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Application of Taguchi OA array and Artificial Neural Network for Optimizing and Modeling of Drilling Cutting Parameters

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Abstract

This paper consists of two phases, in first phase experiments have been conducted with the use of Taguchi FFE (Fractional Factorial experimentation) to find optimal cutting process parameters spindle speed, feed rate and drill diameter with the objective of minimum delamination. Using these data ANN (Artificial Neural Network) based model has been developed for drilling induced delamination while drilling GFRP in the second phase. Delamination in drilling process is important aspect so there is need to minimize delamination while drilling. In the first phase experiments have been conducted by varying spindle speed, feed rate and drill diameter all at three level using high speed twist drills. Using L-9 of FFE, optimal levels of factors have been found out. Three more number of additional experiments has been carried out with input variable values near to obtained optimal levels through Taguchi OA array. Using these total twelve set of experiments (i.e nine + additional three) input-output data ANN has been trained to develop a model in the second phase. Developed model may suit manufacturer to find the lower delamination factor among available choice of process parameters. This developed model has been validated and found to be suitable for predicting delamination for a given spindle speed, feed rate and drill diameter. The R value for training, validation, and test curve was found to be very good.

Keywords: Drilling, delamination, Taguchi, ANN and Back Propagation

INTRODUCTION

The drilling process is considered to be one of the most important manufacturing processes, this is due to both number of operations and the machining time consumed. The significance of this process is even higher in heat exchanger, die making and in aircraft manufacturing industries [1]. Over the past few decades the use of polymer based composite increasing considerably. Due to this the number of research articles concerning the machinability of this material increasing considerably [2]. Among the polymer based composite glass fibre reinforced plastic (GFRP) composites have widely used engineering application such as automotive, aircraft, aerospace, sport goods, robots, machine tools, spaceships and sea vehiclesindustries due to their significant advantages over other materials. They provide high specific strength/stiffness, superior corrosion resistance, light weight construction, low thermal conductivity, high fatigue strength and resistance to chemical and microbiological attack [3-4]. For making hole on GFRP plate mechanical drilling with twist drill remains one of the most efficient and economical machining process for riveting and fastening structural assemblies in the automotive and aerospace industries [5-7]. During drilling various problems are encounter such as fibre pull-out, delamination, matrix bonding and fibre fuzzing etc. These all problem in GFRP composite material are particularly due to the heterogeneity and anisotropy of material. The delamination caused during drilling has been recognized as one of the major problem [8-13]. Drilling induced damage occurs both at the entrance and exit planes of work-piece. The study on drilling GFRP has been carried out by many authors. However a very few work has been reported to find out the effect of process parameters such as spindle speed, feed rate and drill diameter on delamination factor. Lack of predictive model has also been observed in the literature. Keeping these views present work is focused on investigating the effect of the cutting parameters, such as spindle speed, feed rate and drill diameter on delamination factor produced during drilling of GFRP composite using Taguchi orthogonal experimental design. Further using these nine experimental data (input-output) and additional three set of experimental data (three more number of experiments performed to have a proper training of Artificial Neural Network) a total of twelve input-output data a predictive model using Articial Neural Network has been developed.

EXPERIMENTAL SETUP

In this study, the experiments were conducted on CNC Milling centre (make-Doosan, model- DNM 500 as shown in figure 1. The work material is GFRP composite supplied by Samtech. Engg. & Co. (P) Ltd., Gaziabad UP). The dimension of work-piece material was 400x40x10. The matrix material is epoxy resin contain high thermal, mechanical and corrosion resistance properties. The fiber used is E-glass fiber. Specification of work-piece material was shown in table 1.

Figure 1. Experimental setup

Table 1. Specification of work-piece material

Sr. No	Specification	Values
1	Density	2500kg/m^3
2	Method of formation	Hand layup
3	Construction	Epoxy with glass fiber
4	Tensile strength of E-glass fiber	2400 MPa
5	Tensile modulus of E-glass fiber	69x10^9 Pa
6	Specific modulus of E-glass fiber	27
7	Tensile strength of epoxy resin	8 MPa

The cutting tools used during experimentation were M35 HSS parallel shank Jobber series twist drills (Make: Addison and Co. Ltd., India) with ISO standard are IS: 5101/DIN:338/BS:328/I.S. O. specification have 118° point angle. In order to ensure the initial condition of each experimental run a new cutting tool was used for each experimental run. Delamination was measured using the optical microscope with image analysis. The delamination factor (F_d) was determined by the ratio of the maximum diameter (D_{max}) of the delamination zone to the hole diameter (D).

The delamination factor can be expressed as:

$$F_d = D_{max} / D \tag{1}$$

The diagrammatic representation of delamination in figure 2 (In next section).

