Modeling of Surface Roughness and Tool Wear in Turning using ANN and ANOVA

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Abstract: ***In turning operation surface roughness and tool wear are important parameters. In manufacturing industry always trying to minimize the surface roughness and tool wear parameters. But it is not easy to determine which input parameters like cutting speed, feed, depth of cut, have minimum effect on the above parameters. Therefore it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness and tool wear. Back Propagation Neural Network (BPNN) structure is developed to predict surface roughness and tool wear. For modelling, generally ANN architectures, learning/ training algorithms and nos. of hidden neurons, transfer function are varied to achieve minimum error, but the variation is made in random manner. So here Taguchi method (ANOVA) has been implemented to achieve the optimal of above. The results obtained, conclude that ANN is reliable and accurate for solving the cutting parameter.***

Keywords: Neural network, Turning, Surface roughness, tool wear

1. Introduction

Surface finish of the machined parts is one of the important criteria to judge the success of a machining operation as it is an important quality characteristic that may dominate the functional requirements of many component parts as well as production cost. For example, good surface finish is necessary to prevent premature fatigue failure, creep, to improve corrosion resistance, light reflection, heat transmission, lubrication, electrical conductivity, to reduce friction, wear, noise and finally to improve product life. Therefore, achieving the required surface finish is crucial to the success of machining operations. Surface roughness is a measurable characteristic based on the roughness deviations. Surface finish is a more subjective term denoting smoothness and general quality of a surface. In popular usage, surface finish is often used as a synonym for surface roughness. Surface roughness represents the random and repetitive vertical deviations of a real surface from its ideal or nominal form.

Tool wear is the rate at which the cutting edge of a tool wears away during machining due to the interactions between the tool and work piece. There are three possible modes by which a cutting tool can fail in machining namely Fracture failure mode, Temperature failure mode and gradual wear. In fracture failure mode failure occurs when the cutting force at the tool point becomes excessive, causing it to fail suddenly by brittle fracture. Temperature failure occurs when the cutting temperature is too high for the tool material, causing the material at the tool point to soften, which leads to plastic deformation and loss of the sharp edge. And gradual wearing of the cutting edge causes loss of tool shape, reduction in cutting efficiency, an acceleration of wearing as the tool becomes heavily worn, and finally tool failure in a manner similar to a temperature failure

ANN refers to the computing systems whose fundamental concept is taken from analogy of biological neural networks. Many day to day tasks involving intelligence or pattern recognition are extremely difficult to automate, but appear to be performed very easily by animals. The neural network of an animal is part of its nervous system, containing a network of specialized cells called neurons (nerve cells). Neurons are massively interconnected, where an interconnection is between the axon of one neuron and dendrite of another neuron. This connection is referred to as synapse. Signals propagate from the dendrites, through the cell body to the axon; from where the signals are propagate to all connected dendrites. A signal is transmitted to the axon of a neuron only when the cell 'fires'. A neuron can either inhibit or excite a signal according to requirement. Each artificial neuron receives signals from the environment, or other artificial neurons, gather these signals, and when fired transmits a signal to all connected artificial neurons. Input signals are inhibited or excited through negative and positive numerical weights associated with each connection to the artificial neuron. The firing of an artificial neuron and the strength of the exciting signal are controlled via. a function referred to as the activation function. The summation function of artificial neuron collects all incoming signals, and computes a net input signal as the function of the respective weights and biases. The net input signal serves as input to the transfer function which calculates the output signal of artificial neuron. However ANNs are far too simple to serve as realistic brain models on the cell levels, but they might serve as very good models for the essential information processing tasks that organism perform.

The ANN can be used easily for modeling the process for which difficult to get mathematical model. Generally ANN architectures, learning/training algorithms, nos. of hidden neurons, transfer function in hidden layer, and initial weight are varied. But if the variation have been made in random manner the model obtained is not so efficient. So here, there is a high necessity of developing an orderly manner for selecting process parameters and their levels for improving the performance of ANN. Design of Experiment (Taguchi method) can be applied to create an efficient model. To study the performance of ANN 4 process parameters such as

Training function, number of hidden neurones, transfer function in hidden layer, and transfer function in output layer are selected in 3 levels by creating Taguchi's L9 orthogonal array, and ANOVA is applied to find out which of the above factors have more importance on the ANN modeling. Thus optimal process modeling of Surface roughness and Flank wear of tool in turning process is developed with the best levels of above parameters.

