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Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis

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ABSTRACT

In recent years, the utilization of metal matrix composites (MMC) materials in many engineering fields has increased tremendously. Accordingly the need for accurate machining of composites has also increased enormously. Despite the recent developments in the near net shape manufacture, composite parts often require post-mold machining to meet dimensional tolerances, surface quality and other functional requirements. In the present work, the surface roughness of Al–SiC (20 p) has been studied in this paper by turning the composite bars using coarse grade polycrystalline diamond (PCD) insert under different cutting conditions. Experimental data collected are tested with analysis of variance (ANOVA) and artificial neural network (ANN) techniques. Multilayer perceptron model has been constructed with back-propagation algorithm using the input parameters of depth of cut, cutting speed and feed. Output parameter is surface finish of the machined component. On completion of the experimental test, ANOVA and an ANN are used to validate the results obtained and also to predict the behavior of the system under any condition within the operating range.

1. Introduction

Metal matrix composites (MMC) materials possess high specific strength and stiffness compare to common structural materials and are extensively used in automobiles, recreational industries and aerospace applications. The most popular type of MMC is aluminium alloy reinforced with ceramics particles. These low cost composites provide higher strength, stiffness and fatigue resistance (Kennedy et al., 1997; Ravikiran and Surappa, 1997) with a minimal increase in density over the base alloy. Owing to the addition of reinforcing materials, which are normally harder and stiffer than matrix, machining becomes significantly more difficult than those of conventional materials, as reported in the earlier publications (Kennedy et al., 1997; Ravikiran and Surappa, 1997; Schwartz, 1997; Allision and Gole, 1993; Tomac and Tonnessen, 1992; Muthukrishnan et al., 2008).

Attempts had been made to extend the classical metal cutting theory to the machining of MMCs and to find a finite element model-based solution to the issues of machining MMCs. Pramanik et al. (2006) developed the analytical model extending the classical Merchants Theory, Slip line theory and Grifith's theory of brittle fracture to the machining of ceramic particle reinforced MMCs. This model predicted the cutting forces and was validated experimentally. The authors also contend that the classical metal cutting theories are also, by and large, valid for understanding the machining of MMCs.

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Davim et al. (2007) extended the classical Merchants theory of metal cutting to machining of MMCs and concluded that while machining MMCs the Merchants prediction of shear angle was an overestimate of the observed shear angle.

Pramanik et al. (2006, 2007) used finite element modeling to investigate the tool–particle interaction during machining of MMCs. The model simulates the complete de-bonding of the reinforcement particles, which get separated from the chip. These de-bonded particles were responsible for the three-body wear observed in machining MMCs.

Davim (2003) established a correlation between cutting velocity; feed and the cutting time with the tool wear using multiple regression analysis and compared with the experimental results. He used the techniques of Taguchi with orthogonal array and analysis of variance for his investigation. He reported that error associated to tool wear and surface roughness is higher than the power required.

Arno et al. (2006) investigated the performance of coated diamond tools on machining fibre-reinforced polymers and results were discussed with various parameters of the composites.

Davim (2007) investigated to evaluate the chip compression ratio, shear angle, shear strain, shear strain rate, normal stress and shear stress using merchant theory on particulate metal matrix composites used K20 carbide cutting tool in radial turning. He concluded that normal stress and shear stress decreased with the increase of feed rate. The above literature stated about the various works carried out by researchers in machining MMC. Some researchers used the application of artificial intelligence in modeling the machining parameters.

In this issue, Dornfield (1990) effectively used neural network for tool condition monitoring. Purusothaman and Srinivasa (1994) have used back-propagation algorithm (BPA) for evolution of turning tool wear. Hans Raj et al. (1998) have used artificial neural network (ANN) for predicting cutting force components.

Lin et al. (2003) has investigated the relationship of machining forces and tool wear of MMC using multiple regression analysis (MRA) and ANN. The force–wear relationship derived from MRA was found to be an accurate way of predicting the tool wear. ANN models were found to further improve the accuracy of predicting tool wear particularly because the functional dependency is non-linear.

