COMPARATIVE STUDY OF SURFACE ROUGHNESS PREDICTION FOR SELECTIVE LASER SINTERING PROCESS USING MULTIPLE REGRESSION MODEL AND ARTIFICIAL NEURAL NETWORK

K.Swarna Lakshmi1, G. Arumaikkannu2

Address for Correspondence
1,2Department of Manufacturing Technology, Anna University Chennai, TamilNadu, India

ABSTRACT:
In Selective Laser Sintering process, setting of process parameters is important to obtain better surface roughness for customized implants as it induces cell growth. Unfortunately, conventional trial and error method is time consuming as well as high cost. The purpose for this study is to develop mathematical model using multiple regression and artificial neural network for surface roughness prediction. Computer Tomography scan data of the femur bone was taken for the study. The scan data was converted to standard triangulation file format using Medical image segmentation for Engineering in Anatomy software. Taguchi’s design of experiments were conducted where layer thickness, fill scan spacing and orientation, have been chosen as predictors in order to predict surface roughness. 27 polyamide samples were run by using selective laser sintering. Analysis of variances shows that the most significant parameter is orientation followed by layer thickness and lastly by fill scan spacing. After the predicted surface roughness has been obtained by using both methods, average percentage error is calculated. The mathematical model developed by using multiple regression method shows the accuracy of 92.02 % which is reliable to be used in surface roughness prediction. On the other hand, artificial neural network technique shows the accuracy of 97.19% which is feasible and applicable in prediction of surface roughness. The result from this study is useful to be implemented in laboratory to reduce time and cost in fabrication of implant for surface roughness prediction which influences the speed and strength of osseointegration.

KEYWORDS: Selective laser sintering, surface roughness, multiple regression, artificial neural network.

1 INTRODUCTION
Additive Manufacturing technology is a relatively new concept that attracts increasingly more attention by the scientific community in the field of medicine and health care and it also opens new opportunities for scientific research activities[1,2]. Additive manufacturing technology has been applied in reconstruction for various customized anatomical structures[3,4]. The primary concern for any manufacturing industry is quality which normally refers to dimensional accuracy, form and surface finish which is made possible with the Additive manufacturing technology. Selective laser sintering has the greatest potential in the fabrication of implants among other Additive Manufacturing technology. Surface roughness plays an important role in osteointegration [5] and as well as Cell adhesion [6, 7].

In case of conventional manufacturing the traditional stylus method is the most widely used technique in measuring the surface roughness. A precision diamond stylus is drawn through the surface being detected and the perpendicular motion is amplified electronically [8-11]. The accuracy of stylus method depends on the radii of diamond tips. Large system error is encountered when surface roughness falls below 2.5µm using traditional stylus method. The major disadvantage for such methods is that they require directed physical contact and line sampling which may not represent the real characteristics of the surface.

According to the literature survey it is clear that conventional estimation of surface roughness is time consuming. Process parameters are the key factors to control the surface roughness. Therefore, correct setting and control of these parameters is a primary requirement for successful application. Hence an intelligent way of predicting the surface roughness has to be implemented. Hence an attempt is made to predict the surface roughness of the laser−sintered polymeric implants built by different process parameter settings using two models, where the first model is a mathematical model using multiple regressions and the second model is based on artificial neural network.

Here Computer Tomography (CT) of the femur bone of a 21 year male has been taken. The three dimensional Computer Aided Design (3 D CAD) model is converted to standard triangulation file format (.stl) using Medical Image Segmentation for Engineering in Anatomy (MIMICS) software. Surface measurements were taken. The data acquired is used for mathematical modeling as well as to train the neural network model using Mat lab software.

2 EXPERIMENTAL SET UP
DTM Sinterstation 2500 plus with build dimensions 381mm x330 mm x 457 mm is employed for this study. The experiments were conducted inside an inert gas chamber by supplying nitrogen gas. Therefore a set point of less than or equal to 5.5 liter per minute (lpm) is maintained to avoid any oxidation during sintering operation. Sintering of the first layer of polyamide powder takes place by the laser movement. After sintering of the first layer required quantity of unsintered powder is applied and the whole procedure was repeated several times till the required implant is obtained.

