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Additive Manufacturing in Production: a Study Case Applying Technical Requirements

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Abstract

Additive manufacturing (AM) is expanding the manufacturing capabilities. However, quality of AM produced parts is dependent on a number of machine, geometry and process parameters. The variability of these parameters affects the manufacturing drastically and therefore standardized processes and harmonized methodologies need to be developed to characterize the technology for end use applications and enable the technology for manufacturing.

This research proposes a composite methodology integrating Taguchi Design of Experiments, multi-objective optimization and statistical process control, to optimize the manufacturing process and fulfil multiple requirements imposed to an arbitrary geometry. The proposed methodology aims to characterize AM technology depending upon manufacturing process variables as well as to perform a comparative assessment of three AM technologies (Selective Laser Sintering, Laser Stereolithography and Polyjet).

Results indicate that only one machine, laser-based Stereolithography, was feasible to fulfil simultaneously macro and micro level geometrical requirements but mechanical properties were not at required level. Future research will study a single AM system at the time to characterize AM machine technical capabilities and stimulate pre-normative initiatives of the technology for end use applications.

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Keywords: Additive Manufacturing; 3D Printing; Rapid Manufacturing; Design of Experiment; Standardization

1. Introduction

The aim of this research is to explore an experimental methodology for pre-normative activities in Additive Manufacturing (AM) process characterization to be used at initial engineering design stages. The long-term vision of this work is to develop a standard methodology to characterize machine capabilities, such as dimensional repeatability and help engineering design and manufacturing community to use AM machines in end use applications. The background of this research is founded on evidences in which AM can potentially replace conventional methods to produce goods when production volumes are small (Campbell, et al., 2012). Current systems are capable to directly manufacture functional engineering components economically, especially suitable when production volumes are low and complexity of the geometry is high (Levy, et al., 2003). In addition, implementation of AM systems could potentially limit the fix cost in small series production, and therefore reduce cost and time-to-market during the product development of organizations (ElMaraghy, et al., 2013).

Over the past years, mechanical properties as well as the reliability and repeatability of AM processes have improved significantly (Wohlers, 2014). Hence, it is expected that AM systems will be used in the near future to produce parts for end use applications (Santos, et al., 2006); this process is defined as Rapid Manufacturing (Mellor, et al., 2014).

However, to drive manufacturing application the technology requires significant developments (Holmström, et al., 2014). AM machines have different architectures and material processing capabilities. The characterization and standardization of the technology is not yet mature and the part quality differences are substantial from machine to machine in terms of achievable mechanical and dimensional properties (Clemon, et al., 2013). Technical performance of the technology in manufacturing has not been standardized to penetrate in regulated industries (Gibson, et al., 2010). Hence, technology roadmaps emphasize that AM success in the future, is highly correlated to certification and standardization methods of the technology capabilities (Gausemeie, et al., 2013). Specially, in regulated high value product development industries, such as aerospace, automotive, defense, medical industry as well as consumer electronics.

Geometrical stability and material properties of AM produced part are strongly dependent on the manufacturing process planning and machines architecture (Hu and Kovacevic, 2003). Research has indicated that the part orientation, the part location of the geometry on the build tray as well as quality of the digital data has an effect on the achievable geometrical and topological quality. Hence, these parameters need to be studied further (D. Dimitrov, et al., 2006), (Brajlih, et al., 2010) and (Anand and Ratnadeep, 2011) in order to stimulate pre-normative activities towards AM certification and standardization.

Fused Deposition Modelling (FDM), Selective Laser Sintering (SLS), Stereolithography (SLA) and Polyjet technology are some of the most common alternatives to produce engineering functional plastic parts, final quality of the produced parts changes are machine and process dependent (Pham and Gault, 1998) making its characterization more difficult. Research in the field has not presented a systematic experimental method to characterize AM machine capabilities, applying a harmonized experimental approach for quality assurance.

