Multivariable Regression Analysis for Optimised Mass Calculation of MEX 3D Printed Parts

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ABSTRACT
Since its introduction in the early 1990s Material Extrusion (MEX) has become the most popular additive manufacturing technology for a variety of applications. One of the reasons of its popularity amongst users is the affordability of the equipment, materials and the open source software. Given the large variety of combinations optimisation of MEX process parameters can be quite elaborate. The paper provides a method for optimisation of mass calculation using multivariable regression analysis. Layer thickness, printing temperature and printing speed were considered the independent variables for a two level factorial experimental program. DOE was used to plan 12 sets of programs, out of which four were found to have significant models. The four models were validated through measured and calculated responses.

KEYWORDS: Optimised Mass Calculation, Regression Analysis, Material Extrusion, Design Of Experiments

1. INTRODUCTION
Material Extrusion (MEX) is the most widespread Additive Manufacturing (AM) technology, followed by Selective Laser Sintering (SLS) and Stereolithography (SLA) [1, 2]. MEX adoption has known a consistent increase over the last few years, using PLA as the most common material, followed by ABS [2]. As MEX application areas expand [1] 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 MEX are the layer thickness, printing temperature and printing speed [3, 4, 5]. Print orientation, infill and raster angle have also been shown to highly influence final part properties [5, 6, 7]. Optimisation of process parameters specific to certain goals is quite complex, given the large variety of possible combinations provided by slicing software. Using 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 wher material costs are quite high and final part mass is important in overall fit and evaluation of the corresponding assemblies.
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 [8]. This type of statistical model has been previously used to attempt to assess the relationship between a number of variables, especially in the medical field for statistical processing of large volume data [9].

2. METHODS AND MATERIALS

The goal of the present research is to determine a more accurate method for mass calculation of MEX 3D printed parts, using multivariable regression analysis (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 design of experiments (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 program 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.
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 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** [°]	200°	210°	220°
3	Printing speed – **v** [mm/min]	40 mm/min	60 mm/min	80 mm/min

The base experimental program 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. For a significant evaluation of the three selected independent variables, a series of other process parameters were maintained constant, such as: Diameter of filament – 1.75mm; Nozzle size – 0.4 mm; Infill – 100%; Printing platform temperature – 60°C; Support structures – none; Build plate adhesion – blue tape; Wall thickness – 2 mm; Top/ Bottom thickness – 0.8 mm; Material flow – 100%; Fan: on.

Table 2: Design of experiments for three variables– Base experimental program

Experiment No.	Natural variables			Coded variables		
	s [mm]	**t** [°]	**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

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 DISCUSSIONS

Gcodes for all specimens were prepared using Cura 3.4 software, which gave a mass estimation of 10g for the tensile test specimens and 4g for both flexural and Charpy impact test specimens. Mass estimations are given by the Cura 3.4 software considering the filament diameter and a standard material type density. As, all PLA materials have the same material density input, the mass calculation will always be the same, regardless of the chemical composition of each material batch. Regardless of the changes in printing parameters, according to Table 2, the same two mass values were estimated by the software.

132 PLA material specimens were 3D printed and weighted individually using an analytical scale with a 0,0001 g precision (Figure 1).

Standard deviation for each set of parameters (E1 ÷ E11) was calculated, regardless the used material (Figure 2). 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 $t = 200^oC$; a printing speed of $v = 40\ mm/min$.

Figure 1: Example of coded specimens – a) tensile test specimens printed horizontally from M1; b) flexural test specimens printed normal from M2; c) Charpy impact test specimens printed normal from M3; d) weighing of tensile test specimen printed horizontally from M4

