Process Parameters Optimization to Improve Dimensional Accuracy of Stereolithography Parts

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Abstract: Stereolithography process limits wider applications due to low dimensional accuracy comparing with CNC process. Hence, to improve accuracy and reduce part distortion, understanding the physics involved in the relationship between the setup input parameters and the part dimensional accuracy is prerequisite. In this paper, a model is proposed to find and optimize important parameters to achieve higher accuracy and also predict dimensional accuracy using various parameters values. For this purpose, the result of a previous study is used, where it is found that in stereolithography process these factors in order of importance with respect to dimensional accuracy are: layer thickness, hatch style, hatch spacing, hatch fill cure depth and hatch overcure. Moreover, in this research the proposed neural network model is able to predict dimensional accuracy with 6% error.

Keywords: Dimensional Accuracy, Neural Network, Rapid Prototyping, Stereolithography

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1 INTRODUCTION

Stereolithography (SL) is the first process developed in rapid prototyping. It is a 3D printing process which can product objects straightly from 3D CAD model. The stereolithography apparatus (SLA) produces parts by scanning an ultra violet laser beam over a resin liquid, causing the monomers of liquid resin to polymerize into a solid. During polymerization, the resin can undergo between 5% and 7% volumetric shrinkage out of which between 50% and 70% is regarded as the initial shrinkage that occurs within the vat. The rest occurs during post-curing. Shrinkage leads to an increase in part density.

The degree of shrinkage is strongly influenced by the resin itself, part building style and operational parameters. Although stereolithography is able to produce complex geometric forms in shortest time which are impossible in normal conditions and need long time to be built in conventional machining processes, dimensional accuracy and physical stability in prototypes built by this process, in comparison with conventional machining processes, still haven't achieved to ideal magnitude where limits its application. Figure 1 shows the schematic view of a SLA machine [1-4]. In general, induced errors in SLA process may stem from five sources [5]:

1- CAD/CAM induced error
2- Laser beam width induced error
3- Material shrinkage error
4- Setup parameters error
5- Post-processing error

Among above sources of error, the problem applicable to approximation of 3-dimensional surfaces by triangular facets in STL files has been solved with newer files called SLC, presented by 3D Systems Company in 1992. Second source applicable to Laser beam width has been solved by today computer softwares. The error stemming from Acrylate resins has been improved by Epoxy resins, presented by 3D Systems and Ciba Geigy in 1994, where these resins were called XB5170 with only 2%-3% shrinkage in volume. New hatch style which was introduced along with these resins, pretty largely solved the problems applicable to post-processing. So, parameters setup optimization is primarily important for researchers in order to achieve the best dimensional accuracy in SL parts [5-8].

Various parameters are influencing distortion of SLA parts which are namely: Layer thickness, Z wait, Hatch spacing, Hatch overcure, Hatch style, Part orientation, Gap of blade, Scanning speed, etc. Some of these parameters are found more effective than the others by many researchers as per their methods and experiments. They have selected their desired parameters and investigated complex and non linear relations between them.

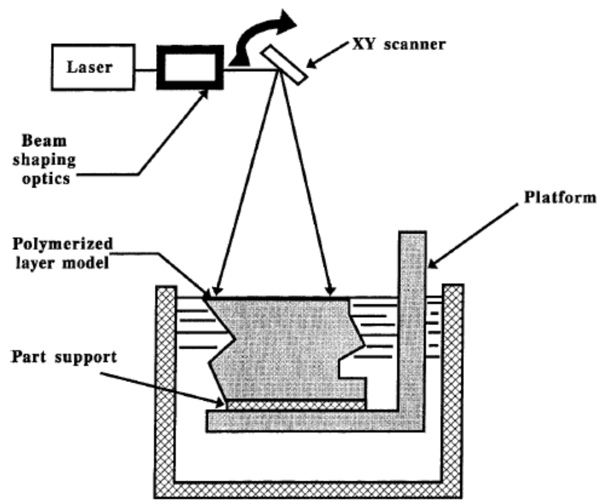

Fig. 1 Schematic view of a SLA machine

Layer thickness (l_t) is any individual layer of the photopolymer surface which is solidified using laser beam. Based on most of the previous studies, it may be claimed that the layer thickness is the most important parameter in dimensional accuracy of SLA parts. According to the Jacob's investigation, when l_t is smaller, then exposure of laser would be less and therefore, it would lead to less shrinkage and better dimensional accuracy [9].

