International Engineering Research Journal Page No 2089-2093

# A Neural Network Tool Based Model for Optimization of Surface Roughness of Hard Turning Process

Pramod B. Chavan and Satish S. Chinchanikar

***Abstract*— Machining is one of the most important and widely used manufacturing processes. Due to complexity and uncertainty of the machining processes, soft computing techniques are being preferred to physics-based models for predicting the performance of the machining processes and optimizing them. An artificial neural network (ANN) is capable of learning from an experimental data set to describe the nonlinear and interaction effects with great success. From last decades a group of researcher optimized machining operating parameter using neural network. This paper presents a model for predicting and optimization of surface roughness using artificial neural network.With the study of past research this paper gives brief idea about neural network model and its application. It also includes study of neural network predictive models for surfaces roughness input parameter as speed, feed, depth of cut etc. Feed forword Backprop this network type and levenberg-marquadt training type was used for developing the model. 20 data points were used for training which gives 7.25% error when predicated values were compared with actual. The paper highlights the progress made in the area of neural network and discusses the issues that need to be addressed. The hard turning (hardness greater than 45 Rc) process has become a very popular technique in manufacturing of shafts, bearings, cams, gears etc. Current hard turning practice, industry tries to choose the correct tool geometry, use proper machining parameters, and use proper cutting tools. This can lead to less machining time, low machining cost and good machining quality. For such improvements Optimization has done to hard turning process by developing the mathematical model from neural network tool.**

***Index Terms*— Artificial neural network, optimization, hard turning.**

## I. Introduction

Metals have been used for decades in various engineering Automated intelligent control of computerised numerically controlled (CNC) machines has been attracting the attention of a number of researchers. Attempts are being made to impart human-like intelligence to the machine tools. The artificially intelligent machine tool is supposed to predict the job quality based on the sensory feedback and proper analysis of the feedback signals [1].

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With the advent of capital intensive CNC machine tools, this need has strengthened. The prediction of surface roughness, cutting force, and tool life in machining is a challenging task, but is necessary for proper optimization of the process. Of late, with the development of computer technology, finite element and soft computing methods are being used for modeling and optimization machining processes. The soft computing differs from conventional (hard) computing in that it is tolerant of imprecision, uncertainty, partial truth and approximation, and metaheuristics may play an important role in soft computing.Based on the predictions, the machine tool should also be able to take a corrective action.

One important attribute of job quality in the turning process is surface roughness. A reasonably good surface finish is desired for improving the tribological properties, fatigue strength, corrosion resistance and aesthetic appeal of the product. On the other hand, excessively better surface finish may involve more cost of manufacturing [2]. Hence, much attention was paid to the estimation of surface roughness.

The surface finish prediction strategy has been developed using four main methods: the multiple regression technique, mathematical modelling based on the physics of the process, the fuzzy set-based technique and neural network modeling. Among these, neural network modeling seems to be more promising because of the ability of neural networks to model complex processes and its similarity with the humancognitive system [2, 3].

An artificial neural network (ANN) is capable of learning from an experimental data set to describe the nonlinear and interaction effects with great success. It consists of an input layer used to present data to the network, output layer to produce response, and one or more hidden layers in between. The neurons in the input layer receive input signals from the user and provide the output through the neurons in the output layers. Only the neurons in the input and output layers interact with the user; the rest are hidden. ANNs are characterized by their topology, weight vectors, and activation function that are used in hidden and output layers of the network. A neural network is trained with a number of data and tested with other set of data to arrive at an optimum topology and weights. Once trained, the neural networks can be used for prediction. The number of types of ANNs and their uses is very high. The first neural network model developed by McCulloch and Pitts in 1943, there have been developed hundreds of different neural networks models [3, 4].

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## II. Literature Survey

**M. Chandrasekaran et al. [1]** reviewed the application of neural networks, fuzzy sets, genetic algorithms, simulated annealing, ant colony optimization, and particle swarm optimization tools to four machining processes—turning, milling, drilling, and grinding. They presented review of application of soft computing techniques in machining performance prediction and optimization. They concluded that the neural networks models have been effectively employed for predicting the surface roughness of machined components in turning and drilling.

