Dimensional accuracy improvement of part fabricated by low cost 3D open source printer for industrial application

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***Abstract*—3D open source printer (3D-OSP) based on fused deposition modelling (FDM) technique is one of the newly developed rapid prototyping (RP) process for the fabrication of parts. It has been observed from research finding that the contribution of parameter such as raster width, slice height, and path speed are the most significant to the dimensional accuracy of 3D open source product. In this paper, an attempt has been made to find out the influence of the process parameter along with their interactions on the 3D-OSP. Taguchi parameter design has been used to find out the optimum parameters level to minimize percentage change in length (L1), length (L2) and height (H) of test specimens. Experimental result reveals that there is different optimal parameters level setting for each dimensional characteristic namely change in length (L1), length (L2) and height (H). Therefore, grey relational method is used to obtain optimum factor level of each dimensional characteristic simultaneously. From obtain result it is conclude that appropriate control of machine process parameters improve the dimensional accuracy of parts fabricated by a low cost 3D open source printer for industrial/commercial application.**

Keywords—3D open source printer (3D-OSP); Contraction; Grey relational analysis; Part dimensional accuracy

I. INTRODUCTION

Manufacturing processes are radically challenged worldwide by economic, socio-political and technological dynamics that have a tremendous impact on enterprise behaviour in the market, and consequently, on the research priorities of the scientific community. Many exogenous factors are modifying the way products are being designed and exploited, among them the introduction of novel materials, technologies, services and communications, for reducing design and manufacturing lead time, cost and the attention paid to the end user requirements are critical to gain an edge over competitors [1]. The introduction of new legislation in manufacturing to diminish the product development time has a reflective influence on manufacturing processes and resulted in the origin of a new invention of production equipment which fabricate parts/component directly from the CAD (computer aided design) model on a layer by layer deposition principle without the need of any part specific tooling, dies, fixtures and human intervention [2]. The method of such layer by layer part generation process is known as Rapid Prototyping. The basic principle of additive manufacturing process is very similar to Non-Traditional manufacturing (NTM) processes. In NTM processes the material is removed from the job to obtain the required geometry of part for this reason the NTM processes are known as subtractive manufacturing process. Rapid prototyping is known as additive manufacturing process because in rapid prototyping the material is bonded together in layered fashion to form the entire object. These process are classify according to the type base material (Liquid, Solid and Powder) used but the availability of material within each category is limited by constraint offered by Rapid prototyping process itself. Advantage of RP has been in term of reduction of product development time and fabrication of complex shaped parts without need of any part specific tooling. Part accuracy, surface roughness, mechanical strength and build time has leaded key issues of rapid prototyping before recommending for industrial application. For this reason, existing rapid prototyping are modified in order to improve their key issues and capabilities of machine [3].

