METHOD TO DEFINE MEASUREMENT UNCERTAINTY FOR DESIGN SPACE EXPLORATION IN ADDITIVE MANUFACTURING

Cazaubon, Valentine (1,2);
Abi Akle, Audrey (2);
Fischer, Xavier (1,2)

1: Arts et Metiers Institute of Technology, University of Bordeaux, CNRS, Bordeaux INP, INRAE, I2M Bordeaux, F-33400 Talence, FRANCE;
2: Univ. Bordeaux, ESTIA Institute of Technology, F-64210 Bidart, FRANCE

ABSTRACT

Additive manufacturing is a process used for quick prototyping in industries. Geometrical defects are observed on printed parts. The aim of the paper is to propose a design method to implement measurements uncertainties into a Design Space for Additive Manufacturing parameters selection. To do so, two tests have been realized. The first test consists in determining the instrument's uncertainty by measuring a standard length several times by an operator. The second test aim to determine the uncertainty within operators mesurement of geometric outputs (clad's height, clad's width, dilution's height, dilution's width and contact angle). Based on the results of our tests, uncertainties have been applied in our Design Space populated with 31 real printed clads. The uncertainties display with error bars on scatterplots allow to capitalize the knowledge for his/her exploration of the Design Space for future prints. The given information provides to ease the engineer to select the optimal solution (laser power, tool speed and wire feed speed) for his/her given Additive Manufacturing problematic among candidate points

Keywords: Design for Additive Manufacturing (DfAM), Additive Manufacturing, Uncertainty

Contact:
Cazaubon, Valentine
ESTIA
ESTIA RECHERCHE
France
v.cazaubon@estia.fr

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1 INTRODUCTION

Additive manufacturing (AM) is a process initially used for rapidly prototyping parts. Nowadays, this process is used by industries as aerospace or automotive (Bikas et al., 2016) to develop and manufacture parts in a scope of reducing raw material costs and decreasing the ratio buy-to-fly to 1:1 (Lundbäck and Lindgren, 2017). Initially additive manufacturing process was defined by starting with the design of the part and ending with its printing (Frazier, 2014). Moreover, additive manufacturing is a complex process due to the multiphysics involved as Mechanics, Thermal and Metallurgy. Problematics from Robotics field are also involved by industrializing the process. According to (Vaneker et al., 2020) three steps should be considered and added in all the process, i.e. the build preparation, the inspection and the post-treatment, Figure 1.

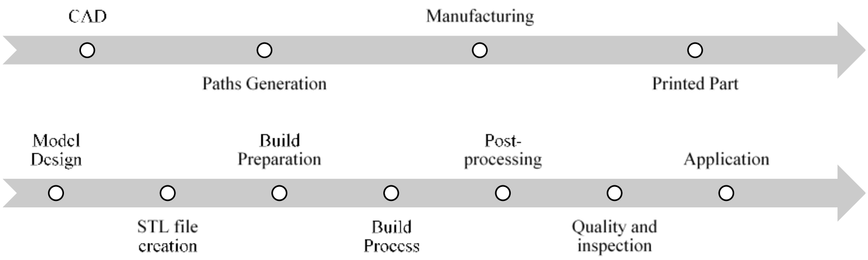

Figure 1. Additive manufacturing process according to (Frazier, 2014) above and (Vaneker et al., 2020) below

