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Artificial Neural Network Model to Predict Process Performance in Ultrasonic Drilling of GFRP

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Abstract — *The prediction of process performance is essential to select the control parameters for obtaining the goals of production. Ultrasonic machining is popular material removal process brittle materials like glass, ceramics etc. Glass Fiber Reinforced Plastic (GFRP) is a widely used engineering material in number of engineering applications. Experiments are conducted to obtain data regarding the effect of process parameters on ultrasonic drilling of GFRP. Amplitude, pressure and thickness of the glass sheet are chosen as control parameters. Three levels of each of these parameters are selected giving 3^3 = 27 trials. Material removal rate (MRR), overcut (OC), taper produced on the drilled holes, delamination on top and bottom surfaces are determined as response parameters. Artificial Neural Network (ANN) model is developed to capture relationship between control and response parameters as a predictive tool to predict the performance of the process.*

Keywords*-Ultrasonic Machining, GFRP, ANN*

I. INTRODUCTION

Ultrasonic machining offers a solution to the problem of brittle materials increasing complex operations to provide intricate shapes and workpiece profiles. Ultrasonic machining process is non-thermal, non-chemical, creates no change in the microstructure, chemical or physical properties of the workpiece and offers virtually stress-free machined surfaces. Ultrasonic machining is therefore used extensively in machining hard and brittle materials that are difficult to cut by other conventional methods [1]. The nature of ultrasonic process is so complex that the selection of the process parameters for this process requires a lot of experience and understanding and in many cases a lot of preliminary trials are essential to establish the correct parameters. ANN modeling encompasses very sophisticated techniques capable of modeling complex functions and processes. Advantage of neural networks lies in their ability to represent both linear and nonlinear relationships as well as having the capability of learning by example. For processes that have non-linear characteristics such as those found in manufacturing processes, traditional linear models are simply inadequate. In comparison to traditional computing methods, neural networks offer a different way to analyze data and to recognize patterns within that data by being generic non-linear approximations. Artificial Intelligence (AI) techniques seem to be best solution for prediction for multivariable controlled systems [2].

Experiments are conducted to perform ultrasonic drilling on GFRP and data is generated for development of ANN model. Full factorial experiments are conducted for ultrasonic drilling of GFRP and data obtained as an outcome of experiments is used for developing and validating ANN model.

II. ULTRASONIC DRILLING EXPERIMENTS ON GFRP

A full factorial design of experiment with replication is used with three control factors – amplitude, pressure and thickness of the GFRP sheet. Three values selected for the low, medium and high level for each of the control parameters as listed in Table 1. The amplitude is varied in terms of percentage of amplitude delivered at full power by the converter.

Table 1. Parameters and their Levels

Amplitude	Pressure	GFRP Thickness
A_1 = 70%	P_1 = 1 bar	t_1 =1.3 mm
A_2 = 80%	P_2 = 2 bar	t_2 =2 mm
A_3 = 90%	P_3 = 3 bar	t_3 = 2.3 mm

Material removal rate (MRR), overcut (OC), taper and delamination on top and bottom surfaces are selected as response parameters. Conical sonotrode is designed and manufactured as amplitude of propagated sound wave is inversely proportional to the cross-sectional area in solids. The shape of the tool is obtained at the end of the sonotrode itself. An approximate gain of 3 is selected for the sonotrode. The design of the sonotrode is carried out using CARD (Computer Aided Resonator Design) software.

The detailed procedure followed for ultrasonic blanking is described as under:

1) Select glass sheet and measure its weight.

2) Melt the mounting wax in beaker and pour it in petri-dish.
3) Place the GFRP sheet having aluminium foil attached at its bottom in wax and allow curing.
4) Prepare slurry having 27% concentration.
5) Securely tighten the sonotrode.
6) Start slurry circulation and adjust the flow.
7) Set the control parameters.
8) Start vibrations using foot switch.
9) Start machining holding petri-dish in hand.
10) Machining is completed when through cut is obtained.
11) Record machining time using stopwatch.
12) Switch off slurry pump and clean the blank by washing it in Acetone.
13) Remove workpiece from petri-dish.
14) Measure the weight of cut blank and slide.

