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Analysis of Surface Roughness in Turning Process Using Neural Network

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Abstract: *Machine parts are significantly influenced by surface roughness quality. For efficient use of machine tools, optimum cutting parameters are required. Therefore it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness. The turning process parameter optimization is highly constrained and nonlinear. Many researchers have used an artificial neural network (ANN) model for the data obtained through experiments to predict the surface roughness. In this study two experimental data are analysed through Neural Network fitting tool using MATLAB software. The results obtained, conclude that ANN is reliable and accurate for solving the cutting parameter optimization.*

Keywords: *Neural Network, MATLAB, Turning, Surface Roughness*

1. INTRODUCTION

Surface roughness quality of a machine part ensures its performance and fatigue life. It depends on various factors such ascutting speed, Feed rate, Depth of cut. Vibrations, tool wear, tool life, surface finish and cutting forces etc. Hence to improve the efficiency of process and quality of the product it is necessary to control the process parameters.Therefore it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness.It is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness.ANN is found to be very useful with simulations tasks which have complex and explicit relation between control factors and result of process.Neural network is one of the important components in Artificial Intelligence (AI). It has been studied for many years in the hope of achieving human-like performance in many fields, such as speech and image recognition as well as information retrieval.Artificial Neural Network can be created using feed forward back propagation technique for simulation of the process. With assurance of accuracy of the predictive capabilities of the neural network; it may be then used for optimization.

Artificial Neural Network Analysis—A Brief Review

A neural network model (or neural model) is an interconnected assembly of simple processing elements, units or nodes, whose functionality is based on the biological neuron. It resembles the brain in two respects:

- Knowledge is acquired by the network from its environment through a learning process;
- Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

An Artificial Neural Network has three components: network architecture, an activation function and a learning rule.

- Network architectures
- Activation function
- Learning rules
- Training methods

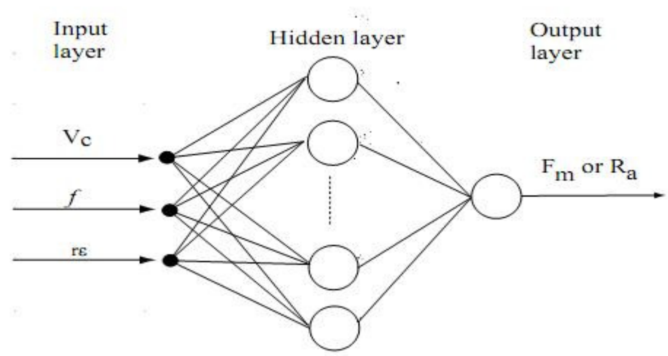

Fig. 1. Architecture of multilayer feed forwardneural network

There are different types of Neural Network

1. Perceptron
2. Back propagation networks
3. Associative memory neural networks
4. Radial basis function networks (RBFN)

5. Adaline networks
6. Probabilistic networks

There are many applications of ANN such as in arts, bioinformatics, forecasting, health care,intrusion detection, communication, robotics, control, pattern recognition etc.

1.1 NEURAL NETWORK FITTING TOOL

The Neural Network Fitting Tool helps us select data, create and train a network, and evaluate its performance using square error and regression analysis. In fitting problems, we want a neural network to map between a data set of numeric inputs and a set of numeric targets.A two layer feed-forward network with sigmoid hidden neurons and linear output neurons (fitnet), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer.The network will be trained with Levenberg-Marquadt backpropagation algorithm (trainlm), unless there is not enough memory, in which case scaled conjugate gradient backpropagation (trainscg) will be used.

1.2 MATLAB

MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment and fourth-generation programming language. Using MATLAB, we can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable us to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java. We can use MATLAB for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing.

Its various key features are:

- High-level language for numerical computation, visualization, and application development
- Interactive environment for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration, and solving ordinary differential equations
- Built-in graphics for visualizing data and tools for creating custom plots
- Development tools for improving code quality and maintainability and maximizing performance
- Tools for building applications with custom graphical interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages such as C, Java, .NET, and Microsoft Excel.

