Artificial neural network (ANN) based prediction of process parameters in additive manufacturing

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Abstract. In recent years, selective laser melting (SLM), a part of additive manufacturing (AM) is one of the most encouraging ones that permit fabricating metallic parts from metal powder with complex geometry. Diversities in these cycle boundaries become an imperative system to improve the nature of the outcome. Cycle boundaries, for example, laser power, scan speed, hatch spacing, layer height used as input parameters and have a significant impact on the mechanical property taken as an output parameter of the manufactured part. The Artificial Neural Network (ANN) model includes a multi-layer perceptron (MLP) learning algorithm named as Levenberg-Marquardt and tangent sigmoid function consider as preparing and testing functions respectively utilizing MATLAB toolkit. Ideal cycle boundaries are attained dependent on the mean square error function (MSE) and correlation coefficient (R²).

Keywords: Additive manufacturing, artificial neural network, MATLAB, ANOVA

1. Introduction

Over the past decade, Additive Manufacturing (AM) has been made from the Rapid Prototyping industry and is getting recognized as an amassing elective for a wide extent of things. American Society for Testing and Materials (ASTM – F2792) describes added substance manufacturing as "the path toward joining materials to create objects from 3D model data, commonly layerwise manner, as an alternative to subtractive gathering techniques" [1][2][3]. AM has increased significant consideration in the aviation, biomedical and car businesses because of its numerous expected advantages, for example, more mathematical opportunity, abbreviated plan for item time, decreased in measured steps, segment mass decrease, and material adaptability[4][5][6][7]. Selective Laser Melting (SLM) is the most widely recognized technique in added substance fabricating that permits creating metallic parts by the totally liquefying of metal powder with the capacity to deliver complex geometrical components that are difficult to produce with traditional subtractive manufacturing processes[8][9][10][11].

It is acknowledged that the cycle boundaries, specifically laser power, scan speed, layer height, and hatch spacing have a major impact on the final strength of the parts. Therefore, an ideal combination of these parameters leads to enhance the final strength of the part[12][13]. Scan speed and laser power have a very close relationship, as The power indicates the amount of energy transferred per second,
and the speed directly affects the time spent in the same area. So, both values will define the amount of energy transferred in this area[14]. Moreover, hatch spacing indicates the area affected by a laser beam. Increasing value leads to less energy being transferred to the outer zone than the center of the laser beam track. The decreasing value causes an overlap of the tracks and some powder is struck by the adjacent laser track. So, the highest hatch spacing to have more productivity by ensuring a proper melting of the powder[15]. As the layer height has a significant influence on the part’s resolution, layer height must be as high as possible, but short enough to ensure the attachment between layers and avoid possible breaks to achieve high resolution[16]. The specific effect of these values has a significant impact on part’s quality. Therefore, an optimal combination of these cycle boundaries can enhance the strength of the final part[17][18].

There are numerous forecasting techniques and models to find out ideal limits in additive manufacturing. Among all techniques, ANN models have been broadly developed as a forecasting tool for predicting ideal cycle boundaries in several materials and manufacturing processes. This methodology has a wealth of expertise in predicting network boundaries when the input cycle boundary relationships are highly volatile[19][20][21]. As to AM process, Saedi et al[22] researched the impact of SLM cycle boundaries on microstructure and thermomechanical response on the fabricated parts that demonstrate a cautious selection of cycle boundaries that lead to distinctive features and behaviors of the parts. Mehrpouya Met al[23] applied the NN model for finding the optimal laser parameters of NiTi parts. According to this model, they found worthy correlation ship between input and predicted values.

2. ANN Methodology

In recent years, artificial intelligence (AI) research has been progressively used in computing, physical sciences, engineering, and statistics to model complex problems. ANN is an information processing tool with the capability of learning and adopts them to the environment for solving the problem related to pattern recognition or data classification or application-based which are difficult to solve by conventional techniques[24][25][26]. In the present study, the MATLAB toolkit utilizes various developed functions such as MLP neural network model and algorithms, namely feed-forward back propagation algorithm to accomplish precise forecasted models with the help of inner basics such as activation functions and numerous learning procedures which can be adjusted so the user needs to analyze the model to review all the inner essentials implement code accurately with minimum limitation.

2.1. MLP Neural Network Model

Figure 1. Architecture of input/output boundaries in neural network.
MLP neural network contains of three layer named as input layer, hidden layer and output layer. The function of each hidden neurons is depended on the conduction of input and the weights on the networks between the input components and the hidden components. The weights concerning the input components and hidden components can be found out when all hidden components are active. The representation of hidden layer can be chosen by modifying these weights. Overall, the way in which the neurons are connected to each other has a significant impact on the operation of the system. The MLP model, which generally embraces the back-propagation (BP) algorithm corresponds to gradient descent (GD) training function with adaptive learning rate in function estimation that tells about the values of weight and bias that kept abreast in the direction of the negative drop of the performance function to achieve minimum error between a network and actual outcomes [27][28][29]. It consists of three-layer followed as input layer, hidden layer, and output layer. 10 numbers of hidden neurons are considered in the hidden layer. The cycle boundaries were considered as an input layer, namely as laser power, scan speed, layer height, and hatch spacing, and ultimate tensile strength was considered as the output layer for ANN modeling as shown in Figure 1.