II. RESEARCH BACKGROUND

The strengths and weaknesses of each RP processes have depend on the type of material and building styles used for the fabrication of parts. In literature a wide variety of approaches have been addressed the problem of analyzing and improving the dimensional accuracy, surface roughness, mechanical strength, etc. of Rp parts by optimization of different machine process parameters. Kim et al. [4] have study the quantifications and compared the various RP processes based on mechanical properties, such as tensile strength, compressive strength, hardness, impact strength, heat resistance, surface roughness, geometric and dimensional accuracy, manufacturing speed, and material costs. It was concluded that the stereolithography (SL) process is advantageous in hardness, accuracy, and surface roughness and the Poly-jet process in tensile strength at room temperature. The selective laser sintering (SLS) process was advantageous in compressive strength and manufacturing speed, the three dimensional printing (3DP) process in speed and material costs, and the laminated object manufacturing (LOM) process in heat resistance. The FDM and LOM processes were superior in impact strength in the scanning direction, but the change of building direction significantly reduced the tensile and impact strengths [5]. Dao et al. [6] calculated shrinkage compensation factors to improve dimensional accuracy of parts fabricated using Stratasys FDM 1650 rapid prototyping machine. Result shows that shrinkage compensation factors of 1.010 will produce a 53% reduction in mean error of the dimensions. Xu et al. [7] studies four dominant rapid prototyping processes currently available in the market such as stereolithography, selective laser sintering, fused deposition modelling, and laminated object manufacturing (LOM) with respect to dimensional accuracy and surface finish. He concluded that that the stereolithography process gives the best dimensional accuracy for the most of the measured dimensions followed by LOM, FDM, and SLS. SL is the most excellent process with fine features and dimensions while FDM and SLS perform at same level but LOM gives worst performance. SL and LOM give best results than SLS when roundness of cylinder is measured while FDM gives worst performance. Further, FDM Process has an advantage over the SL process due to easily broken material can be used to build the support, making the removal of the support easier. Many authors have reported regarding the superiority of the SL model for medical applications. Nizam et al. [8] determine the dimensional accuracy of the skull models fabricated using stereolithography process. Computed tomography (CT) images were captured from four dry skull models. The results reveal that the accuracy of the replica 3D models produced by stereolithography machine is appropriate within a margin of error that is acceptable for clinical applications. Liu et al. [9] introduced the concept of disturbance error to describe the effect of accumulated errors in the part fabrication process. Error occurs due to many process related parameters such as tool scan speed, material feed uniformity, glue thickness uniformity, machine path control accuracy, tool shape stability, part thermal distortion, material properties, and part thermal shrinkage and distortion. Data preparation error combined with this error to determine final geometrical accuracy of the part produced. Shrinkage plays an important role to affect the dimensional accuracy of the SLS parts. Shrinkage was compensated by the calculation of material shrinkage coefficient or scaling factor in each direction and is to be applied to stereolithography (STL) file. Raghunath et al. [10] have been investigated the relationship between shrinkage and the various process parameters namely hatch spacing, scan length, laser power, part bed temperature and beam speed in SLS. He concluded that laser power and scan length are to be most significant process parameters that influencing shrinkage along X- direction and for Y-direction laser power and beam speed are the most influencing process parameters while for Z-direction beam speed, hatch spacing and part bed temperature are most influencing process parameters. Senthilkumaran et al. [11] have been investigated that certain compensations other than shrinkage are needed to get accurate estimate of the shrinkage. Beam offset inertia of scanning mirror and positioning errors in hatch generations are found to delude the shrinkage pattern. The exposure strategies and part orientation influence the dimensional accuracy of fabricated parts. Ning et al. [12] have been proposed that dimensional accuracy of part during fabrication can be significantly improved if laser scan speed is adjusted according to the scan length. Zhu et al. [13] study the effect of shrinkages namely thermal shrinkage and sintering shrinkage on the part accuracy of direct metal laser sintering (DMLS) process. Densification is the main cause for sintering shrinkage while process parameters namely scan speed, scan spacing and laser power are cause for thermal shrinkage. Campanelli et al. [14] studied various process parameters such as layer thickness, hatch overcure, hatch spacing, border overcure, fill spacing and fill cure depth of stereolithographic process to improve dimensional accuracy of part/component without the need of post-processing. He concluded that hatch overcure and border overcure play an important role to improve the dimensional accuracy of parts and also eliminate the post-processing of parts. In high resolution the part accuracy improve when hatch overcure and border overcure set respectively to maximum and minimum value of the considered range. For normal resolution the hatch overcure and border overcure set respectively to medium and maximum value of the considered range. Due to technological evolution of 3-D printers, the present research work focused on the fabrication of parts from these open source printer for dimensional accuracy investigation. Therefore, authors investigate the relationship between the 3D open source printer process parameters along with their interactions and the dimensional accuracy of the product in different direction of built parts using Taguchi parameter design method. Taguchi design method gives different optimal parameters level setting for each different dimensional characteristic but this method is inappropriate to obtain optimum factors level setting when we considered each different dimensional characteristic simultaneously. Therefore, grey relational method can effectively establish a single optimum factors level setting for each different dimensional characteristic. Three different dimensional characteristic known as percentage change in length (L1), length (L2) and height (H) are considered to obtain the single optimum factors level setting.

