Predictive Model for Ultrasonic Slitting of Glass using Feed Forward Back Propagation Artificial Neural Network

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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 is a widely used engineering material in number of engineering applications like microscopy, optics etc. In this paper, experiments are conducted to obtain data regarding the effect of process parameters on ultrasonic slitting in common glass. Amplitude, pressure and thickness of the glass sheet are chosen as control parameters. Three levels of each of these parameters are selected giving 33 = 27 trials. Material removal rate (MRR), overcut (OC), taper produced on the slits 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.

Key words: Material Removal Rate, Overcut, Artificial Neural Network

I. INTRODUCTION

Ultrasonic machining is a preferred solution to the problem of machining brittle materials requiring 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 slitting on common glass and data obtained by experimental trials is used for development of ANN model and validating it.

II. ULTRASONIC SLITTING EXPERIMENTS

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

Amplitude (A)	Pressure (P)	Glass Sheet Thickness (T)
A1 = 70%	P1 = 0.5 bar	t1 =1.23 mm
A2 = 80%	P2 = 2 bar	t2 =2.16 mm
A3 = 90%	P3 = 3.5 bar	t3 = 3.12 mm

Table I: Parameters And Their Levels

Material removal rate (MRR), overcut (OC) and taper generated during slitting are taken as response parameters representing process behaviour. Taper cylindrical sonotrode is designed and manufactured as amplitude of propagated sound wave is inversely proportional to the cross-sectional area in solids. Sonotrode with and approximate gain of 3 is designed using CARD (Computer Aided Resonator Design) software.

The experimental procedure for slitting in glass using ultrasonic machining process is described as under.

1) Select glass sheet and measure its weight for the trial.
2) Melt the mounting wax & pour it in petri-dish.
3) Place the glass sheet 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 sheet by washing it in Acetone.
13) Remove workpiece from petri-dish.
14) Measure the weight of slide.

The material removed during the slitting process is determined by subtracting the mass of glass sheet after machining from the mass of sheet before machining. The MRR is then obtained in terms of volumetric material removal rate considering density of common glass as 2.5 gms/cc. OC is calculated considering the tool thickness of 0.38 mm at the cutting edge as the ideal dimension required and evaluating half of the difference between the largest widths of slit and the ideal dimension. Taper is calculated as a ratio of the half of difference between the top and bottom width of the slit produced to the thickness of the glass sheet. The experimental results are listed in Table II.

SN	T mm	A	P bar	MRR mm^3/min	Overcut mm	Taper
1	1.23	70%	0.5	0.04071	0.10148	0.0412
2	1.23	70%	2	0.0454	0.11873	0.0482
3	1.23	70%	3.5	0.04876	0.13825	0.0562
4	1.23	80%	0.5	0.05336	0.14405	0.0585
5	1.23	80%	2	0.06241	0.1459	0.0593
6	1.23	80%	3.5	0.07383	0.15535	0.0631
7	1.23	90%	0.5	0.07483	0.15618	0.0634
8	1.23	90%	2	0.08701	0.16358	0.0664
9	1.23	90%	3.5	0.09734	0.17268	0.0701
10	1.64	70%	0.5	0.0257	0.1365	0.0416
11	1.64	70%	2	0.02877	0.14545	0.0443
12	1.64	70%	3.5	0.03327	0.1532	0.0467
13	1.64	80%	0.5	0.03081	0.15628	0.0476
14	1.64	80%	2	0.03703	0.1691	0.0515
15	1.64	80%	3.5	0.04342	0.17683	0.0539
16	1.64	90%	0.5	0.05025	0.18463	0.0563
17	1.64	90%	2	0.05416	0.18575	0.0566
18	1.64	90%	3.5	0.05678	0.20065	0.0611
19	3.12	70%	0.5	0.02237	0.1483	0.0237
20	3.12	70%	2	0.02853	0.1585	0.0254
21	3.12	70%	3.5	0.03	0.15933	0.0255
22	3.12	80%	0.5	0.02	0.1712	0.0274
23	3.12	80%	2	0.03	0.18383	0.0294
24	3.12	80%	3.5	0.03	0.19255	0.0308
25	3.12	90%	0.5	0.02722	0.21778	0.0349
26	3.12	90%	2	0.03256	0.21843	0.0342
27	3.12	90%	3.5	0.04152	0.23498	0.0368

Table II: Experimental Results

III. ANN MODELING

Out of the various kinds of ANN approaches used in modeling of systems and processes, the back propagation learning algorithm has become the most popular in engineering applications and is selected for use in this study. Networks have one input layer, one or more hidden layer(s) and one output layer. Input data patterns and corresponding targets are required to train and test the neural networks. The data obtained by experimental tests for ultrasonic slitting of glass is utilized for developing ANN model. The amplitude, pressure and thickness of work are represented as input data while material removal rate (MRR), taper and overcut (OC) are taken as output. A number of architectures of feed forward back propagation type of neural network are tested for modeling of the ultrasonic slitting process parameters in this work. The procedure involved in developing neural network model for ultrasonic slitting is depicted in Fig. 1

