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Surface Roughness Prediction in CNC Turning using Artificial Neural Network

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Surface roughness, an indicator of surface quality, is one of the most specified customer requirements in machining of parts. In this study, the experimental results corresponding to the effects of different feed rates (0.10, 0.16, 0.24, 0.30, 0.36, 0.40 mm/rev), different cutting speeds (355, 380, 405, 430, 455, 490 m/min) and various depth of cuts (0.3, 0.7, 1.1 mm), on the surface quality of the EN8 steel workpieces turned on industrial production CNC Turning Centre Power DX 150, have been investigated using Artificial Neural Networks (ANN). The data set obtained from the measurements of surface roughness was employed to and tests the 70 neural network models. The trained neural network models were used in predicting surface roughness for cutting conditions. Neural network-based models were used to generate data for 3D graphs showing effects of machining parameters on surface roughness in turning. A comparison of prediction accuracy of 70 neural network models was carried out. The Levenberg-Marquardt (LM) model with 16 neurons in hidden layer has produced absolute fraction of variance (R2) values of 0.9997 for the training data, and 0.9042 for the test data. This model has MEP value of 0.237 for training data, and 2.286 for the test data. This model has only 2.228% prediction error that shows its better surface roughness prediction capability and applicability to such industrial CNC turning leading to effective selection of machining parameters for better quality products.

Keywords: Machining parameters, CNC turning, Full Factorial Design, Surface roughness prediction, Artificial Neural Network, Linear Regression Fitting.

1. Introduction

Surface roughness is mainly a result of process parameters such as tool geometry (nose radius, edge geometry, rake angle, etc.) and cutting conditions (feed rate, cutting speed, depth of cut, etc.) [1][2].

If we can predict surface roughness, we can optimize quality and quantity before actual machining operation. Several different statistical modelling techniques have been used to generate models, including regression, surface response generation, and Taguchi methods. Though many attempts have been made to generate a model, these current models only describe a small subset of the overall process.

The Neural Network models are also compared to the regression models. 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* than linear and exponential regression models can offer.

Objective of the experiment was to generate an ANN (Artificial Neural Network) model to predict surface roughness considering controllable machining parameters like feed, cutting speed and depth of cut as input parameters in turning of EN8 material and use of this model to select optimum parameters for better quality and quantity in industrial turning environment leading to economic and value gain.

1.1. Surface Roughness

The surface parameter used to evaluate surface roughness in this experiment is the roughness average (*Ra*). *Ra* (arithmetic mean roughness value, arithmetic average (AA), or centerline average (CLA) is recognized universally as the commonest international parameter of roughness.

Surface finish describes the *geometric* features of surfaces; *surface integrity* pertains to properties, such as fatigue life and corrosion resistance, which are influenced strongly by the type of surface produced. The built-up edge, with its significant effect on the tool-tip profile, has the greatest influence on surface roughness that damages the surfaces considerably [4].

The average roughness is the area between the roughness profile and its center line, or the integral of the absolute value of the roughness profile height over the evaluation length (Refer Figure 1) [3]. Therefore, *Ra* is specified by the following equation:

$$Ra = \frac{1}{L}\int_0^L |Y(x)|dx \qquad (1)$$

When evaluated from digital data, the integral is normally approximated by a trapezoidal rule:

$$Ra = \frac{1}{n}\sum_{i=1}^{n} |Y_i| \qquad (2)$$

where *Ra* is the arithmetic average deviation from the mean line (μm), *L* is the sampling length, and *Y* is the ordinate of the profile curve. Graphically, the average roughness is the area (as shown in Figure 1) between the roughness profile and its center line divided by the evaluation length (normally five sample lengths with each sample length equal to one cut-off).

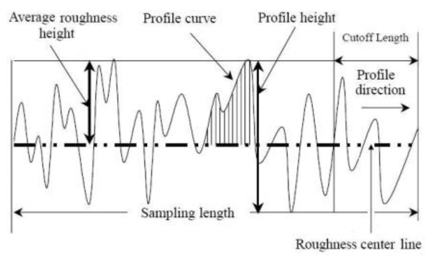


Figure 1. General surface roughness profile [3]

2. Materials and Methods

As shown in Table 1 three machining parameters visualizing Cutting Speed-V_c (m/min), Feed Rate-f (mm/rev) and depth of cut-a_p (mm) were considered as input parameters which are easily controllable by operator. Output parameter was surface roughness which was measured by surface roughness tester. Other parameters are considered as constant parameters.

Table 1. Input Parameters Levels and Values

No.	Factors	Levels	Factor Levels Values
1	Cutting Speed, V_c	6	355, 380, 405, 430, 455, 490 (m/min)
2	Feed Rate, f	6	0.10, 0.16, 0.24, 0.30, 0.36, 0.40 (mm/rev)
3	Depth of Cut, a_p	3	0.3, 0.7, 1.1 (mm)

This experiment was a 3 factors 6 - 6 -3 level full factorial design of experiment. These all three factors and their unique factor level combinations (6 V_c X 6 f X 3 a_p) results in a total 108 observations.

