Analysis of angular shrinkage of fused filament fabricated poly-lactic-acid prints and its relationship with other process parameters

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Abstract. Undoubtedly, fused filament fabrication (FFF), a class of additive manufacturing has established as one of the most efficient process for the development of a wide range of functional/non-functional products. However, the process suffers from poor geometrical and mechanical characteristics that are limiting its potential for the fabrication of sophisticated parts. In the present work, an effort has been made to investigate the effect of build orientation angle, head scan speed, and layer thickness on the shrinkage of resulting poly-lactic-acid (PLA) prints by using design of experimentation and machine learning based statistical methodologies. Firstly, a total of 20 test samples, with replication of 5, were prepared by using an open source based commercial fused filament fabrication (FFF) setup and then investigated for their dimensional accuracies by using Coordinate Measuring Machine (CMM). Finally, the obtained data was investigated, statistically, in order to find out the significance of selected process variables on resulted dimensional features. The regression models developed for the prediction of shrinkage by using Statistical and artificial neural network were possessed R² ~ 97.66% and ~ 97.78%, respectively. Further, scanning electron micrographic analysis has been carried out to observe the changes occurred in the geometrical features of the produced prints. Overall, the study concluded that rate of angular shrinkage increased with an increase in the build orientation angle and decrease in the layer thickness & head scan speed.

1. Introduction
Nowadays, industries are focusing, stringently, on the key features such as cost, time and quality of the products in order to sustain the huge pressure of today’s competitive world [1]. Therefore, more and more number of industries is considering additive manufacturing (AM) technologies either as a replacement of their conventional practices or to assist the same [2]. There exists a wide range of AM technologies which are able to process almost all types of materials, irrespective to their physical states [3], however, the implications of one or another technology in different manufacturing sectors are a function of numerous constraints, being cost, accuracy, and time as most crucial [4-7]. Despite all, AM technologies are the recent trends of production systems wherein physical prototypes are made directly from the three-dimensional (3D) computed based design models [8]. In this technology, the parts are created through the deposition of the material in layer form in a way that one layer is loaded on another in the vertical direction [9]. Moreover, as regards to principle of operation, AM is entirely opposite to conventional machining, also known as subtractive manufacturing that manufacture part by removing the materials and creating a huge amount of waste [10, 11].

Fused filament fabrication (FFF), refer Figure 1, is one of the oldest and most widely used processes for the fabrication of polymer based products [12-14]. It was first developed for prototyping for marketing applications [14]; however, it emerged in almost all types of manufacturing with the passage of time as well as timely innovations made in-terms of the upgradation of the technology and development of new materials [15-17]. In contrast of the other similar technologies, FFF has numerous merits in-terms of possible shape complexities, material availability, short processing cycle, lower operational temperature, little supervision, and low maintenance [18]. The working procedure
of FFF is normally defined as a thermally controlled process wherein a thermoplastic filament melts in the moving head (along x and y axes) and thereafter pushed by a mechanical mechanism onto a fixtureless platform (along z-axis) to settle down [19-21]. Although, FFF is very useful for the fabrication of conceptual models, prototypes and engineering components, but, the resulting characteristics of the final parts such as dimensional accuracy, surface finish, strength, and porosity are entirely depend on its process parameters and therefore should be controlled critically [19, 22, 23].

Bakar et al. used FFF technique to produce parts with different shapes as well as different process parameters in order to investigate effect of the resulted dimensional accuracy and surface quality [24]. Their study outlined that FFF system is very less accurate for making circular shape on significant deviations, ranging from 0.1-0.2μm. In a similar study, Dyrbuset al. studied the linear and angular shrinkage of FFF parts [25]. Nanchariaiahet al. observed the effect of layer thickness, road width, raster angle, and air gap on dimensional accuracy of the specimens. It was found in their research that the layer thickness and road width affected the accuracy, substantially [26]. It was revealed by Murugesanet al. that amongst the three considered AM processes, the FFF based part qualified with best dimensional accuracy [27]. The geometric model developed for the prediction of dimensional accuracy of FFF parts showed that the shrinkage increased almost symmetrically at deposition angles varied from 90° [28]. Further, Schutzleret al. studied the various types of defects in part FFF parts such as shrinkage, curling, shape deformation, etc. Various mathematical models were developed in order to compensate these defects based on the basis of quantitative data [29]. In the same line, various other researchers also studied the influence of input process parameters on shrinkage by using a wide range of methodologies, however, in the research work executed by the Yaodonget al. the impact of material shrinkage on the accuracy of parts was observed with the help of data analysis and by a recreation equation [30-33].

