International Journal of Scientific Research in Science, Engineering and Technology
Print ISSN: 2395-1990 | Online ISSN : 2394-4099 (www.ijsrset.com)
doi : https://doi.org/10.32628/IJSRSET207636

Model Development for Prediction of Surface Roughness by using of AI Technique

Mohd. Tauseef, Dheeraj Kumar Verma
Department of Mechanical Engineering, Maharishi University of Information and Technology, Lucknow, Uttar Pradesh, India

Article Info
Volume 7 Issue 6
Page Number: 286-292
Publication Issue :
November-December-2020

Article History
Accepted : 15 Dec 2020
Published : 30 Dec 2020

ABSTRACT

The surface roughness of manufactured product is final results of the turning technique parameters, and an critical characteristics that outline product first-rate, aesthetics etc. It imposes one of the most essential constraints for the choice of machines and slicing parameters in manner planning. In this paper, Artificial Neural Network (ANN) method has been used to develop surface roughness prediction model the use of experimental statistics, wherein Feed Forward Neural Network (FFNN) the usage of Back Propagation set of rules and Levenberg-Marquardt education function has been used. The work has been done using Neural etwork Toolbox in MATLAB. The overall performance of the version has been assessed based totally on Regression analysis, Mean Square Error (MSE) and Magnitude of Relative Error (MRE). A three-2-1 model with two neurons in the hidden layer turned into discovered to be the excellent developed model, having universal regression (R) cost of zero.9923 and pleasant validation overall performance MSE value of 0.00913. The ANN model confirmed incredible consequences for forecasting

Keywords: ANN, FFNN, MSE, MRE, Regression, MATLAB

I. INTRODUCTION

Surface roughness is an the essential standards for comparing workpiece best for the duration of the machining technique due to the fact its first-class influences the operational traits of the workpiece along with compatibility, fatigue resistance and floor friction. The factors that affect the floor roughness encompass device geometry, feed rate, depth of reduce and reducing pace. Surface roughness also affects several functional traits such as, touch causing surface friction, wearing, light reflection, warmness transmission, potential of distributing and protecting a lubricant, load bearing capacity, coating or resisting fatigue. Hence, the desired completed floor is usually detailed and the correct techniques are selected to get the desired first-class. To gain the desired surface finish, an amazing predictive version is vital for stable machining. Hence ANN, an data processing systems are the maximum suitable soft computing method for the development of a predictive model.

II. RELATED WORK

ANNs have programs in solving nonlinear issues that are difficult to resolve with the aid of conventional strategies. Very often, time series techniques display temporal and spatial variability, and are suffered by nonlinearity of bodily techniques, contradictory spatial and temporal scale and ambiguity in parameter estimates. ANNs were able to address theses issues effectively. A lot of labor has been performed in this direction.

Work has been accomplished using conventional methodologies like response floor technique (RSM) to find out the effect of reducing parameters as cutting velocity, feed fee and axial depth of reduce. Alauddin et al. [7] developed a mathematical version to expect the surface roughness of metallic after cease milling. Fuh and Hwang [5] used RSM method to construct a model that may forecast the milling force in end milling operations.

Compared to standard computing techniques, the artificial neural networks (ANNs) are strong and international. Srikanth and Kamala [10] proposed a actual coded genetic algorithm (RCGA) to find pleasant possible reducing parameters and defined its blessings over the prevailing approach of binary coded genetic set of rules (BCGA). Franic and Joze [3] used binary coded genetic set of rules (BCGA) for the optimization of slicing parameters. Yang and Tarng [11] used Taguchi approach for layout optimization on floor pleasant. An orthogonal array, the sign-to-noise (S/N) ratio and the analysis of variance (ANOVA) had been employed to research the slicing characteristics. Avisekh et al.[1] carried out a look at of feasibility of on-line tracking of floor roughness in turning operations the usage of a advanced opto-electrical transducer. Regression and neural community (NN) fashions were used to forecast surface roughness and as compared to actual and on line measurements. Sakir et al. [9] expected floor roughness the use of synthetic neural network in lathe and investigated the impact of device geometry on surface roughness in commonplace lathe

III. Data Used as Model Input and Output Variables

For the present model development the data has been taken from the experimental study carried out by K. Adarsh Kumar, et.al. in their paper " Optimization of Surface Roughness in Face Turning Operation in Machning of EN-8" published in International Journal of Engineering Science and Advance Technology, Vol.2, Issue 4, 2012, pp 807-812. The cutting parameters are shown in the Table-1. Three levels of cutting speed, three levels of feed and three levels of depth of cut has been used. In order to keep the model complexity within reasonable limits the number of input variables have been kept to three only. Consequently the available dataset for this study comprised of three input variables and one output variable as surface roughness.

