
Mass optimisation of 3D printed specimens using multivariable regression analysis

Cristian-Vasile Doicin and Mihaela-Elena Ulmeanu*

University Politehnica of Bucharest,
Bucharest 060042, Romania
Email: cristian.doicin@upb.ro
Email: mihaela.ulmeanu@upb.ro
*Corresponding author

Allan E.W. Rennie

Engineering Department,
Lancaster University,
Lancaster, UK
Email: a.rennie@lancaster.ac.uk

Elena Lupeanu

National Institute of Geriatrics and Gerontology “Ana Aslan”,
Bucharest 011241, Romania
Email: elenalupeanu@yahoo.com

Abstract: Fused deposition modelling popularity is attributed to equipment affordability, materials availability and open-source software. Given the variety of optimisation combinations, process parameters can be elaborate. This paper provides methods for optimisation of mass calculation using multivariable regression analysis. Layer thickness, extrusion temperature and speed were considered independent variables for a two-level factorial experiment. DOE was used for 12 sets of programs and analysis (two stages) undertaken using Design-Expert® V11 Software. In stage-1, four models were found to be significant. Stage-2 involved redesigning the remaining eight models, iteratively increasing the number of replicates and blocks. Adequacy of models was analysed, demonstrating that: model is significant, F-value is large, $p < 0.05$; lack of fit is insignificant; adequate precision > 4.00 ; residuals are well behaved; R^2 is as close as possible to 1.00 or for models with multiple replicates, the adjusted R^2 and predicted R^2 differential < 0.2 . All models were validated through measured, calculated responses.

Keywords: optimised mass calculation; material extrusion; design of experiments; DOE; multivariable regression analysis; MRA.

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Biographical notes: Cristian-Vasile Doicin is the Dean of the Faculty of Industrial Engineering and Robotics at the Politehnica University of Bucharest and Head of the Laboratory of Innovative Product Development at the Manufacturing Engineering Department. He is the Manager for 14 projects and participated in more than 30 projects in the various industrial and economic domains.

Mihaela-Elena Ulmeanu is an Associate Professor at the University Politehnica of Bucharest (UPB). She is also responsible of the Joint Office FhG-IAO@UPB-IMST (Romanian – German Innovation Network) and the Additive Manufacturing Laboratory at UPB. Her main fields of competences are additive manufacturing/3D printing, product design and development, design for manufacture, CAD and technical functional analysis.

Allan E.W. Rennie is a Senior Lecturer in Manufacturing Engineering and Director of the Lancaster Product Development Unit (LPDU) at Lancaster University. Under his direction, LPDU have delivered in excess of £20M of grant funded projects, consulting for or collaborating with more than 1,000 organisations (industry, governmental, education, charities, etc), providing input to policy documents and taking leading roles in the additive manufacturing community both nationally (UK) and internationally.

Elena Lupeanu is a Senior Researcher in Medical Biology, Master in Cell Biology and PhD in Physiology and her main area of expertise in biology of aging includes: cell biology, biochemistry, anthropometry and nutrition; the development of experimental animal models for hypoxia, diabetes and Parkinson's syndrome, assessing the influence of GH3 and Aslavital on the process of aging and generating radical oxygen species; nutritional evaluation.

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1 Introduction

Material extrusion (MEX) is the most widespread additive manufacturing (AM) technology, followed by selective laser sintering (SLS) and stereolithography (SLA) (Moreau, 2018; 3D Hubs, <https://www.3dhubs.com/trends>). Fused deposition modelling (FDM) adoption has known a consistent increase over the last few years, using PLA as the most common material, followed by ABS (3D Hubs, <https://www.3dhubs.com/trends>). As FDM application areas expand (Moreau, 2018) the need arises to optimise printing process parameters in relation to certain goals, amongst which can be mentioned: print time, final part quality and costs. Some of the most significant process parameters considered as influencing FDM are the layer thickness, printing temperature and printing speed (Li et al., 2017; Chacón et al., 2017; Gordon et al., 2016). Print orientation, infill and raster angle have also been shown to highly influence final part properties (Gordon et al., 2016; Nancharaiyah, 2011; Kohad and Dalu, 2017; Hernandez et al., 2016). Optimisation of process parameters specific to certain goals is quite complex, given the large variety of possible combinations provided by slicing software. Using design of experiments (DOE) the current research optimises the calculation of mass for natural PLA 3D printed specimens, considering the variation of three process parameters.

Most available slicing software offer a rough estimate on the final mass of the 3D printed parts, making it hard to use as an input variable into other processes. The results of the paper can be useful in AM areas where material costs are quite high and final part mass is important in overall fit and evaluation of the corresponding assemblies. Researchers previously pursued methods for volume conservation in 3D printed models (Hidalgo and Goodman, 2013) using FDM technology. Their results included a new computationally efficient method which allows geometry simulation of 3D printed filaments. Although the method is validated with printed specimens, the experiments were chosen and run in a random order, without any predefined scientific criteria.

Considering the abovementioned, the aim of the paper is to find a more accurate relationship between the final mass of a 3D printed product and a selection of printing parameters. Due to the nature of the physical process, one identified dependent variable and multiple independent variables, multivariable regression analysis (MRA) was

proposed as a scientific method of statistical calculation. MRA refers to statistical models in which there are multiple independent or response variables (Katz, 2003; Kundra et al., 2018). This type of statistical model has been previously used to attempt to assess the relationship between number of variables, especially in the medical field for statistical processing of large volume data (Sanatgar et al., 2017).