Abdul (2004) developed a multilayer perception feed forward neural network to evaluate and compare the cutting forces developed during the machining of Glass/epoxy, graphite/epoxy and Kevlar/epoxy composites.

Palanikumar et al. (2005) has developed a predictive model for the prediction of tool flank wear in machining Glass fiber reinforced plastics (GFRP) composites. Back-propagation neural network (BPNN) was used to construct the model.

In this aspect an attempt has been made to develop a model for the prediction of surface roughness in machining aluminium silicon carbide metal matrix composite. The type of MMC studied in this paper for its machinability is an aluminum alloy casting with the silicon particles of 20% by weight having grain size ranging from 56 to 185 μm stirred in to the melt. In the present work 30 experimental patterns were carried out. Out of this 18 patterns were considered to train the network and 12 patterns were used to validate the model. The network was trained by using suitable scaling factor for the input variables. The selection of parameters for ANN is a major problem existing so far. After attaining convergence, the trained weights are fed in to the testing network model, which is same as that of training network except having only the capacity to determine the outputs for the corresponding input variables. Finally the neural network outputs are compared with the desired output values and the testing error is calculated.

2. Experimental procedure

In order to achieve the objective of this experimental work, MMCs of type A356/SiC/20p (aluminium with 7.5% silicon, 2.44% magnesium, reinforced with 20% volume particles of silicon carbide (SiC)) were tested. The silicon carbide particle size ranges from 56 to 185 μm. A medium duty lathe with 2 kW spindle power was used to perform the experiments. The CNMA 120408 inserts with PCLNR 25 X25 M12 tool holder with PCD were used to turn the billets of 150-mm diameter. The used tool geometry was as follows: Top rake angle 0°, nose radius 0.8 mm. The work material is machined at five different cutting speeds ranging from 100 to 600 m/min with two feed rates of 0.108 and 0.200 mm/rev and depth of cut as 0.25, 0.5 and 0.75 mm. The microstructure of the work material is shown in Fig. 1 and the chemical composition of the work material is given in Table 1. Each experimental trial was carried out for 3 min duration. Experimental parameters are given in Table 2. The average surface finish (R_a) in the direction of the tool movement was measured in three different places of the machined surface using a surface roughness tester, Mitutoyo Surf test—301 with a cut-off and transverse length of 0.8 and 2.5 mm, respectively. Finally surface mean roughness (R_a) in microns value of the three locations was considered for the particular trial.

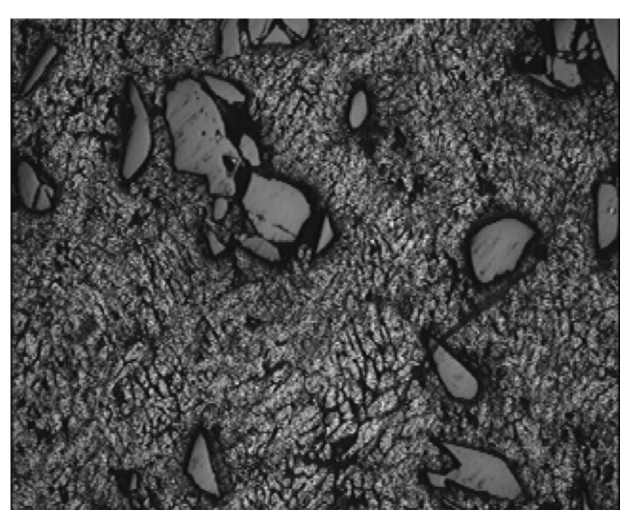

Fig. 1 – Microstructure of the Al–SiC(20 p) MMC (100×).

