Grey Taguchi Method for Improving Dimensional Accuracy of FDM Process

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The effect of five factors viz., layer thickness, part build orientation, raster angle, raster to raster gap (air gap) and raster width each at three levels together with their interactions is studied on dimensional accuracy of fused deposition modelling (FDM) build part. Experimental results indicate that measured dimension is always more than desired value along thickness direction but length and width dimensions of test part are less than the desired. Percentage change in length, width and thickness are expressed as grey relational grade for minimization of all responses simultaneously. Optimum factor levels are determined by maximizing the grey relational grade.

Keywords: FDM; Dimensional accuracy; Shrinkage; Grey relational grade

1. Introduction

Fused deposition modelling (FDM) by Stratasys Inc., USA is one of the rapid prototyping (RP) processes that build part of any geometry by sequential deposition of material on a layer by layer basis. Unlike other RP systems which involve an array of lasers, powders, resins, this process uses heated thermoplastic filaments which are extruded from the tip of nozzle in a prescribed manner. Simplicity of operation, inexpensive machinery and durability of parts together with ability to fabricate with locally control properties results in its wide spread application not only for prototyping but also for making functional parts (Rosochowski and Matuszak, 2000). However, FDM process has its own demerits related with accuracy, surface finish, strength etc. Hence, it is absolutely necessary to understand the shortcomings of a process before recommending for industrial application. It has been proposed that improvement of surface quality, part strength, build time, accuracy and repeatability are key issues to be addressed for successful implementation of RP technology (Upcraft and Fletcher, 2003). Several attempts have been made to improve the part accuracy, surface finish, strength etc. by proper adjustment of process parameters by numerous researchers (Es Said et al., 2000; Khan et al., 2005; Anitha et al., 2001). These works reveal that properties of RP parts can be significantly improved with proper adjustment of build parameters without incurring additional expenses for changing hardware and software. Further, literature suggests that studies on effect of process parameters in improving quality of FDM built parts, specifically, dimensional accuracy, have been devoted to a limited extent. Therefore, there is a need for in-depth study to understand process parameters and their interaction effects on responses like accuracy of dimensions in different directions of FDM built parts. Taguchi's parameter design is adopted; not only to reduce the number of experiments but also identify the influencing factors and their interactions responsible for minimization of percentage change in dimensions of test parts. Then, optimal process parameters are selected to minimize dimensional inaccuracy. However, conventional Taguchi method can effectively establish optimal parameter settings for single performance characteristic. When multiple performance characteristics with conflicting goals are considered, the approach becomes unsuitable. Therefore, grey Taguchi method is used in this work to generate a single response from different performance characteristics. The multiple performance measures considered here are percentage change in length, width, and thickness of build parts. All the responses need to be individually minimized whereas overall grey relational grade, the multiple performance characteristic, is maximized.

2. Experimental Detail

Previous researches on FDM process suggest that major part of output quality is dependent on few primary control factors. Based on this, five factors viz., layer thickness (A), part build orientation (B), raster angle (C), raster width (D) and raster to raster gap (air gap) (E) each at three level, as shown in Table 1 are considered. Other factors are kept at their fixed level as mentioned in Table 1. Orientation is an important parameter for part strength, dimensional accuracy, surface finish, part build time and cost etc. (Venkata Reddy et al., 2007; Byun and Lee, 2006) and its influence seems to be more than any other parameter. Hence, interaction of other parameters with part orientation is also considered.

Since five factors each at three level and four interactions are considered in this study, the total degree of freedom happens to be 26. The appropriate orthogonal array for this case is L_{27} (3^{13}). To avoid incorrect analysis, faulty conclusions and minimize the confounding effect of factors and interactions, assignment of factors and interactions is done as per linear graph. The final L_{27} orthogonal array is as shown in Table 2.

