Modeling, analysis, and optimization of dimensional accuracy of FDM-fabricated parts using definitive screening design and deep learning feedforward artificial neural network

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Abstract Additive manufacturing (AM) technologies such as fused deposition modeling (FDM) rely on the quality of manufactured products and the process capability. Currently, the dimensional accuracy and stability of any AM process is essential for ensuring that customer specifications are satisfied at the highest standard, and variations are controlled without significantly affecting the functioning of processes, machines, and product structures. This study aims to investigate the effects of FDM fabrication conditions on the dimensional accuracy of cylindrical parts. In this study, a new class of experimental design techniques for integrated second-order definitive screening design (DSD) and an artificial neural network (ANN) are proposed for designing experiments to evaluate and predict the effects of six important operating variables. By determining the optimum fabrication conditions to obtain better dimensional accuracies for cylindrical parts, the time consumption and number of complex experiments are reduced considerably in this study. The optimum fabrication conditions generated through a second-order DSD are verified with experimental measurements. The results indicate that the slice thickness, part print direction, and

number of perimeters significantly affect the percentage of length difference, whereas the percentage of diameter difference is significantly affected by the raster-to-raster air gap, bead width, number of perimeters, and part print direction. Furthermore, the results demonstrate that a second-order DSD integrated with an ANN is a more attractive and promising methodology for AM applications.

Keywords Artificial neural network (ANN) · Optimization · Definitive screening design (DSD) · Analysis of variance (ANOVA) · Fused deposition modeling (FDM) · Dimensional accuracy

1 Introduction

The use of additive manufacturing (AM), such as fused deposition modeling (FDM) technology, has increased significantly over the past few years [1–3]. Owing to increased global competitiveness and market pressures, improvements in AM in terms of productivity, product quality, and innovation have become extremely important. Hence, more accurate and reliable AM technologies are sought in various industries [4, 5]. Determining whether an AM process is appropriate for industry requires an understanding of the quality aspects of the technology in terms of productivity and dimensional accuracy. An ideal AM technology would have a dimensional accuracy of 100%, but such a manufacturing process does not exist. For an AM technology such as FDM, the quality and continuous improvement of the FDM process are crucial and must be evaluated systematically by validating and controlling the dimensional accuracy of systems. When an appropriate measurement procedure is used, the measurements of product quality and dimensional stability are accurate;

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hence, the quality characteristics can be controlled and the dimensional variations in the FDM manufactured products can be minimized [6]. However, a sizing operation to rectify the dimensions of the products after printing is difficult because the processed products exhibit apparent distortions and shrinkages. Furthermore, industries are becoming increasingly concerned and aware of the quality of FDM owing to its widespread use and expect a higher level of product performance than before. Therefore, the dimensional change must be controlled within a narrow range to avoid product rejection after manufacturing [7]. It is well known that FDM-processed parts tend to vary in dimensional accuracy and are often prone to distortions and shrinkages [8]. Numerous factors contribute to these undesirable effects on the product quality.

Some studies have proposed different approaches for FDM process parameter optimization. Camposeco-Negrete [9] investigated the effects of FDM process conditions on the processing time, energy consumption, and dimensional accuracy of FDM parts using the Taguchi method and desirability function. The results showed that layer thickness, road width, and printing plane were dominant factors. Mahmood et al. [10] used the Taguchi method to optimize the dimension and tolerance of FDM-built parts based on the fabrication parameters. It was discovered that the most influential parameters were the layer thickness, infill speed, infill shell spacing multiplier, number of shells, and extruder temperature. Furthermore, optimized FDM process parameters for better dimensional accuracies and geometric characteristics were also proposed. Maurya et al. [11] proposed a gray relational analysis to study the effects of FDM process parameters on the dimensional accuracy and international tolerance grades of FDM-built polycarbonate parts. It was observed that layer thickness was the most influential factor affecting the accuracy of FDM-printed parts. Recently, Aslani et al. [12] applied a robust Taguchi design based on an orthogonal array to determine the optimum process settings to optimize the dimensional accuracy of polylactic acid (PLA) printed via FDM. The results confirmed that the proposed approach was efficient, reliable, and could be successfully used for optimizing FDM process parameters. Nieciag et al. [13] investigated the accuracy of parts printed using different materials based on the FDM process with infill density ratios of 10%, 50%, and 90% for each material. The results showed that the accuracy of parts manufactured using the FDM process depended on the type of material used and the infill density. Ahmad and Mohamad [14] used the Taguchi approach to establish a relationship between FDM process parameters and accuracy of built parts. The results showed that the Taguchi method was promising for optimizing and predicting the accuracy of FDM-fabricated parts. Armillotta et al. [15] investigated the effects of geometric variables,