As referenced previously, neurons in each layer get weighted contributions from a need layer and shift them to the ensuing layer. Equation (1) computes the sum of weighted input signals, and that sum is communicated through the nonlinear activation function in equation (2).

\[
Y_{net} = \sum_{i=0}^{n} X_i W_i + W_0 
\]

\[
Y = f(Y_{net}) = \frac{1}{1 + e^{-Y_{net}}} \]  

The network error was then determined by equation (3) in light of the correlation between the predicted and actual outcomes. Generally, the preparation cycle emerge still this error accomplishes an acceptable value.

\[
MSE = \frac{1}{k} \sum_{i=1}^{k} (Y_i - O_i)^2 
\]

Where \( Y_i \) is the reaction of the neuron \( i \), \( f(Y_{net}) \) is the nonlinear activation function, \( Y_{net} \) is the summation of weighted data sets, \( X_i \) is the neuron input, \( W_i \) is the weight coefficient of each neuron input, \( W_0 \) is bias, MSE is the mean square error concerning the predicted and actual outcomes, and \( O_i \) is the actual value of neuron \( i \). Likewise, the sigmoid activation function is utilized for training and testing of models. E(Y) is the expectation of \( Y_i \) to find the correlation coefficient \( R^2 \) [25].

2.2 Neural Network Setup
The data sets of input cycle boundaries such as laser power, scan speed, hatch spacing, and layer height, and ultimate tensile strength as the target cycle boundary considered for modeling the network are taken from the research study reported in [30]. A total of 40 datasets are taken for modeling purpose on a random basis in the subdivision of 80% training, 10% validation, and 10% testing stages. Levenberg-Marquardt (LM) algorithm utilized to train the model through training and testing stages. These models examined the desired outcomes to predict the ideal boundaries of additive manufacturing samples.

3. Results and discussion
Here ANN constructions, learning set of rules, number of hidden neurons on performance factors, MSE and correlation coefficient for training, validation, and testing of data sets were examined. Tables and graphs show the predicted value with ANN modelling as well as the influence of the deviation in input boundaries and measured output. The predicted results of ANN models are compared with the results reported in [30].

Figure 2 exhibits a title window of the NN during the preparation. It likewise shows preparing advancements and allows the client to intrude on preparing anytime by utilizing the quit preparation button. This window shows the algorithm table that represents data divided on random distribution, training algorithm used as Levenberg–Marquardt algorithm, and performance of the model is determined based on the mean square error distribution. This shows a linear regression between the network predicted results and the actual results. When an ANN model provides supreme standards of the coefficient of correlation ($R^2$) and least possible standards of the mean square of error (MSE), it can be certainly accepted to be the precise ANN model.

Figure 2. Neural Network training window.

Figure 3(a) shows the description window of NN training performance. This shows the best validation performance is 251.21 at epoch 5. It predicts the best combination of optimal mean square error (MSE) is achieved when training, validation, and testing curves meet at the ideallocation.
The neural network training histogram is shown in Figure 3(b) represents the error between actual output and predicted output of the processing data. The ideal line for minimum errors during the training, validation, and testing stages displays the efficiency of the ANN model.

Figure 3. Neural Network window for (a) Training performance, and (b) Error histogram.

It is comprehended from Figure 4 that output routes are directed particularly for preparing (R=0.94873), approval (R=0.94899) and testing (R =0.99889). These values predicted by ANN modeling would correspond to the total response of R-value=0.95932. These regression plots display the relevance amongst the targets that regards as the actual outcomes and the ANN output that regards as network outcomes. R= 0.95932 represents that ANN outcomes extremely matches with the targets. The regression value has specified the consequence targets and outcomes.

Figure 4. Neural Network regression plot.
**Table 1.** Training data sets taken for modelling shows the combination of an input cycle boundaries along with the actual values and the network predicted values of UTS for the particular combination which are taken for training the model to minimize the error between actual and predicted data sets.