III. Material and Experimental Procedure

An open source (Accucraft i250+) 3D printer was selected to fabricate the test specimens. The extrusion head has a single nozzle to extrude the model material against the part/specimens fabrication direction. Extrusion head move in the X-Y plane and the platform move in Z plane to deposit the model material according to part geometry. The ABS filaments material supplied to the extruder via a feeding system. Diameter and density of ABS filaments material is respectively 1.75mm and 1.05g/cm^3. ABS filaments fused at 245 °C when it enters in the extrusion head. The pressure applied by feeding system leads changes in the diameter of filaments from 1.75mm to 0.45mm. Extrusion head ejected the ABS filament in the form of semi-viscous material onto platform during deposition of layer. The first layer adhesion is carried out using acetone with moistened cardboard. Three dimensional software (CATIA) was used to generate 3D CAD model (Fig. 1) of the parts and exported to STL (Stereolithography) file format. STL file format then transferred to the Accucraft i250+ software. This machine software performs some necessary operation such as tessellation of 3D model, generation of head movement path and machine parameters. Further command and control instructions is given to machine for the fabrication of 3D parts. In this research three process parameters each at two levels with their total three interactions are considered. Three parameters such as raster width, slice height, and path speed each at two levels are considered as shown in Table I. Minitab 17 was used to perform 2^3 full factorial design of experimental plan. Experimental process was completed into two steps. In the first step fabrication of test specimens is done by varying the process parameter (slice height, path speed, and raster width). Per experiment four parts are fabricated using 3D printer. In the second step dimensional measurement such as length (L1), length (L2), and height (H) of test specimens are performed. Digital verniar calliper was used to measure the dimension of the test parts. Formula "(1)" given below is used for the calculation of percentage dimension changes [10].

$$\text{Percentage dimension change} = \frac{|Measured\ value - Oroginal\ value|}{Oroginal\ value} \times 100 \quad (1)$$

Fig. 1. Test Specimen

IV. Methodology

Traditional experimental design methods are too intricate and difficult to use to solve these problems because a large number of experiments have to be performed as in increase of process parameters. To solve this problem Taguchi method uses a special design of orthogonal arrays to study the entire attribute space with a small number of experiments. Experimental results are then transformed into a signal-to-noise (S/N) ratio. Optimization function expressed in terms of S/N ratios. Signal-to-noise ratio approach finds the effect of each process parameter and deviation relative to desired value. The S/N ratio is the ratio of mean (signal) to the standard deviation (noise). Depending on the type of process characteristics there is various type of S/N available but important among them are given in "(2)"-"(4)". Objective of experimental plan is to reduce the percentage change in length (L1), change in length (L2), and change in height (H), respectively. Here the S/N ratio is calculated using smaller the better quality characteristic [15].

$$\text{Signal} - \text{to} - \text{noise} \left(\frac{S}{N}\right) \text{ratio for smaller is the better:} \quad \eta = -10 \log \frac{1}{n} \left(\sum x^2\right); \quad (2)$$

$$\text{Signal} - \text{to} - \text{noise} \left(\frac{S}{N}\right) \text{ratio for larger is the better:} \quad \eta = -10 \log \frac{1}{n} \left(\sum \frac{1}{x^2}\right); \quad (3)$$

$$\text{Signal} - \text{to} - \text{noise} \left(\frac{S}{N}\right) \text{ratio for nominal is the better:} \quad \eta = -10 \log \frac{1}{n} \left(\sum \frac{\bar{X}}{X^2}\right); \quad (4)$$

Where, is the average of observed data value, the deviation of , the total number of observations, and the observed data value.

