**COMPARISON OF NEURAL NETWORK MODELS ON
MATERIAL REMOVAL RATE OF C-SiC**

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ABSTRACT

In this work, two artificial neural networks (ANNs) models: Back propagation neural network (BPN) and Radial basis function neural network (RBFN) are presented for the prediction of material removal rate (MRR) of C-SiC using vertical milling machine. The spindle speed, feed and diameter of the drill are chosen as input variables and material removal rate is the output parameter for the artificial intelligence models. Using the factorial design methodology, drilling experiment is conducted on C-SiC to acquire data for training and testing the neural network. It is found that neural models could predict the process performance with reasonable accuracy. However RBFN model is faster than BPN for this experimental data set. Moreover, the neural network models are considered as valuable tools as they can give reliable predictions and provide a way to avoid time and money consuming experiments.

KEYWORDS

Artificial neural network(ANN), Back Propagation Neural Network(BPN), Radial Basis Function Neural Network (RBFN), Carbon silicon carbide (C-SiC), material removal rate(MRR.)

1. INTRODUCTION

Ceramic composites are highly potential materials for applications involving high temperatures due to their properties like high strength, high service temperature, high stiffness and low density [1-4]. However, it is these properties which make them difficult to machine and hence limit their use. Machining composites, particularly drilling, is extensively used for producing riveted and bolted joints during assembly operations. Any weakness arising in the machined structure during machining has a significant safety, reliability and economical impact. Thus it is necessary to study the various drilling process parameters.

In the recent past ANN's have emerged as highly flexible modelling tool for manufacturing sector. ANNs are found to be effective as computational processors for various associative recall, classification, data compression, combinational problem solving, adaptive control, modelling, forecasting, multisensor data fusion and noise filtering. In the literature, Back propagation technique and Radial basis function have been employed for modelling processes. Tsai [4] used RBFN on the neural network for predicting MRR in EDM process using aluminium and iron as work piece. However, Kao [6], Panda [7] and Angelos [9] used BPN for predicting MRR and surface roughness respectively in EDM process.

The application of applying ANN models for the prediction of MRR using C-SiC material is discussed in this paper. The proposed model uses data for training procedure from an experimental research of C-SiC composite. The spindle speed, feed and diameter of the drill are considered as input parameters of the models. These parameters are varied over a range in accordance with the capability of the machine tool available for experimentation. The proposed neural networks are trained with feed forward back propagation algorithm and radial basis algorithm. These models are able to reasonably predict MRR thus avoiding costly experimentation.

The objective of this work is to establish better process models for the new C-SiC composite based on neural network by comparing their predictions on MRR using the vertical machining centre.

Table 1 Machining Parameters and their levels

Sample	Machining Parameters	Unit	-1	0	1
A	Spindle speed	rpm	1500	2250	3000
B	Feed rate	mm/min	30	35	40
C	Drill size	mm	1	2	3

2. EXPERIMENTATION

2.1. Experimental Setup

It is planned to study the effect of input parameters on MRR for C-SiC material during drilling using the factorial approach. Experiments are conducted on Denford CNC machine with Fanuc controller. The VMC has a maximum cross travel of 170 mm, maximum long travel of 290 mm and head travel of 235 mm and has a six station automatic tool changer. The spindle speed range available on this machine is 0-4000 rpm and feed range available is 0-1000 m/min. The MRR is calculated by taking the difference between initial weight (before machining) and final weight (after machining) of the work piece using the Libror AEG – 220 balance, Shimadzu make with accuracy of 0.0001 g. The machining parameters used are shown in Table1. The experiments are planned according to 2^3 factorial design with 4 centre points. The design matrix with the response parameter MRR is shown in Table 2.

Table 2: Design Matrix with response parameter MRR

Experiment No	Factors			MRR(g)
	A	B	C	
1	-	-	-	0.0145
2	+	-	-	0.0159
3	-	+	-	0.0132
4	+	+	-	0.0248
5	-	-	+	0.0222
6	+	-	+	0.0003
7	-	+	+	0.0004
8	+	+	+	0.0529
9	0	0	0	0.0206
10	0	0	0	0.0482
11	0	0	0	0.0141
12	0	0	0	0.0003

3. ARTIFICIAL NEURAL NETWORK

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks as shown in Fig.1. An artificial neuron is a computational model inspired by the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron as shown in Fig.2.

