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Process and Resource Selection Methodology in Design for Additive Manufacturing

Shervin Kadkhoda-Ahmadi · Alaa Hassan · Elnaz Asadollahi-Yazdi

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Abstract This paper deals with an integrated design approach for Additive Manufacturing (AM), as a Design for Additive Manufacturing (DfAM) approach. This DfAM approach focuses on two important activities of manufacturability analysis, as well as material and process selection in the concept of Concurrent Engineering and Integrated Design approach (CE/ID). It could be considered as a guideline for the researchers in the early phase of the product development process. For this purpose, a novel process and resource selection problem for AM is formalized as an Additive Manufacturing Process and Resource Selection Problem (AMPRSP). This problem is defined to investigate simultaneously the manufacturability, and process and resource selection issues for AM. A Multi-Criteria Evaluation System (MCES) is proposed to solve this problem by evaluating the manufacturability of the product, and selecting the AM resources. Firstly, the AM process, machine, and material are explored and selected regarding technical and economic evaluation criteria. Then, the most appropriate alternative for fabrication with AM is selected by considering the sub-criteria including build time, accuracy performance, and cost. To solve this multi-criteria

problem, an Analytic Hierarchy Process (AHP) method is employed. Overall, this evaluation system is a step-by-step methodology that includes screening, comparative assessment, and a ranking process to select the most suitable alternative for AMPRSP. Finally, the proposed approach is illustrated by an industrial case study.

Keywords Additive Manufacturing · Design for Additive Manufacturing · Multi-criteria decision making · Manufacturability · Process selection

1 Introduction

Nowadays, Additive Manufacturing (AM) is a popular manufacturing system which brings a new approach to producing the different versions of complex products with a material range [1]. The main advantages of AM include producing complex shapes without any additional cost, operations or tooling; and reducing product development cycles, as well as increasing the demand for customized and personalized products, are the main reasons for using the additive technologies [2–4]. This manufacturing method is derived from Rapid Prototyping and it makes the products directly from the digital model based on a layer-by-layer manufacturing process [5, 6]. AM includes various technologies, such as Fused Deposition Modeling (FDM), Selective Laser Sintering (SLS), Selective Laser Melting (SLM), etc. which differ in terms of process, material, power source, and print ink [2]. Recently, different industries such as aerospace, automotive, engineering, medicine, and biological systems have been using these different AM technologies to fabricate their end-user customized products [2].

It is necessary to provide new design and manufacturing tools and guidelines for AM regarding its unique

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Abbreviations

AM	Additive Manufacturing
DfAM	Design for Additive Manufacturing
CE	Concurrent Engineering
ID	Integrated Design
AMPRSP	Additive Manufacturing Process and Resource Selection Problem
MCES	Multi-Criteria Evaluation System
FDM	Fused Deposition Modeling
SLS	Selective Laser Sintering
SLM	Selective Laser Melting
DfM	Design for Manufacturing
CAD	Computer Aided Design
QCCPP	Quality/Cost-based Conceptual Process Planning
QFD	Quality Function Deployment
FMEA	Failure Mode and Effects Analysis
ABC	Activity Based Costing
TO	Topological Optimization
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
AHP	Analytic Hierarchy Process
EBM	Electron Beam Melting
DMLS	Direct Metal Laser Sintering
DSS	Decision Support System
MCDM	Multi-Criteria Decision Making
MPS	Manufacturing Process System
SLA	Stereolithography
MJM	Multi Jet Modeling
MIM	Metal Injection Molding
3DP	Three-Dimensional Printing
APF	Arburg Plastic Free forming
SLC	Selective Laser Cladding
LC	Laser Consolidation
LOM	Laminated Object Manufacturing
LENS	Laser Engineered Net Shaping
EBW	Electron Beam Welding
TM	Traditional Manufacturing

Symbols

P	Machine Purchase cost	\$
M	Material cost	\$
O	Machine Operation cost	\$
L	Labor cost	\$
T_b	Total build time	hours
Y_{life}	Useful life	Year
K_s	Support structure factor	-
K_r	Recycling factor	-
N	Part numbers	-
v	Part volume	cm ³
c_m	Material rate	\$/g
ρ	Material density	g/cm ³
C_O	Operation rate	\$/h
C_L	Labor rate	\$/h
T_L	Labor Time	hours
T_r	Recoating Time	hours
T_s	Material Processing Time	hours
T_d	Delay Time	hours
T_{rp}	Part recoating Time	s
T_{rs}	Support recoating Time	s
L_p	Part layer number	-
L_s	Support layer number	-
T_{pre}	Delay Time before scanning	s
T_{post}	Delay Time after scanning	s
$T_{startup}$	Startup Time	s
ss_{avg}	Average scan speed or nozzle speed	mm s ⁻¹
sl	Scan length	mm
$T_{s-layer}$	Scan Time per layer	s
D_{Maxx}	Maximum Deviation along x-axis	mm
D_{Maxy}	Maximum Deviation along y-axis	mm
D_{Maxz}	Maximum Deviation along z-axis	mm
X, Y, Z	Part dimensions	mm
A	Typical Accuracy	mm
bb_x, bb_y	Bounding Box Side for part	mm
g_x, g_y	Gap between the parts	mm
g_e	Gap between the part and platform edge	mm
n	Number of parts in Working Envelope	-
A_{fn}	A correction factor called area function	
A_{avg}	Average Cross Section Area	mm ²
sl	Total scan length	mm
d	Nozzle diameter	mm

properties to manage the design and manufacturing process simultaneously during the product development process steps [1]. Despite the existence of several advantages for AM, some disadvantages also exist, such as dependency between the material and physical process, material selection limitation, low efficiency for serial production, and machine capacity limitation, as well as surface finishing and quality problems [1]. Therefore, these constraints must be considered during the product development process. Design for Manufacturing (DfM), which is derived from Concurrent Engineering and Integrated Design (CE/ID) approaches, is one of the basic concepts for helping the designer and manufacturer to investigate the constraints and attributes of the manufacturing process during the design step. DfM can reduce manufacturing costs and improve product quality [7]. Thus, the concept of DfAM has emerged as an integrated design approach for AM to consider its constraints and attributes during the design stage [8].

Systematic DfM consists of two main activities of material and process selection, as well as manufacturability

evaluation [9, 10]. As shown in Fig. 1, this evaluation must be performed in three levels of verification, quantification, and optimization. Providing these activities for AM involves analysis of the conflicting attributes and different specific needs of organizations, making them complex tasks in CE/ID. Moreover, AM properties and its standards, guidelines, tools, and rules which, are not sufficiently developed, increase this complexity. The main objective of this study is to provide a DfM-based approach adapted to AM that could be integrated into a DfAM process. This approach is an estimation for designer and manufacturers that helps them to find the suitable process and material for production with AM technologies due to manufacturability evaluation.

The remainder of the paper is organized as follows: Section 2 provides an overview of the DfAM approaches and it reviews the related literature. This analysis per-

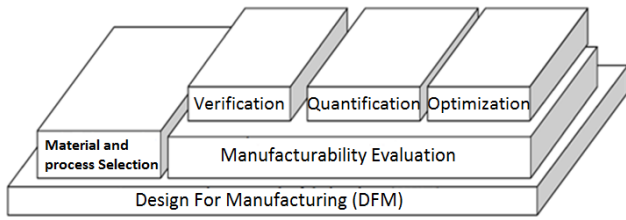


Fig. 1: Systematic DfM [9, 10]

mits us to define the proposed approach. Section 3 describes the applied methodology and the components of the proposed MCES for AM Process and Resource Selection Problem (AMPRSP). Section 4 is devoted to a case study for illustration of the proposed methodology. Finally, Section 5 contains conclusions and perspective works.