$$E_{max} = E_c \exp [(l_t + h_o) / D_p] \qquad (1)$$

Where E_c is the critical exposure and D_p is the penetration depth where both parameters are constants of the resin material. For the purpose of solidification, laser exposure, must be more than the critical exposure, E_c. The effectiveness of process parameters is explicable through their impact on exposure of laser; usually, higher magnitude of exposure usually leads to more shrinkage and subsequently dimensional error. The penalty for this is larger build time, where, smaller l_t necessitates more build time and subsequently increase in cost.

As to process parameters, Lee et al., acknowledged six parameters to be more effective among others and examined their relations and impacts on dimensional accuracy of SLA parts [6]. These parameters are layer thickness, hatch overcure, hatch spacing, border overcure, fill spacing and fill cure depth where the first three are more important. Their studies indicated that for achieving more dimensional accuracy, parameters such as small layer thickness, small hatch overcure and medium to large hatch spacing are desirable.

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Raju et al. have shown that among different layer thicknesses of 50 µm, 100 µm and 150 µm, with respect to the optimum dimensional accuracy, mechanical characteristics and cost, the best layer thickness is 100 µm [10]. Zhou et al. in a study in order to optimize process parameters in SLA, have found that effectiveness of parameters are different in various dimensional, geometrical and surface features; however, based on their findings, the most significant parameter among layer thickness, hatch overcure, blade gap, part location and hatch spacing in dimensional accuracy of SLA parts, is layer thickness, which is prefered to be small, followed by hatch overcure and blade-gap [5].
Onuh and Hon have studied the parts built by Acrylate resin, using newly proposed hatch style, with layer thickness of 190µm which would lead to improved dimensional accuracy and building time [11]. Hatch overcure (h_o) is the depth in which one cured vector band pierces into the lower adjacent layer. This is what keeps the individual layers connected together to form a solid part. When h_o is smaller, then laser exposure reduces, which subsequently results in less shrinkage, but improved dimensional accuracy.
Lee et al. have claimed that the optimized state of laser is when the exposure is neither saturated nor inadequate [6]. If h_o goes beyond the optimum magnitude, the total amount of laser exposure may be saturated, however, if it is less than the optimum magnitude, the laser exposure might be insufficient to connect adjacent layers. Zhou et al. [5] have shown that hatch overcure is the second most important parameter with regard to the dimensional accuracy which its lesser magnitude results in a better accuracy.
Hatch spacing (h_s) is the distance between parallel vectors used to hatch the interior of the part. If the hatch spacing is less than the optimized magnitude, the solidifying vectors would overlap, causing more laser exposure absorption and subsequently more dimensional error. Also, if the hatch spacing is larger than the optimized magnitude, the liquid photopolymer would be trapped within the part to be solidified during postcuring operation, causing additional error.
Lee et al. have investigated that medium to large hatch spacing are more appropriate to achieve better dimensional accuracy [6]. Horton et al. in an experimental study have showed that hatch spacing is the most effective parameter on curl distortion in parts created using stereolithography process [12]. Their observations also indicated that it is impossible to achieve desirable dimensional accuracy without applying fill cure depth. Hatch fill cure depth (h_{fc}) is the depth of solid layers formed on the upper and lower faces of the solid, where it holds the remaining uncured photopolymer inside the part for subsequent postcuring.
In solidifying layers, the borders of each layer are drawn first and then the district between borders would be hatched. Hatch strategy through style and extent of laser exposure transferred to resin has an evident impact on dimensional accuracy. Tri-Hatch and Weave are primitive strategies which are abolished nowadays; au courant methods are accomplished based on Star-Weave strategy; researches, however, have resorted to some changes in hatch strategies in many cases depending on the relevant special geometries and layering.
The Divergent STAR-WEAVE (DSW) is developed by Onuh and Hon based on the results of prior studies by Konig et al. [13]. This new strategy is based on the fact that when layers are scanned in only one direction, it results in one-sided curling of the parts. An alternating exposure of the layers, results in a more homogeneous structure of residual stress in the part and subsequently a higher part stability and dimensional accuracy would be achieved. DSW starts hatching from the middle of the part to one end in such a way that half of the part is first hatched. Then, the other half is scanned from the middle to the other end (Fig. 2). This process is repeated in either X or Y direction, where it results in more dimensional accuracy.