Figure 1 Natural Neurons

Figure 2 Artificial Neurons

When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal through the axon. This signal might be sent to another synapse and might activate other neurons. The complexity of real neurons is highly abstracted when modelling artificial neurons. These consist of inputs (like synapses) which are multiplied by weights (strength of respective signals) and then computed by mathematical functions which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependence of a threshold value). ANNs combine artificial neurons in order to process information. In the past, several studies have been reported on the development of neural networks based on different architectures. Neural networks are characterised by their architectures, activation function and learning algorithm. Each type of neural network would have its own input – output characteristics and therefore it could be applied only on some specific processes.

In this study two neural networks are employed for modelling the material removal rate in drilling of C/SiC composite using the MATLAB neural network toolbox . The two networks used are discussed as follows:

a. Back –Propagation Network

B.Radial Basis Network

3.1. Back-Propagation Network

Back –propagation networks (BPN) are composed of layers of neurons. The input layer of neurons is connected to the output layer of neurons. The training process of BPN is undertaken by changing the weights such that a desired input –output relationship is realised. A schematic diagram of BPN with ‘n’ inputs nodes and ‘r’ output nodes and a single hidden layer of ‘m’ nodes is shown in Fig.3.

Figure 3 Schematic diagram of BPN

In the Figure 3, the number of hidden layers is critical for convergence rate during training of parameters for given number of nodes during training of parameters for given number of nodes at input and output layers [4]. But the experiments conducted did not show any advantage of a double hidden layer over a single layer network as shown in Fig.4.

Figure 4: Comparison of errors for hidden layers

Hence only a single hidden layer is used in this work. The connections have been found by multiplying weights associated with them. The input nodes have a transfer function of unity and the activation function of the hidden and output nodes are sigmoidal $S(\bullet)$ and linear respectively. Referring to Figure 1 the net input to the j^{th} hidden neuron is given by:

$$y_j(x) = \sum_{i=1}^n w_{1ji} x_i + b_{1j} \quad (2)$$

where w_{1ji} is the weight between the i^{th} input node and the j^{th} hidden node and b_{1j} is the bias at the j^{th} hidden node. The output at the j^{th} hidden node is described as:

$$Z_j(x) = 1/(1 + \exp(-y_j(x))) \quad (3)$$

Given an input vector x , the output value $O_k(x)$ of the k^{th} output node is equal to the sum of the weighted outputs of the hidden nodes and the bias of the k^{th} output node and is expressed as

$$O_k(x) = \sum w_{2kj} Z_j + b_{2k} \quad (4)$$

Where w_{2kj} is the weight between the j^{th} hidden node and the k^{th} output node, the b_{2k} is the biasing term at the k^{th} output node.

The back propagation learning process works in small iterative steps:

1. First, one of the example cases is applied to the network.
2. Second, the network produces some output based on the current state of its synaptic weights initially the output will be random.

This output is compared with the known good output and the mean squared error (MSE) is calculated. The error value is then propagated backwards through the network and small changes are made to the weights in each layer. The weight changes are calculated to reduce

the error signal for the case. The whole process is repeated for each of the example cases, then back to the first case again, and so on. The cycle is repeated until the overall error value drops below some predetermined threshold value. It is said that the network will never exactly learn the ideal function, but rather it will asymptotically approach the ideal function.

3.2. Radial Basis Function Network

The schematic diagram of a RBFN with ‘n’ inputs and ‘r’ outputs is shown in Fig.5. It has a feed forward structure consisting of a single hidden layer of ‘m’ locally tuned units (RBFNs) which are fully interconnected to an output layer of ‘r’ linear units. The input nodes pass the incoming input vector to the hidden nodes. The connections between the hidden nodes and the input nodes (first layer connection) are not weighted. The connections between the hidden nodes and the output nodes are weighted and the output nodes are simple simulations. The commonly used Gaussian basis function $\phi(\bullet)$ is used for the hidden units. All hidden units simultaneously receive the n-dimensional real-valued input vector x . It should be noted that the first layer weights are absent, because the outputs of hidden units are not calculated using the sigmoidal activation mechanism. Rather, each hidden units output is obtained by calculating the closeness of the input ‘ x ’ to an ‘n’ dimensional parameter vector μ_j associated with the j^{th} hidden units. Referring to Figure.5, the net input to the j^{th} radial basis neuron is given by