2 Literature review

Until now, different AM processes have been reviewed and classified based on applied technology, application, material, etc. by researchers [11–14]. Recently, considerable attention has been paid to providing an integrated design approach for AM in order to investigate its different constraints and attributes. Thus, the DfM approach for AM is proposed as a DfAM approach.

As mentioned in the previous section, DfM consists of two main activities of manufacturability evaluation, and material and process selection [9].

Manufacturability was evaluated in some studies: A DfAM approach is proposed to consider the manufacturing constraints in the design process [15]. Also, a new numerical chain on a DfAM approach was proposed for optimizing a three-step design process by investigating the manufacturing constraints simultaneously [16]. Moreover, manufacturing complexity is also estimated by Hascoet et al. [17]. In this study, the manufacturability indexes were used to calculate a value for AM complexity based on the CAD model and geometrical features, material, and product specifications [17]. Manufacturability is also optimized through presenting an optimization problem to consider the manufacturing constraints and criteria simultaneously [1]. It can also be analyzed by providing special design rules in the study of Pradel et al. [18]. For assessing the potential quality of the products made by AM, visual design for AM worksheet was utilized to identify the AM mistakes [19].

A multi-criteria decision-making method was presented due to lightweight design, cost, strength, displacement, and surface quality to find the best design

solution without a manufacturability analysis [20]. Mechanical behavior of AM products is also an important criterion that is analyzed by some researchers [21–23]. A comprehensive review of the pore formation, mechanical properties, and application of metallic porous material is presented by Zhao et al. [24]. The primary mechanical properties, such as compressive strength, elastic modulus, fatigue properties, and flexural strength of metallic porous materials depending on pore morphology and porosity are investigated in this study [24]. The fatigue behavior of SLM Ti-6Al-4V components is also analyzed by Fotovvati et al. [25] in order to improve this behavior and look into this mechanical property of AM parts under cyclic loading.

Several design rules were presented to optimize topology, manufacturing time, and mechanical properties of the product [26]. The design guideline is provided through featuring a graph-based design improvement technique to analyze the manufacturability while reducing costs. Moreover, DfAM-constrained topology optimization-based design was used to integrate DfAM design rules with topology optimization (TO) [27].

The manufacturability issues are analyzed by Hassan et al. [28] from different perspectives. A new approach is proposed to develop quality/cost-based conceptual process planning (QCCPP). They used QFD, FMEA, and ABC methods to improve the conceptual process planning.

Some researchers [5, 29] utilized TO in order to suggest design solutions for AM by optimizing the mass and structure of the product in terms of its mechanical behavior. Creating a lattice structure is also another approach that is addressed in some studies [30, 31]. Filtering infeasible and unprintable overhanging sections are also considered to obtain the design solutions through TO [32]. TO is used to analyze multi-functional and multi-material parts of AM [33], as well as self-supporting structures in another study [34].

The importance of process selection in CE/ID as another main activity of DfM encourages the researchers to investigate it. Several studies existed for traditional manufacturing processes but the study on process selection for AM is still lacking and it is a large domain that must be continued. Different approaches like the flexible decision-making technique [35], TOPSIS-AHP-based method [7], exploratory analysis about existence and nature of manufacturing methods [36], and characteristics of key parts [37] have been used for traditional manufacturing processes.

Different methods are used to analyze and select the best manufacturing method between AM and traditional processes like analysis of complexity and production volume by a neural networks approach, considering environ-

mental aspects including energy consumption for three manufacturing categories of bulk-forming, subtractive, and additive processes [38].

The AM process selection is another approach that is used for AM based on a test-part comparison approach. Byun and Lee [39] proposed a Decision Support System (DSS) through analysis of part costs, build time, accuracy, roughness, strength, and elongation as evaluation factors. To evaluate these parameters they applied linguistic values, described by means of fuzzy numbers and a test-part approach. In another study [40], a test-part-based methodology is presented by using graph theory and matrix approach. Moreover, the AMRPSP approach is also addressed by Baumers et al. [41] for two different AM technologies, Electron Beam Melting (EBM) and Direct Metal Laser Sintering (DMLS). A cost-estimation model is provided by considering two direct costs of manufacturing, energy consumption, and raw material cost, as well as total indirect costs which depend on the build time. Build time is also another factor that affects the manufacturing cost [42–46]. Technical specifications of the part are selected as other criteria to select the appropriate technologies and machines through an AHP method [47].

A generic decision-making methodology is introduced in the context of material and Manufacturing Process Selection (MPS) [48]. In another study [49], a concerned literature review is provided for manufacturing technology selection and related criteria. A generic methodology is proposed to take into account the AM applications, DfAM guideline, three design criteria, such as cost, function, and environment. Moreover, an integrated design-oriented framework is proposed by Zaman et al. [50] to define a structure for design knowledge pertaining in conceptual and embodiment design. This framework is a guideline for design and feasible material-machine-process combinations by analysis environmental axioms, like avoid toxic and harmful material, as well as using renewable material.

A brief survey of the literature shows that most of the studies, that addressed the process selection for the AM technology investigate only one evaluation criterion, or the key parameters as qualitative parameters, and use linguistic measurement approaches for evaluating them. Since there are also several studies that consider some key parameters as the quantitative parameters and propose models to estimate them, it will be interesting to investigate them as quantitative parameters in one practical general model. Therefore, this paper aims to evaluate concurrently two evaluation criteria: economic and performance for AMPRSP in order to select the most suitable technology and machine as the resources in the product development cycle.

This paper aims to develop a DfAM approach by focusing on the material and process selection, as well as manufacturability evaluation concurrently. For this purpose, a new kind of process selection problem for AM called Additive Manufacturing Process and Resource Selection Problem (AMPRSP) is presented. This approach helps the designer and manufacturer to reduce the product development cost and time, as well as to modify the design by integrating different steps of the total product development cycle presented by Wright [51] (see Fig. 2).

AMPRSP allows us to find and select the most suitable process and resources among the AM technologies and machines based on the different selection criteria. Furthermore, most of the AM process selection studies are based on the test-part comparing method, which cannot be applicable to the problems with large-scale alternatives. Moreover, a Multi-Criteria Evaluation System is developed for the AMPRSP by considering manufacturability tools and two evaluation criteria of economics and performance. The conflicting key parameters of the evaluation criteria encourage the use of Multi-Criteria Decision-Making (MCDM) methods to deal with this problem. The main contributions of this paper that differentiate it from other studies are as follows:

- Designing a new multi-criteria evaluation system for AMPRSP.
- Evaluation of the manufacturability of the product in verification and quantification levels.
- Investigation of the economic and performance evaluation criteria simultaneously for the proposed MCES.
- Identification of the key selection parameters and development of an assessment approach for each evaluation criteria in the proposed MCES.
- Considering manufacturer preference and experts opinions to specify the importance of different evaluation criteria by weighting them.
- [Applying a developed AHP method for solving and providing a suitable AM process and resources.](#)

Overall, a DfAM approach is proposed, which helps the designers and manufacturers to evaluate the manufacturability of the product with AM technologies, as well as, to find the suitable material and process for fabrication with AM by analysis of important AM criteria, like build time, cost, and accuracy.

