OPEN SOURCE PROCESS OPTIMISATION WITH FUSED FILAMENT FABRICATION

G.P. Greeff[1*] & O.A. Kruger[2]

[1*]National Metrology Institute of South Africa (NMISA),
South Africa
pgreeff@nmsia.org

[2]National Metrology Institute of South Africa (NMISA),
South Africa
oakruger@nmsia.org

ABSTRACT

Parameter optimisation in additive manufacturing is a growing field and the process models are continuously improving. It is, however, a challenge to develop a parameter optimisation method which is rapid and repeatable, since the manufacturing process is used to produce inherently complex and unique parts.

This work develops the idea of single print optimisation, specifically using material extrusion, with the focus on open source technology, as well as cost effective and measurable test artefacts.

*Corresponding author

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INTRODUCTION:

Additive Manufacturing (AM) has a built-in link with digital design. It can even be argued that computer or digital modelling was the main enabling factor of AM (see e.g. [1]). This digital link is not only limited to the part model, but also links the digital process parameters with the process output, which can be used to achieve optimisation.

This manufacturing process is however complex, from digitally *slicing* the part – which creates the machine code – through the physical printing process and finally to the post-processing of the part. All these processes have variables or parameters and many of these are in principle open to be modified to optimise the final part, based on a set of desired outcomes.

Open source AM allows users to modify both the hardware and software parameters. An example is the thermoplastic material extrusion process, called Fused Filament Fabrication (FFF) [2]. One of the major challenges in AM is quality assurance since AM produces complex and unique parts [3]. The complexity also creates new challenges for tolerancing and metrology [4, 5].

The question is how to prove that the new part conforms to a standard or how to provide quality assurance of the part. Furthermore, one set of optimal parameters for one part might not be optimal for another part. Many manufactures opt for keeping the parameters closed, but an open source community could be the solution for finding the ideal parameters, since it provides 'free' testing, with vast diversity of parts and machines. Such a scale of testing, if pursued in-house by a single company, can be prohibitively expensive. Indeed, many test pieces are available online for FFF, but many are hard to measure, takes long to build and only allow for a qualitative process assessment [6].

On the other hand, the freedom to modify parameters and even the machine itself poses risks, such as damage to the machine and failed parts, which are then blamed on the specific printer. This will give the manufacturer a negative reputation as well as AM itself.

The following points should be considered in this context:

1. Design for metrology is as important as design for AM – if the part cannot be measured then it is not possible to prove conformance or improve performance.
2. Test artefacts should give more than a single 'accept' or 'reject' result. Ideally, all the data measured should be used to further develop the process and machine model.
3. Methods which reduce testing cost and complexity, such as open source parameter optimisation, with design of experiments in FFF, can therefore be considered [7].

The general methodology of the proposed method is detailed next, followed by three practical application examples and a conclusion.

1. METHODOLOGY

This work proposes a method for open source characterisation and optimisation of the printing process. The method process flow diagram is shown in Figure 1, which describes the main steps, namely:

1. Define the experimental goal – e.g. solve printing issues such as stringing, dimensional errors or bed adhesion. Alternatively, this goal can be to develop a model for the material flow rate or establish a printer baseline with which new materials or components can be compared to.
2. Define inputs and assumptions as relevant to the experimental goal.
3. Design of the test piece and the experiments – this can be done with Design of Experiments (DOE).
4. Execute the plan – a practical method to achieve this step is shown in this work.

5. Analyse the results.

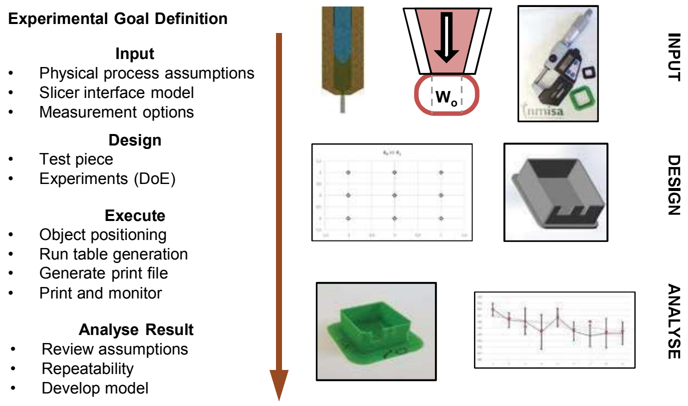

Figure 1 The proposed parameter optimisation process flow – from input, design, execution and analysis on the left and example images on the right.