i.e., the part size in three directions and the thickness of deposited layers, on the distortion (warpage) of FDM-built parts using statistical analysis. The results showed that thicker layers resulted in more warpage. Dilberoglu et al. [16] proposed a particular infill structure to improve the dimensional accuracy of FDM-built parts using finite element analysis (FEA). Additionally, the authors developed a shrinkage compensation approach for additively manufactured acrylonitrile butadiene styrene (ABS) parts. FEA results confirmed that the dimensional accuracy was highly affected by the height of the parts, and that shrinkage was significant at the outer frame of the built parts. Haghighi and Li [17] investigated the relationship between the dimensional accuracy and processing cost of FDM-fabricated parts. The optimum setting of FDM fabrication parameters for simultaneously improving the dimensional accuracy and processing cost were determined using the desirability function. In general, the results indicated that the layer thickness, inclination, and their interactions significantly affected the dimensional accuracy and processing cost. Jafari-Marandi et al. [18] developed an artificial neural network (ANN)-based cost-driven classification approach for the porosity prediction of laser-based AM. Their results demonstrated the potential, accuracy, and cost-effectiveness of the developed method for porosity prediction, unlike recently developed optimization approaches. Karthikeyan et al. [19] applied the Taguchi L9 orthogonal array design to study the effects of wire cut electric discharge machining parameters on the material removal rate and surface roughness of Ti6Al4V. Furthermore, they used an ANN and a genetic algorithm to determine the optimum process settings to minimize material removal while validating the surface roughness. The results confirmed that the proposed approach was efficient, reliable, and could be successfully extended for optimizing FDM process parameters.

It is noteworthy that previous related studies have primarily focused on FDM process parameters to minimize dimensional errors. Many studies and experiments have been conducted to improve the dimensional accuracy through experimental design by optimizing the input parameters and improving the slicing strategy. Previous studies revealed that FDM process variables significantly affected the dimensional stability of FDM prototypes. Many studies have been conducted to optimize FDM dimensional accuracy using traditional experimental designs. The main limitation of those previous studies is that the effects of FDM process parameters are analyzed on rectangular parts. However, FDM can be used to easily manufacture parts of different geometrical shapes. For example, when FDM is used to manufacture a cylindrical shape, inappropriate FDM process parameters can cause visible defects on the cylindrical part. This problem is frequent, particularly for thin

samples, as in the manufacturing of cylindrical bones, rods, and tubes for medical applications. Moreover, previous studies have investigated the effects of FDM process variables on the dimensional accuracy of processed parts using traditional statistical approaches. However, to obtain reasonable results using traditional optimization techniques, numerous simulations and experiments are required for each design. This is cost prohibitive and time consuming. Moreover, the effects of the key parameters of the FDM process and the manner in which they enhance the dimensional accuracy of cylindrical parts have not been elucidated. Unlike previous studies, this study investigates aspects other than the effects of few processing conditions on the dimensional stability of rectangular parts.

The definitive screening design (DSD) technique has been proposed recently [20]. It is a new class of three-level experimental design that demonstrates superior performance to the classical experimental design and provides a better estimation of main and interaction effects that are not confounded with any quadratic terms [21]. Performing an efficient second-order DSD has been discovered to be appropriate for factor screening, fitting a quadratic model, and avoiding the need for follow-up experiments [22]. It is of particular interest to manufacturing engineers who must characterize complex systems such as those used in AM technologies, particularly when many parameters are involved in those systems. FDM systems have an overwhelming number of processing parameters that involve numerous interaction effects [8], which affect the quality and functionality of the manufactured products. Processing a large number of parameters can be challenging. Practitioners and AM users encounter several barriers when adopting experimental design and optimization process parameters. These barriers are cost-effective experimental designs and model selections when the main and quadratic effects are active. When the problem involves more than four variables, it can be cost prohibitive and time consuming to use traditional experimental designs such as conventional response surface designs and full-factorial experimental designs. When the financial resources for performing an experiment are significantly restricted and limited, a suitable method is to use multistage approaches based on a screening design. This can be cost prohibitive because each design stage comprises its own experimental runs. For example, to study the effects of six process variables and validate the presence of a set of main, interaction, and quadratic effects, the required number of experimental runs would be 90 without replication when using traditional response surface designs for optimization. Therefore, it can be cost prohibitive and time consuming to gather data for all experimental runs.