Table 1 illustrates a summary of the investigated literature related to material and process selection strategies in comparison with the proposed methodology in this paper. As shown in this table, manufacturability evaluation is one of the important activity in DfM approach that is still lacking in the AM domain. Quantitative analysis of the significant AM criteria and constraints is another important issue that must be per-

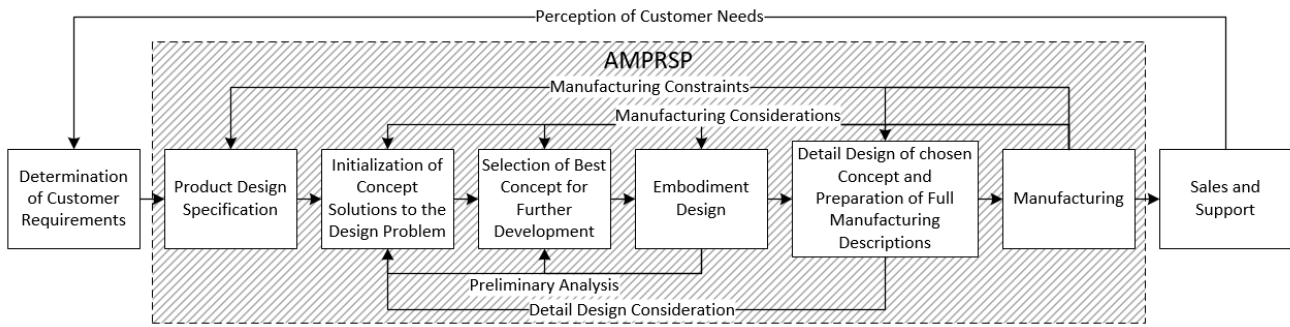


Fig. 2: The status of AMPRSP in the Product Development Process presented by [51]

formed in a DfAM approach. For this purpose, it is necessary to provide the assessment models for AM criteria.

The assessment models are presented in study of Byun et al. and Rao et al [39, 40] for some AM techniques. Fera et al. [38] compared generally the AM and subtractive manufacturing process. Accuracy is analyzed qualitatively in the study of Mancanares et al [47]. Zaman et al. [48] provides the quantitative analysis for cost, but the analyses on the other criteria are qualitative. Environment aspects are also considered by Zaman et al. [49, 50].

In this study, all key parameters have been investigated as quantitative models. These models cover the most important affecting issues for each of the key parameters with a maximum range of application in AM processes. Also, quantitative analysis of significant AM criteria like cost, accuracy, and time permits to define the AM manufacturability in quantification level and providing a precondition to entering into optimization as the next level. Finally, these analyses help to define an integrated approach that helps designer and manufacturers in material and process selection as the first DfM activity (see Fig. 1). Therefore, an integrated DfAM approach will be presented by focusing on the AM material and process selection, as well as manufacturability concurrently.

This methodology will be presented comprehensively in the next section.

3 Proposed methodology for Additive Manufacturing Process and Resource Selection Problem (AMPRSP)

The importance of the selection of resources like materials and machines, as well as process selection in DfAM approaches, illustrates the necessity of providing a multi-criteria evaluation system to deal with this AMPRSP. It

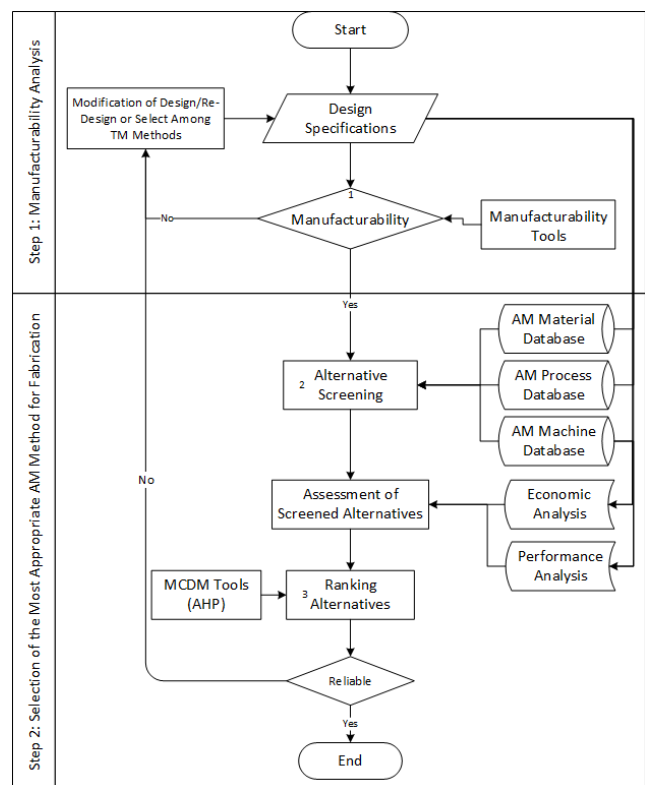


Fig. 3: Methodology for solving AMPRSP

consists of two major steps; manufacturability analysis and selection of the most appropriate alternative in AM technology. The goal is to select the most suitable AM process and machine as the resources. This methodology is formalized by a flowchart in Fig. 3 and each stage is described below:

3.1 Step 1: Manufacturability analysis

Manufacturability analysis is a key activity in DfM approaches to investigate product feasibility for manufac-

Table 1: Analysis of AM process selection studies

Researchers	Manufacturing domain						Evaluation criteria						
	Manufacturability	AM process type						Economic		Performance			
		Laser Melting	Laser Polymerization	Extrusion	Material adhesion	Material Jetting	Electron beam	Cost		Accuracy		Build Time	
								Quantitative	Qualitative	Quantitative	Qualitative	Quantitative	Qualitative
Byun and Lee [39]	*	*	*	*	*	*	*		*		*		
Rao and Padmanabhan [40]		*	*	*		*	*		*		*		
Yim et al. [46]		*	*	*	*	*	*				*		
Mancanares et al. [47]		*	*	*	*	*	*			*			
Baumers et al. [41]		*					*						
Fera et al. [38]	*						*		*				
Zamen et al. [48]		*	*	*	*	*	*			*		*	
Zamen et al. [49]		*	*	*	*	*	*						
Zamen et al. [50]		*	*	*	*	*	*						
This paper	*	*	*	*	*	*	*	*	*	*	*	*	

turing. This analysis determines whether or not it is possible to manufacture the product with its known design specifications through AM. To achieve this goal, manufacturability is assessed based on the selected product-design specifications, provided by the designer, and the characteristics of the different AM techniques such as geometrical accuracy, surface quality, and material class, as shown in Fig. 3. Therefore, the designer can assess the potential geometrical, functional and mechanical product characteristics in terms of their feasibility by an AM process. To perform this assessment, the DfAM worksheet [19] and IT-classes table [52] (see Figs. 4 and 5) are employed as manufacturability tools.