ANOVA is a standard statistical technique to interpret the experimental results. It is extensively used to identify the performance of group of parameters under investigation. Purpose of ANOVA is to investigate the parameters, whose combination to total variation is significant. Experiment analysis is carried out using the software Minitab R17 specifically used for design of experiment. Optimum factor setting is predicted using S/N ratio. ANOVA is a standard statistical technique to determine effect of individual parameters and their interaction on the part accuracy by interpreting with experimental results. Following given below steps are involved in the calculation of [16].

$$\text{Calculation of Sum of Squares of the output variable:} \quad S_{OV} = \sum_{i=1}^{N} OV_i^2; \quad (5)$$

$$\text{Calculation of Improvement Factor:} \quad IF = \frac{(\sum_{i=1}^{N} OV_i)^2}{N} \quad (6)$$

$$\text{Total sum of squares } T_{SS} = S_{OV} - IF \quad (7)$$

Calculation of individual sum of squares of different parameters (Sj) and then find sum of squares error (S_E) for individual parameters using "(8)"

$$S_E = T_{SS} - S_{j;} \quad (8)$$

Calculation of Degree of freedom (DOF) for each process parameter and then individual sum of squares (Sj) is divided by Degree of freedom (DOF) for each process parameter to calculate mean sum of squares (MSS_j)

$$\text{To find out mean sum of square error:} \quad MSS_E = \frac{S_E}{DOF_E}; \quad (9)$$

Variance ratio is calculated using "(10)"

$$\text{Variance Ratio } F_{VR} = \frac{MSS_j}{MSE_E}; \quad (10)$$

Selection of Tabulated Variance ratio F_T for parameters degree of freedom and degree of freedom for error is carried out. Identification of most significant process parameter is obtained by comparing the variance ratio $F_{VR}$and tabulated variance ratio (F_T). Significant parameter is obtained when, $F_{VR} \geq F_T$ condition is satisfied. After that percentage contribution (%PC) of each process parameter is calculated using "(11)".

$$\text{percentage contribution } (\%PC) = \frac{MSS_j}{\sum_{j=1}^{g} MSS_j}; \quad (11)$$

Grey relational analysis involves two steps in the first steps pre-processing of experimental data is done while second step is used for the calculation of grey relational coefficient. Taguchi method was used to analyze optimal process parameters of a single quality characteristic. For grey relational analysis multiple quality characteristics are combined into single objective for optimization. In the grey relational analysis, grey data processing of experimental results were carried out before the calculation of grey relational coefficients. There are several method used for data pre-processing. Data pre-processing converts the original reference sequence $X_0(k)$ to a sequence for comparison X_i (k), $i = 1, 2, \ldots\ldots, m; \ k = 1, 2, \ldots\ldots$, where the total number of experiment and total number of observation represented as "*m" and "n"*. The original sequence is normalized using "(12)" when the target value of the original sequence is "the-larger-the-better". The original sequence is normalized using "(13)" for "the-smaller-the-better", characteristics and "(14)" is used for "a specific target value", characteristics. In this research "the-smaller-the-better", characteristics are used for data pre-processing. Where, $X_i(k)$, $Y_i(k)$, Max.$X_i(k)$ and

Min.$X_i(k)$ represent original sequence, sequence after data pre-processing, largest value and smallest value [17].

$$Y_i(k) = \frac{X_i(k) - Min.\ X_i(k)}{Max.\ X_i(k) - Min.\ X_i(k)}; \qquad i = 1,2,\ldots\ldots,m; \quad k = 1,2,\ldots\ldots,n \qquad (12)$$

$$Y_i(k) = \frac{Max.\ X_i(k) - X_i(k)}{Max.\ X_i(k) - Min.\ X_i(k)}; \qquad i = 1,2,\ldots\ldots,m; \quad k = 1,2,\ldots\ldots,n \qquad (13)$$

$$Y_i(k) = 1 - \frac{|X_i(k) - C_k|}{Max\{Max.\ X_i(k) - C_k, C_k - Min.\ X_i(k)\}} \qquad (14)$$

Where $X_i(k)$, $Y_i(k)$, Max.$X_i(k)$ and Min.$X_i(k)$ and C_k represent original sequence, sequence after data pre-processing, largest value, smallest value and target value.