One of the keys concepts of this method is that the same test object is printed with different slicer parameters, in order to improve understanding of the process and model it. This contrast sharply with the process of printing one large test piece. The concept is to rather print a small part which is focussed on a specific process output. This takes the bottom-up approach by viewing the printed part as the integrated result of the execution of machine commands.

Note that each step in the process can feed back into the previous step until the experimental goal can be achieved. An example of this is print volume versus extrusion stability. A larger test part will ensure that the extrusion process is closer to a "semi-steady" state but require more time to print and reduce the number of experiments which can be performed per print run.

The method proposed here uses Design of Experiments (DOE) to choose a set of parameters. The test part is sliced with different parameters, printed sequentially, but in a single print run, if possible. Design of experiments also allows for the expansion of the experiment, since the test levels are well defined and can therefore be compared. This allows for additional experiments or test prints to further develop the model and means that test prints are not wasted, but that the information gathered from them are used in the future.

1.1 Methodology Motivation

A well-known issue with these printers is that the feed mechanism slippage increases as the pressure required to extrude the molten material increases, usually with lower temperature and faster flow rates [8]. This dependency needs to be modelled to (1) ensure that the print is in the functional parameter range, (2) optimise print speed versus accuracy, (3) improve the dimensional accuracy of the part and (4) to quickly evaluate if a change to the printer or filament has taken place. A method is therefore needed to derive a model for this specific relationship, but this can also apply to any process outcome which can be modified by using different printer parameters.

A method currently used to test printers is to print a large *torture test* part, e.g. a small boat called the *3DBenchy* [9]. Careful visual inspection of such a print can show if a printer has a significant process issue, for example under-extrusion. This method is however inefficient, since it does not give any additional information – such as what the influence of different parameters are on the under-extrusion and by how much. For example, the whole print needs to be repeated if it is assumed that the print temperature was too low, but there is no way of knowing by *how much* to increase the temperature and what to expected at this new temperature.

Another method is to print specialised test pieces, for example a hollow cylinder with sets of layers at different temperatures. This however has the issue that it is printer specific and the test part needs to be manually created. Nor does it gauge in the interaction between print speed and temperature on under-extrusion.

There are also test parts with features designed to show the print limit, for example the maximum overhang angle without supports or smallest hole. These tests parts immediately visualise the printer limitations, albeit only with the current slicer parameter set. The parts also tend to be larger test objects.

Modelling the effect of process parameters and their interaction can however be accomplished with Design of Experiments. DOE is a systematic and rigorous approach to problem solving and can be applied to optimisation problems [10]. This includes the planning of the experiment which ensures the validity, reliability and reproducibility of the data analysis conclusion.

Several works have used DOE methods to model the printing process. Interestingly, one of the first works on FDM® [11] used DOE to investigate material and temperature effects. More than 20 works are cited in [12], where these studied investigated process responses such as surface texture, build time, dimensional accuracy or mechanical properties. Such an approach however can appear complicated, but this work aims to show that it can be relatively straightforward when care is taken to understand how the three inputs (physical process, slicer model and measurement method) affect the result.

1.2 Slicer Considerations

The output of current slicer applications is currently increasingly complicated, since several parameters affect the final machine commands (G-codes and M-codes). It is important however to differentiate between the slicer model and the machine model. The slicer model determines the G-code production, while the machine model determines how the printer responds to a specific G-code. An example is the external perimeter feed rate. This can be influenced by the current layer (first layers, top layer or bottom layer), perimeter position (external or internal) and finally by layer cooling settings.