The material removed on weight basis is obtained by subtracting the sum of mass of blank and mass of slug from the mass of GFRP sheet before machining. The MRR is then obtained in terms of volumetric material removal rate by taking density of GFRP. The top and bottom diameters of each drilled hole were measured using 0.1 micron accuracy travelling microscope four times by changing the position. Average of these values was taken as the value for top and bottom diameters. The value of OC was determined by halving the difference between larger of the top and bottom hole diameters and the tool diameter which is 8 mm. Taper was obtained by dividing the difference between top and bottom diameters by the thickness. The delamination factor is measured by taking ratio of maximum diameter of hole to sum of the diameter of tool and abrasive particle size The experimental results are listed in Table 2.

Table 2 Experimental Results

Sr. No.	Std. Th. mm	Amp. micron	Pre. bar	O.C. H_1 mm	Taper H_1 mm/mm	MRR H_1 mm^3/min	Top DF H_1	Bot. DF H_1
1	1.3	36.82	1	0.085	0.017	28.460	1.000	1.080
2	1.3	36.82	2	0.100	0.186	38.015	1.023	1.037
3	1.3	36.82	3	0.110	0.077	28.409	1.000	1.085
4	1.3	42.08	1	0.123	0.153	30.823	1.000	1.044
5	1.3	42.08	2	0.124	0.111	23.514	1.000	1.082
6	1.3	42.08	3	0.124	0.028	38.010	1.031	1.077
7	1.3	47.34	1	0.126	0.025	33.628	1.000	1.079
8	1.3	47.34	2	0.136	0.094	38.226	1.000	1.074
9	1.3	47.34	3	0.136	0.126	31.140	1.034	1.073
10	2	36.82	1	0.120	0.095	13.508	1.081	1.053
11	2	36.82	2	0.091	0.069	14.441	1.072	1.073
12	2	36.82	3	0.090	0.072	16.815	1.015	1.085
13	2	42.08	1	0.112	0.092	25.802	1.017	1.073
14	2	42.08	2	0.114	0.043	26.192	1.041	1.071
15	2	42.08	3	0.115	0.066	29.632	1.033	1.049
16	2	47.34	1	0.120	0.155	37.998	1.026	1.044
17	2	47.34	2	0.120	0.093	40.785	1.040	1.023
18	2	47.34	3	0.200	0.000	44.995	1.097	1.050
19	2.3	36.82	1	0.069	0.086	14.778	1.000	1.035
20	2.3	36.82	2	0.090	0.050	20.179	1.053	1.073
21	2.3	36.82	3	0.105	0.073	17.603	1.055	1.052
22	2.3	42.08	1	0.126	0.063	21.707	1.000	1.025
23	2.3	42.08	2	0.150	0.017	24.250	1.034	1.044
24	2.3	42.08	3	0.069	0.048	24.908	1.046	1.084
25	2.3	47.34	1	0.158	0.032	27.170	1.000	1.031
26	2.3	47.34	2	0.158	0.066	26.750	1.000	1.029
27	2.3	47.34	3	0.189	0.052	31.734	1.000	1.024

III. ANN MODELING

Among the various kinds of ANN approaches that exist, the back propagation learning algorithm, which has become the most popular in engineering applications, is selected for use in this study. Networks have one input layer, one or more hidden layer(s) and one output layer. To train and test the neural networks, input data patterns and corresponding targets are required. In developing ANN model, the data obtained by experimental tests for ultrasonic drilling of GFRP is utilized. The mathematical background, the procedures for training and testing the ANN and account of its history is available for details [4]. The amplitude, pressure and thickness of work are represented as input data while material removal rate, taper, overcut, top delamination factor (TOPDF) and bottom delamination factor (BOTTOMDF) are output. A number of architectures of feed forward back propagation type of neural network are tested for modeling of the ultrasonic drilling process parameters in this work. The procedure involved in developing neural network model for ultrasonic drilling is depicted in Figure 1