A variety of researchers use statistical analysis to validate behaviour predictions of 3D printed parts in a wide range of applications. Sanatgar et al. (2017) used statistical design to investigate the adhesion properties of direct FDM 3D printing of polymers and nanocomposites on textiles. ANOVA was used to design fitted plots for investigated parameters (extruder temperature, platform temperature and printing speed) in relation to adhesion force. Also, in the textile industry, Mpofu et al. (2019) used first and second-order polynomial regression models to study the effect of fabric parameters on the adhesion of 3D printed PLA polymer onto woven fabrics (Beniak et al., 2017). Beniak et al. (2017) used linear regression models to assess the influence of model infill, infill shape, layer thickness and orientation on the tensile strength of PLA 3D printed specimens (Gleadall et al., 2018).

2 Methods and materials

The goal of the present research is to determine a more accurate method for mass calculation of FDM 3D printed parts, using MRA to establish the relation of mass as a function of printing parameters. MRA entails several stages, as follows:

- 1 establish the form of the regression function
- 2 establish the structure of the experimental program using DOE
- 3 calculate the regression coefficients
- 4 verify the regression functions' form suitability and the significance of the regression coefficients
- 5 determine the statistical errors
- 6 determine the confidence intervals.

MRA was undertaken using Design-Expert® V11 Software by defining the form of the function and the experimental

program type. By running the software, a mathematical expression was determined, in order to define the dependency between the final mass of 3D printed specimens and three process parameters: layer thickness (s , mm), printing temperature (t , degrees) and printing speed (v , mm/min). In this case, the mass is considered the main dependent variable and the three process parameters are the input independent natural variables. Due to the combination between the independent variables in relation to the dependent variable, a factorial experimental program was defined, with two variation levels (2^3 type), with the medium values determined as the arithmetic average of the minimum and maximum limits. Three control experiments were used, leading to a base experimental plan of 11 experiments. Four PLA filament type materials were considered for DOE, from four different manufacturers. Natural filaments were chosen in order to exclude changes in material properties due to various pigments. Three ISO test standards were used to print the specimens in one direction, as follows:

- ISO 527 tensile test specimens printed horizontally
- ISO 179 flexural test specimens printed normal
- ISO 178 Charpy impact test specimens printed normal.

Table 1 Variation levels for the independent natural variables

No. crt.	Independent variable	Minimum	Medium	Maximum
1	Layer thickness – s [mm]	0.10	0.15	0.20
2	Printing temperature – t [°C]	200°C	210°C	220°C
3	Printing speed – v [mm/min]	40 mm/min	60 mm/min	80 mm/min

Considering four material types, three specimen test standards, one orientation and a factorial experimental program with three controls, the final number of undertaken experiments was set to 132. The variation levels for the three aforementioned process parameters are listed in Table 1. The limit values were set in accordance with the four different manufacturers’ requirements. MRA was run by coding the natural variables, as presented in Table 2.

Table 2 DOE for three variables – base experimental plan

Experiment no.	Natural variables			Coded variables		
	s [mm]	t [°C]	v [mm/min]	A	B	C
E1	0.15	210	60	0	0	0
E2	0.10	200	40	-1	-1	-1
E3	0.10	200	80	-1	-1	+1
E4	0.10	220	40	-1	+1	-1
E5	0.10	220	80	-1	+1	+1
E6	0.15	210	60	0	0	0
E7	0.20	220	80	+1	+1	+1
E8	0.20	220	40	+1	+1	-1
E9	0.20	200	80	+1	-1	+1
E10	0.20	200	40	+1	-1	-1
E11	0.15	210	60	0	0	0

The base experimental plan is repeated for four PLA material types and three types of specimens, namely the standard tensile (ISO 527), flexural (ISO 179) and Charpy impact (ISO 178) strength test specimens.

Manufacturing of the 132 specimens needed 12 process data sheets following the encoding proposed in Table 3. Each batch of 11 specimens are printed on the same 3D printer in order to ensure the repeatability of the process parameters.

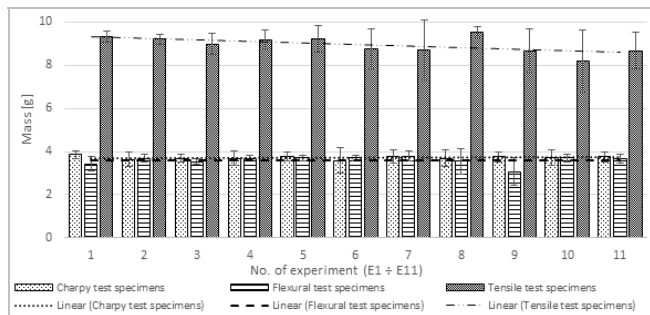
Table 3 Coding of 132 PLA specimens

Program no.	Specimen test type	Material type	Orientation type	Experiment no.	Specimen code
P1	Test 1 – ISO 527 (Code T1)	Material 1 (CodeM1)	Orientation 1 – horizontal (Code O1)	E1 ÷ E11	T1M1O1E1 ÷ T1M1O1E11
P2		Material 2 (CodeM2)		E1 ÷ E11	T1M2O1E1 ÷ T1M2O1E11
P3		Material 3 (CodeM3)		E1 ÷ E11	T1M3O1E1 ÷ T1M3O1E11
P4		Material 4 (CodeM4)		E1 ÷ E11	T1M4O1E1 ÷ T1M4O1E11
P5	Test 2 – ISO 179 (Code T2)	Material 1 (CodeM1)	Orientation 1 – normal (Code O1)	E1 ÷ E11	T2M1O1E1 ÷ T2M1O1E11
P6		Material 2 (CodeM2)		E1 ÷ E11	T2M2O1E1 ÷ T2M2O1E11
P7		Material 3 (CodeM3)		E1 ÷ E11	T2M3O1E1 ÷ T2M3O1E11
P8		Material 4 (CodeM4)		E1 ÷ E11	T2M4O1E1 ÷ T2M4O1E11
P9	Test 3 – ISO 178 (Code T3)	Material 1 (CodeM1)	Orientation 1 – normal (Code O1)	E1 ÷ E11	T3M1O1E1 ÷ T3M1O1E11
P10		Material 2 (CodeM2)		E1 ÷ E11	T3M2O1E1 ÷ T3M2O1E11
P11		Material 3 (CodeM3)		E1 ÷ E11	T3M3O1E1 ÷ T3M3O1E11
P12		Material 4 (CodeM4)		E1 ÷ E11	T3M4O1E1 ÷ T3M4O1E11