Table 1: Factors and their Levels

Fixed Factors			Control Factors					
Factor	*Value*	*Unit*	*Factor*	*Symbol*	*Level*			*Unit*
					1	*2*	*3*	
Part fill style	Perimeter Raster	-	Layer thickness	A	0.127	0.178	0.254	mm
Contour width	0.4064	mm	Orientation	B	0	15	30	degree
Part interior style	Solid normal	-	Raster angle	C	0	30	60	degree
Visible surface	Normal raster	-	Raster width	D	0.4064	0.4564	0.5064	mm
XY & Z shrink factor	1.0038	-	Air gap	E	0	0.004	0.008	mm

Table 2: L_{27} Orthogonal Array with S/N Ratio Data

Exp.	Factors					S/N ratio		
	A	*B*	*C*	*D*	*E*	*%ΔL*	*%ΔW*	*%ΔT*
1	1	1	1	1	1	24.806	4.4370	-9.2977
2	1	2	1	2	2	18.416	7.2636	-
3	1	3	1	3	3	19.439	1.5836	-8.2436
4	1	1	2	2	2	26.315	2.6940	-8.5194
5	1	2	2	3	3	14.386	6.0206	-
6	1	3	2	1	1	15.056	7.2636	-8.5194
7	1	1	3	3	3	30.954	5.4600	-
8	1	2	3	1	1	17.233	3.5218	-
9	1	3	3	2	2	18.599	3.9674	-
10	2	1	1	2	3	38.061	13.9794	-8.5194
11	2	2	1	3	1	29.542	2.3079	-
12	2	3	1	1	2	23.098	6.0206	-
13	2	1	2	3	1	20.294	8.7146	-
14	2	2	2	1	2	17.025	7.2636	-
15	2	3	2	2	3	17.555	8.7146	-
16	2	1	3	1	2	22.402	8.7146	-9.5424
17	2	2	3	2	3	20.755	3.5218	-
18	2	3	3	3	1	26.466	8.7146	-
19	3	1	1	3	2	22.893	18.4164	-
20	3	2	1	1	3	23.967	7.535	-
21	3	3	1	2	1	16.526	12.3958	-
22	3	1	2	1	3	27.604	14.8945	-
23	3	2	2	2	1	28.914	7.9588	-
24	3	3	2	3	2	18.296	10.4576	-
25	3	1	3	2	1	32.041	11.0568	-
26	3	2	3	3	2	24.317	7.9588	-
27	3	3	3	1	3	31.756	7.9588	-

3D solid model of test part is modelled in CATIAV5 software and exported as STL file. STL file is imported to FDM software (Insight). Here, control factors (Table 1) are set as per experiment plan (Table 2) and other factors (Table 1) are kept at fixed level. Three parts per experiment are fabricated using FDM Vantage SE machine. The material used for part fabrication is ABSP400. Three readings of length, width and thickness are taken per sample and mean is taken as representative value for each of these dimensions. Dimensions are measured using Mitutoyo vernier calliper of least count 0.01mm. Measured values shows that there is shrinkage in length (L) and width (W) but thickness (T) is always more than the CAD model value.

3. Results and Discussions

Signal to noise(S/N) ratio is used to determine the influence and variation caused by each factor and interaction relative to the total variation observed in the result. Objective of experimental plan is to reduce the percentage change in length (%ΔL), width

(%ΔW) and thickness (%ΔT) respectively as small as possible. For this, smaller the better quality characteristic is considered. Data analysis is made using Minitab R14 software. Main effect plot for S/N ratio is used to predict the optimum factor level. Relative influence of factors and interactions is determined by ANOVA and results are presented in Table 3.

Table 3: Optimum Factor Level with Significant Factors and Interactions

Factor	% Change in Length	% Change in Width	% Change in Thickness
A	3	3	1
B	1	1	1
C	3	2	1
D	2	2	3
E	3	2	2
Significant	A,B,C, BXD,BXE	A,B AXB,BXE	A,B, AXB BXC,BXD

However, the Taguchi method is best suitable for optimization of a single performance characteristic whereas grey based Taguchi combine the entire considered performance characteristic (objectives) into a single value that can be used as the single characteristic in optimization problems (Yiyo et al., 2008). To apply this method, input attributes (performance characteristic or objective function) need to be normalized. This process is called grey relational generation (GRA). Suppose, there are m alternatives and n attributes, the i^{th} alternative can be expressed as $Y_i = (y_{i1}, yi2,\ldots,y_{ij},\ldots y_{in})$, where y_{ij} is the performance value of attribute j of alternative i. The term Y_i can be normalized using Equation 1 for smaller the better quality characteristic considered in present study.