One main issue dealing with AM process is the inherent defects observed in the printed part. In AM part a defect can be about the geometrical properties (e.g. accuracy, surface waviness, effective wall thickness), on physical properties (e.g. porosity, cracks, delamination, distortions) or on material properties (e.g. tensile strength, corrosion resistance, residual stress) (Cunningham et al., 2018; Wu et al., 2018). Such defects can be corrected using post treatment steps or prevented through the design process. One way to prevent defect during the design process is to focus on fabrication parameters effects. To help designer, the impact of fabrication parameters can be quantified in a Design Space. Inspection of printed part and more precisely the defect and the errors quantification enable the implementation of a Design Space. Design Space Exploration is then used by designers when they solve a parametric sizing problem (for example). However, introducing defects from measurements in these numerical models might have a negative impact for the resolution of these so-called problems. Quantifying measurement fidelity, microscope in our case, means determining the uncertainty of the measuring devices analysis. The uncertainties may come from: (i) the measuring instrument used (the microscope and its software, called measuring system), (ii) the samples preparation protocol, (iii) the measurands' variability (h_c, h_d, w_c, w_d and α) or (iv) the operator. Thereby, in this paper, we propose **a design method to implement measurements uncertainties into a Design Space for Additive Manufacturing parameters selection**. To do so, one experiment divided into two tests was realized. The first test consists in studying the microscope (LEICA DM1750M) and its software (LEICA LAS V14.2) fidelity. The second test is focus on the classification of the uncertainties between two factors: the method used (measuring system and output measurement variability) and the operator. To validate our proposition, the results of the experiment are then implemented in a Design Space for Additive Manufacturing parameters selection.

2 DESIGN SPACE IN THE ADDITIVE MANUFACTURING PROCESS

2.1 Design for Additive Manufacturing

The additive manufacturing process is different from the subtractive methods, due to its definition (Frazier, 2014). According to (Watschke et al., 2019) one of the main limitations of additive manufacturing is the lack of knowledge. Indeed, the physical phenomena involved during printing have a strong impact on the quality of the parts out of the process. Considering them from the start of the process, at the design step (Ponche et al., 2014) it is important to manage the process inerrant defects. Standard design methods are not adapted to these still new processes of manufacturing. Therefore, a new design way, specific to additive manufacturing, was developed: The Design for Additive Manufacturing

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(DfAM). DfAM is a design method focused on specificities of additive manufacturing taking account of its limitations (e.g. process time, process cost, post treatments, printing preparation). Hence, a set of methods and tools guides designers and supports design process of products with new functions, forms and material compositions that are enabled with additive manufacturing (Laverne et al., 2017; Yang et al., 2016). In the domain of Design for Additive Manufacturing, knowledge can be focused on the AM limitations to limit the risk of errors, called restrictive. DfAM can also be opportunistic and aims at designing possibilities to support the product design (Laverne et al., 2017). Moreover, including manufacturing and assembly process early in the design process increase the chance of printing success and shorten the development cycle (Vaneker et al., 2020). Capitalizing the knowledge and access to it facilitated the development of innovative and technical feasibility solution ideas. Therefore, a Design Space is for. Its use and application during the design phase in additive manufacturing is called Design Space Exploration and Design Space Exploitation.

2.2 Design Space Exploration and Design Space Exploitation

In engineering design, once the design has been formalized, a necessary design task is to select from amongst candidate designs or parametric values. This can be done in the detail design as in DfAM, where the designer must choose values to use in a design model. When exploring the Design Space, the design, and so the printed part, is selected after evaluating the elements present in order to identify optimal solutions. Three different situations can be represented with more or less data: (i) representing the single vector of design parameters featuring the printed part solution, (X): this refers to the feasible design parameters space, (ii) representing the single vector of solution performances for feasible solutions, (Y): this refers to the feasible performance space, (iii) representing two sets of design parameters and corresponding performances for feasible solutions (respecting constraints and requirements),$\binom{X}{Y}$: this refers to the Design Space (feasible design parameters and performance space) (Abi Akle et al., 2017).

The rise of models' number increases the number of generated solutions. The Design Space allows the engineers to simulate candidates (i.e. solutions) of DfAM problems by testing several parameters inputs combinations. Exploration of the Design Space is then useful to find the optimal solution. However, the errors exist also in the models used to simulate candidates. According to (Lopez et al., 2016) the mathematical and computational models are based on the physical process and observations from engineers. However, due to the errors during the printing process, and due to the measurement uncertainty taking place during the observations, the numerical model is based on some possible errors. Then, solutions generated by the numerical model and generated in the Design Space would be non-accurate. Thus, when exploring solutions, engineers must consider and manage the uncertainty linked to this type of errors.

