Framework for Additive Manufacturing Adoption Using Evaluation Model

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Abstract

Additive Manufacturing (AM), also known as 3D printing, has emerged as a transformative technology, revolutionizing various industries by offering enhanced design freedom, reduced lead times, and material savings. As AM continues to gain traction in part production, the need for an efficient and reliable method to identify the most suitable components for AM processes becomes increasingly crucial. This research paper presents a comprehensive framework for selecting the right candidates for Additive Manufacturing part selection, considering various factors to optimize part performance and efficiency.

The proposed framework begins with an extensive review of the current state-of-the-art in AM materials, processes, and design considerations. A structured taxonomy is developed, categorizing candidate parts based on complexity, geometric characteristics, material properties, and functional requirements. This classification lays the foundation for systematic part evaluation and selection. Next, the framework integrates multi-criteria decision-making methods to evaluate and prioritize candidate parts. Key evaluation criteria include geometric complexity, mechanical properties, production volume, economic viability, and the potential for performance improvement through AM. Each criterion is weighted based on its relative significance in the specific application context, providing a tailored approach to part selection. Furthermore, the paper investigates the impact of AM-specific design guidelines on part selection. Specific considerations, such as support structures, build orientation, and surface finishing, are analyzed to ensure successful and efficient part production.

The framework is complemented by a user-friendly decision support tool that enables engineers and designers to apply the proposed methodology effectively. The tool integrates sophisticated algorithms, allowing real-time analysis and comparisons of candidate parts to expedite the decision-making process. In conclusion, the presented framework empowers industries to identify and select the most suitable components for AM, maximizing the technology's potential and driving its widespread adoption. By streamlining the part selection process and considering multiple critical factors, this research contributes to accelerating AM's integration into various sectors, promoting resource efficiency, and unlocking new possibilities in design and manufacturing.

Introduction

Additive Manufacturing technological capability and value modelled in an objective and transferrable way.

Additive manufacturing, commonly known as 3D printing, has emerged as a revolutionary technology that is transforming the landscape of modern manufacturing. Unlike traditional subtractive methods, which involve cutting and shaping materials to create objects, additive manufacturing builds three-dimensional structures layer by layer. This innovative approach to production offers unique advantages, and its adoption is increasingly driven by considerations of material conservation, geometric complexity, and enhanced functionality.

Quick-screening and decision-making model for AM candidate part.

Sustainability of the AM process in terms of material conservation, geometric complexity, and functionality

Material Conservation:

One of the key motivations behind the growing adoption of additive manufacturing is its inherent efficiency in material usage. Traditional manufacturing processes often result in substantial material waste, as raw materials are cut away to achieve the desired shape. In contrast, additive manufacturing adds material only where needed, minimizing waste, and promoting a more sustainable approach. This conservation of resources not only aligns with environmentally conscious practices but also contributes to cost-effectiveness, making additive manufacturing an attractive option for industries seeking to optimize their material utilization.

Geometric Complexity:

Additive manufacturing empowers designers to break free from the constraints imposed by traditional manufacturing methods. Complex geometries that were once challenging or impossible to produce are now achievable with relative ease. This capability is particularly advantageous in industries such as aerospace, automotive, and healthcare, where intricate and customized designs can significantly enhance performance and functionality. The ability to create complex structures allows for lightweight components, improved aerodynamics, and intricate medical implants that precisely match the patient's anatomy.

Functionality Enhancement:

Another compelling factor driving the adoption of additive manufacturing is its capacity to enhance the functionality of
manufactured components. Traditional manufacturing processes may struggle with the integration of multiple parts or the incorporation of intricate features. Additive manufacturing enables the production of consolidated and integrated structures, reducing the need for assembly and potentially improving the overall strength and performance of the final product. This capability is particularly valuable in industries where lightweight yet robust components are crucial, such as in the development of high-performance machinery or advanced medical devices.

