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Comparative Analysis of Simulation of Different ANN Algorithms for Predicting Drill Flank Wear in the Machining of GFRP Composites

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Abstract:

Optimum selection of machining conditions significantly results in the increase of productivity and the reduction of costs. So, the present research paper focusses on an Artificial Neural Network (ANN) based approach to optimize the HSS drill flank wear by simulating the machining parameters in the drilling of GFRP composite laminates. The present research paper is also focused on comparison of different ANN algorithms to predict the drill flank wear while machining. ANN is trained with the data collected from the experimentation. The experimental data is generated by performing drilling operation on CNC machine using different machining factors and levels. Further optimization of the ANN structure is done through performance evaluation of the selected algorithms by changing its structural parameters. This optimized ANN can measure drill flank wear under the specified work material, tool material and machining conditions efficiently.

Keywords: Artificial Neural Network, GFRP composites, cutting speed, drill diameter, cutting feed rate, drill flank wear.

INTRODUCTION

The properties of composite materials are superior to those of their individual material constituents. Composite materials take the benefit of the strength to weight ratio and weight to stiffness ratio. Basically there are three different types of composites: Metal Matrix Composites, Ceramic Matrix Composites and Polymer Matrix Composite. Recently, due to light weight, ease of fabrication, less cost, high weight-stiffness ratio and because of aesthetic aspects etc., polymer matrix composites are finding increased engineering applications in aerospace, automotive, marine and civil infrastructure industries.

In the present scenario, almost all the mechanical and manufacturing industries are aiming at higher productivity, quality and overall economy to compete and to face the challenges in their respective industrial sectors. To meet these challenges the manufacturing industries that are into machining, demand cutting tools that produce higher Material Removal Rate (MRR), longer life and stable. But high production machining with the increased level of machining or cutting parameters (i.e., high cutting speed and feed) results in large amount of thermal intensity at the chip-tool interface zone which leads to reduction in the tool life because of tool wear. So, the tool wear is one of the parameters which needs to be controlled at an optimum level to achieve longer tool life, better surface finish and to ensure overall machining economy.

In the past few years, analytical tools were extensively used to predict the mechanical properties and machining behavior of polymer based composites. Most widely used analytical tools were Taguchi’s Orthogonal Array (OA) tool for the experimentation and Artificial Intelligence (AI) tool for the analysis [1,2]. These two tools became popular since they consume less time and optimize 4M’s (Material, Machine, Manpower and Money). Moreover these statistical based tools help the researchers to evaluate the behavior of the material accurately before the fabrication of composite. Out of a number of AI techniques, Artificial Neural Network (ANN) became popular due to its capability to handle multivariable non-linear modeling for which an accurate analytical solution is difficult to obtain.

Artificial Neural networks are one of the most powerful Artificial Intelligence (AI) techniques and are currently being implemented in many engineering fields for modeling complex relationships between the variables, which are difficult to describe with analytical or physical models. Due to this, the application of ANN model to predict the mechanical behavior of machined materials and behavior of cutting tools became popular in the recent days. An Artificial Neural Network (ANN) is an information processing paradigm that functions in the similar lines in which the biological nervous systems, such as the brain, functions [3]. The key element of this model is the structure of the information processing system. The ANN structure combines a large number of highly interconnected processing elements or neurons working in agreement to solve specific problems.