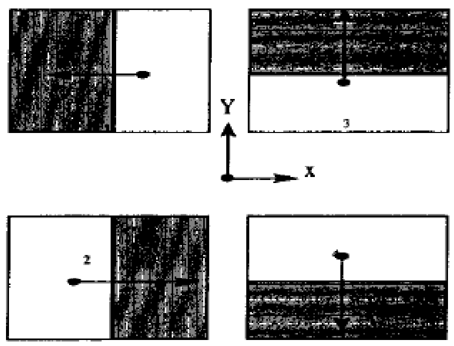

Fig. 2 Divergent STAR-WEAVE [13]

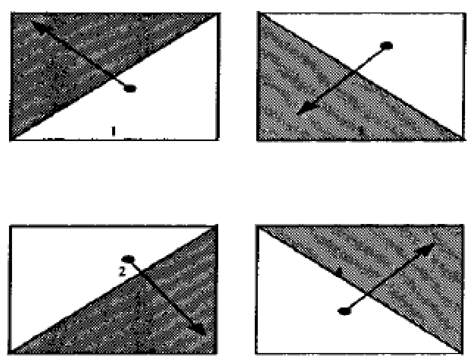

Fig. 3 Diagonal Divergent STAR-WEAVE [13]

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The Diagonal Divergent STAR-WEAVE (DDSW) in fact is the modified DSW which is also proposed by Onuh and Hon [11]. The only difference in this strategy is that scanning is done diagonally from the middle of the part in such a way that half of the part is first scanned from the middle to one end before the other half is completed. In DDSW, scanning is at 45 degree to X and Y directions (Fig. 3).

Onuh and Hon [11] investigated the parts built by Acrylate resin using DSW and DDSW hatch styles. They found that the layer thickness of 190µm would make good results with these new hatch strategies for dimensional accuracy and build time.

The Circular STAR-WEAVE (CSW) is developed by Nosouhi and Rahmati, where this new method is based on the fact that by a more uniform distribution of the shrinkage stress throughout the part, the shrinkage strains decrease relatively [14]. According to this strategy, the hatches in X and Y directions are replaced with circular paths and radial hatches respectively. The circular hatches, in this method, are not joined to the previous layer by which the building shrinkage doesn't apply any stress on the work piece. The radial hatches then join the new layer to the previous layers. Also, the direction of the radial hatches is changing in each layer; one layer from the center to the outside, and in the next layer, from outside to the center. They have acknowledged that those parts produced using CSW hatching method are more accurate than those which are being produced by STAR-WEAVE hatching method.

2 EXPERIMENTAL METHOD

Onuh and Hon [11] have studied also four parameters (i.e., layer thickness, hatch spacing, hatch overcure and hatch fill cure depth) and their impact on dimensional accuracy. In their study, the effects of the parameters shown in Table 1 on the product quality were determined experimentally.

The following equipment were used in their investigation: Sun Sparc 10 and Silicon Graphics Indigo Workstations, 3D Systems Stereolithography Apparatus SLA-250 series 40, and a post-curing unit (PCU). The investigation was conducted in the Rapid Prototyping Centre and all dimensional measurements were taken using a Mitutoyo BHN-706 coordinate measuring machine (CMM) with an accuracy of ±5µm. The related experimental part is shown in Fig. 4.