To explore the Design Space in the context of Additive Manufacturing, (Goguelin et al., 2017) have developed a methodology. Their methodology is composed of three steps: (i) filter the solutions in function of the objectives using a parallel coordinate plot, (ii) display the correlations between the additive manufacturing design variables for the designer with scatter plot and (iii) select the design and evaluate its performance with bar and radar charts. This methodology allows the designer to select the process inputs by evaluate them to limit the manufacture-risk. In addition, (Xiong et al., 2019) have developed a data-driven method for design search and optimization tasks. The aim of their method is to explore then exploit the Design Space in AM process. To explore the Design Space, the method consists in identifying areas of feasible designs with a Bayesian network classification. Moreover, Xiong et al. (2019) used a Gaussian correlation to search for optimal design points in each feasible area. Once found, they use them in a finite element analysis. This way of exploiting the Design Space is a way of capitalizing on the knowledge acquired during the additive manufacturing process.

2.3 Uncertainty in Additive Manufacturing

One of the additive manufacturing limitations is the lack of information about their accuracy and performance. To this end, (Adamczak et al., 2014; Müller et al., 2019) have measured the uncertainties associated with additive manufacturing process and (Lopez et al., 2016) have measured the uncertainties associated with the geometrical aspects of the melt-pool. According to (Lopez et al., 2016), calculating uncertainty of the models is required to validate the simulation models of additive processes, to qualify the parts printed and to be able to prevent the errors occurred during the process. Based on their research, computer models' errors have four origins. The identified sources are the

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physical process (physical phenomenon), the observations (e.g. temperature, geometry), the mathematical model (constitutive equations) and the simulation parameters (e.g. material properties, boundary conditions). The work of (Müller et al., 2019) on the uncertainty for the geometric aspect is focus on the melt-pool accuracy model developed in the process using a laser as a heat source and metallic powder. In their work, they aim to characterize the manufacturing process scatter as well as the measurement uncertainty to establish ways and means to include the information gained into an efficient meta-model in order to optimize it. (Adamczak et al., 2014) propose to quantify the uncertainty of the measurements in order to reduce innovation-related risk by providing, to design engineers, a support to decision making on how to practically use additive manufacturing.
Therefore, based on the former literature, we propose in this paper **a design method to implement measurements uncertainties into a Design Space for Additive Manufacturing parameters selection**.

3 EXPERIMENTAL DESIGN

3.1 Materials and Samples Preparation

To study measurements uncertainty coming from microscopy analysis step of the AM process, we used samples composed of printings with the Laser Metal Deposition with Wire metal additive manufacturing process (LMD-w) with titanium alloy (TA6V). The LMD-w process principle is to deposit on a TA6V substrate a TA6V wire. It is injected into the melting pool with a speed *WFS* co axially to the laser at a power *P* while the robotic head is moving at a speed *TS*, represented in Figure 2. The substrate and wire are made of titanium because of its weld ability properties (Ranatowski, 2008).

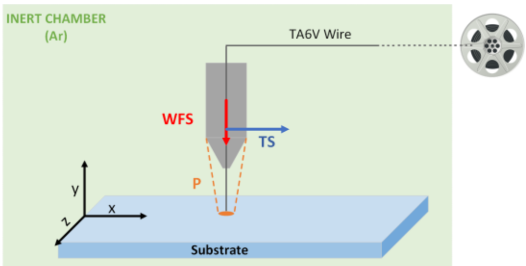

Figure 2. Schematic representation of the LMD-w process input parameters

The substrates were plates of TA6V of dimensions 150 mm x 60 mm x 5 mm which have been sanded with an orbital grinder (grain P60) and degreased with isopropyl alcohol (IPA). This surface treatment helps improving surface laser absorptivity and to remove dusts. The diameter of the deposit wire material is TA6V is 1.2 mm. The substrates were clamped to prevent any translational movements in the plan (x, y). To protect the melting pool from oxidation, the clads were built in an inert chamber with a protective gas, i.e. argon. The inert chamber is part of a robotized cell composed of a 6-axis robot (KUKA KR60-HA) with its controller (KUKA KRC4). The energy is supplied by a laser head (PRECITEC CoaxPrinter) fixed on the robot. As described in Figure 2, the wire deposition is coaxial to the laser (Cazaubon et al., 2021).
From previous experiments, then a database with a total of 31 clads of 100 mm length is composed. Three cuts have been made on each clad (i.e. ¼ cord length, ½ cord length and ¾ cord length) using a silicon disc and a cutting wheel, called samples. Subsequently, the samples were coated, mirror polished and then chemically attacked with Kroll's reagent in conditions where results are obtained by the same method on identical test individuals, in the same laboratory, by the same operator, using the same equipment and for a short period of time. From this point of view, we consider for the remainder of the study the post-processing process has no influence on the uncertainty of the microscopy analysis. The post-treatment process is presented in Figure 3.

