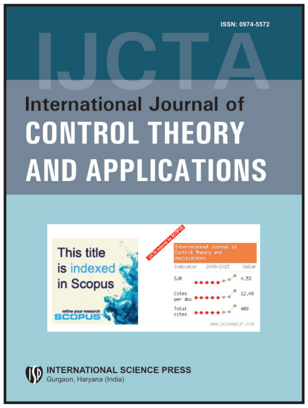

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Parametric Optimization on Quality and Accuracy of Fused Deposition Modeling Prototype using Fuzzy Logic Approach

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Abstract: The acrylonitrile butadiene sterane (ABS) plastic is used to fabricate the fused deposition modeling (FDM) prototype. The quality and accurate dimensions are quite essential specifically for a functional or rapid tool (RT) prototype. Those responses are governed by different parameters controlling the extrusion of semi fluid hot plastic filament and accumulation of layers. To predict and enhance the quality and geometrical accuracy in different working conditions, artificial neural-networks (ANN) combining Taguchi method is applied. Using fuzzy logic decision making and the experimental data, the responses i.e. length, width and thickness are expressed in a single response index. Simultaneously the input parameters are optimized considering all the performance characteristics. Observed predictions of ANN model on overall performance characteristics (OPC) at all operating conditions are of higher accuracy. Finally, the usefulness of the suggested fuzzy approach is experimentally validated.

Keywords: FDM; Dimensional accuracy; Aditive Manufacturing (AM); Fuzzy logic; Taguchi method; ANN.

1. INTRODUCTION

Fit and functional prototypes can be fabricated rapidly make use of applying additive manufacturing (AM). AM is a computer aided growth forming process previously known as rapid prototyping (RP), begins with creating a computer aided design (CAD) file of the object. Then the CAD file is converted into stereo lithography (STL) format i.e. slicing or multiple-layered data file. The layers stand for the horizontal cross sections, corresponding to the CAD model virtual cross section. Stacking the material layers starting from the base till completing the 3D prototype using a computerized fabrication technique and specific material. [Noorani, R. 2006]. The prototype can be fabricated within shortest time, without any spatial tooling and additional cost, [Upcraft and Fletcher, 2003, Mansur and Hauge, 2003]. Uniting sub-assembly designs at the CAD stage reduce part counts, product handling system, time and storage requirement that avoids mating/fitting and inventory problems [Hopkinson et. al., 2005].

FDM extruded parts are widely used today in automobile industries, medical fields, aerospace components, household goods, computer/mobile phone parts, proofing new design. For a RT the prototype can also be designed (pattern, electro discharge machining electrode etc). Fabricating a precise replication of cerebral aneurysms FDM prototype, Frolicha et. al., (2016) conformed its direct use in scientific and medical studies. Still applications of FDM process have not gained much importance because of its quantitative and qualitative responses. Influence of various input parameters on dimensional accuracy, part strength, make time and surface quality have not yet analyzed adequately [Hopkinson et. al., 2005, Pilipovic et. al., 2009]. Thus it is indispensible to comprehend the drawbacks of the FDM, before suggesting it for any application. To reduce the predictive error and revise the surface roughness and edge profile geometry of the FDM models, Taufik et. al., (2016) used theoretical and experimental methods, considering the perimeter, raster and combination of both. Several researches are made to enhance the accuracy, strength and quality of the FDM part by intelligently regulating the input parameters at the fabricating level [Chockalingama et. al., 2008, Ali et. al., 2014]. Wu et. al., (2015) has compared the variations in modulus of elasticity and mechanical property by relating the effects of raster angles and layer-thickness. Bochmann et. al., (2015) studied about the causes influencing imprecision. Using the ABS-Graphane composite filaments to boost the strength, Dul et. al., (2016) observed the increased elastic modulus and dynamic laying segment of all the three differently oriented parts.

It is important to optimize the selected responsive process parameters to attain the elevated geometrical accuracy and quality, specifically for fit and functional or RT prototypes. Rayegani and Onwubolu, (2014) predicted and optimized the responsive parameters experimentally and mathematically, applying group method for data handling and differential evolution. Considering the effect of FDM input parameters i.e. raster width, contour width, slice height, raster angle, orientation and air gap, Srivastava et. al., (2015) optimized the production cost using response surface methodology (RSM).

Generally the desired parameters are selected on the basis of the operating manual (machine) or work experience and skill. However, for a particular machine and/or environment the acquired results may or may not be optimal. Therefore Taguchi method is adopted due to its simplicity and systematic functionality as an efficient alternative method to establish the most desirable combinations of the process parameters. It reduces the sensitivity of the system performances, limits the variations and enhances the quality and cost of the FDM product [Ross, P.J., 1998]. Taguchi method also reduces experimental run counts by predicting the input parameters correctly and their possible interactions for better accuracy of dimensions [Sood et. al., 2009]. Conversely application of Taguchi is found suitable for optimizing a process of single performance characteristic (SPC), but while multiple performance characteristics (MPC) of multiple responses are concerned it becomes incompatible [Elsayed and Chen, 1993].

Consequently it is revealed that using fuzzy logic decision making and fuzzy reasoning, the optimized MPC can be transformed into optimized SPC index. Thus to optimize the MPC problems of the FDM i.e. change in thickness, length, and width, the fuzzy logic approach integrated with the Taguchi method is more appropriate. After minimizing the responses individually, the overall multi response performance index (MRPI) and the MPC are maximized.

To get the FDM part dimensions accurately by conducting trial runs to get the satisfactory result, need substantial amount of cost, materials, time and energy. Hence the artificial neural-network (ANN) i.e. particularly related to parallel architectures, is arranged to solve difficult problems, using mutual aid of highly inter connected and related simple computing elements i.e. artificial layered neurons. ANN is an influential tool to identify the significant parameters, combinations and interactions, particularly when their associations are very intricate and highly non linear. The prognostic representation based on ANN has been presented here for appraisal of exactness in dimensions of FDM prototypes subjected to different operating conditions. To collect experimental data in an organized way, use of Taguchi's orthogonal array (OA) is helpful in developing a suitable ANN predictive model easily. Finally effectiveness of both the models are compared and verified,

2. LITERATURE REVIEW

To select the most significant FDM input process parameters and their levels on the output response results, Ali et. al., 2014) used the design of experiments (DOE). As observed by Es Said et. al., (2000), there are coalitions of polymer molecules in the deposition direction, caused by raster orientation, while fabricating the FDM object. Volumetric shrinkage causes weak bonding of layers and high porosity due to change in phase of the semi-molten extruded filament solidification. Using DOE, Khan et. al., (2005) verified that the parameters i.e. layer thickness, air gap and raster angle along with their levels, control the elastic nature and improve the flexibility of the FDM ABS prototype. Taguchi method is used by Anitha et. al., (2001) to find the surface roughness (SR) of the FDM built part, considering the usefulness of deposition speed, raster width and layer thickness, each at three levels. They marked that layer thickness is mostly affecting the SR, compared to deposition speed and raster width. Adjusting the chamber temperature to recrystalization temperature of the material, deformation gradually decreases to zero. Thus linear shrinkage rate of the part has been minimized by taking lower value of recrystalization temperature and the smallest length of the extruded fiber [Chou et. al., 2008]. Using finite-element analysis (FEA) and simulating the FDM process, Venkata et. al., (2007) observed that during fabrication, accumulated residual stresses cause the distortion at the bottom part of the surface. The part orientation is influencing on: build time, part strength, surface finish, and dimensional accuracy**.** While Sood et. al., (2009) have shown that the flexural and tensile strength of the FDM part uniformly decreases, while increasing the orientation angle due to formation of voids. The detrimental effect can be reduced by lower orientation. Bellehumeur et. al., (2008) have noticed that the adhesion quality and strength of two adjacent filaments is influenced by the envelope temperature.

From the literature studies it is noticed that, the properties of AM products are functions of different related input process parameters. Adjusting those parameters correctly, the built part quality can be remarkably improved without any extra cost [Chockalingama et. al., 2008].

From the above discussions it is cleared that the FDM extrusion process is sensitive to the input parameters, persuade the mechanical strength of the part due to changes in the microstructure. The variation in filament temperature during the laying process, leads to inaccurate dimension due to distortion. The FDM process functions are directly responsible for the weak bonding of the mutual (adjacent) filaments [Ming et. al., 2007]. After various literature studies on FDM process and built parts, it is quite clear that SR is an essential output characteristic of the FDM the effects of the FDM input parameters totally dominant the overall quality improvement of the FDM parts. Specifically the dimensional exactness has not been dedicatedly explored.

Objective: As the surface finish of the FDM prototypes are mostly vital for the fit and functional, direct tooling, RT and direct end use components, it is highly necessary to fix the best possible parameter settings through the structured methodology to provide better FDM part with optimum dimensional accuracy.