3 Results and discussion

Standard deviation for each set of parameters (E1 ÷ E11) was calculated, regardless the used material (Figure 3). Linear trends show that the geometry of the 3D printed part highly influences the mass of the final part in specific combinations of the independent variables. From Figure 2 we can conclude that the most stable (smallest standard deviation for all tests) combination of printing parameters is achieved in experiment no. 2, namely: a layer thickness of $s = 0.10$ mm; a printing temperature of $t = 200^{\circ}\text{C}$; a printing speed of $v = 40$ mm/min.

Figure 3 Average mass for 132 specimens for 11 experiment types



In order to accurately express the dependency of the printed parts' mass to the three independent variables, each of the 12 previously defined programs (Table 3) were subjected to a MRA using Design-Expert® V11 Software in two stages.

3.1 First stage in DOE

In the first stage of DOE all 12 programs were run with identical steps in designing the experiments. The first step is to select the type of design, in this case, due to the three independent variables and one dependent variable, the selected design was a factorial randomised regular two-level design. The analysis required one replicate, one block and three centre points per block (Figure 4). Delta (the 'signal') was set to a value of 3 and sigma (the 'noise') to a value of 1, resulting a ratio of 1. DOE was undertaken so as the

factor power for each of the 12 programs, was over 80% in order to be able to detect the targeted effects.

After defining the characteristics of the DOE, the responses are registered for each of the 132 experiments. A summary of the statistical analysis input information for program P3 is presented in Figure 5.

Figure 4 DOE for 12 programs using Design-Expert® V11 Software (see online version for colours)

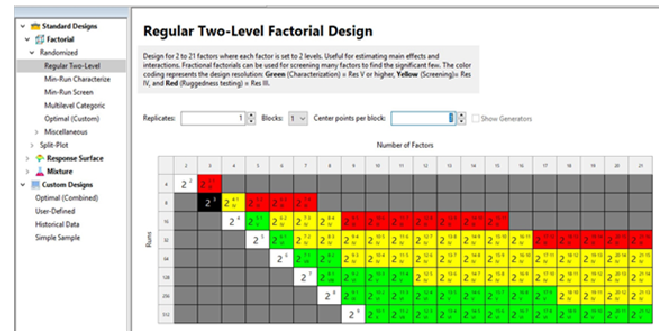


Figure 5 Input data for program P3 using Design-Expert® V11 Software (see online version for colours)

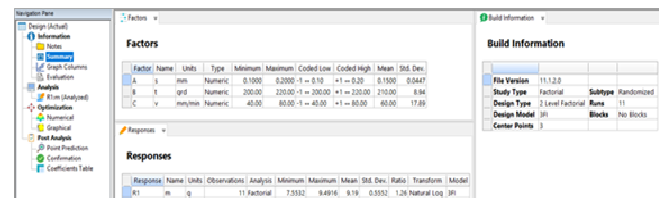


Figure 6 Evaluation of model and factor selection for program P3 (see online version for colours)

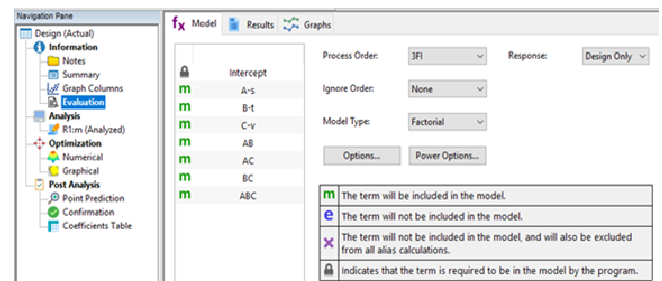
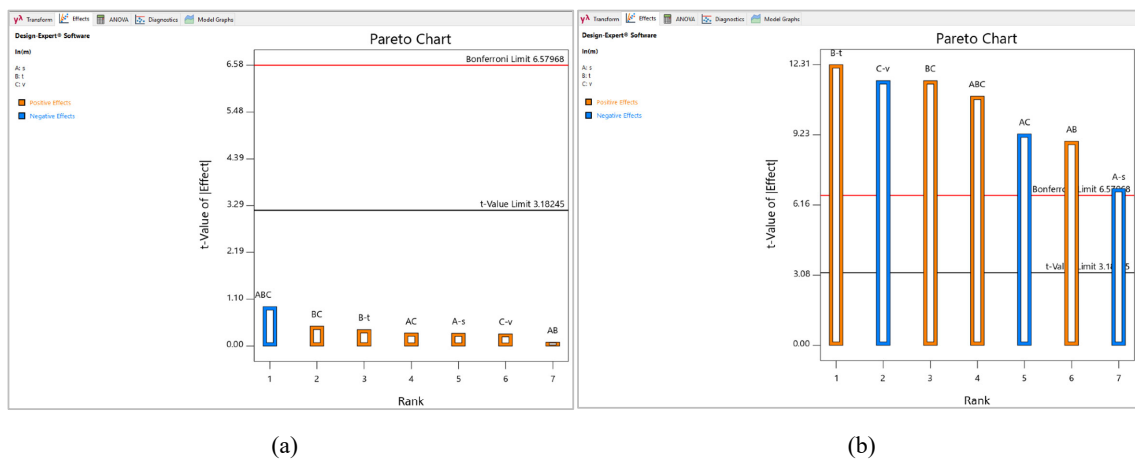