2. Experimentation

In turning operation surface roughness and tool wear are important parameters. In manufacturing industry always trying to minimize the surface roughness and tool wear parameters. But it is not easy to determine at which input parameters like cutting speed, feed, depth of cut, the above output response can be minimized. Even though numbers of optimization approaches are there to determine the optimum machining parameters, the literature survey reveals that there has a scope to combine the different methods in artificial intelligence approach for optimization. Here the turning operation is conducted on AISI 1020 steel bar of 50 mm diameter and 350 mm length in HMT NH26 lathe machine. The composition of AISI 1020 is listed in weight percentage as C 0.23%, Mn 0.60%, P 0.04%, S 0.5% and Fe remaining. It is used in bullets, automotive industries, nuts and bolts, chain, hingers, knives, amours, pipes, magnets and many other applications. P30 carbide inserts uncoated is used as cutting tool. In the present experimental study, cutting velocity, feed and depth of cut have been considered as input parameters. The process variables with their units, notations and levels are listed in Table 1

Table 1: Parameters and their levels for turning operation

Parameters	*Levels*		
Cutting Speed, V_C (m/min)	70	90	120
Feed rate, f (mm/rev)	0.08	0.12	0.14
Depth of cut, d (mm)	0.1	0.4	0.8

Experiments have been carried out using Taguchi's L27 Orthogonal Array (OA) experimental design which consists of 27 combinations of cutting velocity, feed and depth of cut. According to the design catalogue prepared by Taguchi, three process parameters (without interaction) to be varied in three finite levels. Surface roughness (Ra) and flank wear (Vb) are taken as output response. L27orthogonal array and experimental results are shown in table.2

Table 2: Orthogonal array and machining data for turning operation

Expt.	L27 Orthogonal array			Real data				
no:	Vc	f	d	Vc	f	d	Ra	Vb
1	1	1	1	70	0.08	0.1	1.93	0.074
2	1	1	2	70	0.08	0.4	2.02	0.08
3	1	1	3	70	0.08	0.8	2.07	0.079
4	1	2	1	70	0.12	0.1	2.49	0.081
5	1	2	2	70	0.12	0.4	2.59	0.084
6	1	2	3	70	0.12	0.8	2.63	0.082
7	1	3	1	70	0.14	0.1	3.25	0.083
8	1	3	2	70	0.14	0.4	3.34	0.085
9	1	3	3	70	0.14	0.8	2.65	0.072
10	2	1	1	90	0.08	0.1	1.65	0.083
11	2	1	2	90	0.08	0.4	1.88	0.086
12	2	1	3	90	0.08	0.8	1.93	0.079
13	2	2	1	90	0.12	0.1	2.16	0.08
14	2	2	2	90	0.12	0.4	2.3	0.084
15	2	2	3	90	0.12	0.8	2.4	0.081
16	2	3	1	90	0.14	0.1	2.63	0.087
17	2	3	2	90	0.14	0.4	2.77	0.078
18	2	3	3	90	0.14	0.8	2.91	0.082
19	3	1	1	120	0.08	0.1	1.42	0.083
20	3	1	2	120	0.08	0.4	1.55	0.086
21	3	1	3	120	0.08	0.8	1.59	0.087
22	3	2	1	120	0.12	0.1	2.02	0.085
23	3	2	2	120	0.12	0.4	2.16	0.086
24	3	2	3	120	0.12	0.8	2.21	0.08
25	3	3	1	120	0.14	0.1	2.54	0.083
26	3	3	2	120	0.14	0.4	2.63	0.081
27	3	3	3	120	0.14	0.8	2.73	0.088

From 27 numbers of experiments, the variation in surface roughness and flank wear parameters are plotted against experiment number which is shown in Figure 1 and 2, and can be say that process is stochastic and random in nature, and very difficult to predict the output characteristics accurately by mathematical equation.

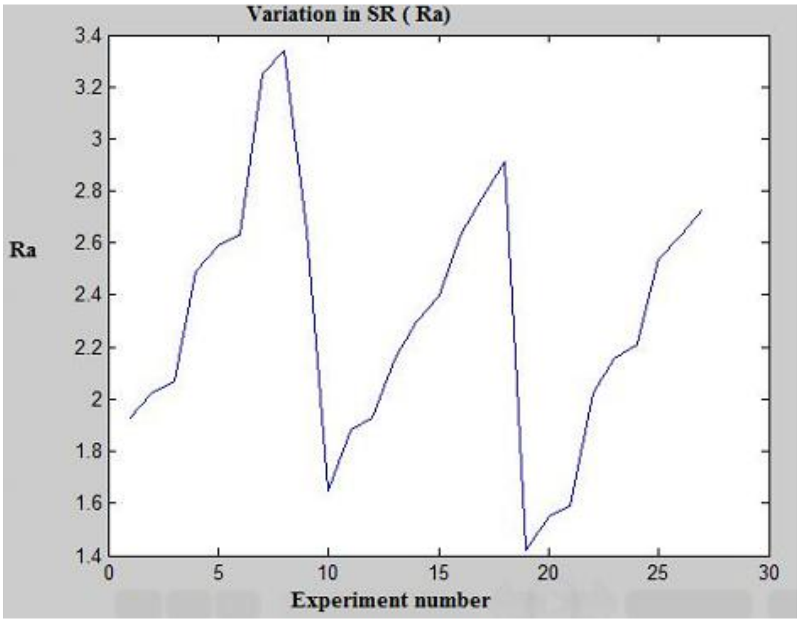


Figure 1: Variation of Surface roughness (Ra) w.r.t experiments

So an ANN with back propagation algorithm has been adopted here to model the turning process. One of the advantages of using the neural network approach is that a model can be constructed very easily based on the given input and output and trained to accurately predict process dynamics.