Table 1 – Chemical composition of the matrix

Al	83.2%
Si	7.5%
Fe	1.34
Mg	2.44
Zn	3.46
Pb	0.184
Ni	0.970
Zr	0.432
Mn	0.379
V	0.0517

Table 2 – Experimental conditions

Machine	Self-centering lathe
Tool insert	CNMA 120408, Nose radius—0.8 mm (PCD1500 grade coarse grain)
Holder size	25 × 25(PCLNR 2525 M12)
Cutting parameters	Cutting speed: 108, 150, 240, 372 and 575 m/min, feed rate: 0.108 and 0.2 mm/rev, DOC: 0.25, 0.50 and 0.75 mm
Surface texture equipment	Surf test—301, Make—Mitutoyo
Coolant	Dry machining

2.1. *Experimental data and S/N ratio*

The experimental work consists of three replications. The term "signal" represents the desirable value and the "noise" represents the undesirable value. The formulae for signal-to-noise are designed such that the experimentalist can always select the larger factor level settings to optimize the quality characteristics of an experiment. Therefore, the method of calculating the signal-to-noise ratio depends on whether the quality characteristics has smaller-the-best, larger-the-better or normal-the-better formulation is chosen (Yang and Tarng, 1998; Chen et al., 1998). The equation for calculating S/N ratio for low band (LB) characteristics (in dB) is

$$S/N_{LB} = -10\log_{10}\left(\frac{1}{r}\sum_{i=1}^{r} R_i^{2}\right) \qquad (1)$$

where R_i is the value of the surface roughness for the test in that trial and r is the number of tests in a trial, high signal-to-noise ratios are always preferred. For lower-the-better characteristics, this translates into lower process average and improved consistency from one unit to the next or both.

However, the cutting parameters for surface roughness still need to be known so that optimal combinations of the cutting parameter levels can be determined more accurately. This will be discussed using analysis of variance in the next section.

Table 4 – Mean response table for S/N ratio

Levels	Cutting speed (m/min)	Depth of cut (mm)	Feed rate (mm/rev)
1	−16.49	−12.03	−12.22
2	−14.37	−12.5	−14.76
3	−13.70	−11.41	−13.5
Max–Min	2.79	1.09	2.54
Rank	3	1	2

Table 5 – Mean response table for experimental data

Levels	Cutting speed (m/min) (*A*)	Depth of cut (mm) (*B*)	Feed rate (mm/rev) (*C*)
1	6.19	3.02	3.77
2	3.52	2.63	5.09
3	5.31	1.54	2.81
Max–Min	2.67	1.48	2.28
Rank	3	1	2

2.2. *Analysis of variance*

Analysis of variance is a method of portioning variability into identifiable sources of variation and the associated degree of freedom in an experiment. The frequency test (*F*-test) is utilized in statistics to analyze the significant effects of the parameters, which form the quality characteristics. Table 3 shows the result of ANOVA analysis of S/N ratio for surface roughness. This analysis was carried out for a level of significance of 5%, i.e., for 95% a level of confidence. The last column of the table shows the "percent" contribution (*P*) of each factor as the total variation, indicating its influence on the result. From the analysis of Table 3 it is apparent that, the *F*-values of cutting speed, feed rate and depth of cut were all greater than $F_{0.05,2,26} = 3.146$ and have statistical, physical significance on the surface roughness.

2.3. *Determination of optimum factor level combination*

Fig. 2 shows three graphs, each of which represent the mean response and the mean S/N ratio for the feed rate, cutting speed and the depth of cut. The values of the graphs have been tabulated in Tables 4 and 5 based on the S/N ratio and

Table 3 – Results of the analysis of variance of surface roughness

Factor	Cutting parameters	Degrees of freedom	Sum of squares	Mean square	F-Test	Contribution (*P*, %)
A	Cutting speed	2	60.70	30.38	28	12
B	Feed rate	2	35.70	17.90	6.2	51
C	Depth of cut	2	16.90	8.40	18.80	30
Error		20	45.40	1.125		7
Total		26	158.50			100