$$X_{ij} = \frac{a_j - y_{ij}}{a_j - b_j} \quad i = 1,2,..,m \quad j = 1,2,...,n$$

$$a_j = Max\ \{y_{ij}, i=1,2,\ldots,m\};\ b_j = Min\ \{y_{ij},\ i=1,2,\ldots,m\}; \qquad ....(1)$$

The performance of alternative i is best choice for attribute j if GRA value X_{ij}, is one or nearer to one. Thus, a reference sequence $X_o = \{x_{0j}: x_{0j}=1 for\ j=1,\ 2,\ldots,\ n\}$ is used to compare comparability sequence. Comparability sequence is a series of alternatives i $(X_{i1}, X_{i2},\ldots X_{ij},..X_{in})$. For this grey relation coefficient (γ) as given by Equation 2 is calculated.

$$\gamma(x_{0j}, X_{ij}) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{ij} + \xi\Delta_{\max}}\ i=1,2,..,m;\ \ j=1,2,\ldots,n \qquad ....(2)$$

where $\Delta_{ij}=|x_{oj}-X_{ij}|$; $\Delta_{min}=\text{Min}\{\Delta_{ij}, i=1,2..,m;\ j=1,2,\ldots,n\}$; $\Delta_{max}=\text{Max}\{\Delta_{ij}, i=1,2,..,m;\ j=1,2,\ldots,n\}$;

ξ is the distinguishing coefficient, $\xi \in [0,1]$. The purpose of distinguish coefficient is to expand or compress the range of the grey relational coefficient. The distinguishing coefficient can be selected by decision maker judgement, and different distinguishing coefficients usually provide different results in GRA. Sensitivity analysis for different distinguishing coefficients (Figure 3) shows that impact of their variation on grey relation coefficient is very small. They all led to the same optimum factor levels. In this paper distinguishing coefficient is taken as 0.5. After calculating the entire grey relational coefficient, the gray relational grade (Γ) can be calculated using Equation 3.

$$\Gamma\ (x_o,\ Xi) = \sum_{j=1}^{n} W_j \gamma(x_{0j}, X_{ij});\ i = 1,2,\ldots,m \qquad .... (3)$$

W_j is the weight of attribute j and usually depends on decision maker's judgement or the structure of the proposed problem. In addition $\sum_{j=1}^{n} W_j = 1$. In this work, weights for percentage change in length, width and thickness are taken as 0.35, 0.35 and 0.30 respectively. The grey relational grade indicates the degree of similarity between the reference sequence and comparability sequence. If a comparability sequence for an alternative gets the highest grey relational grade, it will be more similar to reference sequence and that alternative would be best choice. Thus, the maximization of gray relation grade gives the optimum factor levels. Results of grey Taguchi method are shown in Table 4. Main factor plot for grey relation grade (Figure 1) gives the optimum factor level as A_2, B_1, C_1, D_2, E_3. ANOVA on grey relation grade shows that factor A, B, C and interactions BXC, BXD, BXE are significant. Result of sensitivity analysis (Figure 2) shows that different values of distinguishing coefficient give same factor level.

As FDM process involves large number of conflicting factors and complex phenomena for part build, it is very difficult to predict the output characteristics accurately by mathematical equations. So, an ANN with back propagation algorithm has been adapted to model FDM process. One of the advantages of using the neural network approach is that a model can be constructed very easily based on the given input and output and trained to accurately predict process dynamics. This technique is especially valuable in processes where a complete understanding of the physical mechanisms is very difficult, or even impossible to acquire, as in the case of FDM process. In the present analysis factors A, B, C, D and E are taken as five input parameters.