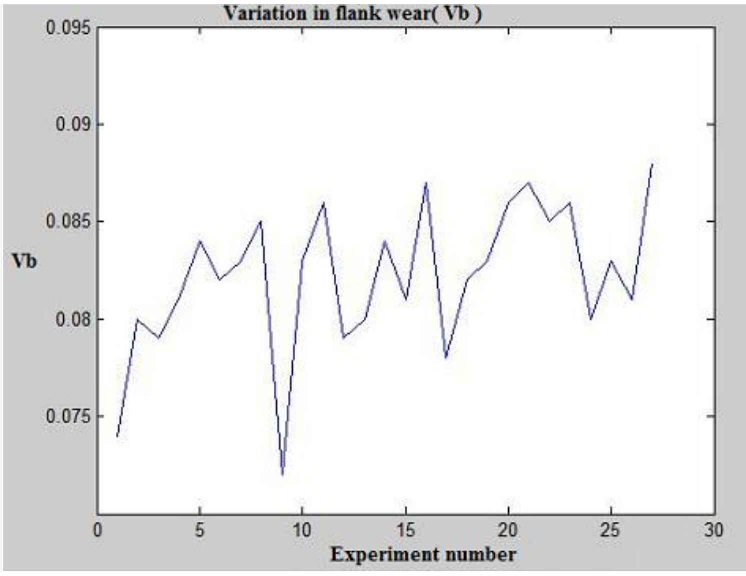


Figure 2: Variation of Flank wear (Vb) w.r.t experiments

3. ANN Modeling

3.1Parameter setting for ANN modeling

There has number of combination of parameters for ANN modeling. It is unrealistic to analyze all combination of ANN parameters and parameter's levels effects on the ANN performance. Therefore L9 orthogonal array are designed to check the performance of ANN model in MATLAB. The parameters and it's level taken and L9 orthogonal array used in this work is shown in Table.3 and Table.4 respectively. Other fixed parameters are network architecture -Feed forward back propagation and numbers of neurons in input layer and in output layers are 3 and 2 respectively.

Table 3: Process parameter and their levels for ANN modeling

S. No	Process parameter	Levels		
		Level 1	Level 2	Level 3
1	Training function	Scaled conjugate gradient (trainscg)	Gradient descent with adaptive learning rate (traingda)	Levenberg-Marquardt (trainlm)
2	Number of hidden neurons	8	4	12
3	Transfer function in hidden layer	LOGSIG	PURELIN	TANSIG
4	Transfer function in output layer	LOGSIG	PURELIN	TANSIG

Table 4: Orthogonal array and data for ANN modeling

Trial No:	L9 Orthogonal array				Training Function	No; of hidden neurons	Transfer Function in hidden layer	Transfer Function in output layer
1	1	1	1	1	SCG	4	LOGSIG	LOGSIG
2	1	2	2	2	SCG	8	PURELIN	PURELIN
3	1	3	3	3	SCG	12	TANSIG	TANSIG
4	2	1	1	3	GDA	4	LOGSIG	TANSIG
5	2	2	3	1	GDA	8	TANSIG	LOGSIG
6	2	3	1	2	GDA	12	LOGSIG	PURELIN
7	3	1	3	2	LM	4	TANSIG	PURELIN
8	3	2	1	3	LM	8	LOGSIG	TANSIG
9	3	3	2	1	LM	12	PURELIN	LOGSIG

3.2 Data Normalisation

Generally the inputs and targets that dealt with an ANN model are of various ranges. These input and targets are needed to be scaled in the same order of magnitude otherwise some variables may appear to have more significance than they actually do, which will lead to form error in the model. Here the data of neural network model was scaled in the range of 0.1 to 0.9.The min-max data normalization technique was used for this purpose using the following equation.

$$N = \frac{(R - R_{\min}) \times (N_{\max} - N_{\min})}{(R_{\max} - R_{\min})} + N_{\min}$$

Where, N is the normalized value of the real variable, Nmin=0.1 and Nmax=0.9 are the minimum and maximum scaled range respectively, R is the real value of variable, and Rmin and Rmax are the minimum and maximum values of the real variable, respectively. After normalization machining data are shown in Table.5

