Neural Network based Optimization of Abrasive Jet Process Parameters in Machining GFRP Composites

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ABSTRACT
Glass fibre reinforced polymer composites were extensively used in automobile and aerospace industries. Due to anisotropic and non-homogeneous structure, machining of GFRP composites are difficult to carry out. In this work holes were made on glass fibre reinforced polymer composites using abrasive jet machine under various levels of process parameter. Pressure, stand-off distance, nozzle diameter and abrasive particle size were used as process parameters. The material removal rate (MRR) and kerf characteristics were investigated. Four factor three levels central composite rotatable design matrix was used for optimizing the required number of experiments. In this work neural network based approach is presented for the prediction and optimal selection of process parameters in abrasive jet machining of GFRP composites. Pressure (P), stand-off distance (L), nozzle diameter (D) and abrasive particle size (S) are selected as network inputs. The material removal rate (MRR), bottom kerf (BK) and top kerf (TK) is the output parameters of the model. Experimental data were used for training and testing the network. The results indicate that the neural model can predict AJM process performance with reasonable accuracy, under different abrasive jet machining conditions.

Keywords: Glass fiber reinforced polymer, Abrasive jet machining, Material removal rate, Kerf analysis, neural model

INTRODUCTION
The special features found in the glass fiber reinforced polymer composites (GFRPs) compared to other materials are high strength to weight ratio, high modulus, high fracture toughness, corrosion and thermal resistance. The applications of glass fiber reinforced polymer composites include automobile industries, marine fields, aircraft industries, household and industrial appliances. The manufacturing process of glass fiber reinforced polymers are often made in a net shape or close to a net shape. However, machining of glass fibre composite materials face a special challenge from conventional techniques, because of the inhomogeneity and anisotropy of these materials. Abrasive jet machining involves the controlled erosion of the target material by the impact of a jet of solid particles. Many researchers focus on the machining of various materials using abrasive jet machining like glass, ceramic and electrical discharge machining die material, 304 stainless steel, plaster of paris, polymethylmethacrylate and acrylic samples using abrasive jet machining, and studied the results on the effect of the process parameters [1, 2].

The mechanical properties of glass fiber composites are based on the fiber orientation and the bonding established between the fibers[3]. Abrasive jet machining is the low cost machining technology which is used for machining difficult to cut and brittle likematerials. The shape of the machined surface was reported to be like abell reversed. Increase in material removal rate (MRR) is possible through increase in the abrasive size, nozzle tip distance and jet velocity; is also mentioned [4]. Increase in the material erosion rate and depth of the holeby the maximum pressure and inclination of the nozzle was noticed[5]. Low pressure and high feed rate significantly affect the quality of hole in woven laminated glass fibre composite by water jet machining [6]. Explicit dynamic analysis of ultrasonic assisted water jet machining of ceramic work piece was investigated. It was observed that the highest material removal rate (MRR) was obtained from 90° nozzle angle [7]. Lower standoff distance and high water pressure causes good kerf in abrasive jet machining of hybrid (carbon and glass fiber) composites [8].