Table-1:- Cutting Parameters

Cutting Parameters	Level-I	Level-II	Level-III
Feed Rate (mm/rev)	0.14	0.15	0.16
Depth of cut(mm)	0.5	1.0	1.5
Cutting Speed (rpm)	100	360	560

The data used as input and output variables for optimum model development are given in the Table-2 below. Here in the present work three input variables have been used which includes depth of cut, feed rate and cutting speed. The output variable is the predicted surface roughness value.

Table-2 :- Model Input / Output Variables

Model	**Input Variables**	**Output Variables**
ANN	Feed Rate (mm/rev)	Surface Roughness
	Depth of Cut (mm)	
	Cutting Speed (rpm)	

ANN Model Development

NN Model is developed using Matlab graphical user interface (GUI). Trials are first conducted by randomly selecting number of processing elements. Judgment of the accuracy of prediction is done on the basis of the mean square error at the end of the training. The range of selection of the processing elements was narrowed down carefully, on the basis of result of performance for prediction. Among the range of 2 to 20 neurons, NN model was observed to perform with very good accuracy for prediction. NN models are created with one hidden layer and varying number of processing elements or neurons.

Optimal network geometry was found out, using trial and error approach, in an attempt to create more optimum model. The training parameters used for model training are given in table-3 below.

Table-3 Model parameter values for Back Propagation Algorithm for all the models

Parameters used for Network Training	
Network Type	Feed Forward Neural Network with Back Propagation
Training Functions Used	LM=Levenberg-Marquardt;
Adaption Learning Function	learnGDM
Performance Function	Mean Square Error (MSE); Regression (R)
Transfer Function	For Hidden layer – tansigmoid For output layer - linear
No. Of neurons used for hidden layer	2 to 20;

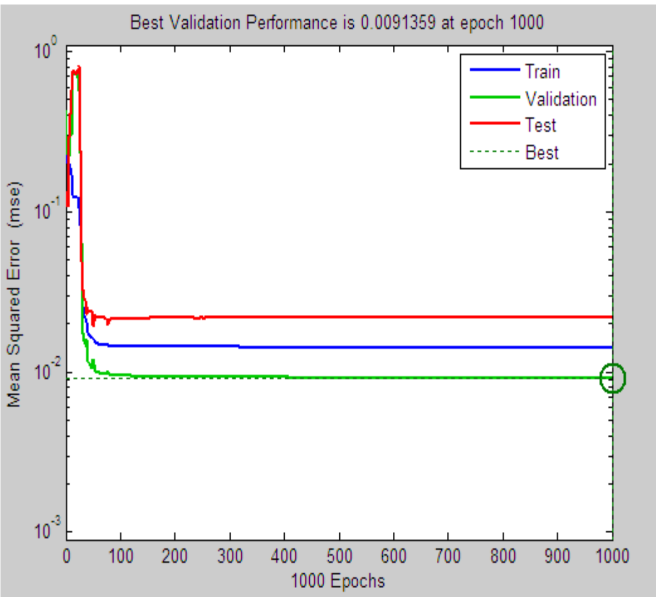
IV. Results and Discussions

Network performance of ANN model is given in table-4 below

Table-4 :- Network Performance for Model M2 for two Month Ahead Forecasting

No. of neurons	**Validation Performance**	**Epochs**	**Reasons for stopping**	**Network Configuration**
2 (best model)	**0.00913**	**1000**	**Val. Stopped/Max. iterations**	**3-2-1**
4	0.027104	44	Val. Stopped/Max. iterations	3-4.1
6	0.058062	2	Val. Stopped/Max. iterations	3-6-1
8	1.4003	0	Val. Stopped/Max. iterations	3-8-1
10	0.75061	17	Val. Stopped/Max. iterations	3-10-1
15	0.2899	2	Val. Stopped/Max. iterations	3-15-1
20	2.737	1	Val. Stopped/Max. iterations	3-205-1

