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Surrogate Based Sensitivity Analysis of Part Strength due to Process Parameters in Fused Deposition Modelling

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Abstract

Fused Deposition Modeling (FDM) is an additive manufacturing process where the part is built using a layer by layer approach. The tensile strength of 3D printed parts using FDM depend upon its process parameters. In this paper, three process parameters, namely, layer thickness, raster angle and infill density were considered. Experiments were conducted based on samples generated by Latin Hypercube Sampling (LHS) to find the tensile strength of printed parts. Based on the experimental response and input parameters, a surrogate model was constructed. Global sensitivity analysis was carried out on the surrogate using Sobol's method to find the parameter variations that affects the strength of parts. Layer thickness has the least effect and infill density has more effect on the tensile strength of FDM parts.

Keywords: FDM; LHS; Surrogate; Sensitivity analysis.

1. Introduction

Additive manufacturing (AM) is an innovative process that produces the product directly from 3D CAD model using a layer based manufacturing technique. Among many AM process, FDM technology uses flexible thermoplastic filament extruded through a hot nozzle to manufacture parts. It uses multiple process parameters while building the part. The strength of resulting parts not only depend upon the material used, but it is also significantly affected by the part built orientation and other process parameters that induce anisotropy in the FDM part. The study

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conducted by Ziemian et al. showed that the raster angle affected the tensile strength of FDM printed parts significantly [1]. Chockalingam et al. considered four process parameters, namely, build orientation, airgap, raster width, raster angle and studied its effect on tensile strength using face centered central composite design and ANOVA [2]. Sood et al. derived relationship among parameters like, layer thickness, air gap, build orientation, raster angle, raster width and tensile strength using response surface [3]. Sood et al. also derived relationship among parameters as used in [3] and compressive strength [4]. From the literature major factors that affect the tensile strength of the part are layer thickness, raster angle, infill density and build orientation. In this study we considered raster angle, layer thickness and infill density parameters and its effect on tensile strength using sensitivity analysis.

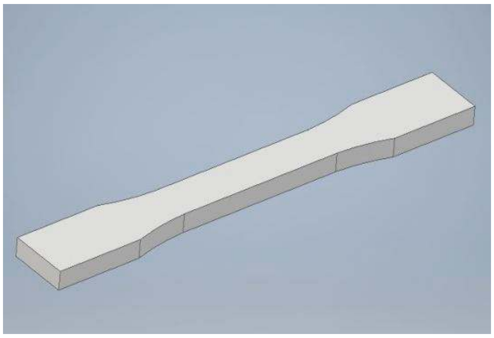
2. Methodology

2.1. Models and Fabrication

Acrylonitrile butadiene styrene (ABS) filament was used as material to print uniaxial tensile specimens as per ASTM D638-14 specification.S300DH™ FDM printer developed by UV Bot®, India has been used to build the parts. CAD models were generated using Auto desk inventor® software and exported in STL file format. Slic3r® an open source software was used to slice the STL file and to set different process parameters for this study. Process parameters namely, raster angle, layer thickness and infill density are examined. The process parameters and its range considered for this study are described in table 1. All the specimen were built in XY orientation as per ASTM F2971-13 terminology. The CAD model and fabricated parts are shown in Figure 1a and 1b .

Table 1. Process parameters and its range for experiments

S.No	Process parameters	Minimum	Maximum
1	Layer thickness(mm)	0.2	0.4
2	Raster angle (deg)	0	90
3	Infill density(%)	40	90



(a)

(b)

Fig.1.(a) CAD model; (b) Prototypes fabricated for experiment.

2.2. Experimental setup and design

Classical sampling methods are frequently used in the additive manufacturing process [2,3,4]. Since most of the variables are continuous, it is impossible to generate sampling points for all combinations. Classical sampling methods will leave the interior of the design space unexplored [5]. So in this study LHS technique was used for studying the effect of process parameters on the tensile strength of printed parts. Based on the parameter levels in table 1, 20 LHS samples were generated using MatlabR2016a® application. Tension test was performed on a Dak system Inc® twin column table uniaxial material testing machine with a minimum speed of 0.001 mm/min accuracy and 50kN load force capacity. For each experiment, two specimens were used and mean value of the tensile strength were computed.

2.3. Surrogate models

Based on the experimental response for different combination of input parameter generated through LHS design, surrogate model was constructed as a function of input parameters (layer thickness, raster angle and infill density). The constructed surrogate model can predict the tensile strength at different points for the new combination of design variables. In this study, three surrogate models namely, Kriging, Polynomial Response Surface and Radial Basis Function were constructed using surrogate tool box [6] in MatlabR2016a ®. A mathematical description of these models is given below.