An experimental setup was created for the purpose of data generation which was necessary to generate ANN. The hardware used in this experimental setup includes a Jyoti CNC Turning Centre Power DX-150 with Simens controller, 18 work pieces (Figure 2) and a Mitutoyo Surface Roughness Tester SJ – 201 setup [4].

EN8 material was selected for experimental work which is widely used as structural material in automobiles, aerospace, ship building, nuclear power plants, machine tools and general engineering applications [5].

Based on above all, experiment was carried out and total 108 experimental results were generated. These results were analysed [2] and further considered for ANN model generation. Figure 3 shows main effect plot for these parameters.

Figure 2. Machined Work Pieces

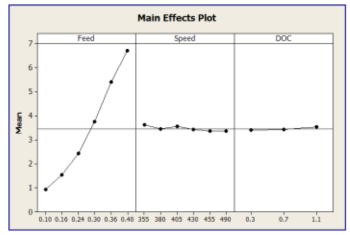


Figure 3. Main Effect Plot [2]

3. ANN Model Generation

This sub section describes pre processes, model design and training, model simulation and post processes in generation of ANN prediction models.

3.1 Pre Processing

Before applying inputs and outputs for ANN training, data have to be converted in to range of 0 to 1 or -1 to 1 i.e. data should be normalized for ANN training. An equation 7.1 was used for data normalization, which ranges the data to [0, 1]. All 108 experimental data sets are divided for training, validation and testing. 50 models were trained by early stopping method, which used 64 data sets for training, 21 data sets for validation and 21 data sets for simulation. 20 models were trained by LM algorithm, which used 85 data sets for training and 21 data sets for testing. It is clear that more data sets in training reduces processing time in ANN learning and improves generalization capability of models, so large number of data sets were used to train the models.

It is desirable to avoid abnormal data sets for ANN model generation, which creates very large errors in prediction results of models. So, 2 data sets were skipped to improve prediction capability of ANN models.

3.2 Neural Network Design and Training

The ANN model design and training was done using MATLAB 7.0 and its associated GUI for Neural Network Toolbox. Total *70* ANN models were created, trained and simulated and each model used 3 layers-one input layer, one hidden layer and one output layer. Numbers of neurons in input and output layer were fixed and they were 3 (feed, cutting speed and depth of cut) and 1 (surface roughness) respectively. Variations were numbers of neurons in hidden layer, transfer function in between input and hidden layer, and in between hidden layer and output layer. In all models *logsig* transfer function was used in between input layer and output layer, whereas in few models *logsig* transfer function was used and other models used *purelin* transfer function in between hidden layer and output layer.

According to Demuth and Beale, and literature review this algorithm is well suited to function approximation or prediction problems with networks of moderate size and number of parameters. It is also well suited to problems that require the approximation to be very accurate [6]. The work in this analysis included a function approximation or prediction problem that required the final error to be reduced to a very small value and, in general, the networks were of moderate size. A series of 21 tests each were conducted on 50 and 30 models which used *SCG* (Scaled Conjugate Gradient) and *LM* (Levenberg-Marquardt) training algorithms respectively. Figure 4 shows retrained performance (MSE) graph of LM16LP model, created during its training. After initial training of LM16LP model, it was retrained for 60 epochs and performance MSE was obtained 9.98989e-005 in 58 epochs in training, which took about 5 minutes on the test laptop.

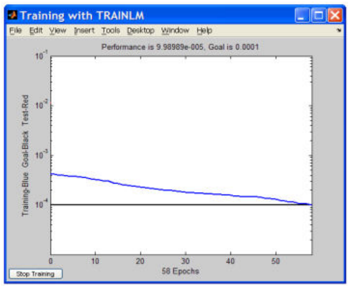


Figure 4. LM16LP Training

$$\mathrm{MAD} = \left(\frac{1}{p}\right)\sum_j |t_j - o_j|$$

$$\mathrm{RMSE} = \left(\left(\frac{1}{p}\right)\sum_j |t_j - o_j|^2\right)^{1/2}$$

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2}\right)$$

$$\mathrm{MEP} = \frac{\sum_j (((t_j - o_j)/t_j) \times 100)}{p}$$

where t is the target value, o the output, and p the number of samples.

Figure 5. Error Statistics

3.3 ANN Model Simulation

After training, all 70 models were simulated using test data and test targets to get the predicted output for given test data by respective trained ANN. Prediction errors result was also created after simulation of model. These predicted results (in training and in simulation) are the base for prediction capability comparisons of various ANN models generated (Table 2).

3.4 Post Processing

After training, all 70 models were tested for prediction capability in training and testing using various error statistics as shown in Figure 5.

