FEATURE-BASED METHOD TO FORMALISE ADDITIVE MANUFACTURING RELATED DATA AT THE MESOSCALE BASED ON A MEREOTOPOLOGICAL DESCRIPTION

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ABSTRACT

Research on additive manufacturing has highlighted methods and guidelines to optimise the design process and improving finished product quality. There is still room for improvement in making AM as reliable as more traditional processes when considering industrial use. In terms of manufacturing, managing print parameters properly can improve reproducibility and repeatability of a part, in addition to its fidelity to the basic geometric model. However, a topological optimised geometry requires more than good parameterisation. Efforts are therefore being made to formalise knowledge so that it is explicit and accessible to designers. This paper proposes an approach based on the spatio-temporal evolution of a geometry during printing to quantify data at the meso scale. Previous studies have been conducted on the description of features in time, space and space-time, and on the influence of their arrangement within a part. Building on this work, a parameterised test specimen was designed to measure the quantitative impact of these arrangements on the final product. The method is then presented and illustrated through a case study to help the designer with quantitative predictive values of geometric parameters.

Keywords: Additive Manufacturing, Design for Additive Manufacturing (DfAM), Design methods, Mereotopology, Design of Experiments

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Cite this article: Douin, C., Gruhier, E., Kromer, R., Christmann, O., Perry, N. (2023) 'Feature-Based Method to Formalise Additive Manufacturing Related Data at the Mesoscale Based on a Mereotopological Description', in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.187

1 INTRODUCTION

Further efforts are needed to make Additive Manufacturing (AM) as reliable as traditional processes. AM must ensure better reproducibility and repeatability of manufactured parts to support its deployment in the industry. Knowledge transfer is a key factor in achieving this (Thomas-Seale et al., 2018). Design, process planning, manufacturing and metrology define different constraints that should be taken into account during the early phases of the design process. Otherwise, a wearisome prototyping process may be required before satisfactory geometry is achieved. This waste of resources can be avoided by formalising knowledge and enabling communication between the different actors in charge of designing and manufacturing the product. Design rules, including preferred shapes, sizes and orientations specific to a process (Ahtiluoto, Ellman, and Coatanea, 2019) and means of communication are thus necessary. There is therefore a need to develop tools to assist designers in optimising their products for a given process.

Many methods and guidelines exist but are very often applied at the end of the design process to ensure the manufacturability of a product (Zhu et al., 2017), to define the most appropriate orientation of a part (Mbow et al., 2021) or to assess the manufacturability of isolated features, i.e. distinctive 3-dimensional geometric elements, typically in the form of benchmark artefacts (Rupal et al., 2018). AM stands out from other processes because of its multi-layer manufacturing. It is therefore necessary to understand the phenomena that occur during the transition from one layer to the next, which corresponds to the meso scale. Some of these phenomena are related to the printing parameters, but others are only due to the geometry of the part. The work of Ghaoui et al. (2020), for instance, shows that there is a direct correlation between the height of an overhanging part and the magnitude of side loss. The designer can compensate for these effects if he is provided with the appropriate knowledge, hence the need for knowledge acquisition at different scales. It is thus necessary to acquire quantitative data on the coexistence of different features within a part, in order to adapt its geometry to remain in line with the characteristics of the process used.

In addition, Design for AM (DfAM) methods are being developed to leverage the knowledge gained. For this purpose, Topological Optimisation (TO) tools are often used, and thus allow the generation of optimised structures, but which may be difficult to interpret by non-expert users. The study proposed here focuses on this type of structures, but may later be extended to other elements, i.e. functional dimensioning, thin walls, etc. This research is part of a project that aims to impart relevant knowledge throughout the product design process. For the purpose of generating data at the meso scale, research efforts have been carried out to describe the layout of a print layer and its transformation on adjoining layers (Douin et al., 2022). The purpose of this approach is not to alter the geometry of the designed product but rather to provide enough relevant data for the user to make well-informed decisions. In this context, questions arise as to how to formalise quantitative knowledge related to geometric pattern configurations at the mesoscale in order to retransmit them when necessary. To address this concern, a state of the art is conducted to assess how AM-related knowledge is formalised at different scales. Existing methods and tools are briefly overviewed, and previous work on the influence of geometries variations in time, space and space-time is presented. Finally, a description of the experimental approach conducted is provided.