In conclusion, Figure 1 explains, the adoption of additive manufacturing can be analyzed with Cost, Flexibility and Time. Various key vitals like Scrap, Complex geometry parts, Various material properties requirements in one part, Service parts fast availability, Quick manufacturing solutions development leads to potential candidate identifications. Manufacturing industry recognizes potential of AM to address challenges related to material conservation, geometric complexity, and functionality enhancement. As technology continues to advance and the range of printable materials expands, the transformative impact of additive manufacturing on various sectors is poised to grow, ushering in a new era of more sustainable, intricate, and functionally optimized production processes.

Research framework for AM adoption Model

| Step 1: Problem Formulation |
| Step 2: Develop Conceptual Model |
| Step 3: Collection and Synthesis of data - Fuzzy AHP approach |
| Step 4: Analyze & collect the relationship factors |
| Step 5: Research findings |
| Step 6: Synthesis the result |
| Step 7: Weightage the factor and find the AM candidacy |

Here’s an elaboration on each step:

**Step 1: Problem Formulation** Identify and articulate the specific challenges or opportunities within your manufacturing process that could be addressed through additive manufacturing. This step involves understanding the limitations of existing methods and pinpointing areas where AM could provide significant benefits.

**Step 2: Develop Conceptual Model** Create a conceptual model that outlines how additive manufacturing might fit into your overall manufacturing strategy. Define the objectives, scope, and key performance indicators (KPIs) for the adoption of AM. This model sets the foundation for subsequent steps.

**Step 3: Collection and Synthesis of Data - Fuzzy AHP approach** Utilize a Fuzzy Analytic Hierarchy Process (FAHP) to collect and synthesize relevant data. This involves gathering input from experts, stakeholders, and relevant data sources. Apply fuzzy logic to handle uncertainties and subjective judgments, which are common in the evaluation of complex factors associated with AM adoption.

**Step 4: Analyze & Collect Relationship Factors** Analyze the relationships between different factors involved in AM adoption. Understand how factors such as geometric complexity, production volume, value for part, design improvement need, functionality of part, time to manufacture, and material removal need interact with each other. Collect data that helps quantify these relationships.

**Step 5: Research Findings** Based on the collected data, conduct in-depth research to understand the current state of AM technology, market trends, and industry best practices. Stay updated on the latest advancements and case studies related to AM adoption, particularly in your specific industry.

**Need of an Evaluation Model**

The adoption of additive manufacturing (AM) necessitates the development and implementation of a robust evaluation model to assess its feasibility and effectiveness in various applications. Such a model is crucial for several reasons, like harness benefits to apply Additive Manufacturing (AM) as opposed to conventional methods of manufacturing. Non-AM experts can use this model to find suitable AM candidate’s part. Minimizes the subjectivity in AM process adoption for a particular part. Integration of components, light weighting, efficient designs and individualization. Widespread use of AM potential. In essence, the implementation of additive manufacturing requires a thoughtful evaluation model to navigate design considerations, financial implications, quality assurance, regulatory compliance, and the evolving landscape of AM technology. This ensures a strategic and informed approach to adopting and integrating AM processes within diverse industrial contexts.

**Methodology**

Certainly, the steps outlined provide a structured approach to adopting additive manufacturing (AM).
Step 6: Synthesize the Result
Synthesize the findings from Steps 3 to 5 to develop a comprehensive understanding of the factors influencing AM adoption. Identify patterns, correlations, and potential challenges. This synthesis lays the groundwork for making informed decisions during the next step.

Step 7: Weightage the Factor and Find the AM Candidacy
Assign weightages to the identified factors based on their significance and relevance to your specific context. Use these weights to assess the candidacy of AM for your application. This step involves combining qualitative and quantitative data to determine the overall suitability of additive manufacturing for addressing the identified problem or opportunity.

By following these seven steps, organizations can systematically navigate the complex process of additive manufacturing adoption, ensuring a well-informed decision-making process that aligns with their strategic goals and manufacturing needs.