Figure 7 Pareto charts with selected effects for programs, (a) P1 – not significant (b) P3 – significant (see online version for colours)



Each run of the software registers standard summary data, which is further used in the statistical analysis. Amongst the most important are the minimum and maximum values of the defined response, which in this case is the specimens' mass, an average mean of these registered values and a standard deviation. A natural logarithmic transformation was used to process all 132 responses. Analysis was run under a factorial study type with three centre points of analysis. For all 12 programs, the base experimental plan is identical, for both natural and coded variables, only the response values are varied according to the obtained results of the physical testing. The simulation is run from the *evaluation* section, by verifying the f_x model and selecting the *results* tab (Figure 6). Simulation results are shown in analysis section under *RI:m (Analyzed)* tab.

Before running ANOVA and determining the significance of the proposed models, the individual effects should be selected from the Pareto diagram. Effects should be selected hierarchically, from left to right (largest to smallest), taking into consideration their relation to the Bonferroni and/or t-value limit (Figure 7). Only selected effects will be compounded in the final model.

The final equations in terms of coded factors have the following general form:

$$\ln(m) = a_0 + a_1 \cdot A + a_2 \cdot B + a_3 \cdot C + a_{12} \cdot A \cdot B + a_{13} \cdot A \cdot C + a_{23} \cdot B \cdot C + a_{123} \cdot A \cdot B \cdot C \quad (1)$$

All eight regression coefficients for the 12 programs are listed in Table 5.

Regression coefficients are significant if they have a probability $p < 0.05$. The model is significant relative to the noise if the majority of the coefficients have a probability value under 0.05 and the confidence is above the standard value. The analysis was run with a two-sided interval and a standard confidence of 95%. Model inadequacies arise from too scattered central point values. As shown in Table 4 only four models are significant, with the following general p values: P3 – $p = 0.0092$; P7 – $p = 0.0030$; P10 – $p = 0.0045$; P11 – $p = 0.0200$. For insignificant models the statistical analysis is repeated with a higher number of replicates and blocks and is detailed later in the chapter.

Table 5 Computation of regression coefficients for coded factors and their probability (p)

Program no.	a_0	a_1	a_2	a_3	a_{12}	a_{13}	a_{23}	a_{123}	Model/confidence
P1 ($p = 0.9512$)	2.206358	0.012417	0.016103	0.011853	0.003737	0.012647	0.019519	-0.03893	NS/4.88%
	p_c	0.7972	0.7406	0.8061	0.9378	0.7936	0.6905	0.4554	
P2 ($p = 0.6995$)	2.175096	-0.00223	0.026592	-0.02037	0.034056	0.003956	-0.00961	0.018891	NS/30.05%
	p_c	0.9336	0.3792	0.4814	0.2880	0.8830	0.7249	0.5097	
P3 ($p = 0.0092$)	2.20857	-0.01793	0.03210	-0.03028	0.02334	-0.02418	0.03027	0.02851	S/99.08%
	p_c	0.0205	0.0065	0.0073	0.0123	0.0114	0.0073	0.0083	
<i>All coefficients are significant and model is adequate for further calculations.</i>									
P4 ($p = 0.3316$)	2.155832	-0.09201	0.019167	0.008861	0.010399	0.002858	-0.10856	-0.10392	NS/66.84%
	p_c	0.1711	0.7051	0.8587	0.8348	0.9540	0.1320	0.1416	
P5 ($p = 0.0991$)	1.287016	-0.01734	0.041709	-0.04039	0.03788	-0.05098	0.039837	0.019665	NS/90.09%
	p_c	0.2884	0.0749	0.0793	0.0887	0.0520	0.0812	0.2458	
P6 ($p = 0.2540$)	1.251581	-0.00181	0.020505	-0.00862	0.004962	-0.00195	-0.00241	0.001329	NS/74.6%
	p_c	0.7439	0.0512	0.2162	0.4122	0.7260	0.6667	0.8089	
P7 ($p = 0.0030$)	1.268285	-0.04946	0.069522	-0.06754	0.061136	-0.06347	0.065085	0.063525	S/99.7%
	p_c	0.0049	0.0025	0.0026	0.0032	0.0030	0.0028	0.0030	
<i>All coefficients are significant and model is adequate for further calculations.</i>									
P8 ($p = 0.5940$)	1.281646	-0.0267	-0.01791	0.036046	-0.04058	0.071188	0.062779	0.03304	NS/40.6%
	p_c	0.6165	0.7317	0.5111	0.4664	0.2579	0.3014	0.5430	
P9 ($p = 0.9789$)	1.2454	0.006734	0.011521	0.042989	0.000102	-0.02919	-0.02265	-0.02132	NS/2.11%
	p_c	0.9237	0.8702	0.5610	0.9988	0.6851	0.7506	0.7645	
P10 ($p = 0.0045$)	1.277278	0.010439	0.010989	-0.0112	0.003879	0.008885	0.003204	0.001534	S/99.55%
	p_c	0.0027	0.0024	0.0023	0.0190	0.0037	0.0275	0.1058	
<i>Six coefficients are significant and model is adequate for further calculations.</i>									
P11 ($p = 0.0200$)	1.308415	-0.00988	-0.01759	0.013368	-0.02107	0.01787	0.025013	0.021191	S/98.00%
	p_c	0.0650	0.0219	0.0371	0.0154	0.0213	0.0110	0.0153	
<i>Six coefficients are significant and model is adequate for further calculations.</i>									
P12 ($p = 0.1650$)	1.40065	0.015785	0.010959	-0.00522	-0.00388	0.00053	-0.00094	0.000951	NS/83.5%
	p_c	0.0412	0.0802	0.2549	0.3618	0.8873	0.8026	0.8008	

Notes: NS – not significant, S – significant, p_c – probability of coefficient.