From the table-4 given above, it is seen that the arrangement of the table is done in ascending order of the number of neurons in the hidden layer and the validation performance is measured accordingly The reason why the network size was chosen to be limited to such a number (N=20) was that as the size of network becomes larger, generalization characteristics suffer due to increased number of connections. Also computational expense increases in proportion to the size of the network. Once the network is trained to the level where the predicted results are fairly accurate, training is carried out to assure that predicted results are in close proximity to the actual values. MSE is used to judge the accuracy of the prediction during training, as well as testing and validation. It was also noticed that the performance did not necessarily improve even when the network error was low. In the following figures-1 given below one can notice that roughly after 50 epochs, the performance of training, testing and validation errors were somewhat stagnant. This shows that after epochs 50 there is no further improvement in the performance of the network and the network seems to have saturated.



Fig;-1 - Training of NN model gauged by MSE for ANN model

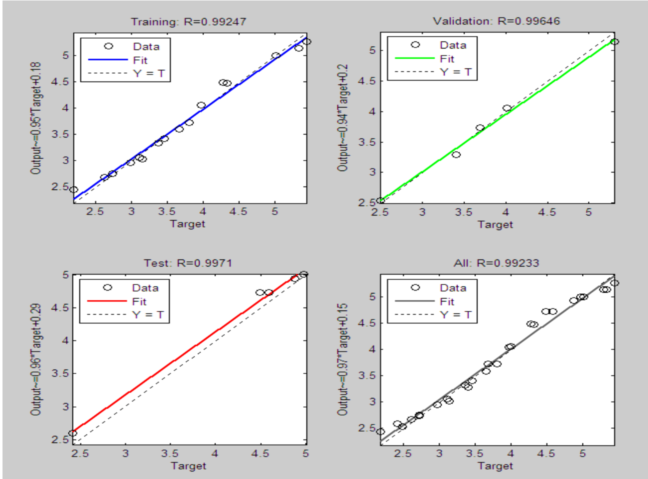


Fig-2.:- Scatter Plot of R Values for Training, Testing and Validating datasets for best developed network

Further figure-2 given above represents a linear regression analysis between the network response and the network output. It can be inferred that NN model does good mapping. 15% of the data which was used for validation was not used for training at all. Hence performance of these machining conditions is something that neural network model has never experienced before. Therefore, one can consider this mapping to be true and representing functional relationship.

Following Table-5 and Fig.-3 given below depicts the comparison between actual and simulated data for surface roughness. It is noticed that except for rare occasions, simulated surface roughness values for the designated parameters are in acceptable proximity with actual values. This representation therefore agrees with the conclusion that, high accuracy of prediction is attained by Neural Network Model after successful completion of training criteria i.e. with the value of MSE being within acceptable range as well as agreeable performance measure. Hence, from the results it is inferred that the performance of thew NN model is acceptable. Thus can further be confirmed from the scatter plots shown in Fig-4.

Table-5:- Observed and Predicted Surface Roughness Values

S. No.	Pre. Val.	Obs. Val.
1	5.005567	4.98
2	5.141501	5.3
3	5.269722	5.44
4	4.729578	4.49
5	5.005252	5.01
6	5.1408	5.34
7	4.476667	4.33
8	4.730485	4.59
9	4.933949	4.88
10	3.723604	3.81
11	4.04999	3.97
12	4.4847	4.28
13	3.414048	3.46
14	3.729643	3.69
15	4.054557	4.01
16	3.022136	3.15
17	3.288433	3.41
18	3.592985	3.66
19	2.743766	2.73
20	3.057039	3.11
21	3.329545	3.37
22	2.591791	2.42
23	2.750142	2.73
24	2.955147	2.98
25	2.433677	2.18
26	2.537144	2.49
27	2.677465	2.62