Each of these parameters is characterized by one neuron and consequently the input layer in the ANN structure has five neurons. The database is built considering experiments at the limit ranges of each parameter. GRG values are used to train the ANN in order to understand the input-output correlations. The database is then divided into two categories, namely: (i) A training category, which is exclusively used to adjust the network weights (ii) A test category, which corresponds to the set that validates the results of the training protocol. A software package NEUNET PRO for neural computing using back propagation algorithm is used as the prediction tool for grey relation grade under various test conditions. The three-layer neural network having an input layer (I) with five input nodes, a hidden layer(H) with seven neurons and an output layer (O) with one output node employed for this work. Learning rate of 5% and momentum of 1% is set as training parameters. Seventy five percent of data is used for training whereas twenty five percent data is used for testing. A comparison between the experimental and the ANN predicted results (Figure 3) shows that error varies from 0-3.5%.

Table 4: Result of Grey Taguchi Method Calculations

Exp.	Grey Relation Generation			Grey Relation Coefficient			
	%ΔL	*%ΔW*	*%ΔT*	*%ΔL*	*%ΔW*	*%ΔT*	GRG
1	0.74766	0.32710	0.95788	0.66459	0.42629	0.9223	0.6585
2	0.39719	0.56074	0.83157	0.45338	0.53233	0.7480	0.5694
3	0.47196	0.00000	1.00000	0.48636	0.33333	1.0000	0.5868
4	0.79906	0.14018	0.98946	0.71333	0.36769	0.9793	0.6721
5	0.00000	0.46728	0.84210	0.33333	0.48416	0.7600	0.5141
6	0.07943	0.56074	0.98946	0.35197	0.53233	0.9793	0.6033
7	0.91121	0.42056	0.92630	0.84920	0.46320	0.8715	0.7208
8	0.29906	0.23364	0.82104	0.41634	0.39483	0.7364	0.5048
9	0.41121	0.28037	0.85262	0.45922	0.40996	0.7723	0.5359
10	1.00000	0.88785	0.98946	1.00000	0.81679	0.9793	0.9296
11	0.88317	0.09345	0.77894	0.81060	0.35548	0.6934	0.6161
12	0.67756	0.46728	0.75789	0.60795	0.48416	0.6737	0.5843
13	0.52803	0.65420	0.86315	0.51442	0.59116	0.7851	0.6224
14	0.28037	0.56074	0.71579	0.40996	0.53233	0.6375	0.5210
15	0.32710	0.65420	0.75789	0.42629	0.59116	0.6737	0.5582
16	0.64486	0.65420	0.94736	0.5847	0.59116	0.9047	0.6829
17	0.55607	0.23364	0.78947	0.52970	0.39483	0.7037	0.5346
18	0.80373	0.65420	0.86315	0.71812	0.59116	0.7851	0.6937
19	0.66822	1.00000	0.49473	0.60112	1.00000	0.4973	0.7096
20	0.71495	0.57943	0.11579	0.63690	0.54314	0.3612	0.5213
21	0.23364	0.83177	0.13683	0.39483	0.74825	0.3667	0.5101
22	0.83644	0.91588	0.23157	0.75351	0.85600	0.3941	0.6815
23	0.86916	0.60747	0.00000	0.79259	0.56020	0.3333	0.5734
24	0.38784	0.74766	0.51578	0.44957	0.66459	0.5080	0.5423
25	0.92990	0.77570	0.49473	0.87704	0.69032	0.4973	0.6977
26	0.72897	0.60747	0.24210	0.64848	0.56020	0.3974	0.5422
27	0.92523	0.60747	0.3578	0.86992	0.56020	0.4377	0.6318