Table 6 Regression coefficients for non-coded factors in significant models

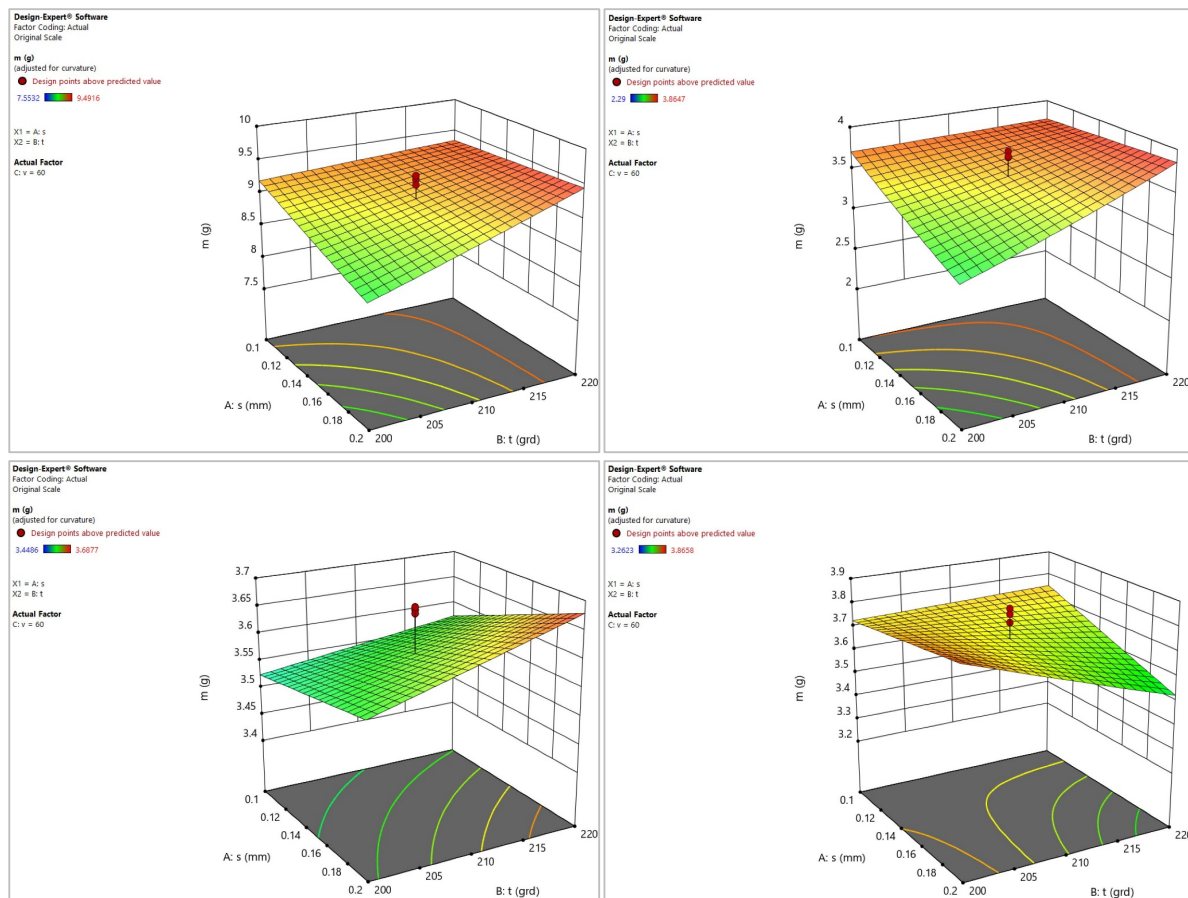
Program no.	b_0	b_1	b_2	b_3	b_{12}	b_{13}	b_{23}	b_{123}
P3	-0.5488632	27.2089437	0.01278318	0.06012228	-0.124367	-0.62281845	-0.000276	0.00285067
P7	-4.4661735	57.1830074	0.02625820	0.13790691	-0.258876	-1.39748544	-0.000627	0.00635246
P10	1.28515438	-0.02101646	0.00035423	-0.0004268	-0.001444	-0.02332026	$-6.9820 \cdot 10^{-6}$	0.00015336
P11	-1.9284124	34.2801101	0.01612945	0.03847543	-0.169285	-0.42713707	-0.0001928	0.00211908

