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Modeling of Laser assisted machining process using Artificial Neural Network

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Abstract. Recently machining with the assistance of laser is the cost effective proven technique to process high temperature alloys in aerospace industries. The challenge in laser assisted machining is to optimize the process parameters to get good surface integrity without changing the metallurgical and mechanical properties. As several input parameters such as feed rate, pulsed frequency, depth of cut, laser power and cutting velocity are involved in LAM, experimental studies are not an effective solution. So the main aim of this work is to develop an Artificial Intelligence model to understand the process mechanics and for the prediction of surface roughness, specific cutting energy and cutting zone temperature during laser assisted machining. ANN model has been developed by considering the topology of the network, selection of algorithm and selection of number of neurons. ANN model is developed by considering Levenberg-Marquardt algorithm and error is minimized by root mean square method. There is a better agreement between experimental and ANN model. The proposed model predicts the surface finish and specific energy with an prediction accuracy of 95.94 and 99.618% respectively during machining of hardened steel.

1. Introduction
Machining is the key secondary manufacturing processes to get desired shape, size and tolerance in aerospace and automobile applications. The challenge in aerospace and automobile industry is to machine difficult to cut material like hardened steel, titanium alloy and inconel. Hardened steel has been used as gears for power transmission, crank and cam shaft in automobile engines and ball bearing rings [1]. The photograph of ball bearing ring has been shown in figure 1. The demand for machining of hardened steel has been increasing for past two decades. So the variation in surface integrity during machining of hardened steel and grinding process has been compared [2]. Different strategies have been proposed in literature by several researchers, but laser assisted machining is more efficient compared to other methods. The high intensity of laser in the power source produce concentrated and control preheating of work material thereby material is getting softened in front of cutting tool. The 3D representation of laser preheating followed by cutting tool to remove the softened material is shown in figure 2.
Machining of hardened steel by conventional methods results in high tool wear and poor surface integrity. In order to overcome these difficulties, a description of hybrid laser micro machining was first reported by [4] and results proved that softening of material by means of laser improves the industrial component dimensional and form accuracy by decreasing the cutting force. Laser assisted micromachining (LAM) of hardened steel results in better surface integrity and a reduced amount of power consumption when compared with conventional technique [3]. A few researchers used finite element method to predict the process output parameters such as cutting, thrust and feed forces, tool chip interface temperature during machining of difficult to cut material [5, 6]. A finite element simulation has been developed to predict the heat affected zone in laser assisted machining process. The temperature in machining zone is less than the critical range than there is no residual heat affected zone in the material [7]. The force, temperature and flow stress during LAM of titanium alloy is simulated by finite element method for biomedical applications[8]. The influence of preheating on chip formation in machining of titanium alloy has been investigated. Results revealed that power of the laser and cutting velocity influence the saw tooth geometries[9]. When preheating temperature on workpiece is increased to 893 K then specific energy consumption is reduced by 25% and there is an improvement in surface finish and tool life. The total cost required to manufacture the component by laser assisted machining is less when to conventional techniques[10].

Figure 1. Ball bearing ring
Reference: www.vxb.com

Figure 2. Laser assisted machining [3]

Figure 3. Block diagram representing Neural Network

Figure 3 shows the block diagram of representing neural network system. Input indicates the input parameters for the particular manufacturing process. The output is the target of the predicted parameter. Before predicting the output parameters neural network is being trained from the
experimental or real time data which is called as trained neural network. Several researchers used soft computing techniques to predict the manufacturing process. Neural network approach has been adopted for monitoring the wear of the cutting tool during turning process [11]. This model can be used for monitoring the wear of the cutting tool in real time machining industries. Surface roughness and flank wear of the turning tool are predicted using neural network system [12]. Results suggested that honed edge of CBN insert enhanced the tool life and surface finish of the component. A few researchers developed several models for prediction of surface finish. But the accuracy of TANMLP neural network model for the prediction of surface finish model is 91.42% and it is better when compared with other models[13]. Based on the experimental data, empirical model has developed for prediction of surface finish in turning process. The influence of machining parameters on the surface finish has been detailed analyzed [14]. A finite element approach has developed for chamfered and honed edge tool for prediction of temperature and forces during machining of hardened steel using CBN tool. Customized honed results in lower cutting force and chamfered edge prepared tool results in lesser temperature in the cutting zone.