3. EXPERIMENTAL DETAILS

3.1. FDM Process

The FDM part is made by the extruded semi molten semi fluid ABS plastics from the nozzle tip. From two different nozzles filaments are extruded, one for the part and second for the support structure material deposition. The structure material lairized by the secondary nozzle on the build platform surface develops the base and support structure. The extruded material from the (part) nozzle tip is systematically deposited from the base. The hot plastic filament rapidly solidifies adhering to adjacent filaments and previous layer. At a pre set temperature and nozzle speed and as per horizontal slices of the STL file, the raster (i.e. filament laid over) is applied perimeter first then fill the interior basis. Completing one layer the next layer is deposited onto it and adhered thereto, up to the 3-D physical model is made.

On the basis of previous researches on part quality [Venkata et. al., 2007, Stratasys, 2004], five FDM process control factors at three different levels are examined to study the dimensional correctness of the built part. The five factors defined briefly are:

Layer thickness: *A* the thickness of one layer deposited by the related nozzle size.

Orientation: *B* angle made by the part to be built on the base platform referred to all: X - Parallel axis, Y - horizontal axis (platform) and Z - vertical axis or along the part build direction.

Raster angle: *C* direction of raster relative to the parallel axis of the build platform.

Raster width: *D* pattern width of the raster used to fill the interior of part.

Raster to raster gap: *E* space between two adjacent raster (in any layer) and air gap.

The selected control parameters and their values at different levels are listed in Table 1(a) and other as fixed parameters, their level are listed in Table 1(b).

To study about the five controlling factors at three different levels generally require $3^5 = 243$ number of experiments, if classically designed but adopting Taguchi method same statistically applicable results can be attained, with reduced number of experiments [Stuart, P. G. 1993].

In the Taguchi design, it is important to select an OA to get the convincing output, so DOE is planned and accordingly the experiments are conducted. The total degrees of freedom (DOF) are computed before selecting an appropriate OA for experiments. For computing the DOF, four FDM process interactions are considered (though during experimentation there may occur more interactions between them) and five factors at three different levels are considered, giving a total DOF of 26. To fit the specific purpose, a suitable OA of $L_{27}(3^{13})$ is selected, consisting 13 columns for factor and/or interaction assignments and 27 rows for putting the values of the trial or experimental runs. To avoid the mystifying effect, factors and interactions are assigned as per the linear graph shown in Figure 1. The dots represent the factors with bracketed number indicating columns, line between dots represents the interaction between and numbers shown above the lines are the factors assigned to the column.

Since part orientation influence the most on the output responses in comparisons to other parameters, the interaction of orientation is considered with all other factors and so it is assigned to column number 5. Recurrently changing the nozzles as required to get change in the layer thickness is consuming time, causes wastage of material. So layer thickness is assigned to column number 1. Assigning the column number 2 to Factor C, factor D and E are assigned to column number 9 and 10 respectively as shown in the Figure 2.

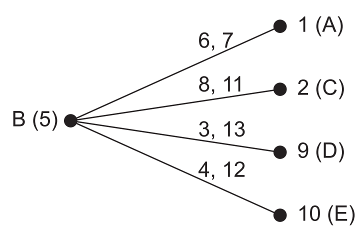


Figure 1: Linear graph

The FDM input process parameters and their levels using L_{27} OA along with the experimental data on dimensional changes observed are listed in Table 2. At this point, control parameters of Table 1(a) are set to a given experimental layout as in Table 2. For one experiment three parts of ABS Plastic 400 are fabricated through the FDM machine FORTUS 400 mc, using the STL file.

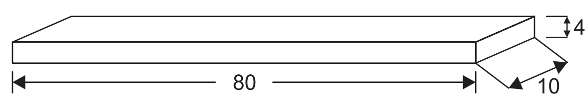
Table 1
(a) Control Parameters and their levels

Control Parameters					
Parameter	*Symbol*	*Level 1*	*Level 2*	*Level 3*	*Unit*
Layer thickness	A	0.127	0.178	0.254	mm
Orientation	B	0	15	30	degree
Raster angle	C	0	30	60	degree
Raster width	D	0.406	0.456	0.506	mm
Air gap	E	0	.004	0.008	mm

Table 1
(b) Fixed Parameters and their levels

Fixed Parameters		
Parameter	*Value*	*Unit*
Part fill style	Perimeter raster	–
Contour width	0.406	Mm
Part interior style	Solid- normal	–
Visible surface	Normal-raster	–
X, Y & Z shrink factor	1.0038	–
Perimeter/raster air gap	0	mm

The FDM test samples are fabricated with the dimensions of (80 × 10 × 4) as shown in Figure 2. FDM samples are fabricated with varried parameters and different measurements are tabulated.



(All dimensions are in mm)

Figure 2: Test specimen for dimensional analysis

Table 2
L_{27} orthogonal array with S/N ratio, experimental data layout

Expt. .No.	*FDM parameter level*					*Responses*			*S/N ratio (dB)*		
	A	*B*	*C*	*D*	*E*	*ΔL*	*ΔW*	*ΔT*	*ΔL*	*ΔW*	*ΔT*
1	1	1	1	1	1	0.0461	0.0598	0.1167	26.7447	24.4514	18.6661
2	1	2	1	2	2	0.0958	0.0434	0.1565	20.3636	27.2703	16.1041
3	1	3	1	3	3	0.0852	0.0832	0.1034	21.3812	21.5872	19.7181
4	1	1	2	2	2	0.0387	0.0732	0.1065	28.2684	22.6979	19.4449
5	1	2	2	3	3	0.1528	0.0498	0.1532	16.3289	26.0381	16.2893
6	1	3	2	1	1	0.1414	0.0434	0.1067	16.9973	27.2703	19.4450
7	1	1	3	3	3	0.0227	0.0534	0.1265	32.9179	25.4656	17.9514
8	1	2	3	1	1	0.1101	0.0665	0.1601	19.1722	23.5306	15.9177
9	1	3	3	2	2	0.0941	0.0634	0.1498	20.5375	23.9720	16.48411
10	2	1	1	2	3	0.0098	0.0201	0.1067	40.0875	33.9795	19.4451
11	2	2	1	3	1	0.0265	0.0765	0.1732	31.5026	22.3155	15.2241

Expt. .No.	FDM parameter level					Responses			S/N ratio (dB)		
	A	B	C	D	E	ΔL	ΔW	ΔT	ΔL	ΔW	ΔT
12	2	3	1	1	2	0.0561	0.0498	0.1801	25.0363	26.0381	14.8946
13	2	1	2	3	1	0.0772	0.0367	0.1466	22.2366	28.7305	16.6774
14	2	2	2	1	2	0.1127	0.0434	0.1932	18.9691	27.2704	14.2755
15	2	3	2	2	3	0.1058	0.0366	0.1801	19.5022	28.7305	14.8944
16	2	1	3	1	2	0.0607	0.0367	0.1198	24.3506	28.7305	18.4247
17	2	2	3	2	3	0.0732	0.0665	0.1701	22.6980	23.5307	15.3911
18	2	3	3	3	1	0.0381	0.0365	0.1465	28.4045	28.7306	16.6775
19	3	1	1	3	2	0.0573	0.0198	0.2634	24.8369	34.0230	11.5911
20	3	2	1	1	3	0.0507	0.0421	0.3832	25.9172	27.5351	8.3293
21	3	3	1	2	1	0.1190	0.0238	0.3768	18.4673	32.4319	8.4823
22	3	1	2	1	3	0.0332	0.0182	0.3464	29.5513	34.8946	9.2035
23	3	2	2	2	1	0.0285	0.0401	0.4199	30.8728	27.9589	7.5351
24	3	3	2	3	2	0.0972	0.0299	0.2565	20.2377	30.4866	11.8149
25	3	1	3	2	1	0.0199	0.0281	0.2635	34.0229	31.0568	11.5912
26	3	2	3	3	2	0.0485	0.0401	0.3432	26.2674	27.9589	9.2866
27	3	3	3	1	3	0.0207	0.0400	0.3065	33.7228	27.9589	10.2687

For each sample three readings are taken, each for the length, width and thickness and the calculated mean is taken as representative value. Mitutoyo vernier caliper is used to measure the dimensions with a least count of 0.01 mm.

Change in dimension is given by the equation:

$$\Delta X = |X - X_{CAD}| \tag{1}$$

Where ΔX is the change in the value of X, as X is the measured value, (length/width/thickness).

X_{CAD} represent the respective CAD model value. From the measured values it is observed that there is shrinkage in length L and width W however thickness T is more than the CAD model value always.

