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ORIGINAL ARTICLE

Single and Multi-Objective Optimisation of Processing Parameters for Fused Deposition Modelling in 3D Printing Technology

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ABSTRACT – This paper presents practice and application of design of experiment techniques and genetic algorithm in single and multi-objective optimisation with low cost, robustness, and high effectiveness through 3D printing case studies. 3D printing brings many benefits for engineering design, product development, and production process. However, it faces many challenges related to parameters control. The wrong parameter setup can result in excessive time, high production cost, waste material, and low-quality printing. This study was conducted to optimise the parameter sets for 3D fused deposition modelling (FDM) products. The parameter sets are layer height, infill percentage, printing temperature, printing speed with different levels were experimented and analysed to build mathematic models. The objectives are to describe the relationship between the inputs (parameter values) and the outputs (printing quality in term of weight, printing time and tensile strength of products). Single-objective and multi-objective models, according to the user's desire, are constructed and studied to identify the optimal set, optimal trade-off set of parameters. The paper illustrates Taguchi parameter design that could yield accurate results with a minimal number of experiments to be performed compared with other design of experiment methods. This method is a simple and systematic methodology that is highly effective in optimising the process parameters with low cost. Besides, the paper proposed an approach which is a combination of the response surface methodology and genetic algorithm to solve the multi-objective optimisation problem. This method can fast identify overall Pareto-optimal solutions which define the best trade-off between competing objectives. 3D printer, testing machines, and quality tools were used for doing experiments, measurement and collecting data. Minitab and Matlab software aid for analysis and decision-making. Proposed solutions for handling multi-objective optimisation through 3D fused deposition modelling product printing case study are practical and can extend for other case studies.

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3D printing; Fused deposition modelling; Multi-objective optimisation; Design of experiment; Genetic algorithm

INTRODUCTION

Additive manufacturing (AM) has raised interesting awareness from society as state-of-the-art technology, in which engineers can build and adjust 3D complex geometry objects quickly to satisfy changes of customer's requirements and market. Several existing technologies with varying material types and forms have been developed intensively in AM field. Some common used AM techniques can include fusing of molten filament material (FDM), selective laser sintering/melting (SLS/M), electron beam melting (EBM), laser-photo resin curing (SLA), and laser cutting of sheet material (LOM). FDM was first introduced in 1992 by American company Stratasys [1]. Currently, FDM technology, works with specialised 3D printers, allows producing accurate parts with geometries and cavities complexity. Nowadays, small commercial machines with FDM based technology has a very reasonable price and become popular appliances in education organisation, company and even at home. The main FDM materials are PLA, ABS, PET, Nylon, TPU (flexible) and PC. This research works with PLA (polylactic acid) which are the most popular material in the market today. PLA provides good visual quality for products. However, it is quite rigid and brittle. Like 3D printing with other materials, FDM 3D printing using PLA is currently facing many problems about parameters control.

The default setting of printing process parameters given by the manufacturers cannot ensure the quality of printing products because many parameters can affect the printing process [2]. Wrong initial set up for printing parameters can result in excessive time, unnecessary weight and low tensile strength, and thus raise the production cost, waste material and make difficulties for individual users. In recent years, there are many research publications for optimising the parameter setup, which concentrates on FDM 3D printing with PLA. Tymrak, et al. investigated the impact of printing parameters at different values, i.e., pattern orientation and layer thickness to tensile strength and modulus elasticity of PLA and ABS parts [3]. In similar research topic, Singh Bual and Kumar found that the surface finish of plastic patterns made by FDM could improve by choosing proper build orientation and reducing layer thickness [4].

Zaldivar et al. researched the print orientation effects on the mechanical and thermal properties, and the strain field behaviour of ULTEM 9085. They concluded that build orientation affects the tensile strength, failure strain, Poisson's ratio, coefficient of thermal expansion and modulus significantly [5]. Johansson (2016) concluded that the main

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factors affected the quality of printing product is printing temperature, printing speed, and layer height. Printing at 250 ºC can help to increase seven times of load capacity than printing at 190 ºC. In term of layer height, 91% load capacity was boosted when printing at 0.1mm layer height instead of 0.4mm. Besides, 10 mm/sec printing speed illustrates better bonding connection than 130 mm/sec printing speed [6]. Other concerned printing parameters such as infill rate, density, raster angle also are studied in current years. In this research, four common printing parameters, i.e., layer height, infill percentage, printing temperature, printing speed, were investigated to show their effects to weight, printing time and tensile strength of printed parts produced by FDM 3D printer using PLA material. Choosing parameter set to optimise multi-objective for 3D printing was studied and suggested by analysing experiments and regression models.