2 RELATED WORK

2.1 Design for AM and knowledge at multiple scales

Designing a product requires proper knowledge of the constraints and benefits of the manufacturing process used. AM is still relatively new and research efforts are still underway to make it as reliable as traditional processes. DfAM methods are therefore developed to optimise the design process through the integration of AM knowledge. A popular DfAM approach is to first define the functional surfaces and then proceed to design the rest of the part building on the advantages of the chosen process (Thompson et al., 2016). In this regard, the development of TO and the use of lattice structures have enabled great improvements in optimising the design of manufactured parts. The method proposed by Boyard et al. (2019) is based on this approach. A graph of functions is designed from the specifications, meaning that a representation of the connections between the geometric and dimensional requirements is defined. From this graph and the specification of the machine used, a

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primary solid is generated. This solid is then oriented and the printing strategy is determined, and finally TO is used to generate an optimised solid. The 3D model is then prepared for manufacturing.

Despite the great advantages of TO to generate lightweight geometries optimised on several criteria, the constraints related to the rest of the product development, including manufacturing and metrology, are not properly taken into account (Vaneker et al. 2020). Hence the need for formalised AM-related knowledge, either as general guidelines, feature level rules or 3D printing rules (Zhu et al., 2017). Different types of knowledge are needed at different scales. At the macro-scale, i.e. studying the part as a whole, the rules defined by Grandvallet et al. (2020) can be used to optimise the orientation of a part. Eight action rules have been developed through expert interviews, then mathematised and implemented in software by Mbow et al. (2021). Suggestions of optimal orientations of a part on the printing plate are computed by assigning desirability scores to the rules. The user can then pick the orientation that best fits his requirements according to the surfaces he prioritises. This tool is highly interesting at the end of the design process as it takes into account the priority surfaces of the product to orientate it, ensuring a great manufacturing result for a given design. However, it does not allow the user to fix the geometry of the detailed geometry of the part. At a smaller scale, by breaking down the product into smaller parts, decisions made at the feature level will have a significant impact on the quality of the product.

Different methods are developed at the meso scale. Quantitative data related to features can be provided through benchmarks. These parts are made up of a variety of features of different sizes to assess their manufacturability with the desired machine and parameters. For example, the benchmark part developed by Vorkapic et al. (2020) is specifically designed for the Fused Deposition Modelling (FDM) process. Once printed, the part is then scanned and deviations from the based model are measured. The user can subsequently adapt his geometry accordingly. Another alternative method to benchmark parts but with a similar approach is the use of the manufacturability criteria. Rules regarding the manufacturability of features are formalised in order to take into account the process limitations while designing a part. Shi et al. (2018) have defined five of these criteria: unsupported features, minimum feature size, maximum vertical aspect ratio, minimum spacing between two features and minimum self-supporting angle. Depending on the process and the material, the value of each criterion varies. The user can therefore check his whole geometry for features that do not meet the requirements for the manufacturing to be successful. Feature-based guidelines and rules are therefore very effective in determining data such as the minimum thickness of a wall, or the maximum height of a feature for a given section. However, depending on the overall surroundings and the complexity of these features, the quality of the manufactured part can be greatly impacted. A feature may print without problem if it stands alone, but in the context of a complete product, what if another larger feature is manufactured on top? Isolated features may be easily manufactured, but can be very problematic depending on how they are arranged within a complex part.

2.2 Influence of geometry variation in time, space and space-time

Studies in the literature provide useful guidelines on how to manufacture a product as a whole, and on isolated features (Bracken et al., 2020; Budinoff and McMains, 2021). However, little research is conducted on the coexistence of different features within a single area. Depending on whether two features are printed at the same time at different locations on the plate, whether they are bonded together or manufactured on top of each other, the result on the manufactured part will change significantly. The specificity of AM is the fact that material is added continuously over time in stacked layers. The spatial, temporal and spatiotemporal (ST) aspects of geometric shapes on layers should therefore not be overlooked.