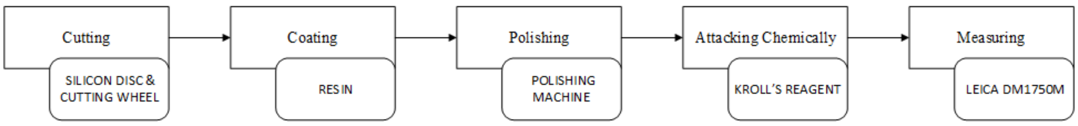

Figure 3. Post treatment steps after printing

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During tests, the measurements are carried out under a microscope (LEICA DM1750 M) and its software Leica Application Suite (LEICA LAS Suite V4.12). Several pictures are taken then assembled to generate a cross-section. Figure 4 shows an example of a clad's cross-section (left) and a schematic representation of the outputs measured by the operators during the test 2.

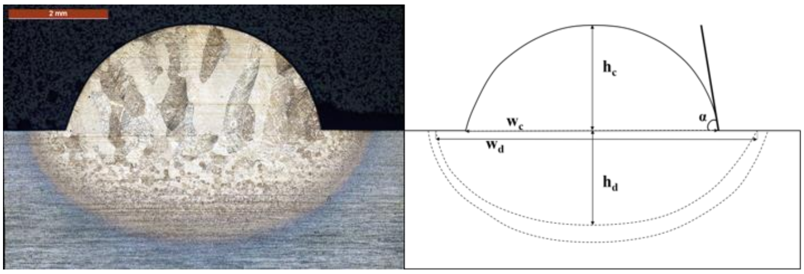
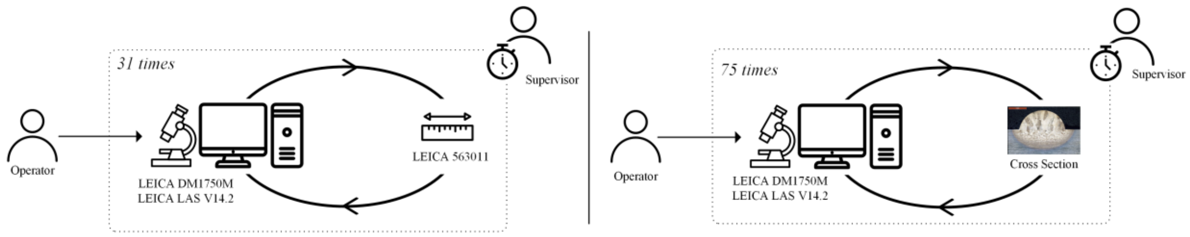


Figure 4. Left: Cross section micrography of TA6V deposit (zoom x5), Right: Representation of the geometrical outputs

3.2 Design of Experiments

One experiment divided into two tests was performed and are presented in this section. The first test was performed to validate the microscope and its software with one operator. The second test was performed to determine the measurement uncertainty method according two factors, i.e. the operators and the variability of the measurand (h_c, h_d, w_c, w_d and α). For this purpose, 5 operators have realised the test with 3 random samples from an existing database containing 93 samples (31 clads x 3 cuts). These two tests protocols are presented in the following subsections and in Figure 5.



