Artificial Neural Network Modeling for Prediction of Performance in Abrasive Jet Drilling Process

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Abstract: Abrasive jet drilling process (AJDP) removes the material by erosion action by simultaneous control of number of process parameters. This paper highlights a logical procedure for selection of optimal process parameters in Abrasive jet drilling process to achieve high quality without cost inflation. In present work authors have tried to investigate effect of various AJDP process parameters such as air pressure, abrasive particle size, stand-of-distance on responses, material removal rate by conducting full factorial experiments. Artificial Neural Network model is developed to capture relationship between input and output parameters as a predictive tool to predict the performance of the process.

Keywords: *AJDP, GRA, Optimization, MRR, ROC.*

Introduction:

Precision machining of fragile material with complex geometries is always of concern being labor intensive and difficult to control. Abrasive jet machining is a process in which the material is removed from the work piece due to the impingement of the fine grain abrasives with a high velocity air jet. Material removal occurs through a chipping action, which is especially effective on hard, brittle material such as glass, silicon, tungsten and ceramics. Difference from the other non conventional machining process there is no thermal, mechanical and chemical damage of the work. This technique has been used to micro-fabricate array of components in glass for use in semiconductor, Micro Electro Mechanical Systems (MEMS), optoelectronic industries etc. [1]. For instance AJM is used for cutting a thread in glass rod, cutting titanium foil, and drilling glass wafers [2]. AJM has been successfully employed to manufacture small electronics devices consisting silicon brazed on tungsten of varying thickness in which the silicon wafer must be trimmed and beveled without harming the tungsten disk [3] and also been used for deburring of crossed-drilled holes as secondary erosion [4]. By adding pure water with abrasive in specified quantity it applied to polishing of electrical discharge machined mold steel to a high degree mirror finish [5].

AJM has been subject of research studies because of complex material removal mechanism which depends on various parameters found affecting on output such as stand of distance, mixing ratio, air pressure, grain size, abrasive types etc. in literature [6-7, 8]. Optimal quality of the work piece in AJM can be generated through combine control of various process parameters. Many researchers have studied and investigated the complex relationship between various machining parameters and tried to optimizes the input parameters that give best output for different multivariable manufacturing processes using various modern optimization tools like genetic algorithm, response surface methodology etc. [9-13]. In the present paper, authors have tries to optimize higher-order influences of the various machining parameters of AJDP like stand of distance, air pressure, abrasive particle size on the most dominant machining criteria, i.e. MRR and Radial overcut using grey relational analysis (GRA) approach because of its ability to simplify greatly the complicated multiple performance characteristics noted by various researchers [9-11].

2. Experimentation

Fig. 1 Experimental setup for Abrasive Jet Drilling Process

High pressure air from the compressor passes through dehumidifier and pressure control valve in to the mixing chamber. The abrasive particle and air are thoroughly mixed in mixing chamber and a stream of abrasive mixed air passes through a nozzle on the glass. It causes the indentation and ultimately results in result in the rupture of the particle from the surface and drilling operation is performed. Abrasive jet drilling experimental setup is shown in Figure

Full factorial designs of experiments are conducted with three controllable factor stand of distance, air pressure and abrasive particle size of SiC abrasives. Levels of input parameters are shown in Table 1.

Table 1: Controllable factor with their level in full factorial Design of Experiments

Machining Parameter	Units	Level 1	Level 2	Level 3
Stand of distance	mm	1	2	3
Air pressure	bar	4	5	6
Thickness	mm	1.5	2.2	3

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Based on The randomized experiments condition of each input variables and summary of response parameters are given in Table 2. Total 27 experiments were performed on 1.5 mm, 2.5mm, 3mm thick glass fibre reinforced plastic plate with each experiment producing through hole in which response MRR and radial overcut (ROC) were measured. The material removal rate is obtained in terms of volumetric material removal rate by taking density of glass fiber reinforced plastic as a **2.7 gm/cc**. The top and bottom diameters of each hole were measured using **3 micron** accuracy digital tool maker's microscope at four different positions. Average of this value is taken as the value for top and bottom diameters. Radial overcut was determined by halving the difference between larger of the top and bottom diameters and nozzle diameter was initially **2.5 mm**.