Figure 1: Factor Plot for GRG

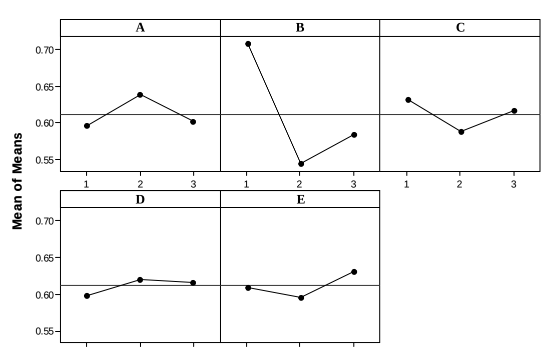


Figure 2: Sensitivity Analysis for Different Distinguishing Coefficients

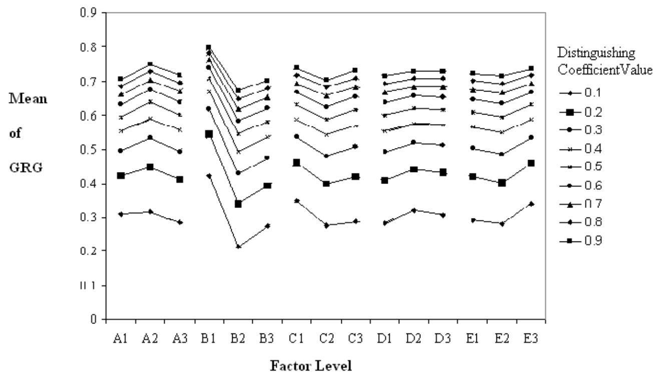
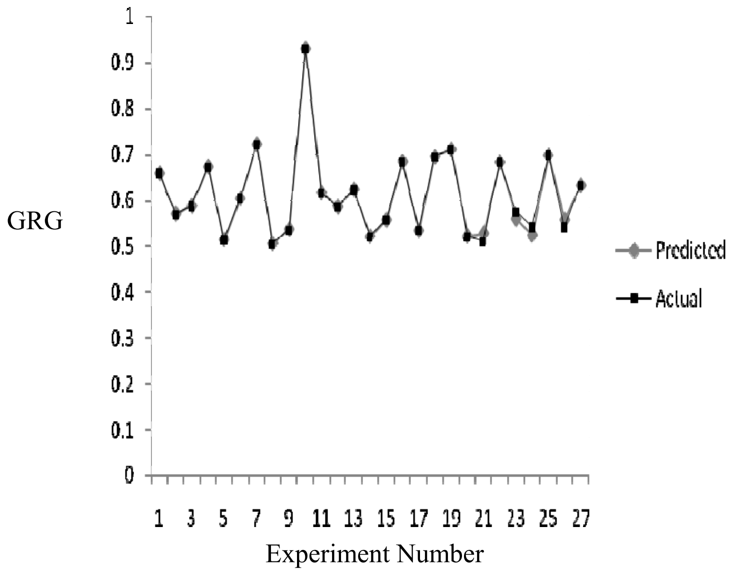


Figure 3: Prediction Graph between Neural Net Work and GRG Value



4. Conclusions

In the present work, effect of five factors viz., layer thickness, part build orientation, raster angle, raster to raster gap (air gap) and raster width each at three levels together with the interaction of part build orientation with all the other factors is studied on the dimensional accuracy of FDM build part. Taguchi's design of experiment is used to find the optimum factor levels and significant factors and interactions. It is found that shrinkage is dominant along the length and width of test part where as thickness is always more than the desired value. For minimizing the percentage change in length, higher layer thickness (0.254mm), 0° orientation, maximum raster angle (60°), medium raster width (0.4564mm) and maximum air gap (0.008mm) are desirable. For minimizing the percentage change in width, medium raster angle (30°) and air gap (0.004mm) will give desired result. Remaining factor levels are same as for percentage change in length. On the other hand, lower value of layer thickness (0.127 mm), orientation (0°), raster angle (0°) and higher value of raster width (0.5064 mm) and medium value of air gap (0.004 mm) will minimize the percentage change in thickness of test part. Study on the observed results show that there are large numbers of conflicting factors independently or in interaction with others may influence the dimensional accuracy. Few of them have more percentage influence as compared to others. Therefore, instead of considering only significant factors and interactions, it is proposed that fabrication process must be based on optimum factor level setting. But fabrication of part is to be done in a manner so that all the three dimensions show minimum deviation from actual value simultaneously, at the common factor level setting. For this grey Taguchi method is adopted. Grey Taguchi method has the ability to combine all the objectives that is minimizing the percentage change in length, width and thickness into single objective known as grey relation grade. Maximization of grey relation grade shows that layer thickness of 0.178mm, part orientation of 0°, raster angle of 0°, road width of 0.4564 mm and air gap of 0.008 mm will produce overall improvement in part dimension. Prediction of proposed model is done using artificial neural networks (ANN) model. Error between predicted data and observed values varies between 0 to 3.5%. This small percentage error proves the suitability of present model.

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