Application of Artificial Neural Network in Surface Roughness Prediction considering Mean Square Error as Performance Measure

Anuj Kumar Sehgal, Meenu

Abstract— **Ductile Iron being a family of materials which offers the wide range of properties obtained through micro-structural control. In this study, the modeling of surface roughness in CNC end milling of Ferritic-Pearlitic Ductile Iron Grade 80-55-06 is conducted, taking into account the parametric effect of spindle speed, feed rate and depth of cut using artificial neural networks (ANN). The models are optimized using cutting parameters as input and corresponding surface roughness values as output. ANN analysis with multilayer feed forward perceptron structure using graphical user interface (GUI) under MATLAB is adopted with the experimental values as input-output pairs. Finally, efficiency of different transfer functions with number of neurons in hidden layers is compared with experimental data considering network's performance according to the mean of squared errors. TANSIG training transfer function along with PURELIN output transfer function is found to be the most appropriate training transfer function to model surface roughness.**

Index Terms— **Intelligent control, Artificial Neural network, CNC End milling, Surface roughness.**

I. INTRODUCTION

Metal cutting is one of the important and widely used manufacturing processes in engineering industries. The study of metal cutting focuses, among others, on the features of tools, input work materials, and machine parameter settings influencing process efficiency and output quality characteristics (or responses). A significant improvement in process efficiency may be obtained by process parameter optimization that identifies and determines the regions of critical process control factors leading to desired outputs or responses with acceptable variations ensuring a lower cost of manufacturing (Montgomery, 1990, 2001). The technology of metal cutting has grown substantially over time owing to the contribution from many branches of engineering with a common goal of achieving higher machining process efficiency. Selection of optimal machining condition(s) is a key factor in achieving this condition (Tan & Creese, 1995). In any multi-stage metal cutting operation, the manufacturer seeks to set the process-related controllable variable(s) at their optimal operating conditions with minimum effect of uncontrollable or noise variables on the levels and variability in the output(s). To design and implement an effective process control for metal cutting operation by parameter optimization, a manufacturer seeks to balance between quality and cost at each stage of operation resulting in improved delivery and reduced warranty or field failure of a product under consideration. Process parameter optimization in these machining operations is required to be undertaken in two stages: (i) modeling of input-output and in-process parameter relationship, and (ii) determination of optimal or near-optimal cutting conditions. Modeling of input–output and in-process parameter relationship is considered as an abstract representation of a process linking causes and effects or transforming process inputs into outputs (Markos et al., 1998). The resulting model provides the basic mathematical input required for formulation of the process objective function. An optimization technique provides optimal or near-optimal solution(s) to the overall optimization problem formulated, and subsequently implemented in actual metal cutting process. With time, as complexity in dynamics of cutting processes increased substantially, researchers and practitioners have focused on mathematical modeling techniques to determine optimal or near-optimal cutting condition(s) with respect to various objective criteria (Fu, 2003). Several modeling techniques proposed and implemented are based on statistical regression, artificial neural network and fuzzy set theory. Optimization tools and techniques proposed are also based on Taguchi method (Ross, 1989), response surface design (Montgomery,1990 & 2001), mathematical programming (Hillier & Liebermann, 1999), genetic algorithm (Goldberg, 2002) and simulated annealing (Kirkpatrick et al.,1983). Despite numerous studies on process optimization problems, there exists no universal input–output and in process parameter relationship model, which is applicable to all kinds of metal cutting processes Hassan & Suliman (1990). Luong & Spedding (1995), claimed a lack of basic mathematical model that can predict cutting behaviour over a wide range of cutting conditions. Optimization techniques also have certain constraints, assumptions and limitations for implementation in real-life cutting process problems. Some of these limitations and assumptions are discussed in the literature (Osborne & Armacost, 1996; Dabade & Ray, 1996; Carlyle et. al, 2000; Youssef et al.,2001).

Rashid & Lani (2010) have recently developed the mathematical model using multiple regression and artificial neural network for surface roughness. The proper setting of cutting parameters viz. spindle speed, feed rate, and depth of cut was chosen as predictors in order to predict better surface roughness. The experiments were executed by using full factorial design. The mathematical model developed by using multiple regression method showed the accuracy of 86.7%

Anuj Kumar Sehgal, Department of Mechanical Engineering, NIT, Kurukshetra, Haryana, 136119, India.