The actual G-code needs to be evaluated and compared with the print result and not with the CAD drawing or with a specific slicer setting. The result of this comparison should then be used to improve the CAD model or the slicer parameter. This is important since many test artefacts do not consider the effect of the file format [6], nor the slicer process.

The open source slicer, called *Slic3r* (version 1.3.0), is used for the all the experiments in this work, since it allows for command line execution. This allows for significant automation of slicing the test part with different parameters.

1.3 Test Part Design and Measurement

The test part design is also integral to the method and should be cost effective and measurable. It should also make it possible to link the measured result with a machine command. The ideal is that the part should be sliced as is, without any modification to the current slicer parameters.

The measurement method should also use available instruments and be fit for the measurement task. The time required to complete the measurands should also be considered when designing the experiment. In this work a cost-effective digital microscope is used to obtain micrographs for qualitative comparisons and an external digital micrometer was used to measure the track width. A micrometer was used instead of a more expensive Coordinate Measuring Machine (CMM). On the other hand, the measurement uncertainty of Vernier calliper would be too large.

1.4 Data Analysis

Ordinary Least Squares (OLS) is used to fit the factors to the response variable. This is done with *Statmodels* Python package [13], using an iterative factor reduction method, where the factor with the largest p-value is removed until the significance of the remaining factors are below 0.05 for a 95% confidence level.

1.5 Automation of the Test File Generation

A Python application, shown in Figure 2, was developed to automate the generation of the test file. This includes the object positioning, run table generation, slicing and merging.

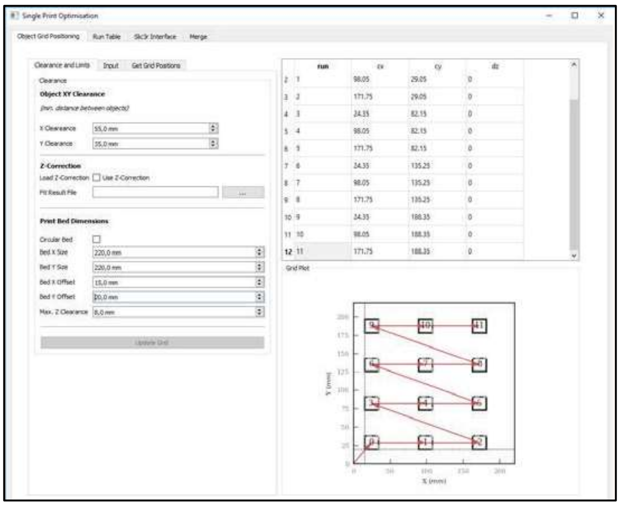

Figure 2 Screenshot of the application developed for this method, with the main tabs the processing steps, namely: object positioning, run table generation, slicing and merging.

2. APPLICATION EXAMPLES

The following application examples show how this method was practically applied to three different desktop type material extrusion 3D printers. Each application details the specific test parts which was used and the results.

2.1 Build Plate Adhesion

This method assumes that the printer is functional, but in some cases, it can even be used to find the functional processing parameters. The first example is build-plate or first-layer adhesion, which is the critical first step for successful printing.

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A Cartesian printer with a ceramic build plate exhibited first-layer adhesion issues, which was investigated with the proposed method. It was assumed that two slicer parameters could improve the adhesion, since the bed level could not be easily mechanically adjusted. These parameters were *first-layer-height* and *first-layer-extrusion-width*. The layer height setting is used to print a higher first layer to compensate for the bed unevenness.

The test object was a rectangle with two diagonals, as shown in Figure 3, where each wall is two perimeters (tracks or extrusions) wide. This gives 16 extrusions in total, if the bed adhesion is perfect. The number of the successful extrusions per experiment was simply counted and used as the response variable in the design experiments analysis.