Additionally, in an AM process, produced parts have to fulfil simultaneously different types of mechanical and dimensional requirements. Frequently, due to the process dependencies of the additive method, the manufacturing set up imply trade-offs between micro and macro level geometrical requirements as well as mechanical requirements, due to the orthotropic behavior of the AM process. To address this issue, research community has used Design of Experiments (DOE) to optimize individual manufacturing parameters of the machines (Hsu and Lai, 2010), (Wang, et al., 2007) and (Rahmati, et al., 2007). However, selecting a combination of machine and process parameters to fulfil simultaneously multiple requirements has not been tackled. There is then a need to research a systematic experimental approach to fulfil multiple production requirements simultaneously and characterize manufacturing capabilities, as proposed in similar manufacturing context (Konda, et al., 1999).

2. Materials and Methods

This research has used a study case geometry, which is typical used in mass produced consumer devices and produced in PC-ABS injection molding. Fig. 1 depicts a functional inner structural plastic part with mechanical, dimensional and geometrical production requirements. The final produced sample requires very tight geometrical and dimension tolerances as well as good surface quality in order to be feasible for the mechanic assembly of the final product. The nominal size of the part is 68.12 mm x 37.24 mm x 14.85 mm and its theoretical volume is about 3308 mm^3.

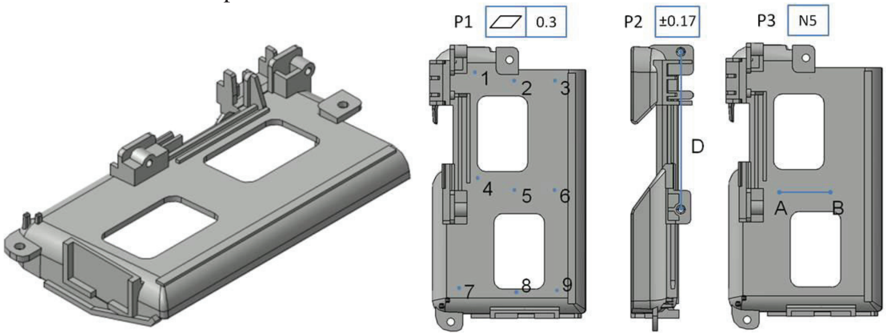

Fig. 1. Geometry used in the case study and geometrical requirements definition

Fig. 2 shows the methodology and process diagram to characterize AM for end use applications. Initial steps of the process imply to select the geometry and the material of the geometry. These parameters will guide the selection of suitable machine alternatives.

