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Research Paper

OPTIMIZATION OF MACHINING PARAMETERS IN MILLING OF COMPOSITE MATERIALS

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In this paper optimization of End milling has been reported. In recent years GFRP have attracted increasing use for many purposes. The material has many excellent properties, such as high specific strength, high specific modulus of elasticity, light weight, good corrosion resistance, etc., the parameters are depth of cut, feed, speed and tool were varied. The experiments were designed based on statistical three level full factorial experimental design techniques. Back Propagation Feed Forward Artificial Neural Network (BPFF-ANN) has been used for prediction of surface roughness and Delamination. In the development of predictive models the cutting speed, feed, depth of cut and tool type were considered as the model variables. Twenty seven data were used for training the network. The required datas for predictive model are obtained by conducting a series of test and measuring surface roughness and delamination data. Good agreement is observed between the predictive model results and the experimental measurements.

Keywords: GFRP, ANN, Back propagation, Delamination, Surface roughness

INTRODUCTION

Surface roughness is an indicator for the surface quality is one of the prime customer requirements for the machined parts. For efficient use of machine tools, optimum cutting parameters are required. During Machining process parameter optimization is highly complex and time consuming. Taguchi parameter optimization methodology is applied to optimize cutting parameters. Then the results analysis show that the cutting parameters have recent significant contribution on the surface roughness and depth of cut and hardness of material have less significant contribution on the surface roughness (Sijo and Biju, 2010). In this experiment is executed by using full factorial design. Analysis of variances shows that the most significant parameter is feed rate followed by spindle speed and lastly depth of cut. After the predicted surface roughness has been obtained by using both methods, average

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percentage error is calculated. The mathematical model developed by using multiple regression method shows the accuracy of 86.7% which is reliable to be used in surface roughness prediction. On the other hand, artificial neural network technique shows the accuracy of 93.58% which is feasible and applicable in prediction of surface roughness (FAb Rashid and Abdul, 2010). In this study mathematical model may be used in estimating the surface roughness without performing any experiments. Finally, predicted values of surface roughness by techniques, NN and regression analysis, were compared with the experimental values and their closeness with the experimental values determined. Results show that, NN is a good alternative to empirical modeling based on full factorial design (Esme *et al.*, 2009). Here to determining suitable training and architectural parameters of an ANN still remains a difficult task. These parameters are typically determined in trial and error procedure, where a large number of ANN models are developed and compared to one another. Taguchi method for the optimization of ANN model trained by Levenberg-Marquardt algorithm. A case study of a modeling resultant cutting force in turning process is used to demonstrate implementation of the approach. The ANN training and architectural parameters were arranged in L18 orthogonal array and the predictive performance of the ANN model is evaluated using the proposed equation. Using the analysis of variance (ANOVA) and analysis of means (ANOM) optimal ANN parameter levels are identified. Taguchi optimized ANN model has been developed and has shown high prediction accuracy. Analyses and experiments have shown that the optimal ANN training and architectural parameters can be determined in a systematic way, thereby avoiding the lengthy trial and error procedure (Milos and Mirislav, 2011). Numerical and Artificial Neural Networks (ANN) methods are widely used for both modeling and optimizing the performance of the manufacturing technologies. Optimum machining parameters are of great concern in manufacturing environments, where economy of machining operation plays a key role in competitiveness in the market. Effects of selected parameters on process variables (i.e., surface roughness and material removal rate) were investigated using Response Surface Methodology (RSM) and artificial neural networks (Soleymani and Khorram, 2010). So based on these surveys to be selected the work piece material as composite because widely used in many purpose now a days, then during machining process the main failure of the materials due to the surface roughness and Delamination. Due to these facts, optimum the surface roughness and delamination values then only able to reduce the material wastage during machining process and also the material widely used in all purposes.

CUTTING CONDITIONS

Experimental Design

Design of experiments is a powerful analysis tool for modeling and analyzing the affect of process variable over some specific variable which is an unknown function of these process variables. The experimental design method is an effective approach to optimize the various machining parameters. The selection of such points in the design space is commonly called Design of Experiments (DoE) or Experimental