RESULTS AND ANALYSIS USING TAGUCHI FFE

Analysis of the signal-to-noise (S/N) ratio

The experimental design was conducted according to Taguchi L_9 orthogonal array which is based on the process parameters consideration as shown in table 2.

Table 2. Process parameters and their levels of interest

Factors	Factor designation	Level 1	Level 2	Level 3
Spindle Speed (RPM)	A	500	1500	2500
Feed rate (mm/min)	B	100	300	500
Drill diameter (mm)	C	6	8	10

Experiments would be conducted to investigate the relationship between various processes and their levels consideration. The results of delamination factor and S/N Ratio of delamination factor were analysed through Minitab 16 statistical software which is shown in table 3. Delamination factor has been calculated through equation 1. For calculating delamination factor signal to noise ratio for lower the better quality characteristics (i.e low delamination is better) considered. The formula of S/N ratio for lower the better quality is:

$$S/N_{LB} = -10\log\left[\left(1/r \sum_{i}^{r} y_i^2\right]\right. \tag{2}$$

Table 3. Experimental Results and S/N ratios

Sr. no	spindle speed	feed rate	Drill Dia.	Delamination Factor	S/N Ratio
1	500	100	6	1.429	-3.10064
2	500	300	8	1.494	-3.48701
3	500	500	10	1.515	-3.60825
4	1500	100	8	1.466	-3.32268
5	1500	300	10	1.499	-3.51603
6	1500	500	6	1.510	-3.57954
7	2500	100	10	1.488	-3.45206
8	2500	300	6	1.551	-3.81224
9	2500	500	8	1.597	-4.06610

From these experimental results the average value of delamination factor was calculated as 1.505 and average value of S/N ratio was -3.5493dB.

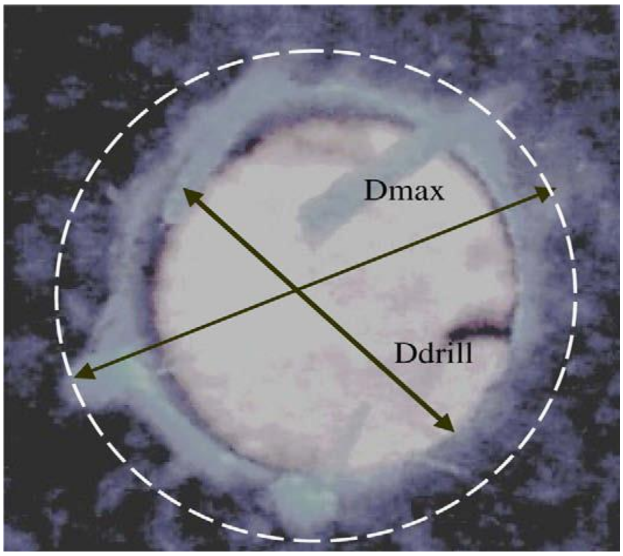

Figure 1. Photographs illustrating the delamination size around the drilled hole [14].

The optimum level of process parameters for delamination factor is shown in table 4 and 5. These optimal values are verified in figures 3 and 4. From these figures it was concluded that for minimizing delamination factor the spindle speed, feed rate and drill diameter should be lower value. This is due to increasing feed rate increase the thrust force which in turn increases the drilling induced delamination. Thrust force is dominant factor affecting delamination [14-15].

Table 4. Response Table for S/N ratio delamination factor

Level	Spindle speed	feed rate	Drill diameter
1	**-3.399**	**-3.292**	**-3.497**
2	-3.473	-3.605	-3.625
3	-3.777	-3.751	-3.525
Delta	0.378	0.460	0.128
Rank	**2**	**1**	**3**

Table 5. Response Table for mean delamination factor

Level	Spindle speed	feed rate	Drill diameter
1	**1.479**	**1.461**	**1.497**
2	1.492	1.515	1.519
3	1.545	1.541	1.501
Delta	0.066	0.080	0.022
Rank	**2**	**1**	**3**

Also increasing spindle speed increase the friction and heat leads to softening of material resulting increase in delamination factor. The optimal process parameter levels for delamination factor are (A_1, B_1, and C1)