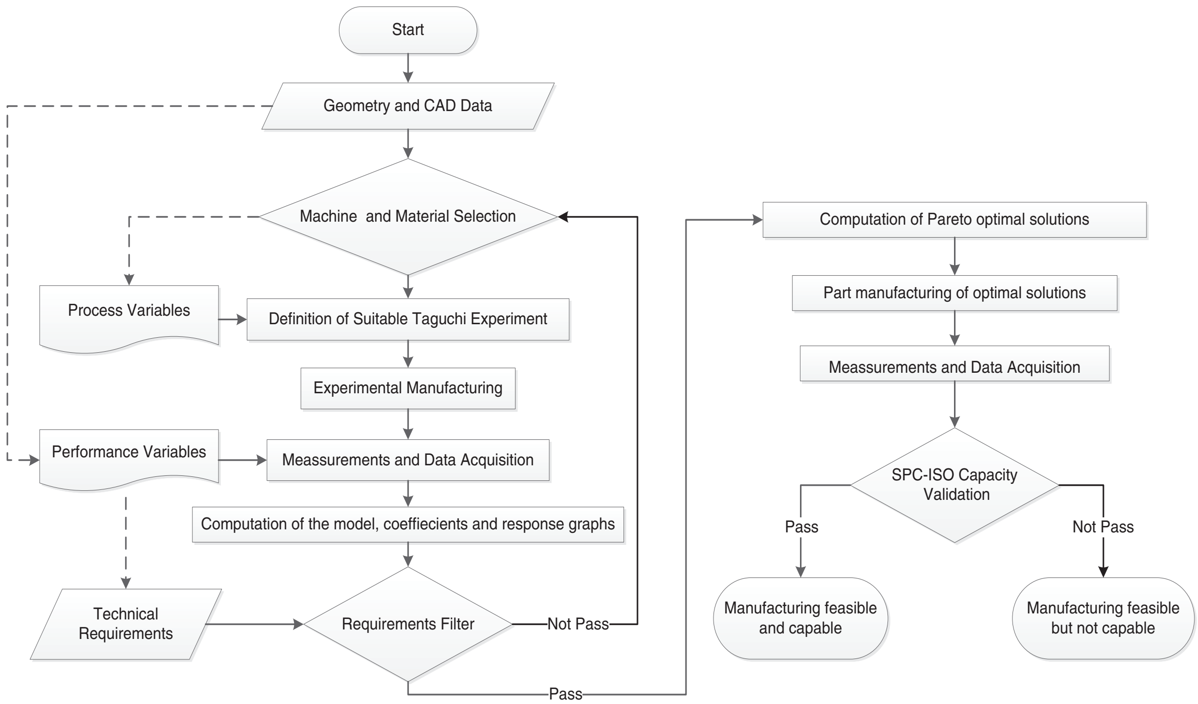

Fig. 2. Methodology and its process diagram

2.1. Selection of the performance variables, process variables and factor levels

This research has considered the following factors affecting to the AM process, which can be separated into three categories, Signal Factors or process variables, Noise Factors and Control Factors or performance variables. Fig. 3 shows the P-diagram of the explored variables.

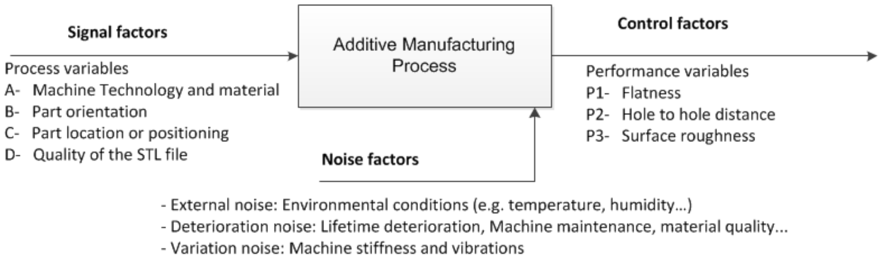

Fig. 3. Parameter diagram used during the DOE

A total of three performance variables and four process variables with three factor levels are included in the DOE. The first process variable (A) describes the machine and material selection, the factor levels of this DOE are explained in Table 1. The machine alternatives included three process categories described in the ASTM, Standard Terminology for Additive Manufacturing Technologies (ASTM, 2013).

Table 1. Process variable (A), machine and material

Machine specifications	**M1**	**M2**	**M3**
Machine type	Viper SI2 (3D Systems)	Objet 500 (Stratasys)	Formiga P110 (EOS)
Industrial process category	Laser Stereo Lithography (SLA)	Polyjet	Selective laser sintering (SLS)
ASTM process category	Vat photo-polymerization	Material jetting	Powder bed fusion
Layer thickness (Z-Axis)	50 μm	30 μm	100 μm
Material	Accura 25 plastic	ABS Like	PA2200

The second process variable (B) is the part orientation on the machine build platform, in which the geometries are manufactured in horizontal, vertical and diagonal orientation (i.e. diagonal 45^{o} from the XY horizontal plane which corresponds to the build tray of the AM machines). The third process variable (C) studies the effect of the part location on the machine over the manufactured part. In this case, the levels included parts printed on the top left, center and bottom right of the build platform. The last process variable (D) studies the quality of the digital data, in which intentionally the chordal errors of the STL files are pre-established. All these variables behave in a non-linear manner. Thus, three levels have been selected per each process variable. The summary of the process variables and factor levels is explained in Table 2.