This worksheet helps the designers to assess the potential quality of an AM part. It reduces print failures by filtering out undesirable designs before printing. The IT-classes table, which was defined initially in DIN EN ISO 286-1, represents the size of the ISO-tolerances by IT-numbers (1-18). It allows providing a qualitative analysis for the product accuracy. The relevant influential factors are identified based on the geometrical accuracy for the material extrusion and laser-based processes of AM technology. Overall, this step is completed through some activities:

1. The manufacturability of the part using the AM process is assessed by the DfAM worksheet (Fig. 4).
2. Different AM processes and technologies are filtered via two steps in order to obtain the available AM processes and techniques for fabricating the part.
 - Initially, AM processes, illustrated in Table 2, are filtered based on the material class used in

the part. The density, tensile strength, flexural modulus, elongation at break, impact strength, hardness, and heat deflection temperature are supposed as the important material properties that are considered for filtering the AM processes having similar material classes as the material to be used for the part.

- The resultant alternatives are filtered by a developed IT-classes table (Fig. 5) and expert opinions for satisfying required interval tolerance and surface roughness of the part.






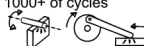









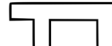
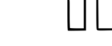
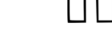
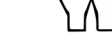
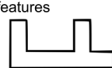

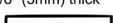




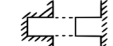
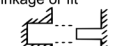
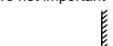






A detailed view of the manufacturability issues are developed to help the decision-makers, for example, the process-design department, the head engineer, the group leader, etc. This step makes possible to determine the available AM techniques to fabricate the product with AM technology.

3.2 Step 2: Selection of the most appropriate AM process and resource through a Multi-Criteria Evaluation System (MCES)

The second step is developed to select the most appropriate AM machine as the resource among the available alternatives of the AM technique. **This step is devoted to MCES that will be completed in four main sub-steps, including alternative screening, economic analysis, performance analysis, and finally ranking the alternatives.** Cost for economic analysis, as well as build time and accuracy for the performance analysis, are considered as

Design for Additive Manufacturing

A quick method for reducing the number of printing and prototyping failures, by **Joran Booth**
Instructions: Mark one for each category for the part you plan to print. Check daggers and stars first, then scores

Mark One	Mark One	Mark One	Mark One	Sum Across Rows	Totals
Complexity Simple parts are inefficient for AM †○ The part is the same shape as common stock materials, or is completely 2D  ○* The part is mostly 2D and can be made in a mill or lathe without repositioning it in the clamp  ○ The part can be made in a mill or lathe, but only after repositioning it in the clamp at least once  ○ The part curvature is complex (splines or arcs) for a machining operation such as a mill or lathe  ○ There are interior features or surface curvature is too complex to be machined 	Functionality AM parts are light and medium duty ○* Mating surfaces are bearing surfaces, or are expected to endure for 1000+ of cycles  ○ Mating surfaces move significantly, experience large forces, or must endure 100-1000 cycles.  ○ Mating surfaces move somewhat, experience moderate forces, or are expected to last 10-100 cycles  ○ Mating surfaces will move minimally, experience low forces, or are intended to endure 2-10 cycles  ○ Surfaces are purely non-functional or experience virtually no cycles 	Material Removal Support structures ruin surface finish ○ The part is smaller than or the same size as the required support structure  ○ There are small gaps that will require support structures  ○ Internal cavities, channels, or holes do not have openings for removing materials  ○ Material can be easily removed from internal cavities, channels, or holes  ○ There are no internal cavities, channels, or holes 	Unsupported Features Unsupported features will droop ○ There are long, unsupported features  ○ There are short, unsupported features  ○ Overhang features have a sloped support  ○ Overhanging features have a minimum of 45deg support  ○ Part is oriented so there are no overhanging features 	x5 = x4 = x3 = x2 = x1 =	
Thin Features Thin features will almost always break ○ Some walls are less than 1/16" (1.5mm) thick  ○ Walls are between 1/16" (1.5mm) and 1/8" (3mm) thick  ○ Walls are more than 1/8" (3mm) thick 	Stress Concentration Interior corners must transition gradually ○ Interior corners have no chamfer, fillet, or rib  ○ Interior corners have chamfers, fillets, and/or ribs  ○ Interior corners have generous chamfers, fillets, and/or ribs 	Tolerances Mating parts should not be the same size ○ Hole or length dimensions are nominal  ○ Hole or length tolerances are adjusted for shrinkage or fit  ○ Hole and length tolerances are considered or are not important 	Geometric Exactness Large, flat areas tend to warp ○ The part has large, flat surfaces or has a form that is important to be exact  ○ The part has medium-sized, flat surfaces, or forms that are should be close to exact  ○ The part has small or no flat surfaces, or forms that need to be exact 	x5 = x3 = x1 =	+
Starred Ratings * Consider a different manufacturing process † Strongly consider a different manufacturing process				Total Score 33-40 Needs redesign 24-32 Consider redesign 16-23 Moderate likelihood of success 8-15 Higher likelihood of success	
 					

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Fig. 4: DfAM worksheet [19]

Table 2: Classification of different AM processes based on ASTM International standard (modified by the authors)

Process	AM technology	Material class	Materials
Vat photo-polymerization	Stereolithography (SLA)	Plastic	UV curable resins, waxes, ceramics
Material jetting	Multi-Jet Modeling (MJM) Metal Injection Molding (MIM)	Plastic Metal	UV curable resins, waxes
Binder jetting	Three-Dimensional Printing (3DP)	Plastic Metal	Composites, polymers, ceramics, sand
Material extrusion	Fused Deposition Modeling (FDM) Arburg Plastic Free forming (APF)	Plastic Plastic	Thermoplastics, waxes Thermoplastics
Powder bed fusion	Selective Laser Sintering (SLS) Selective Laser Melting (SLM) Electron Beam Melting (EBM) Direct Metal Laser Sintering (DMLS) Selective Laser Cladding (SLC) Laser Consolidation (LC)	Plastic Metal Metal Metal Metal Metal	Thermoplastics
Sheet lamination	Laminated Object Manufacturing (LOM)	Plastic Paper	Thermoplastics
Direct energy deposition	Laser Engineered Net Shaping (LENS) Electron Beam Welding (EBW)	Metal Metal	

Process	IT-Classes (DIN EN ISO 286-1)											
	5	6	7	8	9	10	11	12	13	14	15	16
Casting												
Sintering												
Drop forging												
Precision forging												
Cold extrusion												
Milling												
Cutting												
Turning												
Drilling												
Face milling												
Planing												
Stripping												
Circular grinding												
Additive manufact.												
FDM												
LS												
LM												

Fig. 5: Achievable tolerances of the selected traditional and AM processes [52]

the significant criteria of this production system for the proposed MCES. In the following, this MCES system will be discussed comprehensively.

3.2.1 Alternative screening

Primary screening is performed on the available alternatives in this step. For this purpose, an AM database has been presented which contains the AM processes, materials, and specifications. This database is developed based on the machine applicability to the different evaluation models of AM processes. To create this database, this approach focuses on several models that exist in the literature for evaluation of the AM process, and the machine specifications are introduced regarding their required information as listed by the vendors. In this study, the AM machine specifications will be used in the economic and performance analysis as listed in Table 3. It must be mentioned that this database covers more than 100 different types of AM machines, such as 3D Systems, EOS GmbH, Stratasys, etc. These screened alternatives must meet the geometrical specifications of the product derived from the first step.