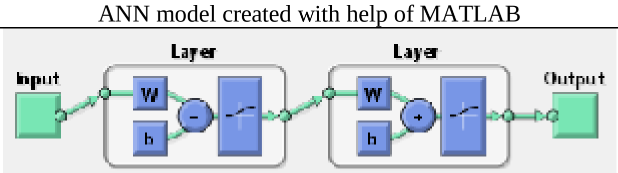
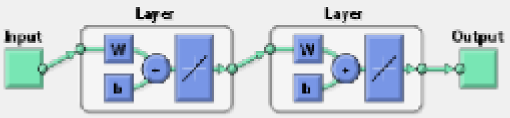
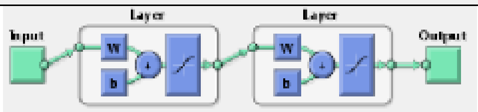
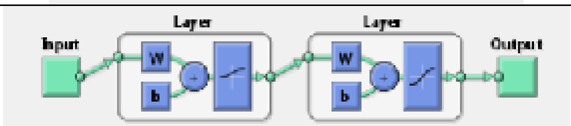
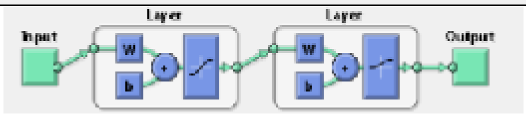
Table 5: Machining data after normalization

Expt. no:	Real data					Normalised data				
	Vc	f	d	Ra	Vb	Vc	f	d	Ra	Vb
1	70	0.08	0.1	1.93	0.074	0.1	0.1	0.1	0.3125	0.2
2	70	0.08	0.4	2.02	0.08	0.1	0.1	0.443	0.35	0.5
3	70	0.08	0.8	2.07	0.079	0.1	0.1	0.9	0.370833	0.45
4	70	0.12	0.1	2.49	0.081	0.1	0.63	0.1	0.545833	0.55
5	70	0.12	0.4	2.59	0.084	0.1	0.63	0.443	0.5875	0.7
6	70	0.12	0.8	2.63	0.082	0.1	0.63	0.9	0.604167	0.6
7	70	0.14	0.1	3.25	0.083	0.1	0.9	0.1	0.8625	0.65
8	70	0.14	0.4	3.34	0.085	0.1	0.9	0.443	0.9	0.75
9	70	0.14	0.8	2.65	0.072	0.1	0.9	0.9	0.6125	0.1
10	90	0.08	0.1	1.65	0.083	0.42	0.1	0.1	0.195833	0.65
11	90	0.08	0.4	1.88	0.086	0.42	0.1	0.443	0.291667	0.8
12	90	0.08	0.8	1.93	0.079	0.42	0.1	0.9	0.3125	0.45
13	90	0.12	0.1	2.16	0.08	0.42	0.63	0.1	0.408333	0.5
14	90	0.12	0.4	2.3	0.084	0.42	0.63	0.443	0.466667	0.7
15	90	0.12	0.8	2.4	0.081	0.42	0.63	0.9	0.508333	0.55
16	90	0.14	0.1	2.63	0.087	0.42	0.9	0.1	0.604167	0.85
17	90	0.14	0.4	2.77	0.078	0.42	0.9	0.443	0.6625	0.4
18	90	0.14	0.8	2.91	0.082	0.42	0.9	0.9	0.720833	0.6
19	120	0.08	0.1	1.42	0.083	0.9	0.1	0.1	0.1	0.65
20	120	0.08	0.4	1.55	0.086	0.9	0.1	0.443	0.154167	0.8
21	120	0.08	0.8	1.59	0.087	0.9	0.1	0.9	0.170833	0.85
22	120	0.12	0.1	2.02	0.085	0.9	0.63	0.1	0.35	0.75
23	120	0.12	0.4	2.16	0.086	0.9	0.63	0.443	0.408333	0.8
24	120	0.12	0.8	2.21	0.08	0.9	0.63	0.9	0.429167	0.5
25	120	0.14	0.1	2.54	0.083	0.9	0.9	0.1	0.566667	0.65
26	120	0.14	0.4	2.63	0.081	0.9	0.9	0.443	0.604167	0.55
27	120	0.14	0.8	2.73	0.088	0.9	0.9	0.9	0.645833	0.9

3.3 Creation of ANN Models

Here the influence of input parameters i.e. learning/training algorithms, transfer function in hidden layer nos. of hidden neuron on performance parameters, mean square error (MSE), correlation coefficient (R) are investigated by creating 9 ANN models with help of NN tool box of MATLAB (R2010a). Results are shown in Table.6