Design. The choice of the experimental design can have a large influence on the accuracy and the construction cost of the approximations. Randomly chosen design points make an inaccurate surface to be constructed or even prevent the ability to construct a surface at all. Several experimental design techniques have been used to aid in the selection of appropriate design points. In a factorial design variable range is divided into levels between the lowest and the highest values (Arbizu and Perez, 2003). Experiments were conducted through the established Taguchi's design method. In this work, the machining characteristics are investigated based on surface roughness and tool wear. The machining parameters are also optimized by employing statistical techniques, using the technique of analysis of variance obtained from regression analysis (Myers and Montgomery, 1995). Taguchi method is a powerful design of experiments tool for engineering optimization of a process. It is an important tool to identify the critical parameters and predict optimal setting of each parameter. Analysis of variance is used to study the effect of process parameters and establish correlation among the cutting speed, feed and depth of cut with respect to the major machinability factor, cutting forces such as cutting force and feed force. Validations of the modeled equations are proved to be well within the agreement with the experimental data (Dinesh *et al.*, 2008). A three level full factorial design creates 3n training data, where n is the number of variables. In these study four independent variables such as depth of cut, speed, feed rate and tool type has used for experimental runs are shown in the Table 1. Ranges of process parameters are shown in the Table 2.

Table 1: Levels of the Variables Used in this Work

Factors	Level 1	Level 2	Level 3
Cutting velocity	24	48	72
Feed	300	600	900
Depth of cut	0.5	1.5	2.5
Type of tool	1	2	3

Table 2: Experimental Results Obtained from Machining Surface and Cutting Parameters

S. No.	Input Parameters				Output Results	
	Speed	Feed	DOC	Tool Used	Surface Roughness	Delamination
1.	24	300	0.5	1	4.77	1.308
2.	24	600	1.5	1	9.03	1.462
3.	24	900	2.5	1	6.84	1.462
4.	48	300	1.5	1	6.94	1.308
5.	48	600	2.5	1	4.61	1.308
6.	48	900	0.5	1	5.64	1.462
7.	72	300	2.5	1	3.59	1.462

Table 2 (Cont.)

S. No.	Input Parameters				Output Results	
	Speed	Feed	DOC	Tool Used	Surface Roughness	Delamination
8.	72	600	0.5	1	3.18	1.154
9.	72	900	1.5	1	9.75	1.462
10.	24	300	0.5	2	8.87	1.462
11.	24	600	1.5	2	9.21	1.308
12.	24	900	2.5	2	9.23	1.462
13.	48	300	1.5	2	5.27	1.154
14.	48	600	2.5	2	4.48	1.308
15.	48	900	0.5	2	4.63	1.462
16.	72	300	2.5	2	3.47	1.77
17.	72	600	0.5	2	6.15	1.924
18.	72	900	1.5	2	4.92	1.924
19.	24	300	0.5	3	4.07	1.154
20.	24	600	1.5	3	4.72	1.308
21.	24	900	2.5	3	4.32	1.462
22.	48	300	1.5	3	3.3	1.308
23.	48	600	2.5	3	4.49	1.462
24.	48	900	0.5	3	5.91	1.462
25.	72	300	2.5	3	5.47	1.462
26.	72	600	0.5	3	4.74	1.462
27.	72	900	1.5	3	4.17	1.154

Measurement and Result

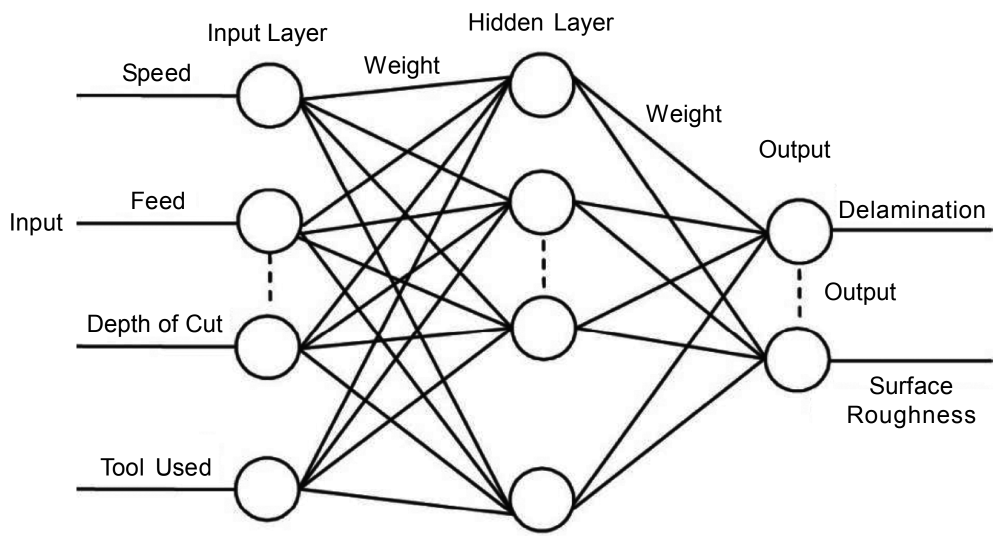
Terms and Units

Cutting Velocity: m/min, Feed: mm/min, Depth of cut: mm Surface roughness: µm, Delamination: µm.