In step second the grey relational coefficient was calculated from the normalized experimental data to express the relationship between the desired and actual experimental data. The grey relational coefficient (γ) can be calculated using "(15)".

$$\gamma(Y_0(k), Y_i(k)) = \frac{\Delta_{Min} + \zeta\Delta_{Max}}{\Delta_{0i}(k) + \zeta\Delta_{Max}}; \qquad i = 1,2,\ldots\ldots,m; \quad k = 1,2,\ldots\ldots,n \qquad (15)$$

$$0 < \gamma(Y_0(k), Y_i(k)) \leqq 1$$

$$\Delta_{0i}(k) = |Y_0(k) - Y_i(k)|$$

$$\Delta_{Max} = \text{Min}\{\Delta_{0i}(k); \quad i = 1,2,\ldots\ldots,m; \quad k = 1,2,\ldots\ldots,n\}$$

$$\Delta_{Min} = \text{Max}\{\Delta_{0i}(k); \quad i = 1,2,\ldots\ldots,m; \quad k = 1,2,\ldots\ldots,n\}$$

$$\zeta \in [0,1];$$

Where, ζ is the distinguishing coefficient and $Y_0(k)$ is the ideal normalized value of response. The effect of distinguishing coefficients on grey relation coefficient is very less. In present analysis distinguishing coefficient is taken as 0.5. After calculation of grey relational coefficient the grey relational grade was computed using "(16)", by averaging the grey relational coefficient corresponding to each process response, and is defined as follows

$$\gamma(Y_0, Y_i) = \sum_{k=1}^{n} W_k\, \gamma(Y_0, Y_i); \qquad i = 1,2,\ldots\ldots,m; \quad k = 1,2,\ldots\ldots,n \qquad (16)$$

W_k is the weight percentage of total number of data observed. It is generally taken as one but for this experiment W_k is taken as 0.34, 0.34 and 0.32, for change length (L1), change length (L2) and height (H). Grey relational grade represents the relationship between the reference and comparability sequences. It also indicates the degree of influence exerted by the comparability sequence on the reference sequence. Maximum grey relation grade gives the optimum parameter levels setting [18].

V. Result and Discussion

Experimental analysis is carried out to find out the percentage change in length (L1), length (L2) and Height (H) as shown in Table II. Smaller the better quality characteristic "(2)" is used to convert percentage change in dimensions into S/N ratio value as shown in Table III. Analysis of variance (ANOVO) shown in Tables IV-VI for percentage change in length (L1), length (L2) and Height (H) is used to identified important process parameter and their interaction. Main effect plot for S/N ratio is shown in Fig. 2. Table VII shows optimum factor levels for different dimensional characteristics. Table II reveals that shrinkage is occur in the direction of length (L1) and length (L2) but dimension increases in the direction of height (H). Development of Inner stresses causes shrinkage along the direction of length (L1) and length (L2) resulting the contraction of material. The contraction of deposited thermoplastic material subjected due to cooling from melted temperature (Tm) to the glass-transition temperature (Tg). However, deposited material can acquire a larger deformation with less force, and the capacity to resist outside force is small when the cooling temperature ranges between the melted temperature and glass-transition temperature. Therefore, in spite of the contraction, the inner stresses of the deposited material are not accumulated. The inner stress is mainly produced in the course of the cooling temperature changing from the glass-transition temperature (Tg) to the chamber temperature (Te). Inner stresses resulting from uneven temperature gradients can affect the part size precision, part deformation, inner-layer delaminating or cracking, destroy the supporting structures between the main body of the part and the worktable [19]. The reasons behind the uneven temperature gradients are explained below:

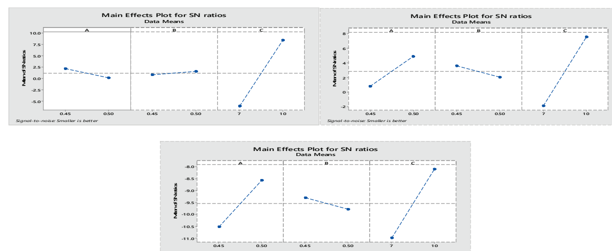

Fig. 2. Main effect plot (a) %change L1 (b) %change L2 (c) %change H for S/N ratio (smaller is better)