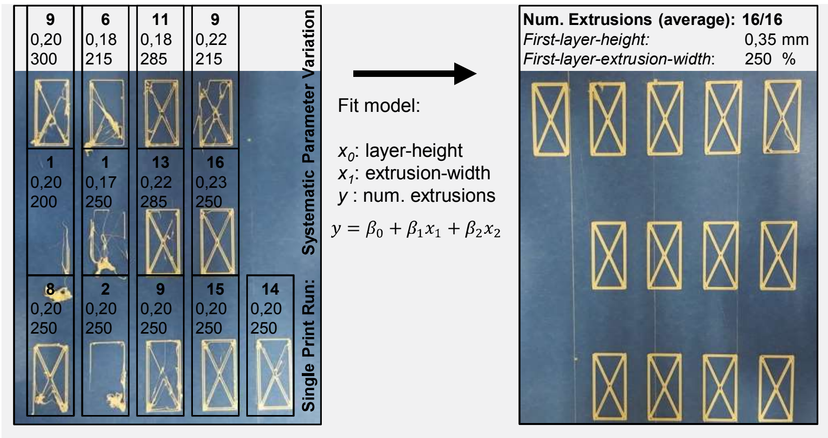

Figure 3 Build adhesion improvement with parameter optimization. The left photo is the experimental print run and right is the verification run.

The photo on the left in Figure 3 is the experimental run, where each rectangle was printed with different values for *first-layer-height* and *first-layer-extrusion-width*. Certain rectangles completely failed and resulted only in a blob of plastic, whilst other prints were more successful. Importantly, all 13 prints were completed, one after the other, in a single print run. The failure of one print did not prevent the completion of the following experiment.

The test found that the first layer height was more significant in this case and that it must be increased. The height was therefore increased from 0.2mm to 0.35mm, while the extrusion width was kept at 250%. The result of these settings is shown on in Figure 3 on the right.

2.2 Extrusion Characterisation

Successful extrusion of a single track of plastic is a fundamentally important building block of a successful print. A test object, as shown in Figure 4, was designed to model the extrusion parameters. The object is 17 mm wide, 16 mm long and 7 mm high. The wall is 0,5 mm thick to force the slicer to extruder only one perimeter, i.e. the walls of the object above the base layers are only one extrusion track wide. This allows for a direct comparison between the commanded G-code of a single extrusion and the width measured with the micrometer.

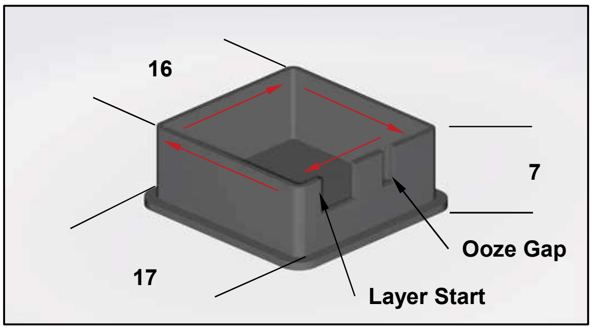

Figure 4 The test piece (17 x16 x 7 mm) for extrusion characterisation, where the red arrows indicate the print direction.

The top half of the object has two gaps in the wall, with one gap shorter than the minimum distance for a retraction move to trigger and the other gap longer than this length. This means that the printer will move straight over the *ooze gap*, without pausing to perform a retraction move. This gap, or the amount of material inside of it, can then be used to gauge the material ooze rate – defined as the flow of unwanted material after extrusion stop.

The slicer used in this work forced a layer change before the longer gap (see Figure 4 for the print direction and layer start). The resulting G-code first moves the printer up one layer, then retracts, after which it moves with the travel-speed to the layer start point. It then performs a single continuous extrusion which builds the wall.

2.2.1 *Applied on an Ultimaker 2 Extended*

The first tests were performed on an Ultimaker 2 Extended printer, with a 0,6 mm nozzle and green Ultimaker brand PLA which has a diameter of 2,85 mm. The printer was not mechanically adjusted in anyway and was used as is. The positioning of the objects was accomplished using the Python application. The perimeter-speed and extrusion temperature slicer parameters were varied according to Table 1, with 12 experiments, where four of these were centre runs.