Machining of hybrid natural fibres with and without fillers [9] led to the conclusion that the traverse speed influences the kerf wall thickness and the removal of material depend upon the fillers in the hybrid composite. A maximum material removal rate of 0.097g/min was obtained in
machining fibre reinforced composites [10]. Abrasive slurry machining [11] of talc filled thermo plastic olefin (Polypropylene, ethylene propylene rubber, talc) using aqueous slurries was investigated and the maximum erosion was obtained at 45 degree angle of attack. Machining of graphite filed bidirectional glass fabric reinforced with bisphenol-A based epoxy resin shows the pressure, the standoff distance as be significantly affecting the top kerf width [12]. Bidirectional plain weave type glass fibers reinforced polymer composites machined using abrasive slurry jet and abrasive water jet technology showed increase in the top kerf width, increase in SOD and kerf width increase with increasing of abrasive particle concentration and standoff distance [13]. Glass fibre reinforced polymer composite material was drilled using an abrasive machine. The maximum material removal rate obtained in this work was 0.0657 g/min [14]. Reduction in kerf taper angle was seen with maximum pressure (150 MPa) and higher abrasive particle (120 mesh) size when naturally woven coconut sheath (CS) and glass woven matrix (GM) reinforced thermoset polyester matrix composite were machined using abrasive water jet technology [15]. Maximum MRR of 0.156 g/min was obtained on glass fibre composite with [16] SiC abrasive particles and tungsten carbide nozzle. Lower traverse speed leads to high material removal rate and hence the kerf width increases while machining banyan tree saw dust powder (BSD) filled Polypropylene (PP) green composites [17]. The effect of abrasive jet process parameters on carbon fibre composites used with Al2O3 abrasive particle revealed obtaining of maximum material removal rate of 0.01 g/min at a pressure of 6 bar [18]. Carbon fibre sheets using SiC abrasive particles were drilled using abrasive jet. The maximum MRR obtained was 0.1394 g/min. Another study by the same author [19] in machining of carbon fibre sheets using abrasive jet machining fetched a MRR of 0.065 g/min.

Investigations were carried out to study the influence of orifice size and focusing tube size variations on the cutting performance such as depth of cut, top kerf width and average surface roughness using Taguchi’s experimental design methods. A hybrid strategy employing adaptive neuro fuzzy approach and empirical relations, is demonstrated to predict the process parameters for achieving the desired performance considering the variations in orifice and focusing tube diameter [20].

A neuro-genetic approach was proposed to suggest the process parameters for maintaining the desired depth of cut in abrasive waterjet (AWJ) cutting by considering the change in diameter of focusing nozzle. An artificial neural network based model is developed for prediction of depth of cut by considering the diameter of focusing nozzle along with the controllable process parameters [21]. Neural Networks (ANN) is used to predict the geometrical characteristics of a micro-channel fabricated through Abrasive Water Jet Machining (AWJM) technique. The process parameters considered are abrasive size, traverse speed, abrasive flow rate and standoff distance respectively. The quality of the micro-channel can be assessed in terms of its width, depth, taper and surface roughness [22]. Standoff distance, abrasive mass flow rate, are studied for obtaining different results for the kerf angle. Data belonging to the trials are used for construction of ANN and regression models. The results of regression analysis are also used to determine the significant operating variables affecting the kerf angle [23]. An attempt has been made to develop a fuzzy logic based expert system for optimization of process parameters and prediction of optimal surface roughness in AWJM process during the machining of GC. Initially, Taguchi method is used for design of matrix and identifying the optimal level of process parameters of AWJM process [24].

Earlier studies have discussed only the optimization of abrasive jet machining process parameters and the influence of these parameters (pressure, abrasive size, SOD) on the machining quality of glass fibre composites. Only a few studies have been made on modeling and prediction of machining of glass fibre composite using artificial neural network (ANN). However, the work related to abrasive jet machining of glass fibre epoxy reinforced polymer (GFRP) composite is scanty. In this work, artificial neural network (ANN) model was developed to predict the material removal rate (MRR), kerf characteristics (top and bottom kerf) in abrasive jet machining (AJM) process. In the development of predictive models, machining parameters of pressure, stand-off distance, nozzle diameter and abrasive grit size were considered as model variables. For this purpose, Taguchi’s design of experiments was carried out in order to collect the output values. A feed forward neural network based on back propagation was made up of 13 input neurons, 22 hidden neurons and one output neuron. The 13 sets of data were randomly selected from orthogonal array for training and residuals were used to check the performance.
The aim of this investigation is to machine glass fibre reinforced composite material using an abrasive jet machine (AJM). The Influence of abrasive jet parameters on material removal rate (MRR) and kerf characteristics (top kerf, bottom kerf and kerf angle) are investigated. Holes were made on glass fibre reinforced composite layers with different diameter nozzles under various process parameter conditions. From the previous studies, the important process parameters such as (i) pressure (P) (ii) stand-off distance (SOD) (iii) nozzle diameter (D) (iv) abrasive size (S) were identified.