Meenu, Department of Mechanical Engineering, NIT, Kurukshetra, Haryana, 136119, India.

which is reliable to be used in surface roughness prediction. On the other hand, artificial neural network technique showed the accuracy of 93.58% which was feasible and applicable for the prediction of surface roughness. Sanjay & Jyothi (2006) used back propagation neural networks for the detection of surface roughness in the drilling operation. Various factors as inputs were considered to the neural network structure in estimating surface roughness. Drilling experiments were performed at three cutting speeds and feeds. The numbers of neurons are selected from 1 to 20 with the learning rate of 0.01 and no smoothing factor was used. The best structure of neural network was selected based on a criterion including the minimum of sum of squares with the actual value of surface roughness. For mathematical analysis, an inverse coefficient matrix method was used for calculating the estimated values of surface roughness. Comparative analysis was performed between actual values and estimated values obtained by mathematical analysis and neural network structures.

II. Experimental Description:

2.1 Material Selection: The Intelligence approach are chosen for modeling of cutting parameters to predict the surface roughness in end milling of Ductile Iron Grade 80-55-06, which is commercially available and known for the multiple use in automobile industry. The specification of work material is listed (Table I).

2.2 Data Collection and Experimental Setup: The effect of spindle speed (rpm), feed rate (mm/min.) and depth of cut (mm) are studied on the quality characteristic surface roughness (R_a) in CNC end milling operation (Sehgal & Meenu, 2013). The set up employed a VMC (Vertical Milling Centre), two 4-flutes, and 10 mm diameter SGS-48554 cemented carbide end mill cutters. The machining is performed in dry environment and the R_a value of the machined workpiece is measured using the Federal Pocketsurf-3 Profilometer (Table II). The dimension of work material is taken as 80 mm x 75 mm x 15 mm. The cutting process parameters and their levels selected are as shown in Table III. The machining of specimen is done according to Table IV. Before conducting the measurement, the instrument is calibrated using a standard roughness specimen to ensure the consistency and accuracy of R_a values. Five measurements are made at the location of the length of cut on each workpiece and the average R_a value is recorded.

Table I: Specification of Work Material

Particulars	Value
Material	Ductile Iron Grade 80-55-06
Minimum Tensile Strength	80 psi (552 MPa)
Yield Strength	55 psi (379 MPa)
% Elongation	6%
Typical Brinell Hardness	200 BHN
Matrix-microstructure	Pearlite and Ferrite

3. Development of Mathematical Model by Artificial Neural Network

An Artificial Neural Network (ANN) is non linear information processing structure in which the elements called neurons process the information. Signals are transmitted by means of connection links. The links possess an associated weight, which is multiplied along with the incoming signal (net input) for any typical neural network. The output signal is obtained by applying activations to the net input. Input and output pairs obtained by experiments mare taken as training data.

Table II: Experimental Setup and Conditions

Particulars	Experimental conditions
Machine	Agni BMV- 45, MODEL No. BMV- 45, 12 stations automatic tool changer.
Tool	*4 flute, 10.0 mm diameter, SGS 48554,Cemented carbide end mill cutter,*
Collet	Size 8-10 mm
Cutting parameters	*Depth of Cut, Cutting Speed, Feed Rate*
Surface roughness tester	Profilometer, Federal Pocketsurf-3, Piezoelectric contact type stylus, stylus travel: 0.1 inch/2.54 mm, maximum stylus force: 15 MN, measuring capacity: R_a or R_{max}/R_y or R_z
Coolant	*Dry machining*

Table III Cutting Process Parameters and Their Levels

Process Parameters (units)	Levels -1.5	-1.0	0	1.0	1.5
Spindle Speed (rpm)	1350	1500	1800	2100	2250
Feed Rate (mm/min.)	12.5	15	20	25	27.5
Depth of Cut (mm)	0.075	0.1	0.15	0.2	0.225

Before the ANN modeling process, the data normalization of the quantitative variables is done to the standard range from 0 to 1 so that the minimum and maximum values of each row are mapped to default mean and STD of 0 and 1 using mapstd function under MATLAB. The actual numerical weights assigned to network are determined by matching the target (experimental data) and output of the network during training session. Under the two phases of training, first the input information is propagated from the input layer to the output layer and, as a result it produces an output. Then the error signals resulting from the difference between the networks predicted value and the target value are back propagated from the output layer to the previous layers for them to update their weights accordingly. The update of weights continues until the network error goal is reached. Once the training is completed, ANN is used to predict the output of the required samples, and this process is known as testing. Neural network modeling consists of the minimum of 3 layers of neurons viz. input layer neurons, hidden layer neurons and the output layer neurons. In the present study, ANN predictive model is established using 20 data sets based on the research [18] and as given in Table IV.