Table 1 Experimental plan for the ooze length test

Run	cx	cy	Perimeter-Speed (*mm/s*)	Temperature (°*C*)	x_0	x_1
0	24	29	25	200	0	0
1	98	29	25	200	0	0
2	172	29	10	215	-1	1
3	24	82	40	185	1	-1
4	98	82	25	215	0	1
5	172	82	40	200	1	0
6	24	135	25	200	0	0
7	98	135	40	215	1	1
8	172	135	25	185	0	-1
9	24	188	10	185	-1	-1
10	98	188	10	200	-1	0
11	172	188	25	200	0	0

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The resulting difference in levels of extruder ooze is shown in Figure 5 and a qualitative value from zero to five was assigned for each experiment, where a score of five indicates that the ooze gap feature is filled.

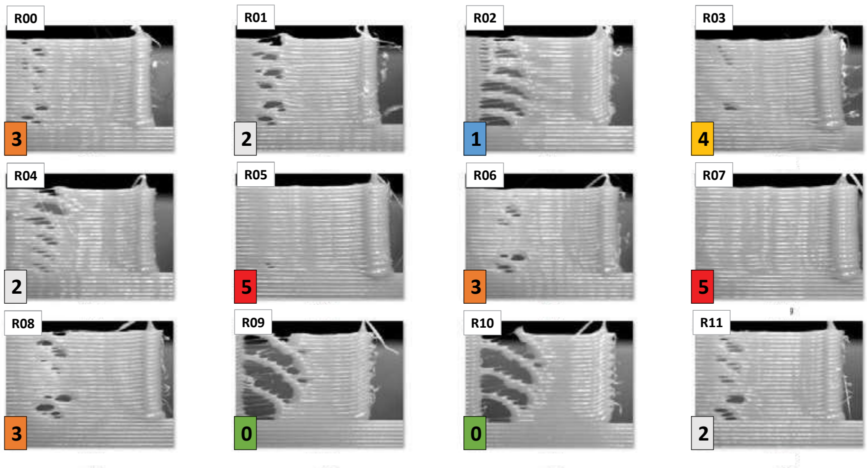

Figure 5 Micrographs of different levels of material flow after extrusion stop. The number in the bottom left indicates the qualitive ooze length, with zero indicating less ooze and higher numbers indicating more ooze.

The run plot of the ooze length value is shown in Figure 6 along with the values predicted by the fitted model. The centre runs (Run 0, 1, 6 and 11) repeat well indicating that the deviation from the mean was probably caused by the parameter variation and is not only due to normal process variation.

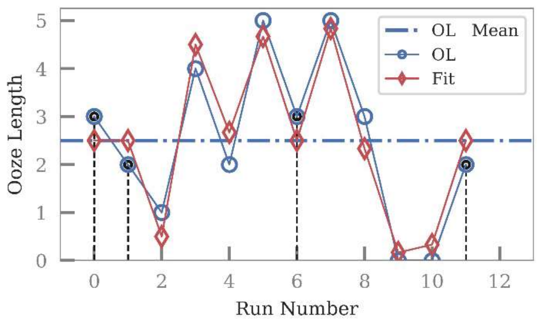

Figure 6 Run plot of the ooze gap length (OL), where unfilled circles indicate the qualitative value and the unfilled diamonds the fitted model prediction. Dashed vertical lines indicate centre runs.

This is further investigated with the factor plot shown in Figure 7, where the perimeter speed box plot reveals a clear trend, i.e. the amount of ooze increases with increasing printing speed. Temperature does not have an apparent effect, nor does the part position.