The main objective of the present study is to assess the extent to which variations in several key fabrication parameters of FDM affect the dimensions of cylindrical

parts. In contrast to previous studies, this study analyzes the effect of the interaction of build factors on the part dimensional accuracy, as well as introduces the application and performance of a new class of experimental “second-order DSD” integrated with an ANN in AM technologies. The outline of the proposed approach combining the response surface DSD and an ANN is shown in Fig. 1. The applications of an integrated second-order DSD and an ANN will benefit researchers and the AM industry in developing future engineering applications.

2 Methodology

2.1 Experimental study

A total of 16 cylindrical samples measuring 40 mm in length and 10 mm in diameter were fabricated using the FDM Fortus 400 system based on the DSD matrix presented in Table 1. All test samples were prepared using a polycarbonate/acrylonitrile butadiene styrene (PC-ABS)

Fig. 1 Schematic diagram of experimental procedure

blend developed by Stratasys Inc. The samples used in this study were modeled in PTC Creo and then exported in stereolithography format. Subsequently, the stereolithography file was exported to the FDM Fortus 400 system (Insight Software version 9.1) to set up all the process parameters. Dimensional accuracy measurements were conducted along the length and diameter using a digital caliper of accuracy 0.01 mm. Three measurements were performed and repeated four times; subsequently, the average percentage differences in the length and diameter were obtained. The dimensional accuracy of the FDM-built parts for each fabricated sample was compared with the nominal dimension (CAD model) to determine the percentage difference in the dimensional accuracy using Eq. (1).

Percentage difference

$$= \left| \frac{\text{Measured value} - \text{Designed value}}{(\text{Measured value} + \text{Designed value})/2} \right| \times 100. \quad (1)$$

2.2 Experimental design

In this study, the effects of six input variables, i.e., slice thickness, raster-to-raster air gap, deposition angle, part print direction, bead width, and number of perimeters were investigated, and the dimensional accuracy in terms of the percentage difference in part length (ΔL) and part diameter

(ΔD) between the computer-aided design (CAD) model and the manufactured part was selected as the primary responses of interest. Owing to the FDM system constraints at the center level of the slice thickness and the number of perimeters, the center level for those variables was modified. Table 2 shows the six main FDM process parameters, their designated symbols, and the range of levels selected for this study. Figure 2 graphically shows the meaning of all the selected process parameters.

The DSD required a minimum of $2k + 1$ experimental runs, where k is the number of considered process variables [20]. Therefore, the investigation of the effects of the six process parameters required a minimum of 13 runs, including one center point. A DSD matrix with 13 runs was augmented with three additional replicate center points, which were then added to the experimental runs, resulting in a total of 16 runs (see Table 1). This was performed to improve the accuracy and performance of the experimental design and determine the curvature of the response.

Figures 3a and b show the prediction variance plots for the augmented DSD. The plot views the prediction variance across the region of interest in the center for each factor. As shown in Figs. 3a and b, the augmented DSD matrix had a constant and extremely low prediction variance (prediction error). The low prediction variance implies that the difference between the predicted and experimental values would be extremely low.

Table 1 DSD matrix and measured responses

Run	Process parameters						Dimensional accuracy/%	
	X_1	X_2	X_3	X_4	X_5	X_6	Percentage difference in length	Percentage difference in diameter
1	0.127 0	0	0	90	0.517 7	10	0.672 730	– 1.816 350
2	0.330 2	0.25	0	90	0.578 2	1	1.3656 110	8.061 420
3	0.127 0	0.50	45	90	0.457 2	1	0.647 894	– 1.918 220
4	0.127 0	0.50	0	0	0.578 2	5	– 0.325 530	1.291 605
5	0.127 0	0	90	45	0.578 2	1	0.174 847	– 1.409 870
6	0.330 2	0.50	0	45	0.457 2	10	0.697 559	– 1.714 570
7	0.254 0	0	0	0	0.457 2	1	0.821 611	1.192 843
8	0.330 2	0.50	90	0	0.517 7	1	1.192 843	1.882 120
9	0.127 0	0.25	90	0	0.457 2	10	0.224 747	– 0.803 210
10	0.330 2	0	90	90	0.457 2	5	0.871 189	– 2.122 280
11	0.254 0	0.50	90	90	0.578 2	10	0.647 894	– 1.714 570
12	0.254 0	0.25	45	45	0.517 7	5	0.937 097	3.729 146
13	0.330 2	0	45	0	0.578 2	10	0.772 008	1.587 302
14	0.254 0	0.25	45	45	0.517 7	5	0.995 025	3.632 793
15	0.254 0	0.25	45	45	0.517 7	5	0.908 133	3.052 683
16	0.254 0	0.25	45	45	0.517 7	5	0.951 579	3.439 803