Onuh and Hon [11] used the Taguchi method for the selection of the experimental parameters in their work and as well as the analysis of the results. In the present study, distortion values measured by previous researchers, is modeled by Artificial Neural Network (ANN) in order to achieve correct prediction of dimensional accuracy and investigate the impact of these parameters on dimensional error. The value of *dx1* is measured along the top edge *DC*; *dx2* is measured along the top edge *AB*; and the value of *dy* is measured along the top edge *BC*, as shown in the experimental model in Fig. 4. Also, the experimental runs and level combination are shown in Table 2, where in next section it will be explained how these experimental data is modeled by neural network.

Table 1 List of experimental parameters and their factor levels [11]

	Level 1 (mm)	Level 2 (mm)	Level 3 (mm)
Layer thickness	0.125	0.190	0.250
Hatch spacing (A)	0.210	0.200	
Hatch overcure (B)	-0.04	-0.035	
Hatch fill cure depth (C)	0.250	0.200	

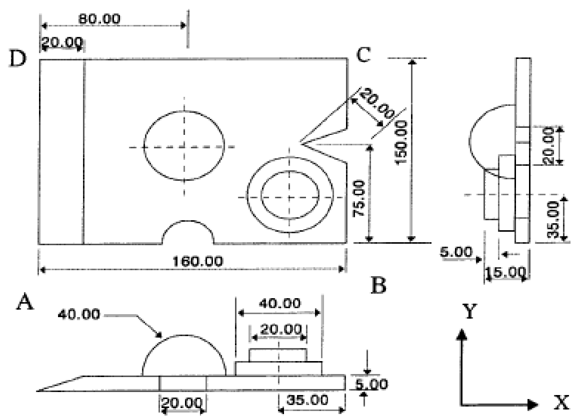

Fig. 4 The experimental model [11]

Table 2 The experimental runs and level combination [11]

	Factor Level	Factor Level	Factor Level
Runs	A	B	C
R_1	1	1	1
R_2	1	2	2
R_3	2	1	2
R_4	2	2	1

The results achieved from these experiments were presented by different graphs, however in this study these results are transformed in to numerical values in order to be used in Neural Network, as shown in Table 3 (Appendix A).

3 NEURAL NETWORK MODELING

The artificial neural network mimics the function of human brain, simplifying the structure and function, and makes a mathematical model. The theory of ANNs

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will be discussed briefly to show how the ANN can be used to model the functional relationship between $\boldsymbol{y}$ and $\boldsymbol{x}$. Several neural networks have been developed that are able to represent very accurate functions within certain parameter spaces. The network adopted here is the multilayer perceptron whose structure is fully connected as shown in Fig. 5 [6, 15].

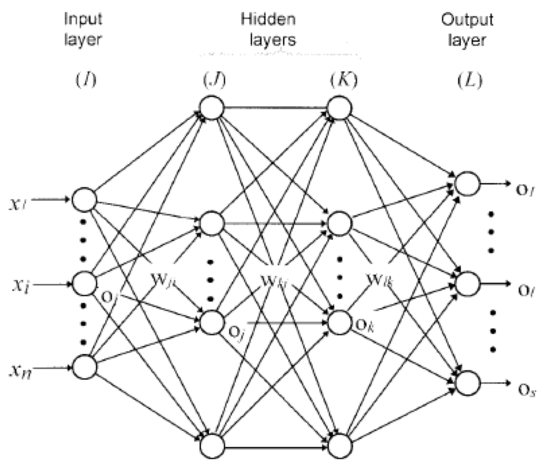

Fig. 5 The perceptron neural network structure [6]

As the figure indicates, the network consists of a fixed number of layers and nodes on each layer (in this case, one hidden layer): w_{ji} denotes the weight, the strength between the i^{th} node of the layer I and the j^{th} node of layer J; o_i , o_j , o_k and o_l are the outputs of the i^{th}, j^{th}, k^{th} and l^{th} node of the corresponding layers respectively. This estimator has a few inputs (here: hatch style, layer thickness, hatch spacing, hatch overcure and hatch fill cure depth) and a few outputs (here: dimensional errors such as dx_1, dx_2 and dy). The perceptron has been trained first with experimental data (here: 35 cases), within certain cycles (here: 381 cycles) with definite learning rate (here: 0.6) and certain momentum (here: 0.7), and then one or more validated data.