Artificial Neural Network Mode for Prediction of Surface Roughness

Artificial Neural Network is a capable computation model for a weight diversity of problems. For manufacturing process where no satisfactory analytic model exist or a low order empirical polynomial model is inappropriate, Neural networks offer a good alternative approach. Until today many different neural network models have been developed. They include perceptrons, Kohonen, Hassoun, Yuille, Hebbian, Oja, Hopfields, Back propagation and Kolmogorov Networks, to mention a few of the better known network models. Among the various neural network models Back Propagation (BP) is the best general purpose model and probably the best at generalization. The typical neural networks architecture is shown in the Figure 1. The input layer, the hidden layer and the output layer include several processing units known as neurons. The input layer is used to present the

Figure 1: Neural Network Architecture



data in the network model and the output to create the ANN's response.

There are several transfer functions such as threshold function, piece wise-Linear function, sigmoid/hyperbolic function and logarithmic used in neural network models. Tangent hyperbolic activation function was selected in this work. For the prediction of surface roughness, in this study a multilayer perceptrons consisting of an input, two hidden layers and an output layer was used as shown in Figure 1. The optimal ANN architecture was designed by means of MAT Lab Neural Network toolbox. Neurons in the input layer correspond to depth of cut, cutting speed and feed rate. The output layer corresponds to surface roughness and Delamination. In this model, the inputs are fully connected to the outputs. Input and output layers have 4-36-2 neuron, respectively as shown in Figure 1. In the neural network model, the output neurons on the input layer reach the jth neuron on the next layer and become its input as stated as in Equation (1).

$$Net_j = \sum_{J=0}^{N} w_{ij} \qquad ...(1)$$

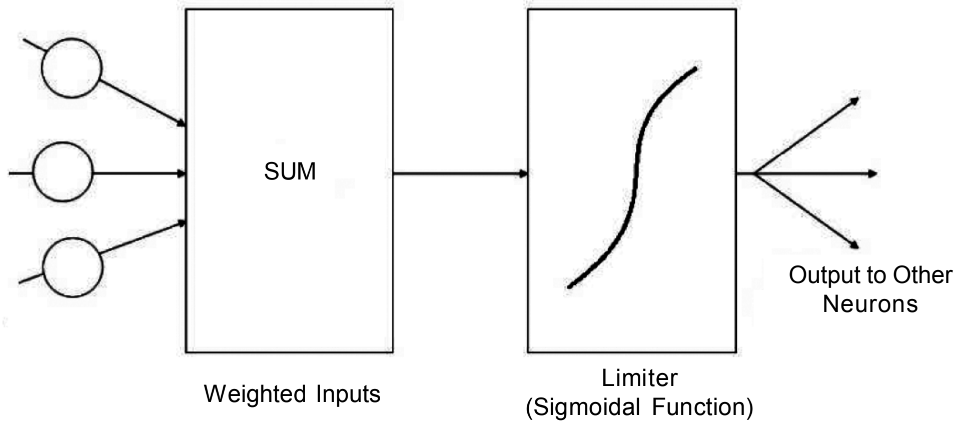
Where N is the number of neurons of the inputs to the j^{th} neuron in the hidden layer and Net_j is the total or net input. X_i is the input from the i^{th} neuron in the preceding layer and w_{ij} is the weight of between the i^{th} neuron on the input layer and the j-th neuron on the next layer. A tangent hyperbolic function (f) that transforms the input value of the hidden layer to produce its output (out_j)

The back propagation algorithm

$$X_{k+1} = X_k \alpha_k g_k \qquad ...(2)$$

The back propagation is used as learning procedure for multi layer perception network. The algorithm makes it possible to propagate error from the output layer to the input layer and correct the weight vectors, which will result in minimum error. The back propagation algorithm minimizes the square of the differences between actual output and desired output units and for all training pairs.

Figure 2: A Typical Network Architecture



The error obtained when the training pair (pattern) consisting of both input and output given to the input layer of the network is given by equation (MSE).

$$E_p = \frac{1}{n}\sum_i \left(T - O_{pi}\right)^2 \quad ...(3)$$

where,

T_{pi} is the i^{th} component of the desired output vector;

O_{pi} is the calculated output of ith neuron in the output layer.