4. METHODOLOGY

In methodology, discussions are made on various associated models and methods, applied to achieve the optimized setup. Along with the signal to noise ratio, analysis of variances and fuzzy logic are used to get the results and compared. Mamdani fuzzy model and its frameworks are discussed, that to: selection of input and output variables, selection of membership functions for input and output variables, formation of linguistic rule base and finaly on defuzzification. Artificial neural computation is also applied and found most suitable in this present work.

4.1. Signal-to-noise (S/N) Ratio

To calculate the difference between the experimental value and the desired value, a loss function is definite in the Taguchi method. To find the differences between the performance characteristic value and the desired values, the S/N ratio is used. The benefit of using S/N ratio is the one piece measure loss function, which is directly related to the effect of changes in the mean and standard deviation (variations) with equal priority. As mostly the results are linear in accomplishment, is an indispensable assumption while expressing it in term of the s/n ratio, to express the optimum performance condition. Generally to analyze the S/N ratio, the performance characteristics are considered in three categories: (i) lower the better, (ii) higher the better and (iii) nominal the better. Apart from the categories, the performance characteristic is better co-relating to the larger S/N ratio. Thus the optimal process parameter level is with the highest S/N ratio. The experimental planning is made to reduce the variations in ΔL, ΔW and ΔT, i.e. change in length, width and thickness respectively, considering lower the better quality characteristic is justifiable. The expression of S/N ratio η_{ij} for lower the better performance characteristic is given by:

$$\eta_{ij} = -\log(L_{ij}) \qquad ...(2)$$

and

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} Y_{ijk}^2 \qquad ...(3)$$

where, the loss function L_{ij} is the i^{th} performance characteristic for the j^{th} experiment, with n number of repetitions. The experimental value y_{ijk} is the i^{th} performance characteristic of the j^{th} experiment for the k^{th} observation.

4.2. ANNOVA, the Analysis of Variance

Minitab R14 software is used for analyzing the experimental results. To predict the optimum factor level, S/N ratio plot of main-effect is used. To identify the parameters and few of their interactions which influence significantly on the process performance characteristics, the statistical analysis of variance ANOVA is considered to be useful. The contribution percentage % P of various parameters and interactions of the process with some selected performance characteristic can be anticipated by conducting ANOVA test. The significance of factors and interactions can also be indomitable by comparing intended F-value with standard F-value at a fastidious level of confidence, taken 95% in this study. Likewise all information related to the quality characteristic of interest, influenced by each controlled parameter can be obtained. All ANOVA calculations are made using equations 4, 5 and 6. Where, for factor A the sum of square is SS_A, sum of the observed data is A_l related with l^{th} level of factor A, number of observations η_{A_l}, allied with l^{th} level of factor A, sum of all the observation is T and total number of experimental observations is N.

$$SS_A = \left[\sum_{l=1}^{3} \frac{A_l^2}{\eta_{A_l}}\right] - \frac{T^2}{N} \qquad ...(4)$$

Without chauvinism to the above expression given in the equation 4, variations can also be found calculated that is caused by other control factors by using the following equation:

$$SS_{A\times B} = \left[\sum_{m=1}^{c}\left(\frac{(A\times B)_m^2}{\eta_{(A\times B)_m}}\right)\right] - \frac{T^2}{N} - SS_A - SS_B \qquad ...(5)$$

where, variation of interacting factors A – B is $SS_{A\times B}$, sum of data considering m^{th} order of the combined factors A and B is represented by $(A\times B)_m$, c is the possible number of the interacting factor combinations and conditional number of data points is $\eta_{(A\times B)_m}$. Without intolerance to the equation 5, the variations in other control factor interactions $B\times C$, $B\times D$ and $B\times E$ are also determined using the equation given below:

$$SS_T = \sum_{k=1}^{N} y_k^2 - \frac{T^2}{N} \qquad (6)$$

where, the total sum of square is SS_T, each observed experimental value is y_k, with $k = 1$ to N.

If the error in DOF becomes zero, then factors and interactions give small SS values in comparison to maximum SS present, are unified in the ANOVA table. Sooner the significant factors and interactions are known, the final step in the DOE is to predict and verify the improvements in performance characteristic values, through the combination level of significant control parameters using Taguchi's predictive model. To minimize three performance measures simultaneously in a single factor level setting, change in length, width and thickness are considered. Afterall, Taguchi method is found suitable for optimizing a SPC and the fuzzy logic unit combine all the considered performance characteristic into a single usable characteristic of the optimization problem. Now to consider the three different responses for the Taguchi method, the S/N ratios corresponding to the ΔL, ΔW and ΔT are processed by the fuzzy logic unit.

4.3. Fuzzy logic

Here it is discussed on fuzzy logic unit in brief. Detailed analysis made on fuzzy logic are explained in many articles [Stuart, P.G., 1993, Mendel, J.M., 1995]. The fuzzy logic unit with three input giving one output is outlined in Figure 3, In a fuzzy logic model, there are three main components, a fuzzifier, the knowledge base i.e. an inference engine, and a defuzzifier. Fuzzifier is the reciver and convertor, it receives the real input known as 'crisp input', containing precise informations about the specific parameters, then converts this quantity to imprecise quantity such as small, medium or large assinging a membership value, typically the degree ranges from 0 to 1. Heart of the fuzzy system is the knowledge base. Now both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets, and the rule base contains number of fuzzy conditional rules such as 'if - then'. Inference engine is the fuzzy inference engine or system or decision maker, performs the inference operations according to the combined rules. Defuzzifier is the output generator using the inference block, always fuzzy in nature. The defuzzifier provides real output, after receiving the fuzzy input.

x_1: S/N Ratio, change in length

x_2: S/N Ratio, change in width

x_3: S/N Ratio, change in thickness

y: Multi-Response Performance Index (MRPI)

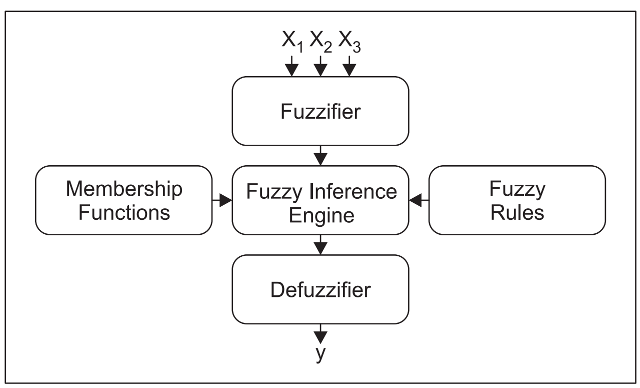


Figure 3: Structure of the three-input-one-output fuzzy logic unit

Out of several fuzzy inference system models, two most popular and generally available are: Mamdani fuzzy model and Sugeno fuzzy model. The selection is made on the basis of the fuzzy reasoning and with the formulation of fuzzy IF-THEN rules. Mamdani fuzzy model [Mamdani and Assilia, 1975] is based on both fuzzy previous circumstances and consequential predicts along with the collections of IF-THEN rules. The rule base is generally prepared by experts and hence to a certain degree it is lucent to explanation and study. To solve numerous real world problems, Mamdani model is most frequently used.

4.3.1. Mamdani Fuzzy Model System

In the present study the performance index for the MPC is estimated using the Mamdani fuzzy model. With using set of measured data input, the fuzzy system would be able to evaluate, the output for any given input even without heading a specified input condition in the building stage. The Mamdani fuzzy model proposed for evaluating MRPI is outlineded in Figure 4.

The methodology for the development of fuzzy model involved the following steps:

(i) Selection of input and output variables,

(ii) Selection of membership functions for input and output variables,

(iii) Formation of linguistic rule base, and

(iv) Defuzzification.

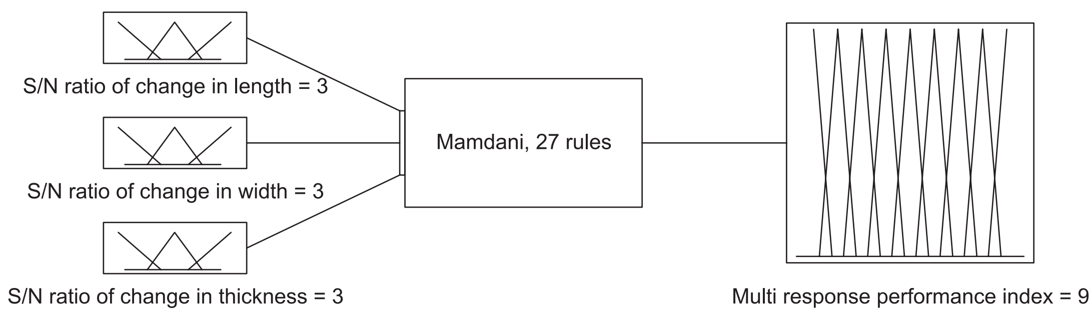


Figure 4: Mamdani fuzzy rule based Structure to evaluate MRPI

Input and Output Variable Selection

Identification of input and output variables are known as system variables and the fuzzy system input variables are S/N ratio of change in length, width, thickness and output variable is MRPI.