**Karpat and Ozel [2]** developed a multi-objective optimization model for single pass turning to model surface roughness and tool wear. They used particle swarm optimization (PSO) based neural network optimization scheme to optimize finish hard turning processes using cubic boron nitride tools. The Levenberg - Marquardt method was used together with Bayesian regularization to train neural networks. A 5-15-2 network structure was developed by trial and error method. Training of the neural network performed by using 173 data points covering the cutting speed range (100-200 m/min) and feed rate range (0.05-0.2 mm/rev). Neural network (NN) model predicts surface roughness and tool wear during machining and PSO used to obtain optimum cutting speed, feed rate, and tool geometry. The authors found that PSO takes less number of iterations to reach optimal conditions.

**Azouzi and Guillot [3]** proposed neural network model to predict surface finish and dimensional deviation of the job based on the feedback from various sensors. They developed several network models to find out the influence of feedbacks from a number of sensors. The author observed that feed, depth of cut, radial force, and feed force provide the best combination to build a model for online prediction of surface roughness and dimensional deviation.

**Pal and Chakraborty [4]** predicted surface roughness by taking main cutting force, feed force, cutting speed, feed, and depth of cut as input parameters of the network. A methodology for the prediction of surface roughness in turning using back propagation neural network has been developed. A number of experiments have been conducted on mild steel work-piece using HSS as the cutting tool material. Different combinations of learning rate, and momentum coefficient and number of hidden layer have been tried. Depending upon the mean square error and convergence rate, optimum network architecture has been arrived at 5-5-1 network. The predicted surface roughness from the present neural network model is very close to the values measured experimentally, thus showing the importance of back propagation neural network for predicting surface roughness in turning.

**Kohli and Dixit [5]** present work was concerned with predicting the surface roughness by taking the feedback of the radial vibration of the tool holder in the turning process. A computer code was written in object oriented C++ language in a modular fashion. A neural network based code is developed, in which, the size of training and testing data is increased until desired prediction accuracy is obtained. The code predicts the upper and lower estimates of surface roughness. The proposed methodology was validated by means of experimental data on wet and dry turning of steel using HSS and carbide tools.

**Risbood et al. [6]** predicted the surface roughness for the dry and wet turning of mild steels using carbide and high-speed steel tools. For each tool job combination and cutting condition (dry or wet), different networks were used. The acceleration of radial vibration was taken as an input for online prediction of surface roughness. The authors also developed a neural network model for predicting the dimensional deviation of the job. For training the network, the TRAINLM function of MATLAB was used. This function works on back propagation algorithm. For this purpose, the radial cutting force, the radial acceleration of vibration, cutting speed, feed, depth of cut, length-to diameter ratio of the job, and position of the tool was taken as input parameter.

**Abburi and Dixit [7]** developed a knowledge base system with the help of neural network and fuzzy set theory to predict surface roughness in turning process. The neural network was trained with experimental data. The trained network generates a huge data set that is fed to a fuzzy set based rule generation module. A large number of IF-THEN rules were generated that are reduced by using Boolean operations. This rule base module was used for predicting surface roughness for given process variables as well as for the inverse prediction of process variables for a given surface roughness. The performance of the developed knowledge based system was found satisfactory based on the validation with shop floor data.

**Basak et al. [8]** used artificial neural network's radial basis function (RBF) models to predict surface roughness in finish hard turning process of AISI D2 cold rolled steel with mixed ceramic tools. For better modeling of an RBF network, assistance of multiple-linear regression was taken. With the help of experimental data at 27 different cutting conditions, radial basis function neural network models were fitted for predicting the surface roughness and tool wear as functions of cutting speed, feed, and machining time. Authors observed that in RBF neural network training, the spread parameter, which was essentially the zone of influence of a neuron, plays a significant role. Authors have proposed a strategy for the optimal selection of process parameters.

**Sharma et al. [9]** in his work, machining variables such as cutting forces and surface roughness are measured in turning of adamite. The effect of cutting parameters such as approaching angle, speed, feed and depth of cut on machining variables is evaluated. The back-propagation training algorithm was used which iteratively minimized the cost function with respect to the interconnection weights and neuron thresholds. The model was formulated for all cutting parameters and machining variables using neural networks. Then the models are compared for their prediction capability with the actual values. The model gave overall 76.4% accuracy.

**K. Divya Theja et al. [10]** worked on end milling process parameter optimization. Full factorial design was used to carry out the experimental design. Artificial neural networks (ANN) program available in MATLAB software was used to establish the relationships between the input process parameters and the output variables. The models were developed to predict the material removal rate (MRR) and tool wear resistance through artificial neural networks techniques. The best model was

selected based on the best performance error for different network configurations. Also the models have been evaluated by means of the percentage deviation between the predicted values and the actual values. It was shown that the ANN predicted results showed good agreement with the experimental results, Hence ANN proved its efficiency in optimizing the end milling process parameters.