APPROACHES TO THE EXPERIMENTAL DESIGN AND OPTIMISATION

Approach to the Experimental Design

An experimental design is a critical step that requires knowledge and techniques to conduct experiments economically, efficiently. Trial and error methods are traditional approaches in the technical and scientific investigation to verify and explain the observed phenomenon. They may include one-factor at-a-time or several factors one-at-a-time experimentation. However, these are poor experimental strategies, which may require expensive and prolonged testing. Mainly, the effect of interaction between factors cannot be studied. Therefore, the results may be not suitable or cannot be validated. Design of experiment (DOE) is a scientifically designed experiment strategy to provide a predictive knowledge of multi-factors and their interaction effects with fewer trials compared to traditional ones.

A full factorial experiment is one of the major approaches of DOE. It is designed for two or more factors. Factors with all-discrete possible levels and all possible combinations of all those factors were tested. A full factorial design with two factors is a common experimental design in product and process development. With 2k runs where k is the number of factors, two levels full factorial DOE is a comprehensive and effective approach to study the effect of each factor as well as the effects of interactions between them on the response variable.

However, when investigating higher numbers of factors with multi-levels, the number of experiments required by full factorial design is huge. Fractional factorial experiments can be used to reduce the number of runs and more cost-effective. These designs use only a portion of the total possible combinations of a full factorial design. An alias structure determines which effects are confounded with each other. The structure is carefully defined in a fractional factorial experiment for choosing a subset to estimate the main factor effects and some of the interactions. However, this may lead to the study limitation of interactions between factors. Dr. Genichi Taguchi, a Japanese statistician, developed a family of fractional factorial experimental designs, called Orthogonal Arrays (OAs). OAs maintain the orthogonality among the various factors and interactions and allow studying the entire parameter space with a very limited number of runs. Many researchers proved that optimisation with experimental designs using Taguchi OAs able to give valuable quantitative information, simultaneously optimise numerous factors and provides robust design solutions [7].

This research adopts Taguchi L16 orthogonal array to account for studied factors and their levels. Four-level four-factor design requires 4^4 or 256 experiments to study the effects of main inputs and their combination to the outputs in full factorial DOE technique. By using the Taguchi technique, the number of runs can be reduced significantly; therefore, the cost decrease. List of main parameters and their levels are shown in Table 1. Table 2 shows an experimental design of L16 orthogonal array. There are 16 experiments to be conducted based on the combination of independent design variables and their level values, as shown in the table. For example, the fifth experiment is conducted by keeping the independent design variable A (Layer height) at level 2, variable B (Infill percentage) at level 1, variable C (Printing temperature) at level 2, and variable D (Print speed) at level 3.

Approaches to Optimisation

There are numerous methods used to optimise 3D printing parameter set such as Taguchi method, full factorial, Respond Surface Method, gray relational, fuzzy logic, Genetic Algorithm (GA) and others. In this research, for the single objective optimisation, authors using the Taguchi method to study the critical factor and their suggested optimal value for each objective.

When dealing with multi-objective optimisation, authors propose building regression models for each objective by response surface methodology (RSM) and using GA to figure out the tradeoff optimal parameter set. GA is very flexible in dealing with integer, real variables or combination of both. It can solve problems with both continuous and discontinuous objective functions [8, 9, and 10]. NSGA-II algorithm, one of the most popularly applied GA for multi-objective optimisation, is used in this research. A brief description of NSGA-II procedure is described as follow. Firstly, a random parent population (size N) is generated. Next, by usual genetic operators namely selection, crossover and mutation, offspring population (size N) is created. NSGA-II uses binary tournament selection, SBX crossover, and polynomial mutation operators. Then offspring and parents are combined to form a population of size 2N. This population is classified into several non-dominated fronts by a non-dominated sorting. Then the members belonging to different non-dominated levels (starting from the first level) fill the new population (size N). Several non-dominated fronts were discarded. Only a few members of last fronts can be selected to enter the new population based on the crowding distance technique. The process was repeated until the termination conditions reach. Pareto optimal sets were displayed as the suggested solutions. NSGA-II shows the advantages of dealing with multi-objective optimisation problems compared with other methods [11, 12, 13, 14, and 15]. Therefore, it was adopted in this research.

Table 1. Control factors and their level.

Control factor	Level			
	1	2	3	4
A. Layer height	0.06	0.1	0.2	0.3
B. Infill percentage	20%	40%	60%	80%
C. Printing temperature	190	210	215	200
D. Print speed	30	40	50	60

Table 2: Design matrix L_{16} used in the experiment.