Table 2. Summary of process variable and control levels

Process variables		**Level 1**	**Level 2**	**Level 3**
A	Machine and Material	M1	M2	M3
B	Part Orientation	Horizontal	Vertical	Diagonal
C	Part Location	Top Left	Centre	Bottom Right
D	Digital Quality	High (0.001mm)	Medium (0.01mm)	Low (0.1mm)

Regarding the performance variables, three measurable variables are included in order to integrate typical manufacturing requirements present in injection-molded parts. The combination of these three requirements is an important constraint to the AM process. Two of them, at the macro level, the flatness (P1) and the distance from hole to hole (P2) studied the geometrical and dimensional stability of the produced parts. The last variable, at the micro level, measured the surface quality (P3) of the produced parts. Table 3 makes a summary of the performance variables and their requirements, as well as the optimization objective per performance variable.

Table 3. Optimization objective of the performance variables

Performance Variables		Optimization Objective	Requirement
P1	Flatness (mm)	Minimize	0.3 mm (max.)
P2	Hole to hole distance D (mm)	On target	37.55 +/- 0.17 mm
P3	Surface roughness Ra (μm)	Minimize	0.8 μm (max.)

2.2. Definition of the Design of Experiment (DOE) and suitable Taguchi Orthogonal Array

The Table 4 shows the array used in the DOE. The columns represent the process variables and the rows correspond to the individual experiments.

Table 4. Taguchi L9 orthogonal array for the DOE

Exp.	A (Machine & Material)	B (Part Orientation)	C (Part Location)	D (Digital Quality)	Encoding of the Experiment
1	M1	Horizontal	Top Left	High	1HLH
2	M1	Vertical	Centre	Medium	1VCM
3	M1	Diagonal (45º)	Bottom Right	Low	1DRL
4	M2	Horizontal	Centre	Low	2HCL
5	M2	Vertical	Bottom Right	High	2VRH
6	M2	Diagonal (45º)	Top Left	Medium	2DLM
7	M3	Horizontal	Bottom Right	Medium	3HRM
8	M3	Vertical	Top Left	Low	3VLL
9	M3	Diagonal (45º)	Centre	High	3DCH

When planning a DOE, several process variables or input factors can be varied simultaneously in a controlled manner in order to obtain reliable, repeatable and structured data (Fisher, 1935). To simplify and limit the experimental approach, a Taguchi DOE was implemented, choosing a L9 orthogonal array to drive the experiment. In Taguchi method on the contrary to Fisher approach, noises are considered valuable and can also be integrated and analyzed in the experimental protocol. The advantage of Taguchi methods, in addition of limiting the amount of experiments, is to propose a set of orthogonal arrays specially created for automatically randomizing the experiments and to create an optimal DOE.

The objective function of the DOE is described in the following Eq. (1). For simplification reasons in the experimental set up, the interactions between the designs variables have been omitted. The formulation of the function is a linear additive mathematical model (Phadke, 1998). The model is presented in a matrix representation form due to the number of performance variables (P1, P2 and P3) that the DOE is considering.

$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix}_i = \begin{bmatrix} \text{mean value}_1 \\ \text{mean value}_2 \\ \text{mean value}_3 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} .+ \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix} \quad (1)$$

Where, Pi represents the three objective functions to optimize: Flatness (P1), the hole to hole distance (P2) and the surface roughness (P3). The objectives to fulfil for those performances are the following, the Flatness (P1) should be minimized, the hole to hole distance (P2) should lead to a target value and the surface roughness (P3) should be minimized. In the model, the mean values are computed for each of the three Performances. The general formula for computing the mean values is represented by the following notation:

$$\text{mean value}_i = \frac{\sum_{j=1}^{9} P_{ij}}{9} \quad (2)$$

In which Pi is representing one of the 3 performances (P1, P2 and P3) of interest in this study. j is representing the set of 9 experiments required in a Taguchi L9, implemented in this DOE. In the general additive model of Eq. (1), the coefficients aij, bij, cij and dij are representing the effects of the factor levels of the different design variables on the performances Pi. The general formula considered to compute those effect coefficients are represented by the following equations:

$$a_{ij} = \frac{\sum_{j=1}^{3} P_{ij}}{3} - \text{ General mean value}_i \quad (3)$$