Table 2 Experimental Schema and Results

Run Order	Thickness	Air Pressure	Stand of Distance	MRR (mg/sec)
1	1.5	4	1	0.0042
2	1.5	4	2	0.0052
3	1.5	4	3	0.0022
4	1.5	5	1	0.0060
5	1.5	5	2	0.0030
6	1.5	5	3	0.0015
7	1.5	6	1	0.0028
8	1.5	6	2	0.0050
9	1.5	6	3	0.0059
10	2.2	4	1	0.0004
11	2.2	4	2	0.0005
12	2.2	4	3	0.0017
13	2.2	5	1	0.0027
14	2.2	5	2	0.0008
15	2.2	5	3	0.0006
16	2.2	6	1	0.0007
17	2.2	6	2	0.0030
18	2.2	6	3	0.0022
19	3	4	1	0.0002
20	3	4	2	0.0005
21	3	4	3	0.0009
22	3	5	1	0.0008
23	3	5	2	0.0004
24	3	5	3	0.0006
25	3	6	1	0.0010
26	3	6	2	0.0022
27	3	6	3	0.0020

3. 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 glass is utilized. The mathematical background, the procedures for training and testing the ANN and account of its history is available for details (Haykin, 1994). The amplitude, pressure and thickness of work are represented as input data while material removal rate, taper and radial overcut 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 (Fig. 1).

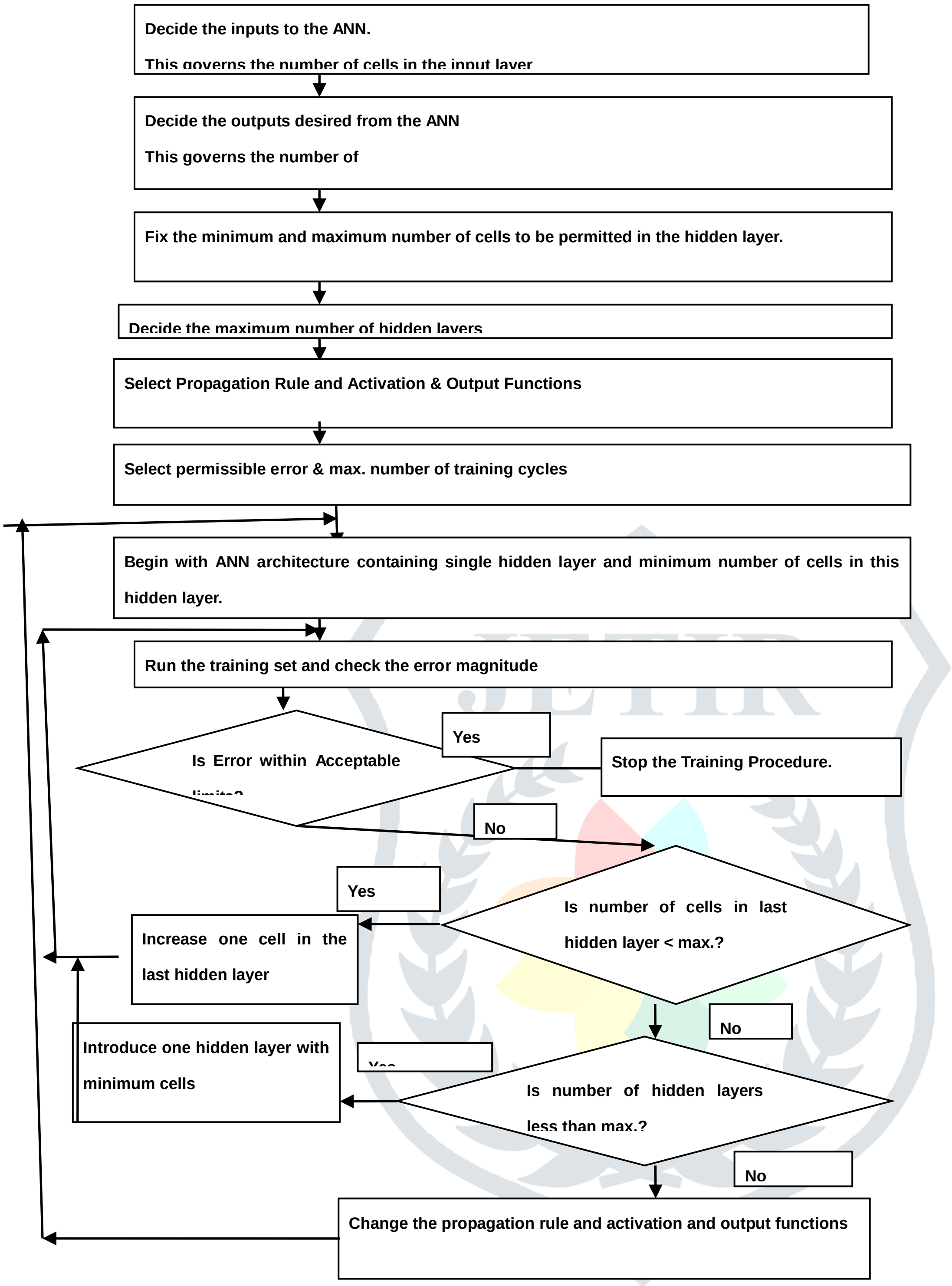

Fig. 5 ANN Modeling Approach

The steps listed in the flow chart for development of neural networks models (Fig. 1) are applied to this case as indicated in Table III. 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 1000000 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 3,4,2 architecture and training parameters as described, the first architecture with single hidden layer is evaluated. It does pass the error criteria. Subsequently, following the strategy discussed in Figure 5. the number of cells in the hidden layers are increased one at a time up to 8. Thereafter, ANN architectures with two hidden layers are evaluated in a similar fashion.