Table 2. Prediction Error Comparison of selected ANN Models

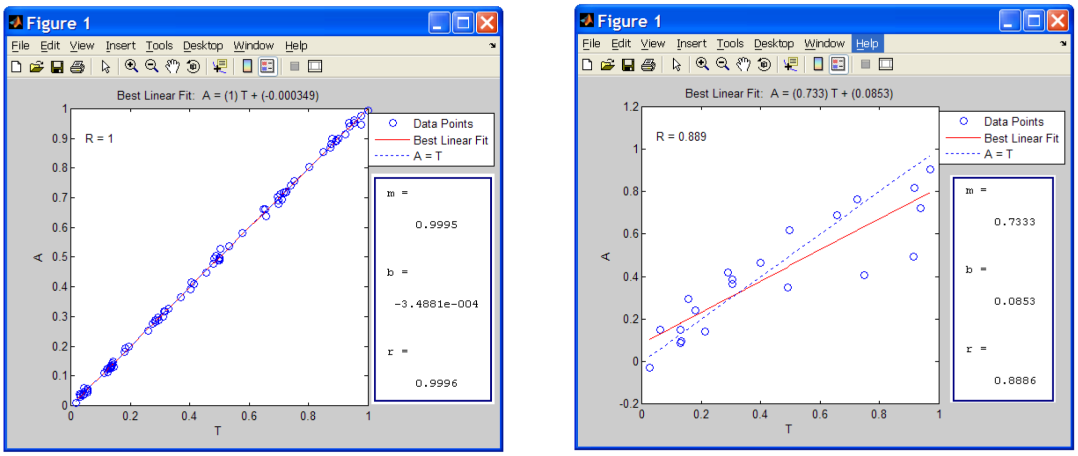
	Training Errors				Testing Errors			
Model	**MAD**	**RMSE**	**R^2**	**MEP**	**MAD**	**RMSE**	**R^2**	**MEP**
LM9LL_64	0.0312	0.0459	0.9922	2.6211	0.0455	0.065	0.9831	1.4429
LM13LL_64	0.0184	0.0268	0.9974	-4.584	0.0421	0.0467	0.9923	-2.9078
LM8LL_85	0.018	0.0252	0.9978	-2.6864	0.0302	0.0419	0.9937	-0.3546
LM13LL_85	0.0197	0.0262	0.9976	-2.9024	0.0433	0.056	0.9884	0.5995
LM16LP_85	**0.0065**	**0.0088**	**0.9997**	**0.2372**	**0.1112**	**0.1493**	**0.9042**	**2.2855**

Among all 70 models LM16LP (LM- LM training algorithm, 16- number of neurons in hidden layer, L-Logsig transfer function in between input layer and hidden layer, P-Purelin transfer function in between hidden layer and output layer) model was considered the best model for surface roughness prediction capability. Figure 6 shows linear fitting of created model LM16LP in Training and Testing. Figure 7 shows Comparison of Actual surface roughness value, predicted surface roughness value using regression model and predicted surface roughness value using ANN Model LM16LP in Training and testing.

4. Conclusion

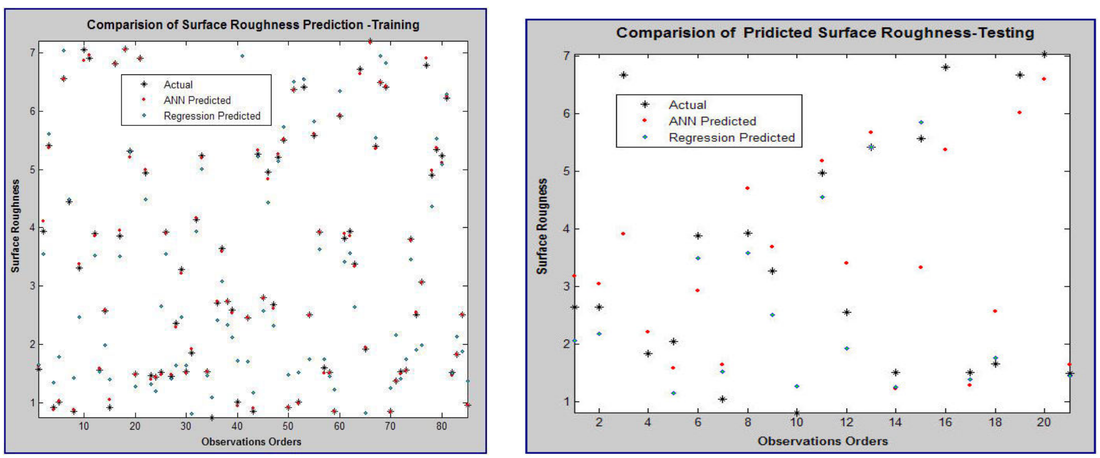
The *Levenberg-Marquardt (LM)* model with *16 neurons* in hidden layer has produced absolute fraction of variance (R^2) values of 0.9997 for the training data, and 0.9042 for the test data. This model has MEP value of 0.237 for training data, and 2.286 for the test data. Figure 1 and 2 shows comparison of actual value, regression model predicted value and ANN model predicted value of surface roughness in training and testing respectively. This model has only 2.228% prediction error that shows its better surface roughness prediction capability and applicability to such industrial CNC turning leading to effective selection of machining parameters for better quality products.

Future work would focus on expansion of the work by considering other parameters such as nose radius, wiper inserts, CBN cutting tool, cutting forces, cutting temperature.



(a)Training (b) Testing

Figure 6. LM16LP Model Linear Fitting in Training and Testing



(a)Training (b) Testing

Figure 7. Comparison of Actual, Regression and ANN Results in Training

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