Fig. 1. shows the ANN computational model with the representation of the tansig transfer function used in the hidden layer and purelin for the output layer. Scaled inputs are fed to the input layer. The inputs get multiplied by the weights and act as the inputs to hidden layer. The neurons in the hidden layer perform two tasks. First, they sum up the weighted inputs to neurons, including bias θ as shown by the following Eq. (1).

$$E_i = \sum_{i=1}^{n} w_i I_i + \theta \qquad (1)$$

where I_i are the input parameters: the cutting speed, feed rate, and depth of cut, respectively. The weighted output is then passed through activation function. Two types of activation functions (tansig and logsig) are used for hidden layer to choose the best activation function that gives the minimum error at the output neurons. The output produced by a hidden layer becomes an input to the output layer. The neurons in the output layer produce the output using the same procedure as that of neurons in the hidden layer; purelin transfer function is used for output layer. Fig. 2 shows the transfer functions used for hidden and output layer. An error function based upon the difference between calculated output and target (experimental data) is fed back and weights are modified. Training the ANN involves minimizing this pre-specified error function by adjusting the weights appropriately in an iterative manner. The employed error function is the mean squared error (MSE), which is defined as:

$$MSE = \left(\left(\tfrac{1}{N} \right) \sum_i | t_i - o_i |^2 \right) \qquad (2)$$

Where, t is the target value and o is the output value and N is the number of neurons in output layer. The change in weight is given by;

$$\Delta W_{ij} = \frac{\alpha \partial E(\tau)}{\Delta w_{ij}} + \eta \Delta w_{ij}(\tau - 1) \qquad (3)$$

where, η is the moment term, α is the learning rate and r is the no. of iteration. Back Propagation training algorithm makes use of two adjustable parameters, namely, the learning rate α (0< α ≤1) and momentum coefficient (η) (0 < η ≤1). The magnitudes of both of these parameters are optimized heuristically along with the number of hidden layer neurons. The basic steps adopted in the development of the model are as illustrated;

(i) Collection of input-output dataset
(ii) Normalization of the input-output dataset between suitable ranges.
(iii) Designing and Training of the neural network
(iv) Performance evaluation of the designed neural network

Table IV: PROCESS PARAMETERS & THEIR LEVELS

Uncoded Input Data			Normalized input Data			Output Data
Spindle Speed (rpm)	Feed Rate (mm/min.)	Depth of Cut (mm)	X1	X2	X3	Ra (μm)
0	0	0	0.5	0.5	0.5	1.74
-1	1	1	0.83	0.17	0.17	4.45
-1	1	-1	0.83	0.17	0.83	3.79
0	0	0	0.5	0.5	0.5	1.64
1	-1	-1	0.17	0.83	0.83	1.58
1	1	1	0.17	0.17	0.17	3.69
1	-1	1	0.17	0.83	0.17	1.78
0	0	0	0.5	0.5	0.5	1.84
-1	-1	-1	0.83	0.83	0.83	2.39
-1	-1	1	0.83	0.83	0.17	1.6
0	0	0	0.5	0.5	0.5	1.62
1	1	-1	0.17	0.17	0.83	3.62
0	0	0	0.5	0.5	0.5	1.98
0	-1.5	0	0.5	1	0.5	1.38
0	0	0	0.5	0.5	0.5	1.77
0	0	-1.5	0.5	0.5	1	1.81
0	1.5	0	0.5	0	0.5	4.52
0	0	1.5	0.5	0.5	0	2.29
1.5	0	0	0	0.5	0.5	2.12
-1.5	0	0	1	0.5	0.5	1.96