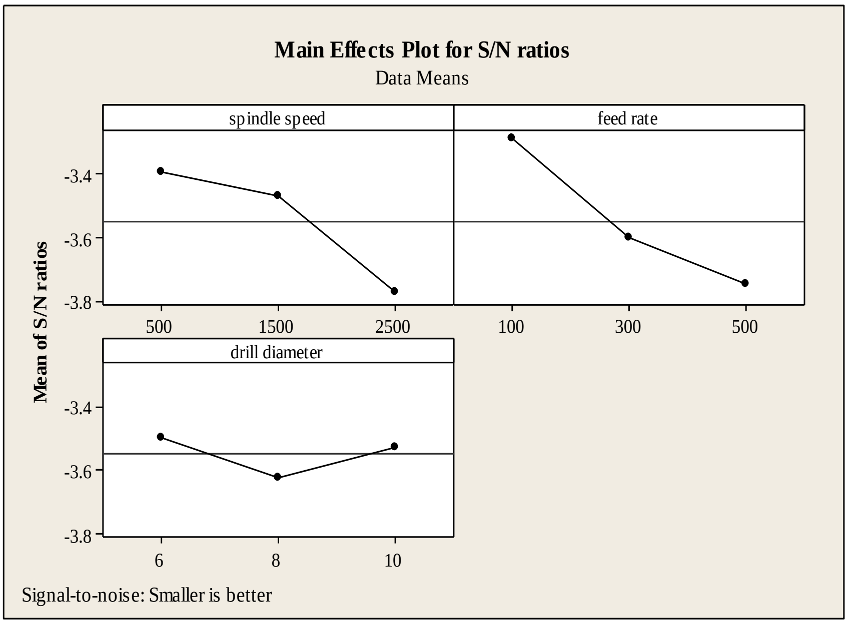

Figure 2. Main effect plot for delamination of S/N ratio

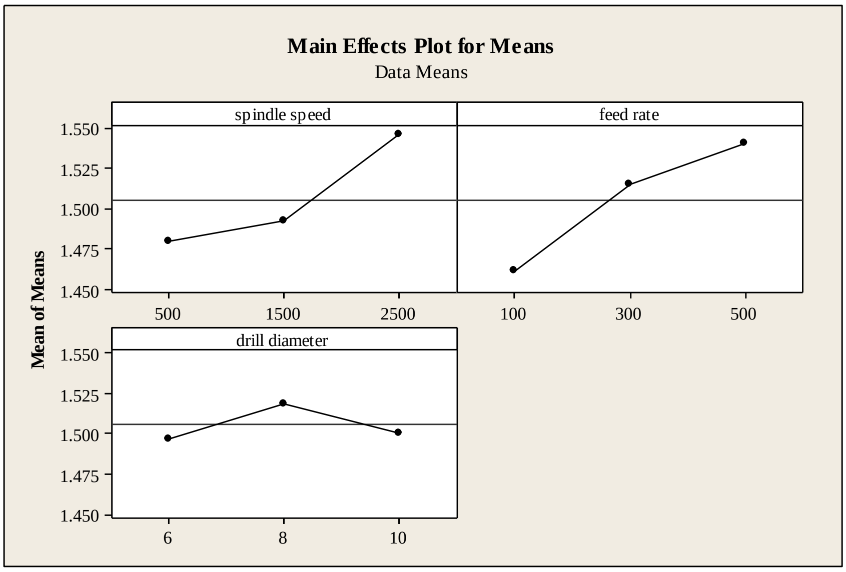

Figure 3. Main effect plot for mean delamination

Artificial Neural Network based Modelling Approach

In second phase of this paper first three additional experiments have been performed and presented in Table 6. This is named as 10, 11 and 12th number of experiments, It is to be noted that experiments no 1 to 9 have been performed with the help of

Taguchi OA array [16]. Using this, ANN based modeling approach has been attempted by author which is discussed in this section.

Table 6. Additional three experiments for better training of ANN

Sr. no	spindle speed	feed rate	Drill Dia.	Delamination Factor
10	550	100	6	1.433
11	500	150	6	1.445
12	500	100	7	1.439

Artificial neural network attempts to imitate the learning activities of the brain [17]. It does aggregation of its input from other neurons or the external environment and generation of an output from the aggregated inputs. ANN is suitable for correlations that are hard to describe by physical model because of the ability to learn by example and to recognize patterns (Examine patterns from their background, and make decisions about the categories of the patterns) in a series of input and output values from examples and cases. Its structure is based on the concept of a biological neuron. It is a processing element in a nervous system of brain which receives signals through synapses located on the dendrite or membrane of the brain. If the signal is strong enough, the neuron is activated and emits a signal through axon, which connects to dendrites of thousands of other neurons. Inputs, after multiplied by weights (signal strength) determine the activation of the neuron. The acceleration and inhibition depends on weights which are positive or negative. The adjustment of weight is achieved through training of neural network.