Previous work has enabled the development of a means to describe complex parts by discretising them into geometric shapes at the meso scale (Douin et al., 2022). This description is based on the concept of mereotopology, the study of the relations of connectedness and interactions between parts, wholes and boundaries (Smith, 1996). Interactions take place between elements known as "regions". These entities are either spatial, their precise nature depends on the application domain concerned, or temporal, they can be assimilated to a time interval or a specific time point. The relationships linking regions together are called primitives and can be spatial, temporal or spatiotemporal. Mereotopology offers great potential for product engineering. In the early stages of design, mereotopology allows a qualitative description of the interactions between different elements, making the logical study of the product architecture easier. The JANUS theory (Gruhier et al., 2015) enables the description of an

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assembly by decomposing the evolution of its parts from a spatial, temporal and ST point of view. A set of ST primitives is developed to define the changes taking place during an assembly, such as the addition or deletion of a part. In the field of AM, Khan and Kim (2015) used ST mereotopology to describe the different stages of an AM assembly, i.e. the evolution of the surfaces that interact during the bending process of an AM-manufactured part.

Table 1. Sets of spatial, temporal and ST primitives used to describe the AM process

Spatial primitives (Smith, 1996)		Temporal primitives (Allen, 1983)		Spatiotemporal primitives (Douin et al., 2022)	
x**P**y	Part	x<y	Before	x**Ac**z	Area constant
x**IP**y	Interior part	x=y	Equals	x**Ai**z	Area increases
x**O**y	Overlaps	x**m**y	Meets	x**Ad**z	Area decreases
x**D**y	Discrete	x**o**y	Overlaps	x**Mo**z	Moves
x**X**y	Crosses	x**d**y	During	x**Cg**z	Changes geometry
x**T**y	Tangential	x**s**y	Starts	x**Se**y	Separates
x**B**y	Boundary	x**f**y	Finishes	x**Me**y	Merges

Different theories have enabled the development of several sets of spatial, temporal and ST primitives. In the context of this study, the primitives summarised in Table 1 are used. Upon isolating a layer of a 3D part, one or more geometric shapes are observed, meaning regions of matter outlined by a continuous border. Their spatial layout can be described using spatial primitives. For instance, x**D**y means that x is discrete from y, they are distant from each other and don't have any common points. These same shapes change slightly on adjacent layers and these transformations can be described by ST primitives. One layer of a sliced part will hereafter be considered as being a time unit. A set of layers will therefore be considered as a time region called Time Region (TR). The notion of "feature" will hereafter refer to a spatial region "x" undergoing an ST transformation during a time interval "TR". This means that a feature consists of a stack of geometric shapes undergoing a regular transformation over a defined number of layers. If a 3D model is composed of several features, the order in which they are printed is described using temporal primitives. If two equal-sized cylinders are printed next to each other, considering x being the time interval during which the first cylinder is printed, and y for the second cylinder, the description of this setup would be x=y, as the manufacturing of both features start at the same time and end simultaneously.
Based on this means of description, a method has been developed (Douin et al., 2022) to generate information by correlating physical defects to primitives. The studied part is discretised into features and is described using the above-mentioned primitives. It is then printed and compared to the 3D model to record any deviations. This approach allows the effects of different feature interactions within a part to be qualitatively assessed. However, qualitative data is insufficient to be able to design a proper part for AM. A means to quantify the influence of these interactions must therefore be established.

3 PROPOSED APPROACH

3.1 Inputs and outputs

In order to formalise useful input for the designer, it is necessary to generate quantitative data linked to the specificities of a primitive. A disk "x" of matter "z" on one layer "n" is considered. If that same disk has a bigger area on the layer "n+1", which corresponds to $(xAiz)_{TR1}$ with "TR1" the time interval from "n" to "n+1", the geometry will not be the same depending on the cross-section increase. The aim of this experiment is therefore to quantify the effects of these primitives on the quality of a manufactured product. Taking as input a 3D model and a specific characteristic that the user wants to optimise, the aim is to be able to propose a quantitative prediction of the result on certain portions of the part, presented as graphs that can be easily interpreted by a designer wishing to optimise his geometry. A predictive model is developed for this purpose, by interpolating experimental data. In order to build an approximate model that is as accurate as possible, using only a limited number of trials, a space-filling Design of Experiment (DoE) is used. This type of DoE allows to build a predictive model in an iterative way, by choosing the optimal experiments to improve gradually the fidelity of the model until a satisfactory threshold is reached.