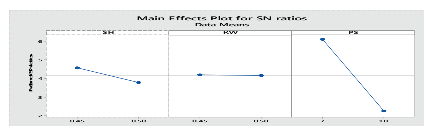

Fig. 3. Factor effect plot for GRG

In 3D-OSP, the temperature quickly reduces due to heat dissipation by conduction and convection processes to solidify the filaments. Bonding between the filaments is occurring due to the diffusion between previously solidified layer and depositing layer. The result of uneven temperature gradients is cause by uneven heating and cooling of material. Results reveals that contraction of deposited thermoplastic material occurs due to generation of uneven inner stress. The path speed depositing the material in layered fashion alters the heating and cooling frequency and results in different degrees of thermal gradients in the part, which in turn affect the accuracy of the part. For lower slice thickness, path speed is slower as compared to higher slice thickness. During deposition, nozzle stops depositing material in random manner and return to service location for tip cleaning. Nozzle speed has to be decreased near to the boundary of part and then increase to maintain at constant speed while depositing the layer. Uneven stress develops if the length of part boundary for deposition is small [20, 21]. The raster pattern used to deposit a layer of material has a significant effect on the deflection of the manufactured part. For a beam substrate, a raster pattern with lines oriented 90 from the beam's long axis produces the lowest deflections and higher stresses will be found with lines oriented 180 from the beam's longest axis [22]. Part distortions are related to the stress accumulation during the deposition of layer. Stress accumulations increase with increasing the thickness of layer and road width. These two parameters also affect the number of layers and the tool paths required at each layer. Heating and cooling cycles may reduce by a thick layer having fewer layers. On the other hand, a smaller raster width will input less amount of heat into the system within a definite amount of time, but requires more loops to fill a certain area. This will complicate the temperature and influence the contraction of previously deposited material will be forced [20]. During deposition of a single layer or multiple layers, the cavity or air gap created between two raster in a same layer or between multiple layers may influence the heat dissipation.

TABLE I. FACTORS AND THEIR LEVELS

Factors and their levels				
Factors	Symbol	Level		Unit
		1	2	
Raster Width	A	0.45	0.50	mm
Slice Height	B	0.45	0.50	mm
Path Speed	C	7	10	mm/s

TABLE II. L8 ORTHOGONAL ARRAY WITH CHANGE IN DIMENSION

L8 orthogonal array with change in dimension						
Exp. No.	Factors			Change In Dimensions		
	Slice Height (A)	Raster Width (B)	Path Speed (C)	%Change L1	%Change L2	%Change H
1	0.45	0.45	7	2	2.9444	3.25
2	0.5	0.45	7	1.722	1.2777	3
3	0.45	0.5	7	1.055	0.8333	3.5
4	0.5	0.5	7	0.666	5.277	4.625
5	0.45	0.45	10	0.5	0.6667	4.25
6	0.5	0.45	10	0.1111	0.27778	1.75
7	0.45	0.5	10	0.666	0.2222	2.625
8	0.5	0.5	10	0.8333	0.5	2.125

TABLE III. L8 ORTHOGONAL ARRAY WITH S/N RATIO DATA

L8 orthogonal array with S/N ratio data						
Exp. No.	Factors			S/N Ratio		
	Slice Height (A)	Raster Width (B)	Path Speed (C)	%Change L1	%Change L2	%Change H
1	0.45	0.45	7	-6.0206	-9.3799	-10.2377
2	0.5	0.45	7	-4.7207	-2.1286	-9.54243
3	0.45	0.5	7	-0.4650	1.5840	-10.8814
4	0.5	0.5	7	3.5305	-14.4477	-13.3022
5	0.45	0.45	10	6.0206	3.5214	-12.5678
6	0.5	0.45	10	19.0857	11.1260	-4.86076
7	0.45	0.5	10	3.5305	13.0651	-8.38259
8	0.5	0.5	10	1.5840	6.0206	-6.54718