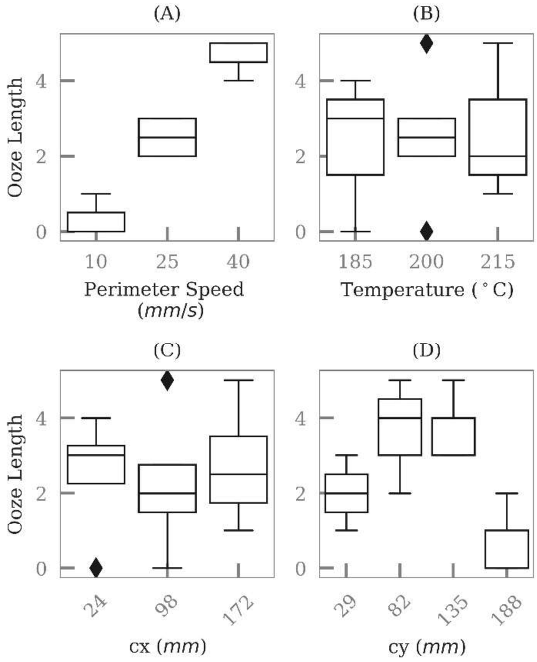

Figure 7 Factor box plot for the ooze length test, with diamonds indicating possible outliers.

The iterative factor reduction method finds that the perimeter speed is a significant factor and has a relatively large positive coefficient, as shown in Table 2. This means that that increasing speed will increase the amount of material oozing into small gaps. Interestingly, temperature has a smaller but positive coefficient. This agrees with the general expectation that a colder extruder will ooze less, due to the higher viscosity of the melt.

Table 2 Qualitative ooze length as response to perimeter-speed (x_0) and temperature (x_1), where a larger ooze length value indicates increased unwanted material flow.

Factor	Coef.	Std. Err.	T	P>|t|
Intercept	2,500	0,157	15,91	0,000
x_0	2,167	0,217	9,97	0,000

The final OLS fit achieved a R-squared value of 0,914 and the residual mean is 0,0 with a standard deviation of 0,5. The residual is shown in Figure 8 and the residual appears normally distributed with no clear trends relative to either of the two input factors.

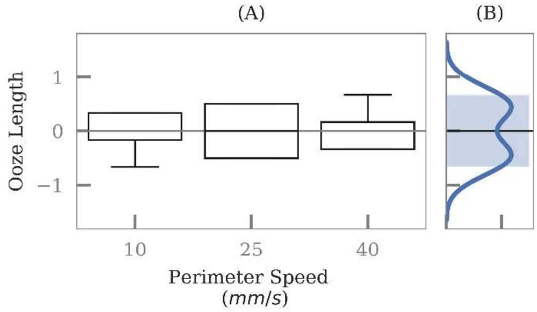

Figure 8 Residual plot for the ooze length fit, with (A) and (B) the box plots against the two input factors and (C) the histogram.

2.2.2 Applied on a Delta Printer

The same test part and method were used to characterise an entry level delta printer, with 1,75 mm black PLA. This was done, since the printer configuration was lost and there was no known supplier recommended slicer settings.

The first test run was a centre run and aimed to evaluate the printer functionality. A perimeter speed of 40 mm/s and a temperature of 200 °C were applied. It was found that the wall thickness varied, and that the layers seemed to delaminate. It was assumed that the print speed was too fast. The next test run varied perimeter- and travel-speed to investigate this further, with (10; 25; 40) mm/s and (50;75;100) mm/s for each respectively, with the same design as in Table 1.

The track width was measured over the top layers with a digital micrometer, with a measurement uncertainty of ± 2 µm and the result is shown in Figure 9. The centre run prints have an average track thickness of 473 µm with a standard deviation of 2 µm, while the average of all the objects is 477 µm and a standard deviation of 23 µm. This indicates that the process is in control and that the response variable reacted well to the input factors. Since the experimental design is balanced it is reasonable to expect the reaction to be balanced as well. That is if the parameters is in the linear process space.