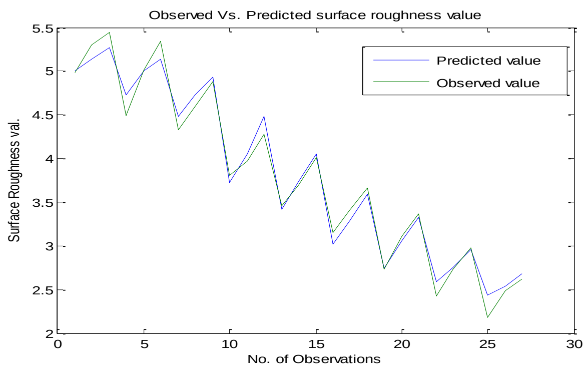


Fig-3:- Comparison of observed and predicted values by best ANN Model

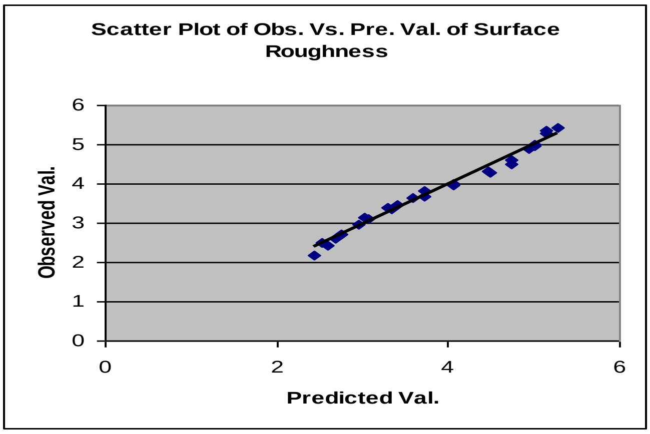


Fig-4:- Scatter Plot of Observed Vs. Predicted Surface Roughness Value

Further analysis of the observed and predicted values for best ANN model on the basis of MRE valuers is shown in figure-5 below.

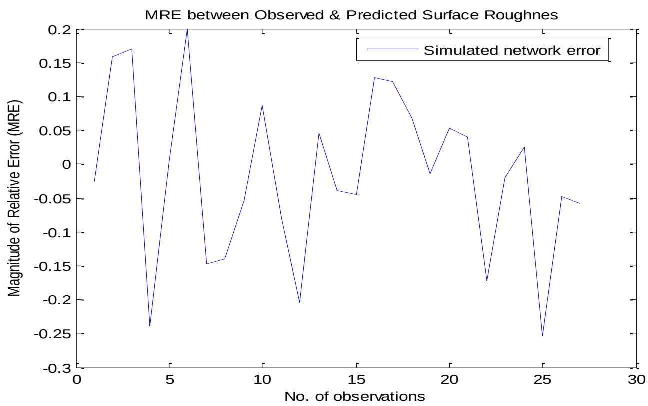


Fig-5:- Deviation of Predicted value from Observed value for M1& M2 Models

Further, Table-6 given below shows the computed values of Regression and MSE values for the model considering different network structures. For the network identification used in the second column of table the first number indicates the number of neurons in the input layer, the last number indicates the number of neurons in the output layer, and the numbers in between represent neurons in the hidden layer.

From table-4 given earlier and Table-6 given below, it is clear that for ANN model 3-2-1 is the best model developed with the least MSE value of 0.00913 and the best regresion values of 0.9924, 0.9964 and 0.9971 for training, validating and testing data sets respectively and overall regression value of 0.9923. The same has been depicted graphically in figure-6 given below. From the perusal of Table-6 it is evident that as the number of neurons in the hidden layer increases the performance of the ANN model in terms of regression as well as MSE values decreases, although there is an improvement in the training dataset regression value for 3-4-1 and 3-6-1 network models.