Table 6: Tabulation of ANN model and its response

Trial No:	ANN model created with help of MATLAB	R	MSE
1		0.61458	0.06187
2		0.73063	0.02219
3		0.31429	0.05385
4		0.35499	0.10324
5		0.67325	0.066764

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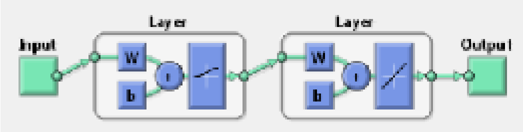
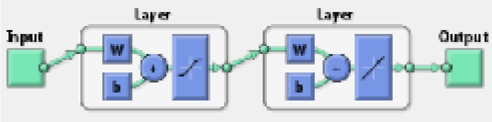
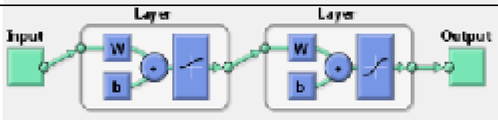
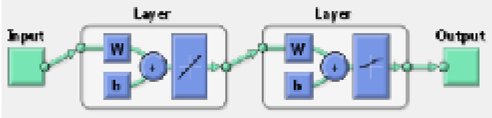
6		0.61589	0.00803
7		0.92828	0.033647
8		0.998	0.033737
9		0.68339	0.016479

4. Analysis of Variance and Main Effect Plot

4.1 Data for ANOVA

To find the effect of each artificial neural network parameters on performance measure such as Mean square error (MSE) and correlation coefficient (R) is investigated through ANOVA in MINITAB software. Data used for this analysis are consolidated as shown in the Table 7. The main effect plot for MSE and R are drawn.

Table 7: Data for ANOVA

Trial No:	Training Function	No; of Hidden neurons	Transfer Function in hidden layer	Transfer Function in output layer	R	MSE
1	SCG	4	LOGSIG	LOGSIG	0.61458	0.06187
2	SCG	8	PURELIN	PURELIN	0.73063	0.02219
3	SCG	12	TANSIG	TANSIG	0.31429	0.05385
4	GDA	4	LOGSIG	TANSIG	0.35499	0.10324
5	GDA	8	TANSIG	LOGSIG	0.67325	0.066764
6	GDA	12	LOGSIG	PURELIN	0.61589	0.00803
7	LM	4	TANSIG	PURELIN	0.92828	0.033647
8	LM	8	LOGSIG	TANSIG	0.998	0.033737
9	LM	12	PURELIN	LOGSIG	0.68339	0.016479

4.2 Effect on MSE

Figure 3 shows the main effect plot for MSE. From the figure assessments drawn are; Levenberg-Marquardt training function/ algorithm and 12 nos. of neuron at hidden layer, transfer function LOGSIG in hidden layer, transfer function PURELIN in output layer are liable for the lowest MSE.