Building an ANN that can predict the surface roughness under a variation of fabrication conditions, a training database need to be established with regard to different processing parameters and surface roughness. The feasible spaces of the processing parameters of the sintering process were selected by varying the layer thickness in the range of .11 to .15 mm, fill scan spacing in the range of .13 to .15 mm, orientation in the range of 0° to 45°. The surface roughness Ra, which aids for bone tissues to grow faster, is selected in this study. Here CT scan data of the femur bone was converted in to 3D CAD model using mimics software as shown in Fig 1a, 1b. A number of experiments were carried out on SLS (Sinteration 2500plus DTM Corporation) using CO2 laser for fabrication of sintered bone implants and the fabricated implants were measured for roughness.
From the mathematical model the value of predicted surface roughness for each of the experiments can be calculated.

\[ y = a + b x_1 + c x_2 + d x_3 \]  

The above matrix is solved the regression coefficient estimates are determined and are substituted to the following regression model to predict surface roughness.

\[ y = a + b x_1 + c x_2 + d x_3 \]  

Table 1: surface roughness obtained from the experiments

<table>
<thead>
<tr>
<th>S.No</th>
<th>Layer thickness (millimeter)</th>
<th>Fill scan spacing (millimeter)</th>
<th>Orientation (degrees)</th>
<th>Surface roughness ( R_a ) (micrometer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1</td>
<td>0.14</td>
<td>0</td>
<td>1.72</td>
</tr>
<tr>
<td>2</td>
<td>0.1</td>
<td>0.14</td>
<td>30</td>
<td>1.74</td>
</tr>
<tr>
<td>3</td>
<td>0.1</td>
<td>0.14</td>
<td>45</td>
<td>1.88</td>
</tr>
<tr>
<td>4</td>
<td>0.1</td>
<td>0.15</td>
<td>0</td>
<td>1.64</td>
</tr>
<tr>
<td>5</td>
<td>0.1</td>
<td>0.15</td>
<td>30</td>
<td>1.49</td>
</tr>
<tr>
<td>6</td>
<td>0.1</td>
<td>0.15</td>
<td>45</td>
<td>1.85</td>
</tr>
<tr>
<td>7</td>
<td>0.1</td>
<td>0.16</td>
<td>0</td>
<td>1.57</td>
</tr>
<tr>
<td>8</td>
<td>0.1</td>
<td>0.16</td>
<td>30</td>
<td>1.67</td>
</tr>
<tr>
<td>9</td>
<td>0.1</td>
<td>0.16</td>
<td>45</td>
<td>1.70</td>
</tr>
<tr>
<td>10</td>
<td>0.13</td>
<td>0.14</td>
<td>0</td>
<td>1.55</td>
</tr>
</tbody>
</table>

4. ARTIFICIAL NEURAL NETWORK (ANN)

An ANN is a parallel, distributed information processing structure that mimics the human brain to learn from examples or mistakes [11]. ANN is one of the most popular nonlinear mapping systems in artificial intelligence which has the ability to solve many problems including modeling, predicting, and measuring in experimental knowledge [11]. ANN learns the problem from examples by creating functional relationship between inputs and outputs. Here network is created using the following equation

\[ Y = f \sum_{i=0}^{n-1} w_i x_i - \theta \]

Where \( x \) the input corresponds to layer thickness, fill scan spacing, and orientation of the component; \( \theta \) is the internal threshold or offset of a neuron; and \( f \) is the nonlinear transfer function, tan sigmoid logistic function is used in this work, \( Y \) is the desired output.

\[ f(x) = \frac{1}{1 + e^{-x}} \]

Backpropagation algorithm is a commonly used learning algorithm is employed in this network. This algorithm has a rule known as gradient descent method that minimizes the mean square error between the desired output and the network output. The training procedure for a back propagation network is usually iterative and involves a trial and error method approach. First step is to initialize the weights and offsets, starting from a small random value. The input and output values are fed in to the network model. Actual outputs are calculated, further followed by the calculation of error between the output from the neural network and the desired output by \( E \).

\[ E = \frac{1}{2n} \sum_n (y_n - t_n)^2 \]