In which a is the effect of the first design variable, the machine technology, i is associated with the performance variable Pi and j is associated with the level of the design variables (1, 2 or 3). Similar formulas are created for b (the part orientation), c (the part location) and d (the digital quality).

2.3. Measurements and experimental set-up

The experiments in the L9 array were repeated three times to take into consideration the variance in the experiment. In addition, each sample was measured twice per performance variable for integrating the variance of the measurement processes. Altogether, 54 measurements were taken, 6 measurements per each experiment. In the SPC capacity validation phase of the methodology, 3 more parts were produced per feasible solution and measured again using the same process described previously. Fig. 4 shows the picture of sample number 1. In the top side of the picture the part code is shown.

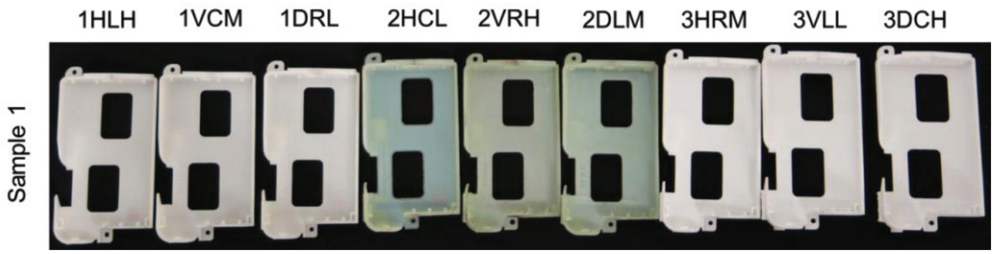

Fig. 4. Sample 1 of the DOE

The measurement of the performance variables P1 and P2 was performed with an image based 3D laser coordinate measurement system, Nikon VMR-3020. Regarding the performance variable P2, the machine measured directly the distance between hole centers. Last measurement of the performance variable P3 was obtained by using a profilometer, Taylor-Hobson Surtronic 3 Roughness Gage, the measuring distance or sampling length for calculating Ra was set to 4mm shown in in Fig. 3.

2.4. Multi-objective optimization and Statistical Process Control (SPC)

After obtaining the data, the next phase implies to compare all combination results of the model against the requirement of the system, by doing so an initial filtering of not feasible solutions is implemented. If results are obtained after this filter, there are potentially feasible solutions to manufacture the part within requirements. Otherwise, new machine alternatives or less restrictive requirements need to be considered (see process diagram in Fig. 2). Next move is to study the dominance between solutions is. To do so, a pairwise comparison algorithm is used in this research to compute the Pareto optimal solutions (Miettinen, 1999). The final step consisted on applying a SPC capacity test to the manufactured Pareto optimal solutions (Shewhart, 1986). This is performed to evaluate the robustness of the manufacturing process (i.e. robust to noise and deviations in the process) (Montgomery, 1992). For that purpose, the standard ISO was used (ISO7870-2, 2013). In this research the minimum level for an acceptable capability index was set to 1 (Larsson, 2002).

3. Results

3.1. Geometrical requirements

Fig. 5, 6 and 7 display the response graphic of the performance variables P1, P2 and P3 respectively.