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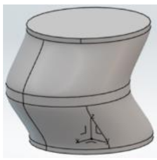
A first attempt is performed to evaluate the dimensional deviation between the design and the manufactured part, depending on the geometrical features of a part at the meso scale. A specimen is designed to depict all the above-mentioned ST primitives by varying only four geometrical parameters. Specimens are manufactured following a space-filling DoE. A metrological study is conducted to collect quantitative data for a given process, material, and manufacturing parameters. The results of this study are then used to build the predictive model, through which response surfaces are generated for two coupled parameters, making it possible to predict the influence of two parameters on a desired criterion. Depending on the criterion chosen, the user can then use these graphs to choose the optimal geometric parameters for each portion of the part. In future works, these charts will then be implemented in a tool that will automatically provide the user with data related to his design. The optimum values for each feature can then be selected while taking into account the influence of the choices made on the desired criterion thanks to the predictive model.

3.2 Development of a configurable artefact at the mesoscale

In order to develop the above-mentioned predictive model, a test specimen was designed to represent any ST primitives by making a few hypotheses. The elementary pattern of the specimen is set to a stack of two features so that the separation and merge primitives can be represented. Three sections parallel to the printing plate are thus identified: S1 represents the initial surface, S2 represents the interface between the two features, and S3 is the upper section of the second feature. The first section, S1, is set to be a disk so the influence of sharp angles on the result can be neglected. Four variable parameters are then defined to control the geometry of both features:

- R: The ratio between the surface areas of S1 and S2, and between S2 and S3. R ranges from one-third to three.
- NB: Corresponds to the number of branches of the second feature. NB ranges from 1 to 3.
- x_2: Corresponds to the horizontal offset of S2 from the centre of S1. It ranges from 0mm to 4mm.
- x_3: Corresponds to the horizontal offset of S3 from the centre of S1. It ranges from -4mm to 0mm.

Table 2. ST primitives depending on the values of four defined parameters

Area constant x**Ac**z	Area increases x**Ai**z	Area decreases x**Ad**z	Moves x**Mo**z	Changes geometry x**Cg**z	Separates x**Se**y	Merges x**Me**y
						
$x_2 = 0$ $x_3 = 0$ $R = 1$	$R > 1$	$R < 1$	$x_2 \neq 0$ $x_3 \neq 0$	$x_3 < x_{3\text{lim}}$ $NB > 1$	$x_3 > x_{3\text{lim}}$ $NB > 1$	$x_3 > x_{3\text{lim}}$ $NB > 1$

Depending on the value of these parameters, a different primitive is represented, as shown in Table 2. The radius of S1 has been defined based on the smallest section manufacturable. The smallest section corresponds to a setting where the ratio is at its minimum and the number of branches is at its maximum. In this case, each circle of S3 will have a radius fixed at 1.2mm, i.e. three wall lines and no infill. This results in a radius of 6.2mm for S1. Regarding the second feature of the elementary pattern, its nature will depend mainly on the value of NB. If the number of branches exceeds one, the primitive will be considered as "changes geometry" if its genus is zero, and "separates" if it's greater than zero. If S3 can be enclosed by one single boundary element, without any disruption within this cross-section, the primitive is a change of geometry and not a separation. The definition of a limit value of x_3, $x_{3\text{lim}}$, corresponding to the centre of S3 being coincident with the boundary of S3, is specified in equation 1.

$$x_{3\text{lim}} = x_2 - R_1 R \sqrt{\frac{1}{NB}} \tag{1}$$

The height of a single feature is set at 5mm, equivalent to 25 layers of 0.2mm thickness. A 1mm extrusion has been added between each feature in order to facilitate the metrology process on the manufactured test piece. Finally, the elementary pattern is mirrored and duplicated to obtain a sequence of 12 features, enabling a significant number of measures per configuration. The purpose of this artefact is to capitalise data, therefore a base has been added to ensure the stability of the chain during manufacturing while making the metrology process easier. The first feature is the geometric element starting from section 1 and ending with section 2. Section 2 is extruded vertically over 1mm. Feature 2 goes from section 2 to section 3, which is also extruded. This superposition of two features is mirrored, resulting in a pattern of four features, which is then duplicated three times in order to evaluate the impact of a sequence of features on the desired criteria compared to an isolated feature. The final design of the specimen is presented in Figure 1.