On the basis of the physical nature of the problem the universe of discourse is decided. As said above, the inputs and output are in the form of linguistic format. The linguistic variables are words from an artificial or natural language without changing the meaning with a varying form. The linguistic variables, linguistic value and related fuzzy intervals are resulting from Table 2 and the output ranges are shown in Table 3.

Membership Function Selection for the Input and Output Variables

Linguistic values are expressed as fuzzy sets, typically defined by its associated functions. Generally, triangular and/or trapezoidal type membership functions are used because of their simplicity and computational effectiveness to normalize the crisp inputs. A triangular membership function is used given in Equation 7, to change the linguistic values between 0 to 1.

$$\text{triangle}(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{7}$$

takeing x as the input variables range and a, b and c, the linguistic value parameters.

In this present study a model is proposed with three triangular membership functions for each input and nine triangular membership functions as the output. The input variables of the system are converted in to linguistic values, as per the membership grade and the linguistic variable. Similarly the MRPI, the output is divided in nine zones. On the basis of grade membership, the output is expressed in linguistic terms. Based on x_1, x_2, x_3 and y values, various fuzzy set membership degrees are calculated.

Table 3
Inputs, outputs, linguistic values and fuzzy intervals

S. No.	*System's linguistic variable*	*Variables*	*Linguistic values*	*Fuzzy interval*
1		S/N ratio of change in length	Small	15 – 25 (dB)
			Medium	17 – 37 (dB)
			Large	31 – 40 (dB)
2		S/N ratio of change in width	Small	20 – 27 (dB)
	Inputs		Medium	24 – 32 (dB)
			Large	29 – 35 (dB)
3		S/N ratio of change in thickness	Small	5 – 12 (dB)
			Medium	7 – 18 (dB)
			Large	14 – 20 (dB)
4		Multi-response-Performance Index MRPI	Tiny	0 – 0.112
			Very small	0.012 – 0.237
			Small	0.137 – 0.362
			Small medium	0.262 – 0.487
	Output		Medium	0.387 – 0.612
			Medium large	0.512 – 0.737
			Large	0.637 – 0.862
			Very large	0.762 – 0.987
			Huge	0.887 – 1

Formation of Linguistic Rule Base

The input and the output relationship are represented by the logic, if-then rules. The inputs x_1, x_2, and x_3, each has three membership functions according to the fuzzy system, thus $3^3 = 27$ rules can be made. Applying the maximum minimum assumption to Mamdani fuzzy model, taking x_1, x_2, and x_3 as three inputs, and y as one output, are generated as follows:

Rule 1 – if (x_1 is A_1, x_2 is B_1 and x_3 is C_1) then y is D_1 else

Rule 2 – if (x_1 is A_2, x_2 is B_2 and x_3 is C_2) then y is D_2 else

...

Rule n – if (x_1 is A_n, x_2 is B_n and x_3 is C_n) then y is D_n (8)

Where x_1, x_2 & x_3 are the inputs and output is y and A_i, B_i, C_i, and D_i are the linguistic parameters (membership functions) of the inputs. The optimum factor levels and better performance characteristi are attainable by considering larger MRPI. Based on 'larger the S/N ratio, better the performance characteristics, twenty seven fuzzy rules are derived as shown in Table 4. Considering the maximum minimum combinational operation fuzzy reasoning rule yield a fuzzy output [Zimmerman, H.J. (1991)].

Defuzzification

In this model a defuzzification method, centroid of area (COA) given in Equation 9, is used to change the fuzzy inference output into a non-fuzzy value known as MRPI [Jang et. al., 2005].

$$\text{COA} = \frac{\int_y \eta_D(y)\, y\, dy}{\int_y \eta_D(y)\, dy} \tag{9}$$

where, $\mu_D(y)$ is the membership function of the output of fuzzy reasoning, y is output variable (range 0 to 1).

Table 4
MRPI and fuzzy rule

MRPI		*S/N ratio of ΔL*								
		Small			*Medium*			*Large*		
S/N ratio of ΔT		*Small*	*Medium*	*Large*	*Small*	*Medium*	*Large*	*Small*	*Medium*	*Large*
S/N ratio of ΔW	Small	Tiny	Very Small	Small	Small	Small Medium	Medium	Small	Medium	Large
	Medium	Very Small	Small Medium	Medium	Small Medium	Medium	Medium Large	Medium	Large	Very Large
	Large	Small	Medium	Medium Large	Medium Large	Medium	Large	Medium Large	Very Large	Huge

4.4. ANN Computation

As the FDM process is based on number of interrelating and complex combination of factors, mathematically it is difficult to predict the accurate performance characteristics to fabricate the part. The relative actions of the FDM input process parameters over output responses is highly non linear. As a result the ANN, a robust statistical method, is adopted to associate the operating parameters responding to the constraints. An ANN is a groupe of simple elements operating parallelly, are organised into a sequence of layers, each are linked with a certain weight. An ANN structure can be represented by correlating the patterns of the function, transforming from the input to output in the elements.

As shown in Figure 5, an ANN is to carry out trails of a typical function to get a explicit pre required output from a particular input by putting the weight values for each element, adjusting the network upto raeching the target by differentiating the targeted values with the output. The logical function varifiy, until the value of the network output matches with the target value [Hagen et. al., 1996]. Considering the input, output and trained values to predict the process activities accurately, an ANN model is constructed. For the FDM process, this method is particularly valuable while it is difficult to predict or even impossible to achieve the physical mechanism i.e. Rajasekaran et. al., (2003).

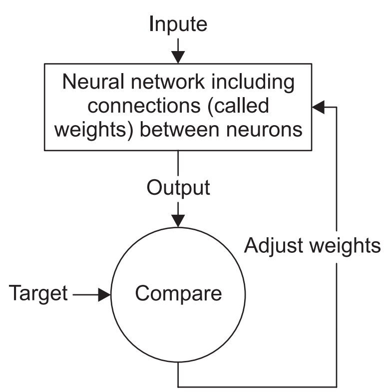


Figure 5: ANN Structure

5. RESULTS AND DISCUSSIONS

5.1. Model Analysis

As per the experimental layout, experimental data on change in dimension is converted in to S/N ratio, using Equation 2, taking lower the better quality characteristic, values are given in Table 2.

The significant factors and interactions are identified using ANOVA are given in Table 5 for ΔL, Table 6 for ΔW and Table 7 for ΔT along with the optimum factor level with significant factors and interactions are tabulated in Table 8. Comprising Table 1 and Table 8, the change in length is minimum at $A_3 = 0.254$ mm, $B_1 = 0°$, $C_3 = 60°$, $D_2 = 0.4564$ mm and $E_3 = 0.008$ mm, change in width is minimum at $A_3 = 0.254$ mm, $B_1 = 0°$, $C_2 = 30°$, $D_2 = 0.4564$ mm and $E_3 = 0.008$ mm and change in thickness is minimum at $A_1 = 0.127$ mm, $B_1 = 0°$, $C_1 = 0°$, $D_3 = 0.5064$ mm and $E_2 = 0.004$ mm.

The factors and interactions found significant are A, B, C, B × D, B × E for affecting change in length, A, B, A × B, B × E for affecting change in width and A, B, B × D for affecting change in thickness as given in Table 8.