From the literature survey, it has been found that various research efforts have made for the investigation of linear shrinkage, surface roughness, and other topographic details, however, very limited work is reported on the study of angular shrinkage of the FFF parts. In the present work, an effort has been made to find out the effect of the selected input process parameters on the angular shrinkage by using standard statistical approaches. Moreover, regression models have been developed to predict the angular shrinkage under the different parametric combinations, which were justified for their accuracies through confirmatory experimentations.
2. Material and Method

In this work, a total of 20 parts (with five repetitions) were designed, by using licensed version of CREO 4.0 design software package, at variable angles ranging between 20 to 60° (refer Figure 2(a). The computer aided design (CAD) files were then converted into standard tessellation language (.STL) format with ASCII conversation style. Chord height and angle conversation format for each test model were maintained to a precision of 0.0593 and 0°, respectively. Then, the test parts were fabricated by using an open source FFF setup (model: Flash Forge Guide 2; make: Flash Forge Corporation, China). The bed size of the selected FFF printer is 230×150×140 mm, able to run two filaments simultaneously, and controlled temperature of the build area. Commercially available PLA material (supplier: Divide by Zero Technologies, India) was used in as-received form. Figure 2(b) shows the finally produced test specimens for angular shrinkage study. All the dimensional records, for analyzing angular shrinkage, were made by using a computer controlled Coordinate Measuring Machine (CMM), shown in Figure 3.

![Figure 2](image_url)

Figure 2. Geometrical details of the test specimens (a) and finally fabricated parts (b).

![Figure 3](image_url)

Figure 3. Pictorial view of the CMM machine (Courtesy: Auto Parts, Ludhiana).

Table 1 shows the list of selected process parameters and their levels. Further, Table 8 shows the control log of experimentation as per design of experimentation.
Table 1: Parameters with selected levels.

| Factors                              | Units | Levels       |
|--------------------------------------|-------|--------------|
| Build orientation angle              |       |              |
| Layer thickness                      | µm    |              |
| Head scan speed                      | mm/sec|              |
|                                      | 20    | 45           |
|                                      | 150   | 250          |
|                                      | 2500  | 3500         |
| 60                                   | 150   | 250          |
| 60                                   | 350   | 4500         |
| 45                                   | 150   | 3500         |
| 60                                   | 250   | 3500         |
| 20                                   | 150   | 4500         |
| 45                                   | 250   | 4500         |
| 20                                   | 150   | 2500         |
| 45                                   | 250   | 3500         |
| 60                                   | 150   | 3500         |
| 45                                   | 250   | 4500         |
| 60                                   | 250   | 3500         |
| 45                                   | 250   | 4500         |
| 20                                   | 150   | 2500         |
| 20                                   | 350   | 3500         |
| 45                                   | 250   | 3500         |
| 60                                   | 250   | 4500         |
| 45                                   | 250   | 3500         |
| 20                                   | 350   | 4500         |
| 45                                   | 250   | 3500         |

Table 2: Control log of experimentation.

| Build orientation angle (°) | Layer thickness (µm) | Head Scan Speed (mm/sec) |
|-----------------------------|----------------------|--------------------------|
| 60                          | 150                  | 2500                     |
| 60                          | 350                  | 4500                     |
| 45                          | 150                  | 3500                     |
| 60                          | 250                  | 3500                     |
| 20                          | 150                  | 4500                     |
| 45                          | 250                  | 4500                     |
| 20                          | 150                  | 2500                     |
| 45                          | 250                  | 3500                     |
| 60                          | 150                  | 3500                     |
| 45                          | 250                  | 4500                     |
| 60                          | 250                  | 3500                     |
| 45                          | 250                  | 4500                     |
| 20                          | 150                  | 2500                     |
| 45                          | 250                  | 3500                     |
| 60                          | 250                  | 4500                     |
| 45                          | 250                  | 3500                     |
| 20                          | 350                  | 4500                     |
| 45                          | 250                  | 3500                     |