MATERIALS AND METHODS
Unidirectional glass fibre reinforced epoxy composite was prepared using hand layup method. The epoxy resin was mixed with hardener. The epoxy resin and fibers were mixed with hardener and make the GFRP samples with hydraulic press. The test specimens were cut into a rectangular shape of dimensions 50 X 15 X 5mm and used as the work piece for abrasive jet machining. Nozzles were fabricated in different diameters (1.5, 2.5, and 3.5) mm. Fig. 1 shows the fabricated nozzles with different diameters made with hardened steel. All the fabricated nozzles underwent heat treatment process for increasing the life of the nozzles. The important abrasive jet machining parameters were identified from literature and the previous work done by the authors as pressure (P), stand-off-distance (SOD), nozzle diameter (D) and abrasive size (S).

An experimental investigation was performed in an abrasive jet machine which was fabricated in the workshop. The silicon carbide (Sic) abrasive particles having different grit sizes (50, 70, 90μm) were blown through the fixed nozzle, with different pressure, SOD and nozzle diameters. Silicon carbide (Sic) abrasive particles were used for impinging the target materials. Fig. 2 shows the abrasive jet machined glass fibre reinforced samples.
Test runs were performed using the fabricated nozzle in abrasive jet machine under process parameters specified in Table 1. Sometimes, there were not enough resources to run a full factorial design. Instead, only a fraction of the total number of treatments could be run. However, not all factor effects could be estimated. Factors were aliased with one another. In other words, factors were confounded, and estimation of their effects could not be done separately. Main effects and low order interactions were of large interest, and were usually more significant than higher order interaction terms. So, by aliasing the main effects with higher order interactions, fairly accurate estimates of the main effects could be obtained. A total of 9 experiments were carried out according to a full factorial CCD. For finding the material removal rate, all the samples were measured using a digital weighing machine. The measurements of top kerf (entry side diameter) and bottom kerf (exit side diameter) width were made from the macro image captured by optical microscope. Material plus software was used for measuring the top and bottom diameters of the machined surfaces of the hole. Table 2 shows the experimental results obtained from the machining of GFRP samples using abrasive jet machine.

Table 1. Important Factors and their working range

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Factor</th>
<th>Notation</th>
<th>Unit</th>
<th>Levels</th>
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<tr>
<td>1</td>
<td>Pressure</td>
<td>P</td>
<td>Bar</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>SOD</td>
<td>L</td>
<td>mm</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>Nozzle diameter</td>
<td>D</td>
<td>mm</td>
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<tr>
<td>4</td>
<td>Abrasive Size</td>
<td>S</td>
<td>Microns</td>
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Table 2. Design matrix and experimental results

<table>
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<tr>
<th>Expt. No.</th>
<th>P</th>
<th>L</th>
<th>D</th>
<th>S</th>
<th>MRR (gm/s)</th>
<th>BK (mm)</th>
<th>TK (mm)</th>
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<tr>
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<td>1.5</td>
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<td>2.53</td>
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NEURAL NETWORK

Neural networks were used in artificial intelligence, have traditionally been viewed as simplified models of neural processing in the human brain. The origins of neural networks are based on efforts to model information processing in biological systems, which may rely largely on parallel processing as well as implicit instructions based on recognition of patterns of “sensory” input from external sources. A portion of them is the nerve cells called “neurons”. These neurons have different shapes and sizes[20]. A neuron collects signals from others through fine structures called dendrites. The neuron sends out spikes of electrical activity through a long, thin stand known as axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes.

Batch pack propagation

Even though several learning methods have been developed, the back propagation method has been proven to be successful in applications related to surface finish prediction[19,22]. In this study, back propagation learning algorithm, which has a unique learning principle, generally called delta rule, is used. The three layer of the network architecture include the input layer, hidden layer and output layer. Layers include several processing units known as neurons. They are connected with each other by variable weights to be determined. In the network, the input layer receives information from external source and passes this information to the network for processing. The hidden layer receives from the input layer, and does all information processing. The output layer receives processed information from the network, and sends the results to an external receptor[19].