Neural Network Toolbox supports a variety of training algorithms, including several gradient descent methods, conjugate gradient methods, the Levenberg-Marquardt algorithm (LM), and the resilient backpropagation algorithm (Rprop). The toolbox's modular framework let us quickly develop custom training algorithms that can be integrated with built-in algorithms. While training neural network, we can use error weights to define the relative importance of desired outputs, which can be prioritized in terms of sample, time step (for time-series problems), output element, or any combination of these. We can access training algorithms from the command line or via apps that show diagrams of the network being trained and provide network performance plots and status information to help us monitor the training process.

2. LITERATURE REVIEW

Diwakar Reddy V. et al, "ANN Based prediction of Surface Roughness in Turning", December 2011[3] have carried out machining process on Mild steel material in dry cutting condition in a lathe machine and surface roughness was measured using Surface Roughness Tester. To predict the surface roughness, an artificial neural network (ANN) model was designed through back propagation network for the data obtained. Comparison of the experimental data and ANN results showed that there is no significant difference and ANN was used confidently. Three cutting parameters speed, feed, depth of cut have been considered. The machining tests have been carried out by straight turning of medium carbon steel (mild steel) on a lathe by a standard HSS uncoated and carbide insert with ISO designation-SNMG 120408 at different speed-feed and depth combinations. By using the MATLAB command 'postmnmx' the network values have been predicted, regression analysis was adopted to find the coefficient of determination value (R^2) for both training and testing phases to judge performance of each network. The multilayer feed forward network consisting of three inputs, 25 hidden neurons (tangent sigmoid neurons) and one output (network architecture represented as 3-25-1) was found to be the optimum network for the model developed in their study. They concluded from their results obtained that ANN is reliable and accurate for solving the cutting parameter optimization. TugrulOzel et al, [17] studied the effects of tool corner design on the surface finish and productivity in turning of steel parts. Surface finishing has been investigated in finish turning of AISI 1045 steel using conventional and wiper (multi-radii) design inserts. Multiple linear regression models and neural network models have been developed for predicting surface roughness, mean force and cutting Power. The Levenberg-Marquardt method was used together with Bayesian regularization in training neural networks in order to obtain neural networks with good generalization capability. Neural network based predictions of surface roughness were carried out and compared with a non-training experimental data. These results showed that neural network models are suitable to predict surface roughness patterns for a range of cutting conditions in turning with conventional and wiper inserts.

IlhanAsiltürk a, Mehmet Çunkas [5] used Artificial neural networks (ANN) and multiple regression approaches to model the surface roughness of AISI 1040 steel. Full factorial experimental design is implemented to investigate the effect of the cutting parameters (i.e. cutting speed, feed rate, and depth of cut) on the surface roughness. The multiple regression models are tested by aiding the analysis of variance (ANOVA). The data have been used to build the multiple regression model. Multilayer perception (MLP) architecture with back-propagation algorithm having two different variants is used in neural network. The performances of multiple regression and neural network-based models are compared by means of statistical methods. The back-propagation learning algorithms such as scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) were used to update the parameters in feed forward single hidden layers. The cutting speed (V), feed (f), and depth of cut (d) were considered as the process parameters. The input layers of the neural network consist of three neurons whereas the output layer had a single neuron that represents the predicted value of surface roughness. The logsig processing function and single hidden layer had been used. They concluded that ANN is a powerful tool in predicting surface roughness.Ranganath M S, et al, [11] analyzed surface roughness of Aluminium (6061) through neural network model. To predict the surface roughness, neural network model was designed through Multilayer Perceptron network for the data obtained. The predicted surface roughness values computed from ANN, were compared with experimental data and the results obtained showed that neural network model is reliable and accurate for solving the cutting parameter optimization. They concluded that the appropriate cutting parameters can be determined for a desired value of surface roughness.

DurmusKarayel[4],has used neural network approach for the prediction and control of surface roughness in a computer numerically controlled (CNC) lathe. A feed forward multi-layered neural network was developed and the network model was trained using the scaled conjugate gradient algorithm (SCGA), which is a type of back-propagation. The adaptive learning rate was used. He concluded that the appropriate cutting parameters can be determined for a desired value of surface roughness.