TABLE IV. ANALYSIS OF VARIANCE TABLE FOR % CHANGE L1

Analysis of Variance table for % Change L1					
Source	DOF	Seq SS	F	P	PC (%)
A	1	33.678	0.86	0.524	7.96
B	1	4.782	0.12	0.786	1.12
C	1	179.519	4.58	0.278	42.42
A*B	1	18.961	0.48	0.613	1.00
A*C	1	4.239	0.11	0.798	4.48
B*C	1	142.793	3.64	0.307	33.74
Residual Error	1	39.194			
Total	7	423.164			

TABLE V. ANALYSIS OF VARIANCE TABLE FOR % CHANGE L2

Analysis of Variance table for % Change L2					
Source	DOF	Seq SS	F	P	PC (%)
A	1	8.447	0.91	0.516	1.33
B	1	1.188	0.13	0.782	0.187
C	1	422.029	45.29	0.094	66.363
A*B	1	179.856	19.30	0.142	28.28
A*C	1	10.905	1.17	0.475	1.71
B*C	1	4.196	0.45	0.624	0.66
Residual Error	1	9.318			
Total	7	635.940			

TABLE VI. ANALYSIS OF VARIANCE TABLE FOR % CHANGE H

Analysis of Variance table for % change H					
Source	DOF	Seq SS	F	P	PC (%)
A	1	7.6378	8.05	0.216	13.22
B	1	0.4535	0.48	0.615	0.78
C	1	16.8356	17.74	0.148	29.13
A*B	1	10.0974	10.64	0.189	17.46
A*C	1	15.8711	16.72	0.153	27.46
B*C	1	5.9552	6.27	0.242	10.30
Residual Error	1	0.9491			
Total	7	57.7997			

TABLE VII. OPTIMUM FACTORWITH SIGNIFICANT FACTORS INTERACTIONS

Optimum factor level with significant factors and interactions			
Factors	% Change L1	% Change L2	% Change H
A	0.50	0.45	0.50
B	0.45	0.50	0.45
C	10	10	10
Significant	A,C, BXC	C,AXB,AXC	C,AXB,AXC

TABLE VIII. L8 ORTHOGONAL ARRAY WITH NORMALIZED DATA

L8 orthogonal array with normalized data									
Exp .No	Factors			Change In Dimensions			Normalized Data		
	Slice Height (SH)	Raster Width (RW)	Path Speed (PS)	%Change L1	%Change L2	%Change H	%Change L1	%Change L2	%Change H
1	0.45	0.45	7	2	2.944	3.25	0	0.462	0.478
2	0.5	0.45	7	1.722	1.278	3	0.147	0.791	0.565
3	0.45	0.5	7	1.055	0.833	3.5	0.500	0.879	0.391
4	0.5	0.5	7	0.666	5.277	4.625	0.706	0	0
5	0.45	0.45	10	0.5	0.667	4.25	0.794	0.912	0.130
6	0.5	0.45	10	0.111	0.277	1.75	1	0.989	1
7	0.45	0.5	10	0.666	0.222	2.625	0.706	1	0.696
8	0.5	0.5	10	0.833	0.5	2.125	0.618	0.945	0.870

TABLE IX. RESULT OF GREY TAGUCHI METHOD

Result of grey Taguchi method							
Exp No.	Deviation Coefficient			Grey Relational coefficient			Grey Relational Grade
	%Change L1	%Change L2	%Change H	%Change L1	%Change L2	%Change H	
1	1	0.538	0.522	0.333	0.482	0.489	0.43195
2	0.853	0.209	0.435	0.370	0.705	0.535	0.53675
3	0.5	0.121	0.609	0.5	0.805	0.451	0.59205
4	0.294	1	1	0.630	0.333	.333	0.43695
5	0.206	0.088	0.87	0.629	0.850	0.365	0.62715
6	0	0.011	0	1	0.978	1	0.9923
7	0.294	0	0.304	0.630	1	0.622	0.7571
8	0.382	0.055	0.13	0.567	0.901	0.793	0.7517