## III. A NEURAL NETWORK MODEL

### A. ANN

A feed forward artificial neural network trained using the backpropagation algorithm has been employed. The process parameters considered are cutting speed ($v$), feed ( $f$ ) and depth of cut ($d$). A feedback of this also obtained for online prediction of center line average (CLA) surface roughness ($Ra$). Thus, the input layer of the neural network contains four neurons while the output layer has a single neuron corresponding to the predicted value of surface roughness. The accuracy, reliability and effectiveness of the neural network depends on a number of factors like number of training and testing data, learning rate, number of hidden layers, number of neurons in the hidden layers and processing function used. By modelling different problems, it was observed that both *logsig* and *tansig* produce almost the same performance. Hence, only the *logsig* processing function has been used, in this work. Also, only single hidden layer networks are used. Preliminary numerical experiments did not show any advantage of double hidden layer network over single hidden layer network. A typical network architecture with three neurons in the hidden layer is shown in Fig. 1.

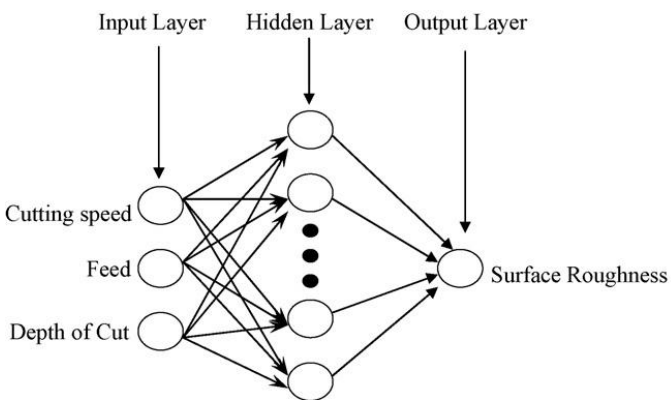


Fig. 1. Neural Network Structure

### B. Modeling in MATLAB

Step-1: First we have to enter P and T to the NN Network Manager. This is done by clicking New Data once.

Step-2: Type P as the Name, and corresponding matrix as the Value, select Inputs under DataType, then confirm by clicking on Create.

Step-3: Similarly, type in T as the Name, and corresponding matrix as the Value, select Targets, under DataType , then confirm. In fig 2.

Network Type = FeedforwordBackprop
Train Function = TRAINLM
Adaption Learning Function = LEARNGDM
Performance Function = MSE
Numbers of Layers = 2

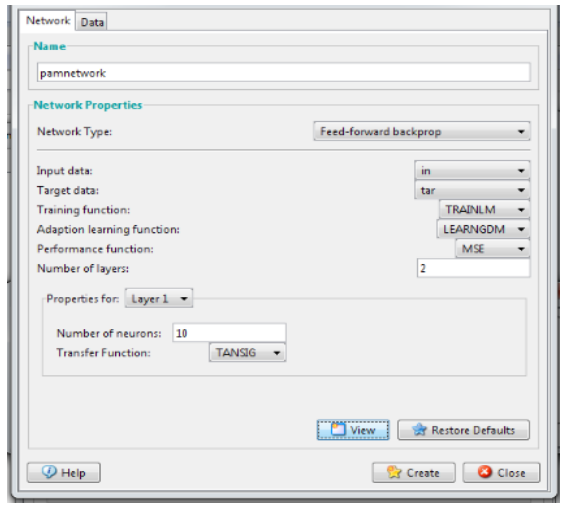


Fig. 2. Create a Network

### C. Training Neural Network

When the network weights and biases are initialized, the network is ready for training.The multilayer feedforward network can be trained for function approximation (nonlinear regression) or pattern recognition. The training process requires a set of examples of proper network behavior—network inputs p and target outputs t.

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function net perform Fcn. The default performance function for feedforward networks is mean square error mse—the average squared error between the network outputs a and the target outputs t.