Table 7 Function validation for significant models

Exp. no.	Program P3			Program P7			Program P10			Program P11		
	m [g]	$\ln(m)$ [g]	m_c [g]	m [g]	$\ln(m)$ [g]	m_c [g]	m [g]	$\ln(m)$ [g]	m_c [g]	m [g]	$\ln(m)$ [g]	m_c [g]
E1	9.3904	2.2086	9.1027	3.7767	1.2683	3.5547	3.6688	1.2773	3.5869	3.7665	1.3084	3.7003
E2	9.2591	2.2256	9.2591	3.7247	1.3150	3.7247	3.602	1.2815	3.602	3.7552	1.3231	3.7552
E3	9.1146	2.2099	9.1146	3.683	1.3037	3.683	3.4486	1.2380	3.4486	3.6932	1.3065	3.6932
E4	9.3896	2.2396	9.3896	3.7759	1.3286	3.7759	3.6414	1.2924	3.6414	3.7526	1.3225	3.7526
E5	9.3086	2.2309	9.3086	3.757	1.3236	3.757	3.5097	1.2555	3.5097	3.7475	1.3211	3.7475
E6	9.4463	2.2086	9.1027	3.7847	1.2683	3.5547	3.6576	1.2773	3.5869	3.8003	1.3084	3.7003
E7	9.4916	2.2504	9.4916	3.8462	1.3471	3.8462	3.6877	1.3050	3.6877	3.8088	1.3373	3.8088
E8	9.4098	2.2418	9.4098	3.8647	1.3519	3.8647	3.6699	1.3002	3.6699	3.2623	1.1824	3.2623
E9	7.5532	2.0220	7.5532	2.29	0.8286	2.29	3.5459	1.2658	3.5459	3.7518	1.3222	3.7518
E10	9.4729	2.2484	9.4729	3.8489	1.3478	3.8489	3.5963	1.2799	3.5963	3.8658	1.3522	3.8658
E11	9.3088	2.2086	9.1027	3.8452	1.2683	3.5547	3.6641	1.2773	3.5869	3.823	1.3084	3.7003

Notes: m – measured response, m_c – calculated response using proposed model.

Figure 8 Response surfaces for adequate models of programs, (a) P3 (b) P7 (c) P10 (d) P11 (see online version for colours)



Note: Where, $C: v = 60$ mm/min.

The final equation in terms of actual factors has the general form set by relation (2). Using expression (2) and the coefficient values provided in Table 6, the calculated responses are summarised in Table 7 for the four significant programs.

$$\ln(m) = b_0 + b_1 \cdot s + b_2 \cdot t + b_3 \cdot v + b_{12} \cdot s \cdot t + b_{13} \cdot s \cdot v + b_{23} \cdot t \cdot v + b_{123} \cdot s \cdot t \cdot v \quad (2)$$

The proposed significant models have been validated with a precision of 0.0001 g in relation to the measured response values. Response surfaces have been constructed for the validated models and are presented in Figure 8.

3.2 Second stage DOE – redesign of models

Second stage DOE involved the optimisation of the eight remaining programs. A new analysis was designed, with 33 experiment numbers for each of the eight programs which resulted not significant from the previous step. For safety reasons, three replicates, three blocks and three centre points were used for all redesigned experiments. In this case, the power of each factor is now set at 99.9%. From Table 8 it can be observed that out of eight programs, six were significant and two remained not significant, namely P1 and P9. For these two, the process of MRA is repeated by increasing the number of replicates, blocks and, consequently, the number of experiments per software run. Third stage of DOE involved testing of not significant programs with four replicas and the fourth stage tested the programs by running five replicas. P1 was found to be significant in a MRA with four replicates, four blocks and 44 experiments, whilst P9 was found to be significant in a MRA with five replicates, five blocks and 55 experiments. The obtained results are compounded in Table 9.

Actual factors of the models are calculated using equation (2) and for the redesigned models are presented in Table 10.

The mass of the samples was calculated using equation (2) and the non-coded factors for the redesigned models and compared with the measured response. The redesigned models have been validated with a precision of 0.0001 g.

The fitted surface adequately represents the analysed process if the following conditions are met (Table 11):

- a designed model is significant – the model F-value should be large, with $p < 0.05$
- b for programs with more than one replicates the lack of fit is insignificant – the F-value should be near one with $p > 0.10$
- c the models' precision should be adequate – parameter *adeq precision* should register a value greater than 4.00
- d the residuals are well behaved
- e the coefficient of determination is relevant – R^2 is as close as possible to 1.00 or for models with multiple replicates, the difference between *adjusted R^2* and *predicted R^2* is less than 0.2.

These criteria are evaluated hierarchically and iteratively. Redesign of models should lead to meeting all the above-mentioned criteria.

Adequate precision measures the signal to noise ratio, the desirable value being a ratio greater than 4. All designed models with an adequate precision above 4 can be used to navigate the design space, which is the case for all 12 proposed programs. For all redesigned models the *lack of fit* was registered as *not significant*, with an F-value of 0.00 and a p -value of 1.00. The *lack of fit* f-value of 0.00 implies the *lack of fit* is not significant relative to the pure error. There is a 100.00% chance that a lack of fit F-value this large could occur due to noise. Non-significant lack of fit is good, as the target is that the model fits to the prediction.

MRA was undertaken using ANOVA. In this case, residual analysis is necessary to confirm that the assumptions for the ANOVA are met. The Design-Expert® V11 Software uses a variety of residual plots and tools in order to offer appropriate diagnostics of the designed model. For the current research, the following have been used to validate the designed models: predicted vs. actual; residuals vs. predicted; residuals vs. run; residual vs. factor; cook's distance; leverage vs. run; DFFITS (difference in fits); DFBETAS (difference in beta coefficients). All residual plots were generated using externally studentised residuals.

