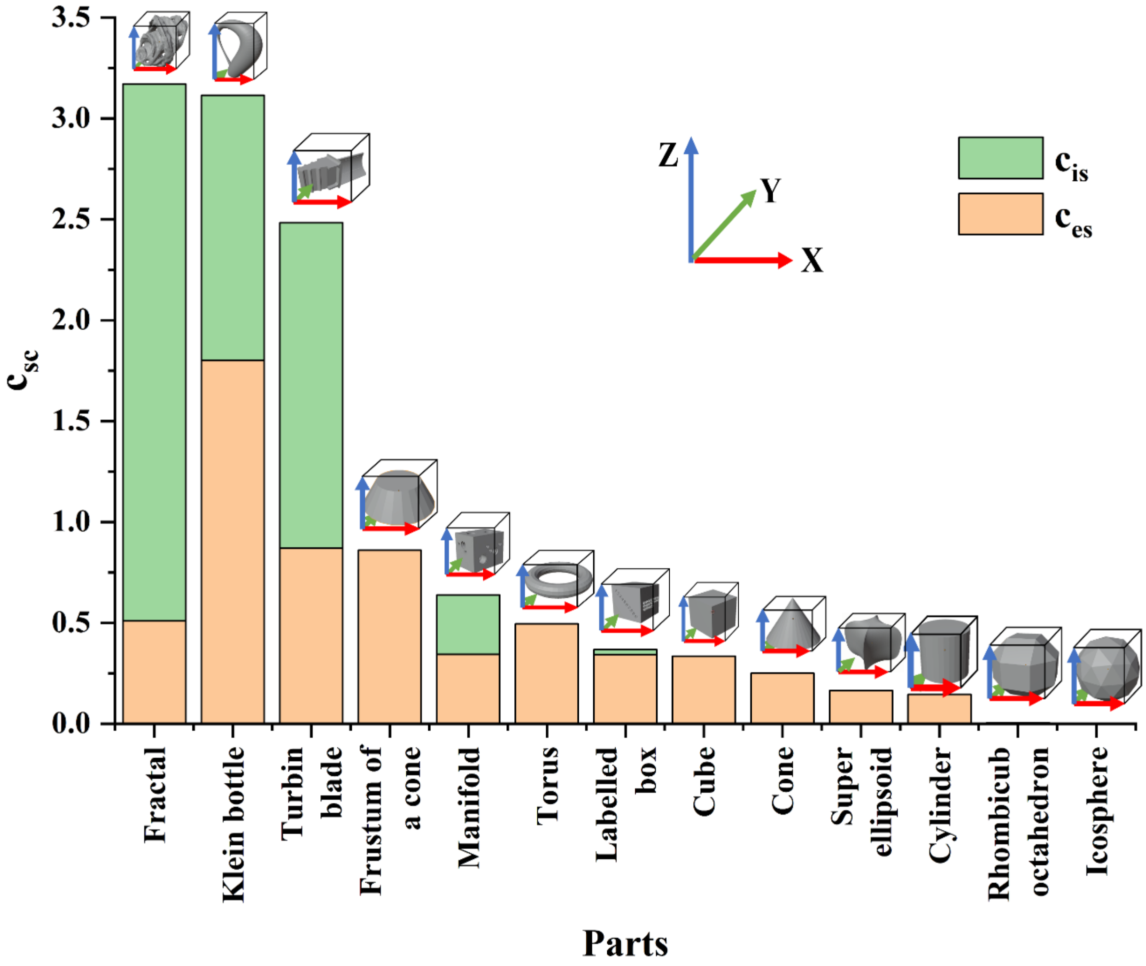


Fig. 8 c_{sc} of 3D models selected for validation.

Similarly, to identify candidates for lattice optimization, $c_{is} < 1$ is chosen, whereas $c_{is} \geq 1$ is selected for AM. The calculated shape complexity values of the redesigned parts are shown in figure 9(b). The lower increase in c_{is} for the engine bracket compared with the other models is due to the non-prismatic nature of the model. For prismatic models, the percentage increase in c_{is} is 100%, but for non-prismatic models, it is always <100%.

4.3 Evaluation of Computationally optimized Design Variants for Additive Manufacturing Using a Fuzzy MCDM Approach

The selected parts for redesigning in the previous section are optimized using various computational tools such as Topology Optimization (TO), Generative Design (GD), and Lattice Optimization (LO) in DfAM and generate multiple design variants. So, selection of these design variants should be done using both opportunistic and restrictive DfAM. Therefore, economic factors such as the cost-benefit ratio (C_{br}) and incremental cost (C_i) are developed to assess the economic viability of the designs. Then a Fuzzy Powered Maclaurin Symmetric Mean (FPWMSM) operator [6] is used for the aggregation of the shape complexity metric and economic factors. The effectiveness of the proposed composite complexity metric is studied using three different sets of design variants.