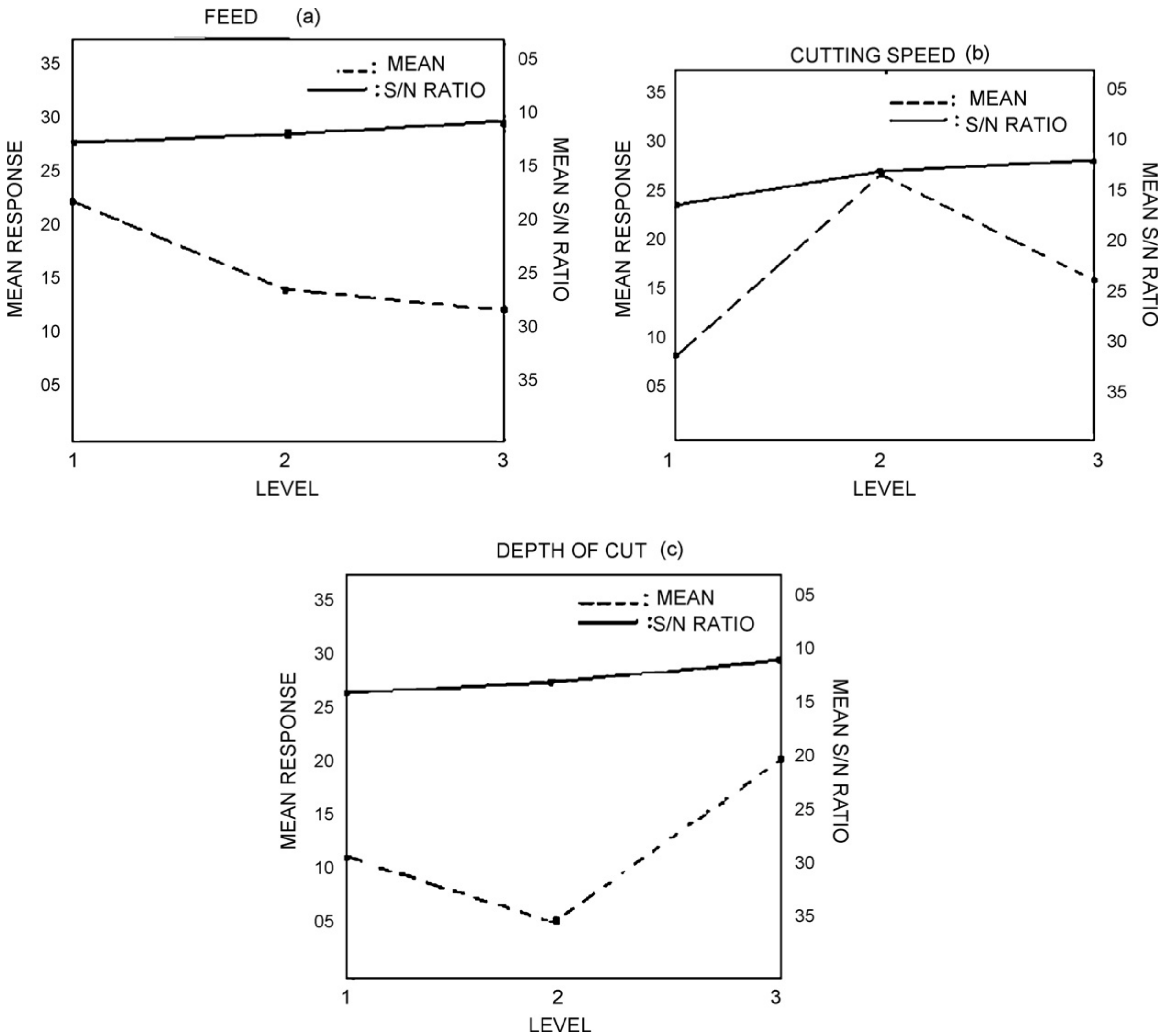

Fig. 2 – Determination of optimum factors using ANOVA (a, b, and c).

ANOVA analysis. The optimal cutting parameters for surface roughness are A_1, B_1, and C_2.