Table 5
ANOVA for ΔL

Source	*DOF*	*SS*	*MS*	*F*	*%P*
A	2	150.35	75.175	34.22	44.44**
B	2	52.264	26.132	11.89	15.44
C*		9.932	4.966	2.26	2.93
D*		2.248	1.124	0.51	0.66
E*		0.593	0.297	0.14	0.21
A × B	4	53.452	13.363	6.08	15.79
B × C*		15.277	3.819	1.74	4.51
B × D*		2.703	0.676	0.31	0.79
B × E	4	51.534	12.883	5.86	15.23
Error	14	30.753	2.197		
Total	26	338.353			100

Table 6
ANOVA for ΔW

Source	*DOF*	*SS*	*MS*	*F*	*%P*
A	2	100.892	50.446	2.76	10.67
B	2	226.056	113.03	6.19	23.91**
C	2	95.39	47.695	2.61	10.08
D*		12.376	6.188	0.33	1.34
E*		62.016	31.008	1.69	6.55
A × B*		68.116	17.029	0.93	7.20
B × C*		76.581	19.145	1.04	8.10
B × D	4	169.326	42.331	2.32	17.91
B × E	4	134.642	33.66	1.84	14.24
Error	12	219.089	18.257		
Total	26	945.393			100

Table 7
ANOVA for ΔT

Source	*DOF*	*SS*	*MS*	*F*	*%P*
A	2	322.682	161.341	169.3	83.17**
B	2	34.031	17.016	17.86	8.77
C*		0.529	0.265	0.28	0.18
D*		2.52	1.26	1.32	0.64
E*		0.249	0.125	0.13	0.06
A × B*		5.973	1.493	1.57	1.53
B × C*		5.644	1.411	1.48	1.45
B × D	4	14.091	3.523	3.7	3.63
B × E*		2.246	0.561	0.59	0.57
Error	18	17.161	0.953		
Total	26	387.966			100

*Pooled, **Highly significant, Level of significance = 0.05
SS - sum of squares, MS - mean of squares, F - frequency, %P - percentage contribution

It is established from observed values of Table 2 that, shrinkage occurred in length and width are comparatively high but the increase in thickness is also noticed from its preferred value which may not be neglected. The direction of shrinkage in length wise and width wise may be caused by the growth of internal stresses, due to contraction of deposited fiber during cooling from high extrusion temperature to glass transition low temperature. Thus the deposited fiber can attain a large deformation with less force and week to resist outside force at this range of temperatures.

Table 8
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	3	2
Significant	A, B, C, B × D, B × E	A, B, A × B, B × E	A, B, B × D

For these reasons, regardless of contraction, the inner stresses are not concentrated [Ahn et. al., 2002]. However, while the extruded fiber is cooling from glass transition temperature to the temperature of build chamber, a stress σ is developed. With Young's modulus of elasticity as E, co-efficient of thermal expansion as α and change in temperature as ΔT, the stress is given by:

$$\sigma = -E\,\alpha\,\Delta T \tag{10}$$

The rapid heating-cooling cycles of the FDM material during the fabrication process causes build up stresses due to non uniform temperature gradients, resulting in distortion, inner layer crack formation and dimensional inaccuracy, poor inter layer adhesion or de-lamination as shown in Figure 6 [Ming et. al., 2007]. The different reasons and FDM cases are explained as follows:

(i) When the hot extruded material is solidifying quickly onto the surrounding filaments, heat is dissipated by conduction and forced convection, thus the reduction in temperature caused. The bonding between the hot extruded filament and the filaments (material previously solidified) is because of the local re melting and diffusion. This develops non-uniform temperature gradients, development of non-uniform stress in the deposited material and therefore may fail to get back its original dimension absolutely.

(ii) Change in speed of the nozzle due to geometrical condition of the part, influencing the thermal gradient between filament to raster and part accuracy [Chou et. al., 2008].

(iii) Pattern types of the deposited material layer have a significant result on the deformation and the resulting stresses. Due to higher stresses along the axis of long line of deposition, short deposition length is to be chosen along that axis to decrease the stresses [Nickel et. al., 2000].

(iv) Increasing the layer thickness and the road width causes stress accumulation [Chou et. al., 2008], however the thick layer reduces number of layers decreases rapid changes in raster temperature. Thus with smaller road width develop less heat within the particular period of time, but requires more number of loops to fill the same layer, more time to deposit a layer, uneven surface finish due to raster diameter and rapid change in nozzle speed.

(v) The rapid change in nozzle motion, orientation of the under layer, or the supportive structure layer, influence uneven laying and stretching of filaments, may cause the gap between two neighbor filaments in a single layer. As shown in Figure 15, development of voids between the raster of two neighboring layers may be due to one or more reasons i.e. the uneven cooling of the filaments, the residual stress and the effect of heat dissipation.

Note: The test part surfaces are examined by scanning electron microscope (SEM) JEOL JSM-6480LV in the LV mode. The SEM images, Figure 6 and 7, showing the defects such as between two raster / inter layer cracks, air gap, voids and overfilling at two raster contact.

Figure 6: SEM image crack between raster

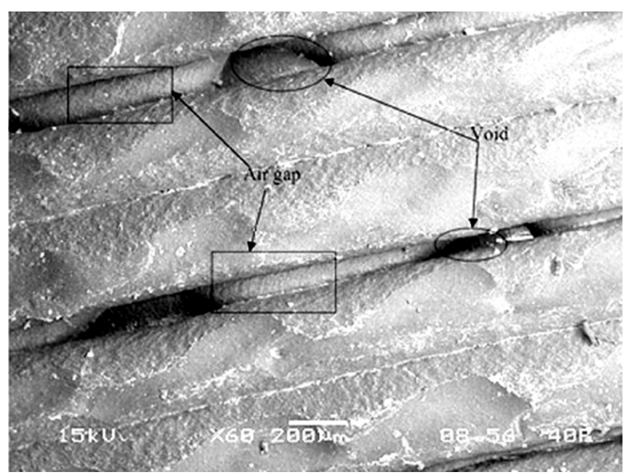


Figure 7:SEM image air gap and void

But according to Liao et. al., 2001 and Pandey et. al., 2003 it seems that, the increase in thickness is mainly due to the method positive slicing and just to avoid the shape error. The test part height H is function of its inclination θ with the build platform, length L and thickness T, refer Figure 8.

For this present work, at maximum inclination angle is of 30° H becomes 43.48 mm, slicing it with a minimum thickness of 0.127 mm, total 342.36 slices are required. As material flow rate is constant, if 0.36 is rounded off to nearest whole number 342, but it rounds off to plus one, that to prevent shape error.

Now machine is to deposit 343 slices. For any orientation angle θ of the part, this will be true.

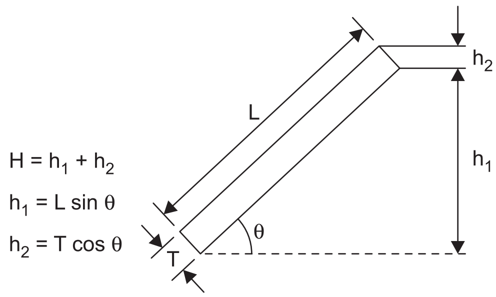


Figure 8: Part Orientation

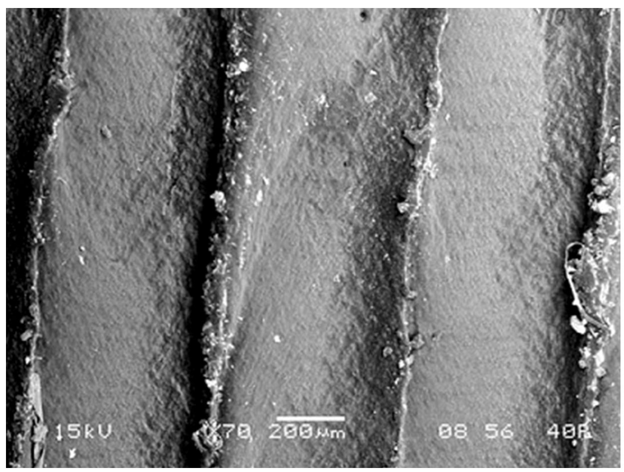


Figure 9: SEM image of raster (contact and overfilling)

Diffusion between adjoining raster, either in the case of short length or change in laying direction or curvatures, also produces the bump because of overfilling (as shown in Figure 9) of materials creates an bumpy layer at the contact surfaces. While the very next layer deposited over this uneven surface, forms wavy surface and increases the part dimension in the part build direction.

According to the studies made on FDM fabrication process and influence of input parameters to the dimensional accuracy of the part, it is clear that a large number of factors, either independent or in combination of multiples are concerned.

It can be noticed from the observation Table 8, that significant factor and interactions are not the same while dimensions are changed, even for the optimum factor levels are also, it is different in three directions. Hence, part fabrication is to be made in such a way that, all the dimensions should reach a preset value, all together at the common factor setting level. Because of the capability of combining all the objectives and transforming them to a single performance index, the fuzzy decision making logic is used and gives such factor levels which simultaneously satisfy all the objectives concerned [Zimmerman, H. J., 1991].

On the basis of above discussions, with larger MRPI, smaller is the variance of performance characteristics around the desired value. Using the experimental layout values of Table 2, the experimental results for the MRPI are given in Table 9.

The optimum factor levels A_2, B_1, C_1, D_2, E_3 are obtained from the main effect plot of MRPI as shown in Figure 10, and applying the combination of these factors ensure least change in dimensions of the FDM built part.