Table 2 Range of FDM process conditions

Variables	Symbols	Levels		
		Low	Center	High
Slice thickness/mm	X_1	0.127 0	0.254 0*	0.330 2
Raster to raster air gap/mm	X_2	0	0.25	0.5
Deposition angle/(°)	X_3	0	45	90
Part print direction	X_4	0	45	90
Bead width/(°)	X_5	0.457 2	0.517 7	0.578 2
Number of perimeters	X_6	1	5*	10

*Modified level

Fig. 2 FDM process variables **a** tool path parameters, **b** part print direction, and **c** slice thickness

3 Results and discussion

3.1 Second-order DSD model

An analysis of the experimental data obtained from the DSD was conducted using a second-order response surface model expressed as follows

$$Y = \beta_0 + \sum_{i=1}^6 \beta_i X_i + \sum_{i=1}^6 \beta_{ii} X_i^2 + \sum_{i < j}^6 \beta_{ij} X_i X_j + \varepsilon, \quad (2)$$

where Y is the experimental response, X_i and X_j the coded factors, β_0 the intercept, β_i the linear coefficient, β_{ii} the quadratic term, β_{ij} the interaction coefficient, and ε the noise observed in the response Y .

For a six-factor problem, the quadratic model can be formulated as shown in Eq. (3).

$$\begin{aligned} Y = & \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 \\ & + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{14} X_1 X_4 + \beta_{15} X_1 X_5 \\ & + \beta_{16} X_1 X_6 + \beta_{23} X_2 X_3 + \beta_{24} X_2 X_4 + \beta_{25} X_2 X_5 \\ & + \beta_{26} X_2 X_6 + \beta_{34} X_3 X_4 + \beta_{35} X_3 X_5 + \beta_{36} X_3 X_6 \\ & + \beta_{45} X_4 X_5 + \beta_{46} X_4 X_6 + \beta_{56} X_5 X_6 + \beta_{11} X_1^2 + \beta_{22} X_2^2 \\ & + \beta_{33} X_3^2 + \beta_{44} X_4^2 + \beta_{55} X_5^2 + \beta_{66} X_6^2, \end{aligned} \quad (3)$$

where β_1 – β_6 are the linear coefficients.

$\beta_{12}, \beta_{13}, \beta_{14}, \beta_{15}, \beta_{16}, \beta_{23}, \beta_{24}, \beta_{25}, \beta_{26}, \beta_{34}, \beta_{35}, \beta_{36}, \beta_{45}, \beta_{46}$, and β_{56} are the interaction coefficients. $\beta_{11}, \beta_{22}, \beta_{33}, \beta_{44}, \beta_{55}$, and β_{66} are the squared coefficients.

JMP software version 11 was used for analyzing the experimental data, and the construction of plots and mathematical model for each response was established. The results of the multiple regression analysis for the

Fig. 3 Prediction variance **a** prediction variance plot, and **b** the fraction of design space

percentage difference in length and diameter derived using the best-fit method are shown in Eqs. (4) and (5) as follows

$$\begin{aligned} \text{Percentage difference in length} &= 0.863 + 0.347 \\ &\times \frac{X_1 - 0.2286}{0.1016} - 0.041 \times \frac{X_2 - 0.25}{0.25} - 0.015 \\ &\times \frac{X_3 - 45}{45} + 0.149 \times \frac{X_4 - 45}{45} - 0.059 \times \frac{X_5 - 0.5177}{0.0605} \\ &- 0.118 \times \frac{X_6 - 5.5}{4.5} + \frac{X_1 - 0.2286}{0.1016} \times \frac{X_1 - 0.2286}{0.1016} \\ &\times (-0.275) + \frac{X_3 - 45}{45} \times \frac{X_4 - 45}{45} \\ &\times (-0.330) + \frac{X_1 - 0.2286}{0.1016} \times \frac{X_6 - 5.5}{4.5} \times (-0.014) \\ &+ \frac{X_5 - 0.5177}{0.0605} \times \frac{X_6 - 5.5}{4.5} \times 0.136. \end{aligned} \quad (4)$$