2.4. *Predicting the optimum performance*

After the optimal level has been selected, one could predict the optimum surface roughness using the following equation:

$$\mu_{\text{predicted}} = \mu_{\text{m}} + \sum_{i=1}^{n} (\mu_{\text{o}} - \mu_{\text{m}}) \tag{2}$$

where μ_{m} is the mean response or mean S/N ratio, μ_{o} is the mean response or mean S/N ratio at optimal level, and n is the number of main design parameters that affect the quality characteristics. It is very essential to perform a confirmation experiment for the parameter design, particularly when less numbers of data are utilized for optimization. The purpose of this confirmation experiment is to verify the improvement in the quality characteristics.

2.5. *Verification of optimal parameters through confirmation test*

It is important to conduct confirmation tests to verify the improvement in the machining characteristics of MMCs, implying that the factors and levels chosen for the experiment provide the desired result. Table 6 shows that the increase in S/N ratio from the initial cutting parameters is 3.99 dB for surface roughness, which implies that the surface roughness qualities have improved. It was observed that experimental results were close to the predicted values and they were falling with in the confidence limits.

From the analysis of Table 3, we can observe that the feed rate (P = 51%), depth of cut (P = 30%) and cutting speed (P = 12%) have statistical and physical significance on the surface roughness obtained, especially the feed rate Davim (2003). In this study, it is noticed that the error associated to the ANOVA for surface roughness is 7.0%. These results have good agreement with other similar work carried out by Davim (2003).

Table 6 – Results of confirmation experiment for surface roughness using ANOVA

	Initial cutting parameters	Optimal cutting parameters	
		Predicted	Experimental
Setting level	$A_1B_1C_2$	$A_3B_3C_2$	$A_3B_3C_2$
Surface roughness	5.11	3.93	3.89
S/N ratio	−16.49	−12.93	−12.50

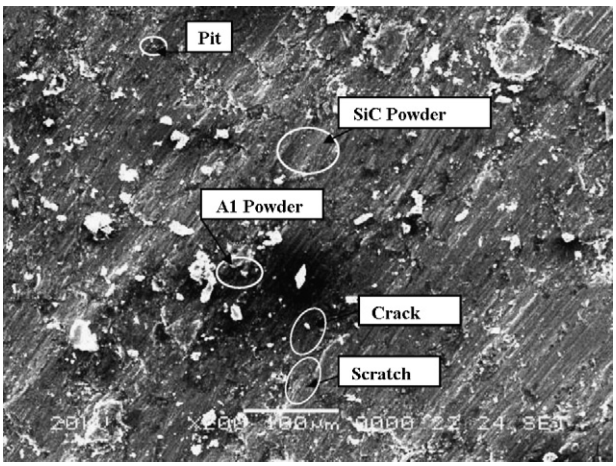

Fig. 3 – Typical surface texture observed on the machined workpiece.

Fig. 3 shows the SEM image of machined surface. The SEM image shows the surface texture of machined workpiece. It was found that SiC and matrix have good stick on the workpiece. The surface of the machined workpiece contains tiny surface cracks and very small pit holes (Palanikumar and Karthikeyan, 2008). The white particles shows the transformation of aluminium powder during machining of Al–SiC particulate composites. These white particles embedded around the SiC particles and made the matrix and SiC as a homogeneous composite (Xiaping and Seah, 2001).

3. Artificial neural network modeling

In the recent years, the application of artificial intelligence is tremendous in virtually all fields of engineering. Modeling and optimization are necessary for the understanding and control of any process. Precise control is a prerequisite to achieve improved quality, and productivity.

Artificial neural network plays an important role in predicting the linear and non-linear problems in different fields of engineering. Many researchers attempted to develop model from experimental data using statistical techniques.

3.1. *Back ground of neural network – multiplayer – perceptron neural network*

Generally a neural network means a network of many simple processors (units) operating in parallel. Each processor is having a small amount of local memory. The units are connected by communication channels (connections), which usually carry numeric data, encoded by one of the various ways (Kecman, 2000). One of the best-known examples of a biological neural network is the human brain. It has the most complex and powerful structure, which, by learning and training, controls human behavior towards responding any problem encountered in every day life. As for the ANN, they have been developed to try to emulate this biological network for the purpose of learning the solution to a physical problem from a given set of examples.