Back propagation algorithm

Back propagation (BP) is the most popular training method used in layered feed-forward ANNs. The artificial neurons are organized in layers and send their signals "forward" and then errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer [18-19]. The training process requires a set of examples of proper network behavior, network input p and target output t. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function, i.e. mean squared error (the average squared error between the network outputs 'a' and target output 't'. [20]. It was also suggested [17] that a minimum of 12 input –output variables are required for better training of the data and results. The training begins with the association of random weights on neurons. In this paper 3-3-1 feed forward back propagation algorithm (3-input, 3 hidden layer, 1-outputlayer). In this study the inputs are dam heights and positions, and output is Delamination factor. For this model learning rate has been opted as 0.30. The epochs of 40,000 and Mean squared error of 0.001 has been taken in this study. The architecture of neural network is shown in Figure 5 below:-

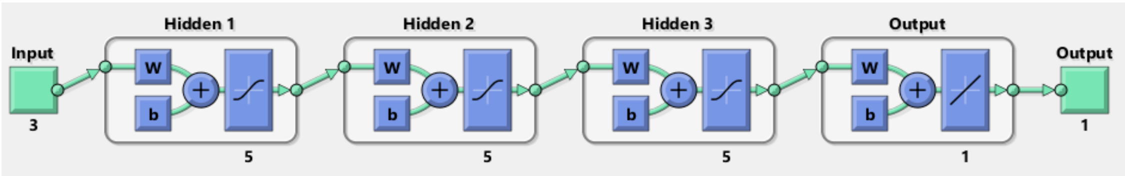

Figure 4. Architecture of neural network

The regression curves (Fig 6.) for this model has been obtained, the higher R value i. e R ≥0.90 suggests that this model is appropriate for prediction of output variable i.e Delamination factor with given input variables of drilling i.e spindle speed, feed rate and drill diameter.

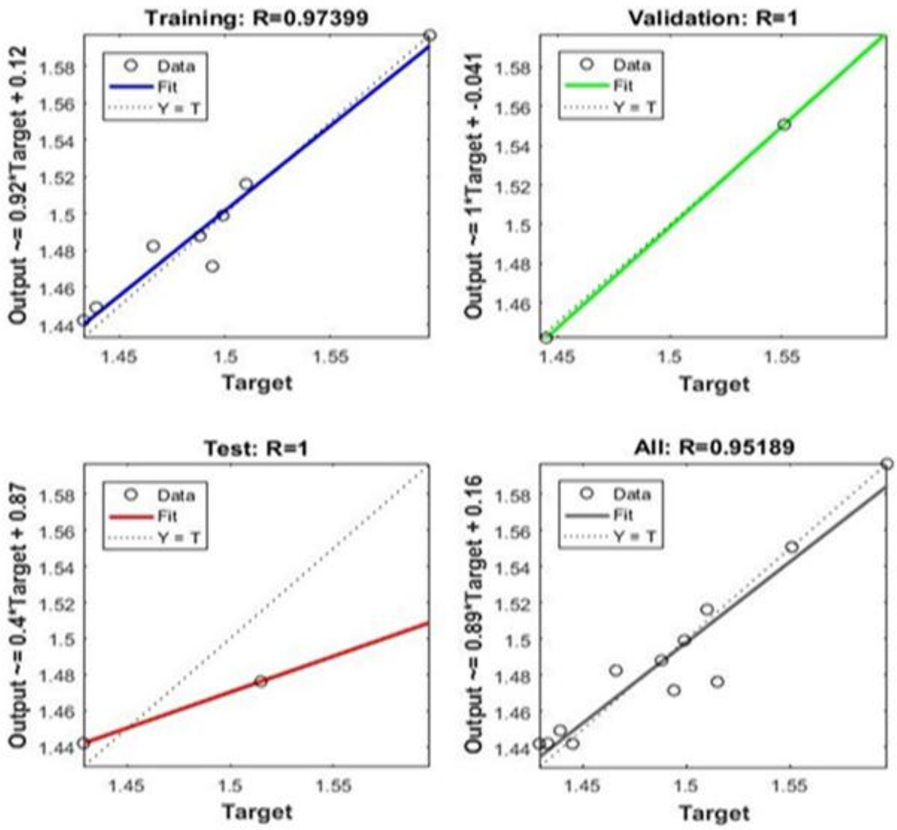

Figure 6. Regression Curves for training, testing and validation

CONCLUSION

The Taguchi OA and ANN based modeling approach were used in this study to determine delamination, which is an important aspect in drilling further its detailed investigation on composite was carried out. From the experimentation followed by modeling approach through ANN the following conclusions are derived:-

1. The optimal values of the process parameters to obtain minimum delamination factor were A_1 (spindle speed, 500 rpm). B_1 (Feed rate, 100 mm/min), C_1 (Drill diameter, 6 mm) respectively. It was also found that feed rate is most significant factor affecting delamination factor (with % contribution of 53.69) followed by spindle speed (with % contribution of 40.05) and drill diameter (with % contribution of 4.61) respectively
2. ANN based developed predictive model may find the output variable i.e delamination factor for given input variables i.e spindle speed, feed rate and drill diameter.
3. Predictive ANN based model was found to be satisfactory as R values are nearby 0.95

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