The *predicted vs. actual* plot is used to analyse if points are scattered along a 45-degree line. For all 12 programs this type of plot did not show any groups of points above or below the line, which could indicate areas of over or under prediction. Models were accurate by *predicted vs. actual* plot. *Residuals vs. predicted* plot showed a random scatter arrangement of registered points for all designed models, which was the target. *Residuals vs. run* plot also showed a random scatter of points for all 12 models and no trends were registered. Externally studentised residuals outside limits were not registered when analysing these plots. *Residual vs. factor* plots are very useful for the models designed with more than one block. All plots are split by the zero-line at either end of the range and no obvious main effect (up or down) was registered in any analysed model. Only large differences were sought out. Cook's Distance is a tool which helped with identifying more than one residual outside the limits. No significant distances were observed in all runs. *Leverage vs. run* plot is significant when observing values at or beyond twice the average. These runs will excessively influence at least one model parameter. It was not the case for the proposed designed models, all runs were well within the average. The DFFITS evaluates the difference in fits which helps identify influential runs. No significant difference in fits was identified for the analysed models. The DFBETAS helps identify the difference in beta coefficients, breaking down the impact of any given run on a particular model item. No excessive values were observed, and all designed models were found to be significant.

An example of all analysed plots is given in Figure 9, for program P9.

Table 8 Regression coefficients for coded factors, probability and significance of models in second stage of DOE

Program no./probability	a_0	a_1	a_2	a_3	a_{12}	a_{13}	a_{23}	a_{123}	Model/confidence
P1/($p = 0.065$)	2.206358	0.012417	0.016103	0.011853	0.003737	0.012647	0.019518	-0.038928	NS/93.5%
P2/($p = 0.0001$)	2.175096	-0.002235	0.026592	-0.020372	0.034056	0.003956	-0.009611	0.018891	S/99.99%
P4/($p = 3.36 \cdot 10^{-9}$)	2.155832	-0.092008	0.019167	0.008861	0.010399	0.002858	-0.108563	-0.103916	S/< 99.99%
P5/($p = 2.30 \cdot 10^{-15}$)	1.287016	-0.017340	0.041709	-0.040392	0.037880	-0.050976	0.039837	0.019665	S/< 99.99%
P6/($p = 1.29 \cdot 10^{-10}$)	1.251581	-0.001810	0.020505	-0.008619	0.004962	-0.001946	-0.002414	0.001329	S/< 99.99%
P8/($p = 8.03 \cdot 10^{-6}$)	1.281646	-0.026704	-0.017910	0.036046	-0.040578	0.071188	0.062779	0.033040	S/< 99.99%
P9/($p = 0.054$)	1.245399	0.006734	0.011521	0.042989	0.000102	-0.029191	-0.022655	-0.021319	NS/94.6%
P12/($p = 7.89 \cdot 10^{-13}$)	1.400650	0.015785	0.0109589	-0.005224	-0.003876	0.000530	-0.000942	0.000951	S/< 99.99%

Note: Three replicates, 33 experiments per program.

Table 9 Regression coefficients for coded factors, probability and significance of models in third and fourth stage of DOE

Program no./probability	a_0	a_1	a_2	a_3	a_{12}	a_{13}	a_{23}	a_{123}	Model/confidence
P1/($p = 0.0087$)	2.206358	0.012417	0.016103	0.011853	0.003737	0.012648	0.019519	-0.038929	S/99.13%
P9/($p = 0.0124$)	1.245399	0.006734	0.011521	0.042989	0.000102	-0.029191	-0.022655	-0.021319	S/98.76

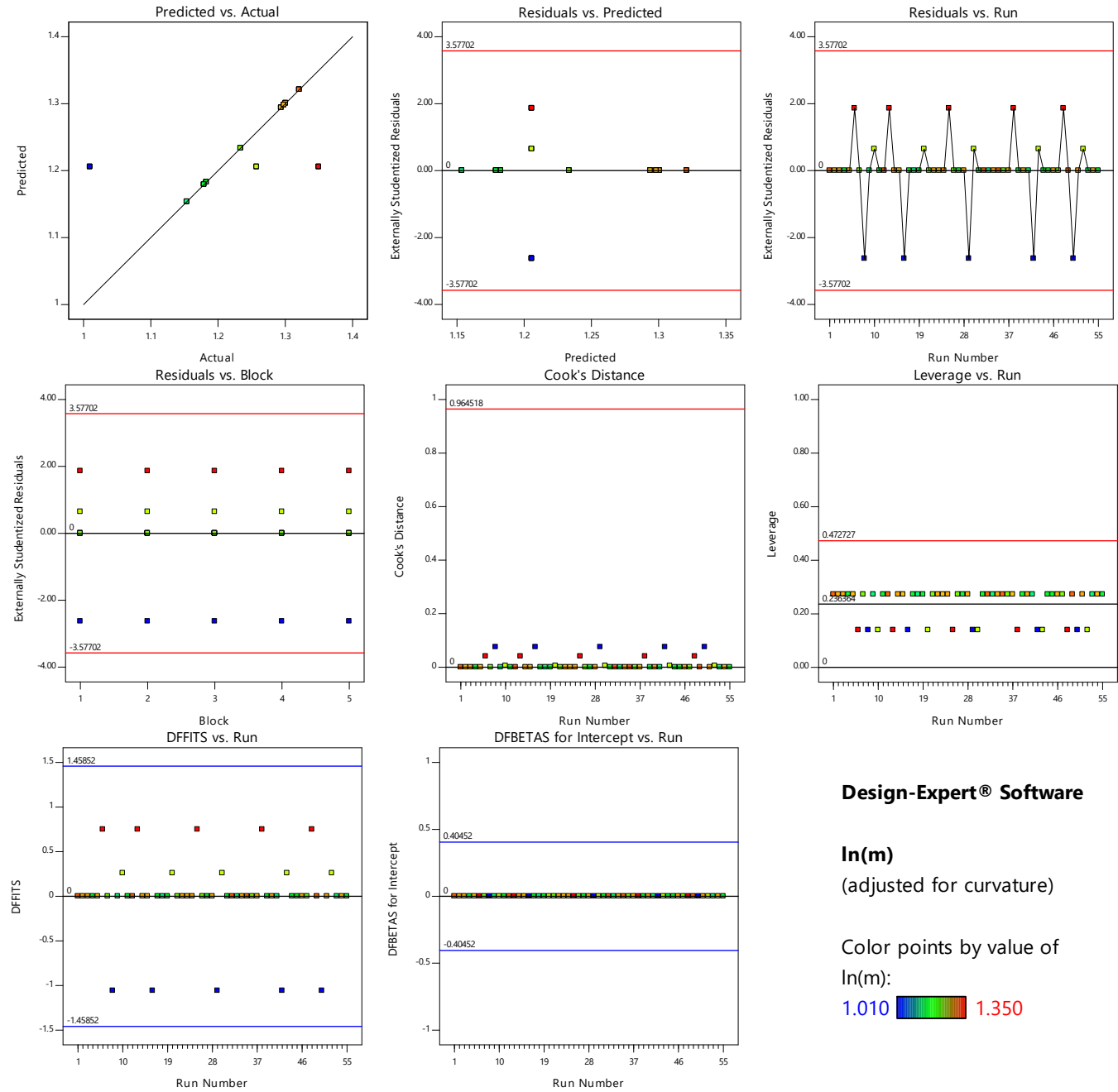
Table 10 Regression coefficients for non-coded factors in redesigned significant models