Table-6 :- Statistical Parameters for different netwok structures for M1 Model

Structure No.	No. of Neurons	Regression Values			
		Training Val.	Validating Val.	Testing Val.	All
1	**3-2-1**	**0.9924**	**0.9964**	**0.9971**	**0.9923**
2	3-4-1	0.999	0.86342	0.97044	0.97411
3	3-6-1	1.000	0.7921	0.95209	0.96575
4	3-8-1	0.675	0.331	0.910	0.337
5	3-10-1	0.968	0.6566	0.2268	0.72087
6	3-15-1	1.000	0.75698	0.76441	0.84615
7	3-20-1	0.508	0.659	0.019	0.293

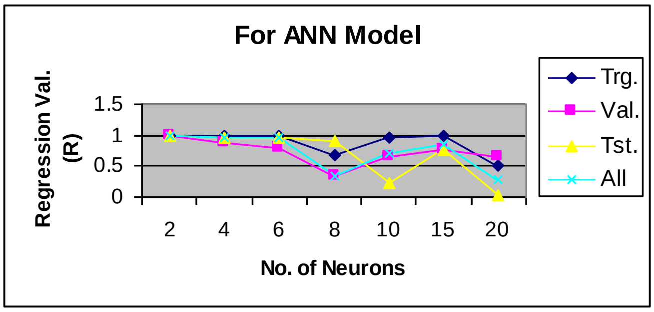


Fig-6 :- Graphical representation of Regression values for ANN Model

In general the R values for training are better than testing and validating datasets except for 3-2-1 model wherein testing and validating datasets have performed better.

V. CONCLUSION

In this study, applicability and capability of ANN technique for surface roughness prediction has been investigated. For this the experimental data has been procured from the earlier published work in International Journal of Engineering Science and Advance Technology, Vol.2, Issue 4, 2012, pp 807-812. ANN model having variable number of neurons in the hidden layer were trained and tested using ANN technique. It is seen that ANN model is very robust, characterised by fast computation, capable of handling the noisy and approximate data. In ANN model, 3-2-1 network structure was found to be the best model for surface roughness prediction, having overall regression value of 0.9923 and best validation performance (MSE) of 0.0091 at epoch 1000.

VI. REFERENCES

[1]. Avisekh B, Evgueni V, Bordatchev S, Kumar, (2009). “On-line monitoring of surface roughness in turning operations with opto electrical transducer”,. Int. J. Manuf. Res., 4(1): 57-73.

[2]. Faraway, J. and Chatfield, C., (1995), “Time Series Forecasting with Neural Networks : A case study. Research report 95-06 of the Statistics group”, University of Bath, UK. 16

[3]. Franci Cus, Joze Balic, (2003) “Optimization of cutting process by GA approach”, Robotics and Computer Integrating manufacturing, 19, pp113-121.

[4]. Huang, Y.,(2009.), “Advances in Artificial Neural Networks – Methodological Development and Application”, Algorithms, 2, pp 973-1007. 21

[5]. K.H. Fuh, R.M. Hwang, (1997) “Predicted milling force model for high-speed end milling operation”, Int. J. Mach. Tools Manuf. 37 (7) 969-979.

[6]. K. Adarsh Kumar, et.al. (2012), “Optimization of Surface Roughness in Face Turning Operation in Machning of EN-8”, International Journal of Engineering Science and Advance Technology, Vol.2, Issue 4, pp 807-812.

[7]. M. Alauddin, M.A. El Baradie, M.S.J Hashmi, (1995) “Computeraided analysis of a surface-roughness model for end milling”, J. Mater. Process. Technol. 55123-127.

[8]. R. C. Eberhart and Y. Shi, (2005), “Computational Intelligence: Concepts to Implementations.

[9]. Morgan Kaufmann, Sakir T, Suleyman N, Ismail S,suleyman Y(2006), ”prediction of surface roughness using artificial neural network in lathe.”,International conference on computer systems and technologies”-Compsys tech’08.

[10]. T.Srikanth and V. Kamala, (2008),. “A Real Coded Genetic Algorithm for Optimisation of cutting parameters in Turning”, International Journal of Computer Science and Network Security, Vol. 8No.6,

[11]. W.H. Yang, Y.S. Tarng, (1998), “Design optimisation of cutting parameters for turning operations based on the Taguchi”, Journal of Materials Processing Technology 84, pp122-129.

Cite this article as :

Mohd. Tauseef, Dheeraj Kumar Verma, "Model Development for Prediction of Surface Roughness by using of AI Technique", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 7 Issue 6, pp. 286-292, November-December 2020. Available at doi : https://doi.org/10.32628/IJSRSET207636
Journal URL : http://ijsrset.com/IJSRSET207636