3.2.2 Economic analysis

Cost is defined as one of the key parameters for economic analysis in this proposed approach. The main focus of this step is evaluating the total cost of different AM machines as resources for the manufacturing process. Regarding the reviewed literature and the application

range in AM processes, the cost model developed by Yim and Rosen [46] was selected to make a preliminary estimation of the overall cost of manufacturing a product with an AM machine. The applied cost model consists of four sub-costs: machine purchase cost (P), material cost (M), machine operation cost (O), and labor cost (L), as shown in Equation 1. Machine operation cost is build time cost and it can be calculated based on the recoating time, material processing time, and delay time that will be explained in build time (T_b) estimation section. Therefore, the cost model applied in this paper is elaborated as follows:

$$Cost_{Total} = P + M + O + L \quad (1)$$

Where:

$$P = \frac{\text{Purchase Price} \times T_b}{0.95 \times 24 \times 365 \times Y_{life}} \quad (2)$$

$$M = K_s \cdot K_r \cdot N \cdot v \cdot c_m \cdot \rho \quad (3)$$

$$O = T_b \cdot C_O \quad (4)$$

$$L = C_L \cdot T_L \quad (5)$$

Equation 2 illustrates how the machine purchase cost is calculated. It was computed based on the purchase cost per hour during build time (T_b). Also, the useful life (Y_{life}) was used for calculating the purchase cost per hour, so that it has been assumed to have 95% of the machine up-time during the useful time of a machine. Equation 3 presents the detail computation of the material cost (M) which was computed based on the support structure factor (K_s), recycling factor (K_r), material

Table 3: AM machine specifications (proposed by the authors)

Machine specifications	Unit
Machine Name	-
Technology	-
Manufacturer	-
Dimensions ($W \times D \times H$)	cm \times cm \times cm
Build Envelope Capacity (Pl_x, Pl_y, Pl_z)	mm \times mm \times mm
Purchase Price	\$
Min Layer Thickness	mm
Min Resolution	μ m
Scan Speed/Nozzle Speed (Min, Max, Avg)	mm s ⁻¹
Typical Accuracy (X, Y, Z)	mm
Laser or Nozzle Diameter	mm
Laser Power	$\frac{W}{CO_2}$
Electrical Requirement	VAC
Energy Consumption	MJ h ⁻¹
Useful Time	year
Part Recoat Time	s
Start-up Time (Warm-up Time)	h
Cool Down Time	s
Materials list	-

rate (C_m), number of parts (N), part volume (v), and material density (ρ), where K_s is captured in order to consider the cost of additional material consumption. It ranges from 1 to 1.5 and is supposed to equal 1 for the cases without the support structure. K_r is presented to capture the cost related to the contribution of wasting loose powder, which is not recycled after the building and ranges from 1 to 7. In Equation 4, machine operation cost (O) was computed by the build time (T_b) as a parameter, and operation rate of the product (C_o) as an empirically determined constant. The operation rate is related to factory overhead. Finally, Equation 5 calculates the labor cost based on the labor rate (C_L) and the labor time (T_L).

3.2.3 Performance analysis

In this approach, the performance of the AM process is evaluated based on the two parameters, build time and accuracy performance, which were previously used in several studies [48, 53, 54]. In the previous related studies, authors considered only one aspect or merely used expert opinions for evaluating performance. However, it is important to analyze simultaneously all effective parameters for providing a comprehensive evaluation. For each parameter, the validated approach was applied and explained as follows:

Build time estimation: Build time is a crucial parameter for AM which affects the strategy of machine selection, cost, and production scheduling processes. For computing the build time, most of the existing models are process- or machine-specific. In this study, the build

time estimation model proposed by Yim and Rosen [46] is chosen, as it can be applied to most of the different types of AM processes. The applied build time estimation model is explained as follows:

$$T_b = T_r + T_s + T_d \quad (6)$$

where:

$$T_r = L_p \cdot T_{rp} + L_s \cdot T_{rs} \quad (7)$$

$$T_d = L_p \cdot (T_{pre} + T_{post}) + T_{startup} \quad (8)$$

$$T_s = \frac{\frac{N}{n} \times Sl}{3600 \times ss_{avg}} \quad (9)$$

$$n = \left(\frac{PL_x + g_x - g_e}{bb_x + g_x} \right) \left(\frac{PL_y + g_y - g_e}{bb_y + g_y} \right) \quad (10)$$

$$\begin{aligned} sl &= (bb_x \times bb_y \times A_{fn}) \left(\frac{N \times L_p}{hr \times d} + K_s \times \frac{L_s}{d} \right) \\ &= A_{avg} \left(\frac{N \times L_p}{hr \times d} + K_s \times \frac{L_s}{d} \right) \quad (11) \end{aligned}$$

$$T_s = T_{s-layer} \times (L_P + L_S) \quad (12)$$

Equation 6 illustrates the total build time (T_b), which is estimated by the accumulation of recoating time (T_r), material processing time (T_s), and delay time (T_d). Recoating time is defined as the process of laying or depositing material on each layer for further processing. Also, some AM processes, such as extrusion, do not have the recoating process; therefore, T_r is 0 in such cases. In Equation 7, the detailed computation of the recoating time is shown, where L_p and L_s represent the number of layers of the part and support. Also, T_{rp} and T_{sp} are part recoat time and support recoat time per layer.

The detailed computation of delay time was presented in Equation 8, where T_{pre} and T_{post} are the delay time before and after scanning each layer respectively, and $T_{startup}$ is start-up time. Equation 9 calculates the material processing time for different AM processes applied in this study, except laser-polymerization, based on average scan speed or nozzle (ss_{avg}) and scan length (s_i). Equations 10 and 11 represent the material processing time calculation. For laser-polymerization AM processes, Equations 9 to 11 are not directly applicable. Hence, the material processing time for this type of AM processes is computed based on scan time per layer ($T_{s-layer}$) and the number of total layers, as shown in Equation 12.

Accuracy performance: For the evaluation of accuracy performance, the approach proposed by Brajlilih and Igor [55] is used. The accuracy performance is evaluated by the average of the maximum expected deviation of the dimensions X, Y, and Z (D_{Maxx} , D_{Maxy} , D_{Maxz}) for each alternative, as shown in Equation 13. This evaluation is based on the typical accuracy (A) of machine and CAD dimensions of the part (X , Y , and Z). It is crucial to separate the deviations due to the nature of the AM machine, according to the coordinate directions of the machine. Therefore, Equations 14 to 16 represent the maximum deviation for each coordinate.

$$\text{Accuracy} = \frac{D_{Maxx} + D_{Maxy} + D_{Maxz}}{3} \quad (13)$$

$$D_{Maxx} = X.A \quad (14)$$

$$D_{Maxy} = Y.A \quad (15)$$

$$D_{Maxz} = Z.A \quad (16)$$

3.2.4 Ranking alternatives

The main goal of this proposed approach is to determine the most appropriate AM technology and machine for a company to fabricate a product. Alternatives were pre-evaluated in the previous steps based on economic and performance analysis. **In this step, the AHP method is used to define the most appropriate alternative. In particular, a developed AHP as an MCDM method is applied to solve the proposed MCES for AMPRSP. The applied method is defined as follows:**

Constructing hierarchical structure of the problem: The three main parts of a decision-making system include the main objective, evaluation criteria or sub-criteria, and available alternatives. A multi-level hierarchical structure is constructed based on these three main parts. Fig. 6 presents the multi-level hierarchical structure proposed in this paper. It consists of four levels:

- **Objective:** Selecting the most appropriate AM machine and technology for AMPRSP.
- **Criteria:** Considering two evaluation criteria: economic and performance.
- **Sub-criteria:** Investigating the three key selection parameters, such as build time, accuracy performance, and cost.
- **Alternatives:** Evaluating the different alternatives.