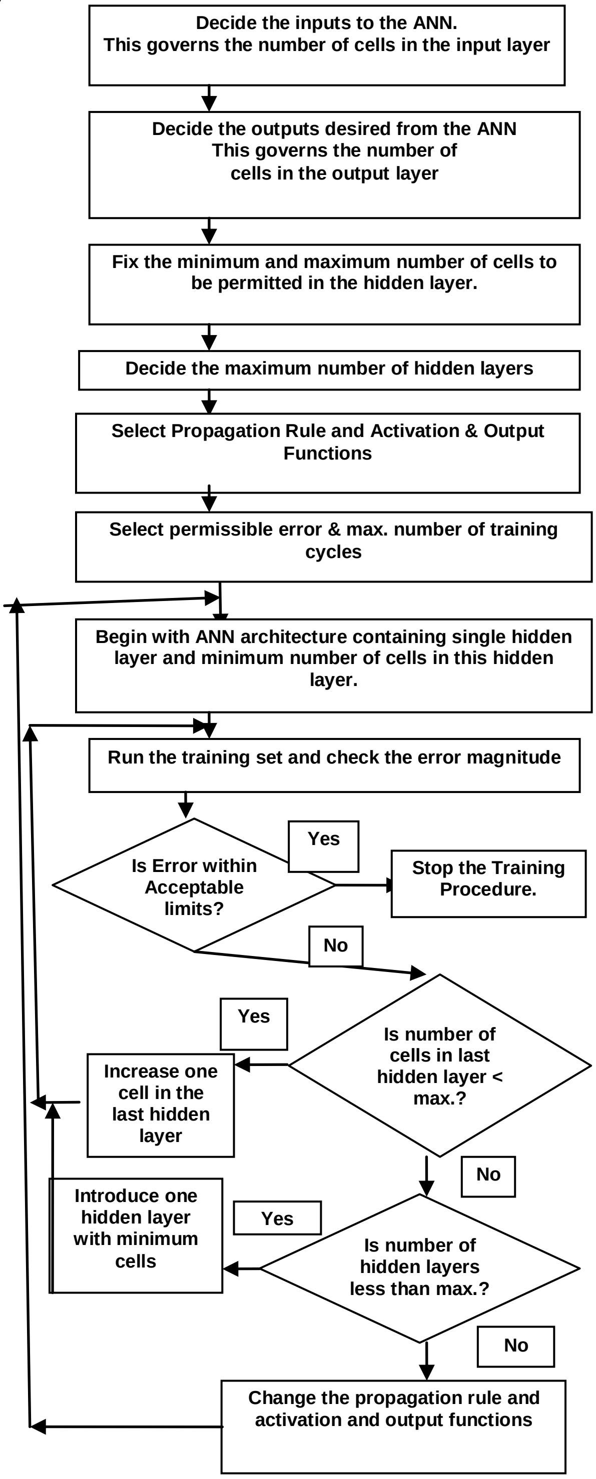

Figure 1. ANN Modeling Procedure

The steps listed in the flow chart for development of neural networks models in Figure 1 are applied to this case as indicated in Table 3 for decision of the inputs, outputs, number of hidden layers and number of cells in each hidden layer. The criteria for the termination of training selected are permissible error for training & validation sets and maximum number of cycles in training. For this case, the limiting value of maximum, minimum and average error is set as 2% and the permissible error for validation sets is specified as 5% of the target value. It is observed that for many attempts, the all errors are limited below 2% but not for all architectures. Some of them do not yield a trained network even after the 100000 number of training cycles. Thus, training stops when any one of the above criteria, namely, all errors being less than 0.05, all validation points within 0 5% of target values being completed. The learning rates and momentum are kept as 0.6 and 0.8 respectively to facilitate stable and quicker learning by larger variation in weights so that a larger set of weight values are explored within the number of learning cycles permitted. Beginning with a 3,11,5 architecture and training parameters as described, the first architecture with single hidden layer is evaluated. It does not pass the error criteria till the end of prescribed 100000 cycles . Subsequently, following the strategy discussed in Figure 1. the number of cells in the hidden layers are increased one at a time up to 15. Thereafter, ANN architectures with two hidden layers and three hidden layers are evaluated in a similar fashion.