As several machining parameters like power of laser, laser scan speed, spot size, focal length, type of laser, cutting velocity, feed per revolution and depth of cut are involved in laser assisted machining, it is difficult to predict and incorporate all the process parameters in finite element, analytical and empirical approach. In view of this, in the present work soft computing model i.e ANN model has been developed to understand the physics of hybrid laser machining process and prediction of the process parameter prior to experimental investigation.

2. Formulation of artificial neural network model

Artificial Neural network approach is one of the potential soft computing techniques used for the prediction of process parameter in complex manufacturing process and non-linearity in manufacturing system. It also involves verifying the accuracy of the predicted data. ANN helps to understand the complex manufacturing process in better way when compared with other model since it involves several networks. Laser assisted hybrid machining is one among such complicated processes where different laser and machining parameters are having nonlinear control on the output parameters. MATLAB software is used in the present work to run the simulation of the proposed model.

![Figure 4. Design of neural network modelling for laser assisted machining](image-url)
The design of neural network modeling for laser assisted machining is shown in figure 4. The basic neural network has input, hidden and output layer of 4, 5 and 2 neurons respectively. Each circle in the Figure 4 represents a neuron and the link is present between every neuron. The structure represents that four inputs such as feed, depth of cut, laser power, cutting speed and two targets such as surface roughness and specific cutting energy were given into the network. The aim of the network is to find the outputs by finding a relation between the inputs and the targets. Every neuron inside a network have a bias value and every link have a weightage such that the link weightage should be greater than the bias value then only the certain combination in a network works. There can be several combinations in a network possible. For every combination the way of reaching the target through the links is changed. For every combination different outputs will be produced. The methodology used to create the ANN model is Selection of network, Topology, Comparison of algorithms, Training of network are shown in figure 5.

The selection of network can be represented as the percentage of training, testing and validation data allotted to the network and also the number of input, hidden and output layers. In addition to this, the selection of an pertinent algorithm. The topology of the network is the formation of the neural network. The only way to select the number of neurons in hidden layer in a neural network is trial and error method. We need to select the number of neurons such that the RMS error is to be minimum. Generally, in an ordinary neural network the number of hidden neurons will be 10. The trial and error method works as follows: Increase the neurons from 0-N, keeping inputs and outputs of neural network constant, and compare the RMS errors of every network and select the least possible RMS error. In the present work, we found the least RMS error is achieved at 10 hidden neurons. Hence, the topology of the network is 4-10-2.

There are three different algorithms used in ANN,

- Levenberg-Marquardt
- Bayesian regularization
- Scaled conjugate gradient

The method to find the best training algorithm is by training the entire neural network with the three algorithms and compare their RMS errors and coefficient of determination(R) values of training, validation and testing data sets. The neural network is trained exactly three times with each algorithm and credited out the RMS error. The comparison of different algorithm is shown in figure 6.

![Figure 5. Methodology of proposed ANN model](image-url)
Figure 6. Comparison of RMS error for different algorithms

Figure 6 shows the comparison of RMS errors of three different algorithms (Levenberg, Bayesian, scaled conjugate gradient). From this comparison we can infer that Levenberg-Marquardt algorithm is having least RMS error in training data and testing data. So, we are choosing Levenberg algorithm as training algorithm for the proposed model. Further training of network had been done with Levenberg algorithm. The comparison of coefficient of correlation for different algorithm is shown in Figure 7. All the training, validation and testing data for different algorithm remains same. So RMS method is used for different algorithm to minimize the error.