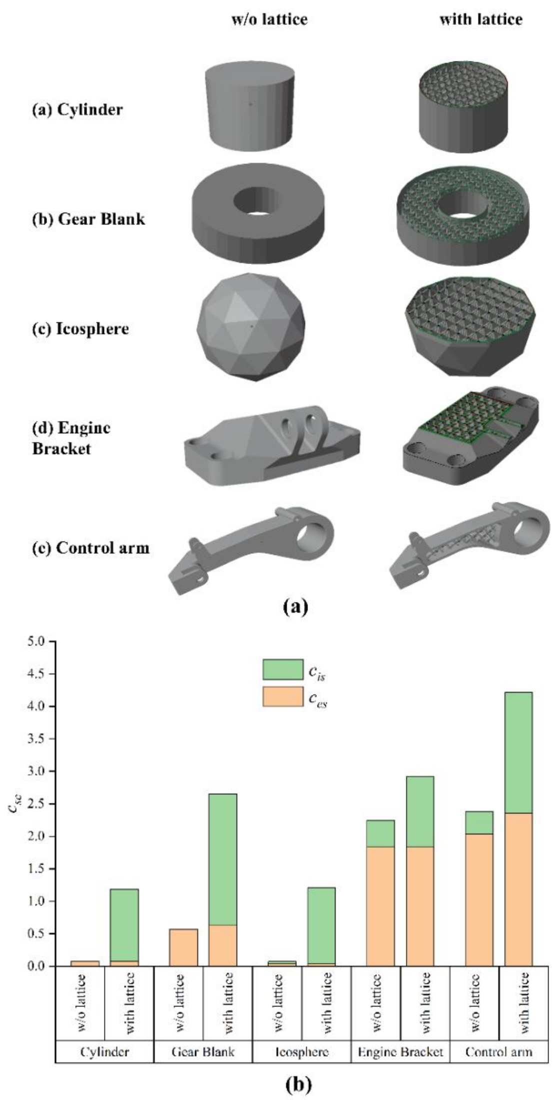


Fig. 9 (a) Different design variations with and without lattice structures **(b)** c_{sc} value of design variation

4.3.1 Evaluation of Economic Viability

The definition of the cost benefit ratio and incremental cost are given below.

Cost-benefit ratio (C_{br}) is the ratio of the benefit in the processing cost after optimization to the total processing cost of an unoptimized part using the L-PBF process. It represents the cost savings of the optimization effort. The probability of selecting a design variant is higher for an optimized design variant with a larger ***C_{br}***.

Incremental cost (C_i) is the additional cost incurred in processing the design variant compared to the unoptimized design variant using L-PBF. The design variant with the high incremental cost is not preferred for manufacturing using L-PBF.

$$\text{Cost-benefit ratio, } C_{br} = \frac{\text{Processing cost benefit}}{\text{Total processing cost of unoptimized design}} \quad (6)$$

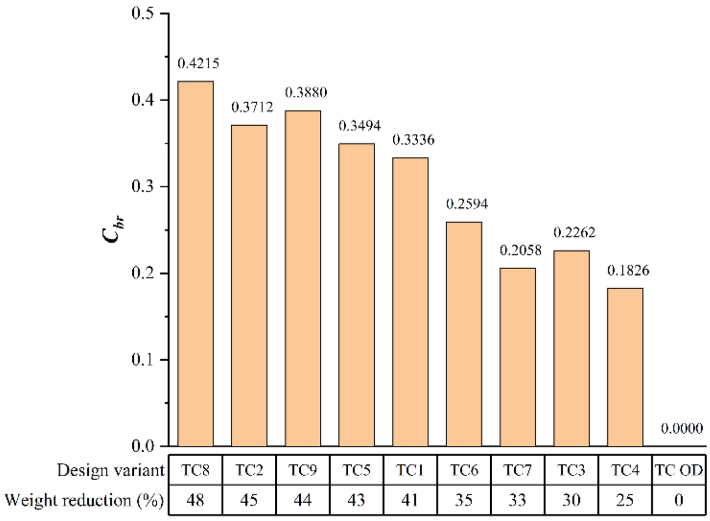
$$C_{br} = \frac{(C_{BO} - C_{AO})\,\lambda}{C_{BO}} \tag{7}$$

$$\text{Where, } \lambda = \begin{cases} 0 & \text{if } C_{BO} - C_{AO} < 0 \\ 1 & \text{if } C_{BO} - C_{AO} > 0 \end{cases}$$