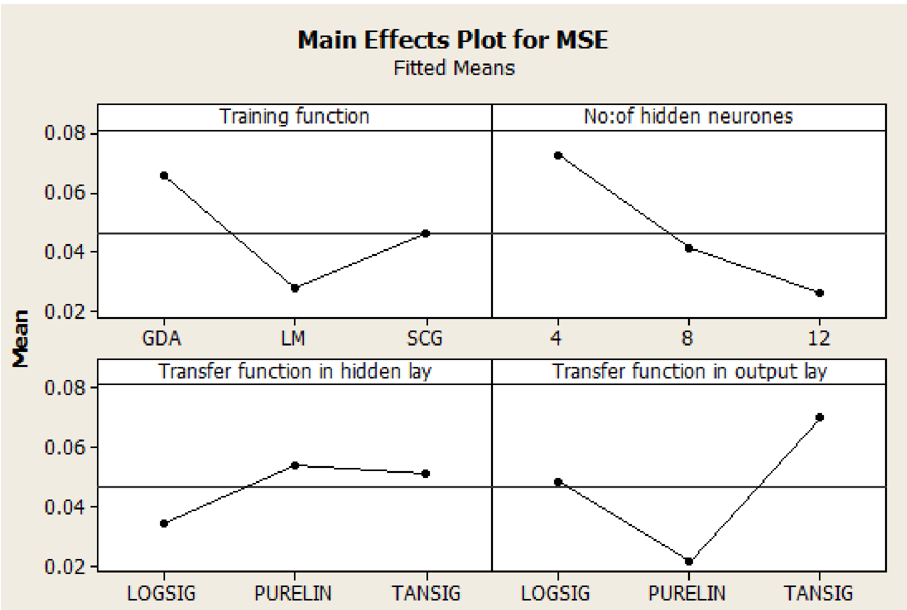


Figure 3: Main effect plot for MSE

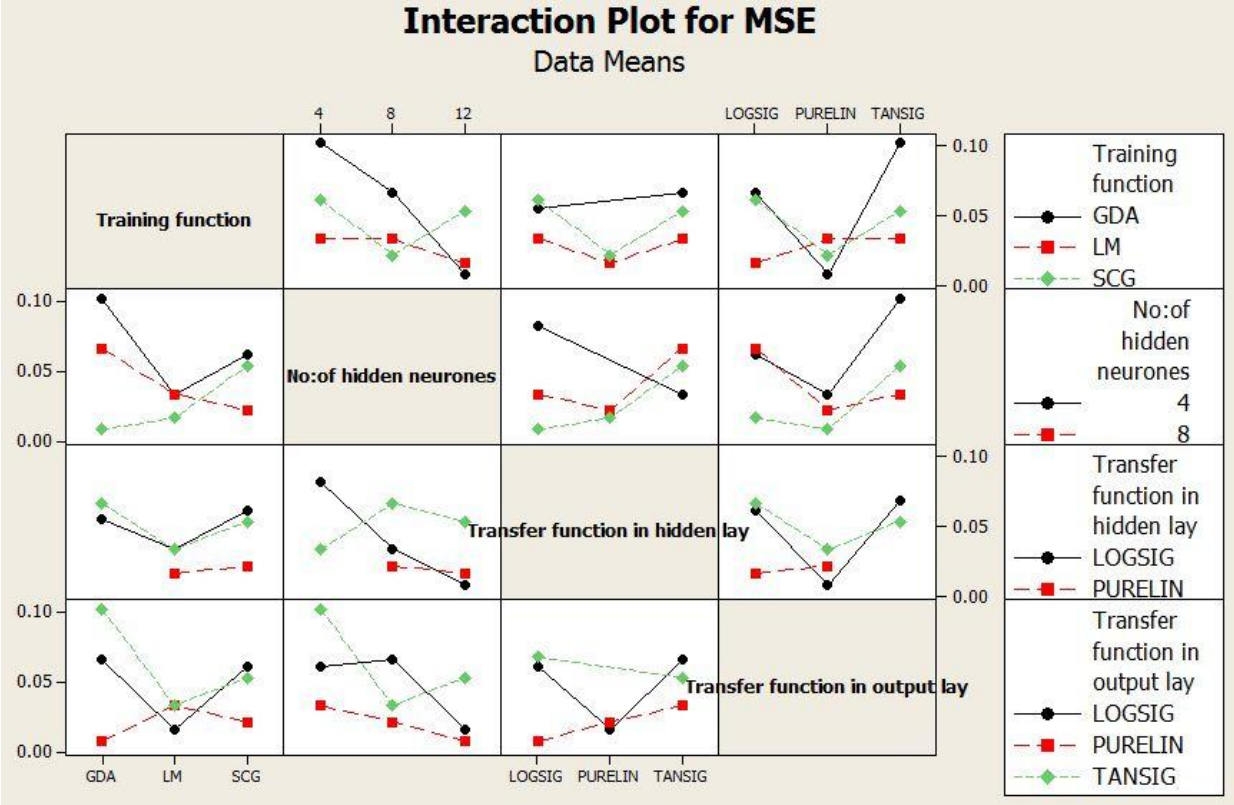


Figure 4: Interaction plot for MSE

4.3 Effect on R

Figure 5 shows the main effect plot for R. From the figure assessments drawn are; Levenberg-Marquardt training function/ algorithm and 8 nos. of neuron at hidden layer, transfer function LOGSIG in hidden layer, transfer function PURELIN In output layer are liable for the highest R. Main effect plot and interaction plot for R are drawn in Figure 5 and Figure 6 respectively..