Expt. No.	Factor and interaction			
	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	1	4	4	4
5	2	1	2	3
6	2	2	1	4
7	2	3	4	1
8	2	4	3	2
9	3	1	3	4
10	3	2	4	3
11	3	3	1	2
12	3	4	2	1
13	4	1	4	2
14	4	2	3	1
15	4	3	2	4
16	4	4	1	3

SPECIMEN, PREPARATION, AND EXPERIMENTS

Figure 1 shows the steps involved in the experiment and optimisation process. In the first step, with the aid of 3D designing software, the testing sample is designed based on the ASTM D638 standard. ASTMD638 – Standard test method for tensile properties of plastic is the most common standard, which covers all tensile properties [16]. Dimensions of the specimen are given in Figure 2. After stereolithography (STL) file was exported from a 3D file, setting parameters for the printing process (given in Table 2) and slicing data created by the slicing software is uploaded to G-code (step 2) to insert to FDM printer. CURA slicing software, an open source software, used to process a 3D model into 3D printing structure for 3D printers. The printer builds up layer by layer and makes a finished object with prepared setup parameters (figure 3). Some post-processing can be implemented to increase the surface quality of objects after detaching from the printer platform (step 3).

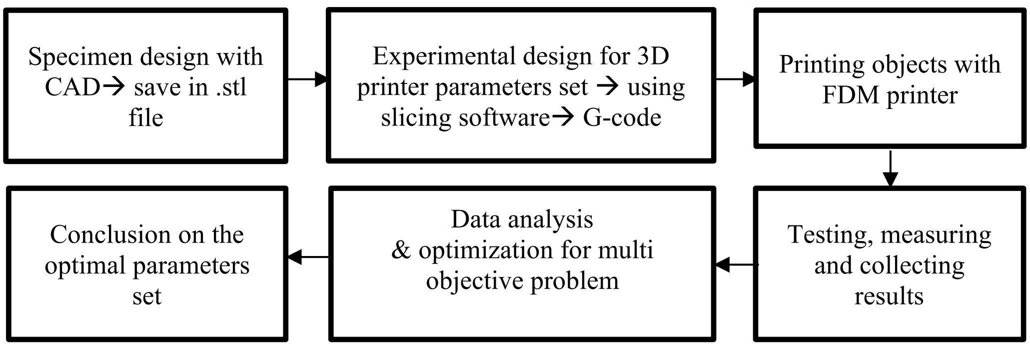


Figure 1. Flow chart showing preparation and performing steps.

In CURA software, the data of a printed part (weight and printing time) were estimated and displayed in the software interface. Nevertheless, to ensure the precision of the collected data, a mini scale is equipped for recording the weight of printed objects. Also, a stopwatch was used to record the printing time (start from extruder heating period until finished the object and take extruder back to a starting point of the machine). Shimadzu tensile testing machine was used for tensile strength experiment. During the tensile test, the printed objects were applied with force until they start to deform. Ultimate tensile strength (UTS) is the maximum stress that material can withstand.

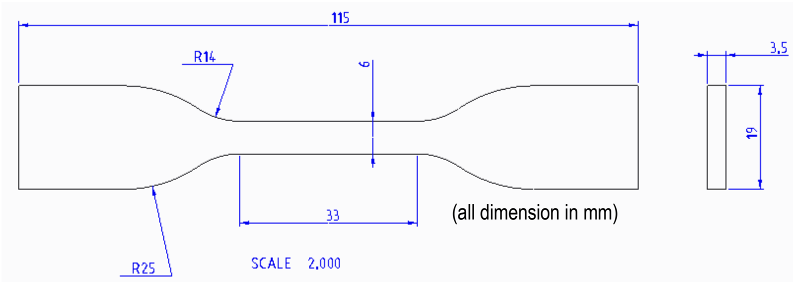
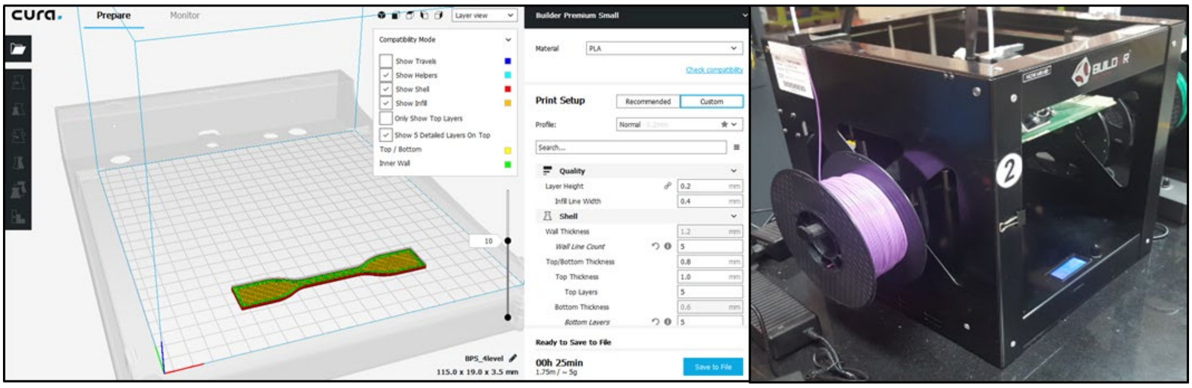


Figure 2. Specimen design according to ASTM D638.