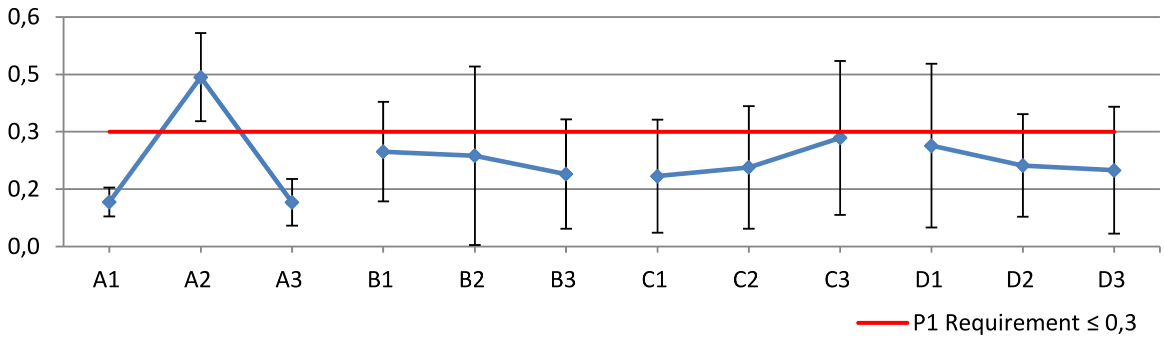

Fig. 5. Response graphic of the performance variable P1 (Flatness)

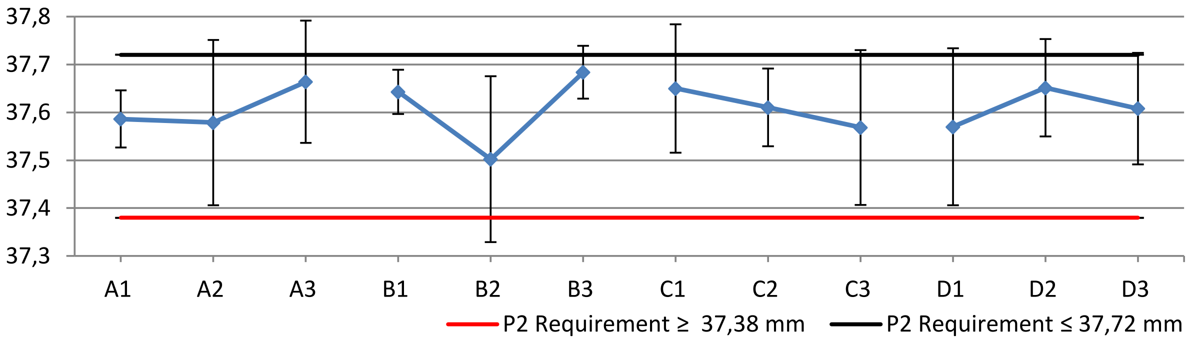

Fig. 6. Response graphic of the performance variable P2 (Hole to hole distance)

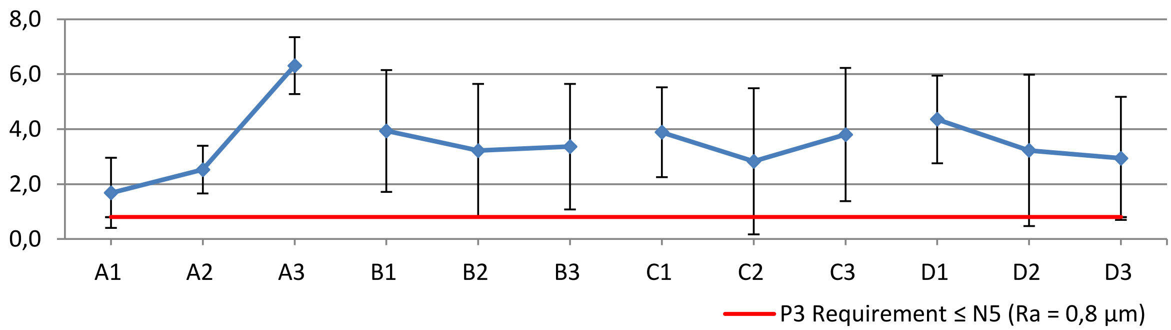

Fig. 7. Response graphic of the performance variable P3 (Surface quality)