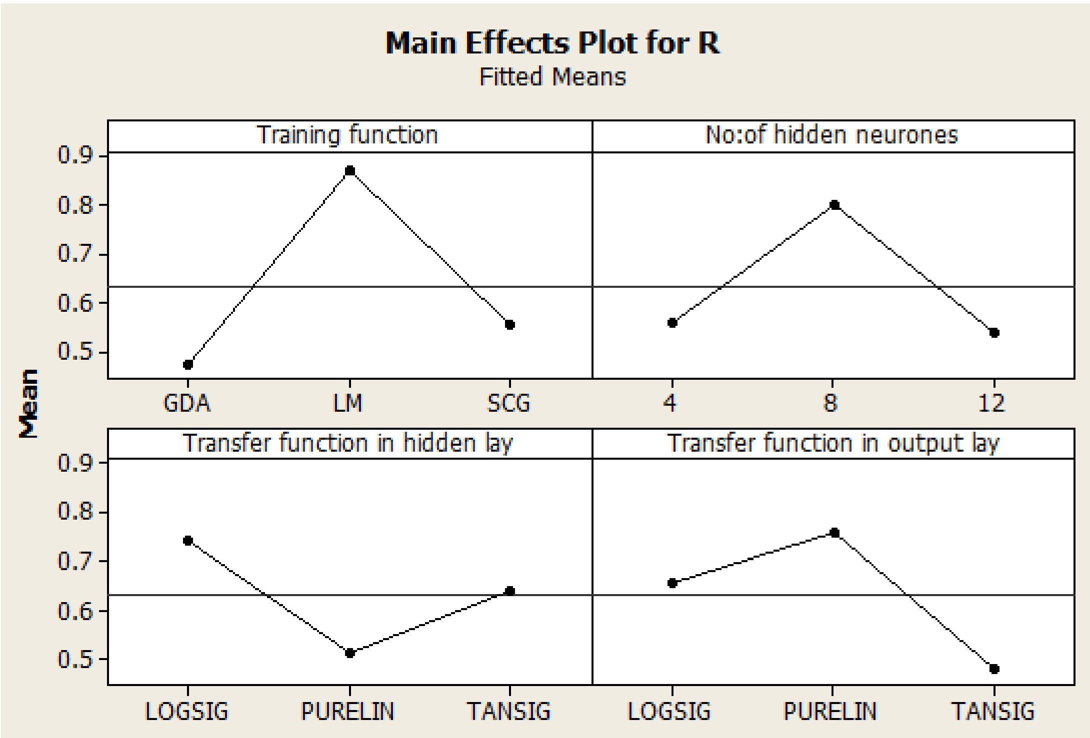


Figure 5: Main effect plot for R

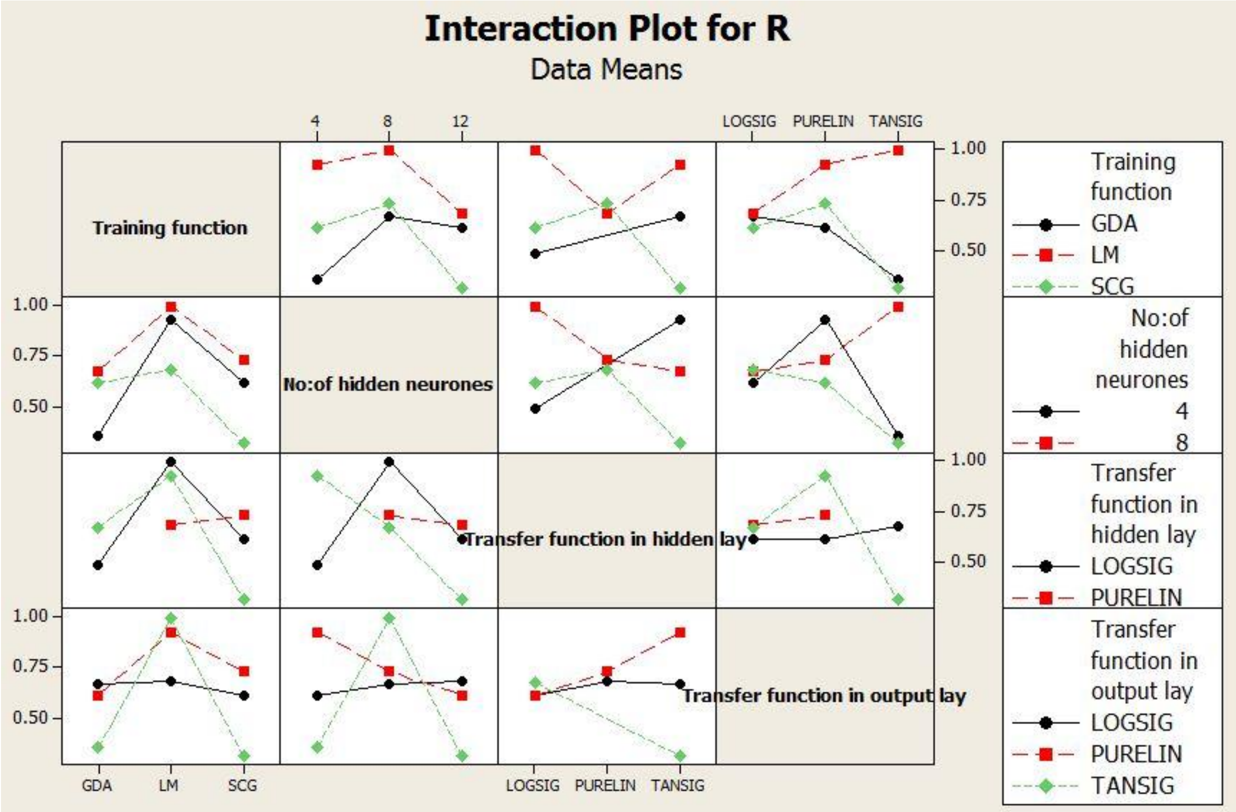


Figure 6: Interaction plot for R

5. Results and Discussion

An Orthogonal array of L9 is created and ANOVA is done to study the effect of ANN parameters such as training algorithm, transfer function and number of hidden neurons. From the main effect plot for MSE it is found that the optimum ANN model will have Leveberg-Marquadart algorithm for training, LOGSIG transfer function in hidden layer, PURELIN transfer function in output layer and 12 number of neurons in hidden layer. But from the main effect plot for training R all parameters are same as in MSE except number of neurons, which is found be 8. Since correlation plot is coincident with target value for training R, the number neurons be selected in this work as 8. The proposed ANN model is shown in Figure 7

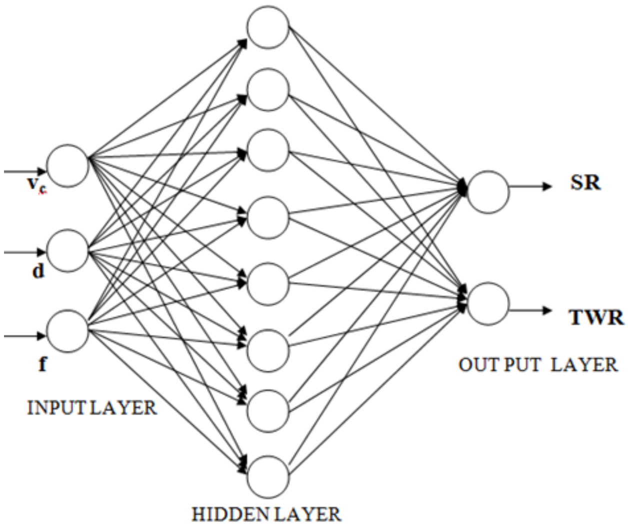


Figure 7: Proposed ANN model

The best process parameter setting for ANN modeling was selected with the help of ANOVA. The chosen optimal process parameters are Levenberg-Marquardt training algorithm, 8 nos. of hidden neurons, LOGSIG transfer function in hidden layer, and PURELIN transfer function in output layer in the basis maximum test R value. A new ANN model is created by neural network toolbox in MATLAB (2010a). By simulating the ANN model, the output response for 27 numbers of experiments is predicted which is shown in the Table. 8 and the predicted data is very much coincides with the actual experimental result.

Table 8: Result of simulation of ANN model

Expt No:	By Experiment		Prediction by ANN	
	Ra (μm)	Vb (mm)	Ra(μm)	Vb (mm)
1	1.93	0.074	1.92	0.0740
2	2.02	0.08	2.06	0.0800
3	2.07	0.079	2.03	0.0790
4	2.49	0.081	2.50	0.0810
5	2.59	0.084	2.59	0.0839