The overall error of all patterns is given by

$$E = \sum E_p \quad ...(4)$$

Training Function and learning functions are mathematical procedures used to automatically adjust the network's weights and biases. The training function dictates a global algorithm that affects all the weights and biases of a given network. The learning function can be applied to individual weights and biases within a network.

$$X_{k+1} = X_k\left[J^T J + \mu I\right]^{-1} - J^T e \quad ...(5)$$

The activation function $f(x)$ is a non linear function and is given by

$$f(x) = a = \tan sig(n) = 2/(1 + \exp(-2^*n)) - 1 \quad ...(6)$$

where $f(x)$ is differentiable.

Purelin is a neural transfer function. Transfer functions calculate a layer's output from its net input

$$a = purel\ in\ (n) = n \quad ...(7)$$

Thus, the result found after the development of the ANN model the result comparison to be given in the Table 3. In that comparison the machine data and the ANN output having too less variation between them.

ANN APPROACH: RESULTS AND COMPARISON

Training of neural network model was performed using twenty seven experimental. The trained network model was tested using other experimental data points, which were not used in the training process. The results predicted from the ANN model are compared with those obtained by experimental test in

Table 3: Machining Output vs. ANN Output for Surface Roughness and Delamination

Test No.	Surface Roughness			Delamination		
	Actual Output	ANN Output	Error	Actual Output	ANN Output	Error
1.	4.77	4.7696	0.0004	1.308	1.3072	0.0008
2.	9.03	9.0331	–0.0031	1.462	1.4620	0
3.	6.84	6.8402	–0.0002	1.462	1.4565	0.0055
4.	6.94	6.9399	0.0001	1.308	1.3046	0.0034
5.	4.61	4.6098	0.0002	1.308	1.3080	0
6.	5.64	5.6398	0.0002	1.462	1.4603	0.0017
7.	3.59	3.5911	–0.0011	1.462	1.4622	–0.0002
8.	3.18	3.1809	–0.0009	1.154	1.1561	–0.0021
9.	9.75	9.7500	0	1.462	1.4635	–0.0015
10.	8.87	8.8699	0.0001	1.462	1.4618	0.0002
11.	9.21	9.2099	0.0001	1.308	1.3051	0.0029
12.	9.23	9.2302	–0.0002	1.462	1.4742	–0.0012
13.	5.27	5.2707	–0.0007	1.154	1.1573	–0.0033
14.	4.48	4.4800	0	1.308	1.3081	–0.0001
15.	4.63	4.6301	–0.0001	1.462	1.3925	0.0695
16.	3.47	3.4601	0.0099	1.770	1.7589	0.0111
17.	6.15	6.1483	0.0017	1.924	1.9236	0.0004
18.	4.92	4.9201	–0.0001	1.924	1.9244	–0.0004
19.	4.07	4.0711	–0.0011	1.154	1.1536	0.0004
20.	4.72	4.7204	–0.0004	1.308	1.3751	–0.0671
21.	4.32	4.3199	0.0001	1.462	1.4553	0.0067
22.	3.30	3.2950	0.005	1.308	1.3034	0.0046
23.	4.49	4.5009	–0.0109	1.462	1.3163	0.1457
24.	5.91	5.9098	0.0002	1.462	1.4684	–0.0064
25.	5.47	5.4780	–0.008	1.462	1.4699	–0.0079
26.	4.74	4.7401	–0.0001	1.462	1.4626	–0.0006
27.	4.17	4.1639	0.0061	1.154	1.3023	–0.1483

Table 3 and the training set patterns in the Table 2 that ANN prediction is in good agreement with the experimental results. Figures 3 and 4 compare the neural network surface roughness and Delamination prediction with the experimental test result and the ANN result.