Based on the results shown in Fig. 5 and 7, most of the combinations of process variables will not be feasible to produce the part within geometrical requirements. Nevertheless, certain combinations of the process variables could potentially be feasible to produce parts that fulfil the imposed requirements. In order to evaluate this possibility, an initial filtering of the objective function was implemented. The filter result of the model provided a set of four theoretical solutions able to satisfy the requirements. The following move is to study if these four solutions are Pareto optimal or non-dominated solutions. After studying the dominancy between solutions, theoretically only three Pareto efficient solutions were potentially feasible to fulfil all the requirements simultaneously. The feasible solutions are displayed in Table 5.

Table 5. Feasible non-dominated solutions to manufacture the case geometry

Process variable	Solution 1	Solution 2	Solution 3
A (Machine and material)	A1 (M1)	A1 (M1)	A1 (M1)
B (Part Orientation)	B2 (Vertical)	B2 (Vertical)	B3 (Diagonal)
C (Part Location)	C2 (Centre)	C2 (Centre)	C2 (Centre)
D (Digital Quality)	D2 (Medium)	D3 (Low)	D3 (Low)

At this stage two AM processes, the material jetting (M2) and the powder bed fusion (M3) have been eliminated. Vat photo-polymerization (M1) is better than the two other processes for surface quality (P3) and as good as the best option for the two other performances (Flatness, P1 and hole distance, P2). Considering the set of 3 feasible solutions the re-manufacturing of the theoretically feasible solutions needs to be performed and then tested in the SPC capability analysis for robustness analysis. In this experiment, for simplification reasons, solution 2 has been ruled out and only solution 1 and 3 were re-manufactured to evaluate the statistical model.

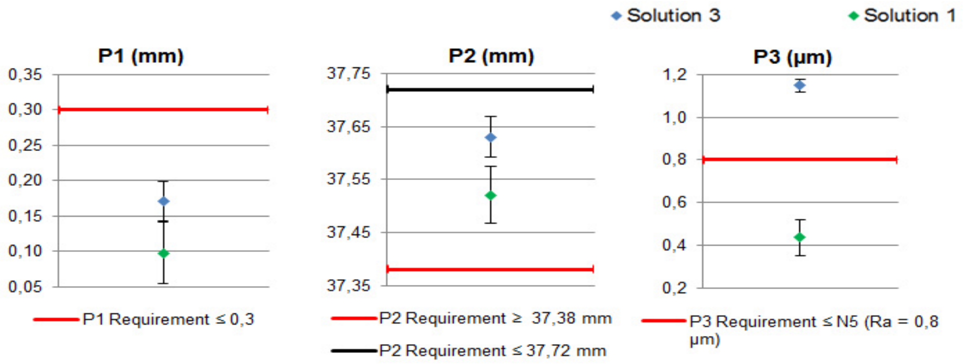

Fig. 8. Representation of the mean value, standard deviation and requirements for the Pareto optimal re-manufactured parts

Fig. 8 shows the measurement results of the non-dominated manufactured solutions. Results indicate that the mean value of solution 1 is within the requirements for all the performance variables. This is not the case for Solution 3, in which the mean value of the roughness is outside the requirements, thus the solution is not technically feasible. The last step as described in the process diagram of Fig. 2 is to evaluate the capability of solution 1 (i.e. its robustness to deviations in the process). The results of the ISO-SPC capability analysis are displayed in Table 6. Cp and CpK indexes of solution 1 show that the process is capable but not centered. This is due to a too high standard deviation of the measured sample.

Table 6. Capability analysis for the solutions 1

Solution 1	P1		P2		P3	
Cp	1.156	Capable	1.074	Capable	1.560	Capable
CpK	0.756	Not Centered	0.892	Not Centered	0	Not Centered
Mean	0.098		37.521		0.436	
Stdev	0.046		0.053		0.085	

3.2. Mechanical requirements

Table 7 shows the quantitative comparison of the mechanical technical requirements imposed to the case study injection moulded component. The rightmost column shows the ISO and ASTM mechanical requirements.