$$\begin{aligned} \text{Percentage difference in diameter} &= 4.564 - 1.867 \\ &\times \frac{X_1 - 0.2286}{0.1016} + 10.075 \times \frac{X_2 - 0.25}{0.25} + 2.713 \\ &\times \frac{X_3 - 45}{45} + 3.365 \times \frac{X_4 - 45}{45} + 11.354 \\ &\times \frac{X_5 - 0.5177}{0.0605} + 5.706 \times \frac{X_6 - 5.5}{4.5} + \frac{X_2 - 0.25}{0.25} \\ &\times \frac{X_2 - 0.25}{0.25} \times (-5.006) \\ &+ \frac{X_1 - 0.2286}{0.1016} \times \frac{X_3 - 45}{45} \times (-138.667) + \frac{X_2 - 0.25}{0.25} \\ &\times \frac{X_4 - 45}{45} \times (-139.141) \\ &+ \frac{X_2 - 0.25}{0.25} \times \frac{X_5 - 0.5177}{0.0605} \times 0.186 + \frac{X_5 - 0.5177}{0.0605} \\ &\times \frac{X_6 - 5.5}{4.5} \times 139.602. \end{aligned} \quad (5)$$

In the regression models expressed in Eqs. (4) and (5), positive and negative signs were observed for the regression coefficients. The negative sign indicates a decrease in the percentage difference in dimension with a decrease in the factor levels, whereas the positive sign suggests an increase in the percentage difference in dimension with an increase in those factors. The results obtained from the analysis of variance (ANOVA) for the percentage differences in length and diameter, as presented in Tables 3–6, showed that the quadratic polynomial model was significant ($p < 0.05$) and the lack-of-fit test was not significant ($p > 0.05$). Hence, the second-order model was appropriate for fitting the experimental data for the percentage differences in length and diameter. The quality-of-fit of the developed equations for the percentage differences in length and diameter was performed, and the summary of the fit results are shown in Tables 3–6. The coefficient of determination (R^2) values for the percentage differences in length and diameter were 99.84% and 99.79%, respectively. Moreover, scatter plots of actual versus predicted values are presented in Fig. 4, which depict the fit of the models to the experimental data. It is evident from Fig. 4 that the predicted values correlate well with the actual values. Hence, the established models are discovered to be statistically excellent for all response variables.

Tables 7 and 8 show the sorted parameter estimates for the percentage differences in length and diameter. The sorted parameter estimate report is useful for screening and optimization experiments. The size of the regression coefficient effects depends not only on the strength of the variable, but also on the spread of the levels. The sorted

Table 3 ANOVA for the percentage difference in length

Source	Degree of freedom (DoF)	Sum of squares	Mean square	<i>F</i> ratio	<i>p</i> -value	Remarks
Model	10	2.532 746 40	0.253 275	317.588 0	< 0.000 1	Significant
Lack of fit	2	0.000 055 07	0.000 028	0.021 0	0.979 4	Not significant
Pure error	3	0.003 932 41	0.001 311	—	—	—
Total	15	2.536 733 88	—	—	—	—

Table 4 Summary of fit data of Table 3

Source	Values
R^2	99.84%
R^2 adjusted	99.53%
Root mean square error	0.028 24
Mean of response	0.722 202
Observations	16

Table 6 Summary of fit data of Table 5

Source	Values
R^2	99.79%
R^2 adjusted	99.20%
Root mean square error	0.258 98
Mean of response	1.023 188
Observations	16

parameter estimates presented in Tables 7 and 8 graphically show the strength of the main, interaction, and quadratic effects in terms of their respective *p*-statistics. The *t* ratio is the ratio of the regression coefficient of the parameter to its standard deviation. It evaluates whether the true value of the factor and the regression coefficient are zero.