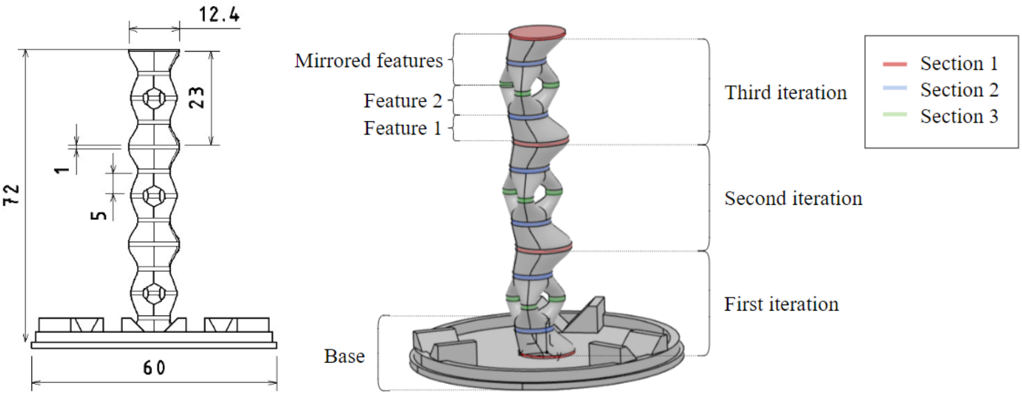


Figure 1. Description of the specimen for a 3-branches configuration

3.3 Process to formalise data at the mesoscale

The previously mentioned method has been applied to this type of specimen. The procedure described in Figure 2 outlines the process to generate the charts that will later be implemented to facilitate the decision-making process. It is broken down into four stages: the adjustment of the model (1), the physical study of the part (2), the mereotopological study of the part (3), and the formalisation of the resulting knowledge (4). Three groups of characteristics must first be determined according to the user's needs. If the aim is to generate data for a particular type of ST configuration, the corresponding geometric parameters (according to Table 2) should be selected. In the case of a comprehensive process and material study, all four parameters are considered, and a significant number of specimens should be manufactured by varying these parameters. Choices regarding the printing of the specimens should also be made depending on the process and the material being studied. In order to distinguish the influence of the printing parameters on the measurements made, these must be kept fixed throughout the entire test campaign. Eventually, the data to be captured must be established. Three types of data will be collected. 1) the manufacturability of the part according to three criteria: Is the manufacturing process carried out without interruption? Is it necessary to add support? If so, is the support accessible for removal? 2) tolerancing criteria are then defined: are all sections circular and do their dimensions correspond to the theoretical values? Is the axis of the specimen vertical? 3) finally regarding the quality of the specimen: does the surface roughness match the desired surface quality?

Once the objectives and requirements have been set, the test specimens are manufactured according to the specifications. The measurements described above are done using an equipment that ensures the accuracy and precision required. These values are listed in a table along with the input parameters. This table is then used to train a machine learning algorithm in order to create a predictive model. The graphs previously mentioned are thus generated, each of them having two geometric parameters as input (Number of branches, ratio, x2 offset or x3 offset), and one of the measured criteria as output (manufacturability, tolerancing or quality criteria). This procedure can be applied to any process and material to generate their own data. Using the charts, it is hence possible to estimate the optimal configurations of primitives according to a given criterion during the detailed design phase.