TABLE III

Neural Network Modeling for Ultrasonic Drilling Process Modeling

Network Type	Feed Forward
Input for the neural network model	Air Pressure, Thickness SOD
Number of nodes in input layer = Number of inputs to the neural network model	3
Output from the neural network model	MRR
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	8
Maximum Number of Cells in a Hidden Layer	8
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

3.1 Results and 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 & σ 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~iv)).

Error! Reference source not found. (i)

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$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R - R_i)^2} \qquad \text{(iv)}$$

Eighteen network architectures are attempted for training and it is observed that the network architectures having one hidden layer with high number of cells could not be trained to meet the error limitations. Eleven different architectures are tested successfully and the results of training these networks are listed (Table IV). It is observed that the maximum error, average error, RMS error, and σ values are found to be the best for 3,8,6,2 architecture and less number of cell in the hidden layer as well. The 3,4,8,2 and 3,4,6,8,2 architectures have competitive values of R compared to the 3,8,6,2 architecture but looking at the values of errors and σ, 3,8,6,2 architecture appears better. It is noted that as number of cells in hidden layers increases the errors tend to increase and the network tends to memorize patterns rather than generalize the weights. Hence, the architecture 3,8,6,2 is chosen as the best representative model for this case. The results of the R and σ test for these models are listed (Table IV). The 3,8,6,2 architecture and its error propagation during training are shown (Fig. 2 and Fig. 3).

TABLE IV

Artificial Neural Network Architectures & Corresponding

Training And Test Results For Ultrasonic blanking Of LTCC

Sr. No	Model Structure	Avg. Error %	Min. Error %	Max. Error %	Number of learning cycles when Training	$Error_{rms}$ %	R

					Stopped		
1	3-8-3	10.13	0	66.62	3692	17.82	1.12
2	3-6-6-3	16.35	0	100	5648	28.96	0.93
3	3-7-7-3	14.19	0	40	3419	18.77	1.15
4	3-6-7-3	18.88	0	71.12	3917	26.61	0.88
5	3-6-8-3	11.25	0	50	74150	17.26	0.98
6	3-7-8-3	15.65	0	150	3135	31.94	0.93
7	3-8-8-3	17.32	0	150	5822	33.17	0.97
8	3-6-6-6-3	15.56	0	100	1952	24.47	1.10
9	**3-7-7-7-3**	**17.76**	**0**	**100**	**5153**	**24.77**	**1.09**
10	3-8-8-8-3	**11.77**	0	**100**	8764	**23.33**	**0.92**
11	3-6-7-8-3	14.48	0	100	8251	25.44	0.94
12	3-5-6-7-3	13.63	0	50	8773	19.14	0.95

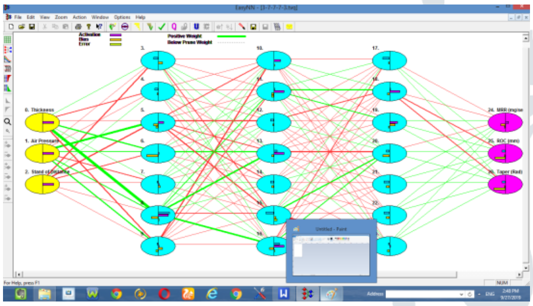

Fig. 2. ANN Model with architecture 3-7-7-3

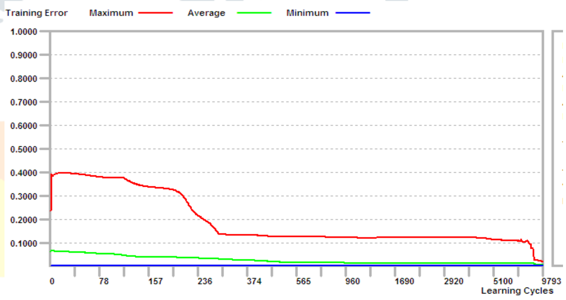

Fig. 3 ANN model training & error propagation

4. Conclusion

Numerous architectures are tried to develop suitable ANN model for predicting performance in terms of material removal rate for Abrassive jet drilling process. A feed forward back propagation neural network model with a 3,7,7,7,3configuration is found most suitable, fast and reliable. The results are in agreement giving less than 0.03% root mean square error compared with those obtained experimentally. This approach can be considered as an alternative to practical technique to predict the process outcome.

Referance

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