Table 1 shows the measured responses in terms of the percentage differences in length and diameter. A positive percentage difference in the dimension indicates an increase in the length and diameter comparing with the designed dimension, i.e., a length and diameter extension. A negative value represents a decrease in the length and diameter, and hence shrinkage. The ANOVA results presented in Tables 7 and 8 indicate that the slice thickness, part print direction, and interaction effect between the deposition angle and part print direction significantly affect the percentage difference in length. It was observed that shrinkage appeared predominantly along the diameter of the part rather than the length. Furthermore, Table 1 shows that the increase in the diameter from its designed value is large. Shrinkage is fully attributed to the contraction of the extruded layer and fiber due to thermal and cooling cycling

from a molten to solid state. Temperature gradients are the main reason for the dimensional instability of the parts. When the FDM system deposits the first layer on the built plastic sheet, the first built layer will not shrink and warp. However, when the FDM system deposits the new layer, the locally remelted bottom deposited layer must be bounded with the new layer. Owing to the remelting process of the built layer, distortion and shrinkage will occur. Therefore, the printed part tends to exhibit dimensional instability. The response surface plots presented in Figs. 5a–d and Figs. 6a–d show that the percentage difference in length increases gradually with the slice thickness (slice height). As the slice thickness and part print direction increase (see Figs. 5a and 6a), the dimensional accuracy of the overall processed part decreases because the staircase effect decreases with the decrease in both the slice thickness and part print direction. Furthermore, Figs. 5b and 6b show that an increase in the deposition angle occurs with an increase in the part print direction because higher deposition angles generate fewer rasters, which are subjected to minimum distortions. This not only improves the dimensional accuracy of the manufactured parts, but also improves the mechanical properties. When

Table 5 ANOVA for the percentage difference in diameter

Source	DoF	Sum of squares	Mean square	<i>F</i> ratio	<i>p</i> -value	Remarks
Model	11	125.367 20	11.397 0	169.925 4	< 0.000 1	Significant
Lack of fit	1	$8.858 01 \times 10^{-8}$	8.858×10^{-8}	0.000 0	0.999 3	Not significant
Pure error	3	0.268 282 75	0.089 428	—	—	—
Total	15	125.635 49	—	—	—	—

Fig. 4 Predicted versus actual plots for percentage difference in **a** length, and **b** diameter

Table 7 Sorted parameter estimates for the percentage difference in length

Term	Estimate	Std error	<i>t</i> ratio	Sorted parameters	Prob > <i>t</i>
X_1	0.347 116	0.008 938	38.83		< 0.000 1
X_3X_4	- 0.330 422	0.013 584	- 24.32		< 0.000 1
X_4	0.149 340	0.008 940	16.71		< 0.000 1
X_1^2	- 0.275 288	0.017 835	- 15.44		< 0.000 1
X_6	- 0.118 202	0.008 942	- 13.22		< 0.000 1
X_5X_6	0.135 883	0.011 858	11.46		< 0.000 1
X_5	- 0.058 770	0.008 977	- 6.55		0.001 2
X_2	- 0.041 125	0.008 977	- 4.58		0.005 9
X_3	- 0.014 670	0.008 940	- 1.64		0.161 7
X_1X_6	- 0.014 229	0.011 907	- 1.19		0.285 7

Note: ■ Prob > |*t*| is smaller than 0.01 ■ Prob > |*t*| is more than 0.01 and smaller than 0.05

the angle of orientation (part print direction) increases, the raster inclination with respect to the deposition plane changes, thereby generating a large number of rasters and a decrease in the part accuracy.

The number of perimeters sets the number of outlines on each printed layer. The more the number of perimeters, the stronger and denser is the structure of the part. Although setting a higher number of perimeters will render the part more functional with better mechanical performances, it also affects the aesthetics of the manufactured product. The percentage difference in the part length can be improved by increasing the number of perimeters (see Figs. 5c and 6c). This is because the number of perimeters is built parallelly along the part length. This higher number of perimeters reduces the number of rasters. Hence, a smoother and more stable surface can be obtained, resulting in the minimum

variation in accuracy along the part length. However, the percentage difference in the part diameter can be enhanced significantly by reducing the number of perimeters. This is because the number of perimeters is built perpendicularly (in the case of building a part with the minimum *z*-height) to the diameter of the printed part. This can cause an overfilling between rasters, resulting in a large variation in the diameter accuracy of the produced part. If 10 perimeters must be used, then it is important to reduce the bead width (see Figs. 5c and 6c). This is because a smaller bead width (road width) generates thinner slice widths and affords more precise control over the extrusion process, resulting in more accurate dimensions while maintaining the high mechanical performance of the produced parts.