Pair-wise comparison: AHP is a pair-wise comparison-based methodology. In this study, the pair-wise comparisons are carried out based on the manufacturer preferences and experts opinions to determine the relative importance of the main criteria and sub-criteria respectively. Manufacturer preferences translate a strategic plan of the company, which are specified by the administrator or any strategic decision-maker of the company. Two evaluation criteria, which include economics and performance are supposed for this decision-making approach. Also, expert opinions are used for determining the relative importance of three proposed key parameters. The applied scales for performing the pair-wise comparisons are shown in Table 4 [56].

Definition of the relative importance of criteria and sub-criteria: In this step, double-entry matrices are made from the collected data in the previous step in order to compute the priority vector of criteria (weights). Then, the relative importance of criteria and sub-criteria are obtained from the eigenvector of the double-entry matrices normalized to 1.

Consistency of judgment: The consistency of judgment is a review of judgment which aims to ensure a reasonable level of consistency of expert opinion and manufacturer preferences in the pair-wise comparison. Thus, the consistency index proposed by Satty [56] is applied for evaluation of the consistency. Also, an inconsistency problem is supposed if this index value exceeds 0.1.

Ranking alternatives based on prioritization: Until now, the importance of the criteria for machines and technologies have been defined and validated. The prioritization of the alternatives must be specified by evaluating the alternatives by giving the normalized results, related to economic and performance analysis due to the importance of each criterion. Overall, this proposed approach helps to develop a DfAM approach which focuses on the process and resource selection as AMPRSP process. **An MCES is developed to find the most appropriate process and resource for AM regarding two evaluation criteria: economic and performance.** This approach considers three main AM criteria simultaneously, including

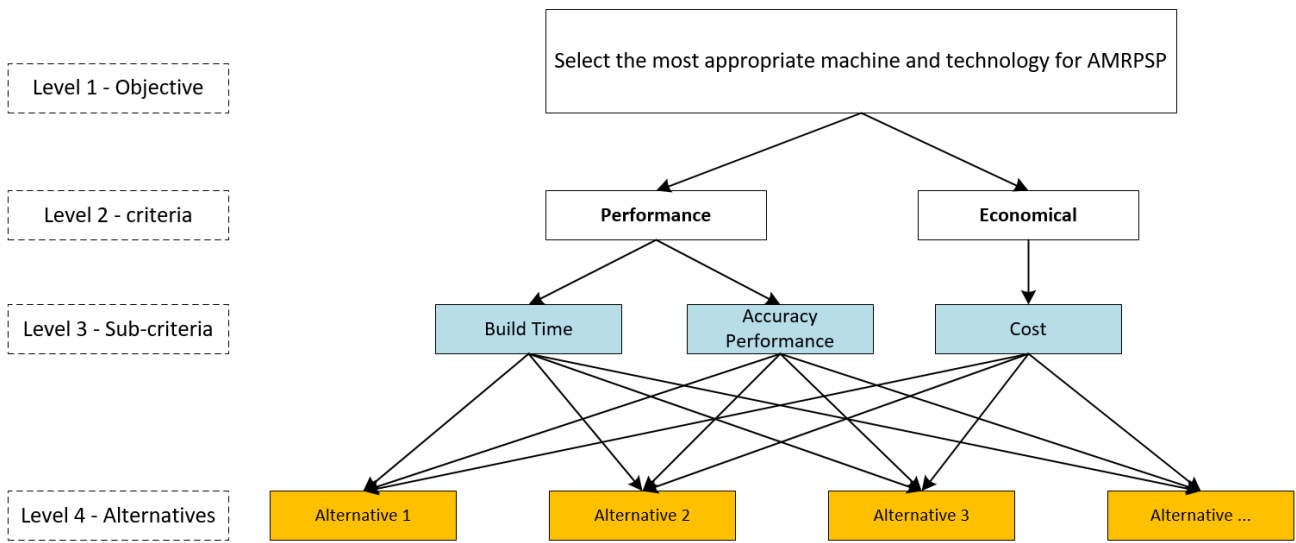


Fig. 6: Hierarchical structure for the proposed MCES

Table 4: Applied scales for the intensity of importance [56]

Intensity importance	Scale
Equal importance	1
Weak plus	2
Moderate importance	3
Moderate plus	4
Strong importance	5
Strong plus	6
Very strong importance	7
Very, very strong	8
Extreme importance	9

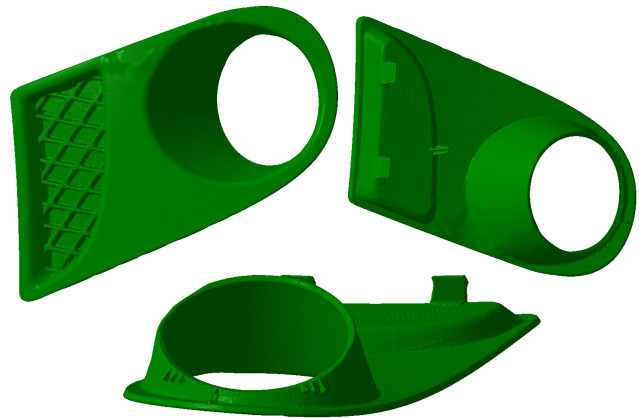


Fig. 7: Solid model of the fog light bezel

build time, accuracy performance, and cost. Finally, the most appropriate process and machine are selected for fabrication. In the next section, this approach will be illustrated and verified through a case study.

4 Case study: Fog light bezel

In this section, the methodology described in the previous section will be explained through an industrial case study which is used in the automotive industry as shown in Fig. 7. The most appropriate process and resource will be selected for the manufacturing of this part. This part is a fog light bezel which is made of Polypropylene TD30 with relatively high accuracy and surface finishing level. This part is manufactured through a traditional molding process. Therefore, the company decided to investigate the possibility of manufacturing this part by using AM technology regarding its benefits. Thereupon, the objective is initially to assess the manufacturability

Table 5: Part design specifications

Factor	Descriptions
Name	Fog Bezel Front Light
Application	Automotive industry
Material Specifications	Polypropylene TD30
Geometrical specifications	
Build envelope	174.65 × 171 × 62.5 mm
Volume	161 730 mm ³
Tolerance	0.2 mm
IT class	11
Surface roughness	N9

of this part by AM technologies and then to select the most appropriate process and resource of AM for fabricating this part. Table 5 shows the required properties of this part as its design specifications.