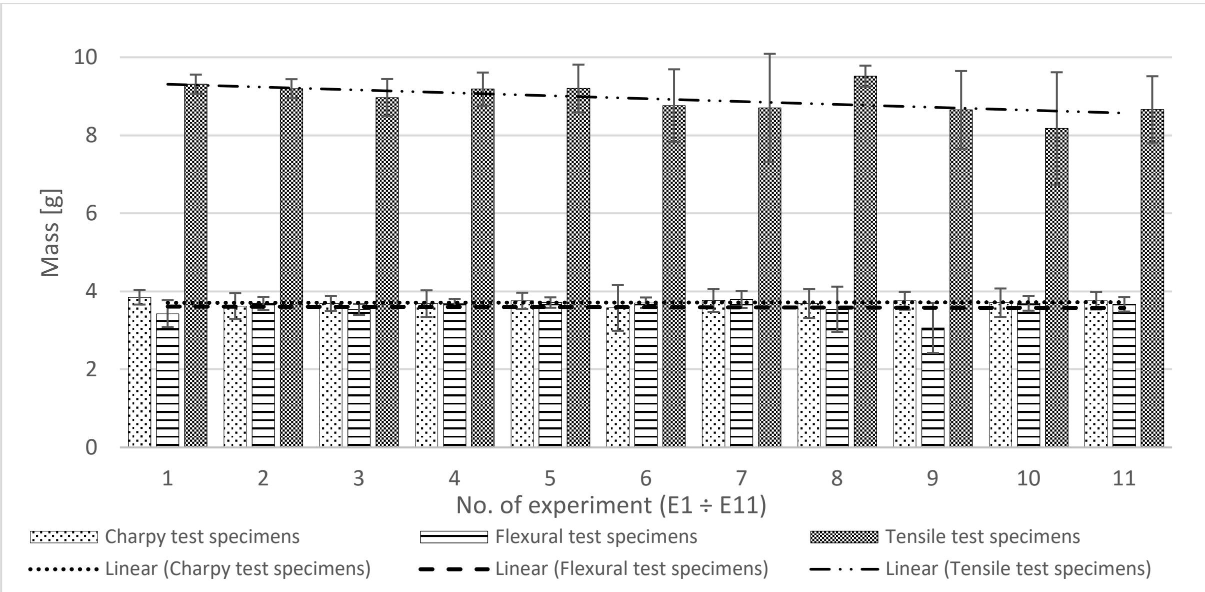

Figure 2: Average mass for 132 specimens for 11 experiment types

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 multivariable regression analysis using Design-Expert® V11 Software (Figure 3).

A natural logarithmic transformation was used to process all 132 responses.

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 4.