Where \( t \) is the number of training data set, and \( n \) is the number of neurons in the output layer, here \( n=1 \) is considered. If the value is \( E \) is small, then no other
learning procedures are needed else the weights of the networks are to be adjusted. The weights are adjusted by using the following equation
\[ w_{ij}(t+1) = w_{ij}(t) + \eta_j x_i \]
Where \( x_i \) is either the output of neuron i or an input \( \eta \) is gain term, and \( e_j \) is an error term for neuron j.the above procedure is repeated until the error is less than the required accuracy.
In the experiments, 27 sintered specimens were operated based on the range of fabricating conditions. The experimental results are listed in Table 1 (experimental parameters and surface roughness) for the training database.
The neural networks model for the surface roughness prediction was trained in the following training procedure. In the training process”, the trial-and-error” method is employed to determine in the number of hidden layers, the neurons in each hidden layer, the learning rate, and the momentum factor in the neural network model. A few neural network structures with varied number of hidden neurons are compared and the structure 3-18-1 that creates the least prediction error is selected. By following the same procedure, the learning rate is set as 1 and the momentum factor is set as 0.5. As a result, the architecture of the ANN model is specified as 3-18-1. As shown in Fig 2.

Substituting all the sums values into the simultaneous equation of linear system (Equation 1-4)
\[ 27a + 3.42b + 4.05c + 675d = 50.33 \]
\[ 3.42a + 0.4446b + 0.513c + 85.5d = 6.4519 \]
\[ 4.05a + 0.513b + 0.6093c + 101.25d = 7.5434 \]
\[ 675a + 85.5b + 101.25c + 26325d = 1340.4 \]
By transforming the above equations into matrix form:
\[
\begin{bmatrix}
27 & 3.42 & 4.05 & 675 \\
3.42 & 0.4446 & 0.513 & 85.5 \\
4.05 & 0.513 & 0.6093 & 101.25 \\
675 & 85.5 & 101.25 & 26325
\end{bmatrix}
\begin{bmatrix}
a \\
b \\
c \\
d
\end{bmatrix}
= 
\begin{bmatrix}
50.33 \\
6.4519 \\
7.5434 \\
1340.4
\end{bmatrix}
\]
After solving the above matrix, the regression coefficients estimated are:
\[ a = 1.302116, b = 6.733918, c = -3.38889, d = 0.008693 \]
5.2 ANN model

![Figure 3. Performance plot of 3-18-1](image)

From the Performance of neural network (3-18-1) is shown in Fig.3 we see that the mean squared error is found to be less at epoch 6.

5.3 Experimental verification and discussion
Verifying the developed networks to predict the surface roughness of implants, test were performed in ten samples. As the orientation, layer thickness, and the fill scan spacing is fed into the ANN, the surface roughness measured by the vision system can be calculated directly. A comparison of Ra’ (measured by vision system) and Ra (measured by stylus method) has been presented in Table2 and Fig 4.

![Figure 4. Validation of Predicted (ANN, Multiple regression) and Experimental values in selective laser sintering process in customized Bone Implant.](image)

% of Error = ((Predicted value-Experimental) /Experimental value)*100
The predicted roughness values through this system result validated by the ten sets of testing data from the experimental value of the surface roughness in Selective laser sintering is shown in Fig 7. The result shows the average error of prediction of surface roughness.

![Figure 5. Structure of the ANN for predicting the surface roughness](image)
roughness in sintering using MRR it is (6.92%) i.e. the accuracy is (93.08%) on the other hand using ANN is (2.438208%) i.e., the accuracy is (97.56179 %) which can be inferred from the Table 2. and Table 3 respectively.

Table 2: Verification of predicted and experimental value in SLS using Multiple regressions