2.1. Machine learning based prediction

The machine learning (ML) embody some of the facets of the human mind that facilitates us to solve hugely complex problems at speeds in order to outperform even the fastest computers [34]. Recently ML approaches have been proposed as an alternative way of predicting software [35]. The methods are available in R open source software, licensed under GNU GPL, for the ML calculations [36-38]. Hornik et al. suggested that with conventional mathematical models, it is difficult to understand the effect of process parameters of shrinkage of AM parts as shrinkage is a non-linear and multivariable characteristics [39]. It is an application of artificial intelligence that is used to predict the accurate results by receiving input values within acceptable ranges. Wang et al. used artificial neural network (ANN) model for validating the relationship between process parameters and shrinkage ratio. It has been suggested by them that with such advance systems, it is possible to investigate process performance, critically [40]. For the present work, depending on the number of input and output parameters, the architecture of models is shown in Figure 4. Further, Table 3 shows the ML method description used in the present work, the detail of the same is discussed elsewhere [41].
Figure 4. Architecture of ML models.

Table 3: ML methods used [41].

| Models          | Method  | Package | Turning parameters and methods                           |
|-----------------|---------|---------|----------------------------------------------------------|
| Decision Tree   | R PART  | R PART  | Minimum split=20; Max. depth=30; and Minimum bucket=7    |
| Random Forest   | R F     | Random forest | m_{bag}=500 and bagging sampling                   |
| Linear Model    | Lm      | glm     | None                                                     |
| ANN             | n net   | Neural Network | h_{layer}=10; Max. NW_{i}=10000; and Max_{i}=100      |

The terminologies of Table 3 are as follows:
- Decision tree (R PART) – A decision tree is a classifier in the form of the tree structure described by Quinlan with two types of nodes (decision and leaf).
- Random forest (R F) – Random forest is a tree based algorithm which involves building several trees, then combining their output to improve generalization ability of the model.
- Linear model (glm) – The output is continuous and simplest linear regression which fits data with the best hyper-plane.
- ANN – It is a neuron based mathematical modeling used for supervised, unsupervised and reinforced learning.

The correlation coefficient developed in order to establish statistical relationships between actual and predicted values has been executed by using following equation:

$$\text{Correlation, } r = \frac{\sum_{i=1}^{n} (ki - \bar{k})(m - \bar{m})}{\sqrt{\sum_{i=1}^{n} (ki - \bar{k})^2} \sqrt{\sum_{i=1}^{n} (m - \bar{m})^2}}$$  \(1\)

Where, is the actual value, is the predicted value, is the mean of the all actual values, is the mean of the all predicted values, and is the number of instances. The correlation lies between \([0,1]\) and is considered to be good if its value tends towards 1.

Afterwards, the statistical measure of data which can be fitted in a regression line was determined as coefficient of determination, by taking the square the r as follows:

$$R = r \times r$$  \(2\)

The error rate, in the form of mean absolute error (MAE), of developed regression model was calculated by using Eqn. 3.
In Eqn. 3, $o_i$ and $q_i$ are the observed value and predicted value. And, $n$ is total number of instances. Further, the accuracy of the regression model was validated, by using 10k-fold, in order to measure the robustness of the predictive method. Here, the original dataset was randomly partitioned into $k$ equal size subsamples, performed $k$ rounds of learning on each round, $1/k$ of data was held out as a test set and the remaining were considered as training data. Further, the average test score of the $k$-rounds was determined. The main advantage of this method over repeated random sub-sampling is that all observations were used for both training and validation, and each observation was used for validation exactly once.

3. Result and Discussion

Table 4 shows the observed results for angular shrinkage of FFF based PLA parts. The angular shrinkage ($\beta$) was calculated by subtracting the mean dimensions of the part from observed dimensions based on CMM machine as per following equation:

$$\beta = L_{\text{original value}} - L_{\text{measured value}}$$

Table 4: Actual values of each experiment.