Table 9
Results for the MPRI

Experiment	*MRPI*	*Experiment*	*MRPI*	*Experiment*	*MRPI*
1	0.549	10	0.963	19	0.564
2	0.473	11	0.498	20	0.407
3	0.360	12	0.446	21	0.307
4	0.521	13	0.505	22	0.556
5	0.364	14	0.406	23	0.442
6	0.501	15	0.438	24	0.446
7	0.645	16	0.572	25	0.669
8	0.303	17	0.358	26	0.433
9	0.346	18	0.566	27	0.563

Results of ANOVA for MRPI are shown in Table 10, indicate: A, B, C, E and $B \times C$, $B \times D$, $B \times E$ are the significant factors and interactions, influence the multiple performance characteristics. Amongst all, the most significant factor is the part orientation.

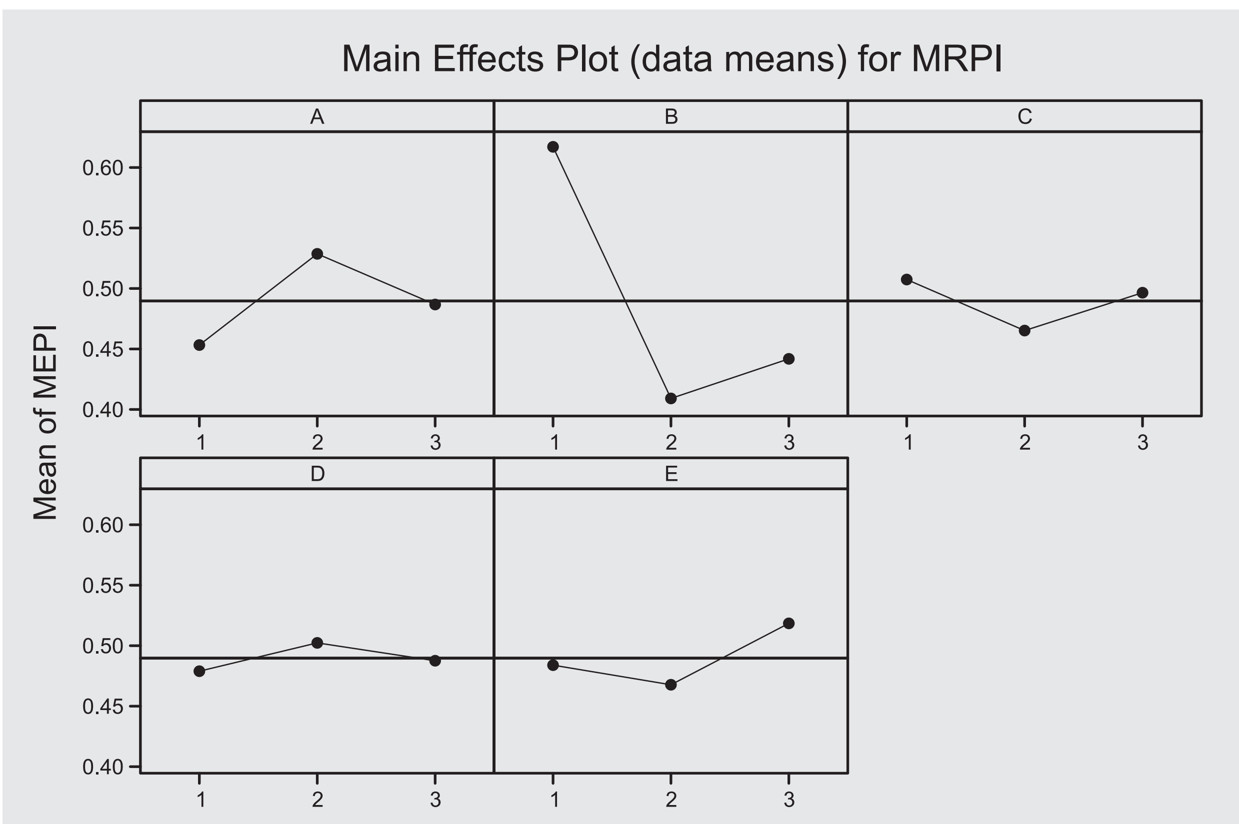


Figure 10: Main factor effect plot for MRPI

The change in raster width D within the given range of Table 1, and interaction A × B have insignificant effect on the defined MRPI. Factors A, B, C, and E have significant effects concerned with minimization of change in dimension while factor D has the least effect. Now as per the above discussions, the optimal combinations of FDM input process parameters are:

(i) the layer thickness at level 2,

(ii) the raster width at level 2,

(iii) the orientation at level 1,

(iv) the raster angle at level 1,

(v) the air gap at level 3.

Table 10
ANOVA for MRPI

Source	*DOF*	*SS*	*MS*	*F*	*%P*
A	2	0.0266	0.0133	8.87	5.56
B	2	0.2227	0.1114	74.27	46.59**
C	2	0.0089	0.0045	3	1.9
D*		0.0026	0.0013	0.86	0.56
E	2	0.0117	0.0059	3.93	2.45
A × B*		0.0066	0.0016	1.06	1.38
B × C	4	0.0697	0.0174	11.6	14.58
B × D	4	0.0807	0.0202	13.47	16.88
B × E	4	0.0483	0.0121	8.07	10.1
Error	6	0.0092	0.0015		
Total	26	0.478			100

*Pooled, **Highly significant

At optimal setting parametric combination this result is consistent with the experimental result reported by Sood et. al., 2009.

To predict the S/N ratio of a response (η_{pre}), the following equation is used taking η_m as the total mean of the MRPI and $\overline{A_i}, \overline{B_j}, \overline{C_k}, \overline{D_l}, \overline{E_n}$ as the mean of MRPI for factors A, B, C, D, E at their respective levels $i, j, k, l, n = 1, 2, 3$.

$$\begin{aligned}\eta_{\text{pre}} = \ & \eta_m + (\bar{A}_i - \eta_m) + (\bar{B}_j - \eta_m) + (\bar{C}_k - \eta_m) + (\bar{D}_l - \eta_m) + (\bar{E}_n - \eta_m) \\ & + [(\overline{A_i B_j} - \eta_m) - (\bar{A}_i - \eta_m) - (\bar{B}_j - \eta_m)] + [(\overline{B_j C_k} - \eta_m) - (\bar{B}_j - \eta_m) - (\bar{C}_k - \eta_m)] \\ & + [(\overline{B_j D_l} - \eta_m) - (\bar{B}_j - \eta_m) - (\bar{D}_l - \eta_m)] + [(\overline{B_j C_n} - \eta_m) - (\bar{B}_j - \eta_m) - (\bar{E}_n - \eta_m)]\end{aligned} \tag{11}$$

Omitting the insignificant factors and interaction from the Equation 11, the MRPI can be calculated using the FDM process parameters.

The two prognostic models: first based on Taguchi and the second using ANN are proposed to predict the MRPI and validated using simulation studies. The OA having significant factors and interactions is used for estimation of MRPI in Taguchi additive model. Due to non-linearity functions of FDM process, MRPI is predicted using conjugate gradient back propagation ANN. ANN divides the data into training sets and testing sets for further studies using MATLAB simulation tool.

The experimental results obtained and the results predicted based on Taguchi along with ANN of OA comparison data are tabulated in Table 11 and it is noted that the mean absolute percentage error MAPE (%) of the MRPI experimental data are 0.15 for the proposed ANN model and 3.16 for Taguchi's additive model respectively.

Table 11
Experimental results, Taguchi and ANN predicted results of OA data

Exp. No.	*MRPI using Mamdani model ($MRPI_{exp}$)*	*MRPI using Taguchi additive model ($MRPI_{th}$)*	*MRPI using ANN model ($MRPI_{ANN}$)*
1	0.549	0.566	0.5503
2	0.473	0.451	0.4726
3	0.36	0.364	0.3604
4	0.521	0.514	0.5209
5	0.364	0.358	0.3636
6	0.5	0.513	0.4995
7	0.645	0.653	0.6454
8	0.303	0.306	0.3038
9	0.346	0.336	0.3457
10	0.963	0.925	0.9627
11	0.498	0.528	0.4982
12	0.446	0.455	0.4486
13	0.505	0.481	0.5047
14	0.406	0.445	0.4053
15	0.438	0.423	0.4358
16	0.572	0.558	0.5717
17	0.358	0.373	0.3586
18	0.566	0.566	0.5661
19	0.564	0.583	0.5639
20	0.407	0.398	0.4069
21	0.307	0.296	0.3069
22	0.556	0.584	0.5564
23	0.442	0.409	0.4393
24	0.446	0.449	0.4457
25	0.669	0.674	0.6691
26	0.433	0.416	0.4354
27	0.563	0.576	0.5628
*MAPE (%) wrt /$MRPI_{exp}$		3.159	0.1499

*MAPE with respect to $MRPI_{exp}$

The regression results of $MRPI_{exp}$ versus $MRPI_{ANN}$ for:

(i) Training data sets, and

(ii) Testing data sets are shown in Figure 11 and Figure 12. The R^2 value for testing is 0.972 from the figure and thus the network said to be well trained.