TABLE 3. Neural Network Modeling for Ultrasonic Drilling Process Modeling

Network Type	Feed Forward
Input for the neural network model	Amplitude, Pressure, Thickness
Number of nodes in input layer = Number of inputs to the neural network model	3
Output from the neural network model	MRR, taper, OC, TOPDF, BOTTOMDF
Number of nodes in output layer = Number of outputs from the neural network model	5
Initial Number of Hidden Layers	1
Maximum Number of Hidden Layers	3
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

IV. RESULTS & DISCUSSION

By principle of a trial and error ANN modeling is processed in terms of determining the most suitable architecture for a given system. The R test is one way of ascertaining the best network model. Another faster method is to compare the average or RMS error values. These values can be determined using standard formulae (Eqs. (i~iii)).

$$\mathrm{Error\%} = \frac{|A_e - A_P|}{A_e} \tag{i}$$

$$\mathrm{Error}_{rms} = \sqrt{\sum_{i=1}^{N} \frac{1}{N}\left(\frac{A_e - A_P}{A_e}\right)^2} \tag{ii}$$

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N}\frac{A_e}{A_P} \tag{iii}$$

Network architectures with 25 different configurations are attempted for training and it is observed that the network architectures having one hidden layer could not be trained to meet the error limitations even with high number of cells. Eighteen different architectures are tested successfully and the results of training these networks are listed in Table 4.

It is observed from Table 4 that the value of R is closest to unity for 3-9-7-6-5 architecture. Hence, the architecture 3-9-7-6-5 is chosen as the best representative model for this case. The 3-9-7-6-5 architecture and its error propagation during training are shown in Figure 2 and Figure 3 respectively.

Table 4 ANN Architecture Test Results

Sr. No.	Model Structure	Avg. Error	Min. Error	Max. Error	Error RMS	No. of Cycle	R value	RANK
1	3-11-5	19.6284	0.1613	93.7217	0.2712	100000	1.1280	14
2	3-12-5	17.3009	0.6700	78.1913	0.2306	1344	0.8815	12
3	3-13-5	15.6445	0.8750	47.0229	0.1986	14396	0.8840	11
4	3-14-5	20.6679	4.1067	70.0174	0.2511	1010	1.1515	17
5	3-15-5	15.9597	1.2063	43.0425	0.2106	1602	1.1532	18
6	3-6-6-5	15.2090	0.0393	41.2407	0.1866	100000	0.8929	6
7	3-6-7-6	23.8570	0.1467	58.6170	0.2836	100000	1.2838	24
8	3-7-7-5	15.1537	0.8094	73.5971	0.2147	42858	1.0770	3
9	3-8-7-5	21.6644	1.1875	50.1890	0.2676	4069	1.1098	7
10	3-7-8-5	11.8710	0.5704	40.9039	0.1499	1216	1.0591	2
11	3-8-8-5	16.7213	0.5391	45.1238	0.2036	2122	1.2067	21
12	3-8-9-5	17.4008	1.0309	38.2409	0.2089	946	0.8856	9
13	3-9-8-5	17.4702	0.9665	61.1024	0.2426	3127	0.8862	8
14	3-9-9-5	13.8688	0.6063	53.5935	0.1837	2499	0.8959	5
15	3-6-6-6-5	24.9829	1.5859	129.2783	0.3511	100000	1.1799	20
16	3-6-7-6-5	21.9431	0.0671	120.2870	0.3211	100000	1.1356	15
17	3-6-7-7-5	18.3722	0.5323	48.7270	0.2221	6663	1.2310	22
18	3-7-7-7-5	32.5930	1.9626	173.8261	0.4618	100000	1.2539	23
19	3-7-8-7-5	30.3915	1.0947	96.9913	0.3680	100000	1.3307	25
20	3-7-6-6-5	12.7229	0.8163	52.5191	0.1632	65745	1.0836	4
21	3-8-8-8-5	20.8929	1.2067	58.9826	0.2474	6061	1.1795	19
22	3-9-7-6-5	12.7625	0.3705	44.6036	0.1680	13457	1.0581	1
23	3-9-8-7-5	17.4958	0.9127	71.2435	0.2249	6249	1.1214	13
24	3-9-9-9-5	23.6770	0.5587	83.1800	0.3070	1025	0.8844	10
25	3-10-10-10-5	18.9548	1.0154	63.2061	0.2590	962	0.8592	16