$$y_j(x) = b1_j(x - \mu_j) \quad (5)$$

where the bias $b1_j$ is a fixed function of the width of the receptive field σ_j that follows the sensitivity of the j^{th} radial basis neuron to be adjusted and is described below:

$$b1_j = \sqrt{-\log(0.5)} / \sigma_j \quad (6)$$

The output of the j^{th} radial basis neuron is described as:

$$Z_j(x) = \exp(-y_j(x))^2 \quad (7)$$

Given an input vector x , the output value $O_k(x)$ of the k^{th} output node is equal to the sum of the weighted outputs of the hidden nodes and the bias of the k^{th} output node. It may be noted that the choice of $\phi(\bullet)$ and the μ_j should be made such that RBFNs are able to closely match the performance of the back propagation neural network. The RBFNs employ a hybrid two stage training scheme which decouples the learning task from both the hidden and the output layers and thus eliminates the need for slow back error propagation. In the training process, the sum of the MSE criterion function is considered as error function, and it is minimized over the given training data sets by adaptive updating the free parameters of the RBFN. These parameters are the radial basis function centres ($\mu_{j,s}$) their widths (σ_j, s) and the second layer (w_{kj}, s). The RBFN is trained in three steps. Firstly the hidden node centres are determined secondly the hidden widths are determined and thirdly the second layer connection weights are determined.

In this section, widths of all radial basis function units are taken to be equal, which is known as spread factor (SF) of the RBFN. If the SF is too small, over fitting can occur, while under fitting may occur if SF is too large. Therefore, it is important to choose a proper value for SF in order to achieve better generalisation ability of the RBFN. Finally once the hidden units are synthesized, the second layer weights are computed by using the supervised least – square method.

Figure 5 Schematic diagram of radial basis function network

4. Results and Discussion

Initially, the architecture and the topology of the networks i.e. the number of hidden layers and the number of neurons in each layer in the networks are decided. The process parameters speed, feed and the diameter of the drill are taken as input parameters and MRR is taken as the output parameter. Hence there are three input nodes and one output node. The variation of the process parameters for different experimental sets (runs) is as shown in Table 1 and Table 2.

Of the experimental data that is generated the training data sets are considered for both the networks to compare the performances of the ANNs. Besides the training data set separate data is used for testing the neural network. Both the ANNs are trained with the above data set to reach an error goal of (0.1). The performance of two neural network models is studied with special attention to their generalization ability and training time.

Figure 6 Comparison of average errors for various nodes for BPN

Figure 7 Learning behaviour of BPN model for MRR

It is always a difficult task to find an optimal configuration for the BPN. There is no exact rule for setting the proper number of neurons in the hidden layer to avoid over fitting or under fitting to make the learning phase convergent. For best performance of the BPN, the proper number of nodes in the hidden layer are selected through trial and error method, based on the number of epochs needed to train the network. It was observed that the network performed well with around 50 nodes. The learning behaviour of BPN model for MRR is shown in Figure 7 where the error goal was met 5 epochs.

The RBFN is auto configuring in the sense that it has one hidden layer with a growing number of neurons during learning to achieve an optimal configuration. The only parameter to be varied to obtain the best generation ability is the spread factor. Computations are carried out for different values of spread factor. It is observed that the best generalisation ability of the network is achieved with a spread factor of 200 for this experimental data set as shown in Figure.8.

Figure 8 Comparison of average error for various spread factors.

The training performance of the same data set for this experiment using the RBFN model is shown in Figure.9.

Figure 9 Learning behaviour of RBFN model

The experimental results and the predicted results of the MRR by the BPN and the RBFN are plotted on the same scale as shown in Figure.10 The plots clearly indicate that the BPN is more accurate but the RBFN is more faster .

Figure 10 Comparison of MRR for the experimental data and predictions made by BPN and RBFN .

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5 CONCLUSION

In this paper two artificial intelligence techniques: Back propagation neural network and radial basis function neural network are projected for predicting the MRR. The results obtained from experiments conducted on C-SiC workpiece material with diverse machining parameters using HSS drill are compared and validated. It is found to be in correlation with experimental results. The BPN demonstrated a slightly better performance compared to the RBFN model. However the RBFN prediction is very fast. It is important to note that for BPN's the required number of nodes in the hidden layer is to be found by trial and error whereas the RBFN's have only one hidden layer with growing number of neurons. Hence, the MRR can be predicted with the above models with reasonable accuracy. The accuracy of prediction by the ANN models can be increased by increasing the number of experiments used to train and test the data.

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