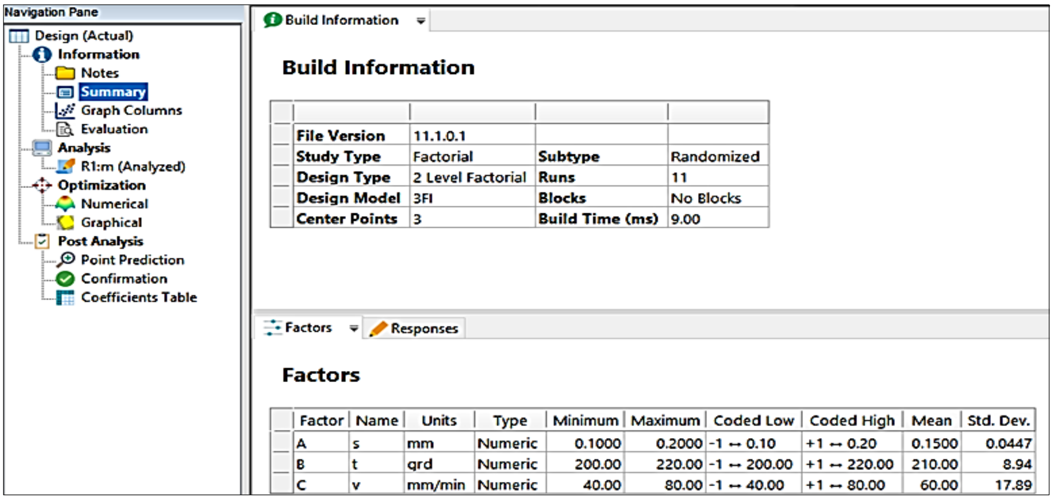

Figure 3: Input data for program P1 using Design-Expert® V11 Software

Table 4: 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	2.206358	0.012417	0.016103	0.011853	0.003737	0.012647	0.019519	-0.03893	NS / 4.88%
	p	0.7972	0.7406	0.8061	0.9378	0.7936	0.6905	0.4554	
	Recommendations: Repeat experiments no. 1 and 11								
P2	2.175096	-0.00223	0.026592	-0.02037	0.034056	0.003956	-0.00961	0.018891	NS / 30.05%
	p	0.9336	0.3792	0.4814	0.2880	0.8830	0.7249	0.5097	
	Recommendations: Repeat experiments no. 6 and 11								
P3	**2.20857**	**-0.01793**	**0.03210**	**-0.03028**	**0.02334**	**-0.02418**	**0.03027**	**0.02851**	**S / 99.08%**
	p	**0.0205**	**0.0065**	**0.0073**	**0.0123**	**0.0114**	**0.0073**	**0.0083**	
	All coefficients are significant and model is adequate for further calculations.								
P4	2.155832	-0.09201	0.019167	0.008861	0.010399	0.002858	-0.10856	-0.10392	NS / 66.84%
	p	0.1711	0.7051	0.8587	0.8348	0.9540	0.1320	0.1416	
	Recommendations: Repeat experiments no. 6								
P5	1.287016	-0.01734	0.041709	-0.04039	0.03788	-0.05098	0.039837	0.019665	NS / 90.09%
	p	0.2884	0.0749	0.0793	0.0887	0.0520	0.0812	0.2458	
	Recommendations: Repeat experiments no. 1 and 9								
P6	1.251581	-0.00181	0.020505	-0.00862	0.004962	-0.00195	-0.00241	0.001329	NS / 74.6%
	p	0.7439	0.0512	0.2162	0.4122	0.7260	0.6667	0.8089	
	Recommendations: Repeat experiments no. 6								
P7	**1.268285**	**-0.04946**	**0.069522**	**-0.06754**	**0.061136**	**-0.06347**	**0.065085**	**0.063525**	**S / 99.7%**
	p	**0.0049**	**0.0025**	**0.0026**	**0.0032**	**0.0030**	**0.0028**	**0.0030**	
	All coefficients are significant and model is adequate for further calculations.								
P8	1.281646	-0.0267	-0.01791	0.036046	-0.04058	0.071188	0.062779	0.03304	NS / 40.6%
	p	0.6165	0.7317	0.5111	0.4664	0.2579	0.3014	0.5430	
	Recommendations: Repeat experiments no. 1, 8 and 11								
P9	1.2454	0.006734	0.011521	0.042989	0.000102	-0.02919	-0.02265	-0.02132	NS / 2.11%
	p	0.9237	0.8702	0.5610	0.9988	0.6851	0.7506	0.7645	
	Recommendations: Repeat experiments no. 1, 6 and 11								
P10	**1.277278**	**0.010439**	**0.010989**	**-0.0112**	**0.003879**	**0.008885**	**0.003204**	**0.001534**	**S / 99.55%**
	p	**0.0027**	**0.0024**	**0.0023**	**0.0190**	**0.0037**	**0.0275**	**0.1058**	
	Six coefficients are significant and model is adequate for further calculations.								
P11	**1.308415**	**-0.00988**	**-0.01759**	**0.013368**	**-0.02107**	**0.01787**	**0.025013**	**0.021191**	**S / 98.00%**
	p	**0.0650**	**0.0219**	**0.0371**	**0.0154**	**0.0213**	**0.0110**	**0.0153**	
	Six coefficients are significant and model is adequate for further calculations.								
P12	1.40065	0.015785	0.010959	-0.00522	-0.00388	0.00053	-0.00094	0.000951	NS / 83.5%
	p	0.0412	0.0802	0.2549	0.3618	0.8873	0.8026	0.8008	
	Recommendations: Repeat experiments no. 2, 3 and 11								

NS – Not significant, S – Significant.

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.

The final equation in terms of actual factors have the general form set by relation (2). Using expression (2) and the coefficient values provided in Table 5, the calculated responses are summarised in Table 5 for the significant programs.

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

Table 5: Regression coefficients for non-coded factors

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 6: 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

m – measured response, m_c – calculated response

The proposed models have been validated with a precision of 0,0001g in relation to the measured response values.

4. CONCLUSIONS

The paper presented an accurate method for mass calculation of PLA 3D printed parts, using multivariable regression analysis. 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. Four programs were validated as their equation models resulted significant. Eight programs still need further improvements in order to be relevant to the measured responses, as follows: P1 – repeat experiments no. 1 and 11; P2 - experiments no. 6 and 11 must be repeated; P4 - repeat experiment no. 6; P5 - repeat experiments no. 1 and 9; P6 - repeat experiment no. 6; P8 - repeat experiments no. 1, 8 and 11; P9 - repeat experiments no. 1, 6 and 11; P12 - repeat experiments no. 2, 3 and 11.

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 the significant programs.

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