| S.No. | Build orientation angle (°) | Layer thickness (μm) | Head scan speed (mm/sec) | Original values (mm) | Measured value, average (mm) | Shrinkage (mm) |
|-------|-----------------------------|----------------------|--------------------------|---------------------|------------------------------|----------------|
| 1     | 60                          | 150                  | 2500                     | 11.3821             | 13.9942                      | 2.6121         |
| 2     | 60                          | 350                  | 4500                     | 11.2113             | 13.8226                      | 2.6113         |
| 3     | 45                          | 150                  | 3500                     | 14.5305             | 15.761                       | 1.2305         |
| 4     | 60                          | 250                  | 3500                     | 10.8562             | 13.5968                      | 2.7406         |
| 5     | 20                          | 150                  | 4500                     | 8.7944              | 10.8888                      | 2.0944         |
| 6     | 45                          | 250                  | 4500                     | 13.5874             | 13.7747                      | 0.1873         |
| 7     | 20                          | 150                  | 2500                     | 8.6232              | 10.6464                      | 2.0232         |
| 8     | 45                          | 250                  | 3500                     | 13.8404             | 13.8894                      | 0.049          |
| 9     | 45                          | 250                  | 3500                     | 13.5722             | 13.6444                      | 0.0722         |
| 10    | 60                          | 150                  | 3500                     | 11.3196             | 13.9936                      | 2.674          |
| 11    | 45                          | 250                  | 4500                     | 13.6194             | 13.7388                      | 0.1194         |
| 12    | 45                          | 250                  | 2500                     | 13.1938             | 13.2076                      | 0.0138         |
| 13    | 20                          | 350                  | 3500                     | 8.4356              | 8.87120                      | 0.4356         |
| 14    | 60                          | 350                  | 2500                     | 11.1832             | 13.8896                      | 2.7064         |
| 15    | 45                          | 250                  | 3500                     | 11.1676             | 12.3352                      | 1.1676         |
| 16    | 45                          | 250                  | 3500                     | 13.6745             | 13.749                       | 0.0745         |
| 17    | 20                          | 250                  | 3500                     | 8.563              | 8.626                         | 0.063          |
| 18    | 45                          | 250                  | 3500                     | 13.4335             | 13.867                       | 0.4335         |
| 19    | 20                          | 350                  | 4500                     | 9.2316              | 9.4632                       | 0.2316         |
| 20    | 45                          | 350                  | 3500                     | 13.5885             | 13.6769                      | 0.0884         |

Analysis of variance (ANOVA) was employed to check the requisite of the model, analysing the statistical significanc of data presented in Table 4, and to obtain a regression equation. Further, the data given in Table 4 was used to study the influence of input process parameters on observed angular shrinkage, refer Figure 5. It can be seen from Figure 5 that with an increase in the build orientation angle from 20° to 45° and further from 45° to 60°, the angular shrinkage of the FFF based PLA parts was also increased. This might be due to the fact that the shrinkage along the angular path was a function of inner stresses developed because of the contraction of the fibers upon cooling from extrusion to glass transition temperature [42]. As the slope of the printed part increased, the inbuilt shrinkage stresses were also multiplied and resulted in large deviation.
From Figure 6(a), it can be seen that as the layers were raised from the building platform, the size of the same has been reduced significantly. Further, in case of layer thickness, it has been found that with an increase in the layer thickness, the shrinkage of the part reduced, noticeably. The main reason behind the same was mainly due to the fact that in case of thicker layers, there was more mass and heat energy contained by the part. Therefore, the layers will take time to eliminate the heat and hence the possible shrinkage was less. Finally, in case of head scanning speed, it has been found that shrinkage was reduced with an increase in the head scan speed of the printer. It has been found that the dimensions of the parts were severely affected by the scan head speed. At 2500mm/sec, the movement of the printing head was found to be slow and deposited slices found to disturb the layout patterns, see Figure 6(b). However, as soon as the scan head speed was increased, the dimensional accuracy of the printed part started reducing, significantly, refer Figure 6(c) [43]. Further, eqn. 6 shows the regression model for the angular shrinkage with coefficient of determination of 97.66%.

Shrinkage = 12.562 - 2.983 OA + 1.740 OB + 1.243 OC + 0.883 LA - 0.561 LB - 0.322 LC - 0.074 SA - 0.094 SB + 0.168 SC + 0.149 OA × LA - 0.078 OA × LB - 0.072 OA × LC + 0.566 OB × LA - 0.254 OB × LB - 0.313 OB × LC + 0.716 OC × LA + 0.331 OC × LB + 0.384 OC × LC - 0.109 OA × SA - 0.220 OA × SB + 0.110 OA × SC - 0.206 OB × SA + 0.104 OB × SB + 0.102 OB × SC + 0.096 OC × SA + 0.116 OC × SB - 0.212 OC × SC

Figure 5. Mean effect plot for angular shrinkage.