(a) (b)

Figure 3. (a) CURA software interface and (b) FDM printer.

OPTIMISATION

Single objective optimisation

Taguchi method recommends the use of the loss function, which is further transformed into signal-to-noise (S/N) ratio in the optimisation process. Higher values of the S/N identify better design factor settings that make the system more robust and minimise the effects of the noise factors. Design factors are those able to be controlled while noise factors are impossible or too expensive to manage. They are sources of system variability. Three categories of performance characteristics, namely nominal-the-best, larger-the-better, and smaller-the-better, are usually used to analyse the S/N ratio. In this research, the authors want to minimise the printing time and weight of printed products. Therefore, the type of S/N analysis is smaller-is-better which is calculated as in Eq. (1) and (2) The goal of the research also is to maximise the tensile strength of printed parts. The larger-is-better S/N ratio is chosen for this analysis:

$$S/N = -10 * log_{10}(\frac{1}{n}\sum_{i=1}^{n} Y_i^2) \quad (1)$$

$$S/N = -10 * log_{10}(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{Y_i^2}) \quad (2)$$

Where Y is response and n is the number of replication. Table 3 shows the experimental results of the work carried out. Each of the 16 experiments (in Table 2) was conducted two times to account for variations that may occur due to noise factors. Minitab 18 software was used to calculate the S/N ratio and generates graphs for Taguchi method. Response tables for Taguchi design in Table 4 shows the average of S/N value corresponding to control factors at their different levels calculated for responses, i.e., weight, printing time and tensile strength. Figure 4(a) to 4(c) show mean S/N ratio versus parameter level for weight, printing time and tensile strength. From these graphs, the optimum values of factors and their levels for each of the objectives can be concluded in Table 5.

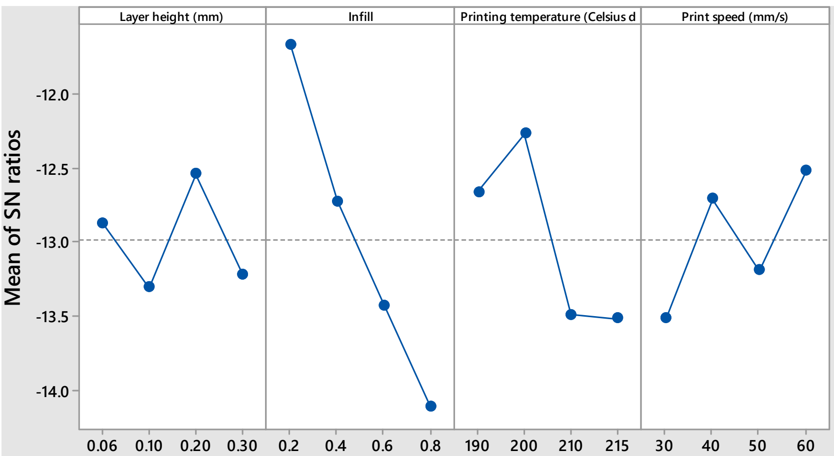
In the response table, the delta value was calculated by taking the highest average response value minus the lowest average response value for levels of one factor. The delta values were used to indicate the level of the factor impact on the response. The smaller order of rank represents the more significant influence on the output. For example, the factor which has the highest delta value was assigned as rank 1. In other words, this factor has the most significant influence on the response.

Table 3: Experimental results.