(a) (b)

Figure 5. (a) Experimental protocol for the test 1, (b) Experimental protocol for the test 2

3.2.1 Test 1: Microscope Validation

The objective of this test was to validate the measuring instrument used (LEICA DM1750M) by studying its repeatability. To do so, an operator had measured 31 times a standard length clad of 1mm (LEICA 563011) with the microscope LEICA DM1750M and its software (LEICA LAS Suite V4.12) in conditions called repeatability conditions, as presented on Figure 5 (a) . According to JCGM 100:2008, repeatability conditions are "conditions where results are obtained by the same method on identical test individuals, in the same laboratory, by the same operator, using the same equipment and for a short period of time." Moreover, the operator was supervised during the test in order to guarantee the conditions of repeatability. The supervisor was also responsible to record the 31 values in a document support to avoid the operator to find his/her previous values.

3.2.2 Test 2: Operators and Measurand Variability Influences

The material used in this test is the microscope LEICA DM1750M, its software LAS V14.2 and 3 random samples' cross-sections selected from the existing database, and stay remained for the test 2, as presented in Figure 5 (b).
The objective of this test was to quantify the influence of the operators and the measurand variability on the measurement uncertainty. For this purpose, 5 operators have performed the test in conditions called intermediate repeatability conditions. Repeatability conditions are defined as "conditions where the test results or measurement results are obtained by the same method on identical test/measurement individuals under different given operating conditions; these data being: time, calibration, operator and equipment" by the norm JCGM 100:2008. The conditions of time and calibration were considered

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constants. The operators have realised the test, the same day, and the microscope was calibrated equally for every operator by the supervisor.
It was asked to each operator to measure these 3 samples 5 times, and to measure the five outputs (h_c, h_d, w_c, w_d and α) each time as illustrated in Figure 6. At the end of the test, the supervisor has gathered 75 values by operator.

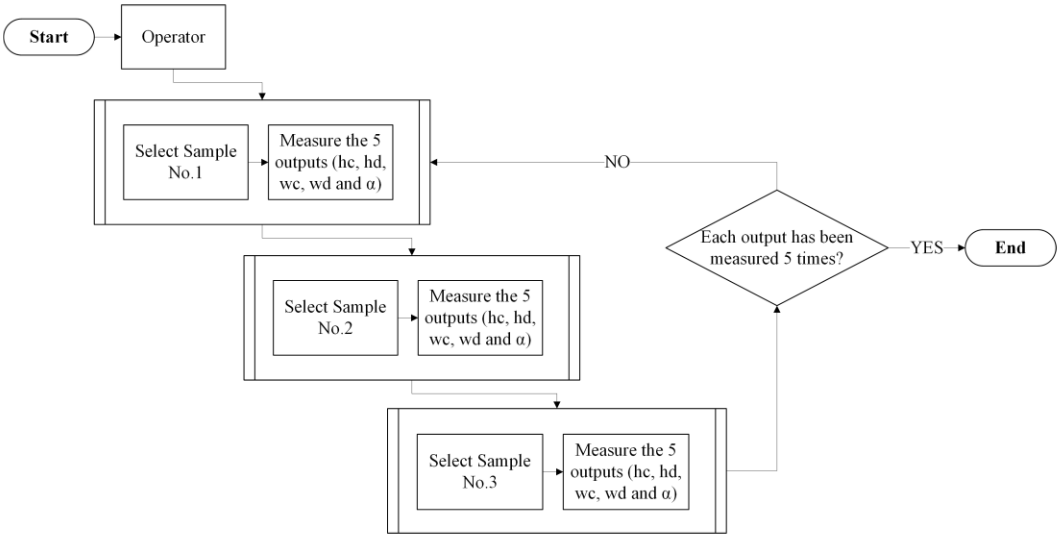

Figure 6. Experimental protocol for experiment No.2 to be followed by each operator

The five outputs to be measure are presented in Figure 4. The length vertically h_d and horizontally w_d of the dilution zone until the grains' size are considerate as non-significant by the operator.