Table 4 The neural network characteristics

Number of hidden layer(s)	1
Learning cycles	15501
Training error	0.001912
Validating error	0.030265
Input columns	5
Output columns	3
Training example rows	33
Validating example rows	3
Input nodes	5
Hidden layer nodes	7
Output nodes	3
Learning rate	0.6000
Momentum	0.7000
Validating 'correct' target	100.00%
Target error	0.0100

Fig. 6 shows the neural network which has been developed in this study. This model can predict dimensional accuracy with about 6% error probability which is considered a good prediction. It will be useful for users that can select best parameters for setup and can predict dimensional accuracy to be achieved. Furthermore, it shows that this model enjoys a good structure with precise analyses which can represent SLA process. The structure used in this study is a multilayer perceptron with characteristics as shown in Table 4.

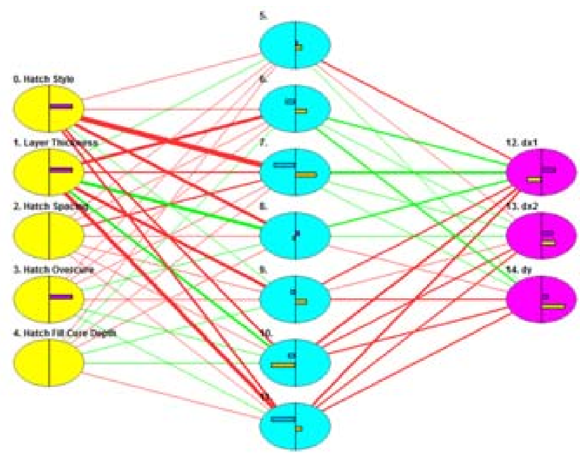

Fig. 6 Multi-layer perceptron developed in this study

Table 5 Prediction of dimensional accuracy for 30^{th} data

	dx_1	dx_2	dy
Real Value	1.6	1.4	1.2
Predicted value	1.5766	1.5023	1.1707
Error%	1.46	7.3	2.44

4 RESULTS AND DISCUSSION

The neural network was used to predict the dimensional accuracy of the 3 samples in post-train step. Table 5 shows the predicted values against real values for 30^{th} data, where error is defined Eq. (2).

$$\text{Error}/100 = |\text{Real Value} - \text{predicted value}| / \text{Real Value} \quad (2)$$

Average error for 30^{th} data amounts to 3.73%. Also, this prediction was done for 20^{th} and 10^{th} data, respectively, with average errors of 4.73% and 9.56%. The average of prediction errors for these three data is about 6%. This prediction is pleasing which demonstrates that the ANN developed in this study represents satisfactory SL process and its analyses are true.

In artificial neural network, nodes with a higher sum of weights are more important than other nodes or

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parameters. These weights are determined in training step through using experimental data. The sum of the weights connected to every node, actually signifies the “importance” of each parameter.

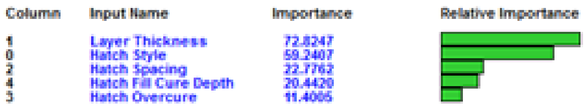

Fig. 6 The importance of parameters

As shown in Fig. 6, layer thickness is the most important parameter in dimensional accuracy (with 72.8247 as its sum of weights), and then, respectively, hatch style (59.2407), hatch spacing (22.7762), hatch fill cure depth (20.4420) and hatch overcure (with 11.4005 as its sum of weights).

So, the model proposed in this study, indicates that these five parameters have a significant impact on dimensional accuracy in SLA parts; the layer thickness enjoys highest importance among the abovementioned parameters. Moreover, this study demonstrated that ANN is able to predict precisely the dimensional accuracy for SLA parts.