Design for Additive Manufacturing

A quick method for reducing the number of printing and designing features, by Jason Booth
 Instructions: Mark one for each category for the part you plan to print. Check daggers and stars first, then scores

Mark One	Mark One	Mark One	Mark One	Sum Across Rows	Totals
Complexity The part is mostly 2D and can be made in a mill or lathe without repositioning it in the clamp. The part can be made in a mill or lathe, but only after repositioning it in the clamp at least once. The part curvature is complex (ridges or arcs) for a machining operation such as a mill or lathe. There are interior features or surface curvature is too complex to be machined.	Functionality Mating surfaces are bearing surfaces, or are expected to endure for 1000+ of cycles. Mating surfaces move significantly, experience large forces, or are expected to endure 100-1000 cycles. Mating surfaces move somewhat, experience moderate forces, or are expected to last 10-100 cycles. Mating surfaces will move minimally, experience low forces, or are intended to endure 2-10 cycles. Surfaces are purely non-functional or experience virtually no cycles.	Material Removal The part is smaller than or the same size as the required support structure. There are small gaps that will require support structures. Internal cavities, channels, or holes do not have openings for removing materials. Material can be easily removed from internal cavities, channels, or holes. There are no internal cavities, channels, or holes.	Unsupported Features There are long, unsupported features. There are short, unsupported features. Overhanging features have a sloped support. Overhanging features have a minimum of 45deg support. Part is oriented so there are no overhanging features.	1 x 5 = 5 4 x 4 = 16 3 x 3 = 9 2 x 2 = 4 2 x 1 = 2	
Thin Features Some walls are less than 1/16" (1.5mm) thick. Walls are between 1/16" (1.5mm) and 1/8" (3mm) thick. Walls are more than 1/8" (3mm) thick.	Stress Concentration Interior corners must transition gradually. Interior corners have no chamfer, fillet, or rib. Interior corners have chamfers, fillets, and/or ribs. Interior corners have generous chamfers, fillets, and/or ribs.	Tolerances Making parts should not be the same size. Hole or length dimensions are nominal. Hole or length tolerances are adjusted for shrinkage or fit. Hole and length tolerances are considered or are not important.	Geometric Exactness Large, flat areas tend to warp. The part has large, flat surfaces or has a form that is important to be exact. The part has medium-sized, flat surfaces, or forms that should be close to exact. The part has small or no flat surfaces, or forms that need to be exact.	1 x 5 = 5 2 x 3 = 6 1 x 1 = 1	
Starred Ratings * Consider a different manufacturing process † Strongly consider a different manufacturing process				Total Score 33-40 Needs redesign 24-32 Consider redesign 16-23 Moderate likelihood of success 8-15 Higher likelihood of success	Overall Total 23

REID DESIGN LAB
 PURDUE ENGINEERING

Fig. 8: Manufacturability verification through AM worksheet for the fog light bezel

In the following, the proposed approach will be implemented in the case study in two steps:

4.1 Step 1: Manufacturability analysis of the fog light bezel

This step aims to investigate the feasibility of manufacturing the part through AM technology. Initially, manufacturability of the part is assessed based on the AM work-sheet as shown in Fig. 8; its rate is 23, which shows that the design of the part studied has a moderate likelihood of success. Then, regarding the material class of the part, plastic-based processes are filtered based on similarity in the material properties of Polypropylene TD30. Further, for satisfying the needed IT-class, the manufacturability tools defined in step 1 are applied. The final set of available AM processes are listed due to the selected product design specifications, i.e. material properties, IT-class, and average surface quality of the molding process, as shown in Fig. 9.

4.2 Step 2: Selection of the most appropriate AM method and resource for the fog light bezel

This step is performed in several activities:

- **Primary screening:** After obtaining available AM processes, some alternatives related to these AM processes will be available based on AM database alternatives. Primary screening is performed based on a comparison between geometrical specifications

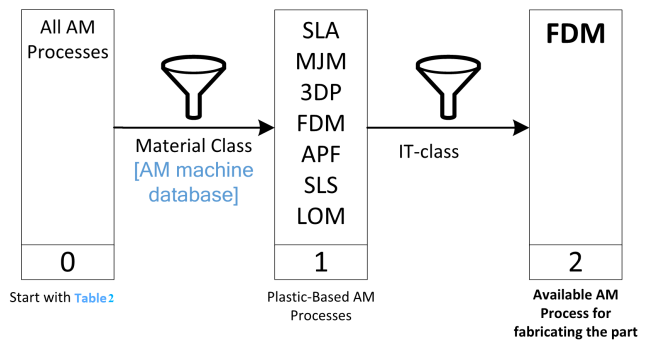


Fig. 9: Selection of the available AM process for the fog light bezel

of the product and machine specifications. Table 6 presents the list of screened alternatives of available AM processes as resources for fabricating the part.

- **Assessment of the screened alternatives:** Every screened alternative is evaluated and assessed based on two evaluation criteria: economic and performance. This evaluation enables having a detailed view of economic and performance issues for alternatives and it helps us to select the most appropriate one in the AMPRSP.

Three models were defined in the previous section in order to estimate the values of key parameters (total cost, build time, and accuracy performance) for each of the screened alternatives. Several parameters and variables are investigated as inputs for these models, which are related to the machine, part, and either machine or part (machine-part). The information of the parameters related to part and machine is presented in Tables 5 and 6 respectively. Moreover, Table 7 also demonstrates the information of the machine-part parameters, provided by AM experts and manufacturers. The results obtained correspond to the assessment of the screened alternatives, as shown in Table 8. In this table, total cost and time are calculated for N parts.

- **Ranking and decision-making:** The AHP method must be applied to select the most appropriate alternative as a final result of the proposed MCES for AMPRSP. Tables 9 and 10 represent the double entry matrices obtained from pairwise comparisons of criteria and sub-criteria by experts. These priorities are devoted to these criteria due to the decision makers and experts' opinions. The relative importance of the criteria and sub-criteria are shown by the weights (see Fig. 10). As shown in this Figure, the economic factors are supposed more important than the performance criteria in this case study. These weights could be modified according to the company's strat-

Table 6: Screened alternatives

Process	Machines	Manufacturer	Price (\$US)	Build Envelope (mm ³)	Material
FDM	Fortus 360 mc	Stratasys	100000	355 × 254 × 254	ABS-M30, PC-ABS, ASA, PC, Nylon 12
	Fortus 450 mc	Stratasys	185000	406 × 355 × 406	ABS-M30, ABS-M30i, ABS-ESD7, ASA, PC-ISO, PC, Nylon 12, ULTEM 9085
	Fortus 900 mc	Stratasys	250000	914 × 609 × 914	ABSi, ABS-M30, ABS-M30i, ABS-ESD7, PC-ABS, ASA, PC-ISO
	Sigma R17	BCN3D	3100	210 × 297 × 210	PC, Nylon 6, Nylon 12, ULTEM 9085, ULTEM 1010, PPSF
	Sigmax	BCN3D	5225	420 × 297 × 210	PLA, ABS, PVA, TPU, Nylon, HIPS, Specials
	Replicator Z18	MakerBot	6500	300 × 305 × 457	PLA, ABS, PVA, TPU, Nylon, HIPS, Specials Tough PLA, PLA, ABS

Table 7: Machine-part parameters related to screened alternatives for fog light bezel