Zhang and Fedrich [4] in their work applied ANN in predicting fatigue life, wear and dynamic loading behavior of Polymer Matrix Composite (PMC) and conclude that ANN tool could be efficiently used for predicting the mechanical behavior of PMC’s because of its likeness with the biological neurons. Hany El kadi and Yousuf Al Assaf [5] used a number of ANN models to forecast the fatigue life of unidirectional GFRE (glass fiber/epoxy) composite. Their analysis come out with a conclusion that the performance of modular network is better in predicting the fatigue life compared to feed forward network and radial basis function network. Hany El Kadi [6] in his research work made an attempt to review different work carried out on mechanical modeling of fiber composites using ANN. The work concluded that by fine tuning the ANN architecture, number of hidden layers and number of neuron in each layer, the accuracy of the result could be improved. Al-Assadi et al. [7] applied ANN to predict the fatigue life of different fiber materials like glass, carbon, kevlar which were used with polyester/epoxy matrix materials. The result showed that there is no unique ANN architecture or the training method which can produce the best result for all the materials eventhough the parameters used for manufacturing the composite remain the same. Junhui Jia, Julio F. Davalos [8] considered bonded FRP-wood composite as the study material and used ANN for forecasting the fatigue and observed that the developed ANN model had predicted the fatigue life data effectively and efficiently in comparison with experimental data. Zhenyu Jiang et al. [9] used ANN technique to predict the mechanical and wear behavior of short fiber reinforced polyamide composites. Two different sets of data were used (101 experimental data from wear test and 93 experimental data from impact, tension and bending test) to train the ANN model. The study concluded that the prediction quality improves with the increase in the number of neurons but then it decreases when the neuron number exceeds the saturation value. Wei Sha [10] investigated the machinability of non-reinforced and reinforced PEEK composite using ANN. Kranik [11] studied the effect of specific cutting pressure and the power on PEEK composite (unreinforced and carbon reinforced) using multilayer feed forward network. The outcome of the research inferred a nonlinear relationship between response parameter and input parameter (cutting conditions). Zhang et al. [12] has used back propagation multilayer perceptron neural network training algorithm for predicting the coefficient of friction and specific wear rate of polymer composite and come out with the results informing that the ANN can be effectively and efficiently used as a mathematical tool in material design, process parameter study and characterization analysis of polymer matrix composites.

2. Materials and Methods

2.1 GFRP Material Fabrication:

The GFRP composite laminate was fabricated using hand lay-up process (Figure 1). A fiber weight fraction of 33% was considered by taking Isophthalic polyester as resin and structural glass fiber with random orientation as the fiber material. Poly Ether Ether Ketone was added as the hardener material during the processing of the GFRP composite. Each laminate measuring a volume of 600×600×10 mm^3 was fabricated. The laminate was hardened under atmospheric temperature and pressure conditions for a period of 24 hours. The GFRP laminate thickness was maintained at 10mm and was used for machining operation.

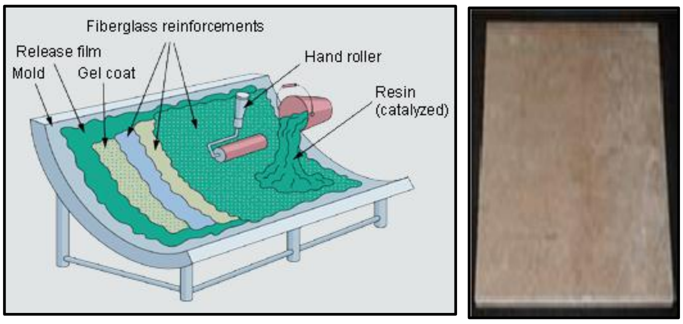

Figure 1: Schematic of hand lay-up technique and fabricated GFRP

The wear data is collected from the experimental work by considering drilling process parameters and their different levels [19]. In order to maintain accuracy and data reliability, the dry drilling operation on the GFRP composite was carried out using Computer Numerically Controlled (CNC) Vertical Machining Center (VMC) (Figure 2).

Figure 2: CNC Vertical Machining Centre

Figure 3: Holes drilled on the work piece for each experimental run

The machining was carried out by drilling 80 holes (Figure 3) on the GFRP composite laminate using 3 machining factors and 3 levels of each factor as shown in Table1. Taguchi's Design of Experiments (DoE) was applied and 81 experimental runs (L27 orthogonal array with 3 trials for each run to maintain the accuracy) were planned by considering these factors and levels. The drilled holes were spaced on the GFRP laminate as per the drill hole specifications and standards for fasteners. Figure 3 shows the 80 holes drilled on the GFRP composite laminate [20].

Table 1: Machining Factors and levels

Symbol	Factors	No. of Levels		
		Level 1	Level 2	Level 3
A	Speed (rpm)	1200	1500	1800
B	Feed (mm/rev)	0.1	0.2	0.3
C	Drill diameter (mm)	6	8	10

Dataset preparation and data collection for Artificial Neural Network (ANN)

The ANN network structure of input and output parameters for training and testing the flank wear prediction is shown in Figure 4. The data set containing 81 observations was split into training and testing sets. Approximately 75% of the total observations (i.e., 60 observations) were used for ANN training and 25% of the total observations (i.e., 21 observations) were used for testing the ANN model. The data sets were designed for fixed data method (i.e., considering first 60 data for training and the next 21 for testing).