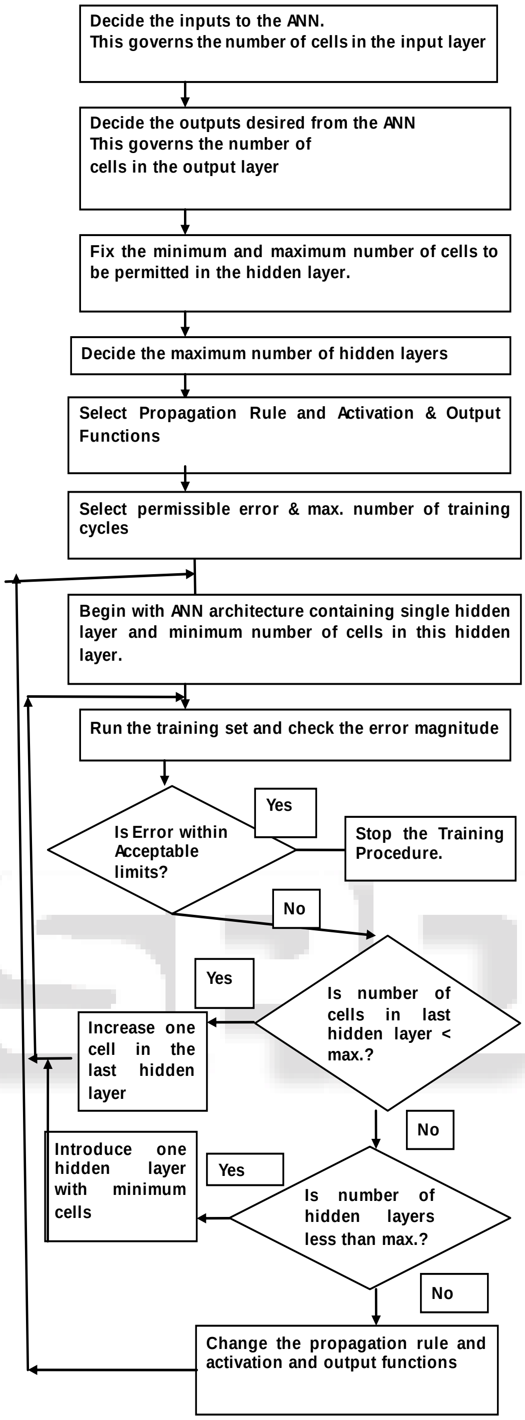

Fig. 1: ANN Modeling Procedure

The steps listed in the flowchart in Fig. 1 for development of neural network models are applied to this case as indicated in Table III. As per the Table III, beginning from one hidden layered neural network model to three hidden layers model having initially 3 nodes in the hidden layer, the number of nodes in hidden layer is increased up to 9 while monitoring the error resulting at the end of training. The criteria for the termination of training selected are a) permissible error and b) maximum number of cycles in training and validation. The limiting value for all the errors over the entire data is selected as 0.05 (5%). The maximum number of training cycles is limited to 1,00,000 for each learning set. The training stops when any one of the above criteria, namely, all errors being less than 0.05 or 1,00,000 training cycles being completed. The learning rate is kept as 0.6 and momentum as 0.8 for the stable learning and convergence of weights.

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, POC and Taper.
Number of nodes in output layer = Number of outputs from the neural network model	3
Initial Number of Hidden Layers	1
Maximum Number of Hidden Layers	3
Initial Number of Cells in a Hidden Layer	3
Maximum Number of Cells in a Hidden Layer	9
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

Table III: Ann Model Parameters for Modeling Ultrasonic Slitting

S. N.	Model	Avg. Error%	No. of learning cycles	Error rms %	R
1	3-3-3	11.826	228	0.147	0.9112
2	3-4-3	9.899	766	0.137	0.9198
3	3-5-3	19.946	1349	0.239	0.8459
4	3-6-3	11.382	110	0.133	0.9216
5	3-7-3	13.958	134	0.172	0.8954
6	3-8-3	12.730	112	0.155	0.9069
7	3-9-3	19.668	323	0.238	0.8512
8	3-3-3-3	16.087	100000	0.181	1.1964
9	3-4-4-3	19.148	586	0.238	0.8932
10	3-5-5-3	16.498	1041	0.202	0.8703
11	3-6-6-3	12.423	372	0.138	1.1436
12	3-7-7-3	18.288	405	0.217	1.2305
13	3-8-8-3	14.224	251	0.162	1.1263
14	3-9-9-3	15.055	247	0.190	0.8841
15	3-3-4-3	18.155	1097	0.216	1.1999
16	3-4-3-3	16.004	100000	0.185	1.1776
17	3-4-7-3	24.878	560	0.312	0.8486
18	3-4-8-3	16.078	1013	0.190	1.1891
19	3-5-7-3	19.667	367	0.224	1.2369
20	3-6-8-3	17.121	290	0.197	1.1969
21	3-6-9-3	15.341	367	0.171	1.1541
22	3-7-3-3	16.615	577	0.200	1.1278
23	3-7-4-3	16.316	646	0.187	1.1699
24	3-7-5-3	12.869	541	1.152	0.1471
25	3-8-4-3	17.194	979	0.213	0.8675
26	3-8-6-3	17.081	382	0.209	1.1111
27	3-9-6-3	11.696	273	0.133	0.9244
28	3-3-7-3-3	21.562	10406	0.265	0.8443
29	3-4-2-4-3	12.197	15253	0.146	1.1466
30	3-4-3-3-3	19.260	100000	0.237	0.8913
31	3-4-5-7-3	14.451	1983	0.188	0.8849
32	3-4-6-8-3	21.591	3333	0.260	0.8769
33	3-5-5-7-3	17.161	1950	0.199	1.1720
34	3-7-3-3-3	14.963	100000	0.176	1.1873
35	3-7-3-7-3	21.562	10406	0.265	0.8443
36	3-7-5-4-3	58.412	1247	0.730	1.1806
37	3-7-5-5-3	12.117	1282	0.137	1.1424
38	3-8-6-4-3	10.929	4656	0.131	1.1127
39	3-11-8-8-3	15.881	801	0.185	1.1726
40	3-8-11-8-3	17.570	654	0.203	1.2056