2.3.1. Kriging (KRG)

In Kriging, the surrogate is built by approximating the function as a combination of polynomial model and deviations [7] from it as shown in Eq. 1.

$$\hat{y}(x) = f(x) + Z(x) \tag{1}$$

$f(x)$ is the polynomial function and it globally approximates the design space and $Z(x)$ is the realization of the Gaussian process of mean zero, variance σ^2 and non zero covariance. $Z(x)$ accounts for the local deviation at each sample points and its covariance matrix is given in Eq. 2.

$$\mathrm{cov}[Z(x_i), Z(x_j)] = \sigma^2 R(x_i, x_j) \tag{2}$$

where $R(x_i, x_j)$ gives the correlation between any two sample points x_i and x_j. In this study, different correlation models such as: linear, spherical, cubic, exponential, Gaussian, cubic-spline and regression models constant, linear and quadratic are used. The Gaussian correlation model is of the following form.

$$R(x_i, x_j) = \exp\left(-\sum_{k=1}^{d} \theta_k \left| x_{i,k} - x_{j,k} \right|^{P_k} \right) \tag{3}$$

where d is the number of design variables, θ_k and P_k are correlation and smoothness parameters that vary for each design variable for given sample point vector to fit the model, and $x_{i,k}$ and $x_{j,k}$ are k^{th} component of sample points x_i and x_j respectively.

2.3.2. Polynomial response surface (PRS)

It is one of the widely used surrogate model and it approximates function as the linear combination of the polynomial basis function[7]. The second order polynomial model is given in Eq. 4.

$$\hat{y}(x) = \beta_0 + \sum_{i=1}^{m} \beta_i x_i + \sum_{i=1}^{m} \sum_{j=1}^{m} \beta_{ij} x_i x_j \tag{4}$$

where β_0, β_i and β_{ij} are unknown coefficients calculated based on least-square regression to fit the surrogate using sample points and its response, m is the number of design variables.

2.3.3. Radial basis function (RBF)

This method interpolates the function by combining the basis function which is radially symmetric at each sample point, using Euclidean norm .It approximates the function locally and size of basis function at each sample point is controlled by its weights [8]. The simple RBF form is given by Eq. 5.

$$\hat{y}(x) = \sum_{i=1}^{N_c} w_i \varphi(\|x - x_i\|) \tag{5}$$

where $\|x - x_i\|$ is the Euclidean norm and it is radial distance between the design variable x and center of i^{th} sampling point x_i, φ is a basis function, w_i is the basis function weights. In this study, basis function: bi-harmonic, inverse multi-quadric, thin plate spline, gaussian model, multi quadric are used.

2.4. Cross-validation

To measure the correctness of the constructed surrogate model and to select the appropriate model for analysis PRESS (Prediction error sum of squares) is used. PRESS is calculated by fitting the surrogate to experimental response by leaving out the response at a point. The response at left out point is predicted by the constructed surrogate model [9]. In this study $PRESS_{RMS}$ as given in Eq. 6 is used for evaluation and it is compared

$$PRESS_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i^{(-i)}\right)^2} \tag{6}$$

Where,
N = number of sample points
y_i = actual response
$\hat{y}_i$ = predicted response at the left out point

2.5. Global sensitivity analysis

In Global sensitivity analysis, all parameters are modified simultaneously to find the relative contribution of each design parameter as well as the interaction between each parameter to the output response of the system. Parameters that have less effect on the response can be identified and ignored, so the design space dimension can be reduced. In this study variance based, Sobol sensitivity analysis method [10] using global sensitivity analysis tool - box in MatlabR2016a® [11] is used. This method splits the output response into sum function of individual parameters, the combined effect of parameters as given by Eq. 7. After finding the variance of the combined terms and individual term as given in Eq. 8 & Eq. 9., the importance of individual design parameter can be measured by Sobol sensitivity indices as given in Eq. 10. It is calculated to find the first order contribution from each parameter and total order sensitivity indices.

$$f(x) = f_0 + \sum_{i=1}^{s} f_i(x_i) + \sum_{i=1}^{s}\sum_{i<j}^{s} f_{ij}(x_i, x_j) + \ldots + f_{12..n}(x_1, x_2, \ldots, x_n) \tag{7}$$

$$D = \int f^2 dx - f_0^2 \tag{8}$$

$$D_{i_1 \ldots i_s} = \int f_{i_1 \ldots i_s}^2 \, dx_{i_s} \ldots . dx_{i_s} \tag{9}$$