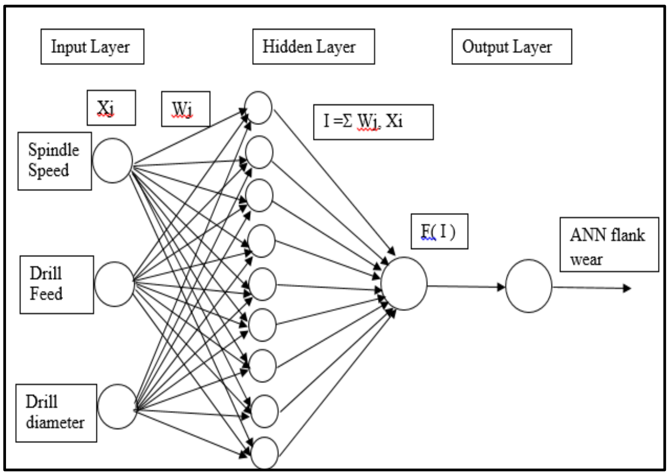

Figure 4. ANN network structure of input and output parameters for the flank wear prediction.

The optimum training method was selected based on the R^2 value, number of neurons in the hidden layer, training and testing accuracy, mean square error and minimum number of epochs required to converge the network.

For almost all the ANN simulation models some amount of pre-processing is always carried out on the input and output raw data in order to normalize and make it suitable for the network. The dataset used in the present study was normalized using column normalization in MATLAB software.

Each experimental run was executed with a fresh GFRP composite laminate and a fresh drill bit. 80 holes were drilled on the laminate by considering the optimum GFRP material consumption using CATIA software. The drill flank wear was calculated by measuring the difference in the drill land width before and after the machining. The calculated flank wear values for each experimental run and for training and testing the ANN are shown in Table 2.

Table 2. Experimental Flank wear data used for training and testing ANN

Expt. No.	Spindle Speed (rpm)	Drill Feed (mm/rev)	Drill Diameter (mm)	Flank wear (Experimental) (mm)
1	1800	0.1	6	0.312
2	1800	0.1	8	0.319
3	1500	0.2	10	0.296
4	1200	0.2	8	0.238
5	1200	0.1	8	0.284
6	1500	0.3	6	0.225
7	1500	0.3	10	0.292
8	1800	0.2	8	0.31
9	1200	0.2	10	0.298
10	1200	0.2	6	0.256
11	1500	0.1	8	0.311
12	1800	0.1	10	0.365
13	1500	0.2	8	0.284
14	1500	0.1	10	0.314
15	1200	0.3	6	0.218
16	1800	0.2	10	0.323
17	1200	0.1	10	0.272
18	1200	0.1	6	0.316
19	1500	0.1	6	0.273
20	1800	0.3	8	0.304
21	1500	0.2	6	0.254
22	1200	0.3	8	0.222
23	1200	0.3	10	0.271
24	1800	0.3	6	0.233
25	1800	0.2	6	0.281
26	1500	0.3	8	0.248
27	1800	0.3	10	0.306
28	1800	0.1	6	0.323
29	1800	0.1	8	0.318
30	1500	0.2	10	0.287
31	1200	0.2	8	0.241
32	1200	0.1	8	0.274
33	1500	0.3	6	0.226
34	1500	0.3	10	0.286
35	1800	0.2	8	0.336
36	1200	0.2	10	0.275
37	1200	0.2	6	0.233
38	1500	0.1	8	0.29
39	1800	0.1	10	0.34

Expt. No.	Spindle Speed (rpm)	Drill Feed (mm/rev)	Drill Diameter (mm)	Flank wear (Experimental) (mm)
40	1500	0.2	8	0.261
41	1500	0.1	10	0.302
42	1200	0.3	6	0.216
43	1800	0.2	10	0.334
44	1200	0.1	10	0.263
45	1200	0.1	6	0.287
46	1500	0.1	6	0.296
47	1800	0.3	8	0.29
48	1500	0.2	6	0.252
49	1200	0.3	8	0.219
50	1200	0.3	10	0.234
51	1800	0.3	6	0.238
52	1800	0.2	6	0.302
53	1500	0.3	8	0.259
54	1800	0.3	10	0.318
55	1800	0.1	6	0.325
56	1800	0.1	8	0.31
57	1500	0.2	10	0.301
58	1200	0.2	8	0.268
59	1200	0.1	8	0.246
60	1500	0.3	6	0.212
61	1500	0.3	10	0.274
62	1800	0.2	8	0.286
63	1200	0.2	10	0.261
64	1200	0.2	6	0.246
65	1500	0.1	8	0.29
66	1800	0.1	10	0.336
67	1500	0.2	8	0.268
68	1500	0.1	10	0.287
69	1200	0.3	6	0.214
70	1800	0.2	10	0.336
71	1200	0.1	10	0.269
72	1200	0.1	6	0.301
73	1500	0.1	6	0.304
74	1800	0.3	8	0.26
75	1500	0.2	6	0.256
76	1200	0.3	8	0.213
77	1200	0.3	10	0.263
78	1800	0.3	6	0.225
79	1800	0.2	6	0.291
80	1500	0.3	8	0.251
81	1800	0.3	10	0.322