Anna Zawada- Tomkiewicz[2], have estimated the surface roughness parameter with use of a neural network (NN). The optical method suggested in this paper is based on the vision system created to acquire an image of the machined surface during the cutting process. The acquired image is analyzed to correlate its parameters with surface parameters. In the application of machined surface image analysis, the wavelet methods were introduced. A digital image of a machined surface was described using the one-dimensional Digital Wavelet Transform with the basic wavelet as Coiflet. The increment of machined surface image parameters was applied as input for the neural network estimator. Five cross-sections of the image were loaded, from which six statistical parameters of the six levels of wavelet decomposition were computed. These six parameters were chosen via the Optimal Brain Surgeon Method. They found that by applying the increments of these parameters and of the estimated value in a given time, it made possible to establish the *Ra* estimator for the points in time when the surface roughness parameters were unknown.Ranganath M S et al., [8, 10, 14], have reviewed the works related to Artificial Neural Networks ANN, in predicting the surface roughness in turning process. They studied in papers that some of the machining variables, that have a major impact on the surface roughness in turning process, such as spindle speed, feed rate and depth of cut were considered as inputs and surface roughness as output for a neural network model. They found that the predicted surface roughness values computed from ANN, were compared with experimental data and the results obtained. These results showed that the neural network model is reliable and accurate for solving the cutting parameter optimization.

RuturajKulkarni et al, [15], carried out tests on AISI 4140 steel. 12 speed Jones and Lamson Lathe model was used for turning operation. The specimen with a diameter of 60mm, 500mm length and hardened 35 HRC is used. The operating parameters that contribute to turning process are cutting speed, Feed rate, Depth of cut, Vibrations, tool wear, tool life, surface finish and cutting forces. These readings were used to train and validate the Neural Network. They found ANN to be very useful with simulations tasks which have complex and explicit relation between control factors and result of process. They created Neural Network using feed forward back propagation technique for simulation of the process using the Matlab Neural network toolbox. With assurance of accuracy of the predictive capabilities of the neural network, it was then used for optimization. Particle Swarm Optimization Algorithm, an evolutionary computation technique is used to find out the optimum values of the input parameters to achieve the minimum surface roughness. The objective function used here is to minimize the surface roughness. Limits of the operational variables are used as constraints for developing the code for optimization algorithm.

3. DATA AND ANALYSIS

For surface roughnes analysis, data from two experiments values has been taken. Data 1 is taken from the paper "Neural Network Process Modelling for Turning of Aluminium (6061) using Cemented Carbide Inserts, [16]" and Data 2 is taken from the paper " Optimization of surface roughness and material removal rate on conventional dry turning of aluminium (6061)". Software used is MATLAB R2011b(7.13.0.564). In this software Neural network fitting tool is used in which cutting speed, Feed rate, Depth of cut are taken as inputs and measured surface roughess values are taken as output and 10 is entered as number of hidden neurons. The following observations are obtained by runing NN fitting tool:Data 1 is explained with tables 1and 2.

TABLE 1. Neural Networks Multilayer Perceptron predicted values [11] : 27 readings

S	f	d	Ra	MLP_PredictedValue
1700	0.1	0.2	0.82	0.83
1700	0.1	0.3	0.94	0.86
1700	0.1	0.4	0.96	0.87
1700	0.13	0.2	1.12	0.99
1700	0.13	0.3	1.06	1.09
1700	0.13	0.4	1.1	1.1
1700	0.15	0.2	1.44	1.38
1700	0.15	0.3	1.54	1.44
1700	0.15	0.4	1.5	1.45
1900	0.1	0.2	0.86	0.84
1900	0.1	0.3	0.92	0.88
1900	0.1	0.4	0.76	0.88
1900	0.13	0.2	1.04	1.01
1900	0.13	0.3	1.2	1.12
1900	0.13	0.4	1.1	1.13
1900	0.15	0.2	1.44	1.4
1900	0.15	0.3	1.6	1.46
1900	0.15	0.4	1.5	1.46
2100	0.1	0.2	0.88	0.84
2100	0.1	0.3	0.78	0.88
2100	0.1	0.4	1.16	0.89
2100	0.13	0.2	1.08	1.03
2100	0.13	0.3	1.14	1.14
2100	0.13	0.4	1.26	1.15
2100	0.15	0.2	0.58	1.41
2100	0.15	0.3	1.42	1.46
2100	0.15	0.4	1.86	1.47