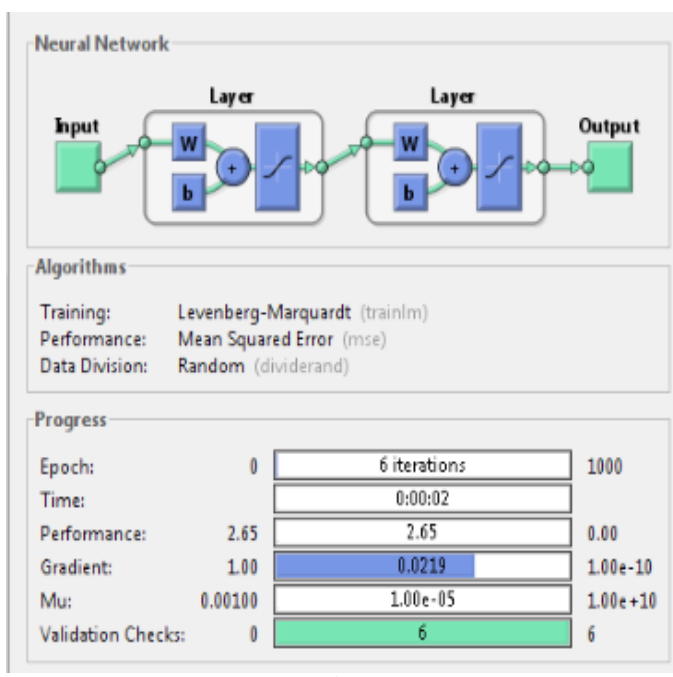


Fig. 3. Training of Neural Network

The fastest training function is generally trainlm, and it is the default training function for feedforwardnet. The quasi-Newton method, trainbfg, is also quite fast. Both of these methods tend to be less efficient for large networks (with thousands of weights), since they require more memory and more computation time for these cases. Also, trainlm performs better on function fitting (nonlinear regression) problems than on pattern recognition problems. The size of training dataset is important from the point of view of reliability. If the network has been fitted with large number of testing data, it is expected to be more reliable, i.e., there will be fewer cases in which the error in prediction will be more than prescribed. However, the data generation process may be costly and time consuming.

On Training Info, select P as Inputs, T as Targets.

On Training Parameters, specify: epochs = 1000

Goal = 0.000000000000001

Max fail = 50

After, confirming all the parameters have been specified as indented, hit Train Network. Fig 3 shows training parameters. Table no. 1 shows the data used for training [5].

| Sr.no. | v(m/min) | d(mm) | f(mm/rev) | a(m/s2) | Ra |
|---|---|---|---|---|---|
| 1 | 107.82 | 0.3 | 0.04 | 0.56 | 2.44 |
| 2 | 106.47 | 0.3 | 0.08 | 0.72 | 3.48 |
| 3 | 105.12 | 0.3 | 0.16 | 1.05 | 3.23 |
| 4 | 104.8 | 0.6 | 0.04 | 2.69 | 2.21 |
| 5 | 103.55 | 0.6 | 0.08 | 2.07 | 3.92 |
| 6 | 106.02 | 0.6 | 0.16 | 2.28 | 4.45 |
| 7 | 42.98 | 0.4 | 0.1 | 1.33 | 4.65 |
| 8 | 47.17 | 0.3 | 0.04 | 2.07 | 3.15 |
| 9 | 46.55 | 0.3 | 0.08 | 1.65 | 3.82 |
| 10 | 45.95 | 0.3 | 0.16 | 1.39 | 5.56 |
| 11 | 48.75 | 0.6 | 0.04 | 1.92 | 5.92 |
| 12 | 48.14 | 0.6 | 0.08 | 0.89 | 3.84 |
| 13 | 47.52 | 0.6 | 0.16 | 1.97 | 5.39 |
| 14 | 27.71 | 0.3 | 0.04 | 2.36 | 5.68 |
| 15 | 27.35 | 0.3 | 0.08 | 1.76 | 6.35 |
| 16 | 26.99 | 0.3 | 0.16 | 2.18 | 6.14 |
| 17 | 27.71 | 0.6 | 0.04 | 0.65 | 3.32 |
| 18 | 27.35 | 0.6 | 0.08 | 0.82 | 3.96 |
| 19 | 26.99 | 0.6 | 0.16 | 1.26 | 6.2 |
| 20 | 81.56 | 0.4 | 0.1 | 1.26 | 4.8 |

Table.1. Training data of Neural Network

## IV. Results and Discussions

ANN model has been tested using the training data and regression graphs were plotted. The results indicate that ANN model has been successfully applied to the machining parameters of MMC hard steel. As shown in table no. 2 the result of predicated values by neural network and actual values were compared.