3.3 Mathematical Models

3.3.1 Test 1

According to JCGM 100:2008, the Type A evaluation of an uncertainty, characterizing the minimum dispersion that a method can express is calculated with the equation (1).

$$u_A = \frac{\sigma_{n-1}}{\sqrt{n}};\ \sigma_{n-1} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(m_i - \overline{m})^2} \tag{1}$$

$$\overline{m} = \frac{1}{n}\sum_{i=n}^{n} m_i \tag{2}$$

With u_A the uncertainty Type A, σ_{n-1} the standard deviation, m the value of the i[th] measurand and $\overline{m}$ the average. In practice, the uncertainty is expanded by a coefficient k because the number of measurements is limited. To choose the value of the coefficient k, known as the Student's coefficient, the number of samples measured, and the desired confidence interval must be defined. The table of the k coefficients can be found in the norm JCGM 100:2008. In our case, the k coefficient value is equal to 2.75 because 31 measurements are performed and the confidence interval desired is 99%. The expand uncertainty is expressed following the equation (3).

$$U_A = k\frac{\sigma_{n-1}}{\sqrt{n}},\ \text{k=2.75} \tag{3}$$

3.3.2 Test 2

Three variances are determined:

- The intraseries variance (S^2_r): the mean dispersion of the series (measurand variability + microscopy) expressed with the equation (4). With ($\overline{x}_i$) the average values and xi the value of the measurement.

$$S_r^2 = \frac{1}{Number\ of\ operators - 1} \times \sum_i (x_i - \overline{x}_i)^2 \tag{4}$$

- The interseries variance (S^2_g): the dispersion of the means (interoperator effect) and is calculated with the equation (5). If the S^2_g value is negative, then the kept value is 0.

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$$S_g^2 = Variance\ of\ averages - \frac{S_r^2}{Number\ of\ measurements\ repetitions} \tag{5}$$

- The total variance (S^2_r + S^2_g): the total dispersion of the results, determined by equation (6)

$$Total\ variance = S_r^2 + S_g^2 \tag{6}$$

In order to best generalize the intervals of uncertainty, these intervals are expressed with percentages called Variance Coefficient (VC) according to equations (7).

$$VC_{repeatability} = \frac{\sqrt{S_r^2}}{Average} \times 100,\ VC_{operator} = \frac{\sqrt{S_g^2}}{Average} \times 100, VC_{total} = \frac{\sqrt{Total\ Variance}}{Average} \times 100 \tag{7}$$

4 ANALYSIS AND RESULTS

4.1 Validation of the measuring system

The minimal resolution available with the microscope analysis is a pixel. The pixel's length value is 1.542µm. The value 1000µm will never be reached. The measurements realized by the operator were always a multiple of 1.542µm. The average of the operator's 31 length measurements is 1010.35 µm. According to the equation (1), its standard deviation is 1.23, and the microscopy measurement's uncertainty u_A is 0.22 µm. According to the equation (3) and the JCGM 100:2008 norm, the expanded uncertainty for a confident interval of 99% is 0.61µm. The analysis of this uncertainty shows that for a confidence interval of 99%, the operator's measurements dispersion around its mean is in a range of [1010.35-0.61µm;1010.35+0.61µm]. To generalize the uncertainty interval for measurements of distances under the microscope LEICA DM1750M with zoom (x5) and its software (LEICA Application Software), the expanded uncertainty will be expressed by a percent coefficient such as:

$$Coefficient = \frac{Standard\ Deviation}{Average} \times 100 = \frac{1.23}{1010.35} \times 100 = 0.12\% \tag{8}$$

The uncertainty interval of distance measurement can be then generalized and expressed as $X = \overline{x} \pm 0.12\%$. Then, as first results, the measurements realized under the microscope LEICA DM1750M and its software LAS V14.2 are repeatable.

4.2 Operators and Measurand Variability Influences on the Uncertainty

The variance coefficient of the microscope and measurands variability, and the operator have been calculated with the formulae (4-9). The results are grouped in Table 1.