RESULTS AND DISCUSSIONS

Using three different diameter nozzles all the experiments were conducted on the glass fibre composites with defined sets of input parameters. Material removal rate, top kerf, bottom kerf of E-glass fibre reinforced polymer composite were plotted to understand the effects of the process parameters. Experimental results and artificial neural networks are used to establish input and output relationships in abrasive jet machining of glass fiber reinforced polymer composites are discussed.

Estimation of material removal rate by ANN

The optimal neural network architecture used in this study is indicated in Fig. 3. The network consists of one input, one hidden and one output layer. Hidden layer has 22 neurons, whereas output layer has one neuron. 13 neurons with five features have been used as an input of ANN. Iteration number versus mean square error (MSE) is shown in Fig.4(a). It can be seen that training of neural networks can be achieved quickly. After 200001 cycles of training, the training error of network reaches stabilization value. The mean error is 0.042% for material removal rate is shown in figure 4(b). The error is lower than 80%, which show that the well-trained network model takes on optimal performance and has a great accuracy in predicting surface roughness[20]. The results predicted from the artificial neural network model is compared with experimental measure. Material removal rate during machining of GFRP composite using threaded and unthreaded nozzle was calculated by using the following equation,

\[ \text{MRR (g/min)} = \left( \frac{W}{t} \right) \times 60 \]

Where, “W” is the weight of the material removed and “t” is the time taken for machining.

Earlier studies on machining of fibre reinforced composites based on taguchi’s orthogonal array yielded a maximum material removal rate of 5.856g/min [25]. Abrasive jet machining of glass fibre was investigated and the material removal rate obtained was 0.0657g/min [29]. When Sic abrasive particles were blasted through the tungsten carbide nozzle to machine the glass fibre composite, maximum MRR of 9.366g/min was obtained [31]. Maximum material removal of 0.6 g/min was obtained, when carbon fibre composites were machined using Al₂O₃ abrasive particles at a pressure of 6 bar [33].
Carbon fibre sheets drilled using Sic abrasive particles resulted in a maximum MRR of 7.8 g/min [34]. Carbon fibre sheets were machined using abrasive jet machining. From the present investigation the maximum material removal rate obtained was 3.91 g/sec. Increasing the pressure would cause increase in the material removal rate. Reduction in pressure is followed by MRR. Maximum material removal rate was achieved in a threaded nozzle when compared to an unthreaded nozzle. When the pressure increased, the kinetic energy of the particle also increased causing increase in the material removal rate [3]. The current work by the authors, shows that when the SOD was minimum (0.5 mm), the MRR obtained was 2.93 g/sec and the 3.55 g/sec MRR was obtained at a maximum SOD (2.5 mm). When the distance between the work piece and nozzle was minimum, the MRR increased. When the SOD increased, the material removal rate decreased.

![Schematic illustration of artificial neural network model](image-url)

**Fig 3:** Schematic illustration of artificial neural network model

![Comparison of ANN results with experimental measurements for MRR](image-url)

**Fig 4 (a):** Comparison of ANN results with experimental measurements for MRR
The maximum material removal rate was achieved when the distance between the nozzle tip and the target material was minimum, the jet reached the target (GFRP) with high velocity and increased the impingement area, causing a high material removal rate. It was observed from the study using the nozzle with the diameter of 3.5 mm that, 2.68 g/sec of MRR was obtained. MRR obtained was more in the maximum diameter nozzle. The maximum diameter nozzle increase the mass flow rate of the jet in the maximum nozzle diameter. Hence the maximum diameter nozzle offer relatively higher material removal rate (MRR). When the Sic abrasive particle of size 50 micron flows through the unthreaded nozzle, the MRR obtained was 2.68 g/sec. When the abrasive particle of size 90 micron was blasted through the nozzle, the MRR obtained was 2.93 g/sec.

Maximum abrasive particle size increased the thrust of silicon carbide abrasive particles on the work piece and increase the depth of craters in the work piece surface. Hence a higher erosion and higher MRR was achieved in GFRP composites. From the experimental results it can be noticed that pressure and stand-off distance are greatly affect the material removal rate. Figure 5(a) shows the effect of pressure on material removal rate and the figure 5 (b) shows the effect of stand-off distance on material removal rate.