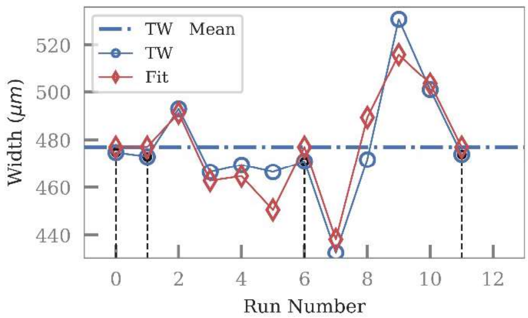

Figure 9 Run plot of the track width (TW) in the delta printer test. The unfilled circles are the measured width and the unfilled diamonds the fitted model prediction. Dashed vertical lines indicate centre runs.

The same process, of iteratively reducing input factors and interaction effects, was applied again. The regression results in Table 3 finds that perimeter speed has a coefficient that is more than double that of the travel-speed. Both factors, however, have a negative coefficient, which means that increasing speed decreases the track width. This confirms the physical process assumption that the flow rate depends on extrusion speed. The effect of the travel speed was however not expected.

Table 3 Track width as the response to perimeter-speed (x_0) and travel-speed (x_1).

Factor	Coef.	Std. Err.	t	P>|t|
Intercept	477	2,938	162,361	0.000
x_0	-27	4,155	-6,388	0.000
x_1	-12	4,155	-2,968	0.016

The fit has an R-squared value of 0,846 and a residual mean of 0,0 µm, which has a standard deviation of 9,2 µm. The residuals are plotted in Figure 10, where the median is slightly higher at the centre values and lower at the extremes.

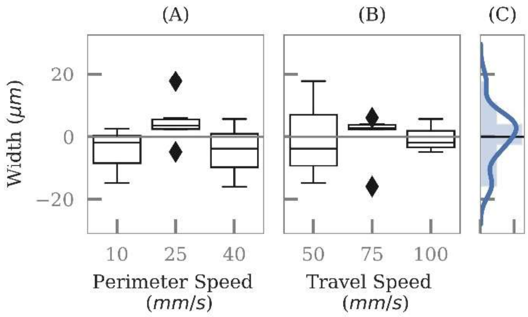

Figure 10 Residual plot for the track width fit, with (A) and (B) the box plots against the two input factors and (C) the histogram.

3. ADDITIONAL POSSIBILITIES

Mechanical settings can also be tested with this method and not just slicer parameters. For example, the pinch force exerted on filament in the feed mechanism can usually be adjusted with a bolt and spring mechanism. The effect of this force can be tested by pausing the print run after completing each object and adjusting to the spring compression according to the experimental plan. Certain printer firmware also allows a pause command in the G-code file, with a message which can indicate the required setting.

Furthermore, firmware such as Repetier, allows for the setting of EEPROM values with M-codes. This enables even more possibilities such as testing different acceleration settings or other non-slicer controllable variables.

In this work only one response factor per printer was shown. It is however possible to combine experimental plans into one plan or to increase the number of experiments, by either printing on top of the previous test layer – which is limited by the print Z-clearance – or by using more than one print run.

4. CONCLUSION

A method was proposed with which 3D printers can be characterised, tested and optimised. The method aims to be a more scientific approach to configure printer parameters than re-printing *torture test* objects and changing one parameter at a time. It also aims to be straightforward to use and to interpret the results. Gauging of interaction effects, establishing baseline performance values, modelling process responses with input factors and testing process assumptions are some of the outcomes.

The method was applied to three different FFF printers, which shows that the method is versatile. Furthermore, open source tools were used to perform the experiments, analyse and graph the data which makes the method free, but also allows future community development.

Important considerations for such works are the establishment of three models, namely the CAD model to G-code (slicer model), G-code to machine response (firmware model) and the firmware command execution to the actual printed object (physical model). This is only possible if the response variables can be accurately measured and if the process output is sufficiently reproducible. Limitations of this method are process reproducibility, control of disturbance or external input factors such a filament inconsistency and environment and slicer interaction – forcing the slicer to produce consistent G-codes for a specific test.

This work therefore makes the community aware of model assumptions and proposes a straightforward methodology of testing these, using a well-established method such as design of experiments.

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