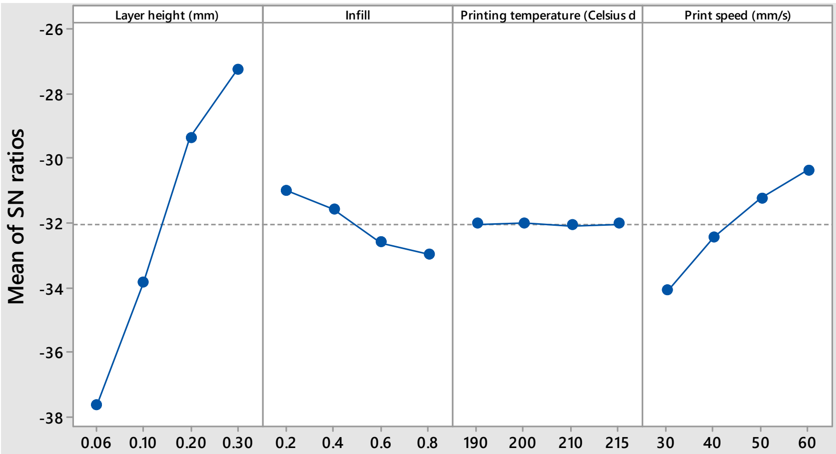
Sample No.	Coded value				Real value				First time			Second time		
									Y11	Y21	Y31	Y12	Y22	Y32
	A	B	C	D	Layer height (mm)	Infill	Printing temp. (°C)	Print speed (mm/s)	Weight (g)	Time (min)	Tensile strength (N/mm^2)	Weight (g)	Time (min)	Tensile strength N/mm^2
1	1	1	1	1	0.06	0.2	190	30	4	88	24.7810	4	88	24.9429
2	1	2	2	2	0.06	0.4	210	40	4.6	78	27.8190	4.6	78	27.1914
3	1	3	3	3	0.06	0.6	215	50	5.1	73	28.8905	5.1	73	28.8190
4	1	4	4	4	0.06	0.8	200	60	4	68	24.4324	4	68	24.0810
5	2	1	2	3	0.1	0.2	210	50	4	39	22.7171	3.9	39	22.3552
6	2	2	1	4	0.1	0.4	190	60	4.1	38	20.6481	4.2	38	22.3029
7	2	3	4	1	0.1	0.6	200	30	5	68	26.5886	5	68	27.9105
8	2	4	3	2	0.1	0.8	215	40	5.6	59	30.5962	5.6	59	30.1500
9	3	1	3	4	0.2	0.2	215	60	3.8	22	20.1767	3.9	22	19.7229
10	3	2	4	3	0.2	0.4	200	50	4	26	17.3995	4	26	18.4324
11	3	3	1	2	0.2	0.6	190	40	4	32	15.1762	3.6	32	13.1919
12	3	4	2	1	0.2	0.8	210	30	5.5	41	28.2352	5.5	41	26.7852
13	4	1	4	2	0.3	0.2	200	40	3.5	21	14.2486	3.6	21	14.9790
14	4	2	3	1	0.3	0.4	215	30	4.6	27	23.7208	4.6	27	23.2443
15	4	3	2	4	0.3	0.6	210	60	5	21	25.8457	5	21	26.3781
16	4	4	1	3	0.3	0.8	190	50	5.4	24	26.5543	5.4	24	25.9610

Table 4: Response table for S/N ratios.

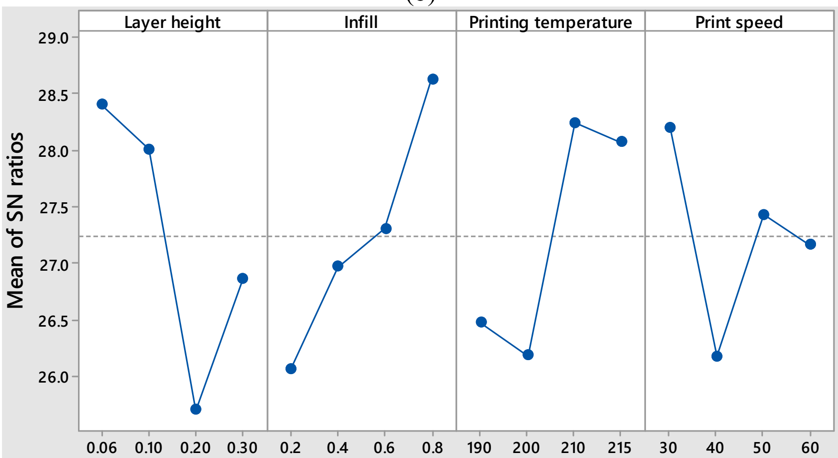
Level	Weight				Printing time				Tensile strength			
	A	B	C	D	A	B	C	D	A	B	C	D
1	-12.87	-11.67	-12.66	-13.52	-37.66	-31.00	-32.05	-34.11	28.40	26.07	26.57	28.21
2	-13.31	-12.73	-12.27	-12.71	-33.87	-31.59	-32.01	-32.45	28.01	26.98	26.19	26.27
3	-12.54	-13.43	-13.49	-13.19	-29.38	-32.62	-32.09	-31.25	25.80	27.40	28.24	27.43
4	-13.22	-14.12	-13.52	-12.52	-27.28	-32.98	-32.04	-30.38	26.86	28.63	28.07	27.17
Delta	0.77	2.44	1.25	1.00	10.38	1.98	0.08	3.72	2.60	2.56	2.05	1.94
Rank	4	1	2	3	1	3	4	2	1	2	3	4



(a)



(b)



(c)

Figure 4. Mean S/N ratio versus parameters for (a) weight, (b)printing time and (c) tensile strength.