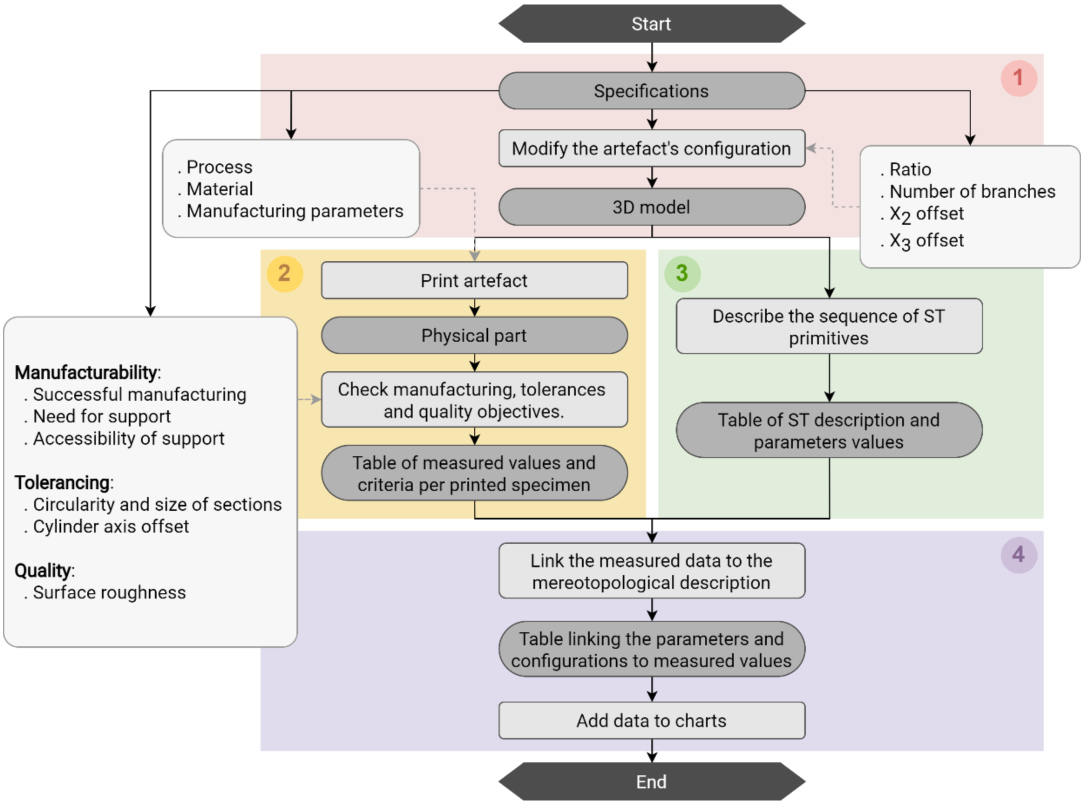


Figure 2. Process description for the formalisation of quantitative data using the configurable artefact

3.4 Process application and generation of data charts

Some experiments are carried out with the printing parameters presented on Table 3. The objective is to assess the reliability of printing, which corresponds in this case to the deviation between the cross-sectional dimensions of the specimens and their theoretical values. Using a space-filling DoE, 3D models of the specimens are generated by varying the four geometric parameters within the limits detailed in section 3.2. They are then manufactured by FDM using a polypropylene filament, with fixed printing parameters.

Table 3. Manufacturing parameters used

Infill (%)	Extrusion temperature (°C)	Bed temperature (°C)	Layer thickness (mm)	Nozzle diameter (mm)
20	225	50	0.2	0.4

For each of these specimens, the diameters of S1 and S3 are measured at their three iterations. The relative deviation of these values is then determined. From the collected data, a predictive model (gaussian process machine learning algorithm) is generated. The model is improved in an iterative way by adding data gradually. A total of 48 specimens were subsequently printed and measured. The results of the sensitivity analysis are presented in Figure 3. The analysis was conducted in order to predict the relative error between the measured values of the diameter of each S3 section and their theoretical values. The graph shows the influence of each parameter on this error, and it can be seen in this case that the ratio has a major influence compared to the other three parameters. This implies that the ratio is the most critical parameter to adjust in order to achieve a geometry as close as possible to the theoretical model. The two graphs of Figure 4 are examples of response surfaces obtained with the predictive model. They represent an interpolation of the relative gap that can be expected between practice and theory with two input parameters. On the left one, the input parameters are the number of branches and the ratio, while for the right one, it is number of branches and the X3 offset. In both cases, the vertical axis corresponds to the relative error on the diameter of S3.