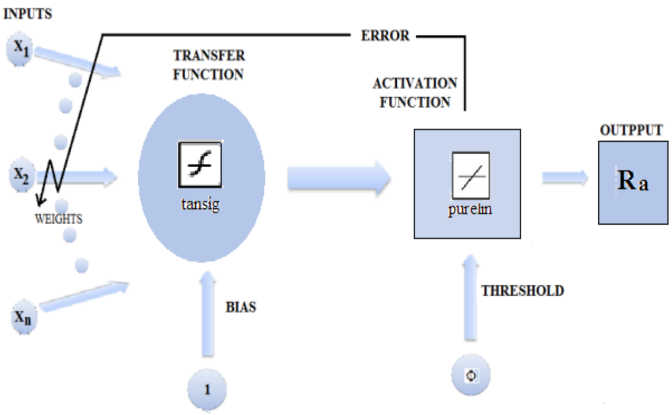
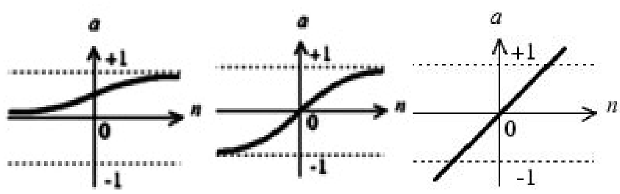


Fig. 1: ANN Computational Model



(a) $a = \tan sig(n)$ (b) $a = \log sig(n)$ (c) $a = purelin(n)$

Fig.2: Transfer functions used in hidden layer (a, b) & output layer (c)

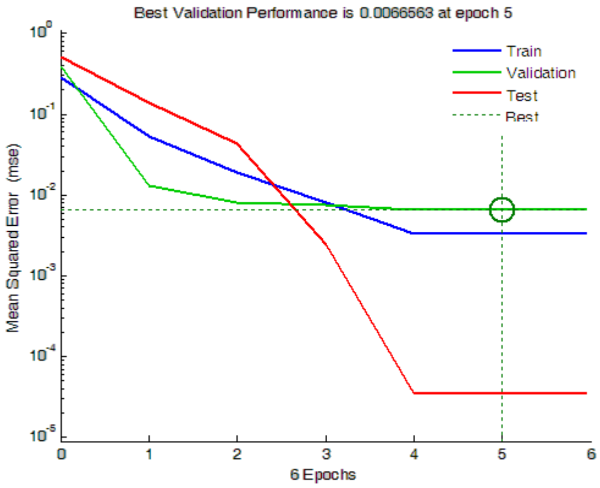


Fig. 3: The variation of MSE with the training epochs

The summary of ANN model, network structure and the learning conditions are depicted in Table V. 70% of data sets were taken for training, 15% data set each for validation and testing are chosen under suitable regularization.

Table VI shows the testing error and the corresponding MSE to obtain the appropriate number of neurons and the optimum transfer function for hidden layer. The testing error and MSE of the network are recorded considering 1-15 neurons as per recommendations in hidden layer.

The nine (9) neurons in hidden layer with tansig transfer function provide the least average percentage testing error of 0.163% with MSE value of 0.007. The performance of the network with 9 neurons in hidden layer with the MSE of 0.007 **is** as shown in Fig. 4. The regression plot of output vs target is obtained and regression value of 0.99999 is reached, representing the validation of the model.

Table V: Summary of ANN Model

Object model : Surface Roughness
Input neuron : v, f, d
Output neuron : Ra
Network structure
Network type : Feed-forward back-propagation
Transfer function : Tansig
Training function : TRAINLM
Learning function : LEARNGDM
Learning conditions
Learning scheme : Supervised learning
Learning rule : Gradient descent rule
Input neuron : Three
Output neuron : One
Sample pattern vector : 70% (train), 15% (valid and test)
Number of hidden layer : 1
Neurons in hidden layer : 1-15
Learning rate, α : 0.1
Momentum constant, β : 0.5

TableVI: Analysis Setup of different networks for Surface Roughness (R_a) by ANN

Hidden layer neuron	Transfer function			
	tansig		logsig	
	MSE	Testing error	MSE	Testing error
1	0.056	2.071	0.012	2.4852
3	0.061	3.636	0.021	4.3632
6	0.012	2.672	0.016	3.3400
7	0.060	1.198	0.055	1.4975
9	0.007	0.163	0.013	0.2722
10	0.076	1.517	0.024	2.8065
12	0.018	1.780	0.035	0.7057
15	0.024	1.201	0.027	1.390