Table 5. Optimum values of factors and their levels.

Control factor	Optimum value to minimise weight	Optimum value to minimise printing time	Optimum Value to maximise tensile strength
A: Layer height (mm)	0.2	0.3	0.06
B: Infill	0.2	0.2	0.8
C:Printing temperature (Celsius degree)	200	No matter	210
D:Print speed (mm/s)	60	60	30

From Table 4, infill and printing temperature are two factors that have the most significant impact on the weight of a printed object. Layer height and printing speed have the largest effect on the value of printing time. The effects of four factors (layer height, infill, printing temperature, and printing speed) on the value tensile strength have not much different. However, layer height and infill are two parameters that have more influent than the rest. From Figure 4(a), minimum infill was recommended for weight optimisation. A higher infill would end with a heavier part. Printing time, however, depend significantly on layer height and print speed. The maximum layer height and print speed resulted in the fastest printing time as in Figure 4(b). This finding was similar to the conclusion by previous researches [17, 18, 19, and 20]. For tensile strength, it was expected that the maximum infill and minimum layer height would result in better properties. It makes sense because with the same material, a solid part is always stronger and stiffer than other structures as in Figure 4(c).

Table 5 shows the optimal values of factors for each separate objective function by Taguchi method. These values should be double check with real conducted experiments. There is a problem when optimising single objective functions. This issue is the optimal calculated parameter set for one objective cannot guarantee good values for others. For example, the analysis of tensile test results in Table 4 and Figure 6 shows that, to increase the strength of FDM parts, smaller layer thickness, higher infill percentage, and lower printing speech were required. This analysis are similar to published research [21, 22, and 23]. From Taguchi parameter design in Table 5, the optimum parameter levels are 0.06 mm layer height, 80% infill, 210 ºC printing temperature, and 30 mm/s of print speed. These levels were not in the L16 conducted experiments. Therefore, one extra test has to do for these levels. The obtained tensile strength is 31.471 N/mm^2. The acquired tensile strength is much higher than the ones of which conducted in L16 Taguchi design experiment matrix. This means that Taguchi parameter design can give accurate results with a minimal number of experiments to be performed. However, this optimal parameter set is to maximise tensile strength and makes the system robust with the noises; it has no relevance to optimise other objectives. The weight of the additionally printed specimen is 5.9 g and printing time is 115 minutes. The achieved weight and printing time are worse than the ones in L16 designed experiments table.

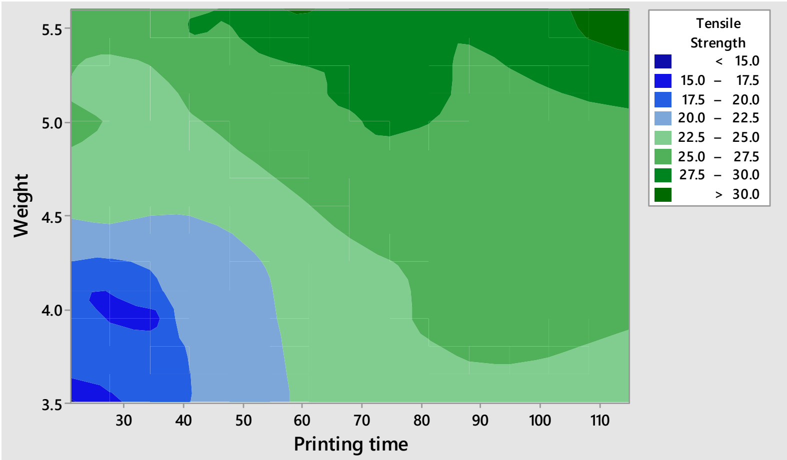


Figure 7. Contour plot of tensile strength vs. weight vs. printing time.

Dealing with several conflicting objectives is not easy, but it is a usual problem in 3D printing optimisation. Figure 7 highlights that a higher tensile strength is usually corresponding to a higher part weight and a longer printing time. Tensile strength and weight have a conflicted relationship. When increasing tensile strength is a priority, compromises on reducing weight cannot be made. However, printed parts can have the same tensile strength, but different weight and require different printing time due to the different printing parameter setup. To figure out the optimal conditions encompassing these objectives, multi-objective optimisation has to be done based on their relative importance to each other. In the next part, the authors propose an integrated method to optimise weight, printing time and tensile strength simultaneously. The decision making is based on multiple criteria which needs to consider trade-offs between objectives.