The raster-to-raster air gap is the gap between the printed rasters. In this study, the effect of the raster-to-

Table 8 Sorted parameter estimates for the percentage difference in diameter

Term	Estimate	Std error	<i>t</i> ratio	Sorted parameters	Prob > <i>t</i>
X_2^2	−5.005 719	0.219 305	−22.83		< 0.000 1
X_5	11.352 883	1.645 229	6.90		0.002 3
X_2	10.074 283	1.645 229	6.12		0.003 6
X_5X_6	139.592 250	22.804 750	6.12		0.003 6
X_2X_4	− 139.130 900	22.757 810	− 6.11		0.003 6
X_1X_3	− 138.656 700	22.728 470	− 6.10		0.003 7
X_4	3.364 683	0.634 970	5.30		0.006 1
X_6	5.705 831	1.136 214	5.02		0.007 4
X_3	2.712 483	0.634 970	4.27		0.012 9
X_1	− 1.867 255	0.507 216	− 3.68		0.021 2
X_2X_5	0.185 732	0.114 704	1.62		0.180 7

Note: ■ Prob>|*t*| is smaller than 0.01 ■ Prob>|*t*| is more than 0.01 and smaller than 0.05

raster air gap on the percentage difference in length was eliminated from the model since it was insignificant. However, it significantly affected the percentage difference in diameter. The response surface effect between the print direction and air gap (see Figs. 5d and 6d) shows that the percentage difference in diameter can be reduced by either the lowest values of the part print direction and air gap or higher values of the part print direction and air gap. However, it is favorable to use the lowest value of the part print direction along with the minimum air gap as the optimal setting of those parameters. This can minimize the percentage of difference in the part accuracy, thereby yielding parts with superior mechanical properties because of the lower raster-to-raster air gap, rendering the adjacent raster tool paths closer to each other (touching each other). Hence, a stronger part can be fabricated.

3.2 ANN model

An ANN is a nonlinear mapping technique that imitates the mechanism of a human brain [23]. In this study, a feed-forward multilayer neural network with a “6-*n*-2” architecture was adopted for both the percentage differences in length and diameter. The schematic diagram of the ANN used in this study is illustrated in Fig. 7. The experimental data presented in Table 1 were used to train the ANN model to evaluate the relationships between the input and response variables. The ANN was trained to understand the input-output relationships, which are mainly used to adjust the weights of the ANN network. Validation was performed to verify the results of the training protocol. In this study, an ANN based on *K*-fold cross-validation was used to determine the optimum process setting for the response

variables. *K*-fold cross-validation was performed with five folds. The *K*-fold cross-validation is one of the best techniques and is used the most frequently by practitioners for model selection because it avoids overfitting, which occurs in other ANN techniques. The *K*-fold cross-validation technique partitions the experimental data into *K*-subsets [24]. Some of the *K*-subsets are used to train the data, whereas the remaining *K*-subsets are used to predict and fit the remaining experimental data. The goodness-of-fit of the optimal ANN model to the experimental data was evaluated based on the R^2 , root mean square error (RMSE), and mean absolute deviation (MAD). The formulas for these statistical parameters are as follows

$$R^2 = 1 - \frac{\sum_{i=1}^N (\text{Predicted}_i - \text{Actual}_i)^2}{\sum_{i=1}^N (\text{Predicted}_i - \bar{y})^2}, \quad (6)$$

$$\text{RMSE} = \frac{1}{N} \sum_{i=1}^N (\text{Predicted}_i - \text{Actual}_i)^2, \quad (7)$$

$$\text{MAD} = \frac{1}{N} \sum_{i=1}^N |\text{Predicted}_i - \text{Actual}_i|, \quad (8)$$

where $\bar{y}$ is the average value of the experimental output, and *N* is the number of experiments.

To determine the number of neurons in the hidden layer, different ANN structures with varying numbers of neurons in the hidden layer were tested with FDM input parameters. The factors, i.e., slice thickness, raster-to-raster air gap, deposition angle, part print direction, bead width, and number of perimeters were considered as the six input variables. After training the experimental data and comparing different tested ANN structures, 10 neurons in the hidden layer were selected as the optimum value based on

Fig. 5 3D response plots for the effect of **a** part print direction and slice thickness, **b** part print direction and deposition angle, **c** bead width and number of perimeters, and **d** raster to raster air gap and part print direction, on the percentage difference in length

the high R^2 and minimum sum of squares of the error (0.003 566 5 and 0.023 913 7 for percent differences in length and diameter, respectively), which can be considered as equivalent to zero (see Table 9). As shown in Table 9, the R^2 for the validation set in both models exceeded 98%, and the RMSE values of 0.034 479 6 and 0.089 281 8 for the percentage differences in length and diameter, respectively, can be considered as zero. This confirms that the models yielded accurate predictions on the experimental data not used for training the models.