Figure 7. Comparison of coefficient of correlation for different algorithm
The mean squared error for training, validation and testing with epochs is shown in figure 8. The blue line correspond to the training data, green line stand for the validation data, red line signify the testing data. In the graph above the x-axis shows epoch which is defined as the training of the neural network for one complete time with certain weights and bias. The y-axis shows the mean squared error which is defined as the difference between square of the difference between the targets and the output. The best validation performance achieved is 0.0007029 at epoch 23. Table 1 shows the comparison of experimental and ANN model results.

The prediction error of surface roughness and specific cutting energy is shown in figure 9. The maximum and minimum errors in surface roughness are 0.06743 and -0.00101 respectively. The maximum and minimum errors in specific cutting energy are -0.13366 and -0.00047 respectively. At the first we have selected the data for predicting the surface roughness and now we are going to determine the cutting forces and cutting temperature.
# Table 1: Comparison of experimental [1] and ANN modelling results

| S. No. | Velocity (m/min) | Feed (mm/rev) | M.R.R Depth of cut (μm) | Experimental Surface roughness (μm) | Experimental Specific cutting energy (w-s/mm³) | Predicted surface roughness (μm) | Predicted specific cutting energy (w-s/mm³) |
|--------|------------------|---------------|--------------------------|-------------------------------------|-----------------------------------------------|----------------------------------|-------------------------------------------|
| 1      | 150              | 0.050         | 25                       | 0.36                                | 0.34                                          | 5.95                             | 0.27                                      | 5.92                                      |
| 2      | 150              | 0.050         | 50                       | 0.36                                | 0.32                                          | 5.85                             | 0.26                                      | 5.82                                      |
| 3      | 150              | 0.050         | 75                       | 0.36                                | 0.28                                          | 5.70                             | 0.25                                      | 5.72                                      |
| 4      | 150              | 0.050         | 100                      | 0.36                                | 0.26                                          | 5.60                             | 0.24                                      | 5.60                                      |
| 5      | 150              | 0.050         | 125                      | 0.36                                | 0.23                                          | 5.48                             | 0.23                                      | 5.48                                      |
| 6      | 150              | 0.050         | 150                      | 0.36                                | 0.2                                           | 5.40                             | 0.22                                      | 5.35                                      |
| 7      | 150              | 0.050         | 175                      | 0.36                                | 0.21                                          | 5.22                             | 0.22                                      | 5.22                                      |
| 8      | 150              | 0.050         | 200                      | 0.36                                | 0.22                                          | 5.10                             | 0.22                                      | 5.07                                      |
| 9      | 150              | 0.050         | 225                      | 0.36                                | 0.22                                          | 4.90                             | 0.22                                      | 4.91                                      |
| 10     | 180              | 0.050         | 250                      | 0.36                                | 0.22                                          | 4.75                             | 0.22                                      | 4.75                                      |
| 11     | 180              | 0.075         | 25                       | 0.36                                | 0.28                                          | 5.00                             | 0.29                                      | 4.99                                      |
| 12     | 180              | 0.075         | 50                       | 0.36                                | 0.28                                          | 4.92                             | 0.28                                      | 4.93                                      |
| 13     | 180              | 0.075         | 75                       | 0.36                                | 0.28                                          | 4.89                             | 0.27                                      | 4.87                                      |
| 14     | 180              | 0.075         | 100                      | 0.36                                | 0.28                                          | 4.80                             | 0.27                                      | 4.80                                      |
| 15     | 180              | 0.075         | 125                      | 0.36                                | 0.28                                          | 4.70                             | 0.26                                      | 4.70                                      |
| 16     | 180              | 0.075         | 150                      | 0.36                                | 0.28                                          | 4.60                             | 0.26                                      | 4.56                                      |
| 17     | 180              | 0.075         | 175                      | 0.36                                | 0.27                                          | 4.40                             | 0.27                                      | 4.40                                      |
| 18     | 180              | 0.075         | 200                      | 0.36                                | 0.27                                          | 4.10                             | 0.27                                      | 4.23                                      |
| 19     | 180              | 0.075         | 225                      | 0.36                                | 0.27                                          | 4.10                             | 0.28                                      | 4.12                                      |
| 20     | 180              | 0.075         | 250                      | 0.36                                | 0.28                                          | 4.10                             | 0.28                                      | 4.11                                      |
| 21     | 180              | 0.100         | 25                       | 0.36                                | 0.36                                          | 4.65                             | 0.35                                      | 4.64                                      |
| 22     | 180              | 0.100         | 50                       | 0.36                                | 0.35                                          | 4.52                             | 0.34                                      | 4.52                                      |
| 23     | 180              | 0.100         | 75                       | 0.36                                | 0.35                                          | 4.42                             | 0.34                                      | 4.41                                      |
| 24     | 180              | 0.100         | 100                      | 0.36                                | 0.34                                          | 4.30                             | 0.34                                      | 4.30                                      |
| 25     | 180              | 0.100         | 125                      | 0.36                                | 0.33                                          | 4.20                             | 0.34                                      | 4.19                                      |
| 26     | 180              | 0.100         | 150                      | 0.36                                | 0.33                                          | 4.08                             | 0.33                                      | 4.07                                      |
| 27     | 180              | 0.100         | 175                      | 0.36                                | 0.32                                          | 3.98                             | 0.33                                      | 3.97                                      |
| 28     | 180              | 0.100         | 200                      | 0.36                                | 0.32                                          | 3.90                             | 0.32                                      | 3.91                                      |
| 29     | 180              | 0.100         | 225                      | 0.36                                | 0.33                                          | 3.90                             | 0.32                                      | 3.89                                      |
| 30     | 180              | 0.100         | 250                      | 0.36                                | 0.34                                          | 3.90                             | 0.32                                      | 3.88                                      |
3. Application of ANN model