Multi Objective Optimisation

There are two main highlight works of this part. Firstly, the response surface methodology (RSM) is adopted for developing mathematical regression models. RSM is a statistical approach that suggests using a second – degree polynomial model to solve the correlation of input parameters with the output. Then NSGA-II is applied to obtain Pareto-optimal solutions. Minitab 18 is used to get the mathematical model based on the L16 designed experiments (Table 3) and three extra experiments mentioned in Table 7. The following second-order polynomial equations below can represent the mathematical models which present the functional relationship between control parameters of the process and output parameters:

$$\text{Weight} = 28.8 - 44.4\,A - 2.5\,B - 0.242\,C + 0.097\,D + 50.4\,A*A - 1.05\,B*B + 0.00051\,C*C - 0.00112\,D*D + 10.70\,A*B + 0.101\,A*C + 0.022\,A*D + 0.0488\,B*C - 0.1302\,B*D + 0.00028\,C*D \quad (3)$$
$(R^2 = 96.01\%)$

$$\text{Printing time} = 615 - 1240\,A + 207\,B - 3.9\,C - 3.95\,D + 1774\,A*A + 5.5\,B*B + 0.0079\,C*C + 0.0080\,D*D - 162\,A*B + 1.31\,A*C + 4.38\,A*D - 0.52\,B*C - 1.37\,B*D + 0.0121\,C*D \quad (4)$$
$(R^2 = 97.88\%)$

$$\text{Tensile strength} = -21 - 519\,A - 46\,B + 0.66\,C + 0.32\,D + 490\,A*A + 10.8\,B*B - 0.0021\,C*C - 0.0019\,D*D + 99.2\,A*B + 1.29\,A*C + 0.28\,A*D + 0.286\,B*C - 0.629\,B*D + 0.0005\,C*D \quad (5)$$
$(R^2 = 91.38\%)$

Where the variable A, B, C, D (defined in Table 1) represent layer height, infill percentage, printing temperature, and print speed, respectively. The statistical measure, R-squared (R^2), shows how well the regression model fits the data. The value of for weight, printing time and tensile strength are 96.01%, 97.88%, and 91.38%, respectively. These means that the regression models are suitable to explain the variation in the response variable significantly. The developed mathematical models are optimised simultaneously by using NSGA-II with the following parameters:

i. Population size: 100
ii. Maximum number of generations: 1000
iii. Crossover probability: 0.8
iv. Mutation probability: 0.2

In this part, two case studies are presented. The first one deals with minimising part weight and maximising tensile strength. These are two essential values in evaluating the quality of printed parts. The second objective (tensile strength) is modified to the standard form by getting its negative for minimisation. Case 1 is to minimise weight and negative tensile strength with objective 1= weight and objective 2= - tensile strength.

Figure 8 and Table 6 show the Pareto front or Pareto optimal results. Among Pareto-optimal solutions, there is no one better than others. Because to improve one objective, another objective has to sacrifice. Therefore all of them are considered equally good based on the different subjective desires of decision-makers. For example, if a user wants the printed part to have the tensile strength approximately 31 N/mm^2, then the set up printing parameters are at 0.06 mm layer height, 80% infill, 210 ºC printing temperature and 32 mm/s of print speed. These result in the best value of the part weight, i.e., 5.849 grams.

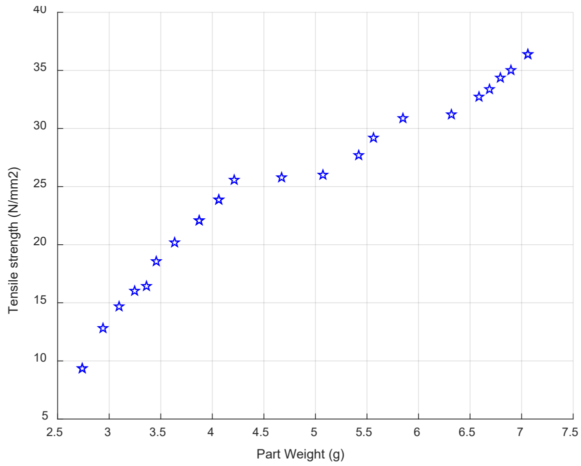


Figure 8. Pareto front of weight and tensile strength optimisation.

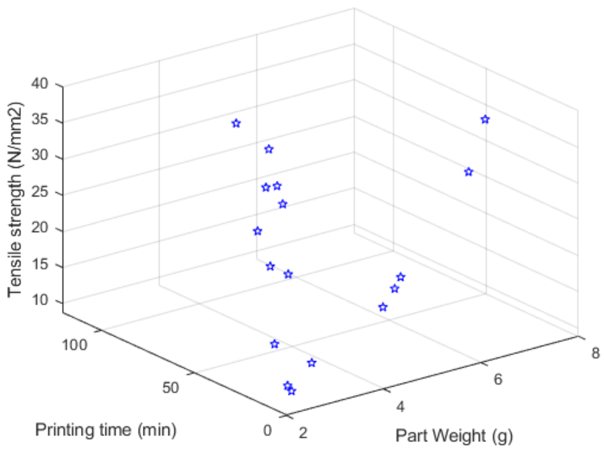


Figure 9. Pareto front of weight, printing time and tensile strength optimisation.