Table 7. Mechanical properties formal benchmark

Machine Specifications	M1	M2	M3	Injection Molded PC-ABS Mechanical requirements
Material	Accura 25 Plastic (1)	ABS Like (1)	PA2200 (2)	
Tensile Strength	38 MPa	55-60 MPa	45 MPa	43.3-65.6 MPa (1) & 44.7-66.4 MPa(2)
Tensile Modulus	2690-3100 MPa	2600-3000 MPa	1700 MPa	1920-2960 MPa (1) & 2000-2810 MPa (2)
Elongation at break	13-20%	25-40%	20 %	1.5-7.4% (1) & 3-5.8% (2)
Impact Strength	19-24 J/m	65-80 J/m	4.4 KJ/m2	68-700 J/m (1) & 9.8-67 KJ/m2 (2)
Rockwell Hardness	80 (Shore D)	85-87 (Shore D)	75 (Shore D)	110-121 (1) & 90-124 (2)

(1) ASTM test method & (2) ISO test method

4. Discussion and Conclusions

The implementation of AM for technical prototyping, pre-production series and short series production can bring benefits in terms of cost reduction and shorten of the time-to-market in product development (Holmström, et al., 2014). However, the results of the research showed that production of plastic components in consumer electronic devices can be challenging when geometrical and mechanical requirements are tight. Results of the DOE show that, P3 (Surface Quality) was the most difficult requirement to satisfy, followed by P1 (Flatness) and P2 (Hole distance). Results of Pareto optimum showed that only three solutions were theoretically feasible. Based on the SPC results, only one solution was feasible and capable at the same time; however, the process was not centered.

M1 was feasible to fulfil geometrical requirements. M2 had flatness values out of specification and the surface quality of M2 and M3 was not within requirements. Moreover, only parts produced vertically and diagonally are usable, the part location had a major impact, as only parts manufactured in the center of the build platform were feasible for production. Process variable C (Digital quality) was not critical; the effect of the digital quality is often visible in geometrical features, such as round surfaces. The selected performance variables did not measure this effect quantitatively. Mechanical properties were evaluated by comparing specification of the suppliers against injection molded part requirements. Result show that the weakest parameter of AM produced part is related to the impact strength other parameter some comparable values but weaker in comparison to injection molded parts.

This research has presented that manufacturing of plastic parts using the selected AM systems is not technically feasible due to the high quality requirements imposed to the case study. Even though the geometrical stability of the laser-based machine (M1) was feasible to produce parts within requirements, mechanical performance of the materials is still not at the acceptable range with the selected set of materials. Nevertheless, future technological advances will certainly open possibilities to use AM systems in high value product development, such as consumer's electronics product, especially when production volumes are low.

This research is a starting point to certify of AM capabilities, integrating manufacturing process planning variability and quality control methodologies. However, this research has also presented more challenges. The experimental approach did not include interactions between process variables, such as orientation and part location. Moreover, a bigger sample could potentially improve the experimental quality. In addition, the sample size to compute Cp and CpK capability indexes was limited, thus a sample of 50 data sets is required, as described in the ISO standard. Further analysis using signal to noises ratio and analysis of variance would be necessary to evaluate the robustness of the statistical model. Nevertheless, implementation of this methodology can stimulate pre-normative activities to use AM machines in production. Future experimentation will evaluate robustness of different AM systems, integrating the effect of noise factors, such as environmental noise, deterioration noise and variation noise (e.g. repeatability from machine to machine). More experiments are planned to study in deep single systems, considering the effects of more critical signal factor of the system, such as geometry and size dependencies as well as specific manufacturing process variables, such as layer thickness, laser parameters and machine dependent process parameters.

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