Here that the Simulated ANN Output for Surface roughness and Delamination were found for the (Table 4) sample Data's and those values are found with good interpolation and then this method is very useful for prediction of various combinations of input data's without undergoing the Experimental process. With

Figure 3: Machining Output vs. ANN Output for Surface Roughness

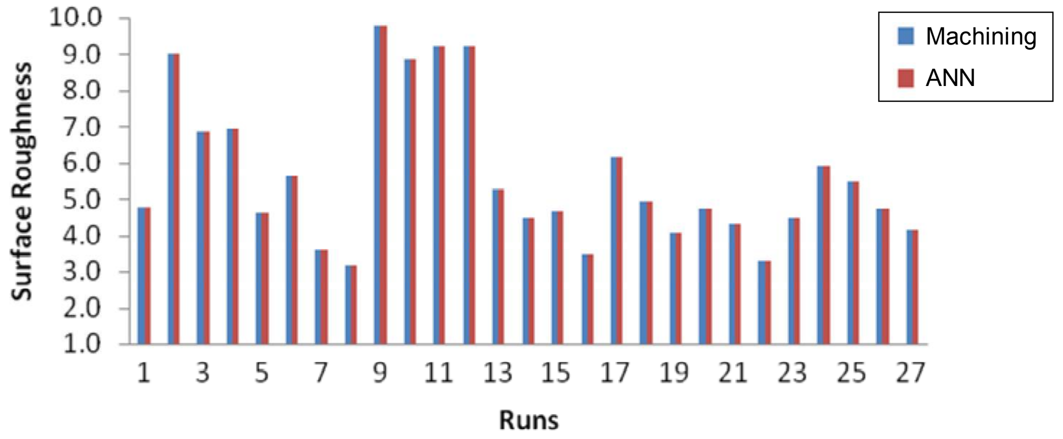


Figure 4: Machining Output vs. ANN Output for Delamination

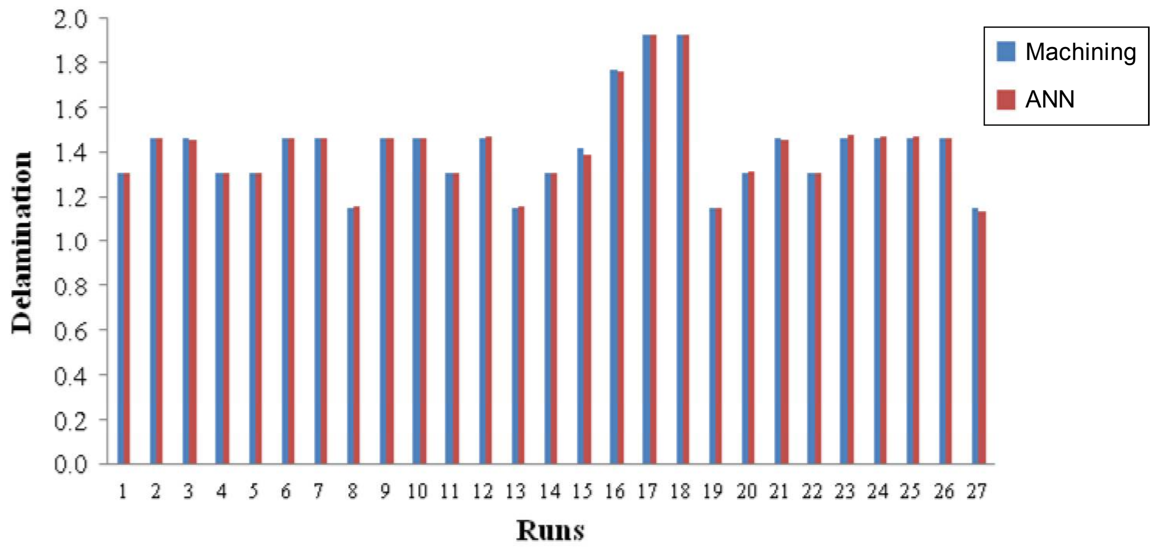


Table 4: Simulated ANN Output for Surface Roughness and Delamination

S. No.	Input for ANN				Simulated ANN Results	
	Speed	Feed	DOC	Tool Used	Surface Roughness	Delamination
1	24	350	0.5	1	4.68	1.326
2	24	620	1.5	3	4.86	1.232
3	48	920	2.5	2	4.72	1.481
4	48	340	1.5	3	4.91	1.431
5	72	680	2.5	1	4.61	1.308
6	72	700	0.5	2	5.02	1.728

help of these method will be reduce the machining time as well as getting good machinability.

It is found that the developed ANN model has good interpolation capability and can be used as an efficient predictive the combinations for good surface roughness and Delamination. Increasing the number of nodes increases the computational cost and decreases the error.

CONCLUSION

The experimental observations were incorporated into the ANN model. A feed forward neural network was developed to predict surface roughness and Delamination. Good agreement was shown between the predictive model results and the experimental measurements. As in future without undergoing the machining process able to get good machining data's and its very useful ANN model for getting good Optimum machining process.

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