5 CONCLUSION

1- The artificial neural network with multi-layer perceptron possessing a hidden layer structure is a good model for modeling SLA process and prediction of dimensional accuracy.

2- The layer thickness is the most important parameter with regard to dimensional accuracy, followed by hatch style, hatch spacing, hatch fill cure depth and hatch overcure respectively.

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APPENDIX

Table 3 The achieved values (inputs and outputs) from experiments for using in neural network

	Runs	Hatch Style	l_t (mm)	h_s (mm)	h_o (mm)	hf_c (mm)	dx_1 (mm)	dx_2 (mm)	dy (mm)
0	R_1	SW	0.125	0.210	0.04	0.250	0.4	0.05	0.2
1	R_4	SW	0.125	0.200	0.035	0.250	1.2	1.2	1.56
2	R_1	SW	0.190	0.210	0.04	0.250	1	1.2	0.5
3	R_4	SW	0.190	0.200	0.035	0.250	2.8	3	3.3
4	R_1	SW	0.250	0.210	0.04	0.250	0.64	0.3	0.64
5	R_4	SW	0.250	0.200	0.035	0.250	0.52	0.6	0.4
6	R_2	SW	0.125	0.210	0.035	0.200	1.1	0.76	0.6
7	R_3	SW	0.125	0.200	0.04	0.200	0.6	0.52	0.8
8	R_2	SW	0.190	0.210	0.035	0.200	2.3	2.5	2.5
9	R_3	SW	0.190	0.200	0.04	0.200	2.3	3.5	3.5
10	R_2	SW	0.250	0.210	0.035	0.200	1.52	1.3	1.8
11	R_3	SW	0.250	0.200	0.04	0.200	1.2	1.3	1.4
12	R_1	DSW	0.125	0.210	0.04	0.250	1.52	1.12	0.88
13	R_4	DSW	0.125	0.200	0.035	0.250	1.12	1.48	1.2
14	R_1	DSW	0.190	0.210	0.04	0.250	1.2	1.5	1
15	R_4	DSW	0.190	0.200	0.035	0.250	0.4	0.8	0.5
16	R_1	DSW	0.250	0.210	0.04	0.250	1	0.8	0.92
17	R_4	DSW	0.250	0.200	0.035	0.250	2.32	2.4	1.6
18	R_2	DSW	0.125	0.210	0.035	0.200	0.8	1.12	1.16
19	R_3	DSW	0.125	0.200	0.04	0.200	1.2	1.12	1.16
20	R_2	DSW	0.190	0.210	0.035	0.200	0.5	0.8	1.5
21	R_3	DSW	0.190	0.200	0.04	0.200	1	1	0.5
22	R_2	DSW	0.250	0.210	0.035	0.200	2.32	2.2	1.6
23	R_3	DSW	0.250	0.200	0.04	0.200	1.8	1.55	1.2
24	R_1	DDSW	0.125	0.210	0.04	0.250	1.6	1.48	1.2
25	R_4	DDSW	0.125	0.200	0.035	0.250	2	2	1.8
26	R_1	DDSW	0.190	0.210	0.04	0.250	0.8	0.9	0.6
27	R_4	DDSW	0.190	0.200	0.035	0.250	0.4	0.5	0.5
28	R_1	DDSW	0.250	0.210	0.04	0.250	1.6	1.7	1.5
29	R_4	DDSW	0.250	0.200	0.035	0.250	1.6	1.3	1.2
30	R_2	DDSW	0.125	0.210	0.035	0.200	1.6	1.4	1.2
31	R_3	DDSW	0.125	0.200	0.04	0.200	1.92	1.88	1.56
32	R_2	DDSW	0.190	0.210	0.035	0.200	0.8	0.9	0.6
33	R_3	DDSW	0.190	0.200	0.04	0.200	0.4	0.4	0.2
34	R_2	DDSW	0.250	0.210	0.035	0.200	1	2	1.4
35	R_3	DDSW	0.250	0.200	0.04	0.200	1.88	2	1.6

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