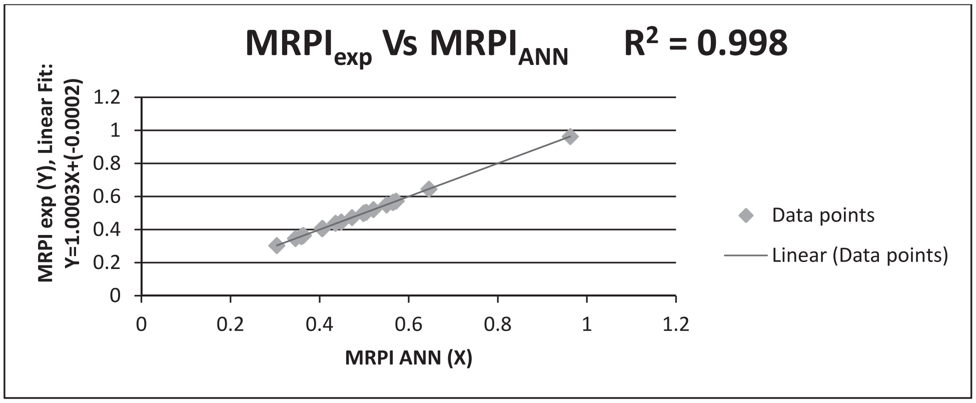


Figure 11: Regression plot of $MRPI_{exp}$ Vs $MRPI_{ANN}$ for training data set

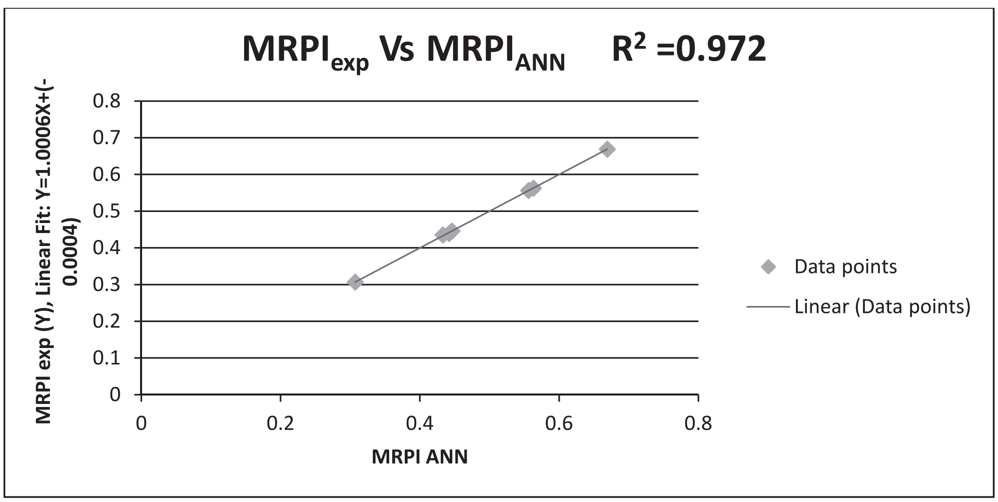


Figure 12: Regression plot of $MRPI_{exp}$ Vs $MRPI_{ANN}$ for testing data set

Generally ANN model is used to predict the output beyond the experimental outline inputting properly trained parameter values in a particular domain. While to process the same, Taguchi's additive model is to have experimental data, which requires a considerable amount of time, materials and energy. ANN model used for studying accuracy in FDM part dimensions, due to its additive in nature, linear in actual conditions, improving Taguchi's predictive model. Selecting part orientation factor and assigning a lower value to obtain accuracy, it is important because of its high influence over part dimensions, in comparisons to any other factor. Thus quality by al., accuracy in dimensions of FDM processed part can be obtained [Campbell et. al., 2002]. To set the most suitable parameter combinations and levels accurately, influences of the FDM input parameters on MPC must be known [Boschetto, et. al., 2013]. So while designing a RP process, prioritizing the part orientation to achieve dimensional accuracy, influence part quality and so on productivity [Pathak et. al., 2012, Paul et. al., 2011]. Due to less time consuming to get accuracy, better surface finish and quality of the build part, directly impact on the cost of manufacturing [Jin et. al., 2011].

5.2. Proof Tests

The experiment is performed with taking an initial set of input process parameter combination other then the experimental layout. Based on Equation 11, the optimal level of input parameters are selected using the FDM optimal parameters, the MRPI can be estimated. Because factor D and interaction $A \times B$ have insignificant effect on the multiple performance characteristics, those are intentionally omitted for all the cases. The differences between the predicted and experimental values are calculated for comparisons. Three times the experiments are conducted with an initial set of the FDM parameters A_1, B_1, C_2, D_2, and E_1. All the dimensions such as, length, width and thickness for every individual samples are measured and tabulated. The mean is calculated and assigned as the correspondent value of these dimensions, for ΔL, ΔW and ΔT it is 0.0391 mm, 0.0768 mm and 0.1079 mm respectively. The confirmation results of the experiments conducted using the best possible FDM parameters are shown in Table 12.

Table 12
Results of the confirmation experiment

	Initial FDM Parameters	*Optimal FDM parameters*	
		Prediction	*Experiment*
Level	$A_1B_1C_2D_2E_1$	$A_2B_1C_1D_2E_3$	$A_2B_1C_1D_2E_3$
ΔL (mm)	0.0391		0.0099
ΔW (mm)	0.0768		0.0200
ΔT (mm)	0.1079		0.1066
MRPI	0.509	0.925	0.963
Improvement MRPI = 0.454			

Considering the tabulated values from Table 12 it is observed that ΔL, ΔW and ΔT are apprached to optimal values from 0.0391 mm to 0.0099 mm, 0.0768 mm to 0.0200 mm and 0.1079 mm to 0.1066 mm respectively. The absolute percentage error calculed is 3.94 considering the values between the experimental and predicted results and the error is within the tolerance limit. Thus Taguchi's model is highly capable to predict the MRPI to a justifiable accuracy.

6. CONCLUSIONS

In this present experimental work, to attain a better accuracy in FDM extruded plastic part dimensions, the Taguchi method (an application of fuzzy logic reasoning) is proposed and applied. The optimized input parameters of the FDM process are attained individually with the least dimensional deviations in length, width and thickness. Simultaneously it is a matter-of-fact that, factors are contradictory and influential to achieve better dimensional accuracy either independently or in combination of other factors, one or in multiples. It is also experienced that some of the factors have more influence comparing others. Thus, it is proposed that instead of considering an uninformed and random approach of setting the factors, processing the part must be carried out on an optimal setting basis through a structured methodology. It is enviable to fabricate the parts with a process such that all the dimensions should deviate from the least possible preset value, simultaneously while setting the common factor levels. Consequently adopting the fuzzy logic method, the characteristics on performances change in length, width and thickness are improved. After the experimental investigations are made on selecting the optimum combination of different process parameters to get better accuracy of the FDM part dimension, the conclusion made is as follows:

- For least change in length, width and thickness, the optimal level input parameters setting of FDM process are taken as: (i) Layer thickness 0.178 mm, (ii) Orientation 0°, (iii) Raster angle 0°, (iv) Raster width 0.4564 mm and (v) Air gap 0.008 mm.

- For controlling the FDM built part dimensions, part orientation influences the most.
- Improvement of MRPI achieved is 0.454 from the confirmation test results using the optimal FDM parameters compared to initial FDM parameters and
- Thus proposed equation for predicting MRPI is valid.

Further proposals are made on two predictive models, on the basis of Taguchi approach and ANN approach. These models replicate well the effects of various factors on dimensional accuracy and their predictive results are reliable with experimental clarifications. The MAPE value found between experimental model and Taguchi model is 3.16 whereas experimental model and ANN model is 0.15.

Lastly it is concluded from the present study that part orientation is the main controlling factor for achieving better dimensional accuracy. Thus, this study may found to be suitable on optimizing the FDM characteristics with larger number of input parameters responsive to intricate geometry parts for achieving better part built quality with a faster rate.

In general in any AM process, using this optimization method may found to be quite favorable.

Future scope: After getting different optimized input parameter settings, parts of different complex geometry, fit and functional or prototypes for rapid tooling may be processed and their quality and dimentional accuracy may be proved to be attained upto the highest level.

High precission components also can be fabricated providing specific rooms to hold components and mechnisms.

REFERENCES

[1] Ahn, S. H., Montero, M., Odell, D., Roundy, S., and Wright, P. K. (2002). “Anisotropic material properties of fused deposition modeling ABS”, Rapid Prototyping Journal. 8(4), 248-257.