DATA 1 RESULTS

TABLE 2: Neural Network fitting tool result

MLP_PredictedValue	Matlab result	error
0.83	0.748016	0.081984
0.86	0.924706	-0.06471
0.87	0.734418	0.135582
0.99	1.113399	-0.1234
1.09	1.054578	0.035422
1.1	1.811298	-0.7113
1.38	1.397261	-0.01726
1.44	1.514902	-0.0749
1.45	1.496657	-0.04666
0.84	1.326844	-0.48684
0.88	0.90934	-0.02934
0.88	0.777333	0.102667
1.01	0.866078	0.143922
1.12	1.180717	-0.06072
1.13	1.113354	0.016646
1.4	1.457345	-0.05735
1.46	1.34779	0.11221
1.46	1.729337	-0.26934
0.84	0.871308	-0.03131
0.88	0.838522	0.041478
0.89	1.162115	-0.27212
1.03	1.098007	-0.06801
1.14	1.19385	-0.05385
1.15	1.268647	-0.11865
1.41	0.558813	0.851187
1.46	1.477801	-0.0178
1.47	1.446139	0.023861

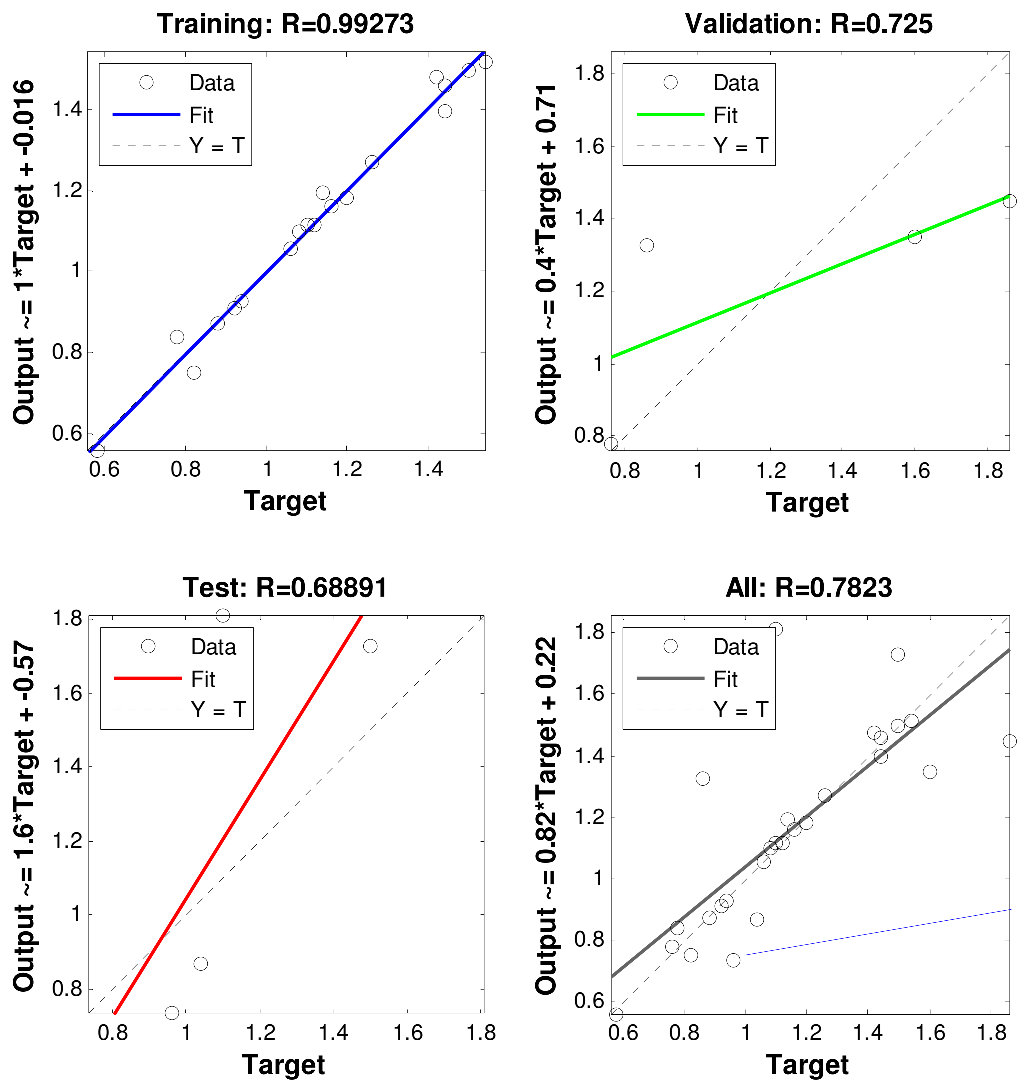

Fig. 2. Regression plot for Data 1

DATA 2

TABLE 3: Machine readings and calculations of Roughness [17]: 27 readings

Speeds (s) (Rev/min.)	Feed (f) (mm per rev.)	Depth of cut (mm)	Measured Ra (µm)	MRR mm3/min	MRR mm3/sec
180	0.2	0.2	1.04	113.927	8.56545
180	0.2	0.4	0.98	212.018	6.86697
180	0.2	0.6	2.2	261.698	4.36163
180	0.315	0.2	2.44	672.129	7.86882
180	0.315	0.4	3.84	333.569	5.55948
180	0.315	0.6	2.4	897.738	1.62897
180	0.4	0.2	2.06	22.443	3.70738
180	0.4	0.4	2.3	953.491	5.89151
180	0.4	0.6	3.66	901.732	8.3622

Speeds (s) (Rev/min.)	Feed (f) (mm per rev.)	Depth of cut (mm)	Measured Ra (µm)	MRR mm3/min	MRR mm3/sec
450	0.2	0.2	0.9	780.859	6.34764
450	0.2	0.4	0.94	528.915	2.14858
450	0.2	0.6	2.9	145.761	35.7627
450	0.315	0.2	1.42	176.76	9.61266
450	0.315	0.4	3.38	303.637	38.3939
450	0.315	0.6	1.34	2263.05	4.3842
450	0.4	0.2	1.74	40.271	4.00451
450	0.4	0.4	1.94	890.513	64.8419
450	0.4	0.6	2.88	4822.2	47.0366
710	0.2	0.2	0.86	130.586	8.84311
710	0.2	0.4	0.92	744.814	45.7469
710	0.2	0.6	1.98	2862.91	14.3818
710	0.315	0.2	1.14	592.809	9.8802
710	0.315	0.4	1.22	3098.48	18.308