The general architecture of a 3-layered multilayer perceptron (MLP) is shown in Fig. 4. MLP uses BPA for training the network in a supervised manner. BPA is a steepest decent method, where weight values are adjusted in an iterative fashion while moving along the error surface to arrive at minimal range of error, when input patterns are presented to the network for learning the network. The learning process consists of two passes through different layers of the network, a forward pass and a backward pass. In the forward pass, the input pattern is applied to the nodes of the input layers and its effect propagates through the network, layer by layer.

During the forward pass, synaptic weights are all fixed. The error, which is the difference between the actual output of the network and the desired output, is propagated as backward pass to update the synaptic weights. The weights are continuously updated every time the input patterns are presented to the network and the process continues till the actual output of the network comes closer to the desired output. If all the input patterns are propagated once through the network, it is called as cycle or epoch.

These networks currently form the basis for majority of practical application. Among the many neural networks that have been developed, most popular neural networks are known as multilayer perceptron and back-propagation application. In this paper, however, BPNN is chosen, since it provides several advantages over the other network and has been proven successful in different applications (Das et al.,

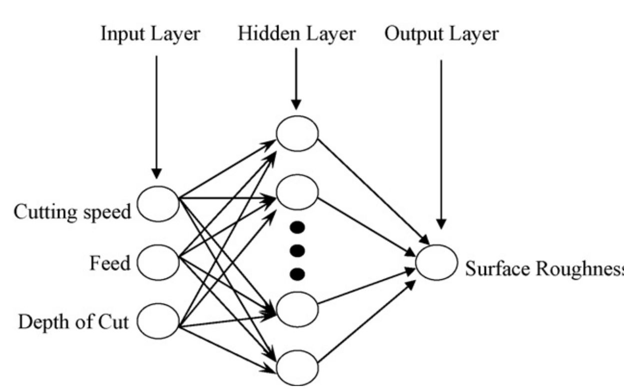

Fig. 4 – Configurations of neural networks.

1997; Kuo and Cohen, 1998) The best-known example of a neural network-training algorithm is back propagation. Modern second-order algorithms such as conjugate gradient descent and Levenberg–Marquardt are substantially faster for many problems, but back propagation still has advantages in some circumstances, and it is the easiest algorithm to understand. There are also heuristic modifications of back propagation which work well for some problem domains, such as quick propagation and Delta–bar-delta.

In the present problem, the BPNN consists of three input neurons corresponding to feed, cutting speed and depth of cut and one output neuron corresponding to surface roughness. The number of hidden layers is one with 10 neurons. The training was performed using normalized input values. Fig. 4 shows the configurations of the neural networks.

3.2. Back-propagation network—algorithm

The algorithm for the back-propagation network program is described below with the help of flow diagram as shown in Fig. 5.

Step 1 Decide the number of hidden layers.

Step 2 Decide the number of neurons for the input layer and the output layer. For the input layer, the number of neurons is equal to the number of input variables and for the output layer it is equal to the number of outputs required. Set small number of neurons for the hidden layer.

Step 3 Get the training input pattern.

Step 4 Assign small weight values for the neurons connected in between the input, hidden and output layers.

Step 5 Calculate the output values for all the neurons in hidden and output layers using the following formula.

$$\text{out}_i = f(\text{net}_1) = f\left(\sum\nolimits_{w_{ij}} \text{out}_j + \theta_1\right) \tag{3}$$

where out_i is the output of the ith neuron in the layer under consideration; out_j is the output of the jth neuron in the preceding layer. f is the sigmoid function can be expressed as:

$$f(\text{net}_1) = \frac{1}{1 + e^{-\text{net}\, i/q}} \tag{4}$$

where q is termed as temperature.