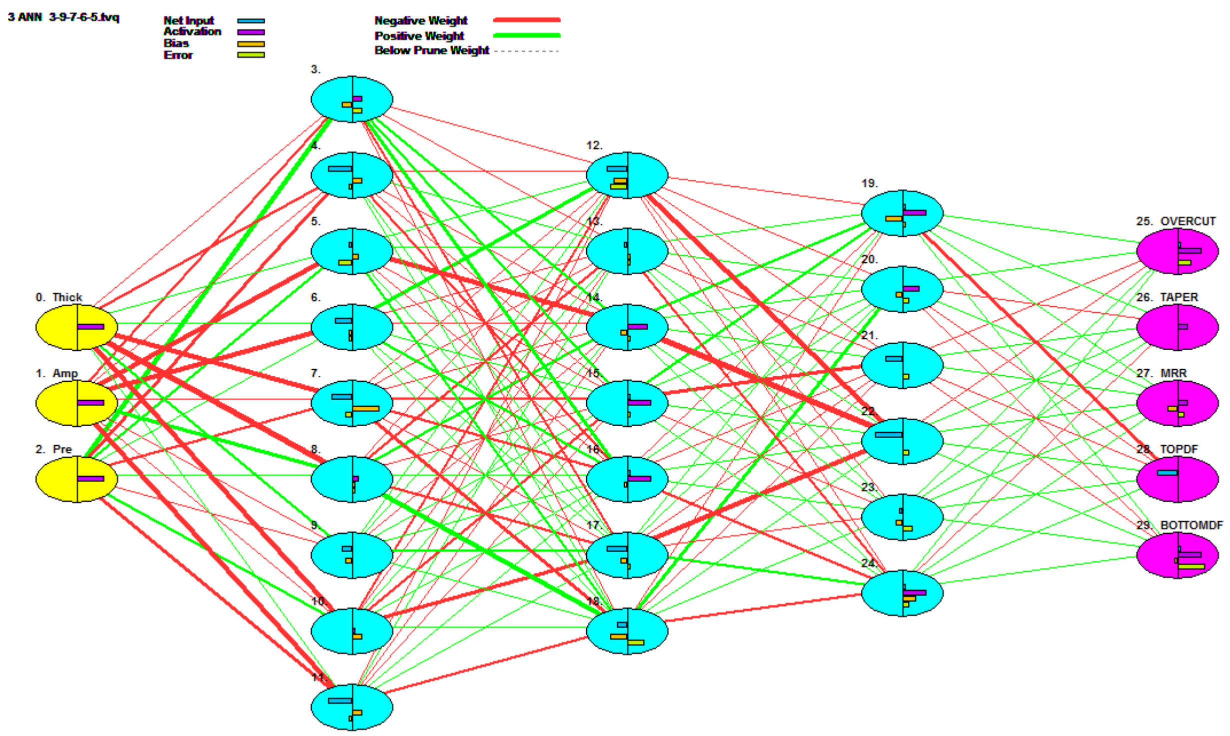

Figure 2. ANN Model Architecture for 3.9,7,6,5 model

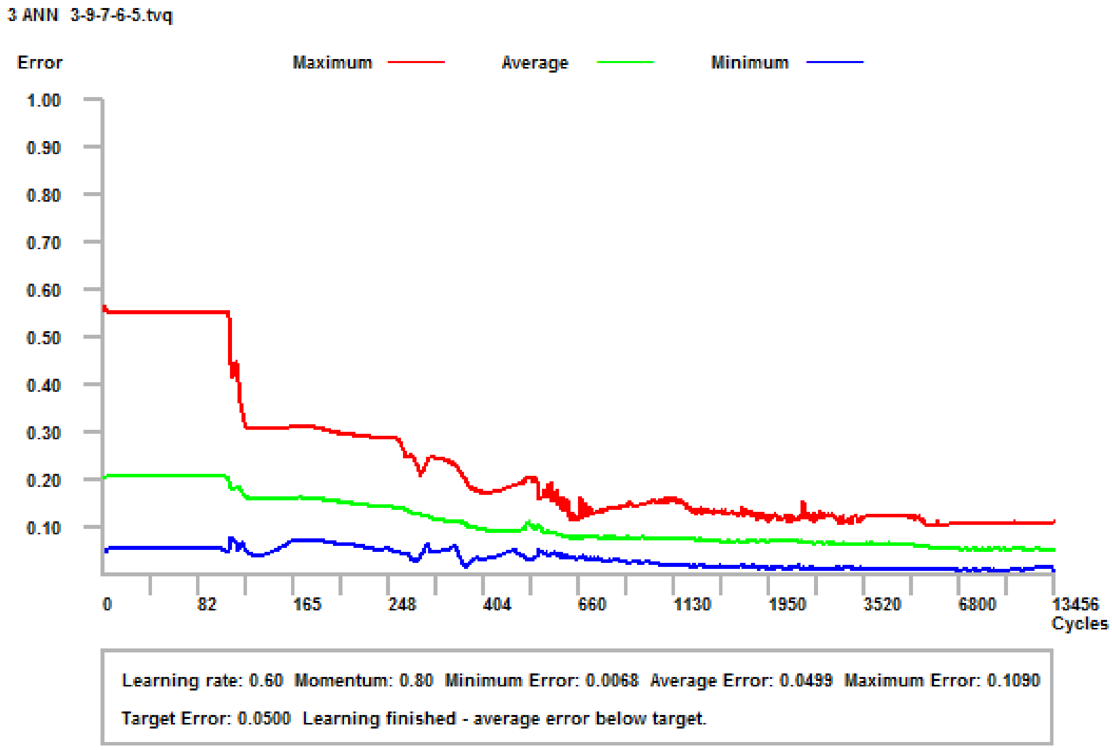

Figure 3. ANN model training & error propagation with increasing training cycles for the 3-9-7-6-5 architecture

IV. CONCLUSION

Numerous architectures are tried to develop suitable ANN model for predicting performance in terms of material removal rate, taper, overcut and delamination for ultrasonic drilling of GFRP. A feed forward back propagation neural network model with a 3-9-7-6-5 configuration is found most suitable. This approach can be considered as an alternative to practical technique to predict the process outcome. template will number citations consecutively within brackets [1]. The sentence punctuation follows the bracket [2].

REFERENCES

[1] P. L. Guzzo, A. H. Shinohara, and A. A. Raslan, “A Comparative Study on Ultrasonic Machining of Hard and Brittle Materials”, Presented at COBEF 2003 – II Brazilian Manufacturing Congress, Uberlândia, MG. Brazil, , pp 57-61, 18-21 May, 2003.

[2] D. Anderson, and G. Mcneil, Artificial neural networks technology, DACS State-of-the-Art Report. ELIN: A011, Rome Laboratory, RL/C3C Griffiss AFB, NY 13441-5700, 20 August 1992

[3] S. Haykin, Neural Networks, A comprehensive foundation, McMillian College Publishing Co. New York, 1994.