Figure 6. Side view of the part printed at 60° (a), top view of the part printed at 2500mm/sec (b), and top view of the part printed at 4500mm/sec.
In eqn. 6, O, L, and S represents build orientation angle, layer thickness, and head scan speed. Further, the subscripts, A, B, and C represent the levels of input process parameters. Further, the predicted results of the all four ML models on the training-testing (70%) and validation (30%) dataset were observed. All models were run on their default parameters (refer Table 2) in order to evaluate the coefficient of correlation), coefficient of determination ($R^2$) and mean absolute error (MAE) using eqns. 1, 2, and 3, respectively. The performance results showed that ANN based learning performed better over rest of the ML models. The ANN has the lowest MAE of 0.111628 on the testing data set as given in Table 5.

### Table 5: Performance comparison of ML models

|        | R        | $R^2$  | MAE   |
|--------|----------|--------|-------|
| RPART  | 0.815806 | 0.6746 | 0.7564|
| RF     | 0.867768 | 0.7587 | 0.5075|
| glm    | 0.929351 | 0.8647 | 0.4245|
| nnet   | 0.988794 | 0.9778 | 0.01116|

Further, Figure 7 shows the scatter plot of actual and predicted values of shrinkage on testing dataset using ML models. The ANN has the highest correlation coefficient ($r \sim 98.87\%$) in the prediction on the testing data-set and coefficient of determination ($R^2\sim97.78\%$). Finally, Table 6 shows the error incurred in the models developed by various methods.

![Figure 7](image-url)

**Figure 7.** Scatter plot of Actual and Predicted values of shrinkage on testing dataset using ML models

As per Table 6, ANN model has minimum error (MAE $\sim 0.12$) as compare to other ML models, therefore, was cross-verified by using K-fold method for the further validation. Figure 8 shows the plots depicting the robustness of the best predictive model. The regression model experienced over fitting issue due to possibility of benchmark used during training the model was not same as the benchmark used to make the judgment on the efficiency of the model [41].
Therefore, the validation was performed on dataset using best predictive model from training testing experiments. For this, a total of ten cross validation were made, as suggest by kohavi [44]. This enabled the reporting of large scale experiments to estimate the effects of difficult parameters on these algorithms on real world data sets.

Table 6: MAE between ML model and mathematical model.

| Model  | MAE  |
|--------|------|
| ANN    | 0.12 |
| glm    | 11.19|
| RF     | 21.79|
| R_{PART} | 30.2 |

![Figure 8.10- k-fold crossed validation of r (a), R² (b) and MAE on ANN model.](image)

4. Conclusion

In the present work, the angular shrinkage of FFF based PLA parts have been studied in response of build orientation angle, layer thickness, and head scan speed. Further, different ML approaches were used to develop mathematical models for the prediction of angular shrinkage. Followings are the brief conclusions that can be drawn from the result findings:

- It has been found that the angular shrinkage of the resulted parts was substantially affected by the build part orientation angle in comparison of the other two. As the build angle increased, the shrinkage of the specimens was also increased. As per the design of experimentation, the best parametric setting suggested was build orientation angle ~ 20°, layer thickness ~ 350um, and head scan speed ~ 4500mm/sec. The effect of the input process parameters was also witnessed in case of scanning electron micrographs of the printed specimens.
- Furthermore, it has been found that amongst the different ML approaches used for
the development of mathematical model for the angular shrinkage, ANN outperformed the others. The regression coefficient ($R^2$) and MEA available in case of ANN model was about 0.9778 and 0.12, respectively.

- Further, the cross-validation run through K-fold advocated the high precision of the ANN model under test-run conditions.