<table>
<thead>
<tr>
<th>S.No</th>
<th>layer thickness (mm)</th>
<th>fill scan spacing (mm)</th>
<th>Orientation degrees</th>
<th>Predicted Roughness (Micrometer)</th>
<th>Experimental Roughness (Micro meter)</th>
<th>Percentage Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1</td>
<td>0.14</td>
<td>0</td>
<td>1.5010632</td>
<td>1.72</td>
<td>14.58545</td>
</tr>
<tr>
<td>2</td>
<td>0.1</td>
<td>0.14</td>
<td>30</td>
<td>1.7618532</td>
<td>1.74</td>
<td>1.240353</td>
</tr>
<tr>
<td>3</td>
<td>0.1</td>
<td>0.14</td>
<td>45</td>
<td>1.8922482</td>
<td>1.88</td>
<td>0.647283</td>
</tr>
<tr>
<td>4</td>
<td>0.1</td>
<td>0.15</td>
<td>0</td>
<td>1.4671743</td>
<td>1.64</td>
<td>11.77949</td>
</tr>
<tr>
<td>5</td>
<td>0.1</td>
<td>0.15</td>
<td>30</td>
<td>1.7279643</td>
<td>1.49</td>
<td>13.77137</td>
</tr>
<tr>
<td>6</td>
<td>0.1</td>
<td>0.15</td>
<td>45</td>
<td>1.8583593</td>
<td>1.85</td>
<td>0.449822</td>
</tr>
<tr>
<td>7</td>
<td>0.1</td>
<td>0.16</td>
<td>0</td>
<td>1.4332854</td>
<td>1.57</td>
<td>9.538547</td>
</tr>
<tr>
<td>8</td>
<td>0.1</td>
<td>0.16</td>
<td>30</td>
<td>1.6940754</td>
<td>1.67</td>
<td>1.421153</td>
</tr>
<tr>
<td>9</td>
<td>0.1</td>
<td>0.16</td>
<td>45</td>
<td>1.8244704</td>
<td>1.7</td>
<td>6.822276</td>
</tr>
<tr>
<td>10</td>
<td>0.13</td>
<td>0.14</td>
<td>0</td>
<td>1.70308074</td>
<td>1.55</td>
<td>8.988461</td>
</tr>
</tbody>
</table>

Table 3: Verification of predicted and experimental value in SLS using ANN

<table>
<thead>
<tr>
<th>S.No</th>
<th>layer thickness (mm)</th>
<th>fill scan spacing (mm)</th>
<th>Orientation degrees</th>
<th>Predicted Roughness (Micrometer)</th>
<th>Experimental Roughness (Micro meter)</th>
<th>Percentage Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1</td>
<td>0.14</td>
<td>0</td>
<td>1.732</td>
<td>1.72</td>
<td>0.697674</td>
</tr>
<tr>
<td>2</td>
<td>0.1</td>
<td>0.14</td>
<td>30</td>
<td>1.781</td>
<td>1.74</td>
<td>2.356322</td>
</tr>
<tr>
<td>3</td>
<td>0.1</td>
<td>0.14</td>
<td>45</td>
<td>1.892</td>
<td>1.88</td>
<td>0.638298</td>
</tr>
<tr>
<td>4</td>
<td>0.1</td>
<td>0.15</td>
<td>0</td>
<td>1.528</td>
<td>1.64</td>
<td>6.829268</td>
</tr>
<tr>
<td>5</td>
<td>0.1</td>
<td>0.15</td>
<td>30</td>
<td>1.396</td>
<td>1.49</td>
<td>6.308725</td>
</tr>
<tr>
<td>6</td>
<td>0.1</td>
<td>0.15</td>
<td>45</td>
<td>1.806</td>
<td>1.85</td>
<td>2.78378</td>
</tr>
<tr>
<td>7</td>
<td>0.1</td>
<td>0.16</td>
<td>0</td>
<td>1.518</td>
<td>1.57</td>
<td>3.312102</td>
</tr>
<tr>
<td>8</td>
<td>0.1</td>
<td>0.16</td>
<td>30</td>
<td>1.686</td>
<td>1.67</td>
<td>0.958084</td>
</tr>
<tr>
<td>9</td>
<td>0.1</td>
<td>0.16</td>
<td>45</td>
<td>1.7</td>
<td>1.7</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.13</td>
<td>0.14</td>
<td>0</td>
<td>1.564</td>
<td>1.55</td>
<td>0.903226</td>
</tr>
</tbody>
</table>

5. CONCLUSION
In this paper, we have proposed multiple regression models and artificial neural network model with three inputs for predicting surface roughness in implants made of PA12. It proves a reliable assessment of surface roughness in bone implants. For faster training of ANN, Levenberg Marquardt algorithm was used. R^2 values predicted the ANN model match very well with that of the measured experiments for training and testing stages. It has been inferred that in MRR the maximum absolute error between the predicted and experimental method is 14.58545, the average error of the prediction is 6.92% with an accuracy of 93.08%. Whereas on the other hand maximum absolute error between the predicted and experimental method is less than 6.82%, the average error of the prediction is 2.83% with an accuracy of 97.168%

REFERENCES