TABLE X. ANALYSIS OF VARIANCE TABLE FOR GRG

Analysis of Variance table for GRG					
Source	DOF	Seq SS	F	P	PC (%)
SH	1	1.2573	44.08	0.095	2.90
RW	1	0.0038	0.13	0.776	
PS	1	29.7387	1042.5	0.020	68.65
SH*RW	1	9.1868	322.07	0.035	21.21
SH*PS	1	2.7320	95.78	0.065	6.31
RW*PS	1	0.3733	13.09	0.172	0.86
Residual Error	1	0.0285			
Total	7	43.3205			

For the case of height, a slicing rule of most rapid prototyping (RP) systems cannot ensure unilateral tolerances on the whole prototype and often results in problems of overcut and undercut on the same part. This drawback leads to inadequate dimensional accuracy of the part in post processing. If all the tolerance is left outside the original work-piece contour, it is called positive tolerance and when all the tolerance is left inside the original work-piece contour, it is called a negative tolerance. Positive slicing method seems as main cause here to increase the height of the part [23]. In present study, the height of test specimen is taken as 8.0 mm. If test specimen is slices with minimum layer thickness of 0.45 mm then total 17.78 numbers of slices will be requisite by simple mathematical computation. Here, material flow rate is consider as uniform and total 17.78 numbers of slices will be rounded off to nearest complete number 18. To prevent profile error Rp system will deposit total 18 slices during part generation. The above given theory about slicing procedure is true for every orientation of part fabrication. Material overfilling is occurring between the two raster during diffusion process leads the non uniform layer fabrication. Due to this new layer deposited on the non-uniform previous layer will leads in increase of part dimension. Most significant process parameter and their interaction for different part dimension are found out from (Table IV-VI). From (Table VII), it is observed that the path speed and interaction between path speed and raster width affect the part accuracy most in length (L1). For the case of length (L2) the path speed and interaction between raster widths with slice height affect the part accuracy. Path speed and the interaction between path speeds with slice height affect the part accuracy in part build direction height (H). When individual process parameters are combined at optimum factor setting the part fabricated with minimum deviation. Taguchi method was used to analyze optimal process parameters of a single quality characteristic. For grey relational analysis multiple quality characteristics are combined into single objective for optimization. In this study %change length (L1), %change length L2 and %change height (H). For all the three quality characteristics the grey relation generation is calculated according to the smaller the better characteristics using "(14)". Results of grey relation generation are shown in (Table VIII).The grey relational coefficient can be calculated using "(15)" and then grey relational grade is calculated using "(16)" by averaging the grey relational coefficients. Results of grey relation coefficients along with grey relational grade are shown in (Table IX). Main effect plot of GRG for S/N ratio shown in (Fig.3) gives the optimum factor levels (Table X).

VI. Conclusion

Machine parameters are the most influencing factors for dimensional accuracy of the parts fabricated by 3D open source printer. In this paper, three parameters namely raster width, slice height, and path speed each at three levels are considered an attempt has been made to find out the influence of these process parameter along with their interactions on the dimensional accuracy of 3D open source printer products. Taguchi parameter design method has been used to find out the optimum parameters level. Result reveals that dimension along the length L1 and length L2 is decrease due to shrinkage of deposition material and along the direction of height is increases due to availability of inappropriate slicing algorithms. The 3D open source printer involves large numbers of contradictory factors which influence the accuracy during part fabrication. For this, a standard optimizing methodology is used to find out the optimum parameter level setting for part fabrication. In this regard, grey taguchi method has the capability to combine all the multiple targets (percentage changes in length (L1), length (L2) and Height (H)) into single target. Maximum grey relation grade gives the optimum parameter levels setting. Result shows that slice height of 0.50 mm, raster width 0.45mm, and path speed of 10mm/s will improve the overall dimensional accuracy of part produced by 3D open source printer.

VII. References

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