Parameters	Fortus 360mc	Fortus 450mc	Fortus 360mc	Sigma R17	Sigma x	ReplicatorZ18
K_s	1.3	1.3	1.3	1.3	1.3	1.3
K_r	1	1	1	1	1	1
C_m (\$/g)	0.15	0.15	0.15	0.15	0.15	0.12
ρ (g/mm ³)	0.001	0.001	0.001	0.001	0.001	0.0012
C_o (\$)	3	3	3	3	3	3
C_L (\$)	23	23	23	23	23	23
T_L (s)	3600	3600	3600	3600	3600	3600
L_P	48	48	48	24	24	120
L_s	48	48	48	24	24	120
T_{pre} (s)	0	0	0	0	0	0
T_{post} (s)	60	60	60	60	60	60
bb_x (mm)	36	36	36	36	36	36
bb_y (mm)	30	30	30	30	30	30
g_x (mm)	50	50	50	50	50	50
g_y (mm)	50	50	50	50	50	50
g_e (mm)	50	50	50	50	50	50
N	100	100	100	100	100	100
n	13	13	13	13	13	13
A_{fn}	0.54	0.54	0.54	0.54	0.54	0.54
A_{avg}	579.75	579.75	579.75	579.75	579.75	579.75
sl (s)	6936453	6967312	15854750	3523718	2349145	39636876

Table 8: Evaluation of screened alternatives according to the three key parameters for N part

Alternatives	AM process	Total cost (\$)	Total build time (h)	Accuracy (mm)
Fortus 360 mc	FDM	24923	3807	0.21
Fortus 450 mc	FDM	15314	1531	0.21
Fortus 900 mc	FDM	4140	353	0.20
Sigma R17	FDM	11081	2757	1.56
Sigmax	FDM	3418	623	1.56
Replicator Z18	FDM	32379	9501	1.66

egy. The consistency of the expert opinion has been tested, obtaining an index of 0.009, which represents that the calculated weights are consistent.

Consequently, the most appropriate alternative for this case is Fortus 900mc with 35% priority, as illustrated in Table 11. Sigmax is ranked second with 33% priority. In addition, Fig. 11 summarizes these results and shows the portion of each parameter in total priority for each of the screened parameters. Moreover, the selection of alternative Fortus 900mc can be explained as it presents the best performance for most of the criteria.

Table 9: Double entry matrix of two evaluation criteria

	Economic	Performance
Economic	1	2
Performance	$\frac{1}{2}$	1

Table 10: Double entry matrix of key parameters as sub-criteria

	Build Time	Accuracy
Build Time	1	3
Accuracy	$\frac{1}{3}$	1

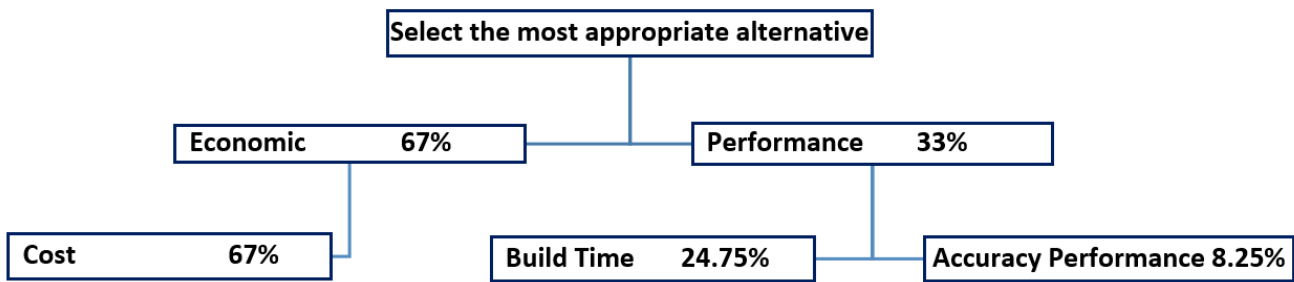


Fig. 10: Weighted hierarchical structure for the proposed MCES

Table 11: Results of the ranking alternatives

	Normalized Value of			Priority	Ranking
	Cost	Build time	Accuracy		
Fortus 360mc	0.137	0.093	0.939	0.076	5
Fortus 450mc	0.223	0.230	0.939	0.113	3
Fortus 900mc	0.826	1.000	1	0.351	1
Sigma R17	0.308	0.128	0.125	0.099	4
Sigmax	1.00	0.567	0.125	0.326	2
Replicator Z18	0.106	0.037	0.118	0.036	6

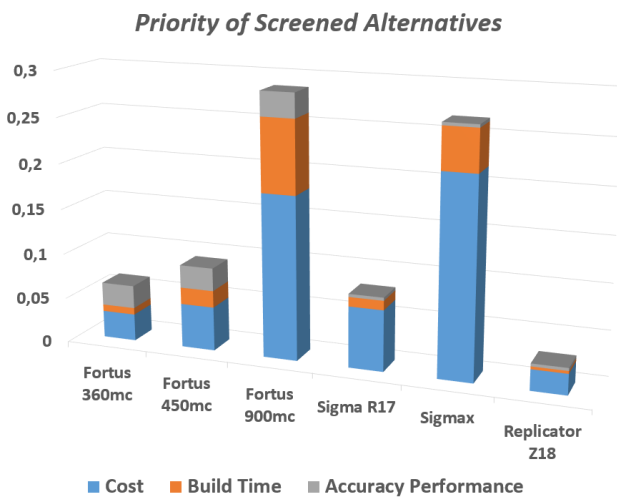


Fig. 11: Priority of the screened alternatives

5 Conclusion

This paper focuses on AM Process and Resource Selection Problem which is an improvement effort in the field of CE/ID which takes inspiration from process selection for rapid prototyping in order to improve the DfAM approaches. In spite of this inspiration, the application area of AMPRSP is more extensive than AM process selection and covers its main limitations, test-part comparison, and large-scale alternatives. Due to the complexity of AM technologies, the selection of process

and resources depends on different functional, technological and economic parameters. The industry needs a pragmatic multi-criteria decision support approach to be able to choose the most appropriate technology for their needs. Our proposed approach integrates these factors into a new systemic framework based on assessment models that have been approved in the literature. Nevertheless, the integration of these models into a single tool framework clearly addresses the need for a return on investment in AM.

The AMPRSP selects the most suitable AM processes and resources for fabricating a part based on different evaluation criteria and key selection parameters. An MCES was proposed in this paper for the AMPRSP. The proposed MCES simultaneously investigates the manufacturability and two evaluation criteria by considering manufacturability tools and key selection parameters respectively. It has been applied as a step-by-step methodology and it is easy to employ procedures such as screening, comparative assessment, and ranking processes to select the most suitable alternative for AMPRSP. As pre-evaluation, the proposed MCES has adopted different models to estimate the key selection parameters, including total cost, build time, and accuracy performance, in order to provide a detailed view of the evaluation criteria. Then, the most suitable alternative is selected by using the AHP method. A case study is presented to illustrate and verify the proposed approach and its DfAM guidelines for researchers in the product development process.

Despite the passage of more than 30 years since the emergence of AM technology, and the achievement of significant improvements during these years, there is still a major lack in regard to the in-comprehensiveness of methods, tools, and rules in this technology. As reviewed in the literature, most of the AM methods and models are process-specific. Due to this fact, the scope of this study does not end here and it can be extended either in the scope of this methodology or in the application of new models and tools with greater precision and comprehensiveness for this MCES. Considering the other evaluation criteria, such as sustainability and innovation, the introduction of key parameters for each new criterion, and analysis of the dependency and interdependency of key parameters, these can be investigated as multiple future works for the scope of methodology. Applying more comprehensive models for the assessment of the key parameters and developing a software tool to effectively support this MCES are other points that can be developed in future prospects.

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