| Sr No | Laser Power (W) | Scan Speed (mms⁻¹) | Hatch Spacing (μm) | Layer Height (μm) | Measured Output (MPa) | Predicted Output (MPa) |
|-------|-----------------|---------------------|-------------------|-------------------|-----------------------|-----------------------|
| 1     | 320             | 800                 | 120               | 30                | 684                   | 674.62                |
| 2     | 320             | 1000                | 90                | 30                | 627                   | 625.30                |
| 3     | 240             | 800                 | 150               | 30                | 660                   | 654.96                |
| 4     | 320             | 1000                | 150               | 30                | 673                   | 658.38                |
| 5     | 320             | 600                 | 90                | 30                | 574                   | 571.502               |
| 6     | 240             | 600                 | 120               | 30                | 684                   | 683.99                |
| 7     | 400             | 800                 | 150               | 30                | 545                   | 559.56                |
| 8     | 320             | 800                 | 120               | 30                | 684                   | 674.62                |
| 9     | 240             | 800                 | 90                | 30                | 652                   | 653.73                |
| 10    | 400             | 600                 | 120               | 30                | 565                   | 557.89                |
| 11    | 320             | 800                 | 120               | 30                | 684                   | 674.62                |
| 12    | 400             | 1000                | 120               | 30                | 607                   | 610.65                |
| 13    | 320             | 600                 | 150               | 30                | 582                   | 579.53                |
| 14    | 320             | 800                 | 90                | 30                | 583                   | 581.79                |
| 15    | 400             | 600                 | 120               | 30                | 565                   | 557.89                |
| 16    | 400             | 1000                | 90                | 30                | 590                   | 598.91                |
| 17    | 360             | 800                 | 150               | 30                | 626                   | 617.44                |
| 18    | 320             | 600                 | 150               | 30                | 582                   | 579.53                |
| 19    | 280             | 600                 | 90                | 30                | 645                   | 651.40                |
| 20    | 280             | 1000                | 120               | 30                | 700                   | 689.68                |
| 21    | 400             | 600                 | 90                | 30                | 492                   | 482.05                |
| 22    | 240             | 1000                | 150               | 30                | 620                   | 642.06                |
| 23    | 240             | 600                 | 90                | 30                | 669                   | 678.37                |
| 24    | 320             | 800                 | 90                | 30                | 583                   | 581.78                |
| 25    | 280             | 600                 | 150               | 30                | 598                   | 622.09                |
| 26    | 360             | 800                 | 90                | 30                | 556                   | 557.35                |
| 27    | 240             | 800                 | 120               | 30                | 739                   | 719.30                |
| 28    | 400             | 800                 | 120               | 30                | 611                   | 596.35                |
| 29    | 240             | 60                 | 90                | 30                | 669                   | 668.92                |
| 30    | 360             | 600                 | 120               | 30                | 580                   | 585.14                |
| 31    | 320             | 600                 | 120               | 30                | 654                   | 645.98                |
| 32    | 360             | 600                 | 120               | 30                | 580                   | 585.14                |

**Table 2.** Validation data sets taken for modelling shows the amalgamation of input cycle boundaries along with the actual values and the network predicted values of UTS for the individual combination which are taken for cross validation to performance evolution of the model.

| Sr No | Laser Power (W) | Scan Speed (mms⁻¹) | Hatch Spacing (μm) | Layer Height (μm) | Measured Output (MPa) | Predicted Output (MPa) |
|-------|-----------------|---------------------|-------------------|-------------------|-----------------------|-----------------------|
| 1     | 320             | 800                 | 120               | 30                | 684                   | 674.62                |
Table 3 shows the combination of input cycle boundaries along with the actual values and the network predicted values of UTS for the individual which are taken for testing to obtain the performance characteristics such as the correlation coefficient of the model. Test data sets are considered as the final network predicted outcomes for neural network modeling.

Table 3. Testing data sets taken for modelling.

| Sr No | Laser Power (W) | Scan Speed (mm/s) | Hatch Spacing (μm) | Layer Height (μm) | Measured Output (MPa) | Predicted Output (MPa) |
|-------|-----------------|-------------------|-------------------|-----------------|----------------------|----------------------|
| 1     | 400             | 800               | 90                | 30              | 484                  | 550.16               |
| 2     | 240             | 1000              | 120               | 30              | 723                  | 734.92               |
| 3     | 240             | 800               | 120               | 30              | 739                  | 719.30               |
| 4     | 280             | 800               | 120               | 30              | 688                  | 712.84               |

Figure 5. Comparison between actual and predicted data sets at Training, Validation, and Testing stages illustrates the least possible variation between actual and predicted outcomes of ultimate tensile strength for training, validation, and testing stages. It can be said that the neural network models are well trained and it can be useful for predicting response when the combination of input cycle boundaries has significant influence on the final strength of the part.

4. Conclusion
This paper has introduced an expectation model utilizing an artificial neural network model to accomplish, especially, ultimate tensile strength dependent on the operational boundaries, including
laser power, scan speed, hatch spacing, and layer height. These modeling results are analyzed and the following conclusions are obtained:

- The results are validated with the existing research study reported in[30]Error! Reference source not found.; according to ANOVA, the best combination of processing parameters for maximum tensile strength using the Taguchi method is as follows: power 240W, scanning speed 1000mm/s, and hatch spacing 120μm, based on the TM and RSM response value, the predicted tensile strength value is 738MPa and 737MPa.
- According to ANN optimization, the predicted tensile strength value for the above processing parameters is 735MPa. Therefore, it can be concluded that the ANN optimization approach gives the most preferable prediction as a statistical approach.
- The predicted values of the ANN model were evaluated by applying the mean square error based on the coefficient of determination (R²). These modeling results predicted by ANN modelling are indicated by the higher value of the correlation coefficient between the actual outcomes and predicted outcomes getting up to 0.95. It indicates that a model gives the satisfactory predictive results when compared to experimental results.
- It can suggest that the artificial neural network solution can be effective in forecasting, supervising plus handling the optimized processing parameters and can be a substitute to analytical and mathematical techniques.

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