Table IV: Ann Architecture Test Results

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 in Equations 1-3

$$\mathrm{Error\%} = \frac{|A_e - A_P|}{A_e} \tag{1}$$

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

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N} \frac{A_e}{A_P} \tag{3}$$

Network architectures with 40 different configurations are attempted for training and it is observed that four network architectures could not be trained to meet the error limitations even with high number of cells. Thirty six different architectures are tested successfully and the results of training these networks are listed in Table IV.

It is observed from Table IV that the value of R is found closest to unity for architectures 3-4-3, 3-6-3 and 3-9-6-3. Amongst them 3-9-6-3 will be the suitable ANN architecture for the performed experiment gives lower R-value - 0.9244, Error rms 0.133% and 273 learning cycle which means a faster response can be obtained The 3-9-6-3 architecture and its error propagation during training are shown in Fig. 2 and Fig. 3 respectively.

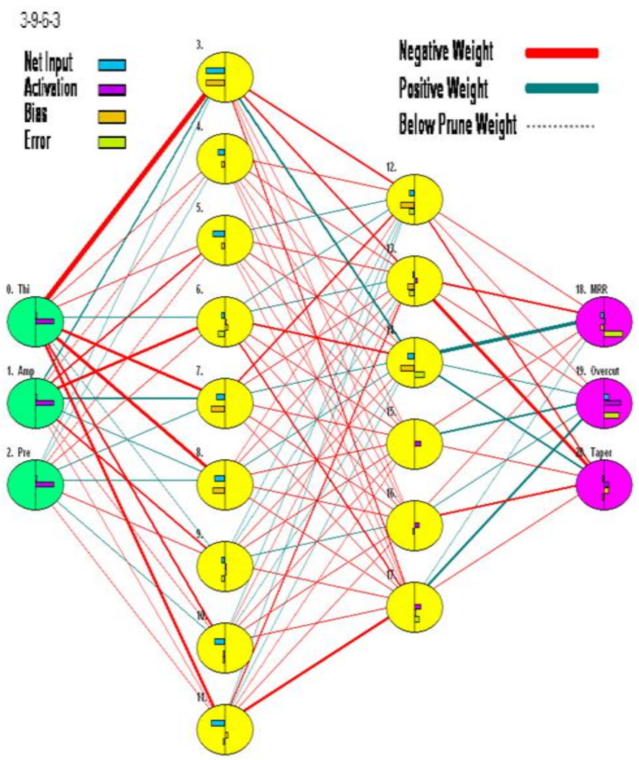

Fig. 2: 3-9-6-3 ANN Model Architecture

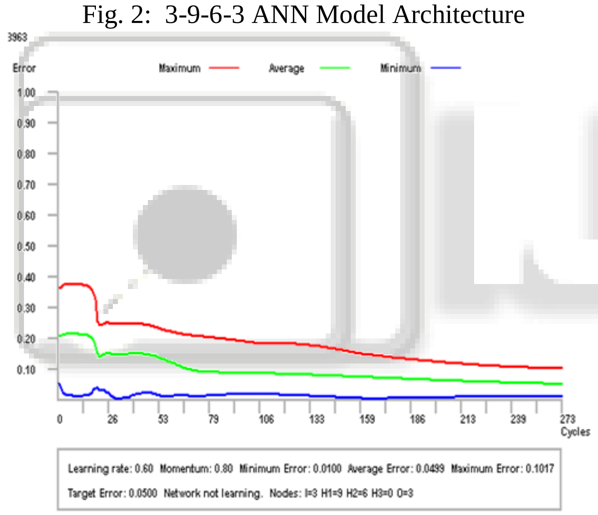

Fig. 3: Error Propagation Graph for 3-9-6-3 ANN Model

V. CONCLUSION

Numerous architectures are tried to develop suitable ANN model for predicting performance in terms of material removal rate, taper and overcut for ultrasonic slitting of glass. A feed forward back propagation neural network model with a 3-9-6-3 configuration is found most suitable. This approach can be considered as an alternative to practical technique to predict the process outcome.

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