Program no.	b_0	b_1	b_2	b_3	b_{12}	b_{13}	b_{23}	b_{123}
P1	10.731838	-51.130207	-0.040402	-0.144424	0.241046	0.830148	0.000682	-0.003893
P2	-0.310291	9.217333	0.012328	0.067986	-0.045235	-0.392757	-0.000331	0.001889
P4	15.484294	-137.313643	-0.062159	-0.213330	0.644295	2.185097	0.0010160	-0.010392
P5	1.305051	11.580007	-0.001446	0.025743	-0.042230	-0.463943	$-9.579 \cdot 10^{-05}$	0.001967
P6	0.744042	-0.328614	0.002482	0.006583	0.001949	-0.029863	$-3.2 \cdot 10^{-05}$	0.000133
P8	-2.575480	53.868020	0.021285	0.029282	-0.279397	-0.622654	-0.000182	0.003304
P9	3.200083	-25.018892	-0.011269	-0.036840	0.128119	0.418510	0.000207	-0.002132
P12	0.660452	3.109428	0.003397	0.003642	-0.013455	-0.019432	$-1.89 \cdot 10^{-05}$	$9.51 \cdot 10^{-05}$

Table 11 Significance parameters for 12 designed models

Program no.	Model p -value	Model F -value	Adeq. precision	R^2	Adjusted R^2	Predicted R^2
P1	0.0087	3.34	4.5230	0.4220	0.2955	0.1971
P2	0.0001	7.67	7.6107	0.7093	0.6168	0.5763
P3	0.0092	107.71	34.2404	0.9974	-	-
P4	$3.36 \cdot 10^{-9}$	25.77	12.9278	0.8913	0.8567	0.8415
P5	$2.30 \cdot 10^{-15}$	103.79	33.1199	0.9706	0.9613	0.9572
P6	$1.29 \cdot 10^{-10}$	35.98	17.4983	0.9197	0.8941	0.8829
P7	0.0030	330.12	58.8921	0.9991	-	-
P8	$8.03 \cdot 10^{-6}$	10.70	10.4723	0.7730	0.7007	0.6691
P9	0.0124	2.98	4.0052	0.3319	0.2206	0.0980
P10	0.0045	223.92	48.2689	0.9987	-	-
P11	0.0200	49.32	25.0397	0.9942	-	-
P12	$7.89 \cdot 10^{-13}$	59.46	22.0011	0.9498	0.9338	0.9268

Figure 9 Residual plots for program P9 (see online version for colours)



Design-Expert® Software

ln(m)
(adjusted for curvature)

Color points by value of
ln(m):
1.010 1.350

Considering the aforementioned, all 12 proposed models have been validated as significant and can be used to undertake optimised mass calculation for FDM 3D printed parts, using the guidelines presented in this research.

4 Conclusions

The paper presents an accurate method for mass calculation of PLA 3D printed parts, using MRA. Dependency between the final mass of 3D printed specimens and three process parameters was expressed through a series of mathematical equations, based on a factorial type DOE. A set of 132 specimens were 3D printed using PLA materials from four different manufacturers. Natural filaments were

chosen in order to exclude changes in material properties due to various pigments. Three ISO test standards were used to print the specimens in one direction, as follows:

- ISO 527 tensile test specimens printed horizontally
- ISO 179 flexural test specimens printed normal
- ISO 178 Charpy impact test specimens printed normal.

In the first stage of DOE four programs were initially validated as their equation models resulted significant. Eight programs were improved by re-running a second stage DOE with a higher number of replicates and blocks. Each of the 12 designed models was evaluated for adequacy using the following criteria: significance of the model (large model

F-value and model p -value < 0.05); insignificant lack of fit; adequate precision of model, with registered values larger than 4.00; well behaved residuals; relevant coefficient of determination. The applicability of the method includes medium to large-scale production of parts, especially in industries where materials are quite expensive and mass variation has an important influence on final costs. Jewellery and medical/dental applications are some of the most appropriate for further development of the optimisation method, due to relatively reduced overall weight of the finished parts and high costs of the materials.

Further research includes validation of the method by manufacturing parts with various geometries using printing parameter values set in all significant programs.

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