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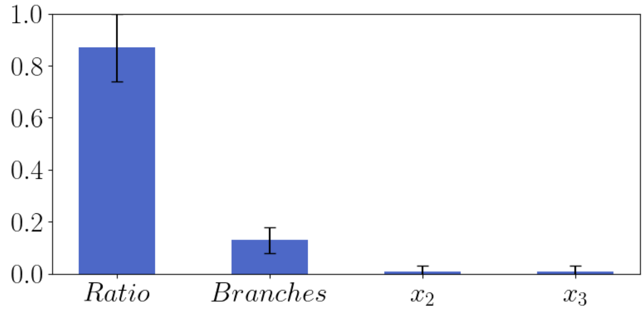

Figure 3. Results of the sensitivity analysis

The colour scale corresponds to the accuracy of the model for each parameter values with regard to the data it was trained with. For example, if a user wants to minimise the deviation of a part, the optimum configuration would be to have three branches and a 0.5 ratio. Consequently, when there are several branches rather than just one, the results are closer to the theoretical values if the ratio is low, i.e. less than 1. Referring to Table 2, this configuration corresponds to the primitive *separation* followed by an *area decrease*, on each of the branches. In the graph on the right, it can be seen that the influence of the offset is lower compared to the number of branches, and that a smaller error will be obtained for 3 branches. To conclude, these examples show an application of the proposed method to build a predictive model. In Figure 4, only two response surfaces are presented. However, depending on the needs and the metrology actions carried out, it could be possible to make many other correlations.

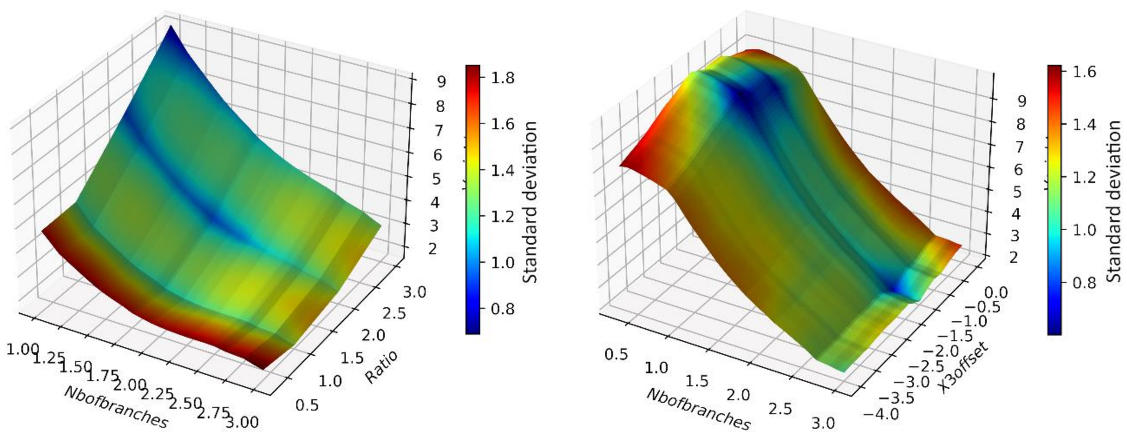

Figure 4. Examples of surface responses for geometrical inaccuracy

4 CASE STUDY

A case study has been chosen to illustrate the use of the above mentioned response surfaces. The studied part is a partial humerus replacement prosthesis for a human arm. The part contains thin sections which have been calculated to resist certain constraints while reducing its mass using topological optimisation. It is therefore necessary to respect the nominal values of the sections as much as possible to ensure a good rigidity of the part. In order to obtain a result as accurate as possible when compared to its 3D model, the designer can select the values corresponding to his expectations in the graphs generated with the above method. In the case of the red highlighted sections, two branches are splitting from a single area and the surface area is reduced.