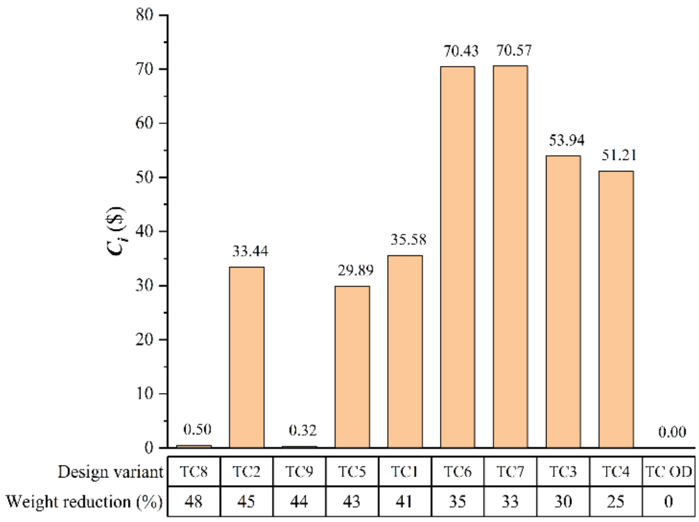
$$\text{Incremental cost, } C_i = (C_S)_{AO} - (C_S)_{BO} \tag{8}$$

Where C_S is the cost of processing the support structure

The cost model for calculating the processing cost and support structure cost is adopted from the literature [7] and [8] respectively. The design variants of an upper triple clamp are selected to study the effectiveness of the $\boldsymbol{C_{br}}$ and C_i using the above equations and shown in figure 10 (a) and (b).



(a)



(b)

Fig. 10 (a) Variation of C_{br} with weight reduction of design variants (b) variation of C_i with weight reduction of design variants

4.3.2 Ranking of design variants using FPWMSM

The design variants obtained from the different computational tools are be ranked using the aggregated measures. Therefore, design variants of a GE engine bracket are selected for ranking using the FPWMSM operator. The steps followed to rank the design variants are shown in figure 11.

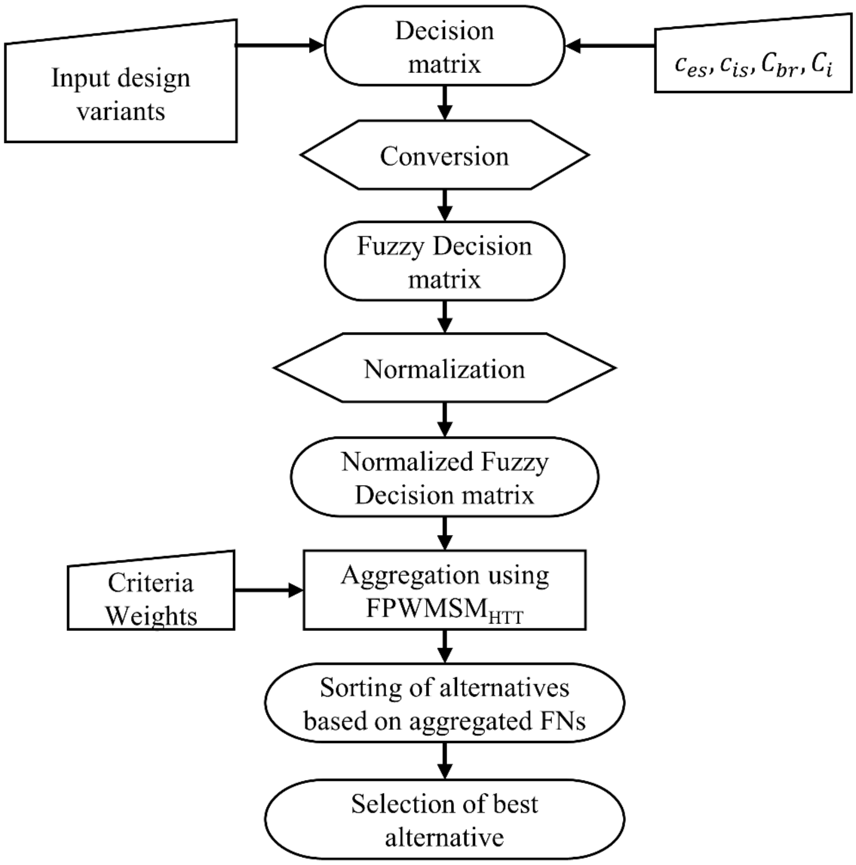


Fig. 11 Proposed MCDM approach

Finally, for each alternative, the composite complexity metric is calculated $\beta_1 = \langle 0.5472 \rangle$, $\beta_2 = \langle 0.4278 \rangle$, $\beta_3 = \langle 0.4150 \rangle$, $\beta_4 = \langle 0.4152 \rangle$, $\beta_5 = \langle 0.3469 \rangle$, $\beta_6 = \langle 0.5346 \rangle$, $\beta_7 = \langle 0.4130 \rangle$, $\beta_8 = \langle 0.5074 \rangle$, $\beta_9 = \langle 0.2516 \rangle$. This number represents a composite complexity metric (c_{co}). The TO1 has the highest c_{co} value compared to other design variants, hence TO1 is selected as the suitable design variant for AM. The proposed approach is found effective for evaluation design variants for AM by considering both technical feasibility and economic viability.