Furthermore, Fig. 8 shows the scatter plots of the network outputs for the training and validation of the data. For a good fit, the data should form a 45° line. As shown in

Fig. 8, the predicted and actual values correlated well through the developed ANN structure.

3.3 Confirmation experiments

Figure 9 shows a comparison between the DSD and ANN models. The actual and predicted results demonstrated a high correlation. Although the ANN model exhibited better prediction accuracy, the results also proved the high capability of the recently developed DSD in predicting the response variables with a minimum number of experimental runs compared with conventional experimental designs. Figure 10 graphically shows the optimum

Fig. 6 3D response plots for the effect of **a** part print direction and slice thickness, **b** part print direction and deposition angle, **c** bead width and number of perimeters, and **d** raster to raster air gap and part print direction, on the percentage difference in diameter

parameter setting to achieve the minimum percentage differences in length and diameter. This figure shows that the optimum parameter settings were as follows: (X_1) slice thickness of 0.127 mm, (X_2) air gap of 0.25 mm, (X_3), deposition angle of 90°, (X_4) part print direction of 0, (X_5) bead width of 0.457 2 mm, and (X_6) six perimeters. The overall desirability index for this optimum setting was 0.930 5. Three confirmation experiments were conducted by manufacturing three additional samples to validate the optimum parameter setting, and the confirmation result is shown in Table 10. Table 10 shows that the minimum percentage difference in the dimensions exhibited extremely small variations between the predicted values and confirmation results.

Fig. 7 Schematic diagram of ANN used in this study

Table 9 Training and validation data

Measures	Percentage difference in length		Percentage difference in diameter	
	Training	Validation	Training	Validation
R^2	99.83%	98.91%	99.76%	99.75%
RMSE	0.016 613 7	0.034 479 6	0.145 392 7	0.089 281 8
MAD	0.013 921 5	0.030 966 6	0.088 984 7	0.071 603 3
– LogLikelihood	– 34.821 680	– 5.845 346	– 6.621 915	– 2.991 056
Error sums of squares	0.003 588 2	0.003 566 5	0.274 807 6	0.023 913 7

Fig. 8 Scatter plots for the network outputs for trained and validated the data **a** in length and **b** in diameter

4 Conclusions

In this study, the effects of different FDM processing parameters on the percentage difference in dimensions were investigated. A second-order DSD was proposed. Based on the experimental results of the second-order DSD and a neural network-based model, the following conclusions were obtained.

- (i) The second-order DSD was able to explain 99% of the variability in the responses with a minimum number of experiments; additionally, it is an appropriate design for investigating and

challenging the design space for future engineering applications. It can be concluded that a second-order DSD is a cost-effective experimental design compared with traditional experimental designs.

- (ii) This study confirmed the capability of an integrated DSD and the ANN for optimizing AM conditions to avoid problems typically encountered in multiple experiments.
- (iii) The ANOVA results indicated that the process parameters (i.e., slice height, air gap, print orientation, bead width, and number of perimeters)

Fig. 9 Graphical comparison of experimental and predicted values for the response variables

Fig. 10 Optimization graph showing the optimum process setting

Table 10 Confirmation experiment of the optimum process setting

Response	Predicted values/%	Actual values/%
Percentage difference in length	0.232 147	0.244 4
Percentage difference in diameter	0.438 470	0.480 3

- (iv) It was discovered that the percentage difference in length decreased with the slice thickness, deposition angle, part print direction, and bead width.

- (v) However, it decreased with the increase in both the air gap and number of perimeters. The percentage difference in diameter improved with the decrease in the print direction, deposition angle, and number of perimeters. However, it improved significantly with the increase in the slice thickness and bead width, with the highest or lowest value of the air gap.

- (vi) The R^2 exceeded 99% for both the DSD and ANN models, thereby validating the prediction capability of those models.
- (vii) By optimizing the process conditions, the minimum percentage differences in length (0.244 4%) and diameter (0.480 3%) can be obtained through a confirmation experiment.

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