710	0.315	0.6	1.16	9365.24	22.7539
710	0.4	0.2	1.2	948.858	32.481
710	0.4	0.4	1.38	5658.57	60.9762
710	0.4	0.6	2.68	3305.82	88.4304

TABLE 4: NN fitting results for data 2

Matlab Ra output	Result error	Matlab mm3/min output	Result Error	Matlab mm3/sec Output	Result Error
0.913232	0.126768	107.8126	6.11437	10.88436	-2.31891
0.644669	0.335331	216.477	-4.45896	7.334996	-0.46803
2.367982	-0.16798	261.7513	-0.05331	34.48975	-30.1281
2.384893	0.055107	-1652.66	2324.79	5.929252	1.939568
3.770516	0.069484	329.0229	4.546104	7.357375	-1.79789
2.591715	-0.19171	364.3161	533.4219	1.568322	0.060648
2.824479	-0.76448	25.46908	-3.02608	-0.48595	4.19333
2.260763	0.039237	-1211.21	2164.706	6.226291	-0.33478
3.793547	-0.13355	880.8359	20.89612	8.48437	-0.12217
1.683223	-0.78322	777.9455	2.913516	6.58626	-0.23862
0.656883	0.283117	523.8659	5.049055	26.42648	-24.2779
2.467942	0.432058	147.6897	-1.92866	35.11149	0.651206
1.651251	-0.23125	169.1197	7.640342	9.45825	0.15441
3.350995	0.029005	288.2407	15.39625	38.49349	-0.09959
1.538269	-0.19827	2243.545	19.5049	4.386742	-0.00254
1.712336	0.027664	462.1214	-421.85	6.840818	-2.83631

Matlab Ra output	Result error	Matlab mm3/min output	Result Error	Matlab mm3/sec Output	Result Error
2.356691	-0.41669	880.1073	10.40575	58.94161	5.900295
3.011701	-0.1317	5083.391	-261.191	25.1766	21.86
0.934006	-0.07401	1690.157	-1559.57	15.71471	-6.8716
-0.06489	0.984886	744.4401	0.373851	26.52107	19.22583
0.936604	1.043396	2878.882	-15.9723	9.494034	4.887766
1.149902	-0.0099	561.6668	31.14223	10.48262	-0.60242
1.125381	0.094619	3088.285	10.19504	18.30693	0.00107
0.972137	0.187863	9340.405	24.83477	22.72939	0.024506
1.095317	0.104683	958.3188	-9.46083	33.28007	-0.79907
1.179694	0.200306	5660.588	-2.01829	62.16878	-1.19258
2.149931	0.530069	9161.016	-5855.2	87.32237	1.108029