Weightage Criteria:
When developing a weightage criteria system for the classification of additive manufacturing projects, it's essential to assign appropriate importance to each factor based on the specific needs and priorities of your organization. Here's a suggested weightage criteria system considering factors such as geometric complexity, production volume, value for part, design improvement need, functionality of the part, and time for manufacturing and material removal need.

<table>
<thead>
<tr>
<th>Criteria/Factors</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geometric Complexity</td>
<td>Low Medium High</td>
</tr>
<tr>
<td>Production Volume</td>
<td>High Medium Low</td>
</tr>
<tr>
<td>Value for part/Price per part</td>
<td>Low Medium High</td>
</tr>
<tr>
<td>Design Improvement Need</td>
<td>No Design Improvement At least one design improvement More than one design improvement</td>
</tr>
<tr>
<td>Part Functionality</td>
<td>Non Critical Partially Critical Critical</td>
</tr>
<tr>
<td>Time to manufacture</td>
<td>Manufacture by AM time is more than conventional Equal manufacture time by AM or conventional Manufacture by AM time is less than conventional</td>
</tr>
<tr>
<td>Material Removal need</td>
<td>Less than 50% material removal by conventional method 50% of material removal by conventional method More than 50% material removal by conventional method</td>
</tr>
</tbody>
</table>

Step 2:
Calculate the geometric mean of fuzzy comparison values for each criterion.

Geometric Mean of fuzzy comparison values of criteria:
Calculate the geometric mean for each column of the fuzzy matrix to obtain the fuzzy comparison values for each criterion. The formula for the geometric mean (P) of fuzzy numbers is given by:

\[
\bar{P} = \left( \prod_{i=1}^{n} a_i \right)^{1/n}
\]

where \(a_i\) are the fuzzy numbers.

Fuzzy Analytical Hierarchy Process
Fuzzy Analytical Hierarchy Process for Triangular Fuzzy to be done:
Step 1: Fuzzy Matrix from pairwise comparison Matrix.

*Step 2:*

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Geometric Mean</th>
<th>Fuzzy weight</th>
<th>Avg.</th>
<th>Norm.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design Improvement</td>
<td>0.96 1.113 1.334</td>
<td>0.086 0.123 0.183</td>
<td>0.101 0.123</td>
<td></td>
</tr>
<tr>
<td>Geometric Complexity</td>
<td>1.87 2.712 3.469</td>
<td>0.168 0.298 0.475</td>
<td>0.184 0.296</td>
<td></td>
</tr>
<tr>
<td>Production Volume</td>
<td>1.795 2.398 2.486</td>
<td>0.159 0.238 0.368</td>
<td>0.225 0.24</td>
<td></td>
</tr>
<tr>
<td>Value for part</td>
<td>1.219 1.399 1.629</td>
<td>0.111 0.153 0.223</td>
<td>0.362 0.152</td>
<td></td>
</tr>
<tr>
<td>Material Removal</td>
<td>2.056 1.011 0.349</td>
<td>0.014 0.033 0.048</td>
<td>0.035 0.033</td>
<td></td>
</tr>
<tr>
<td>Time to manufacture</td>
<td>0.301 0.308 0.405</td>
<td>0.085 0.118 0.17</td>
<td>0.124 0.117</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>7.324 9.195 11.111</td>
<td>0.017 0.073 0.055</td>
<td>0.04 0.038</td>
<td></td>
</tr>
<tr>
<td>Inverse</td>
<td>0.137 0.110 0.09</td>
<td>0.027 0.037 0.055</td>
<td>0.04 0.038</td>
<td></td>
</tr>
<tr>
<td>Reverse</td>
<td>0.09 0.11 0.137</td>
<td>0.001 0.1 1.001</td>
<td>1 1</td>
<td></td>
</tr>
</tbody>
</table>

Geometric Mean of fuzzy comparison values of criteria:
Calculate the geometric mean for each column of the fuzzy matrix to obtain the fuzzy comparison values for each criterion. The formula for the geometric mean (P) of fuzzy numbers is given by:
Step 3 Fuzzy weight of criteria,