Table 1. Average variance coefficient (VC) values per output

	VC repeatability (%)	VC operator (%)	VC total (%)	Uncertainty Expression
h_c	0.3608	0.1049	0.3776	$\overline{Hc} = \overline{hc} \pm 0.38\%$
h_d	4.0494	4.6031	6.2490	$\overline{Hd} = \overline{hd} \pm 6.25\%$
w_c	0.8568	0.0671	0.8773	$\overline{Wc} = \overline{wc} \pm 0.88\%$
w_d	1.0566	0.5445	1.2137	$\overline{Wd} = \overline{wd} \pm 1.21\%$
α	1.5500	0.3159	1.5968	$\overline{A} = \overline{\alpha} \pm 1.55\%$

These results allow concluding:

- The method used to measure the variables is validated because each error leading to uncertainty is less than 10%.
- The operator effect has less impact than the output variability excepts for the dilution's height (hd) with a percentage difference of 0.56%.
- The dilution's height (h_d) is the most uncertain output to measure (6.249%).
- The clad's height (h_c) is the most certain output measured (0.38%)
- It is more uncertain when measuring the contact angle (α) than the clad's width (w_c) and the dilution's width (w_d)

Based on these results, the next section presents the implementation of the measurements uncertainty in the Design Space for Additive Manufacturing.

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4.3 Application of the Measurement Uncertainty to the Design Space in Additive Manufacturing

Based on the results of our experiment, we have introduced uncertainty in a Design Space. Our Design Space consists of geometric outputs (h_c, h_d, w_c, w_d and α) and input parameters (P, WFS and TS) leading the dimension of our Design Space to 8. To populate this Design Space, we used a database of real printed clads. This database contains 31 design points. Each of the point is the average of three samples cut from a clad and prepared as the protocol in Figure 3.

This implementation allows to capitalize the knowledge for future prints. The application of this uncertainty on the design points in the Design Space makes possible to check the uniqueness of the parameters setting, i.e. for a geometry, there is only one set of input parameters. Thus, during the exploration and exploitation of the Design Space, the engineer will be able to select the inputs parameters to answer his/her design problem in additive manufacturing. (Data are available online: http://cazaubon.alwaysdata.net/campagne123/globalc123.html). On Figure 7 and Figure 8, we present two illustrations of uncertainty introduction into Design Space (depicted with bar errors in scatterplots). We have chosen for readability reasons to display the uncertainties into 2-dimensional graph (x-y plots).

In Figure 7, we present the uncertainties applied to geometric values (h_c and h_d) function of the laser power P. On left plot, the uncertainty on the clad's height (h_c) is small. The bar errors are non-visible meaning the uncertainty of this output can be neglected by the engineer during his/her exploration of the Design Space. In fact, the error bars show that not two points are overlapped, each measurement average is distinct. We can conclude to an uniqueness of the point. By contrast, in the right plot, the bar errors are important for the dilution's height (h_d) values. Typically, for dilution's height's values above 1.5mm, the uncertainty interval is 0.2mm. The larger the measured dilution value, the greater its uncertainty. Therefore, the engineer will be guided towards a more certain design point candidate during his/her exploration of the Design Space. The use of the uncertainty into the Design Space brings additional information by letting the engineer to learn about their alternatives candidate solutions before making decisions in function of performance variables. However, the chosen visualisation can be reconsidered. According to (Abi Akle et al., 2019) the visualisation to privilege for the Design Space Exploration is the scatter plot matrix and not simple scatter plot.