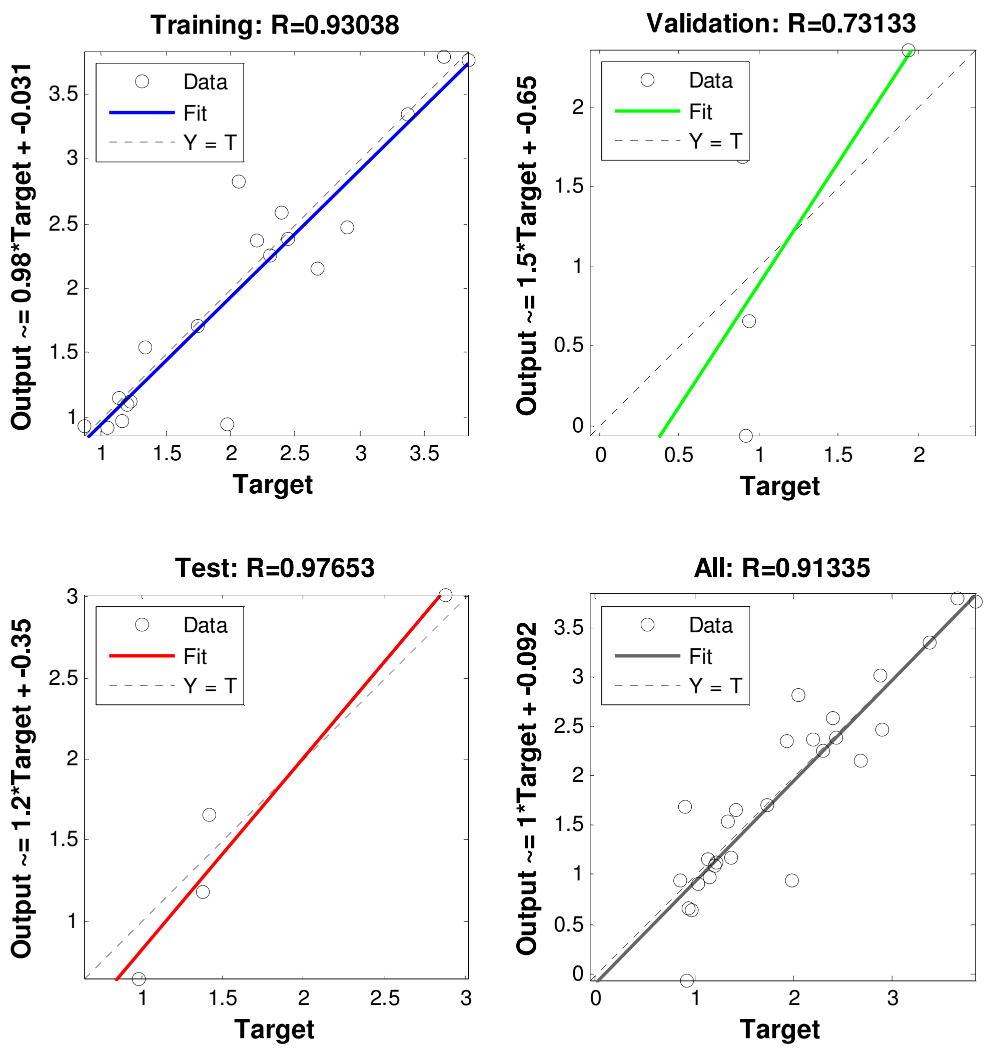

Fig. 3. Regression plot for surface roughness analysis for data 2

4. CONCLUSIONS

Increase in cutting speed improves the surface finish, thus the average surface roughness value decreases. Increase in depth of cut affects the surface finish adversely to a small extent, but as depth of cut increases beyond a certain limit, surface finish deteriorates to a large extent. Small increase in feed rate deteriorates surface finish to a large extent.ANN is reliable and accurate for solving the cutting parameter optimization. Data analysed also showed that there is very minimum error between the MLP/ measured value and the MATLAB values.

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