Where, f(x) is the approximate surrogate function , x=[x_1,x_2,x_3] are the set of input parameters, f_0 is the mean, D is the variance of function and D_i is the partial variance corresponding to input process parameters. Sobol sensitivity indices for input parameters is given by

$$S_{i_1...i_s} = \frac{D_{i_1...i_s}}{D} \tag{10}$$

$S_i = \dfrac{D_i}{D}$ gives the first order sensitivity information for an i^{th} input parameter. The total order sensitivity indices are defined by

$$S_{Ti} = S_i + \underset{i \neq j}{S_{ij}} + ... + S_{1...i...s} \tag{11}$$

3. Results and Discussion

Based on 20 LHS sampling points and its tensile response through experiments as given in table 2, three surrogate models were constructed as a function of input parameters. Each surrogate is evaluated using $PRESS_{RMS}$ error metric and the results are presented in table 3. KRG surrogate performs with better $PRESS_{RMS}$ and Mean as compared to RBF and PRS. RBF and PRS have similar $PRESS_{RMS}$ values. Thus, KRG surrogate is used in this study for sensitivity studies. Sobol global sensitivity analysis method was used to find the effect of the individual parameter. To perform that, the values are varied between minimum and maximum as mentioned in Table1 for each parameter using uniform probability distribution. The total variance, partial variance and Sobol sensitivity indices is calculated using Eq. 8, Eq. 9 and Eq.10 respectively and the results for sensitivity indices are presented in table 4.

Table 2. Experimental points generated by LHS and its tensile response

S.No	Layer thickness (mm)	Raster angle (degree)	Infill density (%)	Average tensile strength (MPa)
1	0.35	52	83.8	14.14
2	0.34	61	63.8	9.45
3	0.31	38	78.8	11.54
4	0.36	83	71.3	10.95
5	0.38	56	73.8	11.51
6	0.40	43	61.3	8.61
7	0.28	2	68.8	21.26
8	0.39	20	66.3	10.67
9	0.30	47	43.8	6.92
10	0.26	7	53.8	13.17
11	0.24	74	81.3	15.15
12	0.37	11	41.3	8.09
13	0.33	79	51.3	8.16
14	0.21	70	46.3	6.33
15	0.32	16	86.3	9.71
16	0.29	88	56.3	9.38
17	0.25	29	88.8	18.17
18	0.22	25	58.8	9.08
19	0.23	65	76.3	12.37
20	0.27	34	48.8	7.19

Table 3. $PRESS_{RMS}$ error metric and Mean of the surrogate models

S.No	Surrogate type	$PRESS_{RMS}$	Avg of actual response	Mean=$PRESS_{RMS}$/Avg of actual response
1	Kriging (KRG)	2.627	11.0912	0.2409
2	Radial basis function (RBF)	3.174	11.0912	0.2862
3	Polynomial response surface (PRS)	3.19	11.0912	0.2877

It is inferred from the study that layer thickness is a least sensitive parameter and infill density is the most sensitive parameter among the three parameters considered for this study. The total effects shows the similar behavior as first order effects. Since the total effects of layer thickness is close to zero so there is not much interaction between layer thickness and other parameters. Results obtained from our studies can be corroborated with findings in work done by Sood et al. [3]. Using the data reported in their paper, we performed an ANOVA analysis. The raster angle contributes more for tensile strength than layer thickness when FDM parts are subjected to tensile load. The above mentioned study doesn't consider the infill density parameter into account. So based on the obtained results it is evident that tensile strength depends on the inter-layer and intra-layer raster to raster bonding. The increase in infill density will increase more number of rasters in given layer, which in turn increases the bonding strength**.**

Table 4. First order sensitivity information and total effects

S.No	Parameters	First order effects	Total effects
1	Layer thickness	0.01034	0.0097
2	Raster angle	0.46	0.4594
3	Infill density	0.533	0.5302

4. Conclusion

In this study, authors have studied the effect of process parameters of FDM such as layer thickness, raster angle and infill density on the tensile strength of printed parts in XY orientation using surrogate based global sensitivity analysis method. Layer thickness has least effect and infill density has more effect on the tensile strength. While building predictive models either based on simulation or based on surrogate models to mimic the behavior of FDM parts, effect of infill density and raster angle should be modelled properly to predict the tensile strength of parts. A detailed study on effect of part orientation in the ZX / ZY orientation shall compliment this study to give a comprehensive understanding of process parameters on strength of FDM parts.

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