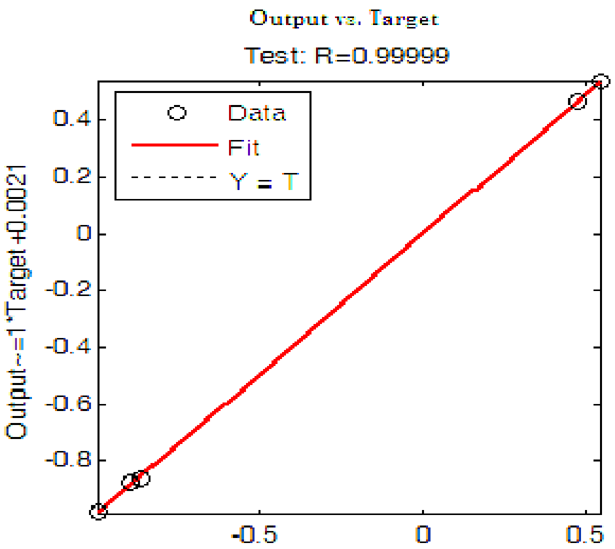


Fig. 4: Predicted Surface Roughness (R_a) against the actual Surface Roughness

3. Result and Discussion

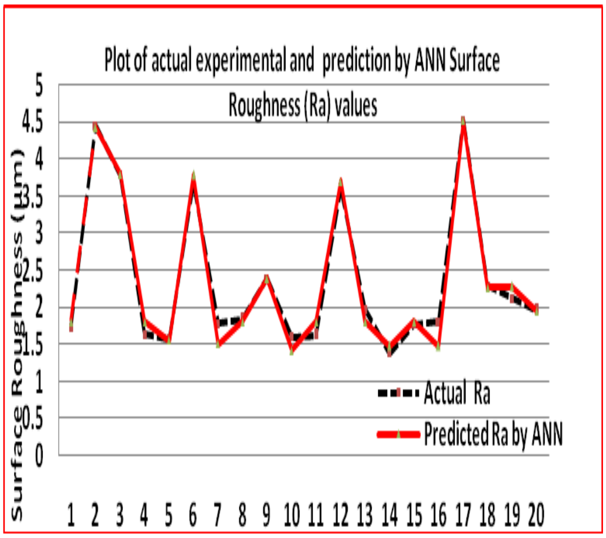


Fig. 5: Plot of actual experimental and prediction by ANN Surface Roughness (R_a) values

Table VII: COMPARISON OF ACTUAL AND PREDICTED VALUES FOR SURFACE ROUGHNESS (R_a) BY ANN

No. of Experiment	Actual R_a (µm)	Predicted R_a by ANN (µm)	Error Actual vs ANN	% Error Actual vs ANN
1	1.74	1.8114	-0.0714	-4.10345
2	4.45	4.4299	0.0201	0.451685
3	3.79	3.7996	-0.0096	-0.2533
4	1.64	1.8114	-0.1714	-10.4512
5	1.58	1.5528	0.0272	1.721519
6	3.69	3.7825	-0.0925	-2.50678
7	1.78	1.509	0.271	15.22472
8	1.84	1.8114	0.0286	1.554348
9	2.39	2.3836	0.0064	0.267782
10	1.6	1.4194	0.1806	11.2875
11	1.62	1.8114	-0.1914	-11.8148
12	3.62	3.7023	-0.0823	-2.27348
13	1.98	1.8114	0.1686	8.515152
14	1.38	1.4764	-0.0964	-6.98551
15	1.77	1.8114	-0.0414	-2.33898
16	1.81	1.4749	0.3351	18.51381
17	4.52	4.513	0.007	0.154867
18	2.29	2.2673	0.0227	0.991266
19	2.12	2.2746	-0.1546	-7.29245
20	1.96	1.9539	0.0061	0.311224
			%Mean Error	0.548695

The results obtained from the ANN are extremely satisfactory with a very high value of regression. The plot of actual experimental and prediction by ANN surface roughness (R_a) is shown in Fig.5. The result obtained by the said methodology and the comparison of actual and predicted values for surface roughness (Ra) by ANN is tabulated in Table VII. The response surface model developed using second order model is found statically significant at 95% confidence interval. The input parameter feed rate has the highest influence on the response followed by spindle speed. The mean absolute percentage error in neural network model is 0.54%. Thus, the prediction model obtained by ANN is found very proximate (surface roughness values) in comparison to the actual experimental values obtained in end milling of Ferritic-Pearlitic Ductile Iron Grade 80-55-06. The depth of cut has shown the least influence on the response variable.

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