[2] Ali, Fahraz., Chowdhury, B.V., Maharaj, J. (2014). “Influence of some process parameters on built time, material consumption, and surface ruughness of FDM processed parts: influences based on the Taguchi design of experiments”, Proceedings of the 2014 IAJC/ISAM joint international conference ISBN 978-1-60643-379-9.

[3] Anitha, R., Arunachalam, S., and Radhakrishnan, P. (2001). “Critical parameters influencing the quality of prototypes in fused deposition modeling”, Journal of Materials Processing Technology. 118, 385-388.

[4] Bellehumeur, C.T., Gu, P., Sun, Q., and Rizvi, G.M. (2008). “Effect of processing conditions on the bonding quality of FDM polymer filaments”, Rapid Prototyping Journal. 14(2), 72-80.

[5] Bochmann, L., Bayley, C., Helu, M., Transchel, R., Wegener, K., and Dornfeld D., (2015).”Understanding error generation in fused deposition modeling”. Surface Topography: Metrology and Properties. 3 (2015) 014002 doi:10.1088.

[6] Boschetto, A., Giordano, V., and Veniali, F. (2013). “3D roughness profile model in fused deposition modeling”, Rapid Prototyping Journal. 19(4), 240-252.

[7] Campbell, R.I., Martorelli, and Lee, H.S. (2002). “Surface roughness visualization for rapid prototyping models”, Computer Aided Design. 34(10), 717-725.

[8] Chockalingama, K., Jawahara, N., Chandrasekarb, and U. Ramanathana, K.N. (2008). “Establishment of process model for part strength in stereo lithography”, Journal of Materials Processing Technology. 208, 348-365.

[9] Chou, K., and Zhang, Y. (2008). “A parametric study of part distortion in fused deposition modeling using three dimensional element analysis”, Proceeding of Institution of Mechanical Engineering: Journal of Engineering Manufacture, Part B. 222, 959-968.

[10] Dul, S., Fambri, L., and Pegoretti, A. (2016), "Fused deposition modeling with ABS graphene Nano composites". Composites Part A: Applied Science and Manufacturing. 85(6), 181-191.

[11] Elsayed, E.A., and Chen, A. (1993). "Optimal levels of process parameters for products with multiple characteristics", International Journal of Production Research. 31(5), 1117-1132.

[12] Es Said, Os., Foyos, J., Noorani, R., Mandelson, M., Marloth, R., and Pregger, B.A. (2000). "Effect of layer orientation on mechanical properties of rapid prototyped samples". Materials and Manufacturing Process. 15(1), 107-122.

[13] F, Rayegani., and G.C, Onwubolu. (2014). "Fused deposition modelling (FDM) process parameter prediction and optimization using group method for data handling (GMDH) and differential evolution (DE)". The International Journal of Advanced Manufacturing Technology. 73(1), 509-519.

[14] Frolicha, A.M.J., Spallekb, J., Brehmera, L., Buhka, J.H., Krauseb, D., Fiehlera, J., and Kemmlinga, A. (2016). "3D printing of intracranial aneurysms using fused deposition modeling offers highly accurate replications." American Journal of Neuroradiology. 37(1), 120-124.

[15] Hagen, M.T., Demuth, H.B., and Beale, M.H. (1996). "Neural Network design", PWS publishing. Boston.

[16] Hopkinson, N., Hagur, R.J.M. and Dickens, P.H. (2005). "Rapid manufacturing: an industrial revolution for the digital age", England, John Wiley & Sons Inc.

[17] Jang, J.S.R., Sun, C.T., and Mizutani, E. (2005). "Neuro-Fuzzy and Soft Computing", Prentice Hall of India Private Limited, New Delhi.

[18] Jin, G.Q., Li, W.D., Tsai, C.F., and Wang, L. (2011). "Adaptive tool-path generation of rapid prototyping for complex product models". Journal of Manufacturing Systems. 30(3), 154-164.

[19] Khan, Z.A., Lee, B.H. and Abdullah, J. (2005) "Optimization of rapid prototyping parameters for production of flexible ABS object", Journal of Materials Processing Technology. 169, 54-61.

[20] Liao, Y.S., and Chiu, Y.Y. (2001). "A new slicing procedure for rapid prototyping systems", International Journal of Advanced Manufacturing Technology. 18, 579-585.

[21] Mamdani, E.H., and Assilia, S. (1975). "An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller", International Journal of Man-Machine Studies. 7, 1-13.

[22] Mansour, S., and Hauge, R. (2003). "Impact of rapid manufacturing on design for manufacturing for injection moulding", Proceeding of Institution of Mechanical Engineering, Journal of Engineering Manufacture, Part B. 217(4), 453-461.

[23] Mendel, J.M. (1995). "Fuzzy Logic Systems for Engineering: A Tutorial", IEEE Proceedings. 83, 345-377.

[24] Ming, W.T., Tong, X.J., and Ye, J. (2007). "A model research for prototype warp deformation in the FDM process", International Journal of Advanced Manufacturing Technology. 33(11-12), 1087-1096.

[25] Nickel, A.H., Barnett, D.M., and Prinz, F.B. (2001). "Thermal stresses and deposition patterns in layered manufacturing", Materials Science and Engineering. A317, 59-64.

[26] Noorani, R. (2006). "Rapid prototyping – principles and application", New Jersey, John Wiley & Sons Inc.

[27] Pandey, P.M., Jain, P.K., and Rao, P.V.M. (2009). "Effect of delay time on part strength in selective laser Sintering", International Journal of Advanced Manufacturing Technology. 43, 117-126.

[28] Pandey, P.M., Venkata, R.N., and Dhande, S.G. (2003). "Slicing procedures in layered manufacturing a review", Rapid Prototyping Journal. 9(5), 274-288.

[29] Pathak, A.M., and Pande, S.S. (2012). "Optimum part orientation in rapid prototyping using genetic algorithm", Journal of Manufacturing Systems. 31(4), 395-402.

[30] Paul, R., and Anand, S. (2011). "Optimum part orientation in rapid manufacturing process for achieving geometric tolerances", Journal of Manufacturing Systems. 30(4), 214-222.

[31] Pilipovic, A., Raos, P. and Sercer, M. (2009). "Experimental analysis of properties of materials for rapid prototyping", International Journal of Advanced Manufacturing Technology. 40, 105-115.

[32] Rajasekaran, S., Pai, G.A. Vijayalakshmi. (2003). "Neural Networks, Fuzzy Logic and Genetic Algorithms - Synthesis and Applications". Prentice Hall of India Pvt. Ltd.. New Delhi.

[33] Ross, P.J. (1998). "Taguchi techniques for quality engineering", Mc Graw Hill, New York.

[34] Sood, A.K., Ohdar, R.K. and Mahapatra, S.S. (2009). "Improving dimensional accuracy of fused deposition modeling processed part using grey Taguchi method", Materials and Design. 30(10), 4243-4252.

[35] "A Study on Existing Protocols and Energy-Balanced Routing Protocol for Data Gathering in Wireless Sensor Networks" published in International Journal of Computing and Technology on Nov 10, 2013..Impact Factor 1.213(Refereed Journal). www.cirworld.com/index.php/ijct/article/view/2780/pdf_293

[36] "Challenges and Authentication in Wireless Sensor Networks by using promising Key Management Protocols" at International Conference in Kristu Jayanthi College, Bangalore on Feb 19th & 20th 2015 and Published in International Journal of Computer Applications.Impact Factor 0.814. www.ijcaonline.org/icctac2015/number1/icctac2005.pdf

[37] Taufik, M., and Jain, P.K. (2016). "A Study of Build Edge Profile for Prediction of Surface Roughness in Fused Deposition Modeling". Journal of Manufacturing Science and Engineering 138(6), 11 pages.

[38] Upcraft, S., and Fletcher, R. (2003). "The rapid prototyping technologies", Rapid Prototyping Journal. 23(4), 318-330.

[39] Venkata, R.N., Pandey, P.M., and Dhande, S.G. (2007). "Part deposition orientation studies in layered manufacturing", Journal of Materials Processing Technology. 185, 125-131.

[40] Wu, W., G eng, P., Li, G., Zhao, Di., Zhang, H., and Zhao, Ji., (2015). "Influence of Layer Thickness and Raster Angle on the Mechanical Properties of 3D-Printed PEEK and a Comparative Mechanical Study between PEEK and ABS". Materials. 8(9), 5834-5846.

[41] Zadeh, L.A. (1976). "A Fuzzy-algorithm Approach to the Definition of Complex or Imprecise concept", International Journal of Man-Machine Studies. 8, 249-291.

[42] Zimmerman, H.J. (1991). "Fuzzy set theory and its applications", Kluwer. London.