Table 2 Continued…

Drill flank wear simulation using different ANN algorithms

Seven different ANN back propagation algorithms were used for the simulation and each algorithm took the data collected from experimental flank wear (Table 2) to simulate the flank wear model. The algorithms selected for flank wear simulation are

1. Resilient back propagation (RP)
2. Gradient descent back propagation (GD)
3. Scaled conjugate gradient back propagation (SCG)
4. BFGS quasi-Newton back propagation (BFG)
5. Conjugate gradient back propagation with Polak-Ribiére updates (CGP)
6. Gradient descent with adaptive learning rate back propagation (GDA)
7. Levenberg-Marquardt back propagation (LM)

Neural Network Toolbox of MATLAB software was used for all the above training algorithms. The learning function could be applied to individual weights and biases within the network. All these network training functions update weight and bias values according to the respective algorithm methods. Learning functions were used to adapt networks and the present research had used Gradient Descent with Momentum weight and bias LEARNing function (LEARNGDM) for learning and TANgent SIGmoid (TANSIG) as the transfer function for the network designed.

In the training stage, in order to obtain the output (drill flank tool wear) precisely and to design the best network architecture, each algorithm was tested with the sigmoid transfer function and the number of neurons in the hidden layer was varied from 2–9. Thus all the seven neural network structures were examined by changing the number of neurons in the hidden layer from 2 to 9. Thus the neural networks with architecture 3-2-1, 3-3-1, 3-4-1, 3-5-1, 3-6-1, 3-7-1, 3-8-1 and 3-9-1 were considered for simulation and optimization of the drill flank wear.

The artificial neural network thus developed was trained by setting the training epochs (cycles) to 1,000 for each network architecture. The objective of the training was to minimize the Mean Square Error (MSE). For this, a computer program was developed in MATLAB software to predict the flank tool wear in the machining of GFRP composites using HSS drill.

Gradient Descent Method (GDM) was used to minimize the mean squared error between the network output and the actual error rate. The training error continued to decrease as the number of epoch's increased. Repeated runs were performed to get the neural network converged. Weights were initialized to random values and networks are run until at least one of the following termination conditions was satisfied:

1. Maximum Epoch

2. Minimum Gradient

3. Performance Goal

Training and learning functions are the 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. For testing, the input data was presented to the ANN without weight adjustment. The output of the ANN was compared with the existing output of the datasets. The different statistical parameters for the comparison of ANN model for all the training algorithms are given in Table 3. The efficiency of the network was measured by taking one of the following parameters into account:

1. R^2 value
2. Number of epochs taken to converge the network.
3. The Mean Square Error (MSE) calculated.

Table 3: Results of the Simulation of flank wear using different ANN algorithm

Algorithm	Nu	Epochs	MSE	Cl_Ac_Trg	Cl_Ac_Tst	MRE_Trg	MRE_Tst	R^2
RP	2	1000	0.0125	61.67	52.38	4.926	5.94	0.99596
	3	1000	0.0078	71.67	80.95	3.77	4.06	0.99762
	4	1000	0.0085	66.67	61.90	4.12	4.69	0.99727
	5	1000	0.0126	60.00	52.38	5.00	5.92	0.99594
	6	1000	0.0125	60.00	52.38	4.97	6.01	0.99597
	7	1000	0.0125	60.00	52.38	4.996	5.98	0.99597
	8	1000	0.0062	76.67	76.19	3.43	3.77	0.99799
	9	1000	0.0125	60.00	52.38	4.999	5.95	0.99596
GD	2	1000	0.0135	56.67	47.62	5.349	6.07	0.99515
	3	1000	0.0134	51.67	52.38	5.396	6.08	0.99575
	4	1000	0.0125	56.67	52.38	4.959	5.84	0.99597
	5	1000	0.0126	58.33	52.38	4.968	5.942	0.99594
	6	1000	0.0125	60.00	52.38	4.984	5.94	0.99597
	7	1000	0.0125	60.00	52.38	5.008	5.91	0.99594
	8	1000	0.0125	60.00	52.38	5.002	5.96	0.99596
	9	1000	0.0125	61.67	52.38	5.006	5.93	0.99596
SCG	2	343	0.008	70.00	57.14	3.78	4.51	0.99749
	3	1000	0.0058	78.33	80.95	3.26	3.76	0.99810
	4	1000	0.0044	83.33	71.43	3.03	4.17	0.99827
	5	1000	0.0041	86.67	66.67	2.98	4.28	0.99829
	6	1000	0.0039	90.00	71.43	2.88	4.21	0.99833
	7	1000	0.0038	90.00	71.43	2.87	4.234	0.99832
	8	1000	0.0039	90.00	71.43	2.86	4.20	0.99832
	9	765	0.0038	90.00	71.43	2.872	4.235	0.99832
BFG	2	116	0.0080	70.00	57.14	3.78	4.50	0.99748
	3	1000	0.0068	71.67	76.19	3.55	3.36	0.99814
	4	1000	0.0056	76.67	80.95	3.10	3.93	0.99812
	5	1000	0.0048	81.67	71.43	3.17	3.57	0.99826
	6	1000	0.0040	83.33	76.19	2.86	6.16	0.99832
	7	1000	0.0052	90.00	76.19	2.87	4.18	0.99835
	8	1000	0.0049	88.33	76.19	2.871	4.21	0.99831
	9	1000	0.0052	90.00	71.43	2.874	4.23	0.99832
CGP	2	165	0.0080	70.00	57.14	3.78	4.50	0.99748
	3	337	0.0061	73.33	76.17	3.42	3.672	0.99804
	4	1000	0.0053	78.33	71.43	3.17	3.673	0.99828
	5	1000	0.0047	86.67	71.43	2.98	3.95	0.99824
	6	1000	0.0039	88.33	71.43	2.91	4.13	0.99834
	7	612	0.0038	90.00	71.43	2.872	4.234	0.99833
	8	738	0.0038	90.00	71.43	2.875	4.235	0.99833
	9	414	0.0038	90.00	71.43	2.873	4.237	0.99832
	2	759	0.0079	73.33	71.43	3.71	4.06	0.99755
	3	976	0.0065	73.33	76.19	3.51	3.813	0.99797

GDM	4	985	0.0071	71.67	76.19	3.61	3.815	0.99784
	5	987	0.0067	70.00	76.19	3.602	3.998	0.99792
	6	983	0.0075	73.33	71.43	3.604	3.980	0.99766
	7	999	0.0066	75.00	76.19	3.61	3.86	0.99793
	8	954	0.0077	73.33	71.43	3.70	4.08	0.99761
	9	996	0.0075	73.33	71.43	3.603	3.984	0.99765
LM	2	1000	0.0077	76.67	57.14	3.72	4.66	0.99749
	3	218	0.0057	80.00	80.95	3.25	3.79	0.99811
	4	225	0.0042	86.67	71.43	2.93	4.05	0.99827
	5	***37***	***0.0038***	***91.67***	***71.43***	***2.870***	***4.22***	***0.99834***
	6	60	0.0039	90.00	71.43	2.874	4.24	0.99832
	7	1000	0.0039	90.00	71.43	2.873	4.20	0.99833
	8	60	0.0038	90.00	71.43	2.874	4.23	0.99832
	9	1000	0.0038	90.00	71.43	2.874	4.24	0.99832

From Table 3 it was evident that the statistical parametric results of Levenberg Marquardt algorithm (LM algorithm) were the best ones compared to other algorithms. TrainLM was a network training function that updated weight and bias values according to Levenberg-Marquardt optimization. TrainLM was found as the fastest back propagation algorithm in the toolbox, and was highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. Because of these reasons, is considered as the best ANN algorithm for the simulation of HSS drill flank wear simulation while machining GFRP composites for the specified experimental conditions**.**

The training stops when any of these condition occurs:

The maximum number of epochs (repetitions) is reached.

The maximum amount of time is exceeded.

Performance is minimized to the goal.

Model summary of Levenberg-Marquardt Algorithm

Table 4 shows the detailed summary of the LM-ANN algorithm.