Normalize the geometric means obtained in Step 2 to get fuzzy weights. The fuzzy weight (\( W \)) for each criterion is calculated by dividing the geometric mean of the fuzzy comparison values for that criterion by the sum of all geometric means.

\[
\overline{w_i} = \left( \prod_{j=1}^{n} P_{ij} \right)^{1/n} = \left( \prod_{j=1}^{n} n_{ij} \right)^{1/n} = \frac{1}{n} \left( \prod_{j=1}^{n} n_{ij} \right)^{1/n}, \quad i = 1, 2, 3, \ldots, n
\]

Step 4 Defuzzify the fuzzy weight,

Defuzzify the fuzzy weights to obtain crisp weights. This can be done using methods like the center of area, centroid, or other defuzzification techniques. For simplicity, you can use the center of area.

\[
Q_i = \frac{w_{i1} + w_{i2} + w_{i3}}{3}, \quad i = 1, 2, 3, \ldots, n
\]

Step 5 Normalize

Normalize the crisp weights obtained in Step 4 by dividing each weight by the sum of all weights.

\[
R_i = \frac{Q_i}{\sum_{i=1}^{n} Q_i}, \quad i = 1, 2, 3, \ldots, n
\]

Triangular Fuzzy

The normalized weights represent the importance of each criterion in the decision-making process. These steps help convert the pairwise comparison matrix with triangular fuzzy numbers into normalized fuzzy weights for each criterion, providing a comprehensive and nuanced evaluation in the context of Fuzzy Analytical Hierarchy Process.

### Case Study:

Cold forming tool for an axle for heavy machinery powertrain. The part is considered a primary function element of the powertrain which is produced in low volumes. The shape of the tool was similar to that of a promised channel to allow for thorough cooling of the part during cold forming. As a result, the tool was exposed to increased thermal wear and tear and the produced corridor didn't have the invariant hardness as demanded. The conventional tool is considered to have a medium complex figure because it didn't have internal heating channels. The tool is produced as a special unit; hence, the product volume is considered low.

The tool manufactured with AM SLM had innovative adaptive cooling channels slots. According to the results, the cooling time was reduced from 10 to 3 s, which translates to a reduction of 70%. Also, the quality of the corridor bettered to increase the hardness uniformity. The additively manufactured tool was anticipated to be more durable because of the reduced thermal wear and tear.

### Summary/Conclusion

Using total weight (V) obtained, the following conditions apply:

1\( \leq V \leq 1.5 \) : Not Suitable for AM

1.5 \( \leq V \leq 2.0 \) : Suitable for AM after changes

2.0 \( \leq V \leq 2.55 \) : Suitable for AM without changes

In conclusion for evaluation model with Fuzzy AHP for studied case study of Cold forming tool for an axle with cumulative manufacturing, an evaluation model for choosing part campaigners for AM operation in the manufacturing sector is developed. To formulate the model, the Fuzzy AHP processes was used to rank the criteria and assign weights.
The calculated weights attained from the colorful case studies agreed with the evaluation model. The proposed model is a suitable tool that can be used to guide the stoner to identify corridor suitable for AM operation. Value addition of the named part campaigners through design enhancement. The case study performed Fuzzy model to speed up the process while reducing bias in the result. This research work further opens the avenues to work on Cost–benefit analysis to further provide the economic justification of the proposed model. Diverse field user of AM technologies to model the candidacy. Other MCDM methods to be explored, compared, and can be validated. Also, Machine Learning part models with synthetic data can be leveraged for smart solution development.

References

6. Sheng Yang , Thomas Page ,Ying Zhang , Yaoyao Fiona Zhao ,"Towards an automated decision support system for the identification of additive manufacturing part candidates”, Journal of Intelligent Manufacturing, Received: 19 September 2019 / Accepted: 6 February 2020, https://doi.org/10.1007/s10845-020-01545-6

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Definitions/Abbreviations

AM Additive Manufacturing
AHP Analytical Hierarchy Process