| v(m/min) | d(mm) | f(mm/rev) | a(m/s2) | Ra | Predicted Ra | % error |
|---|---|---|---|---|---|---|
| 76.43 | 0.6 | 0.05 | 1.14 | 1.89 | 1.260 | 10.6 |
| 42.98 | 0.4 | 0.1 | 1.33 | 4.65 | 4.585 | 1.3849 |
| 36.87 | 0.5 | 0.12 | 1.11 | 4.9 | 4.590 | 6.3122 |
| 35.96 | 0.3 | 0.12 | 0.87 | 4.76 | 4.514 | 5.1617 |
| 78.1 | 0.6 | 0.05 | 0.81 | 2.06 | 1.854 | 11.616 |

Table.2. Comparison of predicted and actual values

It is observed from Fig. 4 (Performance plot of Neural Network) that predicted data based on ANN model is very close to the experimental observation. The validation for the surface roughness values using ANN. This error is a reasonable one and shows that the ANN model predicted satisfactory for surface roughness. 20 data points are used for training which gives 7.25% error when predicated values are compared with actual.

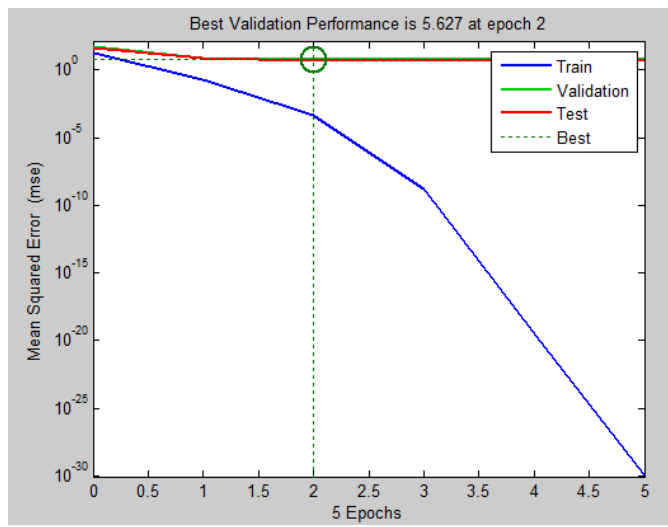


Fig. 4 Performance plot of Neural Network

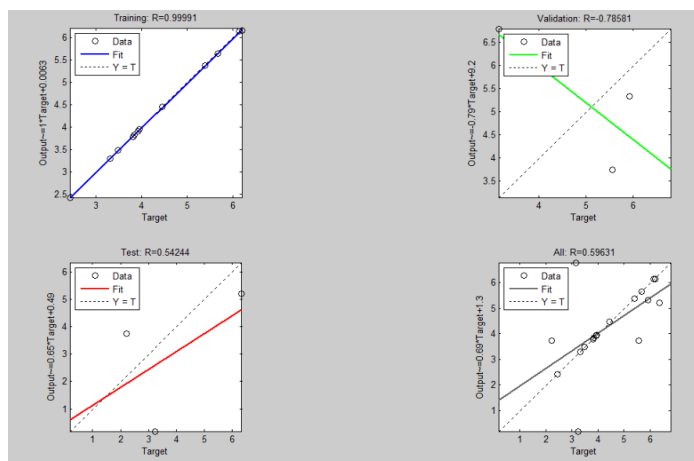


Fig. 5 Regression plot of Neural Network

## V. CONCLUSION

The objective of this study was the development of models based on feedforward neural networks in predicting accurately surface roughness in hard turning. The experimental data of measured surface roughness were utilized to train the neural network models. Trained neural network models were used in predicting surface roughness for various different cutting conditions. The developed prediction system was found to be capable of almost 93% accurate surface roughness prediction for the range it has been trained. As it was anticipated, the neural network models provided better prediction capabilities because they generally offer the ability to model more complex nonlinearities and interactions. In the design of neural networks, our major concern was to obtain a good generalization capability. In this study, Levenberg–Marquardt training algorithm was used. This method is also utilized to overcome the problem of determining optimum number of neurons in hidden layer. The results obtained after simulations proved the efficiency of this methodology. Neural network models with speed, feed, depth of cut as inputs and a single output surface roughness could be develop for more output like tool wear etc. Neural Network models were easy to handle and very user friendly. Developed ANN model could be used in future for multiple parameter optimizations.

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