6	2.63	0.082	2.59	0.0822
7	3.25	0.083	3.23	0.0830
8	3.34	0.085	3.32	0.0850
9	2.65	0.072	2.68	0.0719
10	1.65	0.083	1.69	0.0829
11	1.88	0.086	1.87	0.0860
12	1.93	0.079	1.94	0.0790
13	2.16	0.08	2.09	0.0801
14	2.3	0.084	2.26	0.0842
15	2.4	0.081	2.43	0.0808
16	2.63	0.087	2.67	0.0870
17	2.77	0.078	2.77	0.0780
18	2.91	0.082	2.90	0.0821
19	1.42	0.083	1.42	0.0830
20	1.55	0.086	1.53	0.0860

21	1.59	0.087	1.57	0.0870
22	2.02	0.085	2.04	0.0850
23	2.16	0.086	2.21	0.0859
24	2.21	0.08	2.19	0.0800
25	2.54	0.083	2.52	0.0830
26	2.63	0.081	2.65	0.0810
27	2.73	0.088	2.75	0.0879

6. Conclusion

One of the primary objectives in machining operation is to produce product with low cost and high quality. The objective of this work was to develop an ANN model to predict surface roughness and flank wear while AISI 1020 steel bar of 50 mm diameter and 350 mm length in HMT NH26 lathe machine. An ANN model has been developed for prediction of above responses as a function of cutting parameters. In ANN modeling Design of experiment (TAGUCHI method) is applied to study the effect of various ANN parameters and an efficient model is created. The proposed model is of Back Propagation Neural Network structure, having Leveberg-Marquadart algorithm for training, LOGSIG transfer function in hidden layer, PURELIN transfer function in output layer and 8 number of neurons in hidden layer. The model has been proved to be successful in terms of agreement with experimental results as the relative errors are very less. From the relative error plots it is found that data predicted are significantly fit to the model. The proposed model can be used in optimization of cutting process for efficient and economic production by forecasting the responses in turning operations.

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