Step 6 Determine the output at the output layer and compare those with the desired output values. Determine the error of the output neurons,

error = desiredoutput − actualoutput

Similarly, determine the root mean square error value of the output neurons

$$E_p = \frac{1}{2}\sum (t_{pj} - O_{pj})^2 \tag{5}$$

where E_p is the error for the pth presentation vector, t_{pj} is the desired value for the jth output neuron and O_{pj} is the desired output of the jth output neuron.

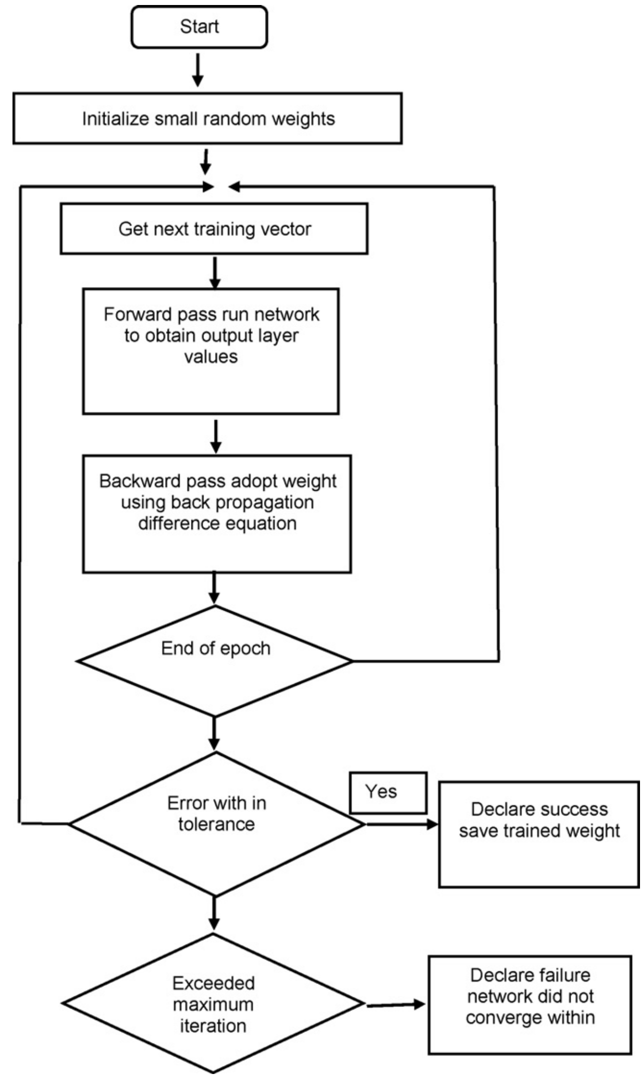

Fig. 5 – Flow diagram.

Step 7 Determine the error available at the neurons of the hidden layer and back-propagate those errors to the weight values connected in between the neurons of the hidden layer and input layer. Similarly, back-propagate the errors available at the output neurons to the weight values connected in between the neurons of the hidden layer and output layer using the

Table 7 – Typical observations of output response

Network configuration	3-10-1
Number of hidden layer	1
Number of hidden neuron	10
Transfer function used	Logsig (sigmoid)
Number of patterns used for training	18
Number of patterns used for testing	12
Sum of squared error	0.0002
Number of epochs	2000
Learning factor (η)	0.6
Momentum factor (α)	1

Table 8 – Validation of results for Surface Finish obtained using ANN

Reading number	Surface roughness (R_a) in experimental value	Predicted value (μm)	Error microns (μm)	Percentage error (%)
1	3.94	3.96	−0.02	0.75
2	2.27	2.25	0.01	0.50
3	4.21	4.30	−0.09	2.17
4	3.87	3.88	−0.01	0.27
5	4.5	4.45	0.04	1.10
6	2.49	2.52	−0.03	1.42
7	6.19	6.10	0.08	1.44
8	5.05	5.03	0.02	0.39
9	5.39	5.13	0.25	4.78
10	2.93	2.86	0.06	2.26
11	5.75	5.66	0.08	1.48
12	4.57	4.60	−0.03	0.84