Estimation of kerf characteristics by ANN
Prediction of bottom and top kerf were conducted using artificial neural network. The Iteration number versus mean square error (MSE) is shown in Fig. 6(a). It can be seen that training of neural networks can be achieved quickly. After 16 0001 cycles of training, the training error of network reaches stabilization value for top kerf and 23000 cycles of training were conducted for bottom kerf. The mean error is 0.022% for bottom kerf and...
0.13% respectively. The error is lower than 70%, which show in 6(b) that the well-trained network model takes on optimal performance and has a great accuracy in predicting bottom kerf and top kerf [22]. Figure 7 (a & b) explains ANN predicted model vs experimental values for bottom kerf. The results predicted from the results predicted from the artificial neural network model is compared with experimental measure.

Fig 6 (a): Comparison of ANN results with experimental measurements for top kerf

Fig 6 (b): Iteration number vs. mean square error for top kerf

The observation on earlier studies is a decrease in the energy of the jet from top to the bottom of the machined surface leading to wider top kerf compared to bottom kerf. Kerf width increased linearly with water pressure. Kerf width also increased with the standoff distance [12]. Top kerf increased with increase of SOD with less influence on bottom kerf. The top kerf obtained was 2.79 mm and the bottom kerf obtained was 1.58 mm [14]. Polymer composite machined with maximum water pressure resulted in a maximum bottom kerf width of 1.5 mm [10].

Fig 7 (a): Comparison of ANN results with experimental measurements for bottom kerf
It can be noticed that when the pressure increased the bottom kerf increased. The decreasing in pressure will reduce the bottom kerf. When the SOD is minimum, bottom kerf obtained was found to increase. Increasing the SOD will decrease the bottom kerf. The smaller diameter nozzle offers maximum bottom kerf. But, the maximum size of nozzle increases the bottom kerf. Kinetic energy of the jet increases due to the smaller nozzle diameter and it reaches the bottom surface without any loss of energy. Increasing of particle size caused increase in the bottom kerf. The bottom kerf value obtained was maximum. The results of fabricated graphite filed bidirectional glass fabric reinforced with bisphenol epoxy resin [27] show the pressure, standoff distance as significantly affecting the top kerf width. Results also showed a maximum top kerf of 1.176 mm and a bottom kerf of 1.55 mm obtained. Bidirectional plain weave type glass fibers reinforced polymer composites machined [28] using abrasive slurry jet leads to the conclusion that the top kerf width increased with increase in SOD and kerf width increase with increasing size of abrasive particle and standoff distance.

The increasing in pressure will increase the top kerf. When the SOD is minimum, wider top kerf was obtained in the machining of GFRP composites. Decrease the size of the nozzle diameter would reduce the top kerf. The significance of abrasive particle size on top kerf. Increase in the size of abrasive particle was seen leading to greater top kerf. This is due to the increase in the jet of particle with maximum mesh size coming out from the nozzle causing increase in the spread and also the removal of the top surface effectively as a result of the kinetic energy of the particle. When the abrasive particle size decreases, the top kerf is also decreased. From this investigation it was noticed that pressure would be the significant parameter affecting the bottom and top kerf. Figure 8 (a & b) explains the effect of pressure on bottom and top kerf.
CONCLUSIONS
To determine the relationship between process parameters and material removal rate, bottom kerf and top kerf characteristics in abrasive jet machining process, an artificial neural network were carried out based on Taguchi’s L9 orthogonal array. Comparisons were made of the above approaches, after testing their performances on randomly selected test cases. The machined surfaces were also the predicted process parameters on validation were found to be close correlation with the actual performance results. However, the experimental results showed a better performance compared to the ANN model. From this, the predictive models can be used for predicting MRR, top kerf and bottom kerf in AJM with a higher reliability. Abrasive jet pressure and stand-off distance were great effective on MRR.

REFERENCES