By manufacturing this part with identical parameters (Table 3) but in two opposite directions, as shown in Figure 5, different results are observed. In the first case, the manufacturing is completed. The cross-section of the thinnest branch (d_1=1.51mm) at the top of the structure is measured, and presents a deviation from the nominal value (d_t=1.93mm) of 21.6%. For the part printed in the opposite orientation, this branch has a diameter (d_2=1.80mm) more in line with the theoretical value (6.5% deviation), while having a visibly better surface finish. However, the structure collapses about halfway through the manufacturing process and cannot be completed. There is a noticeable difference in accuracy between identical features depending on whether they are close to the plate or above a feature chain. To address

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this during the design phase, it could be useful to be able to foresee these effects and to choose a configuration (dimension, offset value, etc.) that would allow to obtain the dimensions and surface finish required by the specifications, considering the geometries printed under this section.

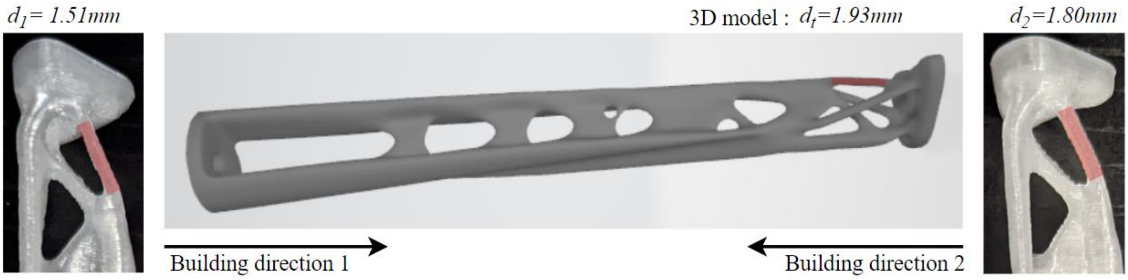

Figure 5. Comparison between two FDM-printed parts along opposite building direction

Orientation 1 is considered, as the manufacturing could be successfully completed with this setup. The aim is to minimise the deviation on the highlighted section. Two branches start from a same section that has a 28.33mm² cross-section area. According to Figure 3, the offset has little influence compared to the number of branches and the ratio. The first graph in Figure 4 is then used to determine that the optimal configuration in this situation would be to have three branches and a ratio close to 1. It is therefore deduced that to maximise fidelity to the model, it would be advisable to add a branch and for each of the three to have a surface area of 9.44mm², i.e. a radius of 1.73mm. It is then up to the designer to also change the offset, or the dimensions of the features below the involved branches, while checking the predicted accuracy of such configurations. Once the final geometry is defined, the part can be manufactured by the appropriate stakeholder who can then optimise the manufacturing parameters and ensure the best possible result. Therefore, this study allows for the evaluation of quantitative geometric features. Future work could add the effect of neighbouring features by carrying out the same process but with a different DoE. In addition, the development of a feature recognition algorithm could later allow for the automatic selection of relevant data charts from a database.

5 CONCLUSION AND FUTURE WORK

A methodology for generating quantitative data at the meso scale has been presented. Previous work on the use of mereotopology to describe the evolution of geometric shapes through successive printed layers has led to the development of a process to formulate qualitative guidelines linked to the interactions of different features. Based on this work, a test specimen adapted to this description formalism was developed and a series of tests were carried out following the established process. This procedure can be used to feed a predictive model by applying it to a sufficient number of specimens. Thus, depending on the criterion sought (accuracy of a diameter compared to its nominal value, surface roughness, etc.), the optimum parameters can be chosen. However, this study has its limitations. In this paper, the general method is presented, but for future applications, different assumptions could be made to enrich the model. For example, a circular cross-section was chosen as the basis, but further experiments could be conducted with other geometries in order to study their influence. In future work, the charts generated through this method will be added to a database of AM-related knowledge. A tool will be developed to assist users with their decision-making while designing a product that will be manufactured with AM. By analysing a 3D model, the feature configurations present in the part will trigger an algorithm that will retrieve relevant data. The user will thus be able to make quick decisions regarding geometry of the parts he wants to design while taking into account the possible consequences of each feature configuration and its surrounding.

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