Reference

[1] Dick J, Hull E and Jackson J 2017 Requirements Engineering. Springer.
[2] Despeisse M, Baumers M, Brown P, Charnley F, Ford S J, Garmulewicz A, Knowles S, Minshall T H W, Mortara L, Reed-Tsochas F P and Rowley J 2017 Technological Forecasting and Social Change 11575.
[3] Singh S, Ramakrishna S and Singh R 2017 Journal of Manufacturing Processes 25185.
[4] Allaire G, Dapogny C, Faure A and Michailidis G 2017 In 12th World Congress on Structural and Multidisciplinary Optimization.
[5] Allaire G, Dapogny C, Faure A and Michailidis F 2017 Comptes. Rendus. Mathematique 355699.
[6] Costabile G, Fera M, Fruggiero F, Lambiase A and Pham D, International Journal of Industrial Engineering Computations 8(2017)263-283.
[7] Lundbäck A, Lindgren L E, Procedia Manufacturing 7 (2017) 127-130.
[8] Lee J Y, An J and Chua C K, Applied Materials Today 7 (2017) 120-133.
[9] Gaal G, Mendes M, de Almeida T P, Piazzetta M H, Gobbi A L, RiuI Jr A 2017 Rodrigues V, Sensors and Actuators B: Chemical 242 (2017) 35-40.
[10] Watson J K and Taminger K M B, Journal of Cleaner Production 176 (2018) 1316-1322.
[11] Paris H and Mandil G 2018, Additive Manufacturing 22 (2018) 687-699.
[12] Guo N and Leu M C 2017 Frontiers of Mechanical Engineering 8215.
[13] Singh S and Singh R 2016 Rapid Prototyping Journal 22123.
[14] Masood S H 1996 Rapid Prototyping Journal 224.
[15] Masood S H and Song W Q 2004 Materials & Design 25587.
[16] Zein I, Hutmacher D W, Tan K C and Teoh S H 2002 Biomaterials 231169.
[17] Ning F, Cong W, Qiu J, Wei J and Wang S 2015 Composites Part B: Engineering 80369.
[18] Nguyen T K and Lee B K 2018 Rapid Prototyping Journal.
[19] Mohan N, Senthil P, Vinodh S and Jayanth N 2017 Virtual and Physical Prototyping 1247.
[20] Ahn S H, Montero M, Odell D, Roundy S and Wright P K 2002 Rapid Prototyping Journal 8 248.

[21] Singh R, Singh S and Fraternali F 2016 Composites Part B: Engineering 9 8244.

[22] Anitha R, Arunachalam S and Radhakrishnan P 2001 Journal of Materials Processing Technology 11 8385.

[23] Salem-Bala A and Bin-Wahab S 2016 In Advanced Engineering Forum 16 33.

[24] Bakar N S A, Alkahari M R and Boejiang H 2010 Journal of Zhejiang University-Science A 11 972.

[25] Dyrbus G, 2010 Citeseer.

[26] Nancharaiha T, Raju D R and Raju V R 2010 International Journal on Emerging Technologies 11 06.

[27] Murugesan K, Anandapandian P A, Sharma S K and Kumar M V 2012 The Journal of Indian Prosthodontic Society 12 16.

[28] Boschetto A and Bottini I 2014 The International Journal of Advanced Manufacturing Technology 73 913.

[29] Schmutzler C, Zimmermann A and Zaehe M F 2016 Procedia CIRP 41 1017.

[30] Sood A K, Ohdar R K and Mahapatra S S 2009 Materials & Design 30 4243.

[31] Hernandez R, Slaughter D, Whaley D, Tate J and Asiabanpour B 2016 In 27th Annual International Solid Freeform Fabrication Symposium, Austin, TX 939.

[32] Ahn S H, Montero M, Odell D, Roundy S and Wright P K 2002 Rapid Prototyping Journal 8 248.

[33] Xu Y 2016 In MATEC Web of Conferences 67 03039.

[34] Aljahdali S H, Sheta A and Rine D 2001 In Computer Systems and Applications, ACS/IEEE International Conference 470.

[35] Mair C, Kadoda G, Leffley M, Phalp K, Schofield C, Shepperd M and Webster S 2000 Journal of Systems and Software 53 23.

[36] Amant K S and Still B 2009 Handbook of Research on Open Source Software—Technological, Economic, and Social Perspectives.

[37] Horký V 2011 Support for NUMA hardware in HelenOS.

[38] Raymond E S 2011 The cathedral and the bazaar-musings on Linux and open source by an accidental revolutionary.
[39] Hornik K, Stinchcombe M and White H 2019 Neural Networks 2359.

[40] Wang R J, Wang L, Zhao L and Liu Z 2007 The International Journal of Advanced Manufacturing Technology 33 3498.

[41] Rana P S, Sharma H, Bhattacharya M and Shukla A 2015 Journal of Bioinformatics and Computational Biology 13 1550005.

[42] Sood A K, Ohdar R K and Mahapatra S S 2009 Materials & Design 30 4243.

[43] Chen C P, Ran Y H, Huang J G, Hu Q and Wang X Y, www.degruyter.com.

[44] Kohavi R 1995 IJCAI 14 1137.