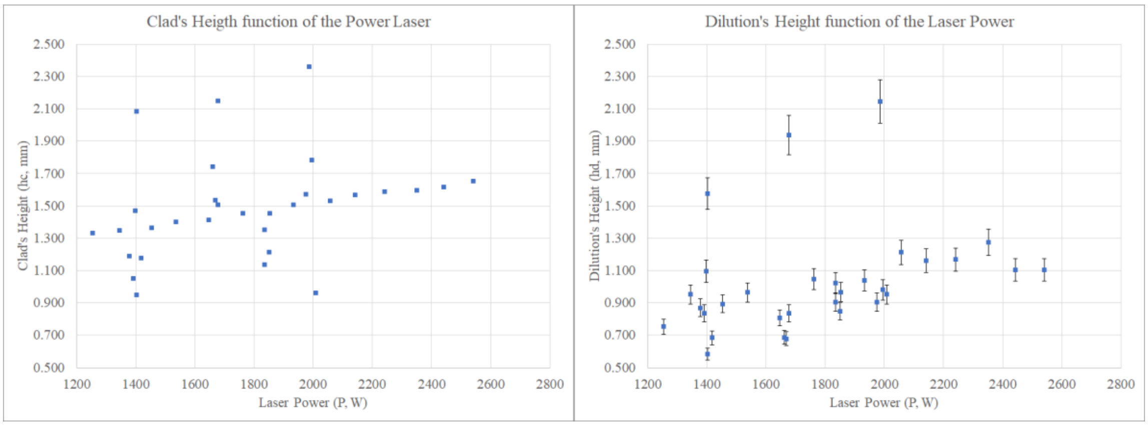

Figure 7. Left: Clad's Height (h_c) in function of the input parameter Laser Power (P), Right: Dilution's Height (h_d) in function of the input parameter Laser Power (P)

In a scatterplot matrix, the process input parameters and outputs are displayed together two by two. We wanted to present at least once, an application of two outputs uncertainties for the dilution's width (w_d) and clad's width (w_c) in Figure 8 represented with error bars.

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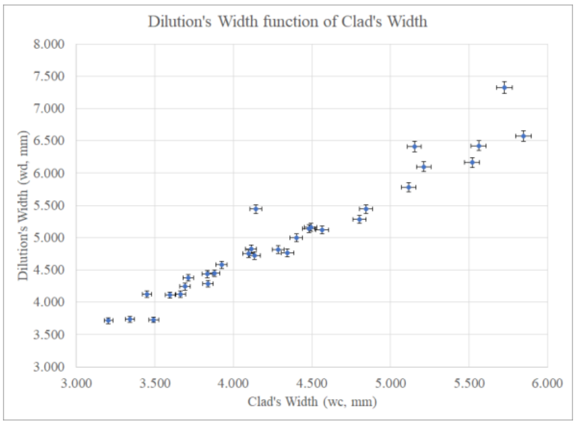

Figure 8. Dilution's Width (w_d) in function of the Clad's Width (w_c)

5 CONCLUSION

In this paper, we propose a design methodology to implement microscopy measurements uncertainties into a Design Space for Additive Manufacturing parameters selection. The Design Space is a tool to capitalize on the knowledge gained during past impressions. Characterizing the influence of measurements is important for the exploration and exploitation of the data constituting the Design Space. Indeed, each print becomes a design point of the Design Space. Its coordinates are the three input parameters, laser power (P), wire feed speed (WFS), and tool travel speed (TS), and the five geometric outputs, clad height (h_c), clad width (w_c), dilution height (h_d), dilution width (w_d), and contact angle (α).

In our paper, we presented a method employed to determine and characterize the influence of the measurement in additive manufacturing for the use in the Design Space. Allowing to verify the uniqueness of the design points. Our method consisted in performing and experimenting two tests. The first test validates the repeatability of the device used (LEICA DM1750M and LAS V14.2). The dispersion around the average of the measurements is 0.12%. However, it does not allow to conclude on the origin of the observed errors nor on the accuracy of the measurement system. The second test shows that the distribution of measurement uncertainties depends on two factors: the repeatability of the method (device + output variability) used and the operator. The measurement uncertainties come mainly from the repeatability of the method. Combined to the first test, we can conjecture the repeatability of the microscope comes mainly from the variability of the output itself.

The uncertainty is then calculated for each output of for the 31 clads applied into the design points forming the Design Space. Due to our Design Space dimension (8), we have chosen to represent them with bar errors into simple scatter plots. If uncertainty does not influence, the error bars are small, and the design points are unique. On the contrary, large bar errors involve an important uncertainty, meaning values can overlapped. Hence, during his/her exploration of the Design Space, the engineer is visually guided towards a more certain design point candidate for his/her given problem, i.e. the desired geometry. For his/her problem, the optimal solution is the candidate point with the least uncertainty. In our paper, the emphasis was on one type of error: geometrical measurement. Two perspectives have been identified for further work. The first perspective is to optimize the display of the additional information of the Design Space for its exploration. The second perspective is to characterize other types of uncertainty from geometrical properties, physical properties, or material properties and add them to the Design Space. Allowing to centralize the knowledge and the information for the engineer.

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