Figure 10. Variation of surface roughness with feed rate at 180 m/min cutting velocity, 0.36 mm depth of cut.

Figure 10 shows the variation of surface finish with feed rate at constant cutting velocity of 180 m/min and depth of cut 0.36 mm. When feed rises from 0.05 mm/rev to 0.1 mm/rev, raise in surface roughness from 0.14 to 0.36 μm are observed. This is due to less interaction of tool and workpiece. Similar trend is observed in experiment, analytical model and ANN model. The prediction of surface roughness by analytical method is developed by Petropoulos has been used for comparison in the present work[15]. In analytical model the surface roughness depends only on feed rate and nose radius which results in large discrepancy between experimental results and model. But there is a good agreement between experiment and ANN model. This is due to incorporation of both machining and laser parameters. This figure 11 shows the variation of surface roughness with spindle speed at different depth of cut 0.2, 0.5, 0.7 mm and constant feed of 0.01 mm/rev. When the spindle speed increases, the contact time of tool and workpiece increases, which generate more smoothing and thereby there is a decrease in surface roughness. At 0.2 and 0.5 mm depth of cut poor surface finish is observed. This is due to rubbing and ploughing action. Good surface finish at 0.7 mm is attributed to shearing action. The figure 12 shows the variation of tool chip temperature with cutting speed at constant feed rate and depth of cut. It is very difficult to predict the cutting zone temperature by experimental method. When cutting speed and laser power increases, rate of plastic deformation increases which tends to rise in cutting temperature.
4. Conclusion

- ANN model has been developed for the prediction of surface roughness, specific energy consumption and cutting zone temperature for difficult to cut material.
- Levenberg-Marquardt algorithm is better for training the neural network when compared with Baeysian regularization and scaled conjugate gradient algorithm.
The proposed model predicts the surface finish, specific energy consumption in machining of hardened steel parts with a prediction accuracy of 95.94 and 99.62% respectively. The accuracy of predicted results is based on the topology of the network and selection of algorithm.

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