Table 4: Summary of the LM ANN algorithm	
Object modeled	Drill Flank wear
Input Neuron	Spindle speed, Drill feed and Drill diameter
Network Structure	
Network Type	Feed forward back Propagation
Transfer Function	Tansig
Training Function	Network training function that updates weight and bias values
Learning Function	Gradient descent with momentum back propagation Method
Learning Conditions	
Learning Scheme	Supervised learning
Learning Rule	Gradient descent rule

Input Neuron	Four
Output Neuron	One
Sample pattern vector	60 (For training), 21(for testing)
Number of hidden layer	01
Neurons in hidden layer	02 - 09
Learning rate	0.1
Minimum performance Gradient	1e-10
Maximum mu	1e10
Performance goal/Error goal	1e-10
Maximum epochs(cycles) set	1000
R^2 at the end of the training	0.99843
MRE at the end of the training	0.0038
Number of Epochs	37

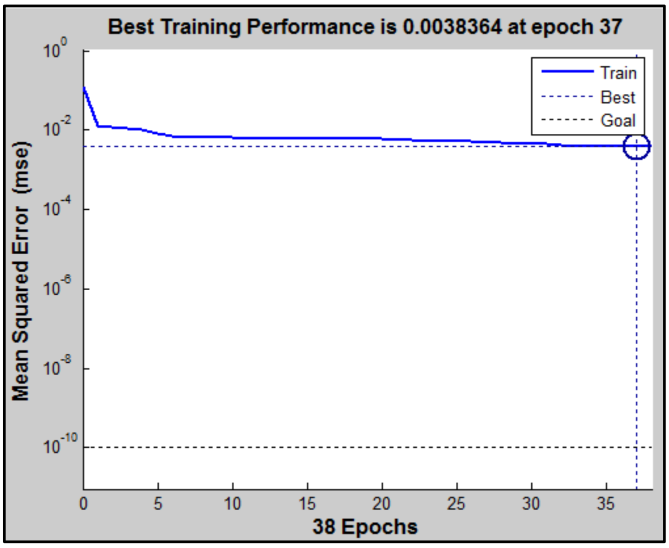

Figure 5. Graphical representation of ANN performance

RESULTS AND DISCUSSION

In this research work, a computer program was developed in MATLAB platform to predict the drill flank wear. The input parameters of the network were spindle speed, drill feed and drill diameter whereas its output parameter was drill flank wear. The network algorithms and statistical parameters of ANN model for the learning algorithms were given in Table 4. It was apparent from Table 2 that, the prediction performances for both training and testing sets of the tool wear showed a quite satisfactory accuracy (error < 5%). The R^2 values of the learning algorithms for both training and testing sets were higher than 0.99 (0.9983). The LM learning algorithm reached to optimal solutions with smaller number of neurons (5) in hidden layer and with minimum number of epochs (37) when compared to other learning algorithms. Also from the results of the simulation (Table 3), it was evident that the performance of LM algorithm in simulating the process parameters for predicting drill flank wear was better even with respect to other parameters. Another remarkable point in Table 3, was that the best results were obtained with 3-5-1 network configuration (with Training Accuracy = 91.67%) of Lavenberg Marquedt (LM) algorithm, which itself indicates the optimal network structure for predicting the drill flank wear.

So, from all the above observations, findings and results it can be concluded that Lavenberg Marquedt algorithm can perform better compare to other ANN algorithms in simulating the drill process parameters for predicting the drill flank wear for the identified work material, tool material and machining conditions

CONCLUSIONS

In this work, ANN simulation of Flank tool wear of the drill was carried out for the machining of GFRP composite material for different combinations of cutting parameters. This study also deals with selection of best ANN algorithm for the prediction of drill flank wear. An ANN model for predicting the drill tool wear was developed using experimental values. Then, the performance of the ANN model were evaluated by comparing the performance of different back propagation algorithms. After training it was concluded that, out of the seven learning algorithms compared, the best and fastest ANN results were obtained by the Lavenberg Marquedt (LM) learning algorithm with the following findings:

1. Best results were obtained with 3-5-1 network structure configuration and with a Training Accuracy of 91.67% using Levenberg-Marquardt (LM) algorithm.
2. It was observed that the R^2 value for all the flank wear data simulation using LM algorithm was found to be 0.998324 which was learned to be very satisfactory.

Therefore, instead of expensive and time-consuming experiments, it was highly recommended the usage of ANN in predicting the tool flank wear in the drilling of GFRP composite materials using HSS tools.

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