5 Conclusions and future scope

An alternate approach for part consolidation using two-level quantitative measures is developed. In the first level from the product network, parts with high centrality scores are identified and the parts around the high centrality node are consolidated without eliminating the functionality of the product. Then the manufacturability of the consolidated design is assessed with the help of MCF in the second level. Compared to the rule-based approach, the proposed network measure reduces 10-15% more parts in the assembly.

A novel shape complexity metric using the view similarity algorithm is proposed and verified it using a variety of 3D models. The combined shape complexity metric is a weighted sum of internal and external shape complexity metrics. The effectiveness of the combined complexity metric to guide opportunistic DfAM strategies such as topology optimization, generative design, and lattice optimization is also studied. The internal structure complexity metric can be used to find lattice optimization opportunities, whereas the combined complexity metric can detect redesign opportunities. So, it assists users in reducing the number of parts recommended for expert judgment in final decision-making.

Multiple design variants can be generated from the computational tools in DfAM. So, to select the most suitable design variant a multi-criteria decision-making approach is proposed. The economic factors and shape complexity metrics are aggregated to evaluate the composite complexity metric of the design variant. Then the design variant with the highest composite complexity value is selected for manufacturing in L-PBF. This approach will be useful for decision-makers when they have multiple design solutions for a single design problem. Ranking and selection of the design variants using the proposed approach resulted in a 50% cost reduction in the case of an airplane bracket and a 75% cost reduction in the case of an engine bracket compared with the original design manufactured in L-PBF. Finally, all these three quantitative metrics-based decision-making have been integrated into a decision support system to enhance the adoption of AM in the industry.

Nomenclature

β_i	- Aggregated measure of different criteria
λ	- Kronecker function
A_p	- Area of the part
A_s	- Surface area of bounding sphere
c_{co}	- Composite complexity metric
c_{es}	- External shape complexity metric
c_{is}	- Internal structure complexity metric
c_{sc}	- Combined shape complexity metric
C_{ar}	- Area ratio
C_{br}	- Benefit ratio
C_i	- Incremental cost
C_{nh}	- Hole ratio
C_{pr}	- Part ratio
C_{AO}	- Processing cost after optimization
C_{BO}	- Processing cost before optimization
C_S	- Support structure cost
$(C_S)_{AO}$	- Support structure cost after optimization
$(C_S)_{BO}$	- Support structure cost before optimization
N_h	- Number of holes
V_b	- Bounding box volume
V_i	- Number of viewpoints
V_p	- Volume of the part
w_1	- Weightage of external shape complexity
w_2	- Weightage of internal structure complexity

Abbreviations

AM	- Additive Manufacturing
DFAM	- Design for Additive Manufacturing
DFM	- Design For Manufacturing
DSM	- Design Structure Matrix
DSS	- Decision Support System
FN	- Fuzzy Number
FPWMSM	- Fuzzy Power Weighted Maclaurin Symmetric Mean Operator
GD	- Generative Design
HTT	- Hamacher T-norm and T-conorm
LO	- Lattice Optimization
L-PBF	- Laser Powder Bed Fusion
MCF	- Modified Complexity Factor
PC	- Part Consolidation
TO	- Topology Optimization

6 Proposed thesis contents

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- 2.7 Objectives

3. METHODOLOGY
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4. PRODUCT LEVEL DECISION MAKING USING QUANTITATIVE METRICS
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- 4.2 Two-level approach
- 4.3 Case study
- 4.4 Results and Discussion
- 4.5 Chapter summary

7 Research outcomes

Journal Publications

1. Jayapal, J., Kumaraguru, S. and Varadarajan, S. (2023), "A view similarity-based shape complexity metric to guide part selection for additive manufacturing", Rapid Prototyping Journal, Vol. 29 No. 3, pp. 655-672. https://doi.org/10.1108/RPJ-04-2022-0122 **(IF: 4.043, Q1)**

Conference Publications

1. Jayapal, J., Kumaraguru, S., & Varadarajan, S. (2021). Part consolidation in design for additive manufacturing: A two-level approach using complexity metrics. In Design for Tomorrow—Volume 2: Proceedings of ICoRD 2021 (pp. 881-892). Singapore: Springer Singapore.

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