In 3D printing practical problems, there can be more than two objectives. In case 2, three conflict objectives were optimised simultaneously, i.e., minimum weight, minimum printing time and maximum tensile strength. While lightweight and higher tensile strength represent for good quality of a printed part, shorter printing time relates to lower operation cost. Again, maximising tensile strength was modified to the standard optimisation format which is to minimise the negative tensile strength where objective 1= weight, objective 2= printing time and objective 3= - tensile strength.

The Pareto-optimal solutions are obtained after operating the NSGA-II program and shown in Figure 9 and Table 7. The most suitable printing parameter combination was selected based on the requirements of engineers or users. The Pareto-optimal solutions suggest the best trade-off solutions for this three-objective optimisation problem.

Table 6. Pareto value set of weight and tensile strength optimisation.

A	B	C	D	Weight (g)	Tensile strength (N/mm^2)
0.07	0.6	200	31	5.073	26.0077
0.12	0.2	198	31	3.247	16.0213
0.07	0.7	207	34	5.420	27.6932
0.08	0.2	198	34	3.873	22.08
0.29	0.8	215	36	6.896	35.012
0.06	0.4	202	33	4.672	25.7835
0.21	0.2	199	30	2.739	9.3522
0.06	0.7	209	32	5.563	29.1971
0.29	0.8	214	38	6.794	34.3608
0.13	0.2	198	30	3.096	14.682
0.15	0.2	199	30	2.940	12.8112
0.12	0.2	198	33	3.361	16.4317
0.06	0.2	198	35	4.212	25.5713
0.1	0.2	198	31	3.457	18.5665
0.07	0.2	198	35	4.063	23.8689
0.28	0.8	213	38	6.587	32.7249
0.28	0.8	214	36	6.688	33.374
0.09	0.2	198	32	3.634	20.1848
0.06	0.8	210	32	5.849	30.8792
0.3	0.8	215	36	7.060	36.3809
0.08	0.2	198	34	3.873	22.08

Table 7. Pareto value set of weight, printing time and tensile strength optimisation.

A	B	C	D	Weight (g)	Time (min)	Tensile strength (N/mm^2)
0.21	0.2	199	30	2.739	18.757	9.352
0.24	0.8	207	60	4.620	7.168	22.318
0.3	0.8	215	30	7.146	27.917	37.084
0.06	0.8	190	30	5.572	121.088	28.414
0.09	0.7	196	31	5.127	87.258	24.546
0.24	0.7	206	59	4.563	8.889	20.615
0.24	0.7	199	58	4.350	9.657	18.349
0.1	0.7	193	32	5.022	81.443	22.918
0.08	0.3	193	32	4.152	72.129	21.864
0.15	0.2	198	31	3.008	32.882	12.939
0.11	0.4	192	30	4.071	63.184	18.193
0.28	0.8	213	42	6.463	18.885	32.124
0.21	0.3	197	32	3.329	21.328	11.121
0.13	0.5	192	30	4.253	58.257	17.346
0.09	0.7	191	30	5.098	92.542	23.766
0.23	0.2	198	30	2.750	16.966	8.788
0.08	0.8	197	30	5.469	100.733	27.423

CONCLUSION

Through 3D fused deposition modelling product printing single and multi-objective optimisation case studies, this paper can conclude that the application of Taguchi design experiment matrix can help to reduce the number of experimentations as compared with other DoE methods and yields similar results. While Taguchi method is a simple and systematic method to deal with a single objective optimisation, the method of integrated RSM and GA (NSGA-II) is an appropriate method to address the multi-objective optimisation problems. The confirmation tests with suggested optimal parameters verified the accuracy of Taguchi method for 3D FDM product printing single optimisation problem. The significant impact factors to the variance of response are also figured out and can be referenced sources for users when considering changes of the input parameters.

The method of integrated RSM and GA (NSGA-II) identify the best non-dominated set for 3D FDM product printing multi-objective optimisation effectively. Building regression models based on designed experiments is an important part before operating optimisation. RSM, using a second-degree polynomial model, is suitable for multilevel multifactor designs 3D FDM product printing problem. NSGA-II is applied and able to discover tradeoff solutions fast and efficient. There is no absolutely optimal solution to obtain minimum weight, minimum printing time and maximum tensile strength simultaneously in 3D FDM printing problem. However, the Pareto front offers adequate input-parameter combinations to get the best trade-off outputs that meet the users' requirements. The method can be applied for analysing other multilevel multi-factor design problems in practice.

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