following formula

$$\text{error}\ \delta_{pi} = (t_{pi} - O_{pi})O_{pi}(1 - O_{pi}) \quad \text{for output neurons} \tag{6}$$

$$\text{error}\ \delta_{p} = (t_{pi} - O_{pi})O_{pi} \sum \delta_{pi} W_{ki}$$

$$\text{for hidden neurons} \tag{7}$$

Weight adjustment is made as follows:

$$\Delta W_{ji}(n = 1) = \eta(\delta_{pi} O_{pi}) = \alpha\, \Delta W_{ji}(n) \tag{8}$$

where η is the learning rate parameter and α is momentum factor.

Step 8 Go to Step 3 and do the calculations up to Step 7. At the end of cycle determine the root-mean-square error value, mean percentage of error and worst percentage of error over the complete patterns. To reach to Step 9 check whether it is of reasonable error or not, if so, go to Step 9 otherwise go to Step 3 and repeat the same from Step 3 to Step 7.

Step 9 Stop the iteration and note the final weight values attached to the hidden layer neurons and also to the output layer neurons.

Step 10 Testing neural network model with the trained weight values, determine the output for the testing pattern and check whether the deviation from desired value is reasonably less or not. If no, try the back propagation with revised network by changing the number of neurons, altering learning rate parameters, altering momentum value and altering temperature value. Table 7 shows the typical observation of network performance while testing the pattern.

3.3. Model verification

The ANN is trained with different number of nodes in the hidden layer. The exact nodes obtained for hidden layer is 10. The reason for using one hidden layer and 10 nodes are used in this configuration is due to reduced error value. Average error for the performance of ANN when testing all the training and testing pattern is 1.47%. ANN is suitable tool, which is used to predict the surface roughness in machining process.

ANN model has been tested using the training data and graphs were plotted using predicted and tested values. The results indicate that ANN model has been successfully applied to the machining parameters of MMC composites. It is observed from Fig. 6 (Validation of ANN model for surface roughness) Fig. 5 that predicted based on ANN model is very close to the experimental observation. The validation for the surface roughness values using ANN has been listed in Table 8.

It is clear from Table 8, the percentage of error between the experimental and predicted values is found that minimum of 0.39 and maximum of 4.78. This error is a reasonable one and shows that the ANN model predicted satisfactory for surface roughness (Lin et al., 2003).

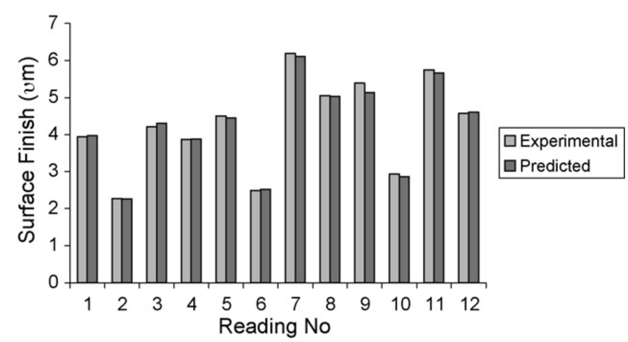

Fig. 6 – Validation of ANN model for surface roughness.

4. Conclusions

Experiments were conducted on Lathe using PCD coarse grade cutting insert, the data surface roughness was collected under different cutting conditions for various combinations of cutting speed, feed rate, and depth of cut.

Two modeling techniques were used to predict the surface roughness namely ANOVA and ANN. ANOVA and ANN approach provide a systematic and effective methodology for the optimization. In ANOVA, it is revealed that the feed rate has highest physical as well as statistical influence on the surface roughness (51%) right after the depth of cut (30%) and the cutting speed (12%).

ANN has been used to learn the collected data. Neural network configuration (3-10-1) was trained using 18 patterns. The results of neural network model shows close matching between the model output and the directly measured surface roughness. This method seems to have prediction potentials for non-experimental pattern additionally. ANN methodology consumes lesser time giving higher accuracy. Hence optimization using ANN is the most effective method compared with ANOVA.

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